FIRM SIZE INEQUALITY: INDUSTRY DYNAMICS, ENTREPRENEURSHIP AND WELFARE

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Elmar Puntaier

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Elmar Puntaier

Abstract

This thesis analyses the dynamics and determinants of the size distribution of firms and examines its implications on welfare. It draws on Schumacher's proposition of a 'balanced' size distribution of firms as a precondition for sustainable economic development, which conflicts with models predicting an increase in firm size inequality in the long run. For the said dynamism to be understood, the historical development from the First Industrial Revolution is reproduced and emerging patterns set in relation to the evolutionary approach to economic development. This leads to the central argument of this thesis, which is the need for a fair share of medium-sized firms in order to maximise innovative capacity, economic resilience, net job creation and sustainability. To identify the forces driving firm size inequality and the extent to which rebalancing is possible, this thesis consolidates the streams Gibrat's Law initiated.

The industry-level analysis of the UK, Italy and Germany from 2001 to 2010 demonstrates that the size distribution of firms converges to a lognormal distribution. For technology-rich firms, firm size inequality is inversely U-shaped and the systemic erosion of diversity reduces the options to rebalance. In service industries, industry dynamics are more intense and cause a faster increase in firm size inequality. The resulting co-existence of small and large firms reduces spill-over effects and the ability to recover from macro-economic shocks, but these, paradoxically, increase firm size inequality. To delay the process of increasing firm size inequality, small and medium-sized firms need to engage with export activities and accumulate intangible assets. As the owner-managed firm commercialises on uncertainty and the large firm escapes from it, preserving the 'middle' is rewarded with a higher degree of innovative capacity and contributes to sustainable growth. There are also windows of opportunity where rebalancing is possible and from these openings new industries emerge.

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List of abbreviations

ANS	Adjusted net savings
AR	Autoregressive (disturbances)
CR4	Concentration ratio of the four largest firms
CR8	Concentration ratio of the eight largest firms
EC	European Commission
EPO	European Patent Office
EU	European Union
FDI	Foreign direct investment
FE	Fixed effects
FGLS	Feasible generalised least squares
FSI	Firm size inequality
G	Gini-coefficient
GDP	Gross domestic product
GLS	Generalised least squares
HHI	Herfindahl-Hirschman Index
ICT	Information and communications technology
IP	Intellectual property
IRC	Industrial Reorganisation Corporation
LPE	Law of proportionate effect
MES	Minimum efficient scale
MNE	Multinational enterprises
NACE Rev. 2	Statistical industrial classification of economic activities (EC 2008)
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary least squares
R&D	Research and development
RE	Random effects
RQ	Research question
SDOF	Size distribution of firms
SME	Small and medium-sized enterprises
TMT	Top management team
UK	United Kingdom
US	United States
WLS	Weighted least squares
WWI	World War I
WWII	World War II

CHAPTER 1: INTRODUCTION

> "For his different purposes man needs many different structures, both small ones and large ones, some exclusive and some comprehensive. Yet people find it most difficult to keep two seemingly opposite necessities of truth in their minds at the same time. They always tend to clamour for a final solution, as if in actual life there could ever be a final solution other than death. For constructive work, the principle task is always the restoration of some kind of balance."
>
> (Schumacher 1973:59-60)

This thesis explores what Schumacher's (1973) concept of 'balance' might be regarding the economy's structure in terms of firm size and how the said balance can be maintained. Before turning to the historical developments that led to the contemporary industrial landscape and which gives an indication of the consequences of imbalances in the size distribution of firms (SDOF), the following sections deal with firm size inequality (FSI) and diversity. The first part, *Context and motivation*, introduces the rationale behind this research and refers to the dominating perspectives in explaining firm size and industry dynamics. Of particular interest are the perspectives of the classic, neo-classic and evolutionary economists that were all built on welfare maximisation, but with contradictory logical reasoning. It becomes evident that a reference to the 'middle', which refers to small and medium-sized enterprises (SMEs[1]), is weak and hard to capture. The subsequent section on research objectives outlines the purpose of this thesis and the approach taken in order to provide a conclusive answer to the dynamics, determinants and consequences of FSI. This then leads to the contributions at theoretical, empirical and methodological level, followed by the chapter structure with a concise summary of the issues discussed in each chapter.

[1] SMEs are defined in accordance with the European Commission (2003): micro firms (<10 employees), *small firms* (10-49 employees), *medium firms* (50-249 employees) and large firms (≥250 employees)

1.1 Context and motivation

The idea that there should be a 'balance' in terms of firms of differing sizes within an economy is one that has received short thrift over the years. For such a balance to be achieved demands a fair proportion of SMEs, who account for two thirds of employment and 58% of value added in the EU27 (European Commission 2013). Such a notion was of little importance to the classical economic writers and this was influenced by the dominating structures of their time. Yet Adam Smith, David Ricardo and Karl Marx showed awareness of firm size and industry dynamics with a "center of gravity" emerging from market forces (Mazzucato 2000:3). This builds the foundation of the SDOF as the product of either individual action (Ricardo 1951; Smith 1776) or the efficiency at which assets are accumulated (Marx 1887). Said dynamism imposes by definition restrictions to economic activity and vanishes with the birth of monopolistic market structures. Since the latter does not serve the common good (Smith 1776), welfare maximisation demands competition. It brought about the industrial revolutions (Lagerlöf 2014) and forces firms to expand in scale and scope, which has led to Reich's (2009) *Supercapitalism*. He refers to the ever-growing multinational enterprises (MNEs), which throughout the post-war period were seen as the drivers of economic prosperity of a modern society (Henrekson and Johansson 1999; Lucas 1978) and the symbols of superiority for Western democracy.

Large firms have been transformed into 'cultural objects' (Clegg 1990) and associated with a greater potential in achieving technological change and progress (Arrow 2000; Drucker 1985; Schumpeter 1947). Neo-classic economics cemented the belief that the cost advantage defined by the U-shaped cost curve is best achieved by the large scale firm and hence ensures increasing living standards (Mazzucato 2000). Its efficiency in accumulating knowledge (Rossi-Hansberg and Wright 2007) and attracting talents for professionally managed specialist departments (Lucas 1978) does not suggest that smaller firms are able to come anywhere close to the scale of the established multinational in the field. Simon and Bonini's (1958) model describing the SDOF indeed suggests a static pattern consisting exclusively of firms operating above the minimum efficient scale (MES). Consistent with Hart and Prais' (1956) analysis of market concentration patterns, firm growth results independent from firm size. This corresponds to the proposition put forward by Gibrat (1931) when searching for statistical regularities of populations.

Although Gibrat's Law means that relative firm growth is equally distributed across firms different in size, changes in absolute numbers cause an increase in FSI. Lucas (1978) and Rossi-Hansberg and Wright (2007) attribute it to economic development, because it leads to an increasing share of large firms. For Lucas (1978) individuals' preference to work for an existing firm is stronger than running their own firm and Rossi-Hansberg and Wright (2007) forecast increasing specialisation. This is equivalent to the pattern Das and Pant (2006) describe as the 'missing middle': a decline in the number of medium-sized firms until they are statistically insignificant. Both classic and neo-classic economics treat medium-sized firms as transitional, because in the long run average firm size within a given industry can only increase. It does so until declining profit margins enforce stagnation and diversification into new industries, which makes any firms of a smaller scale redundant as they are deemed inefficient. And yet since the 1980s it is increasingly the small firm that is associated with flexibility and expected to generate the growth that Europe is desperately waiting for. It is this shift from one extreme to the other that Schumacher (1973) anticipated.

To explain the sudden interest in small firms, we nonetheless need a logic other than the neo-classical rationale. The competitive advantage and dynamism the small firm is believed to produce rests on Schumpeter's (1947) 'creative destruction' and the paradigm shift towards evolutionary economics (Mazzucato 2000). Just like Mises (1951), Schumpeter (1947) needed the entrepreneur to explain technological progress and economic development endowed with the potential to alter existing structures. Since neo-classic economics omits the entrepreneur, the consequences of evolutionary patterns have remained in the shadows. Neo-classics' concern is the equilibrium resulting from quantifiable dimensions and not the forces driving dynamism. This fundamentally differs from the evolutionary perspective to which Gort and Klepper's (1982) industry life-cycle theory and Jovanovic's (1982) 'noisy selection' belong. Equally omitted is the historical dimension that influenced the classics. As Fine and Saad-Filho (2004:5) put it, "social phenomena exist, and can be understood, only in their historical context." Accordingly, the factors causing changes in FSI are as important as the change itself and the resulting consequences, but it still leaves the relevance of the 'middle' unanswered.

As for any other region, structural change in Europe cannot occur without acknowledging its path-dependency and the contribution of the entrepreneur. After the marginalisation of the Ricardian comparative advantage in the late 1990s due to intensifying globalisation, Audretsch and Thurik (2000) see the transition to the knowledge economy as the only viable alternative to lower wages or higher unemployment rates. For Europe, it is an opportunity to regain a competitive position by replacing tangible assets with knowledge and allowing entrepreneurs to escape from scale and scope. But in Europe the entrepreneurial element is still weak. In a political union, where on average more than 90% of all firms employ less than 10 people (Statistical Office of the European Communities 2011), the young and well-educated seek employment in established firms (Blanchflower 2008; Storey 1994) and the dominating legal framework is hazardous to entrepreneurial activity (Audretsch and Feldman 1999), simply encouraging start-up activity is unlikely to succeed. There might be outperformers (Picot and Dupuy 1998) that, from a utilitarian perspective, justify this approach, but it is barely efficient in facilitating the transition to the knowledge economy. Where a lack of employment opportunities encourages self-employment, said economic activities are not entrepreneurial, but it is exactly this which Lenihan *et al*. (2010a) see as the precondition to return to sustainable growth.

For structural change to occur, mere opportunity recognition is not enough. It requires agents in possession of the skills and resources to seize opportunities, whose function Drucker (1985:132) attributes to existing firms: "It is the existing business – and the fair-sized rather than the small one – that has the best capability for entrepreneurial leadership." Having already achieved a competitive position in the market place, SMEs are a safer bet than any inexperienced first-time entrepreneur. Survival rates of spinoffs from successful firms may be higher when run by experienced minds, familiar with existing structures and markets. And yet it remains a paradox to expect economic growth from a firm-size class unable to spread the risk as effectively as the multinational and is subject to systemic erosion. Intensifying macro-environmental uncertainty does not favour small structures nor does the European multi-cultural milieu condition firm growth when compared to the United States (US). In a globalised and technologically intensive world, firm size matters and so too does the SDOF. To respond to the demands of contemporary Europe, diversity in firm size becomes a precondition and draws back to Schumacher’s (1973) assumption with inevitable implications on welfare.

So far, little thought has been given to the possibility that SMEs could become restricted in their mobility across firm-size classes and that the share of medium-sized firms could shrink to a negligible percentage. SMEs’ image is one of a transitional stage that sooner or later dissolves. This implies systemic forces being reflected in the SDOF and questions the ability of the entrepreneur in breaking out from the forces acting upon him/her. The question that arises is to what extent rebalancing is possible once market forces have produced structures that are incompatible with sustainable economic development. At odds with the majority of existing literature on firm growth and industry dynamics, this thesis focusses on FSI, because it represents the diversity Schumacher (1973) referred to. Such diversity cannot be maintained without focussing on the contribution of *all* firms and the SDOF as a whole. Nor can a balance be restored without acknowledging the structural information the SDOF carries. By being the product of market forces, it defines the degree of FSI and reflects the growth pattern of firm-size classes. These appear to be influenced by both random and systemic forces. Knowing their effect allows policies to be put in place that go beyond a general push of entrepreneurial activity and the mere provision of growth incentives for firms belonging to the lower end of the SDOF. Focussing on FSI means promoting an approach to industrial policy that minimises the waste of resources and maximises welfare. This makes it worthwhile to enquire into the FSI's determinants and consequences.

1.2 Research objectives and contribution

This thesis has been inspired by Lucas' (1978) prediction that FSI continues to increase as economic development progresses and hence is in conflict with both Schumacher's (1973) call for a 'balance' and Schumpeter's (1947) 'creative destruction'. In particular, it considers whether extreme constellations of firms different in size are inferior when compared to a moderate SDOF. With regard to this thesis, such inferiority refers to innovative capacity, economic resilience, net job creation and sustainability, which all have implications on welfare. Accordingly, the aim of this work is to link the SDOF to welfare and to identify the forces that determine the degree of FSI. Whereas the SDOF is the phenomenon under investigation, FSI is the measure resulting thereof. The conversion of the SDOF to its operationalised equivalent permits to describe and determine the dynamics of the SDOF. Said dynamism refers to the change in the distribution over time and stems from forces internal and external to firms and industries. Should Lucas (1978) be right, systemic forces homogenise structures regardless of the initial setting: first at industry level and eventually at economy level with potentially negative implications on welfare.

To analyse the determinants and consequences of FSI, the discourse of the subsequent chapters is guided by three research questions (RQs). First, the validation of industrial dynamism in the European context, i.e. to what extent has the SDOF changed? Second, what are the determinants of such change? And third, what are the implications on welfare?

The previous section revealed that industry dynamics are complicated, and multiple perspectives are required to understand the relationship between industry dynamics and welfare. The perspectives taken to explore this relationship are of historical, theoretical and empirical nature and either alternative or complementary. The historical view identifies the sources that have led to the industrial revolutions and the structures emerging thereof. It further assists in explaining the structural change variations in macro-economic conditions and ideologies produced. As imbalances in the SDOF arise from a systemic bias favouring the expansion of a specific firm-size class, the entrepreneur becomes an important source of change. Hence, much of the theoretical discussion is devoted to the entrepreneur's function and contribution to society. This is followed by literature on the SDOF, FSI and firm growth, which all build on Gibrat's Law, but with little reference to any theoretical foundation.

On the basis of the described perspectives, this thesis merges theories of entrepreneurship with the literature on industry dynamics and firm growth, and consolidates the streams Gibrat's Law produced. The empirical part then analyses the dynamics and determinants of FSI. It identifies the circumstances under which SMEs are able to compete and hence permits delaying the emergence of the missing middle. The underlying econometric model is country-specific and includes a combination of industry and firm-specific parameters applicable to all firm-size classes. It is applied to a sample of non-financial firms from the UK, Italy and Germany, and is extended to the EU27 countries when linking FSI with welfare.

Particular attention is paid to the contribution of medium-sized firms individually and in combination with large firms. Since Schumacher (1973) and Stiglitz *et al*. (2010) question the use of gross domestic product (GDP) as a universal measure for welfare, alternative measures with indirect implications on society are used. As indicated earlier, these are innovative capacity, economic resilience, net job creation and sustainability. While innovative capacity reflects future prospects and the potential of new industries to emerge, economic resilience shows an economy's ability to recover from macro-economic shocks, which are by definition unpredictable. Closely linked to firm growth, but with stronger implications at individual level, are net job creation and sustainability, which too are expected to be influenced by the SDOF.

Beyond the consolidation of competing approaches in identifying patterns of firm growth, this work takes a different perspective and contributes to the theoretical, empirical and methodological discourse. Theoretical and empirical research on the SDOF has become sophisticated and in many cases limited to the description of the underlying distribution. Only a few adopt a holistic view and pay attention to its dynamics and the underlying firm population implied by Schumacher (1973) and as noted by Gil (2010). The complexity of the subject also leads to the implication of one or another distribution for the wider society being rarely discussed. Restrictions in samples to one firm-size class, preferably large public listed firms, add further limitations to the generalisability. In contrast, entrepreneurship literature is mainly engaged with the determinants of business demographics, success and net job creation, but frequently isolated from industry-dynamics and macro-economic forces. Equally, studies taking such factors into account do not distinguish the entrepreneurial from the managerial firm.

Following Adelman's (1958) advice, it seemed more reasonable to take a step back and replace complexity with simplicity by focussing on FSI as the variable of primary interest. It is far from perfect and opens the door to criticism, but it is a viable starting point for the consideration of a holistic approach. It permits a link between entrepreneurship with economic development and questions the value of the small independent firm, which may or may not be an inefficient unit and whose economic activity could be integrated in a more efficient way. It too investigates the contribution of specific firm-size classes to welfare and how this can be influenced. These questions have previously been poorly addressed and the small business sector in particular is either prone to glorification or condemnation. The answer to a single question can only be given with the whole in mind, but when the single matters, the whole matters too.

The findings do not fail in providing a more comprehensive understanding of the forces affecting the selection of firms as industries move towards a natural stage. The latter is the statistical distribution that becomes apparent when industries mature and eventually consolidate. Just like raindrop sizes form a lognormal distribution (Maitra and Gibbins 1999), the natural stage of an industry too can be described by the said distribution when measured by firm size. Its byproduct is the missing middle and it is responsible for inefficiencies of industrial policies, which, according to Buigues and Sekkat (2009), have been used as a general approach to encourage growth for a long time. The selected sample countries, each with distinct characteristics allow conclusions to be drawn about the overall pattern. Putting the influential parameters into the national context, it is possible to give a fairly accurate direction for an industrial policy that prolongs and strengthens the share of SMEs by achieving a more sustainable combination of firm-size classes. Given the significant impact of FSI on welfare, the implications of industrial policy – including inaction – are heavier than so far believed. Apart from the meaningful link of FSI and productivity output promoted by Pagano and Schivardi (2003), FSI turns out to be a feasible indicator to judge the potential of spill-over effects and technology gaps.

Methodologically, the empirical findings of most preceding studies are based on samples of manufacturing firms, which in advanced economies account for a relatively small proportion of GDP, and only a few include service firms. The use of FSI as a dependent variable facilitates the analysis of industry dynamics across all firm-size classes and a wide range of seemingly unrelated industries. It satisfies the industry-level condition imposed by Dinlersoz and MacDonald (2009), Pagano and Schivardi (2003) and Teruel-Carrizosa (2010a) and takes crucial industry-specific factors into account, which for Gibrat's Law models remain systemically excluded (Kessides and Tang 2010). The single country approach confirms the strong influence of country-specific peculiarities, but maintains the statistical comparability requested by Gil (2010). The adopted holistic view does not come without a trade-off between detailed firm-level and more general industry-level analyses. Yet the selected approach brings the debate on FSI closer to country-specific patterns, which Santarelli (2006a) sees as essential for promising industrial policy. What might be an appropriate policy is ultimately for others to decide – this thesis sheds light on the importance of a balance in the economy.

1.3 Organisation of chapters

To analyse the determinants and consequences of FSI, the thesis is organised into the following chapters:

Chapter 2, *Industries, entrepreneurship and society,* covers industry dynamics, entrepreneurship and societal aspects in connection to firm size and FSI. The first part, *Evolving industries*, takes a historical stance and outlines relevant developments in European industrial history. It draws on the initiators of the industrial revolutions and introduces the patterns of industry life-cycle theories. It then continues with the structural changes during the interwar and post-war years, followed by a discussion on the end of Fordism, succeeded by a new wave of globalisation as exchanging information becomes more efficient. The second part, *Entrepreneurship, small firms and firm size inequality*, examines the role of the entrepreneur as the agent of change from a theoretical perspective with particular attention to the Austrian School discourse. The third part, *Firm size inequality and welfare*, opens with a definition of well-being and attempts to narrow the wide range of factors with implications on welfare. In contrast to the foregoing sections, which focus on industries from a historical perspective and on entrepreneurship from a theoretical viewpoint, the discussion on the implications of FSI on welfare is largely based on empirical evidence. It includes aspects affecting welfare in both the short and long term, and refers in particular to innovative capacity, economic resilience and net job creation with a link to sustainability.

Chapter 3, *Structural change, firm size inequality and firm growth*, then considers the empirical work in the field of the SDOF and FSI, where firm growth plays an essential role. It opens with a debate on structural change through entrepreneurship and knowledge and discusses to what extent encouraging start-up activity is efficient in rebalancing the SDOF. As it becomes evident that a single-sided focus on the SDOF is insufficient, the research on *The size distribution of firms and firm size inequality* is scrutinised. The section is both theoretical and empirical, with the level of analysis occurring at both economy and industry level. Even more empirical is the work presented on FSI. Since both streams are overshadowed by the debate on the validity of Gibrat's Law, the next section is devoted to firm growth and its determinants. Accordingly, the chapter moves from economy to industry and from there to firm level with the latter aiming to identify key factors that may affect the degree of FSI of any given industry.

Chapter 4, *Methodology*, presents the methodological choices made to address the research questions that result from the preceding discussion. It begins with the description and justification of samples and data sources chosen and a commentary on sources of bias. It then continues with the proxies used to determine FSI and the proposed method to analyse the dynamism of the SDOF. To identify the determinants of FSI, model development and choice of estimator are presented and lead to the empirical regression model to estimate the significance of the predetermined factors. The last part is devoted to the implications on welfare, consisting of four regression models and a dynamic firm-size class analysis.

Chapter 5, *Analysis*, shows the empirical findings of the dynamism of the size distribution and the determinants of FSI. The first part consists of the analysis of changes across industries and firm-size classes, complemented by a distribution property analysis. Its final section covers the changes in FSI, which parameter enters as dependent variable in the regression analysis of the second part. The latter verifies the significance of the parameters suggested by the literature review and concludes with a reduced model comprising the determinants of FSI. Where applicable, the findings are linked with previous studies to comment on consistencies and inconsistencies.

Chapter 6, *Implications*, continues with the empirical analysis, but directs the focus to welfare and is followed by the discussion. The analysis refers to the findings of the selected welfare dimensions, where FSI now becomes the cause and not the consequence, which is the focus of the previous chapter. Although subject to simplification, it gives an indication of the contribution SMEs add to welfare; an argument that is explored in more detail in the subsequent discussion. It recaptures the relevance of FSI with an attempt to incorporate the theoretical elements discussed in Chapter 2. It sets the basis for general policy implications, grounded in the national and historical context.

Chapter 7, *Conclusions*, summarises the key issues and findings in the form of a generalised pattern as has become observable from the empirical analysis and the explanations provided by the theoretical foundations. It restates the contributions to knowledge, reflects on limitations and gives directions for future research.

Tables of variable definitions, firm-size class shares and regression estimates of the empirical analysis can be found in the appendix.

CHAPTER 2: INDUSTRIES, ENTREPRENEURSHIP, SOCIETY

2.1 Evolving Industries

The following sections outline the dynamics of Europe's industrial landscape by synthesising its history back to the eve of the First Industrial Revolution. To contextualise the relevance of firm size and the resulting SDOF in connection with welfare throughout the epochs, a macro perspective is adopted. The cornerstones of the consulted literature are the historical elaborations provided by Bruland and Mowery (2009) with regard to the three industrial revolutions; by Pinder (1998) with regard to Europe's East-West divide throughout the post-war period; and by Buigues and Sekkat (2009) and the collected works presented by Blackburn and Schaper (2012) with regard to industrial policy. Given the presence of regional heterogeneity in a number of aspects throughout the decades, the focus is directed towards the United Kingdom (UK), Germany and Italy, which will become part of the empirical analysis. This does not exclude the consideration of developments in other countries – most notably in the US – as these fits with the context.

Equally, legal, financial and ideological belief systems have influenced tendencies towards specific firm-size classes, entrepreneurial spirit and innovative capacity. The status quo cannot be explained without these dimensions, but it would go beyond the scope of this work to thematically and geographically explore all facets Europe has at its disposition. The reported events and developments represent central aspects to assist in understanding the cause-effect relationship, but are by no means exhaustive. It is important to emphasise this point, because country-specific dynamics and peculiarities are crucial elements in determining the path each economy pursues. Ignoring these aspects would indeed exemplify an act of negligence as it would inevitably lead to misinterpretations and biased generalisations. Hence, the aim of the section is to outline the dynamics in industrialism that Europe has experienced since the industrial revolutions; these, in conjunction with the findings derived from the empirical analysis, will build the quintessence for a contextualised discussion of implications for the countries under scrutiny.

2.1.1 Merits of industrial revolutions

When *The Economist* published its second 2013 issue on 12th January, *The Thinker* covered the front page. It appears as if Europe has not experienced an innovation that has dramatically increased standards of living since indoor plumbing became available to the ordinary citizen at the end of the nineteenth century. During this time the internal combustion engine and electricity also contributed to a wave of pioneering equipment for domestic and industrial use (Gordon 2012). The period was introduced by Bruland and Mowery (2009) and Gordon (2012) as the Second Industrial Revolution. With its zenith from 1870 to 1900 it revitalised economic prosperity as momentum from the First Industrial Revolution (1750-1830) was fading out. The production and operation of textile machinery, steam engines and railways – brought to life by the First Industrial Revolution – established the foundation of the managed large scale firm (Bruland and Mowery 2009; Marshall 1898). Until then, personally liable owner-managed micro firms dominated and remained unchanged until the limited liability company was introduced in the midsummer of the nineteenth century and financial markets began to expand (Bruland and Mowery 2009). The demand for large scale projects favoured structures able to accumulate competences. It reversed the process of outsourcing and contracting (Marshall 1898), but the large firm was complementary rather than contradictory to the existence of micro firms. The concentration of assets became possible and allowed investments that could not be shouldered by the small firm.

The expansion of fast growing firms led to structured management systems with centralised corporate power and laboratories to systemically carry out research, which substituted the innovator who drove the beginnings of the First Industrial Revolution (Bruland and Mowery 2009). Supplying and processing raw materials was replaced with more knowledge intensive activities such as, for instance, the production of chemical and electrical goods (Bruland and Mowery 2009). A generously funded German higher education system supplied a stream of researchers and engineers (Brown and Mason 2012; Freeman cited in Andreosso and Jacobson 2005), who were ultimately incorporated into management positions and by nature linked science with application (Brown and Mason 2012). Accordingly, the innovative power shifted from Britain to central Europe (*ibid*.) and led to Germany's *Gründerzeit*, where many of today's leading firms were founded (Vasagar 2014). But the geographic redistribution of innovative capacity was not just the product of more innovative individuals and superior organisations. The delayed development of the manufacturing industry in continental Europe allowed firms to learn from England's mistakes (Marshall 1898) and to efficiently catch up.

Both the First and Second Industrial Revolutions supplied a stream of new production technologies, leading to new products, industries and markets at an unprecedented international scale. It led to the emergence of the large scale firm, willing to engage with scientific approaches to knowledge generation and by doing so, it replaced the owner-manager and innovator. The function of the latter was in many cases reduced to the provision of new input and incumbent firms soon developed capabilities to systemically monitor and carry forward new developments upon which to commercialise (Bruland and Mowery 2009). As knowledge intensity increased, the contribution of the intuitive approach to innovation declined and the systemic research department could progress on the basis of existing innovations. It required some 150 years to exploit the advancements the First Industrial Revolution brought about and some 100 years to maximise the utility of those of the Second Industrial Revolution (Gordon 2012). Emerging spinoffs, i.e. innovations derived from mainstream technologies, which lie in the nature of each innovation (Audretsch and Feldman 1999), contributed to the process of technology dissemination. It led in itself to a stream of newly founded firms and sub-industries, which are by their nature risk takers and ultimately contribute to the development at aggregate level.

In Gordon's (2012) view, the innovations the two industrial revolutions supplied have contributed most to the present day's living standard, resulting in a sharp increase in life expectancy levels. Governments recognised the value of innovations and to keep the machinery rolling, patent rights were strengthened (Mowery cited in Bruland and Mowery 2009). Rewarding the innovator by enabling the protection of intellectual property (IP) had positive effects, but also consolidated the market position of incumbent firms with restrictive implications for less affluent individuals and firms. FSI increased (Hart and Prais 1956) and in the absence of radical change, existing structures were preserved (Audretsch and Feldman 1999). In combination with stable macro-economic conditions and modest state intervention, it allowed growing firms to benefit from these developments and to spread the business risk by adopting product and geographic diversification strategies; a process that began in the late nineteenth century (Bruland and Mowery 2009). The consequence was an increase in average firm size and MES, which acts as an efficient entry deterrent for new firms (Audretsch and Feldman 1999). The logical consequence is an increasing market concentration and marginal product improvement at the cost of disruptive innovations in both frequency and speed.

2.1.2 Interwar and post-war years

The stable macro-economic conditions of the pre-war period promoted confidence for investment in large scale projects, but this was shattered by the outbreak of World War II (WWII). A disruption of international trade followed, giving way to a mild form of the scenario the continent experienced during World War I (WWI), when disproportionate reallocations of resources to war-related industries induced a structural change (Pinder 1998). An exception was German's chemical industry, which outperformed Britain, France and even the US until WWII (Bruland and Mowery 2009). Its scale and reliance on scientific expertise transformed it to an ambitious driver of systemic research and development (R&D) (Bruland and Mowery 2009) and its attractiveness for the defence industry ensured public procurement (Pinder 1998). It too explains Germany's continued interventionism, however Italy also managed to take control over critical large scale firms (Andreosso and Jacobson 2005) and eventually led to a decline in productivity growth (Giordano and Giugliano 2014). The UK was among the few countries to limit the role of the state to basic framework conditions (Walker cited in Andreosso and Jacobson 2005), but it could not halt the US and Japan in accessing foreign markets and outperforming Europe, which had negative implications for welfare (Pinder 1998). With the increasing demand for petroleum and related products, the US introduced new manufacturing processes able to cope with large volumes and its MNEs continued to benefit from technology accumulation (Bruland and Mowery 2009; Carree *et al*. 2002). At the expense of flexibility, efficiency levels could be increased and a new scale of the large enterprise with a global presence was born.

Europe, separated by the Iron Curtain into East and West, underwent a structural change after WWII. East Europe sympathised with socialism and associated smallness with diseconomies (Pinder 1998). Its early success questioned West Europe's social market approach – a by-product of the Anglo-Saxon model – but its unsustainability soon became apparent (Pinder 1998; Yergin and Stanislaw 2002). East Europe's preference for employment over productivity to ensure political stability contributed to the persistence of the centrally planned large scale firm (Pinder 1998). As a consequence of the Cold War, priority was given to the defence industry and undermined technological development in non-defence industries and infrastructure (Pinder 1998). According to Maciejewicz and Monkiewicz (cited in Pinder 1998), it was the lack of consumer orientation in general and the absence of spinoffs from the defence sector in particular that impeded the emergence of an efficient service sector.

In West Europe, the defence related manufacturing industry, especially in Germany, was scaled back. However, not to the extent initially planned, as it would have resulted in disproportionate economic backwardness with a lack of alternatives (Gareau 1961). This enabled the transition to a consumer market driven economy, built on the application and transformation of technologies by surviving pre-war structures. The latter was characteristic for Italy, where monopolies existed even longer than in Germany (Rossi and Toniolo cited in

Boltho 2013). It allowed firms in Germany and Italy to catch up with technology leaders in the US and Japan (Audretsch and Feldman 1999; Boltho 2013). As restructuring and the catching up process was less intense in the UK, the desire to establish large scale firms to increase efficiency was particularly strong and was achieved by nationalising and agglomerating key industries (Booth 1995). Stable macro-economic conditions favoured the rapid dissemination of adopted radical innovations until the competitive position of the pre-war era was restored (Audretsch and Feldman 1999). By focussing on technological advancement and productivity rather than unemployment targets, and consumer goods rather than sustaining a politically motivated defence sector, Western Europe experienced a rapid economic recovery (Pinder 1998). It was able to exploit accessible technologies to its maximum by continuing to support its large scale factories.

In the 1950s and 1960s, Britain celebrated its “golden age of the welfare state”, France experienced its ‘thirty glorious years’ (*Les Trente Glorieuses)* and Germany’s economic miracle (*Wirtschaftswunder*) led to new levels of prosperity (Yergin and Stanislaw 2002:26) produced by its SMEs (*Mittelstand*). Italy too experienced an exceptional recovery (Andreosso and Jacobson 2005) accompanied by a rapid urbanisation (*ibid*.; Signorini and Visco cited Boltho 2013). Its industrial districts, most of them located in its north – typically consisting of family owned SMEs – specialised in manufacturing and substantially contributed to national economic growth and regional development by creating supplier structures and leveraging employment in both service and manufacturing (Carree *et al*. 2002; Santarelli 2006b). As stated by Yergin and Stanislaw (2002:26), “[b]y 1955, all the Western European countries had exceeded their pre-war levels of production” and in the late 1960s unemployment declined to almost negligible levels.

The possibilities and spinoffs from oil-related activities demonstrated the potential the Second Industrial Revolution unfolded and the expansionary strategy the chemical industry pursued. The opportunities that new materials and processing techniques offered gave a kick start to new industries and niches that did not previously exist. To manage the increasing complexity and specialisation of the 1950s, management as a discipline was introduced (Booth 1995). US companies – the first to implement professional managers – were admired and "viewed as a conduit for bringing modern management techniques to the British economy" (Dunning cited in Brown and Mason 2012:20). Europe's ambition to regain a foothold on foreign markets initiated a transition from personally owned and managed firms to manager-led firms (Chandler 1990). By doing so, continuous growth was achieved through accumulation and maintenance of organisational capabilities, which "provided an underlying dynamic in the development of modern industrial capitalism" and eventually shaped national economies (Chandler 1990:593). The merger wave of the 1960s led to a decline in the number of small businesses across industries of most member countries of the Organisation for Economic Co-operation and Development (OECD) (Carree *et al*. 2002). This resulted in the belief that large scale firms, particularly those in the manufacturing industry, are most capable and efficient at achieving prosperity, because their average unit cost is lowest. It led to the assumption that firm sizes can be homogeneous – at least within industries (Viner 1932) –, which is itself not different from the East European approach.

However, to regain its competitive position, West Europe's structures differed from East Europe's in four ways. First, it rebalanced its unsustainable economic activity from defence-related manufacturing to consumer goods. This enabled it to commercialise on active R&D and allowed the return to national and international trade. Second, its surviving pre-war structures efficiently absorbed the technological advancements achieved by its international rivals and were in a position to invest accordingly. Meanwhile, being professionally managed, the resource allocation can be assumed to be more efficient than East Europe's centralised planning system. Third, private and public investment in new technologies and infrastructure contributed to the formation of supplier and service structures built on opportunities rather than necessity. Fourth, the Second Industrial Revolution provided opportunities to exploit existing expertise and explore new fields, which eventually led to new industries. Most importantly, the emerging service sector allowed entrepreneurial activity on a smaller scale.

Ideology, macro-economic conditions and industry all define a theoretical optimal firm size. Although both East and West Europe much favoured large firms, East Europe's focus on employment and geographically bound socialist ideals imposed a homogeneous limit to firm size with no real need for spinoffs or complementary sectors. Its existing small business sector co-existed with large scale firms and was run by individuals who did so because it was a better alternative to unemployment (Pinder 1998). This suggests extreme FSI with negligible interactions taking place between these two firm-size classes. Western firms were instead driven by an expansionary force that required the enlargement of market share. Foreign markets provided an additional opportunity to grow, which impacted upon the firms' periphery. It demanded an infrastructure – itself an emerging industry – and contributed to spill-overs and spinoffs with positive effects on welfare.

2.1.3 The end of Fordism

Euphoria associated with post-war recovery, overconfidence in the established market system (Pinder 1998), the glorification of large scale enterprises (Andreosso and Jacobson 2005; Booth 1995) and rising trade union power led to an increasingly asset-rich manufacturing industry (Pinder 1998). The return of stable macro-economic conditions, professionalised sales departments and steady demand encouraged competition for technology and Fordist-style mass production. Over-excited by the technological possibilities automated manufacturing processes offered, firms in maturing industries suddenly experienced the limits set by tangible assets on the one side and raising labour costs on the other. The oil crises in 1973-74 and 1979-80 (Odell cited in Pinder 1998) increased production costs and reduced international competitiveness (Pinder 1998). Large firms were simply unable to respond to changes in consumer behaviour and the shift towards individualism was in favour of the more flexible, but weakly represented smaller firms (Carree *et al*. 2002; Voulgaris *et al*. 2005). As technology intensive industries were hit most (Wells and Rowlinson cited in Pinder 1998) and with the expansionary dynamic service industry (Booth 1995; Pinder 1998) yet unable to buffer the drop in demand, high unemployment rates followed. The oil-shock triggered the end of Fordism (Wells and Rowlinson cited in Pinder 1998), but Europe's structural problems were much more deeply rooted.

At the time when the *Industrial Reorganisation Corporation* (IRC) was established in 1966 with the objective to increase efficiency, Britain had already lost its competitive position (Booth 1995; Press 1971). Like France, it followed a policy that was in favour of size and elitism (Bailey and Driffield 2007; Booth 1995; Klapper *et al*. 2012). It was believed that "the entrepreneur and the small enterprise … were just a remainder from the past and that only large enterprises could supply the needed employment and economic wealth in an economic context dominated by international competition" (Klapper *et al*. 2012:126-127). Despite a general awareness that size alone is not sufficient to restore Britain's competitiveness, *The National Plan* of 1965 (cited in Booth 1995) argued that small firms are unlikely to substantially contribute to technological advancements. On the assumption that concentrated large scale factories are most efficient in maximising the benefits of economies of scale and mergers able to deliver synergy effects, the IRC was expected to co-ordinate these activities and to actively influence resource allocation (Pass 1971). The performance however was unsatisfactory and led to its dissolution in 1971 (Massey and Meegan 1979; *The National Archives* 2014).

A particular problem joining the agenda was the increasing disparity in regional wealth distributions, which until the 1950s had received little attention (Barberis and May 1993). Regional differences are present in all member states of the EU, but even more so in the UK's development areas – mainly located in the South-west, Wales and Scotland – and, above all, in Italy's *Mezzogiorno* as the southern Italian regions are called. England and Italy's North benefited from and capitalised on the developments of the industrial revolutions and as a result were able to catch up, but Britain's development areas remained rural and the *Mezzogiorno* underperformed. While Britain's approach to industrialisation was to encourage firm growth through financial aid (Barberis and May 1993), Italy attempted to invest in infrastructure and basic material industries with some ambition to create medium-tech sectors (Andreosso and Jacobson 2005). The success was moderate and eventually led to the *European Regional Development Fund*, which became operative in 1975 (Barberis and May 1993). It has since grown into the largest fund of the European Cohesion Policy with the objective to minimise these disparities.

In Europe in general and in Germany in particular, regional disparities had a renaissance with the fall of the Berlin Wall. Fears of social unrest motivated Germany to speed up the process of its unification (Boltho 2013), but the economic backwardness the social experiment created was considerable. East Europe's inefficient large scale firms were unable to compete in a free market system and led to mass unemployment with attempts to engage in entrepreneurial activity. Although the latter is a necessary condition to facilitate the transition from central planning to consumer driven markets (Acs 2006), efficiency levels were hampered by "a general lack of entrepreneurial expertise in small firm development" and an inadequate banking system or legal framework to protect property (Pinder 1998:14). Equally absent was a functioning service sector and infrastructure (*ibid*.). As Audretsch and Feldman (1999) report, extensive closures applied also to academic institutions and research centres, where valuable human capital and knowledge was irrevocably destroyed. While differences between East and West Germany have been reduced to a sustainable level, East Europe is still catching up.

Italy's preference for large firms allowed to efficiently organise strikes and to dismantle them, industry policies encouraged the formation of a strong SME sector (Boltho 2013). Political support for the small business sector followed also in the UK with the publication of the *Bolton Report*, whose credibility was supported by the *Wiltshire Report* in Australia and the *Miliaret Report* in France in the early 1970s (Klapper *et al*. 2012). It argued "that SMEs were disadvantaged compared to larger firms and hence some intervention from government was justified", which led to some initiatives and recommendations at national, EU and OECD level (Bennett 2012:186). The wave of privatisation and deindustrialisation of the 1980s led to a growing service sector, especially in England's South, where a global financial centre emerged (Booth 1995). This too weakened Britain's trade union power (Booth 1995; Yergin and Stanislaw

2002). Consistent with its long tradition in attracting foreign investment and multinationals (Dijkstra and Roller 2007), the manufacturing sector relied more than ever on foreign owned or managed firms which were assumed to be equipped with superior management skills and production technologies (Booth 1995).

The U-turn of the declining small business sector in OECD countries from the 1970s was less distinct for Germany, where firm birth rates remained significantly below the norm (Carree *et al*. 2002). The country's prospects were based on the future of an aging *Mittelstand* – according to the *Institut für Mittelstandsforschung*, firms with 500 employees are still regarded as medium-sized firms (Buigues and Sekkat 2009). While the US was able to direct social energy towards a rapidly growing small business sector, experimenting with novel innovations and assisting in absorbing surplus workforce (Drucker 1985), Germany relied on traditional industries and incremental rather than radical innovations (Audretsch and Feldman 1999). Its trade unions were sensitive to wide-ranging implications of their actions and opted for the co-operation of workforce and employers (Boltho 2013; Dore 2000), which put Germany in a good position to access foreign markets. Italy has lost ground on the latter, because its SMEs were unable to facilitate the transition to high-tech industries (Boltho 2013), enforced by limited access to capital (Hall and Oriani 2004). The political crisis it entered in the 1980s slowed down further developments, but it distanced itself from nationalisations and large scale factories, and attempted to incentivise technology-related support (Andreosso and Jacobson 2005). This, however, was with limited success (Arshed and Carter 2012; Bridge and O'Neill 2012), suggestive of substantial imbalances in economic activity, technology intensity and firm size.

The disillusion of endless growth and the possibilities the emerging technologies offered, necessitated reflection of the existing production model. Structures and production systems that were appropriate during the post-war period and enhanced economic development and prosperity were no longer sustainable. The shift towards gigantism and capital intensive assets to increase productivity and escape from trade union power resulted in inflexibility and an inability to quickly respond to major changes. It imposed a threat to international competitiveness and demonstrated that large scale firms do not by definition remove inefficiencies, but increase complexity and organisational inertia. The image of the large scale factory as the universal means to maximise welfare was damaged and brought attention to SMEs. The awareness that firms different in size respond differently to macro-economic conditions was retarded and development areas have benefitted poorly from it as they are characterised by more extreme structures. While the latter is absent in Germany, where medium-sized firms prevent imbalances in the SDOF, it is most extreme in Italy and represents another form of unsustainability.

2.1.4 A new revolution

While Europe initially experienced a rapid post-war recovery and was then confronted with an unsustainable industrial structure and regional disparities, the US systemically developed their comparative advantage in high-tech sectors. The latter was fuelled by the developments in information and communications technology (ICT), which Gordon (2012) interprets as the spring of the Third Industrial Revolution. The ambition of the US to seek technological leadership led to significant increases in R&D expenditure and public procurement with newly established small firms commercialising and disseminating the new technologies (Bruland and Mowery 2009). Weak IP protection until the 1980s produced spill-overs and spinoffs through mobile human capital (Audretsch and Feldman 1999; Bruland and Mowery 2009). A stream of high-performers accelerated the evolution of new industries and firms moved from start-up stage to market leadership at ever faster speed (Audretsch and Feldman 1999). It was the consequence of the marginalisation of the transaction cost of accessing and sharing information as it reduced the importance of firm size and capital. Seizing entrepreneurial opportunities was no longer a function of investments in fixed assets.

In Europe, the scepticism of the conservative elite discouraged entrepreneurial activity. Its rigid labour markets impeded knowledge transfer and although governments grasped the growing importance of telecommunication and SMEs' contribution to sustainable economic growth, they failed to recognise the function of the small business sector (Bruland and Mowery 2009; Pinder 1998). A drop in public support for R&D in the UK (Becker and Pain cited in Buigues and Sekkat 2009), Germany and Italy (Boltho 2013; Buigues and Sekkat 2009) – R&D expenditure in Italy is among the lowest across Europe (Carree *et al*. 2002; Pagano and Schivardi 2003) – reflects the lack of awareness of the closing gap of catching up. The shortage of small businesses in Europe was the result of framework conditions hostile to entrepreneurship (Audretsch and Feldman 1999; Carree *et al*. 2002) and Helmuth Gömbel (cited in Audretsch and Feldman 1999:92) highlights this point: "Put Bill Gates in Europe and it just wouldn't have worked out."

Despite Europe's lost opportunity in producing an internationally competitive high-tech sector by the end of the twentieth century, its market structures were reshaped for two reasons. First, the competition from the small business sector intensified as economic unrest, advancements in technology and globalisation shifted the competitive advantage from size to knowledge (Carree *et al*. 2002). Large firms required extensive reorganisation (Carlsson cited in Carree *et al*. 2002) and initiated a wave of spinoffs that enlarged the share of small firms (Jovanovic cited in Carree *et al*. 2002). Second, progressive development of sophisticated and cost-efficient transatlantic logistic networks, which since WWII had been upgraded in both physical capacity and efficiency (Reich 2009), increased global trade and competition for new markets at an exponential order. Unlike the increase in international trade and capital flows during the post-war period, the maturing information technology transformed the value chain. What started as a radical innovation increased the dynamism within existing structures and permitted the geographic separation of knowledge production from manufacturing (Audretsch and Thurik 2000). The fall of the Iron Curtain opened the gate to exploit these opportunities.

The scope to relocate manufacturing and services from West to East was, however, limited. Eastern Europe's backwardness in advanced manufacturing technologies and its shortage in skilled human capital disqualified the immediate relocation of high-tech manufacturing processes (Carree *et al*. 2002). Geographical proximity and a larger than average firm size of a strong export-oriented manufacturing sector put German firms in a better position than the UK or Italy to commercialise on the situation (Boltho 2013). While Britain increased its service sector with a shift away from manufacturing, Italy's growing share of micro firms was unable to capitalise. Investing in large scale production, plant specialisation or outsourcing administration activities to gain from East Europe's cost advantage remained the privilege of the multinational. When knowledge intensity is weak, entry barriers are limited to tangible assets and by definition lie in favour of the large firm. In the case of Italy, the lack of knowledge intensity and raising competition with low wage countries (Boltho 2013) explains the inefficiencies of its small business sector observed by Carree *et al*. (2002). In contrast, East Europe's development has been a function of the technology imported by foreign-owned firms and makes it dependent on inward investments.

With the inclusion of knowledge, the relevance of tangible assets is reduced and so the importance of firm size. Whether this applies in the long term remains open to discussion, but in the early stage of an industry, firm size is irrelevant. Thus, to replace "the era of the hierarchical industrial firm growing progressively larger through exploiting economies of scale and scope" (Carree *et al*. 2002:271-272), a transition to the knowledge economy has become unavoidable (Audretsch and Thurik 2000). It is the remaining resource that promises countries no longer able to benefit from catching up to become more innovative. The precondition to restore the balance is entrepreneurial activity and a sound small business sector: the "agents of change" (Audretsch and Feldman 1999:88). To achieve this, industrial policy in continental Europe has favoured interventionism and financial aid, while the Anglo-Saxons have preferred consultancy and skill development (Buigues and Sekkat 2009). Although the UK is among the most entrepreneurial European countries, i.e. where engagement in entrepreneurial activity and its social acceptance is highest (Klapper *et al*. 2012), small business policies have shown poor effectiveness (Bridge and O'Neill 2012; Huggins and Williams cited in Arshed and Carter 2012). Said policies are also criticised for their "discontinuity, inconsistency [and] reactiveness" (Bailey and Driffield 2007:191).

The potential of industrial policy, long seen as the "panacea to growth and development problems", builds on existing structures and is unsuccessful when opposed to market forces (Buigues and Sekkat 2009:xvii). The generation of clusters observed in today's Britain (Bailey and Driffield 2007) was Italy's success model of the past. But in the absence of knowledge intensity its advantage was eliminated by new ICT (Santarelli 2006b) and globalisation, which puts Italy in a difficult position and adds to the inefficiency of industrial policies. Unfavourable market conditions as, for instance, the bank-oriented financing system, contribute to an underinvestment (Beck *et al*. 2013) with negative implications on firm growth and innovative capacity. In Germany and the UK, where financial markets are more developed and the share of non-growing micro firms smaller, the potential to absorb and produce knowledge is higher. But Germany's efforts to revive the *Gründerzeit* do not reflect any serious engagement (Audretsch and Thurik 2000; Buigues and Sekkat 2009; Carree *et al*. 2002). Environmental dynamics have demanded structural changes from both Italy and Germany, but these have not occurred to a degree that would give confidence of a prosperous future (Boltho 2013).

In Britain it was the overreliance on the financial sector and large multinationals that created imbalances in diversity. Despite the emergence of a strong service sector, the neo-liberalist ideology from the 1980s onwards initiated a shift away from active SME support. State intervention was regarded as market distortion (Buigues and Sekkat 2009) and the present-day structures are largely shaped by policies focussing on high growth firms (Brown and Mason 2012) and competition (Bailey and Driffield 2007). Consistent with the oil crises, the macro-economic shock in 2008 testified the inflexibility and lack of alternatives that structural imbalances bear. History suggests the existence of windows of opportunity that ease the act of rebalancing, which may be conditioned by a more moderate SDOF. The potential of the Third Industrial Revolution has not yet achieved the dimension of its predecessors (Gordon 2012) and whether it is indeed a revolution can be questioned (Bruland and Mowery 2009), but it revolutionised the manufacturing industry. Ignoring its impact suggests an increase in FSI whenever knowledge intensity is low and tangible assets high and has consequences for welfare.

2.1.5 Conclusions

The First Industrial Revolution set a milestone in the evolution of the SDOF and in economic development. Entrepreneurs built the foundation for the large enterprise, whose spinoffs resulted in the Second Industrial Revolution. The Third Industrial Revolution too resulted from spinoffs of active R&D. To theoretically frame the industrial dynamism that shaped the industrial revolutions, the life-cycle theory described by Oliver Williamson in 1975 (cited in Audretsch and Feldman 1999:83) comes to mind: the “exploratory stage” at the beginning of the industrial revolutions was characterised by simplicity in product and process technology, and uncertainty dominated; it followed a stage of “intermediate development” with maturing technology and a sharp drop in output growth, which is then succeeded by the “mature stage”, where products, processes, management systems and even supportive service activities are exhausted to maximise efficiency. The observed pattern fits with the dynamics of firm demographics as a function of the product life-cycle when firms rely on a single product. The five stages described by Gort and Klepper (1982) suggest an initial stage with a low number of active producers, but many more are due to follow until the entry rate stagnates, then declines and eventually leads to a stable number of producers, considered as maturity.

Of particular interest is the decline in the number of producers before an industry matures. When product development is nearly saturated, the emphasis shifts to process innovation, which increases the probability to survive during the so-called ‘shakeout’ (Klepper 1996). The implications of it were analysed by Klepper (1996), who rejects the view that the cost function of a firm is mainly determined by the industry. He introduces firm size as the relevant parameter that attributes a cost advantage to the large firm, because it is able to spread its R&D activities. Since R&D investment peaks before the stage of maturity

(Audretsch and Feldman 1999) and hence before or during the shakeout, the logic applied by Klepper (1996) attributes a systemic disadvantage to the small firm as it has to cope with a disproportionate high share of overhead costs. The said perspective was tolerated and encouraged over the course of the first two industrial revolutions and built the foundation for rapid economic progress until the *Golden Age*. The marginalisation of the transaction cost to access information and accumulate knowledge reduces the importance of scale. Eventually there have been some fast growing firms too, but the Third Industrial Revolution has changed the rules of competition.

The industrial revolutions demonstrate the geographic mobility of innovations and the associated context dependency. Diversity in firm size has positive effects and contributes to sustainability. This is because the scale of a firm determines the type of innovation it produces and its response to environmental changes. While it was the innovator that delivered the radical innovations, it was the large firm that picked up on basic ideas and scientifically increased the complexity. The response firms showed to environmental changes refer in particular to macro-economic shocks. Although the large firm was able to exploit economies of scale and scope and to maximise efficiency, it was sensitive to the crises of the 1970s. The limits of giantism became visible and it was the smaller unit that could react faster to changes in demand. Imbalances in the size distribution and a lack of diversity reduce the flexibility to respond to environmental changes. The increasing frequency and intensity of macro-environmental shocks noted by Stiglitz (2000) make flexibility a precondition for sustainability. To achieve it, a change needs to be initiated by an agent and has been argued as being the entrepreneur, whose contribution shall be discussed in the next section.

2.2 Entrepreneurship, small firms and firm size inequality

The sheer scale of large firms created the belief that small firms were insignificant for economic development and that medium-sized ones were the suboptimal representations of the larger counterparts. Until the *Bolton Report*, SMEs were seen as transitional and their contribution to welfare considered negligible. Neither Marx (1887) nor Mises (1951) considered the medium-sized firm worth noting nor assisted the SDOF in explaining dynamism and welfare. Marx's (1887) theory of collectivism leaves the large scale firm unquestioned. As he predicts profits to fall as technology progresses, increasing volume is necessary to keep the capitalist's income stable (Fine and Saad-Filho 2004). The issue becomes the owner and not the scale of the firm. Mises (1951) revived the debate on profit and loss, but the level of analysis shifted to the individual in the form of the small business owner, whose profits are not the function of economies of scale. He acknowledges the benefits that the large scale firm has for society, but makes the entrepreneur responsible for technological progress. This puts the medium-sized firm in an unconventional position and makes technological progress a function of the SDOF.

The aim of this section is to find theoretical support for the industry structure dynamics observed throughout history by putting the entrepreneur at the centre. To predict the direction in which FSI shifts, the subsequent sections link firm size with technological progress, which then leads to the conflict associated with ownership and entrepreneurial freedom. It follows the function of the entrepreneur and the question of whether the entrepreneur can be separated from the ownership of capital. If it cannot, the asset accumulation of established firms undermines the emergence of a new generation of SMEs in maturing industries and FSI increases. The writings consulted to address these aspects are divided into primary and secondary literature. The primary literature consists of Mises, Schumpeter, Drucker and Casson, who all substantially contributed to the field of entrepreneurship at different times. Schumacher and to some extent Arrow, also part of the primary literature, paid particular attention to firm size. Marshall and Kirzner too contributed to the field of entrepreneurship, but remained less influential and are part of the secondary literature examined by Ibrahim and Vyakarnam (2003) and Praag (1999).

2.2.1 Profits and technological change

While Marx (1887) assumes static conditions and sees equality among individuals as essential to achieve a sustainable economic and social model, Mises (1951) emphasises environmental dynamics and inequality as unquestionable conditions to allow for co-existence. To explain the dynamic forces, he introduced the entrepreneur, whose ability to recognise environmental change results in economic progress. By anticipating future needs and matching supply with demand, the intellectually superior mind generates a surplus, which is "the prize of those who remove this maladjustment" (Mises 1951:19). According to Mises (1951), it is therefore a misconception that profits are a direct function of the capital employed. Profits are temporary and require the entrepreneur to continuously identify new opportunities. And as long as opportunities exist, entrepreneurial activity induces dynamism to existing structures.

It is clear that allowing a minority to accumulate profits, which are to some extent offset by losses, cannot result in more equality. Mises (1951) realises that the successful entrepreneur continues accumulating assets, but it is not the degree of inequality that matters. It is the fact that the worker uses his/her incentives for consumption, while the entrepreneur's interest is to reinvest the majority of the profits to achieve further returns (Mises 1951). By doing so, the entrepreneur is the key contributor to "economic improvement, that makes the employment of technological innovations possible and raises productivity and the standard of living" (Mises 1951:25). Mises' (1951) point is that the worker underestimates the value of the entrepreneur's activity and mistakenly believes that it is him/her who contributes to the increase of the living. As the worker oversees the role of capital accumulation, s/he sees no reason for inequality, be it in income or firm size.

Schumpeter (1947) does not fully reject Marx's hypothesis of capital accumulation, but introduces the concept of 'creative destruction' – *Schumpeter Mark I* (Carree *et al*. 2002) – as an innovative process to explain economic development. According to Schumpeter (1947), it bears the capacity to outperform existing structures by restricting their expansion and in the long run being replaced with newer ones. Since creative destruction is disruptive and unpredictable, it is consistent with Mises' (1951) theory of profit generation, but in conflict with Marx, who considers technological change as a dynamic but non-disruptive process (Fine and Saad-Filho 2004). Schumpeter (1947:131) also contradicts Marx's "theory of vanishing investment opportunity", because "as higher standards of life are attained, these wants automatically expand and new wants emerge or are created". Would this not apply, he adds, the entrepreneur would become unproductive and investments would melt away. As this is not the case, the resulting dynamics make firms vary in size, over time and across different economic activities. But more importantly, Schumpeter Mark I suggests equal opportunities as long as entrepreneurs are active.

Schumpeter (1947) is aware of society's scepticism associated with radical change, which reduces the probability of the successful market introduction of new 'combinations'. This attributes higher success rates to incremental innovation and the entrepreneur is therefore exposed to a higher risk than the large diversified unit. In addition, "[t]echnological progress is increasingly becoming the business of teams of trained specialists who turn out what is required and make it work in predictable ways" (Schumpeter 1947:132). This transforms the entrepreneur into a bad substitute for specialised research departments and reduces its contribution to welfare (*ibid*.). Also, the rare occurrence of the "flash of genius" (*ibid*.:132) induces randomness and uncertainty in economic progress and is in favour of a systemic approach to innovation.

These ideas entered in the literature in *Schumpeter Mark II*, where it was argued that the "strong feedback loop from innovation [leads] to increased R&D activities" (Carree *et al*. 2002:271). It inflates the contribution of entrepreneur and small scale firm to welfare as it would be inefficient to carry out R&D

activities at any smaller than the largest possible scale. Schumpeter (1947) goes a step further and attributes sufficient dynamism to the large firm so that it leads to long-term growth. Consequently, market concentration will increase over time and in the long term industries will be dominated by the largest players. Not being in a position to exert market power would indeed result in less innovative capacity, which, according to Schumpeter (1947), requires at least a temporary monopoly for innovative firms. Mises (1951) too associates the abolishment of profits with stagnating economic progress. Its moderation may decrease FSI once small firms are outperformed, but average firm size continues to increase.

Consistent with Schumpeter (1947), Drucker (1985) concludes that the large firm is generally better prepared to exploit unforeseen opportunities. He agrees with Mises (1951) that a particular character favours the success rate of successful innovations, but in his view it is not so much the Schumpeterian entrepreneur who leads innovation; it is instead the designated commitment of the entire organisation and the systemic approach by which innovation is executed. Since ‘big’ innovations cannot be controlled nor are they predictable, Drucker (1985) puts his emphasis on being focussed rather than general, and evolutionary rather than revolutionary, where the insider plays the key role in closing the innovative gap. The likelihood of having access to the necessary resources to quickly respond to new demands is highest for the existing firm – a factor that gains in importance as efficient communication technologies reduce the ‘window of opportunity’ (Drucker 1985). He implements the Schumpeterian entrepreneur in the large scale organisation and by doing so it becomes entrepreneurial. As much as can be interpreted from the works of Mises (1951) and Schumpeter (1947), the resulting SDOF is dominated by large firms. Small firms are either incorporated or allowed to co-exist and engage with activities that are unprofitable for the large firm.

Whichever the perspective, in the long term existing industries experience an increase in average firm size until all economies of scale and scope are exhausted. Disruptive innovations are still present and bear the potential to alter existing structures or to create new ones. But, according to the above discussion, the largest firms are most capable in responding to change and to seize opportunities. The Second Industrial Revolution in particular showed that the small firm is not in a position to outperform large ones, which suggests an increase in FSI over time. Unless small firms are allowed to co-exist, firm size will continue to increase or otherwise decrease because oligopolistic market structures emerge. In the event of the latter, Schumpeter (1947) predicts a decrease in innovative progress as the incentive to innovate converges to socialist standards. Since the capitalist system itself contributes to market power maximisation with negative implications for welfare (Schumpeter 1947), the preservation of dynamism is most efficient under moderate competition. As Schumpeter (1947) notes, there needs to be space to experiment. Without it, none of the industrial revolutions could have emerged.

2.2.2 Ownership and freedom

The inclusion of firm size into the discussion of entrepreneurship and economic progress was of limited importance to Mises (1951) and Schumpeter (1947). It was simply introduced to analyse the market structure as a central element of economic order in a free market based economy. For Drucker (1985) too, firm size was a by-product of the analysis of the source of innovation. Even though all attribute a competitive advantage to the large firm, their standpoint is fundamentally different. The nature of economic analysis does not require Mises (1951) to pay substantial attention to organisational inefficiencies, because the large organisation is assumed to be rational and would not exist if it was inefficient. But conflicts from the separation of ownership and control over the organisation were noticed by Schumacher (1973) and Schumpeter (1947). Here, the manager-led firm can no longer be assumed to be in harmony with itself.

In sharp contrast to Mises (1951), whose entrepreneur turns capitalist as the firm grows larger, but still contributes to the firm’s success, Schumacher (1973) considers the owner as replaceable. By arguing that “[w]hen we come to large-scale enterprises, the idea of private ownership becomes an absurdity”, Schumacher (1973:247) detaches the entrepreneur from ownership. Although not unaware of the genius' contribution to the firm's success, Schumacher (1973) shows little harmony with Austrian theory with regard to efficient resource allocation. He sees the founder of a firm merely as an owner of assets, in particular capital. Schumpeter's (1947) entrepreneur also appears unable to develop his full potential within the large organisational system and the executives' and managers' behaviour cannot be better than the behaviour of an employee and, at best, their interests are consistent with those of the corporation. The diverging interests of entrepreneur and manager are therefore restrictive and attribute a performance premium to the owner-managed firm.

The ownership struggle is also noted by Arrow (2000). He too attributes most technological and social change to the large firm and makes it essential for a progressing economy. But other than the conflicting interests, he adds the inefficiencies of the organisational decision making process. The rationale of the large firm is to offset the centralised co-ordination activities by exploiting economies of scale (Arrow 2000). These activities, however, increase exponentially with complexity and so too does the loss of information by reducing its quality and increasing the distortion of information flows passing from one managerial level to another. Since the implications of innovations are hardly accessible to those not directly involved in the process, misinterpretations are unavoidable and lead to resource misallocation (Arrow 2000). Uncertain projects then become even riskier and the decision makers' awareness of the risk makes the large firm more risk averse than the small firm. It chooses to spread risk by diversifying and outsourcing uncertain R&D projects to smaller firms and to re-incorporate them when certainty is restored (Arrow 2000). The integration of successful small firms into larger ones due to insufficient resources, lack of diversification and the inability to exploit economies of scale and scope reduce the possibility of organic firm growth. As large firms continue to undertake research projects at moderate risk, FSI cannot but increase.

For risky projects to be undertaken there needs to be space for experimenting. The large firm suppresses such spaces to increase predictability, because "its natural bias and tendency favour order, at the expense of creative freedom" (Schumacher 1973:227). According to Schumacher (1973:227), this demands decentralisation, because "[c]entralisation is mainly an idea of order … and is conducive to efficiency; while freedom calls for, and opens the door to, intuition and leads to innovation." He does not condemn hierarchical structures, but attributes a distinctive experimental capability to the small unit when free from external constraints; however, not without ensuring accountability, the basis of which can only be a profit and loss account that is carried forward. With this, there are limits to freedom and the creativity required to innovate. It is clear that Schumacher (1973) refers to units of large scale firms, but under such conditions creative destruction cannot occur. The ideological regime he adopts implies that past success defines the resources available for future success. Mises (1951) would surely agree with Schumacher (1973), who reduces entrepreneurial success to quantifiable values, hence undervaluing the gains from failure. Taking into account that large firms operate by nature at lower aggregate risk and are most flexible in reallocating resources, industry dynamics are much in their favour and a systemic increase in FSI can be expected.

Critique in judging success according to profit and loss comes from Drucker (1985). For the young firm, "'profits' are an accounting fiction" as it faces disproportionate higher operating costs to catch up with incumbent firms (Drucker 1985:242). The freedom the young firm has in experimenting is highly restricted and an element of randomness is added to firm survival. It is once more the existing firm that is in a better position to experiment, but it might not be the largest firm; it is rather the medium-sized firm. Whereas the latter has a past record, the small firm is unable to provide sufficient securities, while the large firm can count on more attention from investors (Arrow 2000). Arrow's (2000:238) presumption that "[a] small firm can in many cases obtain outside financing by sale of equity" at the expense of control over the firm, is rejected by Drucker (1985), because such undertakings are likely to fail as interpersonal tensions and conflicting interests increase. It enhances the uncertainty associated with innovations and lowers the probability of success. While large firms continue to exist, competition for resources is most intense for small firms.

Despite being written at different times, the 'classics' show consistency in arguing that the small firm, when compared to the large firm, is unable to exploit scale effects. Nevertheless, the small firm benefits from simplicity as it occurs in the early stage of new industries as was the case throughout post-war Europe when firms emerged from catching up and again at the beginnings of the ICT revolution. As shall be explained in the next section, it is the owner-manager who makes the difference. The absence of organisational complexity and conflict allows a commitment to risky projects – the key ingredient of the First Industrial Revolution (Bruland and Mowery 2009). The small firm is free from structural restrictions, which makes it superior in creatively innovating, but this freedom vanishes as soon as firms compete for resources. There is no reward for successful failure, which is the financial loss resulting from knowledge accumulation. It remains the large firm that can afford to systemically offset such losses from profits generated elsewhere within the organisation. As the Second Industrial Revolution demonstrated, the large firm can continue to pursue its R&D programme regardless of uncertainty and at a lower aggregate risk than the small firm. The Third Industrial Revolution lowered the cost of experimenting, but at some point, firm growth cannot occur without resources. There might be exceptions, but the emerging pattern suggests an increase in FSI and, as Arrow (1962) notes, a loss of welfare as the consequence of an underinvestment in risky projects. The firm-size class that finds itself in the best position between these extremes is the medium-sized firm, but in the long term it too will move up or down in the firm-size class hierarchy and needs to be replaced with a new generation.

2.2.3 The entrepreneur and his/her function

Marx (1887) saw merely the capitalist, whose systemic exploitation of the working class leads to the wealth of a privileged minority. To see the capitalist as innovator and contributor to technological progress was alien to him. David Ricardo observed increasing concentration of farmland and assumed it to be the consequence of the developments of the First Industrial Revolution, but with no distinction between the capitalist and entrepreneur (Ibrahim and Vyakarnam 2003). Yet the concept of the entrepreneur was introduced by Richard Cantillon in 1755 – some twenty years before Adam Smith (Blaug 2000). Cantillon associated the entrepreneur with arbitrage motivated from “buying at a certain price and selling at an uncertain price”, but his economic view excluded the possibility of the entrepreneur taking on the managerial function addressed by Jean-Baptiste Say around 1800 (Praag 1999:313). By being the efficient resource allocator within the efficient firm, Say’s conception of the entrepreneur diverges from the idea of a ‘zero-sum game’ (*ibid*.). These competing views led to the entrepreneur associated with a specific economic activity – the main concern of the Austrian School – alongside the organisational entrepreneur – the foundation of organisational scholars, including Drucker.

With the introduction of macroeconomic analysis, the concept of the entrepreneur became obsolete. On the assumption that markets are perfect because all agents are fully informed and rational when it comes to utility maximisation, neo-classical economics is unable to explain innovation and the resulting technological progress (Blaug 2000; Drucker 1985; Ibrahim and Vyakarnam 2003). “The firm runs itself” (Praag 1999:317) with the entrepreneur being “the lightning calculator, the individual who rapidly scans the field of alternative productive processes and chooses the optimum at any given set of prices” (Arrow 2000:229). Coase (1937) perceived that the process of economic planning beyond the scope of the individual has an importance in achieving the market equilibrium. He (*ibid*.:389) attributed it to the “entrepreneur-co-ordinator”, who is the most efficient resource allocator, the conception of which builds on Marshall and Knight.

Marshall (cited in Praag 1999) recognises the entrepreneur as the provider of innovation, essential for economic progress and especially for industrialised economies, who are the first movers. The entrepreneur is willing to bear the risk and able to control the factors of production and is by definition a scarce resource (*ibid.*). Accordingly, the reward differs from both the worker’s wages and the capitalist’s interests (McCaffrey and Salerno 2011) and required Knight (cited in Coase 1937) to introduce uncertainty-bound profits as source of income to a specific economic activity (Blaug 2000). For Knight (cited in Ibrahim and Vyakarnam 2003:13), “[r]isk is a random event with a known probability distribution. Uncertainty is a random event with unknown probability distribution.” This distinction – neo-classical economics treats risk and uncertainty as residual – allowed Knight to define the entrepreneur’s function as the uncertainty-bearer, rewarded by profits and social status (Praag 1999). But even though the entrepreneur has rare talents, in the income distribution s/he would remain unobservable.

In Austrian theory, it was Menger (cited in Salerno 2008) and later Mises (1951), who identified the entrepreneur as the decision maker who ensures the efficient use of the means of production in economic terms. As any other activity is of secondary importance, the worker misinterprets the entrepreneur’s function and continues producing goods as would occur in a static economy (*ibid*.). With Rothbard (cited in Salerno 2008) adding the Knightean element of uncertainty and Kirzner (1979) being influenced by Mises, the idea of the entrepreneur experienced a number of iterations even within the Austrian School itself. Salerno’s (2008) reconciliation of these streams distinguishes between the ‘pure’ entrepreneur – Mises’ analytical tool – and the ‘integral’ entrepreneur as the entrepreneur of the real world. Whereas the integral entrepreneur also bears risk, the pure entrepreneur remains a theoretical construct, who “earns profits by ‘discovering’ and seizing objectively existing but previously unperceived opportunities to arbitrage price discrepancies between a bundle of complementary inputs and the output it yields” (Salerno 2008:189). Should the integral entrepreneur be replaced by a manager and an investor, the firm would operate below its maximum efficiency, because the output is not the product of the entrepreneur’s personality. It is this aspect Drucker (1985) referred to when commenting on the exchange of shares for resources.

Schumpeter (1947) revolutionised the Austrian conception and the entrepreneur is no longer viewed simply as an explanation for profit and loss; instead the main task is to innovate. But in agreement with the Austrians, this is something that cannot be performed by the average citizen, whose perception is limited to routine tasks. The entrepreneurial function becomes temporary and even impersonal (Blaug 2000), which, according to Arrow (2000:229), is erroneous, because the “[entrepreneur] cannot be replaced by a machine or by a multiplicity of individuals, who would inevitably slow him down.” It needs the visionary mind to initiate the process of creative destruction by creating something new from existing goods and knowledge (Schumpeter 1947). Drucker (1985) developed the social function Schumpeter (1947) attributed to the entrepreneur and transformed him/her into the efficient decision maker within the firm – the ‘intrapreneur’ (Wennekers and Thurik 1999) – who may develop his/her own dynamism. For Casson (1987:255), the ability of the entrepreneur is “[t]he identification of profit opportunities [that] involves synthesizing information from diverse sources.” Casson (1982) distinguishes Mises’ (1951) arbitrager, who identifies gaps in the market, from Schumpeter’s (1947) innovator, who understands customer sentiments and Drucker’s (1985) manager, looking for strategies to enhance business growth and ensure its survival. It is the opportunist who understands the need for innovations, without necessarily being an innovator him/herself, but who is willing to bear the risk to explore the technological frontiers (Casson 1987) and equally fulfils a social function.

The latter is also reflected in Praag and Versloot (2007), but it is not simply the innovations the entrepreneur delivers, it is also the employment that follows from economic growth. Their meta-analysis suggests the dominance of the combined profit-maximiser promoted by the Austrian School with the Schumpeterian innovator, which is not to say that less articulated definitions, such as the Marshallian or Knightian entrepreneurs, can be rejected. Particularly strong is the emphasis on the exceptional intellectual capacity and alertness the entrepreneur stands for (Praag and Versloot 2007). Although Casson (1982) and Drucker (1985) state that much can be trained, the entrepreneur remains an outstanding character, which limits the supply of entrepreneurial capacity. By efficiently allocating resources, bearing risk – the Schumpeterian entrepreneur does not – and innovating, the entrepreneur creates value and contributes to technological progress and sustainable economic growth. However, by being exceptional, s/he imposes a limit to firm size too (Casson 1987; Knight cited in Praag 1999).

From the above argumentation it follows that once the entrepreneur has to be complemented with a manager, relative inefficiency increases and innovative capacity decreases. The potential of the young firm to outperform the incumbent firm is therefore highest when owner-managed, which gives the small firm an advantage over its competitors. The ICT revolution demonstrated that small owner-managed firms are efficient in spotting opportunities and efficiently allocating resources. The complication that comes with the identification of an entrepreneur is that "entrepreneurship can always be understood ex post, but it can never [be] understood ex ante" (Ibrahim and Vyakarnam 2003:10). Under Knightian uncertainty entrepreneurial success is therefore totally unpredictable and it can be complemented, but not be replaced by the systemic approach to innovation. It comes back to the freedom required to carry out entrepreneurial activity, which, when restricted, leaves entrepreneurial potential unused or delays technological progress. The consequence is an increase in FSI with a suboptimal employment of scarce entrepreneurial human capital and poses the question to what extent the possession of assets conditions the execution of entrepreneurial activity.

2.2.4 Entrepreneurship and capital

In *Profit and Loss* Mises (1951) argues that the market may fail in selecting and attributing a value to the artist, but not so for the entrepreneur. He separates the entrepreneur from the capitalist, who seeks out new opportunities in which to invest his financial resources. It lies in the entrepreneur's hands to convince the investor to commercialise on opportunities and frees the entrepreneur from material wealth:

> "Entrance into the ranks of the entrepreneurs in a market society … is open to everybody. Those who know how to take advantage of any business opportunity cropping up will always find the capital required." (Mises 1951:16-17)

Although Mises' (1951) entrepreneur is merely a person able to spot the opportunity to generate profits, Schumpeter (1947) too isolates the entrepreneur's function from the possession of capital. Well aware of the need for initial resources, he states that this task can be outsourced to the banker. As the Schumpeterian entrepreneur is primarily an innovator, the risk of failure is the banker's, unless the entrepreneur is both innovator and banker. Yet the notion of Schumpeter Mark II diminishes the function Schumpeter (1947:132) attributes to the entrepreneur:

> "This social function is already losing importance and is bound to lose it at an accelerating rate in the future even if the economic process itself of which entrepreneurship was the prime mover went on unabated."

He refers to the accumulation of capital and knowledge, which puts the large firm in a strong position and questions the separability of entrepreneur and capital; a view that, according to Salerno (2008), still dominates in contemporary entrepreneur literature, including the Austrian theory. According to Salerno (2008:190), Kirzner substantially influenced the creation of this belief by stating that "ownership and entrepreneurship are to be viewed as completely separate functions" and "[p]urely entrepreneurial decisions are by definition reserved to decision-makers who own nothing at all." The distinction between 'pure' and 'integral' entrepreneur represents the former as the present-day Austrian entrepreneur, pictured "as a pure decision-maker possessing superior 'alertness' but owning no resources" (Salerno 2008:189). The difficulties Mises (cited in Salerno 2008:193) faces in explaining loss from employing capital beyond his means, brought him to the conclusion that:

> "[the entrepreneur nevertheless] … remains propertyless for the amount of his assets is balanced by his liabilities. If he succeeds the net profit is his. If he fails the loss must fall upon the capitalists, who have lent him the funds. Such an entrepreneur would, in fact, be an employee of the capitalists who speculates on their account and takes a 100% share in the net profits without being concerned about the losses. But even if the entrepreneur is in a position to provide himself a part of the capital required and borrows only the rest, things are essentially not different. To the extent that the losses incurred cannot be borne out of the entrepreneur's own funds, they will fall

> upon the lending capitalists, whatever the terms of the contract may be. A capitalist is always virtually an entrepreneur and speculator" (Mises cited in Salerno 2008:193)

By allowing the entrepreneur to generate profit and shifting the risk to the capitalist, Knightian uncertainty cannot be removed, but joining the club of capitalists is still possible. Only the capitalists are in a position to remove uncertainty and bear risk, but the lack of foresight suggests that they are de facto gamblers, who do not create value. The integral entrepreneur, promoted by Rothbard and Hayek, requires property to enable a loss (Salerno 2008) and is consistent with the Knightian entrepreneur. He too requires capital as it is otherwise impossible to carry out the risk-bearing function for the social good (Praag 1999). Hence, the entrepreneur has to be a capitalist, but capitalists' abilities in directing the means of production towards the most profitable activities does not by definition make them entrepreneurs (Salerno 2008). According to Salerno (2008), it is the unspecified theoretical construct of the pure entrepreneur that contributed to the misconception. Hence, entrepreneurship and capital are 'sticky'.

Kirzner, Schumpeter and Cantillon consider the entrepreneur's ability as sufficiently distinct to attract investors' funds (Praag 1999). The belief that external capital is easily accessible relies on the assumption that capital markets are at least close to perfection and that banks – whose task is to provide capital – are efficient in allocating resources. However, the insider knowledge required to grasp the entrepreneur's potential leads to information asymmetry and pulls in the opposite direction (Arrow 2000; Drucker 1985). As the banker may himself be an entrepreneur striving for profits and "under the state of incomplete information … is considered as an opportunist" (Williamson cited in Ibrahim and Vyakarnam 2003:7), capital markets are as imperfect as any other market. These conditions were taken into account in Say's (cited in Praag 1999) analysis and require the entrepreneur to be in possession of a bare minimum of capital to carry out entrepreneurial activity. Although Marshall (cited in Praag 1999) imposes fewer restrictions to exercise his/her task, he adds a risk premium to the entrepreneur unable to invest assets, which then results in a disadvantage compared to those who invest their own capital.

For Knight (cited in Praag 1999) and Casson (1982) initial capital requirement is a precondition, but they equip the entrepreneur with emotional intelligence, which lowers his/her own commitment. Mises' (1949) analysis suggests that the entrepreneur is able to lower his/her own uncertainty by shifting risks towards stakeholders, but entrepreneurs who use their own wealth are advantaged as they have more control over their operations. Albeit Blaug's (2000) and Drucker's (1985) strict separation of entrepreneur and capitalist, the efficient decision-maker needs to be in a position to mobilise resources as it lies in the capitalist's interest. The latter takes the risk and presumably exerts control over his/her 'employee', but "[t]he presence of large firms creates logical difficulties for the concept of property" (Berle and Means cited in Arrow 2000:230). Dynamic and complex ownership structures increase uncertainty for the entrepreneur, whose task is the restoration of certainty. It makes the control over assets a weak substitute for the entrepreneur-capitalist. Investment decisions and resource allocation are therefore a function of firm size with entrepreneurial freedom being disproportionally restrictive the stronger the controlling power.

The persistence of Kirzner's belief resulting from Mises' analytical entrepreneur and Schumpeter's assumption of perfect capital markets created the illusion that generating something out of (almost) nothing is possible. The ICT revolution might have increased the probability to do so by marginalising initial capital requirements and tolerating the entrepreneur's labour as the only input factor. The downward risk can still be absorbed by the entrepreneur, but the uncertainty associated with entrepreneurial activity imposes a time limit to the experimental stage. At some point access to capital is necessary. "[A]s the frontier moves forward [and] the law moves along behind" (Casson 1987:254), the entrepreneur is the first to take the risk. Information asymmetry and market imperfection do not allow the entrepreneur to fully shift the risk to the capitalist. If this is nevertheless possible, it changes investment decisions and reduces entrepreneurial freedom. To maximise welfare, entrepreneurial talent needs access to a bare minimum of resources, which the marginal firm is short of, but increases with firm size. As the large firm cannot do more than pursue a systemic approach to R&D, it is the medium-sized firm that bridges the extremities of the SDOF and makes it a relevant dimension.

2.2.5 Conclusions

The theories of the great thinkers are almost exclusively the product of their time and refer in particular to Smith, Richardo and Marx. Both Smith and Ricardo experienced the industrialisation the First Industrial Revolution launched, while Marx witnessed the rise of the large scale firm as the product of the Second Industrial Revolution. For Schumpeter it was the post-war recovery and the shift of economic power from Europe to the US, which ultimately produced the multinational and too influenced Drucker, Schumacher and even Mises. However, Mises' main concern, as of most Austrians, was the state intervention that dominated in Europe at that time, and which in his view leads to inefficient resource allocation. He attributed this task to the entrepreneur. Because, macroeconomic conditions were stable in pre- and post-war Europe, he approved the presence of the large firm and its contribution. The focus was set on aggregate growth and only Schumacher (1973) was sceptical about firm size and called for moderation. Mises' (1951) justification that the large firm's existence is tribute to its efficiency understates the structural complexity it grows into.

According to Arrow (2000), it is the small firm that is more efficient in exchanging knowledge and making decisions. These factors partially offset the gains the large firm achieves from economies of scale and scope. It attributes a competitive advantage to the owner-managed firm, which was testified by the German *Mittelstand* and the Italian industrial districts of the post-war period. Furthermore, the organisational complexity defines the type of innovation that emerges. The experience of the Second Industrial Revolution demonstrates that managed research departments cannot deliver innovations when operating in isolation. Although they invented their own products, acquiring innovations from individuals was inevitable (Bruland and Mowery 2009). While the small firm is good in commercialising on simplicity, the large firm excels in carrying forward basic ideas. Its systemic approach and resources allow the incorporation of the technological sophistication it has at its disposition, but its ownership-structure favours marginal progress and predictability. To achieve sustainable growth it therefore requires both small and large firms.

It is the entrepreneur, be it the efficient decision-maker or the innovator, who delivers the impetus by anticipating what the average citizen cannot see. For the reasons described above, this distinct economic activity has positive effects on aggregate growth and technological progress. To commercialise on entrepreneurial capital, opportunity and freedom are imperative. The 'classics' on entrepreneurship do not suggest industry differences nor do they consider market structures in combination with entrepreneurial success, which persistence is criticised by Klapper *et al*. (2012). With the exception of Drucker (1985), it appears that a constant number of opportunities always exist and it is the occurrence of the rare talent who adds most uncertainty to the technological progress. The industry life-cycle theory discussed in section 2.1.5 suggests a decrease in opportunities within any given industry as we move along the life-cycle. As industry structures consolidate and exclude inefficient firms, the convergence to Schumpeter Mark II intensifies market concentration (Carree *et al*. 2002). By polarising the SDOF it lowers the opportunities of the small firm – the entrepreneur's vehicle to carry out his/her activity (Praag and Versloot 2007; Wennekers and Thurik 1999) – to catch up with the large firm. The latter takes the lead and because its structures favour certainty, the underinvestment in risky projects increases (Arrow 2000). This makes the preservation of Schumpeter Mark I more desirable, because its dynamics contribute to more diversity and reduce the probability of underinvestment. This eventually results in the emergence of new industries with new opportunities, as is the case for the ICT revolution.

The small firm is prepared to take a higher risk than the large firm, because it is the only way to grow larger and to commercialise on the opportunities it recognises. Its ability to buffer risk differs from the large firm and so too does the uncertainty it creates. It is complementary and not contradictory to the large firm, but to exercise its entrepreneurial function it requires freedom. It requires organisational freedom, which is granted by its agile structure (Arrow 2000; Schumacher 1973) and the freedom to learn from failures. But the stickiness of entrepreneurship and capital is restrictive and the control over resources a weak substitute as it limits organisational freedom. To become entrepreneurially active and initiate a process of creative destruction, a bare minimum of capital is required; the inapplicability of this condition is an exception. By defining the maximum physical risk, the need for capital links project size to firm size and reduces the potential of the marginal firm to commercialise on opportunities as it wishes, whereas the large firm is constrained by its organisational inability to understand the innovator's mind. This too applies to markets and attributes a particular task to the medium-sized firm. By being entrepreneurial and having access to a pool of resources, it finds itself at the trade-off point. Until Drucker (1985), the favourable position of the medium-sized firm remained unnoticed. Its presence reduces underinvestment and the misdirection of social energy. In combination with a fair share of small and large firms, it is the missing link in achieving sustainable growth.

2.3 Firm size inequality and welfare

The relevance of firm size in determining welfare has unequivocally come through from the above discussion, but it has rarely been the different firm sizes that were considered to have an impact on economic and even less so on social benefits. It is the aim of this section to fill this void. The correlation of firm size and entrepreneurial activity implies that each firm-size class plays a particular role. While large firms have become the trend-setters (Arrow 2000; Drucker 1985) with the capacity to undertake large scale projects, SMEs are committed to efficiently carry out riskier projects at a smaller scale. They open the door to new industries. The disproportionate risk the small firm is exposed to, coupled with the large firm's unwillingness to engage in risky projects, makes the SDOF relevant for the production and exploitation of opportunities. It is the absence of an insurance against uncertainty for critical projects that the large firm fears, which, according to Arrow (1962), leads to an underinvestment with a loss of welfare. It follows that a more polarised SDOF contributes to a higher degree of underinvestment leading to lower levels of GDP in the long run. There is no evidence of the degree of firm-size diversity needed to maximise economic progress, but historical and theoretical analyses suggest that imbalances in the SDOF produce a suboptimal response to change. The less heterogeneous firms are in size, the more homogeneous their response to change. Since economic progress is influenced by the ability of firms to adjust to new conditions, the SDOF becomes a critical element.

To link FSI with welfare, it first requires a critique of traditional welfare measures. For this, recent developments in the field and issues related to sustainability raised by Schumacher (1973) are worth reconsidering. The definition of “welfare” presented in the *Oxford English Dictionary*, i.e. “[t]he health, happiness, and fortunes of a person or group”, is largely consistent with the wording published in *The Chambers Dictionary*. The latter defines it as “the health, comfort, happiness and general wellbeing of a person or group”. But despite the shared view that welfare is multi-dimensional and that objective measures, especially GDP, should be complemented with subjective measures reflecting the well-being of people (Stiglitz *et al*. 2010), there is little agreement among researchers on the dimensions to be considered and how they are measured and weighted. The difficulties in quantifying the contribution of FSI to the welfare function other than GDP – in itself not uncomplicated (Audretsch *et al*. 2002) – favour a more conservative approach with a focus on more proximate dimensions. These are covered in the subsequent sections and too form part of the empirical analysis. The primary dimensions expected to be in a direct relationship with firm size are innovative capacity, economic resilience and net job creation. Indirectly affected but not limited to the primary dimensions are life satisfaction and happiness. As these dimensions are more abstract and context-specific than the primary dimensions, they are treated as secondary factors. In contrast to the above-mentioned sections, these sections build on empirical work rarely founded in any particular theory, but supportive in justifying the existence of a link between FSI and welfare.

2.3.1 Quantifying welfare

The tribute Schumacher (1973:29) paid to the matter of firm size refers in particular to economic performance and sustainability as a function of structural diversity and a preference for smallness: ”Ever bigger machines, entailing ever bigger concentrations of economic power and exerting ever greater violence against the environment, do not represent progress: they are a denial of wisdom.” Schumpeter (1947), however, recognised the technological progress the large firm of a capitalist society delivers. It offers more efficient methods to extract and process resources and sustainable economic growth is the product of innovative capacity with the large firm at its core. For Schumacher (1973) the large firm is synonymous with the exploitation of all accessible resources to maximise profits. He agrees that the small firm may also harm the ecosystem, but that it does so out of necessity and, whatever the damage, cannot achieve the magnitude of the systemic approach to resource depletion the large firm takes. He appeals to mankind’s wisdom and sees greed and envy as the systemic risk, which prohibits prosperity for a larger population resulting from obsessive growth. Schumacher (1973:17) emphasises the extent to which growth can be achieved and adds that “… the modern industrial system, with all its intellectual sophistication, consumes the very basis on which it has been erected[;] … it lives on irreplaceable capital which it cheerfully treats as income.” Such income enters in the calculation of the GDP and has become the dominant measure for economic development, which, according to Schumacher (1973), is erroneous.

For both Mises (1951) and Schumpeter (1947) such a risk does not exist for an entrepreneurial society keen to reinvest its profits in new ideas. Their assumption is based on the belief that markets are close to perfection in pricing the value of goods and services. Schumacher (1973) denies this and criticises society’s overestimation of quantifiable economic values, especially for finite natural resources. His criticism is also directed to efficiency and forceful growth that capitalism strives for. This reduces diversity and produces a surplus of human capital, and referring to Marx states that “it would be ‘uneconomic’ for a buyer to give preference to home-produced goods if imported goods are cheaper" (Schumacher 1973:40). It becomes financially unsound to ignore economic efficiency, but contradicts human nature (Schumacher 1973). The inability to quantify the value of diversity that the local independent store adds to the whole picture results in gigantism and monotony, and is in disharmony with nature.

The rapid economic growth during Europe's *Golden Age* left Schumacher's (1973) concerns unnoticed, but environmental degradation gradually became an issue in Europe (Pinder 1998). It is the forceful systemic exploitation that Schumacher (1973:29) criticised by appealing to "a new orientation of science and technology towards the organic, the gentle, the non-violent, the elegant and beautiful." With the rise of corporate social responsibility since the late 1990s (Hahn and Scheermesser 2006), MNEs have found a way to differentiate and commercialise on these initiatives (Brønn and Vidaver-Cohen 2009; Ditlev-Simonsen and Midttun 2011; Gray and Eid 2005), whereas small firms have remained in the dark. Yet, 64% of Europe's environmental impact is attributed to SMEs (Blundel *et al*. 2012), which makes the SDOF a determining component of sustainability that GDP fails to take into consideration. Studies analysing the implications of FSI on the sustainability question are gaining momentum, but are still in their infancy.

The *Stiglitz Report* (Stiglitz *et al*. 2010) confirms Schumacher's (1973) concerns over the use of GDP as a measure for economic progress and even more so as a measure for well-being, which has largely replaced the public debate over welfare. Designed to quantitatively reflect economic activity and structures, GDP has become a proxy for living standards. When GDP is growing, unemployment declines and yet, in developed economies, life satisfaction does not increase with GDP (Frey and Stutzer 2002; Wilkinson and Pickett 2010). The same applies to any other quantitative measure associated with economic performance, which "matter only in so far as they make people happier" (Oswald 1997:1815). Stiglitz *et al*. (2010) and Diener and Seligman (2004:1) criticise that "economic indicators omit, and even mislead about, much of what society values." GDP bears the capacity to increase despite the occurrence of natural disasters as it merely reflects the economic activity and fails to quantify the loss of private and public assets (Stiglitz *et al*. 2010). It motivates society to carry on regardless of the negative externalities caused by ignorance and leads to insufficient recognition of environmental degradation (Schumacher 1973).

According to Wolf (2012), the major defects of GDP as proxy for well-being are the property of an aggregate figure, which disregards how material wealth is distributed and its undervaluation of human capital since individual opportunities have become a function of parental resources. Concerns even increase when the use of GDP is overemphasised and instrumentalised to govern societies. As stated by the former French president Sarkozy (cited in Stiglitz *et al*. 2010:XIV):

> "If our measuring systems overvalue the usefulness to society of speculation compared with work, entrepreneurship, and creative intelligence, then this dangerously reverses the value system underpinning our vision of progress and introduces into the heart of capitalism a contradiction that can only end up ruining it."

Yet the use of GDP cannot categorically be excluded from measuring prosperity. It reflects economic activity and structures as much as the relationship with other indicators such as employment, and hence affects aggregate well-being (Stiglitz *et al*. 2010). It matters most in the initial stages of economic development, but marginalises once basic needs are satisfied (Diener and Seligman 2004; Easterlin 1974; Layard 2011; Smith cited in Frey and Stutzer 2002) and eventually needs supplementing with subjective measures (Diener and Seligman 2004; Layard 2011; Oswald 1997; Stiglitz *et al*. 2010). It is the latter that complicates the matter and explains why "responses [to subjective well-being] have been studied intensively by psychologists, studied a little by sociologists, and ignored by economists" (Oswald 1997:1816).

Nonetheless, the erosion of the achieved standard as reflected in GDP per capita is counterproductive (Frey and Stutzer 2002) and even more so are the distributional imbalances noted by Wolf (2012) and Piketty and Saez (2006). This claim is consistent with Wilkinson and Pickett (2010), who observe higher levels of happiness in combination with a lower degree of inequality in nearly all aspects of life. Frey and Stutzer (2002) and Blanchflower and Oswald (1999) associate happiness with choice and alternatives in political participation and employment respectively. This, by definition, demands diversity and draws back to Schumacher's (1973) argument that extreme constellations of the SDOF are unsustainable. GDP in one form or another gives an approximation, but the consequences go beyond strictly quantifiable values. While the effects of innovative capacity are only visible in the long term, the need for economic resilience is unpredictable. Both dimensions have an impact on net job creation, which is the most visible aspect of welfare, particularly at the individual level.

2.3.2 Firm size and innovative capacity

Considering GDP per capita – despite all its limitations – as an indicator for welfare, an increase in economic activity leading to higher levels material wealth can only result from increasing input factors or efficiency. As the East European model demonstrated, the former is unsustainable in the long term and the path of the latter must, at least in part, be pursued. Neo-classic growth theory failed to provide a comprehensive understanding of sustainable economic growth as it sees growth merely as a function of capital and labour (Wennekers and Thurik 1999). The inclusion of the entrepreneur assisted in identifying the force that maintains the disequilibrium and ultimately became the source to progressive economic growth and development. As the entrepreneur's activity consists in increasing efficiency and adding value, the respective literature emphasises the need for a climate that encourages entrepreneurial activity to leverage innovative capacity.

In addition to the entrepreneurial spirit combined with an institutional framework allowing the seizure of opportunities (Acs 2006; Porter and Stern 2001; Wennekers and Thurik 1999), a second factor needs considering. It is the diversity of firms in size and activity and how this links to innovation (Agrawal *et al*. 2012; Arrow 2000; Wennekers and Thurik 1999), which has so far gained limited attention (Pagano and Schivardi 2003). Schumpeter (1947) himself indicated that firm size affects innovation output and although the large multinational benefits from some advantages, it suffers from internal conflict (Arrow 2000), organisational inertia (Clegg 1990) and relies too much on past success (Drucker 1985). To release the entrepreneurial spirit at different levels, Wennekers and Thurik (1999) associate the Schumpeterian ‘intrapreneur’ with economic growth. Intrapreneurs work collectively on innovations and combinations, marginal or new ones at product, process or organisational level (Wennekers and Thurik 1999). Consistent with Drucker (1985:132), the existing firm is in the best position “for entrepreneurial leadership” and it appears indeed that individual entrepreneurs underperform in delivering innovations (Praag and Versloot 2007).

The superiority of existing firms applies in particular to within-industry process innovations that demand a high level of specialised expertise (Davidsson and Honig 2003; Drucker 1985). The insider has then an advantage over the outsider and when s/he feels restricted in executing his/her entrepreneurial freedom is forced to search for new ventures (Drucker 1985). In the absence of alternative venues to commercialise on the newly gained intelligence, knowledge transfer cannot take place and the innovator is likely to give up whenever the expected gains are below the cost of establishing a new venture. As a consequence, marginal improvements and new combinations resulting from intra-industry applications are oppressed and economic progress is delayed. This imposes the need for more evenly distributed firm sizes and requires a framework at industry level enabling the transformation of entrepreneurial energy into applicable solutions. Although knowledge transfer might not be in the interest of the individual firm, it contributes to the development of the industry as a whole. As entrepreneurial activity is influenced by networks (Davidsson and Honig 2003) and the linkages between the resources and accessible technologies available to all actors (Porter and Stern 2001) they determine the probability of knowledge transfer across industries with positive externalities at economy level. However, they can only occur if inequality among firms in size and scope does not exceed a critical level.

On the assumption of Schumpeter Mark II, i.e. the large firm’s leadership in knowledge production, and the small firm’s ability to absorb knowledge, Agrawal *et al*. (2012) find that regional innovative capacity increases with firm size diversity. In contrast, extreme FSI due to policies supporting either the dominance of small or large firms, is hostile to innovative capacity (*ibid*). The mechanism at work is the emerging spinouts, i.e. entrepreneurs that pick up on pre-existing technologies, the effects of which are deemed to be "superior to those of other entrants" and, according to Agrawal *et al*. (2012), is consistent with previous studies. It portrays the phenomenon observed at the beginnings of the ICT revolution, characterised by collective learning, of which the effects are particularly strong in the premature stage of an industry (Peltoniemi 2011; Wennekers and Thurik 1999) and are generally referred to as 'spill-overs'. The gain for young firms might be sufficient to stimulate competition and hence a feedback loop to incumbent firms, which then maximises economic progress. Buckley (2010), Stöllinger (2013) and Wang and Wong (2012) identify firms' capacity to absorb technological advancements as a crucial factor for knowledge transfer. The more homogeneous the firms are, the higher their ability to benefit from spill-overs, whereas extreme heterogeneity impedes technology transfer.

The empirical evidence presented is not necessarily in contradiction with Mises' (1949) inequality theory. Inequality is perfectly acceptable, but it is a critical level that needs to be respected. As Wennekers and Thurik (1999:50) argue, "[v]ariety, competition, selection and also imitation … expand and transform the productive potential of a regional or national economy" and constitutes progressive economic growth. There is not a market for everything new or different and at a crucial point in the product or industry life-cycle the dominant design emerges and defines future trends (Peltoniemi 2011; Wennekers and Thurik 1999). It follows the selection process, which can only be fruitful if sufficient alternative solutions are available (Audretsch and Thurik cited in Audretsch *et al*. 2002; Carree *et al*. 2002) and imposes the need for product and firm diversity, leading to the separation of the wheat from the chaff. Existing firms mobilise new entrepreneurs who contribute to the emergence of novel sub-industries (Peltoniemi 2011; Wennekers and Thurik 1999), but a balanced growth is easier to achieve when diversity is fairly distributed. It ensures competition among equals, whereas extreme inequality results in tacit co-existence and consequently suboptimal economic progress.

Small businesses that carry out entrepreneurial activity are imperative for any economy as they enable the execution of innovative experimentation. However, their restrictions in accessing resources of all kinds limit their capacity to react to windows of opportunity. This draws attention to the established firm, which might suffer from inertia, but has more freedom in reallocating its resources and is likely to maintain its market share. Considering the incumbent firm as a complementary source of innovative capacity, the key to releasing entrepreneurial spirit is to achieve smallness within the large unit, as Schumacher (1973) and Wennekers and Thurik (1999) suggest. Whenever this is not possible or individual interests do not match the corporate strategy, entrepreneurial energy has a tendency to either erode or to flow off. The latter results either in a process of knowledge exchange among firms of equal size and scope or in a stream of new firms. As long as it is possible to commercialise on the newly gained information, morsels of knowledge are preserved and advancements at aggregate level guaranteed. The inability to do so impedes knowledge transfer as the consequence of substantial heterogeneity in firm size, structure and scope. This suggests that firm size diversity consisting of a continuum of firm-size classes bears the maximum potential to enable knowledge transfer from one firm-size class to the other. It conditions innovative capacity and in the long term increases the chance of a higher standard of living at regional or national level.

2.3.3 Firm size, resilience and flexibility

Since the entrepreneur bears uncertainty and the risk bearing function changes with firm size (Arrow 2000; Dhawan 2001), the SDOF determines the degree of uncertainty a society is exposed to. Given that uncertainty is integral to change, the SDOF influences an economy’s responsiveness to new needs. It is the structural component that influences flexibility. The Knightian entrepreneur bears the risk for the ordinary citizen at all times and by concentrating uncertainty, a high level of self-employment suggests positive effects on welfare. Extending the risk associated with firm size to the business owner, which may not be an entrepreneur in the Knightian or Schumpeterian sense, the said businessman too bears risk and absorbs uncertainty. The role becomes passive rather than active, but s/he still contributes to economic resilience as the small business owner's response to fluctuations in demand is the acceptance of a variable income (Storey and Greene 2010), whereas the ordinary citizen seeks to maximise certainty and security (Stiglitz *et al*. 2010).

On the assumption that the large firm offers security and high wages for talent, Lucas (1978) predicted the permanent decline in self-employment as part of economic progress. The pride of ownership and the passion that drives experimentation would be replaced with material reward, leading to a shift towards industries consisting of an increasing number of large firms. The consequences, which became visible at the eve of the first oil crisis, demonstrate that homogeneity of firms in size leads to a homogeneous response to macro-economic shocks. The underrepresentation of the small business sector reduced the effectiveness in rebalancing operations and prolonged the recovery from unexpected events. Despite the productivity gains the large scale firm is able to exploit, it questions the sustainability of such a development. Carree and Thurik (1998) show that the share of European large firms in 1990 had a negative impact on economic growth in subsequent years, which was accompanied with a slower recovery from the recession in 1993. These results are reinforced by removing Spain and Portugal from the sample as Carree and Thurik (1998) assumed these countries to be in a different stage of economic development. Cassia and Colombelli (2010) find that medium-sized Italian manufacturing firms perform better than any other firm-size class, especially when proactively responding to change. Further support is provided by Robson and Gallagher (1994), who find that in times of recession large firms reduce employment as they focus on core activities, whereas small firms increase their employment share, but are reluctant to increase it under certainty. This leaves room for efficient small firms to grow and reduces recessionary fluctuations. It makes SMEs crucial for economic stability and resilience (Robson and Gallagher 1994) and a fairly balanced SDOF is a precondition to achieving a latent source of entrepreneurial labour force when uncertainty increases.

Audretsch *et al*. (2002) attribute a growth penalty to those Western European countries that failed to rebalance the economy towards smaller structures, which is reflected in lower GDP growth rates. However, they also observe that southern European countries have high levels of self-employment, which are likely to be above the optimum and contributes to a loss in welfare too. Entrepreneurial activity is therefore a function of economic stage and this entered into the discussion of Stel *et al*. (2005), who find that entrepreneurial activity is positively correlated with GDP, but is limited to developed economies. The attempt to link entrepreneurial activity and economic development is made by Wennekers and Thurik (1999) and Carree *et al*. (2002). Consistent with Acs (2006), they expect a U-shaped relationship that reflects a decline in entrepreneurial activity when the large industrial firm dominates, and increases with uncertainty as occurred from the 1980s (Carree *et al*. 2002). While Wennekers and Thurik's (1999) explanation remained theoretical, Acs (2006) reveals from Global Entrepreneurship Monitor data that entrepreneurial activity decreases, but increases again in the transition from the manufacturing to the service industry. Carree *et al*. (2002) examined 23 OECD countries from 1976 to 1996 and identified a much slower return to self-employment than expected. Scandinavian countries and Germany in particular show low levels of self-employment, whereas Italy's high self-employment rate has a negative impact on productivity levels and indicates the inefficiencies commented on by Audretsch *et al*. (2002). These firms still act as a buffer, but the majority might be business owners rather than entrepreneurs and reactive rather than active with little or no engagement in innovation. As observed by Pagano and Schivardi (2003), the scale these firms achieve excludes them from capitalising on Klepper's (1996) fixed cost marginalisation. It increases the gains of the large firm and lowers the survival rate of the small firm, which leads to suboptimal performance at aggregate level.

In contrast to Carree and Thurik (1998), Pagano and Schivardi (2003) associate a larger (average) firm size with more productivity growth as the large firm invests in R&D to increase productivity, whereas the comparatively smaller firm holds back on R&D activities. The resulting underperformance is confirmed by Acs *et al*. (1996), who associate high productivity levels with the late industry stage, consisting of high market concentration. Praag and Versloot (2007:377) too reconcile that "[t]he relative contribution of entrepreneurs to the value of productivity levels is low" and Wong *et al*. (2005) argue that just a few outperformers are responsible for significant changes in economic growth. According to Wong *et al*. (2005:345), "only a very small proportion of entrepreneurs engage in true technological innovation" and this is independent from business creations. These findings support Schumpeter Mark II, whose relevance increases as industries approach maturity. It too explains the increase in productivity levels that the established firm can exploit more efficiently and by doing so contributes to economic growth. However, as the weight of economies of scale increases in the profit function, so the ability to respond to changes in demand declines. It is at this point that the small firm enters into the aggregate growth function as its organisational structure allows it to respond more quickly to uncertainty.

Gertler and Gilchrist (1994) support previous evidence suggesting that in recessions small firms suffer more from financial constraints than large firms, which imposes a threat to firm growth as Angelini and Generale (2008) reveal. Nevertheless, when smaller firms are able to show technological leadership, macro-economic uncertainty and liquidity constraints incentivise efficiency (Dhawan 2001). These efficiency gains result in higher profitability, but come at the cost of a higher operational risk, which implies that "small firms are two to four times riskier than large firms" (Dhawan 2001:290). Despite Dhawan's (2001) sample being based on public traded US firms, the findings confirm the relevance of the SDOF with regard to economic flexibility. The dynamics of each firm-size class results in a heterogeneous response to uncertainty and risk, and indicates that a polarised size distribution is hazardous to economic performance. For economies to benefit from high levels of self-employment, firms are required to be entrepreneurial, which is the ability to efficiently allocate resources and to seize opportunities at all times. When these conditions are met, firms contribute to buffer shocks and uncertainty, whereas the inability to recognise opportunities makes firms vulnerable. In an open economy, it ultimately puts at risk the living standard achieved as nations with a high degree of entrepreneurial capital move forward.

2.3.4 Firm size and net job creation

Competition has been argued to be a crucial factor in incentivising entrepreneurial activity and successfully selecting viable innovations (Audretsch *et al*. 2002; Pagano and Schivardi 2003; Peltoniemi 2011; Wennekers and Thurik 1999), but with consequences for employment rates. The risk linked to firm size suggests that variations in net job creation (job destruction resulting from business failure minus the jobs generated by successful start-ups) are firm-size class specific. While medium and especially large firms are diversified and show a good ability to buffer failures and withstand macro-economic turbulences (Arrow 2000; Drucker 1985), a single project can put at risk the existence of the comparatively small firm. Taking into account that 20-40% of newly founded manufacturing firms fail within two years (Bartelsman *et al*. 2005) – the rate might be much higher for service firms – the economic and non-economic damage is of considerable scale. For economic progress experimenting is essential, but the loss in value of human capital, financial resources and social energy resulting from an unsuccessful project has direct consequences on economic growth and life satisfaction for those involved in the process.

The encouragement of entrepreneurial activity as a way to increase net job creation is high on the political agenda and seems indeed to show positive effects when considered at aggregate level (Audretsch and Thurik 2000; Praag and Versloot 2007; Voulgaris *et al*. 2005; Wennekers and Thurik 1999). However, this changes when introducing firm size. According to Acs *et al*. (1996) and Davis *et al*. (1996), large firms create and destroy most jobs, but Lawless and Murphy (2008) find that employment volatility in the Irish manufacturing industry is highest for small firms. Voulgaris *et al*. (2005) confirms this for Greek manufacturing firms and emphasises that volatility is highest for young firms and lowest for old firms, as later noted by Lawless (2014). These findings are consistent with Praag and Versloot's (2007) meta-analysis, which includes Picot and Dupuy (1998), for Canadian firms and Bartelsman *et al*. (2005) for OECD countries, where a mere 10% of the workforce is involved in new business venturing. It strengthens the claim that in absolute numbers net job creation and destruction caused by the small business sector is rather small (Davis *et al*. 1996) and offset by outperforming large firms (Picot and Dupuy 1998), while being historically overestimated.

Picot and Dupuy (1998) observe that differences in net job creation among firm-size classes tend to disappear when only existing firms are considered. Since newly created jobs are largely offset by job losses with little changes in aggregate employment figures (Bartelsman *et al*. 2005), Davis *et al*. (1996) interpret this as evidence for Schumpeter Mark I. Despite small variations across firm-size classes, Picot and Dupuy (1998) notice that net job creation varies more within size classes and originates from a few firms of each cohort. Their analysis shows that under constant entry and exit rates, the number of firms responsible for large fluctuations is particularly small for medium-sized firms. These findings are in accordance with the meta-analysis of 20 studies carried out by Henrekson and Johansson (2010) and reflect the conclusions of Shane (2008), Storey (1994) and Wong *et al*. (2005), who moderate the euphoria of miraculous job creation by a rise in business ventures. Henrekson and Johansson (2010) reduce the effects of positive net job creation to a very few firms – termed 'gazelles' – evenly distributed across firm-size classes; it is rather the young and not the small firm which bears the potential to evolve into a gazelle, with the large gazelles contributing most to net job creation in absolute numbers. It appears to be the product of exceptional entrepreneurial spirit that goes beyond the entrepreneur as innovator or co-ordinator.

The occurrence of gazelles across all firm-size classes indicates that firm size has a limited impact on net job creation and implicitly suggests the influence of other factors (Picot and Dupuy 1998). Moreover, it suggests the presence of the successful entrepreneur within the organisation. Categorising sample firms according to the relevant factors of production, Voulgaris *et al*. (2005) show that high-tech firms and firms with significant capital requirements contribute most to net job creation, while labour intensive firms are characterised by negative job creation. These findings are not confirmed by Henrekson and Johansson (2010), who do not observe higher concentrations of gazelles in high-tech industries, but rather in the service industry. It appears that context dependency plays a significant role, but there are indications that the capacity of young firms to efficiently use human capital is heavily determined by the kind of activity. The latter is emphasised by Davis *et al*. (1996), who promotes job quality over quantity. The importance of knowledge intensity in achieving positive net job creation has also been noted by Baptista *et al*. (2008), but to a larger extent it originates from indirectly related venues. In studying the value of entrepreneurship, Praag and Versloot (2007) underline the importance of the positive effects entrepreneurial firms have on a larger scale. They refer to the “important spillovers that affect regional employment growth rates of all companies in the region in the long run” (*ibid*.:351). It also implies that net job creation matters most at economy level and, as Pagano and Schivardi (2003) indicate, imposes limitations to firm-level analyses.

As new entrants are most likely small, it is by definition the small firms that are most dynamic and mobile across firm-size classes (Lawless 2014), but also the most vulnerable in times of recession (Lawless 2012). It leads to high net job creation rates on one end of the SDOF and a high number of jobs being created and destroyed on the other end, with the middle being moderate in both dimensions. As unemployment has a considerable negative impact on life satisfaction (Oswald 1997; Stiglitz *et al*. 2010), the disproportionate dominance of large scale firms has negative effects. It contributes to self-employment out of necessity (Baptista *et al*. 2006), which hinders the achievement of high satisfaction levels (Block and Koellinger 2009). Likewise, it fails to contribute to growth and spill-over effects, because the entrepreneurial element is absent. It adds to the volatility in job creation and destruction rates and echoes the uncertainty this firm-size class faces. Uncertainty and lack of opportunities motivate the young and well-educated to work for someone else (Blanchflower 2008) and when the large firm is the only alternative to the small firm as it occurs under extreme FSI, entrepreneurial potential remains unutilised and life satisfaction low.

2.3.5 Conclusions

Firm-size classes substantially differ in their contribution to technological progress and in responding to environmental changes, largely influenced by the business owner's aspirations. It has been discussed that the young and marginal business unit fulfils the function of the experimenter, while the large unit is more likely to systemically build on existing operations and structures. Accordingly, the organisational complexity defines the type of innovation it produces, which tends to be simple but revolutionary for the small firm and non-revolutionary but sophisticated for the large firm. It reflects the pattern of historical development since the First Industrial Revolution and the implications for welfare that followed. Yet the occurrence of gazelles across firm-size classes testifies that entrepreneurship is not bound by firm size. There are as many large or medium-sized firms that grow at a fast pace as there are small firms. Their appearance is unpredictable and is the outcome of entrepreneurial foresight. The type of innovation, however, differs and to exercise his/her interest, the entrepreneur needs freedom. Such freedom is restricted when the range of firm sizes is reduced to a polarised size distribution, because it limits the recognition of entrepreneurial potential and the provision of resources. Innovative capacity cannot be realised when the choice is just the small vulnerable firm or the large bureaucratic firm. Apart from the entrepreneur, it requires a diversity of existing firms with an organisational structure allowing accumulated knowledge to be absorbed and commercialised. The choices are fewer when FSI is extreme, which ultimately increases the underinvestment in risky projects and systemically reduces welfare.

No such relationship has been taken into consideration by Marx, Austrian scholars or Schumpeter. If at all, it is Drucker who touches on it and imposes a lower limit to firm size. This gives credibility to Lucas' (1978) prediction, but would it apply, the loss of welfare is vast. The dynamism of net job creation at industry level and its stability at aggregate level suggests that a process of creative destruction takes place and rejects the hypothesis of an ever declining share of self-employment. Arrow's (1962, 2000) association of firm size with innovative capacity gave firm heterogeneity a meaning with regard to the welfare function. To achieve sustainable growth, entrepreneurial activity is imperative, but for welfare maximisation, Audretsch *et al*. (2002) identified an optimum linked to the economic stage. When the ideal level of entrepreneurial activity is exceeded, the activity is unlikely to be entrepreneurial. It might contribute to lower uncertainty by bearing risk, but it would be more efficient to aggregate inefficient activities. The resulting welfare loss is enhanced when the share of large firms exceeds a critical level. As most jobs in absolute numbers are created and destroyed by large firms, a disproportionate share conditions entrepreneurship out of necessity and the co-existence of small and large firms that slows down economic recovery. While the large firm is slow in adjusting to new conditions, the volatility in job creation and destruction of the marginal firm manifests its physical limit to buffer shocks. Certainty favours structures that are opposed to uncertainty, therefore in times of increasing uncertainty, such structures must be resilient. Resilience demands diversity and an economy exclusively relying on either large and/or small firms is unlikely to be a sustainable constellation. To achieve it, it requires the contribution of the medium-sized firm.

Young entrepreneurial firms are needed to ensure the future generation of SMEs, but it is the entrepreneurial medium-sized firm that is capable of absorbing knowledge and commercialising on innovations that would fall through the audit of the large firm, whilst being beyond the accessible resources of the small firm. The medium-sized firm may itself produce spinoffs that mutate into gazelles, which are the outperformers in generating jobs. Its bridging function of extreme positions makes it a substantial contributor to welfare. It faces less uncertainty than the small firm and ranks higher in job security (Davis *et al*. 1996; Praag and Versloot 2007; Storey 1994; Storey and Greene 2010), which allows the attraction of talents. The rational of the entrepreneur might differ from the norm, but for employees, job security, next to income, is the most important factor they are looking for (Clark 2001) and this has positive effects on job satisfaction (Blanchflower and Oswald 1999) and firm performance (Diener and Seligman 2004; Judge *et al*. 2001; Ostroff 1992). A fair share of medium-sized firms can therefore be expected to contribute to life satisfaction and sustainable growth, whereas a declining share weakens innovative capacity and the ability to adequately respond to change with implications on net job creation. Thus, it is desirable to reduce the risk of a convergence towards extreme structures, the possibilities of which are discussed in the next chapter.

CHAPTER 3: STRUCTURAL CHANGE, FIRM SIZE INEQUALITY AND FIRM GROWTH

The previous chapter outlined the evolution of Europe's industries from a historical perspective and linked the emerging patterns to the industry life-cycle theory. To explain these dynamics, characteristics related to firm size and entrepreneurial activity were introduced, which allowed for a theoretical prediction of changes in FSI. When at a critical point in a firm's life the entrepreneur is replaced by the manager or, at best, by the intrapreneur, the constraining organisational system surrounding him/her changes the kind of innovation it produces. The same applies to the firm's response to new conditions and the role it plays in generating employment. This attributes a particular function to each firm-size class and explains why the SDOF has implications for welfare. The foregoing chapter therefore concluded that welfare maximisation necessitates a SDOF free from extreme constellations. But in post-industrial Europe, there is little awareness of nature and consequences of the missing middle, and the importance of FSI. The conventional approach to rebalance an economy is based on the promotion of start-up activity with the expectation that new technologies leverage the success rate. Yet the literature reviewed so far suggests that rebalancing is unattainable without looking at the SDOF as a whole. In addition to new venture creation, this also involves an understanding of industry dynamics and the determinants of firm growth.

The aim of this chapter is to examine the possibilities for structural change, which first requires a discussion of the effectiveness of entrepreneurship policies using start-up activity as a means to induce such change. As such an approach rests on the entrepreneur, whose occurrence is random and unpredictable, an analysis of the logic that industries follow is needed. The industry life-cycle theory explains firm selection, but says little about the SDOF itself. Should it follow a particular pattern – and both industry life-cycle theory and industrial revolutions suggest that it does – the question is then directed towards the systemic forces driving it. Gibrat's Law has been the most significant contribution in the field of size-growth regularities and built the foundation for the competing streams discussed in the second and third parts of this chapter. The second part consolidates influential work on the SDOF and FSI, and makes sense of the theories, models and empirical studies with different backgrounds. There is, however, a point where empirical work begins to replace theoretical models incapable of capturing the complexity of the real world. In particular, research on the SDOF is characterised by generalisation and simplification, and fails to identify individual forces acting upon industries and firms. Less so is the literature on FSI, which is empirical in nature and focusses on specific forces acting at industry level. As for policy design an understanding of the forces at firm level is imperative, the third part consults the literature on Gibrat's Law itself. It identifies which firm-size classes grow fastest and seeks to find explanations for this growth by examining related studies. The chapter then closes with a conclusion bringing together the key theoretical and empirical issues raised in the literature review that formulate the research questions.

3.1 Structural change in the industrial landscape

In an attempt to identify the contribution of entrepreneurship policy to structural change the following sections look at entrepreneurial activity and the knowledge society. It is mainly a theoretical critique of policies built on the belief that structural change and growth can be achieved by simply encouraging start-up activity, frequently put on par with entrepreneurial activity. It is the product of the ambiguities of entrepreneurship as a field and the need to operationalise the theoretical entrepreneur. The first part addresses this and clarifies to what extent self-employment, especially start-up activity, contributes to structural change and sustainable development. The second part recalls the reasons for a structural change and its conditions. It is a new generation of entrepreneurs that is expected to introduce this change and, from a macro-economic perspective, new firm formation might contribute to aggregate growth and net job creation. The context-specific environment and the focus on one end of the SDOF, however, impose restrictions in applying what is a theoretically sound approach. Its failure bears a social cost as it misdirects social energy and, as this section concludes, can be lowered when extending the focus on the contribution of SMEs in addition to the young firm emerging out of an opportunity.

3.1.1 Structural change through entrepreneurial activity

Knight's development of Cantillon's entrepreneur (Praag 1999) set the basis for *entrepreneurship* as a field in its own right. It was enhanced by Schumpeter (1947), who attributed economic significance to the entrepreneur. As source of change and technological progress, the redefined entrepreneur attracted interest in the understanding of his/her contribution. Technological change was also one of Mises' (1951) points, but for him the entrepreneur was merely an auxiliary to explain economic progress. Consistent with the classification as an economic activity or – for organisational theorists – a managerial activity, the emphasis lies on individualism and the outstanding rather than the average citizen. To a lesser extent, entrepreneurship refers to the field as a whole, because it merely fills the "gap[s] in conventional economic theory" (Baumol cited in Casson 1987:252). Unable to reduce the ambiguities associated with entrepreneurship, this initiated a dialogue in economic and organisation theories and generated the awareness that firm size and entrepreneurship are endogenous.

Today, the interest is much about the laws that govern firm creation and survival (Acs 2006), which have become the legitimate boundaries. Entrepreneurship is also engaged with the factors influencing the successful commercialisation of opportunities and its impact on the economy, but it sees the underlying economic conditions as a given and rarely undertakes any attempt to question them. Consistent with Casson (1982), Shane and Venkataraman (2000:219) criticise these limitations and consider the "environmental antecedents and consequences" as complementary and essential. The lack of conceptualisation and the difficulties social scientists face to confine the field – it partly interferes with existing disciplines (*ibid.*) – questions the applicability of the tradition on which it is founded. This refers to the transferability of the theoretical entrepreneur to the real world and the expectations that can be derived from policies aiming to maximise firm creation.

To eliminate the ambiguities associated with the concept of the entrepreneur, Shane and Venkataraman (2000:219) redefine the entrepreneur; he is no longer the exceptional mind with the capability to anticipate future needs and with a willingness to accept risks, but “the tendency of certain people to respond to the situational cues of opportunities—not a stable characteristic that differentiates some people from others across all situations.” They transform the entrepreneur into a context-dependent product, which has been isolated by the Austrian School and Schumpeter (1947), and ignored by management strategists (*ibid*.). Schumpeter’s (1947) definition of the entrepreneur makes logical sense, but becomes unsuitable for empirical work as, for the outsider, it is unclear whether the individual is an entrepreneur or a businessman at a given point in time. Shane and Venkataraman’s (2000) conceptualisation comes close to Kirzner’s understanding, where the spontaneous recognition of new opportunities results in unforeseen learning (Ibrahim and Vyakarnam 2003). This is the operationalised version of the theoretical entrepreneur.

As the entrepreneur needs a legal framework in order to carry out his activity, new firm foundation becomes the observable unit, because it is a common way to implement new innovations and ideas (Acs 2006; Praag and Versloot 2007; Wennekers and Thurik 1999). Hence, the firm becomes the level of analysis, but, according to Klapper *et al*. (2012), needs extending to firm growth. It enables the inclusion of the “developmental process” the entrepreneurial firm undergoes (Klapper *et al*. 2012:126) and its contribution to the wider economy. But profitability and growth should not be seen as a key driver of entrepreneurial activity (Bridge and O’Neill 2012), because the Schumpeterian entrepreneur is driven by passion. This qualifies the small and preferably young firm to alter existing structures. It is the foundation "to use entrepreneurship policies as an instrument of an industrial policy explicitly aimed at promoting structural change” (Piergiovanni and Santarelli 2006:272). The expectation is that such change follows from disruptive mechanisms and attributes entrepreneurship policy as a major role in maintaining a sound industrial dynamism.

The complications emerging from the said bottom-up approach are twofold. First, the operationalised entrepreneur becomes inseparable from the mere self-employed or business person. Second, the laws governing industries and society discussed in Chapter 2 are highly restrictive, which has implications on the first complication. Since the large firm dominates as we move along the industry life-cycle, the efficiency of policies encouraging entrepreneurial activity reduces as soon as the window of opportunity closes. Despite the growth of a few outperformers, the trend is accelerated by the preference for the young and well-educated to work for someone else. Moreover, the inseparability of entrepreneurship and capital contributes to the preselection of entrepreneurial success. It is enforced by changes in wealth distribution, noted by Quadrini (2000) and Wolf (2012), and explains stagnating entrepreneurial activity in the UK – the most entrepreneurial European country – observed by Bridge and O'Neill (2012) and Huggins and Williams (cited in Arshed and Carter 2012). The shortage of skills and capital necessary to accept risk causes a systemic erosion of entrepreneurial activity and applies even more so to the more conservative countries of continental Europe.

The high levels of micro firms in Italy (Carree *et al*. 2002), Portugal (Baptista *et al.* 2006) and southern Europe in general (Pagano and Schivardi 2003; Stenkula 2007), questions the motives for self-employment and determines the expectations of entrepreneurship policies pushing for more start-up activity, which is a single-sided focus on the SDOF. Baptista *et al.* (2006) refer to the economic choice theory, which advocates that individuals consider becoming self-employed whenever they cannot find appropriate employment. It is by definition the not so well-educated and wealthy European, who ultimately faces a higher risk of failure and does not contribute to aggregate growth (Audretsch and Thurik 2000; Baptista *et al.* 2006). According to Acs (2006:97), the crux lies in the crucial distinction between those who start up a business out of necessity ("necessity entrepreneurship") and those who do it to seize an opportunity ("opportunity entrepreneurship"). He (*ibid*.:97) rejects the oversimplified view that “[e]ntrepreneurs create new businesses, and new businesses in turn create jobs, intensify competition, and may even increase productivity through technological change.” Only opportunity entrepreneurship does so (Acs 2006) and, as was discussed in section 2.3.3, this is a function of the economic stage.

Compared to the UK, Southern European countries are in a different stage and suffer from a suboptimal “opportunity-to-necessity” ratio, which Acs (2006:102) finds to be strongly linked to income per capita. To lower the said ratio, framework conditions at firm and individual level have to be balanced in accordance with the stage of economic development and will therefore change over time (*ibid*.). By treating young firm incorporation as entrepreneurial activity, these factors gain insufficient attention and add to the misallocation of social energy. Entrepreneurship policies encouraging self-employment need to be context-specific and economic development can only result in tandem with policies addressing existing SMEs. As the share of necessity entrepreneurship increases, the share of SMEs is predicted to shrink at an accelerating rate and the window of opportunity to rebalance the SDOF closes. It inevitably leads to the co-existence of large and small firms, and marginalises the occurrence of disruptive processes.

3.1.2 Structural change through the entrepreneurial society

As anticipated in section 2.1.4, increasing international trade and efficient means of communication have contributed to Europe’s loss of the Ricardian comparative advantage, the consequences of which are elaborated in Audretsch and Thurik (2000). This resulted in a choice between lower wages and less unemployment in the UK and higher wages and more unemployment in continental Europe (Audretsch and Thurik 2000). Audretsch and Thurik (2000) argue that under progressing globalisation the emigration of production from high wage countries is unavoidable, but it is avoidable when replacing the traditional input factors with knowledge. Unlike pieces of information, knowledge is “geographically bounded within the region where the new economic knowledge was created” (Audretsch and Feldman 1999:86). As knowledge becomes gradually accessible to other market players (Teece 1998), the competitive advantage is temporary. To maintain it requires continuous reproduction.

The generation of new knowledge requires freedom (Schumpeter 1947), experimenting (Bartelsman *et al*. 2005; Koellinger *et al*. 2007) and "ideas that are subjective, uncertain and difficult to explicitly write down" (Audretsch and Thurik 2000:23). This is a fundamental contradiction to the large firm and as the laws of competition change, the small firm has a theoretical chance to outperform its larger counterpart. But it demands patience, because knowledge has the longest lead time of production and often advances through trial and failure with uncertainty as an integral part (Audretsch and Thurik 2001; Drucker 1985). As knowledge takes on the property of "an intermediate good and need[s] to be packed into products or services to yield value" (Teece 1998:72), it is inseparable from access to resources and therefore a function of firm size. Moreover, Audretsch and Elston (2006:139) emphasise that "there is no guarantee that the new knowledge is economic knowledge." They refer to the inefficiencies of knowledge creation, resulting from high uncertainty and the absence of a continuum between success and failure. To commercialise knowledge-based goods and services, endurance becomes a precondition and the need for resources of different magnitudes demands the participation of more than one firm-size class.

With "intangible assets as the main basis of competitive differentiation" (Teece 1998:76), knowledge accumulation can only occur when failure does not put at risk the existence of its producer. It strengthens the incumbent firm and reduces the survival rate of the new and young firm. The innovative entrepreneur becomes a key protagonist in the gamble of economic growth and "[e]ntrepreneurship … an integral part of a knowledge-based economy" (Blackburn and Brush 2008:vii). Drucker (1985:236) was aware of the potential that entrepreneurial behaviour holds and, to maximise innovative output, promotes a shift towards an entrepreneurial society:

> “What we need is an entrepreneurial society in which innovation and entrepreneurship are normal, steady, and continuous. Just as management has become the specific organ of all contemporary institutions, and the integrating organ of our society of organizations, so innovation and entrepreneurship have to become an integral life-sustaining activity in our organizations, our economy, our society.”

Consistent with Drucker (1985), Audretsch and Thurik (2000:24) call it the “entrepreneurial society” and argue that “the ability of people to move into new situations to create and try out new ideas rejected elsewhere is fundamental in a knowledge-based economy.” However, the conceptual implementation of the entrepreneurial society as viewed by Drucker (1985) contradicts Audretsch and Thurik (2000). Drucker (1985) is more pragmatic about the resources and commitment necessary to establish and maintain a business venture and favours a cultural change and the transformation of existing establishments, where entrepreneurial behaviour is systematically developed and entrepreneurial decision-making encouraged. A similar form of entrepreneurial freedom, based on the idea of collective ownership, was expressed by Schumacher (1973). Upgrading existing organisations with a more open and committed human capital is expected to result in economic progress, but conflicts with the entrepreneur described by Mises (1951) and Schumpeter (1947). It requires the entrepreneur to be able to identify opportunities as redefined by Shane and Venkataraman (2000), but the systemic restrictions firm size imposes influence the outcome.

By encouraging the formation of new business ventures, Audretsch and Thurik (2000:24-25) take a utility maximising approach:

> “the knowledge-based economy is in motion and is characterized by a high degree of people starting new firms to pursue, explore or implement new ideas. Those new firms that prove to be viable grow rapidly and expand employment. Those based on an idea that is not viable stagnate and may ultimately exit.”

In other words, structural change is induced by encouraging self-employment and the reliance on gazelles. Audretsch and Thurik (2000) see the need for capital for firm creation, but do not explicitly distinguish the entrepreneur from the self-employed, who may execute an economic activity without being endowed with any particular skills. Well aware of the resulting dynamics, Audretsch and Thurik (2000:25) add that it “is actually the process by which new ideas are generated and explored, ultimately creating new high-paying jobs to replace those lost due to downsizing.” From a utilitarian long-term perspective it is unconditionally justifiable since employment dynamics are part of the structural adjustment process. However, as discussed in the previous section, the expectations associated with higher self-employment do not suggest efficiency. The situation might be different in the US, where it is the young and well-educated who enter self-employment (Bates 1995; Blanchflower 2008; Levine and Rubinstein 2012; Quadrini 2000), but contemporary Europe has not yet shown sufficient commitment nor has it implemented adequate framework conditions for an entrepreneurial society to emerge.

The need for experimentation as a precondition for economic growth is indisputable, however the vulnerability of the small business and the associated social cost are a reality too. The positive correlation of entrepreneurial activity and economic growth identified by Audretsch and Thurik (2000) does not reveal whether growth results from gazelles or large firms’ successful acquisition of promising young firms as Arrow (2000) predicts. Their extension of the association of structural change to SMEs suggests that entrepreneurial activity lowers, or is even the product of, lower FSI. It is therefore not just entrepreneurial activity in the form of young firms that needs encouraging; depending on the economic stage, this can indeed be counterproductive. Even a population purely consisting of opportunist entrepreneurs faces limitations and only a few gain the benefits expected from owning a business (Audretsch and Thurik 2000; Block and Koellinger 2009; Shane 2008). Knowledge intensity certainly gives an advantage, but in reality the ideal entrepreneur able to commercialise rarely exists. The space for mistakes and failure is systematically smaller for the innocent opportunity entrepreneur than for the experienced entrepreneur relying on accumulated resources, including knowledge. Those who overcome the initial resource constraints imposed by the capital requirement are most promising (Praag 1999) and induce the dynamism needed to preserve the middle of the SDOF. Yet it is the middle itself that bears considerable potential to unleash entrepreneurial activity by commercialising on the opportunities it recognises. It is an integral part in achieving sustainable growth.

3.1.3 Conclusions

The use of entrepreneurship to explain phenomena that could otherwise not be explained led to the emergence of a new field of research that, with regard to environmental conditions, has deliberately imposed upon itself the *ceteris paribus* restriction. On the assumption that job creation is a reliable measure from which to determine the success of a policy (Teruel-Carrizosa 2010a), it encourages entrepreneurial activity as the universal means of bringing economies back on track by inducing dynamism. Looking back at the industrial revolutions and the post-war era this was certainly the case, but increasing imbalances in wealth distribution and economic choice have changed the fundamental factors determining entrepreneurial success. It systemically erodes entrepreneurial capital by reducing the supply of talent able to commercialise ideas. It makes Acs' (2006a) differentiation between necessity and opportunity entrepreneurship central to the identification of the quality of entrepreneurial activity. However, it becomes slippery when using the young firm as the operationalised parameter. It requires firm growth to enter into the equation, which makes the potential of entrepreneurial activity visible.

When framework conditions are hostile to opportunity entrepreneurship, employment opportunities are allocated to the well-off and, according to the occupational choice theory, necessity entrepreneurship increases. The latter does not contribute to economic development, because the average man is unable to foresee the future and, as Mises (1951) noted, s/he confuses profits as an instrument to advance technological progress with consumption. This constraints him/her in efficiently responding to environmental changes. Unaware of the implications of his/her actions, it makes the self-employed worker inflexible in absorbing economic shocks and has consequences for welfare. As s/he does not create new opportunities, it is the beginning of a deadly cycle. With the decline of the share of medium-sized firms, innovative capacity vanishes and so too do new opportunities. It leads to even more necessity entrepreneurship and increases FSI, which is unsustainable in the long term and applies to most Southern European countries.

In contrast to necessity entrepreneurs, opportunity entrepreneurs are driven by passion and are rewarded with more life satisfaction (Blanchflower 2008; Praag and Versloot 2007). But even then the glorification of start-up activity is erroneous and does not by definition lead to innovation, growth or structural change for the better. Low skilled self-employment does not lead to more innovation, nor does it significantly contribute to spill-over or spin-out effects. It simply increases the number of market participants competing for resources with a higher probability of inefficiencies at aggregate level. Equally, policies focussing on skill development can only be as successful as the foundation upon which it is build. The infiltration of knowledge and technology opens up new opportunities and changes the competitive power. To maximise welfare, Acs (2006) emphasises the link of economic activity and economic stage. As knowledge intensity is highest in developed regions, these are most likely to benefit from entrepreneurial activity. To flourish, diversity becomes a precondition, because "[d]iversity, not convergence, generates innovation and growth" (Audretsch and Thurik 2001:308). It requires agents to be able to commercialise on ideas, which in contemporary Europe is not just the entrepreneurial micro firm. They assist in the execution of risky experiments, but more can be done.

Since entrepreneurial success is an *ex post* phenomenon, a buffer to absorb the downward risk of uncertainty, which nevertheless leads to knowledge accumulation, is essential. It therefore requires the contribution of entrepreneurial SMEs, which are in possession of more resources than the individual and more entrepreneurial freedom than the large firm. As Lenihan *et al*. (2010b:217) state, it appears indeed that "economic growth can be experienced at a national level without any accompanying (or causing) increase in business creation activity." The preservation of a fair share of SMEs is therefore vital and eventually leads to spinoffs and spill-overs that induce structural change and leverage the opportunities for new entrepreneurial activities. Advances in technology allow the application of new technologies to existing firms, but require a diversity of agents contemporaneously working at the implementation of innovations. It is the SDOF as a whole that matters and not just the single-sided focus. The research area concerned with the SDOF and FSI is therefore addressed in the next section.

3.2 The size distribution of firms and firm size inequality

Entrepreneurship literature focuses by nature on the entrepreneur and the entrepreneurial firm – limited in size – and, if at all, contrasts it with the large firm. As concluded in the previous section, it is the sum of differently sized firms that describes diversity and is assumed to be linked to welfare. It is referred to as the SDOF and represents the frequency of firms according to size, not to be confused with the firm size distribution, which is the change of a firm's size over its lifetime. The latter reflects a firm's growth pattern and takes into account the SDOF as a snapshot of all underlying firms at a certain point in time. In contrast, FSI embodies information of the SDOF in the form of a coefficient.

The next sections are devoted to the SDOF and FSI. The former has been explored more extensively than the latter, which has been replaced by literature on firm growth and will be discussed in more detail in section 3.3. Although seemingly sharing the same phenomenon with its origins in industrial economics and, in particular, market concentration, cross-references are surprisingly rare. For instance, the industry life-cycle theory is widely absent in the literature on the SDOF and, although interesting, comprehensively translating its implications into the SDOF is also beyond this thesis. The striking commonality of the two streams is the strong reference to Gibrat (1931), whose law – the independency of firm growth from size under constant entry and exit rates – implies that the SDOF follows a lognormal distribution. This initiated the debate that forms the foundation of the following discussion.

3.2.1 On the size distribution of firms

In 1958, Simon and Bonini criticised economists for their lack of engagement in finding theoretical support for the SDOF and referred to those arguing that firm size comparisons are meaningless. The large firm is still considered as essential for a modern and wealthy economy (Acs 1992; Lucas 1978), and its superiority in efficiently producing for mass consumption remained unquestioned. As the leader in developing complex products from simple innovations (Bruland and Mowery 2009), there was no need to question the economic model welfare was built on. Among the pioneers to identify patterns for changes in market concentration are Hart and Prais (1956). By raising the issue of "social and political consequences of any increase in the concentration of economic power", Hart and Prais (1956:152) brought the SDOF to the research agenda. Free from any established theoretical foundation, but highly influenced by Gibrat (1931), their interest is exclusively the examination of the dynamics of market concentration.

Their approach is built on Berle and Means' (1932) analysis of the 200 largest US non-banking firms, which observed an increase in large firm dominance. Hart and Prais (1956) examined 3,200 quoted UK firms from 1885 to 1950 using the Lorenz curve analysis and Gini coefficients. It formed the basis to describe business concentration and its change over time. Their findings suggest that the SDOF can be described by the lognormal distribution, i.e. when the log of firm size is distributed normally, and show that business concentration increases over time but declines as new firms enter into an industry. It followed Adelman (1958) with a sample of large US steel firms. In contrast to Hart and Prais (1956), Adelman (1958:903) concluded that the observed "growth pattern is a size-dependent stochastic process", where the SDOF of industries converges to a specified distribution regardless of its initial configuration.

Contemporaneously, Simon and Bonini (1958) used a sample of the 500 largest US firms to support their equilibrium model, which describes a lognormal distribution with a Pareto distribution for the upper tail. The presence of a Pareto distribution implies that the share of small firms is larger than for the lognormal distribution (Coad 2009) and can be explained by the existence of a MES (De Wit 2005). Simon and Bonini (1958) confirm the existence of a MES identified earlier by Bain (1956) and assume the same growth probability distributions for all firms above the critical size. Similar to Hart and Prais (1956), the SDOF is industry-specific with firm entry – assumed at a theoretical constant rate – thus lowering market concentration. In contrast to Hart and Prais (1956), who commented on the determinants of the SDOF's dynamics, the interest of subsequent studies shifted away from the causalities towards the prediction of the change. The essence of the research concerning the SDOF became the identification of the distribution firms sizes follow.

To clarify which distribution fits best, Quandt (1966) tested the Pareto, Champernowne, composite, iterated exponential and lognormal distributions. He finds that the latter three fit better, but there is a best fit for each distribution for at least one sector, whereas the Pareto distribution offers the poorest description. It confirms the relevance of industry-specific peculiarities, which Quandt (1966) attributes to specific short- and long-run cost functions, initial market concentration and the differences in technology and product competition. It further rejects the relevance of the MES. As his sample, similar to Simon and Bonini (1958), consists of the 500 largest US companies listed by *Fortune*, this applies at least to large firms. Yet his findings consolidated the view that the size distribution can either be described by or converges to a natural stage with the lognormal and Pareto distributions emerging as the dominant patterns being considered for future research.

Consistent with Hart and Prais (1956), Growiec *et al*. (2008) model a lognormal distribution with a Pareto distribution for the upper tail and support it with product and firm-level observations from 28 countries whilst controlling for entry and exit rates. Cirillo and Hüsler (2009) and Kaizoji *et al*. (2005) support the presence of a Pareto law for the upper tail for Italian and Japanese firms respectively. However, Kaizoji *et al*. (2005) also find that the size distribution of US multinationals is lognormal and hence consistent with Hart and Oulton (1997) for independent UK firms and Cabral and Mata (2003) for Portuguese manufacturing firms. Hart and Oulton (1997) disagree with the upper tail being described by a Pareto distribution, whereas Rossi-Hansberg and Wright (2007) identify a pattern close to the Pareto distribution for the US and Gaffeo *et al*. (2003) for G7 countries.

The contradictions resulting from empirical work can be attributed to the frequent exclusion of small firms from samples and the conflation of aggregate versus industry-specific samples. Coad (2009) draws attention to Axtell (2001), De Wit (2005) and Luttmer (2007), who also considered smaller firms in their studies and find that a Pareto distribution fits the description of the size distribution better than a lognormal distribution, as found by studies who considered merely large firms. This is consistent with Cabral and Mata (2003), but contradicts Hart and Oulton (1997). De Wit (2005) clarifies that small industries and samples consisting of firms similar in size are more likely to result in a Pareto distribution. Hart and Oulton's (1997) aggregation of 50,441 firms across all size classes and industries might explain this. Industry-specific patterns are found by Marsili (2006) for Dutch manufacturing firms and result in either a Pareto or lognormal distribution. The inclusion of industry also explains the rather stable SDOF found by Axtell (2001), Cabral and Mata (2003), Cirillo (2010), Cirillo and Hüsler (2009), Dinlersoz and MacDonald (2009) and Robson and Gallagher (1994).

The theoretical explanations for the observed patterns are the economic development for analyses at aggregate level and the industry life-cycle theory at industry level. Axtell (2001) establish the link to the former and argue that FSI increases only until it reaches a critical point after which it becomes stable. It can then be described by one or another statistical distribution, with firms that enter and exit cancelling each other out. According to Axtell (2001:1818), the SDOF is "insensitive to changes in political and regulatory environments, immune to waves of mergers and acquisitions[,] … unaffected by surges of new firm entry and bankruptcies[,] … large-scale demographic transitions within work forces … and widespread technological change." Country-specific patterns confirming the influence of the economic stage are also observed by Stenkula (2007) for EU countries with southern Europeans being characterised by a larger share of micro firms and a gradual increase in average firm size. It opens a gap in average firm size between Italy and Spain on the one side and UK and Germany on the other (Pagano and Schivardi 2003).

The argument that the SDOF is a function of economic development is also promoted by Lucas (1978). Against the tradition and with the consequences of monopoly power in mind, he looks at the individual within the organisation and the economic choice s/he has, but also comes to the conclusion that firm size, and with it FSI, increases over time. He returned to the determinants of the changes and, as anticipated in section 2.3.3, interpreted the SDOF as a function of managerial talent and opportunity cost. Since the manager's return increases with a rise in real wages and the span of control, opportunity costs increase and makes it more convenient to work for someone else than for him/herself. Consistent with Boswell (1976), he expects a trend towards larger firms and directs his critique to Viner (1932), who advocated an industry-specific unique size distribution resulting from U-shaped long-run average costs. An optimum firm size within any given industry is therefore existent, but rejected by Lucas' (1978) notion of the multi-product firm active in multiple markets. Furthermore, Lucas (1978) observes an increasing mobility of managers, which justifies his analysis at economy level, while Viner's (1932) theory is based on an industry-level approach.

However, as soon as the SDOF is analysed at industry level, dynamism increases (Dinlersoz and MacDonald 2009; Hashemi 2003; Marsili 2006; Pagano and Schivardi 2003; Stenkula 2007). There is an agreement that size distributions of firms are right-skewed (Axtell 2001; Barbosa and Eiriz 2010; Cabral and Mata 2003; Gil 2010; Kessides and Tang 2010; Lotti and Santarelli 2004; Marsili 2006), but they become more symmetric over time (Cabral and Mata 2003). Pavitt *et al*.'s (1987) survey of over 4,000 innovations occurring in the UK between 1945 and 1983 supports Klepper's (cited in Peltoniemi 2011) argument that the SDOF is a function of industry-specific opportunities. These arise from R&D and technological developments and attract new entrants (*ibid*.). As the dominant design emerges and resources shift from product to process innovation, inefficient firms are forced to exit (Peltoniemi 2011). According to Dinlersoz and MacDonald (2009) and Lotti and Santarelli (2004), it is the shakeout following the large number of entrants that induces the dynamism that the SDOF reflects. Surviving firms are more homogeneous and skewness decreases (Dinlersoz and MacDonald 2009), which too results from an increase in firm age as Cabral and Mata (2003) and Cirillo (2010) demonstrate for Portugese and Italian firms respectively. It eventually leads to the natural distribution, which for Lotti and Santarelli (2004) is the industry-specific lognormal distribution and occurs at a faster rate when technology intensity and MES are high (*ibid*.; Peltoniemi 2011).

The discussion on the SDOF does not give a conclusive answer as sample sizes and context are highly heterogeneous, but suggest a clear distinction between patterns emerging at aggregate and industry level. Yet the literature supports the existence of a natural stage and the firms' converge towards it, which tends to be a lognormal distribution when small firms are excluded. The inclusion thereof increases the right-skewness and leads to a Pareto distribution indicating the significance of a critical firm size above which firm growth becomes independent from size. De Wit (2005:442) considers the lognormal distribution as "transitional" which "will break down and firm size becomes undetermined." Nonetheless, its frequent occurrence in empirical work (De Wit 2005; Hariprasad 2011) might stem from declining growth as an industry ages (De Wit 2005) and initiates a shift towards symmetry.

The emphasis of mainstream papers focussing on size distributions rests on the technical identification of the distribution, with influencing factors and implications – once the justification of the pioneers – being put in the background. There are limitations as to what can theoretically be predicted and this is largely associated with the difficulty in capturing the heterogeneity of industries and firms. As Mairesse (cited in Coad 2009:5) comments, "[t]here is a sense in which different bakeries are just as much different from each other, as the steel industry is from the machinery industry". By focussing on entry, exit and growth, these aspects – except Lucas (1978) – remain understated and ignore firm-specific characteristics other than the industry. Accordingly, the field lacks implications for industrial policy, which gains importance when attempting to identify industry-specific forces affecting the SDOF. It requires the transformation of the structural information the SDOF contains into a coefficient, and is referred to as FSI.

3.2.2 On firm size inequality

As anticipated, studies focussing on FSI barely refer to the same background literature as those referring to the SDOF. It appears to arise from the increasing focus on the theoretically motivated description of the distribution in the one field and the empirical nature of matters concerning market concentration and industry dynamics in the other. Born as an indicator for the degree of competition (Chamberlin 1933), market concentration has direct implications on FSI. This was considered by Hart and Prais (1956) and Simon and Bonini (1958), but lost importance as the SDOF as a field of research progressed. Acs (2006) and Bloch (1981) attribute more dynamism to the SDOF than most other literature on the SDOF suggests. Hariprasad (2011:4) interprets it at as "the means to describe the evolution of market structure over time" and hence is in the first place concerned about the number of firms and their respective market share rather than the distribution itself. Industries rather than economies become the level of analysis and accordingly refer to aspects observable at industry and, in some cases, at firm level.

The increasing number of fast growing firms after WWII reversed the trend of the progressively increasing market concentration in both the US (Collins and Preston 1961) and the UK (Hart and Prais 1956). Hart and Prais (1956) associated the phenomenon with the higher profitability of (relatively) small firms. Hart (1960:58) confirmed this, but concluded that "[t]he general tendency for concentration to increase was not attributed to any systematic force but to a large number of forces acting randomly", where size mobility rather than size-dependent growth rates are responsible for changes in market concentration. This conclusion led to the assumption that the SDOF follows a specific distribution and legitimates the exclusion of competitive forces as they merely reallocate resources with little change in the distribution as a whole. Hariprasad (2011) agrees with the natural stage of the SDOF, but calls for a focus on skewness and the forces leading to it. He refers to the ‘missing middle’ contributing to a lack of competition that, as discussed in Das and Pant (2006), is characteristic of developed economies with a large proportion of mature industries. In disagreement with Hart (1960), Hariprasad (2011:2) argues that “the prevalence of lognormal distributions of firm size indicates that there are stochastic forces at work, such stochastic processes operate along with more systematic influences on concentration.” It is these factors that research focussing on the technical description of the SDOF left largely unaddressed.

Das and Pant (2006) emphasise the complexity of industry dynamics and note that market liberalisation, i.e. lowering entry barriers, does not necessarily lead to the expected increase in competition. India’s liberalisation waves after its independence in 1947 and again in the 1990s incentivised Ghosh (1975) and Das and Pant (2006) to analyse the changes in market concentration. Similar to Hart and Prais (1956), Ghosh (1975) used the Gini-coefficient to measure FSI and added the Herfindahl-Hirschman Index (HHI) for cross-validation to understand the changes among market leaders. From 22 broadly defined industries Ghosh (1975) finds that the structure of most industries shifted from a CR4 concentration ratio of above 50% to a significantly lower degree. In reducing relative market share, industry growth played a major role and applied in particular to fast growing technology intensive sectors (Ghosh 1975). He notices that large firms lost considerable market share, however high initial concentration also preserved established industry structures and caused a convergence towards equal firm sizes. Accordingly, only firms of similar size are able to compete with incumbents. Ghosh (1975) claims his findings are consistent with Nelson and Shepherd (cited in Ghosh 1975) for the US, but with considerably higher explanatory power. Consistent with Hart and Prais (1956), low entry rates result in a low change in concentration. However, due to the biased Gini-coefficient Ghosh (1975) used – this will be discussed in more detail in section 4.2.3 –, the effect of the number of entrants is less relevant than estimated.

Das and Pant’s (2006) analysis of 24 manufacturing industries reveals that new entrants remained small and operate at different margins than large firms. Thus, the small firms' ability to compete is restricted by systemic factors, whereas large firms continue to compete among 'equals'. They attribute this phenomenon to imperfect capital markets, which make external finance practically inaccessible to small businesses. Bloch (1981) and Hariprasad (2011) too recognise the relevance of competition as a key aspect in determining the degree of FSI. Bloch (1981:386) hypothesises that "an increased variance in firm growth rates leads to a greater spread of firm sizes over time." It therefore explains FSI (*ibid*.) and potential imbalances in market structures (Hariprasad 2011). Bloch (1981) extended existing competition models designed to determine the number of firms within an industry and applied it to 97 Canadian manufacturing industries. It provided the basis on which Hariprasad (2011) analysed the effectiveness of strategic entry deterrents (excess capacity, product differentiation, advertising and R&D expenditure) in influencing FSI of 23,000 medium and large Indian manufacturing firms across 8 sectors. He further included firm growth, mean firm size, the number of firms and export openness in his model, and used the variance in market shares as proxy for FSI.

Bloch (1981) confirms the positive influence of industry growth on FSI, whereas the lack of competition between small and large firms consolidates existing market structures. All firms benefit from aggregate industry growth, whereas the different margins at which small and large firms operate are consistent with Audretsch *et al*. (1999) and Das and Pant (2006) and increase FSI. Bloch (1981) also concludes that increasing FSI leads to more market concentration, i.e. initial concentration acts as entry deterrent. Hariprasad (2011) supports the significance of strategic entrance deterrents. In contradiction to Bloch (1981), however, he rejects Gibrat's Law because R&D expenditure, intangible assets, excess capacity and mean firm size are found to increase FSI. The number of firms alongside export openness have the opposite effect, while market liberalisation measures remained insignificant (Hariprasad 2011). In accordance with Bloch (1981) and Das and Pant (2006), Hariprasad (2011:9) concludes "that there are some systematic forces either directly affecting the [SDOF] or accelerating/decelerating the stochastic process leading to [a] lognormal distribution."

The applicability of systemic forces to US 4-digit manufacturing industries being considered as contestable markets, i.e. oligopolistic market structures with price competition, is analysed by Kessides and Tang (2010). They find that low sunk costs result in firm sizes converging to similar sizes as it fits with the environmental forces firms are exposed to. When sunk costs are high, they act as entry barriers and impose restrictive effects to firm entry and exit (Kessides and Tang 2010). With sunk costs, Kessides and Tang (2010) refer in particular to R&D and advertisement expenses as they are irrecoverable and apply to knowledge intensive firms. However, when the MES and barriers of entry are low, entrepreneurial activity increases (Bayus *et al.* cited in Peltoniemi 2011) and markets are no longer contestable. Since most service industries meet both conditions, FSI is almost exclusively determined by the degree of sunk costs and their absence produces a firm size distribution determined by environmental forces. But in contrast to sectors with a high MES, FSI is said to increase because firms can afford to stay operative (Lotti and Santarelli 2004).

In an attempt to predict the SDOF at aggregate level and comprehend the differences in firm size across sectors – these are also observed by Pagano and Schivardi (2003) for European countries – Rossi-Hansberg and Wright (2007) conducted a cross-industry analysis of US firms. Their (*ibid*.:1658) results indicate that such differences result from “the accumulation of industry-specific human capital” and apply most to firms relying on tangible assets and least to labour intensive and less scale dependent firms. For Rossi-Hansberg and Wright (2007) this explains the dominance of large firms in technology intensive industries and corresponds to Pagano and Schivardi’s (2003) conclusion that technology homogenises firms. It therefore accelerates the speed at which firms approach the natural stage (Lotti and Santarelli 2004; Peltoniemi 2011). The backwardness in accumulated industry and product knowledge restricts innovative power, access to efficient scale of economies and the inability to spread R&D expenses over large volumes and over time lowers the survival rate of any firm entering after the shakeout (Peltoniemi 2011).

Consistent with Das and Pant (2006), this leads to industries with predominantly large firms and, if at all, only firms similar in size are able to enter into the late stage of an industry (Acs *et al*. 1996). Mata and Portugal (2004) find that large firms prefer indeed to enter industries with high entry barriers when expanding to foreign markets. They attribute this to lower competition and, according to Rossi-Hansberg and Wright (2007:1659), as an economy develops and specialises it produces “the dominance of large establishments in some industries … [that] will coexist increasingly with large numbers of small establishments in different industries within the same sector”. The possibility of a co-existence of different size classes is also noted by Gans and Quiggin (2003:252) for “multiple organisational modes” and Audretsch *et al*. (1999) and Peltoniemi (2011:355) for “generalists and specialists” resulting in the absence of a shakeout. These findings support the declining share of medium-sized firms within industries and support the argument of the natural stage of an industry-specific SDOF. It too indicates the vanishing middle at aggregate level.

These effects are tempered by recessions (Picard and Rimmer 1999) and increasing globalisation (Nocke and Yeaple 2008). Picard and Rimmer (1999) analysed the performance of US newspaper firms during 1990-91 and, consistent with the conclusion of section 2.3.3, attribute less flexibility to larger firms leading to a slower recovery, the effect of which can be lowered by diversifying the business risk. Deviations from the equilibrium due to the unstable environment were also noted by Simon and Bonini (1958). It is confirmed by Acs *et al.* (1996), who associate firm size volatility with large organisations, and Gaffeo *et al*. (2003:123) who found that G7 “[non-financial] firms are distributed more equally during recessions than during expansions”. Nocke and Yeaple (2008:3) link the SDOF with globalisation and their model, tested on large multiproduct firms, predicts that “globalization induces a merger wave, improves average industry productivity, and leads to a flattening of the size distribution of firms”. It nonetheless contributes to an increase in firm size and forces inefficient firms to exit (Zhou 2010:94), but “firms with greater organizational capability expand their scope to such an extent that, paradoxically, they have higher marginal costs” (Nocke and Yeaple 2008:21). As recessions enforce optimisations, it reverses the trend. Large firms return to their core activities and outsource or exit from unprofitable operations (Robson and Gallagher 1994), which generates opportunities for entrepreneurial activity (Acs *et al*. 1996) and explains the high mobility of small firms across firm-size classes (Marsili 2006; Robson and Gallagher 1994). Accordingly, FSI and average firm size increase under certainty and decline when overtaken by uncertainty.

3.2.3 Conclusions

Until the beginnings of the twentieth century, increasing market concentration remained widely unrecognised and was in itself not considered a threat to economic development. To exploit economies of scale, the large scale firm was needed and the emerging population of multinationals considered as too heterogeneous to be set in relation with any firm significantly different in size. Accordingly, there was no incentive in searching for the pattern that firm sizes follow. Even though a specific pattern would exist, the belief that the large scale firm contributes most to economic development persisted. It was merely the risk of monopoly power and the lack of competition that would follow at the top end of the size distribution that gained interest. The identification of a distribution able to describe a given population of firms gave insurance that the SDOF has a natural stage with entry, exit and firm growth as its determinants. As the SDOF at aggregate level is fairly stable over time, the parameters describing it can be assumed to be constant; Robson and Gallagher (1994) observed a firm births-deaths-ratio of 3:1. Equally stable are size distributions based on samples with large firms, but the dynamism increases with the introduction of industry and MES. When this is the case, the Pareto distribution describes the SDOF better than the lognormal distribution, but in empirical work the latter is most frequently observed. As the SDOF converges towards symmetry, its occurrence implies a relatively low share of medium-sized firms and the underlying forces go beyond the factors considered by the literature addressing the distributional properties of aggregate data.

Interlinked with the economic stage, short-term dynamics become barely observable. As an economy develops it goes through stages where foreign investment and scale effects play a major role and entrepreneurial activity becomes less attractive. This changes when transiting from the manufacturing to the service economy, where average firm size is smaller and economies of scale less relevant (see section 2.3.3). Accordingly, Lucas' (1978) findings are limited to developing economies with dominant manufacturing industries, but increasing entry rates by liberalising markets no longer alters the established structures and supports the concluding argument of section 3.1.1. To understand the dynamics of the SDOF, initial market concentration, nature and stage of an industry – and implicitly its growth rate – gain importance along with entry deterrents. It brings into consideration the industry life-cycle theory discussed earlier and contextualises the SDOF. Entry and exit rates as proxy for entrepreneurial activity are then no longer stable over time, but associable with the industry stage. Thus, the degree of FSI reflects the degree of competition and matters most when seen from an industry-level perspective. Its convergence to a natural stage does not appear to be reversible and is accelerated when technology imposes an entry barrier. In line with the observations recorded for net job creation, FSI decreases during recessions and globalisation. While the former leads to downsizing of large firms as occurred during the 1970s, the latter gained in importance following the ICT revolution and intensifies competition with an increase in average firm size.

Although responsible for disruption and structural change, the entrepreneur remained utterly unnoticed and becomes subordinated to systemic forces acting upon him/her. The SDOF is given and, despite being dynamic, follows a particular pattern as industries age. It would not do so if entrepreneurial activity is able to revolutionise existing structures. Hence, disruptive innovations are more likely to lead to new industries with a new population of firms that only in the very long run replace existing structures. This proposition is consistent with Bruland and Mowery (2009) and Peltoniemi (2011), who refer to the historical evolution of industries that led to knowledge and technology spill-overs from established industries. It further indicates that large firms have an ability to absorb entrepreneurial capital and learn from smaller firms. Entrepreneurial activity has certainly an effect on average firm size, but has a limited impact on the development of the SDOF. It does however affect the position of individual firms competing for resources and market share and eventually leads to firm size polarisation at both industry and aggregate level. Once the said stage is achieved, only the large firm is able to enter into established industries and increasing entrepreneurial activity to increase competition is no longer an option. It mirrors the superiority Mises (1951), Schumpeter (1947) and Drucker (1985) attributed to the large firm. However, the efficiency gains from stable macro-economic conditions are offset when the climate changes, which has negative consequences on welfare.

It puts the preservation of the middle on the agenda and shifts the attention to the determinants of FSI rather than the size distribution per se. A central element is the competition forces at firm level pushing the FSI in one direction or another. The next section is dedicated to the literature on firm growth as it sets the basis for the conditions necessary to maintain a fair number of medium-sized firms.

3.3 Gibrat's Law and firm growth

The previous section identified the dynamics of the SDOF and the parameters affecting FSI mainly at industry level – both fields inspired by Gibrat (1931). With his law, also known as the law of proportionate effect (LPE), Gibrat (1931) set the foundation for the lognormal distribution as the natural stage of the SDOF. Where firms do not grow independently of their size, the hypothesis that the size distribution follows a lognormal distribution is rejected. The inconsistencies of early studies with regard to the observed distribution – initially based on samples of large firms – initiated a research area in its own right dedicated to the validation of the LPE. It moves from industry level to firm level and permits the consideration of firm-specific parameters that cannot be captured at industry level. As samples are typically restricted to 4-digit industries, it allows the categorical distinction between the manufacturing and service sector, which in cross-sectoral analyses is hard to achieve. Should the

LPE apply unconditionally, no firm-size class is able to outperform another, but it gives large firms an advantage in absolute firm growth and as the SDOF approaches the natural stage, FSI increases. It too implies that the absence of random firm growth across size-classes is temporary and considered as a transitional stage (Hariprasad 2011). This suggests that firm growth is systemically influenced by industry-specific factors as long as the natural stage has not been achieved. The next section discusses the literature and rationale behind Gibrat's Law, which has as yet not been examined within this thesis. It then deepens the discussion of the drivers of firm growth of firm and non-firm specific factors. The subsequent conclusion consolidates the findings with the literature review presented so far, which eventually leads to the final research questions.

3.3.1 Firm size and firm growth

Motivated by the occurrence of natural regularities, Gibrat (cited in Sutton 1997:40) assumed that the logarithmic transformation of firms according to size generates a normal distribution resulting from "a large number of small additive influences, operating independently of each other". In its functional form $\ln S_{i,t+1} = \ln \alpha + \beta \ln S_{it} + U_{it}$, derived from $\frac{S_{i,t+1}}{S_{it}} = \alpha\, S_{it}^{\beta-1}\, e^{U_{it}}$ with *S* for size of firm *i* at time *t*, *ß < 1* indicates that small firms grow faster relative to large firms and *ß > 1* the contrary (Hariprasad 2011). Thus the LPE applies when *ß = 1* and the probability that it does so increases as the coefficient approaches 1. The growth-size relationship it establishes simplifies the complexity of both micro and macro-environmental forces and was first applied to the income distribution (Sutton 1997) and later to the growth of cities (D'Amato *et al*. 2014). The elegance it incorporates attracted interest for exploring the patterns that describe the SDOF. According to Sutton (1997), it was mainly the inconsistencies in finding a unique distribution to a random selection of firms that redirected the focus to the validation of the LPE, which intensified in the 1980s.

Bloch's (1981) findings support the applicability of the LPE revealed by early research (Hart and Prais 1956; Simon and Bonini 1958) and attributes it to the insignificance of the mean firm size in determining the variance of market share. However, the existence of size-dependent differences in margins indicates that firm size and growth cannot be seen as totally independent (Bloch 1981) and "conflicts with economic intuition and the most fundamental theories of the firm" (Kessides and Tang 2010:217). Mansfield (1962), whose empirical study includes US manufacturing firms of all size classes, finds indeed that small firms grow faster than large firms in their infancy when they are innovative. His interest in understanding the implications of innovation on growth patterns brings him to the conclusion that firm growth is a function of age and innovative capacity with the former being consistent with Sutton (1997), who refers to Evans (1987) and Dunne *et al*. (1988). As firms age, survival rates increase and growth rates decline (Geroski 1995; Mansfield 1962; Rossi-Hansberg and Wright 2007; Sutton 1997).

Faster growth rates for small firms are also identified by Teruel-Carrizosa (2010a) for Spanish firms and, although consistent with Evans (1987), there is also evidence in favour of the LPE. Hardwick and Adams (2002) find that over a sample period of 10 years until 1987, British life insurance firms grew independent of their size, but add that either small or large firms grow faster during certain times. Audretsch and Elston (2006) argue that a context-dependency, such as institutional differences, time and, to some extent, industry-specific characteristics determine the validity of the LPE. They find weak support for the LPE when applied to German firms, but identify its relevance for high-tech firms, where firm success or failure seems to be a function of knowledge rather than size. This is inconsistent with the prediction that "firms engaged in knowledge-based activity are subject to *hyper-uncertainty*, *hyper-knowledge asymmetries*, as well as *non-exclusivity*", where Audretsch and Elston (2006:139) would have expected a positive size-growth relationship. It echoes the ongoing inconsistencies that produced a substantial amount of research papers validating the LPE. So far, these have failed to provide a clear pattern (Coad 2009; Kessides and Tang 2010). Lotti *et al*. (2006) and Pagano and Schivardi (2003) criticise the fact that most LPE validations do not take into account the low survival and high exit rates of small and young firms, which marginalises the effect of fast firm growth originating from that firm-size class. The inclusion thereof generates disproportionate fluctuations on the left tail of the SDOF and, according to D'Amato *et al*. (2014), complicates the applicability of the law relative to cities and income distributions. Enhanced by the exclusion of industry-specific peculiarities (Kessides and Tang 2010), the empirical findings of the LPE have launched a debate and indicate the presence of systemic forces, but lack a comprehensive conceptualisation.

With the attempt to identify a general pattern, Santarelli *et al*. (2006) reviewed some 60 studies concerning the LPE. It too consists of contradictory findings, but provides a dominant view that small firms – subject to survival – have more opportunities to grow in their early years, which, according to Teruel-Carrizosa (2010a), is due to their flexibility to deal with market forces. In most cases the law holds up for the service sector or large firms (Santarelli *et al*. 2006), but tends to be rejected when applied to small firms as they grow fastest (Lambertini 2006). In line with Mansfield (1962) and Evans (1987), growth patterns become size-independent as firms become older, larger and more established (Lotti *et al*. 2006). And because size-dependent growth does not persist in the long run (Becchetti and Trovato 2002; Geroski *et al*. 2003; Lenihan *et al*. 2010a; Santarelli *et al*. 2006), it ultimately suggests an increasing market concentration over time, as predicted by Dinlersoz and MacDonald (2009), Hariprasad (2011), Hart and Prais (1956), Lucas (1978) and Rossi-Hansberg and Wright (2007). Accordingly, the dependency of firm growth on size is industry-specific and temporary. It is industry-specific because the LPE tends to apply to service firms, where growth is less bound to tangible assets, and it is temporary for manufacturing firms because the LPE holds as soon as firms reach a critical age and size.

As much as the theoretical and empirical research on the SDOF, the mechanics of the LPE leave considerable room for interpretation and speculation of the cause-effect relationship. The exclusion of firm entry and exit from the early models suggests that firms were assumed to operate with similar organisational structures, where only scale and scope can make a difference. This refers to the aggregate cost function and firms are then assumed to have a homogeneous decision-making process. Hopenhayn (1992) and Pagano and Schivardi (2003) criticise the fact that most neo-classical models exclude firm-specific characteristics and treat firms as homogeneous organisations, which until Jovanovic (1982) remained unaddressed. By including firm entry and exit in the model, Jovanovic (1982:649) identified the process of 'noisy selection', according to which "[f]irms learn about their efficiency as they operate in the industry." He was among the first to observe a higher growth rate for small firms, which violates Gibrat's Law, but failure rates of new entrants are high too as they are unable to absorb economic shocks. As he sees it, it is the consequence of firm-size heterogeneity and explains why models of optimal firm size failed to give explanations about firm growth patterns (Coad 2009). The learning effect is also observed by Peltoniemi (2011) in her assessment of 216 industry life-cycle studies and by Lotti and Santarelli (2004) for young Italian firms. It defines common standards (Peltoniemi 2011) and occurs at a faster rate in knowledge intensive industries, where firm performance determines a firm's survival. Since the learning effect declines as firms grow older (Jovanovic 1982), it supports the temporary variation in firm growth and is by definition industry-specific.

The described learning effect mirrors the catching-up process in post-war Europe, but does not hinder the shakeout from taking place. Aggregate industry growth reduces these effects, but in the competition for resources and markets, firms are exposed to competitive forces complemented by macroeconomic conditions. These enter in the LPE equation as a single coefficient regardless of the inclusion of entry and exit rates. Unless restricted by sample composition, there is no distinction between labour and knowledge intensive industries, but whichever forces are at work, the size-growth relationship eventually breaks down and firm growth becomes gradually independent from size. Firm size is then no longer a restrictive factor to growth with forces other than size gaining importance. As firm growth is randomly distributed across firm-size classes, it leads to the pattern modelled and observed by studies focussing on the SDOF and FSI. The relevance of systemic forces increases the further away the SDOF is from its natural stage and influences the speed at which the SDOF reaches the equilibrium. To understand these forces, the next section attempts to identify critical factors that drive firm growth at the individual level and have the capacity to influence FSI as a whole.

3.3.2 Drivers of growth and structural change

Based on the most notable literature in the field, Cassia and Colombelli (2010) summarise the factors that have a significant impact on firm growth. These are classified as firm specific and non-firm specific factors with the latter referring to environmental aspects. In accordance with the previous section, firm age and size, including “relative size compared to the largest enterprise in the sector” (Cassia and Colombelli 2010:442), play a major role. Furthermore, assets, productivity, efficiency, export orientation and strategy along with organisational characteristics, such as human capital and networks, come into consideration (*ibid.*). As has been extensively discussed, ownership plays a central role because it reflects the abilities and skills of both manager and owners. Among the non-firm specific properties – these show parallels with Porter and Stern’s (2001) diamond framework – firm growth is mainly determined by industry, competitive forces, supportive peripheral structures and the degree of uncertainty. Yet in their empirical work, consisting of a sample of medium-sized Italian manufacturing firms – observed from 1999 to 2004 – Cassia and Colombelli (2010) find that only age, investments, economic growth and financial innovation positively affect firm growth, while increasing competition has the opposed effect.

The stickiness of entrepreneurial activity and assets attributes a particular importance to tangible assets as one of the listed firm-specific factors. Although Cassia and Colombelli (2010) failed to find any significant relationship, the outperformance of medium-sized firms suggests that they are more entrepreneurial than larger firms and hence more efficient. It further indicates that firms operating above the MES have more freedom in diversifying and accessing foreign markets. In contrast to Audretsch *et al*. (1999), Acs *et al*.

(1996) find that most increases in productivity are achieved by large, not small, firms, but the contribution of outperforming small firms is offset by the weak performance of less successful firms. In addition, Gil (2010) concludes that productivity levels are higher for large firms, which might be the direct consequence of the MES that a firm has to reach to be able to achieve a competitive position in the market place. As a function of industry-specific mean firm size, it is lowest for service firms and industries with low entry costs (Teruel-Carrizosa 2010a). This is confirmed by Barbosa and Eiriz (2010) for Portuguese firms, with the addition that a higher MES implies fewer firms and vice versa. Although low sunk costs permit firms to capitalise on operational inefficiencies of established competitors (Kessides and Tang 2010), service firms are found to grow slower than manufacturing firms (Teruel-Carrizosa 2010a).

It is intuitive that firm size tends to decline with an increase in the degree of specialisation. Markets are then less competitive allowing firms to follow a niche market strategy to balance out the diseconomies resulting from a smaller firm (Lenihan *et al*. 2010a). Although not among the growth enhancing factors identified by Cassia and Colombelli (2010), firm growth cannot occur without spreading risk through diversification. It increases the flexibility of resource allocation within the firm, but the larger and more differentiated a firm, the less efficient it is (Arrow 2000). Instead, Drucker (1985:217) warns of becoming too specialised, because an “ecological niche” limits growth opportunities and reduces a firm’s responsiveness to environmental changes with the biggest risk “to cease being a specialty and to become universal” (*ibid*.:221). With reference to small high-tech firms, Slatter (1992) highlights the need to diversify and Hardwick and Adams (2002) find insurance companies benefit from higher growth rates when diversified. Nevertheless, the advice to diversify is utterly rejected as the degree of diversification is managed by the markets (Davis 2009). For Drucker (1985:222) niche market positioning is an intermediate stage applicable to “a new technology, a new industry, or a new market” and “therefore limited – in scope as well as in time”. It allows a firm to seize opportunities, but in the long term needs complementing with a diversification strategy to ensure sustainable growth, which applies in particular to firms with low barriers of entry.

Firm growth occurs at a faster rate when firms are engaged in import-export activities and hence proactively respond to globalisation (Teruel-Carrizosa 2010a). The intense competition export-oriented firms have to cope with to withstand the innovative power of their international rivals (Santarelli 2006b) comes with more relaxed competition in the home market (Görg and Strobl cited in Buckley 2010). However, it is mainly the large firm that is engaged in export activities (Hariprasad 2011; Lenihan *et al*. 2010b). A competitive advantage is also attributed to firms that are part of a group (Santarelli 2006b; Teruel-Carrizosa 2010a). Santarelli (2006b) analysed the firm growth pattern of medium and high-technology Italian firms located in the Emiglia Romania and assumes that multi-plant firms use more sophisticated management tools and are run more efficiently. It allows plant specialisation to fully exploit economies of scale and scope with positive effects on firm growth (Sutton 1997). In contrast to single plant firms, Sutton (1997:47) finds “net growth rate of [multiplant firms] to increase with size and age”. Yet, their inefficient factories are the first to exit (Liberman cited in Sutton 1997), especially when “diversified and financially strong” (Sutton 1997:56). It attributes more alternatives to multiplant firms, but MNEs also invest more in human capital than domestic firms, which may explain their faster firm growth rate and their superiority in running new establishments (Mata and Portugal 2004).

Although Santarelli (2006b) could not find support for more innovative activity and IP protection for exporting firms, these findings indicate that MNEs are more flexible in reallocating resources and accessing external funds, while access to countries with low wages and low tax is in their favour too. This is consistent with Larrea *et al*. (2010:49), who argue that SMEs suffer from a “[s]carcity of resources, not only of financial ones, but also of human resources, which have an important incidence in management capacity.” However, the claim that small firms are chronically underfinanced (Löfsten and Lindelöf 2003; Storey 1994) is rejected by Watson (2010), who finds that only a small proportion of Australian SMEs face difficulties in accessing external sources of finance. This suggests that small firms prefer equity over debt (Braga and Andreosso-O'Callaghan 2010) with no intention to push firm growth (Larrea *et al*. 2010), or that they fear loss of control (Ampenberger *et al*. 2012) and hence do not explore all available opportunities to expand their operations. Thus, liquidity constraints do not impede growth, but might be the consequence of small firms' lack of strategic direction and environmental consciousness (Larrea *et al*. 2010), which plays into the hands of the multinational.

The marginalisation of the cost of communication allowed MNEs to efficiently exploit geographical diversification and to build global networks. In doing so, they have reduced the competitive advantage clusters offered to SMEs with regard to innovation (Santarelli 2006b). Nonetheless, Teruel-Carrizosa (2010a) finds that geographical location has an impact on growth rates and Audretsch and Feldman (1999), Buckley (2010) and Iammarino and McCann (2006) confirm that advances in ICT cannot undo the efficient knowledge transfer of geographically concentrated areas. Innovations are most likely to occur where opportunities exist (Iammarino and McCann 2006) and higher innovative capacity results in higher employment within the respective industry (Baptista and Swann 1998). Since "technical knowledge tends to be prevalently tacit, complex and systemic", it requires different levels of knowledge transfer and the relevance of geographic concentration breaks down when knowledge intensity is low (Iammarino and McCann 2006:1033). Thus, a functioning communication infrastructure reduces the need for geographic concentration, but clusters continue to influence growth patterns of technology and knowledge-rich firms and reduce the importance of size.

On the above assumption, geographic proximity incentivises engagement in new product development, whereas firms operating in isolation are less likely to perceive the dynamism of the industry they are in. Unless a firm's future depends on the success of its next invention, which applies to poorly diversified firms, investments in R&D are marginal (La Croix cited in Lenihan *et al*. 2010a). Calvo and Culebras (2010) find that SMEs in the Spanish fashion industry are reluctant to invest in R&D and new technology, which is confirmed by Larrea *et al*. (2010). As it delays productivity gains (Gil 2010; Pagano and Schivardi 2003) and reduces firm survival (Esteve Perez *et al*. cited in Cefis and Marsili 2006; Peltoniemi 2011), the observed risk-averseness hampers firm growth and gives firms engaged in continuous research a competitive advantage. According to Gil (2010), R&D and firm size are uncorrelated, but larger firms are more productive and this results form R&D commitment. Hence, R&D has no impact on productivity growth rates (Gil 2010), but imposes a logical contradiction. R&D is then at least industry-specific and, given the large firm's ability to spread risks and costs at a larger scale (Fishman and Rob 1999), the advantages of engaging in R&D activities are biased towards the large scale firm.

Equally deterministic with regard to productivity levels is the technology that firms use. In a survey of US manufacturing firms, Doms *et al*. (1995) identify higher survival and growth rates to technology and capital intensive firms. By introducing the latest technology, young firms are given the opportunity to catch up with incumbents reluctant to invest in new equipment (Pagano and Schivardi 2003). The preference to adopt only approved technologies is also observed by Larrea *et al*. (2010) for Spanish SMEs. Grass *et al*. (2012) modelled the disruptive process of the adoption of innovation and indeed find that large firms delay the implementation of the latest technologies. The size of the large firm is unlikely to be affected as it is able to be more productive once it switches to the newer technology, even if at a late stage (*ibid*.). Thus, technology intensity is both an opportunity for small firms to catch up and a means to increase productivity for incumbent firms.

For an economy to benefit from entrepreneurial activity, Stel *et al*. (2005) indicate the need for technology holders, which is a fair share of large firms. As it is not always the domestic firm population that holds the knowledge – this too depends on the economic stage (Acs 2006) – foreign firm presence can significantly influence technology and productivity levels. Despite poor empirical evidence, Bellandi and Caloffi (2010) observe such effects for specialised Chinese manufacturing districts. Buckley (2010:137) identifies three ways to achieve spill-over effects from the presence of superior foreign-owned firms to domestic firms: 1) "demonstration effects", 2) "competitive pressure" and 3) "labour market" due to the mobility of the workforce. Buckley (2010) analyses the spill-overs from foreign owned MNEs to the Irish software industry and finds that the technology transfer is not beneficial for all firms operating at suboptimal productivity levels. Although knowledge-intensive firms were expected to benefit most from the presence of foreign owned MNEs, Buckley (2010:150) finds that only firms associated with a “medium absorptive capacity” benefit from the presence of foreign firms and hence this results in increased labour productivity. When the disparities of the applied technology between domestic and foreign firms are either too high or too low, spill-overs are unlikely to take place (*ibid*.). Under high disparity conditions domestic firms seem to be discouraged and unable to adopt new technologies due to their low organisational capacity to commercialise on newly accessible, albeit considerably superior, knowledge (Buckley 2010).

In an extensive cross-country study over a period of 20 years, Wang and Wong (2012) conclude that a certain amount of absorptive capacity and an appropriate infrastructure are a precondition for the domestic industry to benefit from FDIs in the form of R&D. This reflects empirical evidence of previous work on spill-over effects, cited in Buckley (2010) and Stöllinger (2013), and is further confirmed by high FDIs flowing into China (The World Bank 2010). Liu (2008) identified a negative short-term effect derived from FDIs, but an increase in productivity of domestic firms in the long term. Inter-industry spill-overs are found to be limited and occur most likely backwards the value chain (Liu 2008), which indicates technological incompatibilities among industries and the superiority of foreign firms. For Portugal, Barbosa and Eiriz (2010) find no evidence of positive spill-over effects for the local industry following FDIs. Despite being considered as a developed economy, overall net firm entry rates decline in both manufacturing and service industries, except for the high-tech industry (Barbosa and Eiriz 2010). The inability of the SME-dominant Portuguese firm sector to withstand foreign competition – young domestic firms exit before foreign firms (Mata and Portugal 2004) – indicates an unfavourable form of firm heterogeneity. It further suggests that in high-tech industries technological disparities are lower and absorptive capacity higher, which accelerates the process of catching up.

Although foreign firms operate at a larger scale (Mata and Portugal 2004), the performance of Portuguese MNEs – in contrast to other EU member states – corresponds to that of domestic firms with no incentive to share ownership and technologies with domestic firms (Barbosa and Louri cited in Barbosa and Eiriz 2010). Where differences between knowledge-intensive domestic and foreign firms are small, neither party is willing to adopt the other's technology (Flores *et al*. cited in Barbosa and Eiriz 2010). According to Cantwell (cited in Buckley 2010:153), "there must be some disparity in the level of technology between foreign and indigenous firms for productivity spillovers to occur." Since technology-transfer is a function of the costs involved (Teece 1977), switching technology remains – despite the developments in ICT – an expensive undertraining (Liu 2008) and the absence of technology disparities explains firms' unwillingness to change their use of technology. Consequently for domestic SMEs, the presence of foreign firms is only beneficial when a technology or organisational gap exists that can gradually be closed. Such benefits vanish when closing the gap is unachievable and may have reverse effects on domestic firm growth.

The picture that emerges from the above discussion is that the impact of the drivers of growth varies across firm-size classes and either enhances or reduces FSI. There remains some ambiguity in understanding the effects of the examined dimensions for each firm-size class with no conclusive answer to what extent each dimension affects the SDOF. Yet, firms operating below the MES face disproportionate constraints and choosing a niche market strategy to escape from intense competition is a short-term solution, but rarely sustainable in the long term. Achieving the MES is therefore essential for survival and firms operating above it have more choice and freedom. It opens the possibility to explore foreign markets, which increases the competitive position in the domestic market and gains importance when foreign owned firms enter. As these are by definition multi-plant firms, they have a strategic advantage in either management tools or technology from which domestic firms may benefit. However, it requires a common standard that allows reducing the discrepancy in knowledge, considered as spill-over effects. Given that said spill-overs are industry-specific (Buckley 2010), geographic concentration bears a distinct advantage as it enhances the speed at which knowledge transfers take place, but only when knowledge intensity is complex and high.

3.3.3 Conclusions

With the LPE, Gibrat (1931) altered the belief that firm growth is associated with firm size and identified it as a random process, equally applicable to all firm-size classes. Influenced by the increasing popularity of the large scale firm and the restrictions of the time in accessing data, SMEs did not enter into the analysis of early research papers and the resulting empirical evidence was much in support of the LPE. As most large firms were well diversified, there was no need to take industry-specific characteristics into account and a stream of theoretical models attempting to formulate an emerging pattern followed.

The confirmation of random firm growth signalled the irrelevance of the entrepreneur, whose contribution to economic development was neither discussed nor seen as sufficiently distinctive to be integrated in any theoretical work. The simplification of entry-exit parameters surely contributed to the continuance of inconsistencies with empirical observations and led to the conclusion that statistical regularities cannot fully describe what is observed. Though industry-specific distributions have shown a better fit than distributions at aggregate level, the convergence to a semi-perfect natural stage has become indisputable even when smaller firms are included. This has consolidated the view that the SDOF is determined by independent forces which are simultaneously acting upon firms of a given population. Accordingly, when the LPE applies, entrepreneurial activity – if any – is evenly distributed across firm-size classes and unevenly otherwise.

The by-product of the inconsistencies in statistically describing the SDOF, and the indefinable implications such regularities have for industrial policy (D'Amato *et al*. 2014), has increased the interest in the validation of the LPE at firm level (Sutton 1997). Research in this field has successfully distanced itself from the debate on the SDOF and was carried out in parallel to the determinants of FSI with neither assuming that the forces at work are exclusively non-systemic. The literature on FSI takes into account industry structures, but like the models concerning the SDOF, it ignores the entrepreneur as a root cause for structural change. The literature on the LPE acknowledges the existence of the entrepreneur, but assumes the probability of creative destruction being randomly distributed across all industries with negligible attention being paid to the industry life-cycle. Apart from a distinction of service from manufacturing industries and low-tech from high-tech industries, there is only weak reference to evolutionary patterns and context-specific factors. This adds to the persistence of inconsistent findings, but nonetheless the results indicate that small and young firms grow faster than old or large ones. The additional opportunities small and young firms are able to commercialise upon suggest higher levels of entrepreneurial activity, but this declines with increasing firm size and systemic R&D and opportunity recognition. Given that most findings are based on surviving firms – this ignores the high failure rate and volatility of young firms – and that survival rates are found to be higher for large firms, the expectation that a substantial small business sector is key to sustainable growth is questionable.

Diversification, export openness and R&D as well as financial resources and resource allocation are in favour of large firms with the presence of an MES imposing a lower limit to scale. Although much smaller for service and low asset intensive industries, the occurrence of a Pareto-like distribution in some industries makes entrepreneurial success a function of the industry life-cycle. The increase in technological sophistication at both product and process level lifts the MES and the possibilities of small firms growing into large firms requires control over assets. It is a systemic disadvantage sustained by the ability of the large firm to accumulate and preserve knowledge – even from failure. Protected by its market share, the large firm raises the barrier for young firms attempting to achieve a similar size. It is a pattern that corresponds to the evolution of industry structures as well as the superiority of the large firm predicted by Schumpeter (1947) and Drucker (1985).

As the small firm is forced to escape to niche markets unattractive to the large firm and limited in market share, its size is likely to stay small with the consequence of increasing FSI. The ability of the young firm to learn and benefit from spill-overs is highest in the early stage of an industry and is conditioned by geographic proximity and aggregate industry growth. Foreign firm presence may act as a catalyst, but only when absorptive capacity and knowledge intensity are high. The shift from asset to knowledge intensity lowers the barriers of entry and increases the freedom to carry out entrepreneurial activity, but when knowledge intensity is low and plant specialisation high, the competitive advantage lies in scale and scope. As occurred at the beginning of the ICT revolution, said conditions allow small firms to compete and prolong the dynamism within an industry and with positive effects for welfare.

Since small and large firms differ in nearly all noted dimensions, it makes the large firm a poor substitute for any class of smaller sized firms. The SDOF carries structural information as it reflects the degree of innovative capacity and the ability to respond to economic shocks. Diversity in firm sizes is associated with a higher probability in achieving technology transfer implemented by entrepreneurs and intrapreneurs, whereas non-entrepreneurs experience more freedom in choosing between alternatives. While perfect equality among firms in size and structure impedes disruption and imposes limits to buffer economic shocks, extreme inequality causes tacit co-existence with little opportunities to outperform. Since net job creation, and hence firm growth, are mostly driven by outperformers across all firm-size classes, economic progress is expected to be maximised when the structural conditions to seize opportunities are favourable. It is necessary to have the large firm engaging in systemic research and large scale projects on the one side and the experimental entrepreneurial firm on the other, but diversity along the continuum contributes to economic progress. For sustainable growth, all elements are essential and higher levels of life satisfaction may follow.

The focus on either small or large firms, or on individual or aggregate growth, means that the dynamics and consequences of FSI are widely unaddressed. The examined literature suggests that firm size matters and, by definition, so too does diversity. It is the product of the growth of the individual firm, which is not merely the outcome of advantageous environmental conditions randomly distributed across firms, but to a large extent the result of distinct forces. Since the implications of systemic forces vary across firm-size classes, the SDOF cannot remain unaffected. The size-effect relationship changes when the SDOF reaches its natural stage and the LPE becomes applicable. Rebalancing becomes disproportionately harder and general policies aiming to re-establish the middle by simply encouraging start-up activity is ineffective. As it is opposed to market forces, it bears the risk of increasing necessity entrepreneurship and the acceleration of the diminishing middle. The combination of co-existing small and large firms is efficient under stable macro-environmental conditions, but the more industries are affected by extreme FSI, the less resilient the economy, the lower the innovative capacity, and with it, the fewer new jobs are created.

The formation of new industries has been part of the evolutionary industrial process, but with the increasing dominance of the international large-scale firm, entrepreneurial activity is systemically eroded. As this generates uncertainty, it contradicts the logic of the large firm and is either suppressed or incorporated. Yet, without inducing uncertainty, existing structures cannot be altered and kept dynamic. There are windows of opportunity, characterised by high uncertainty, which require an agent who not only recognises and seizes these opportunities, but who is able to cope with the forces that suppress change. This refers to the entrepreneur, who foresees what others cannot and is prepared to take the risk needed to realise visions. To do so, s/he needs freedom and a vehicle to carry out his/her activity. While the marginal firm is event driven and subject to environmental forces with a physical limit to absorb shocks, the large firm is systemically and deliberately unwilling to take high risks. The innovative capacity these size classes stand for is different in nature, but the large firm cannot expand without the impetus from the other. Knowledge intensity reduces the disadvantages firm size imposes, but the windows of opportunity are reduced by efficient methods of communication (Drucker 1985) and both the increasing frequency and intensity of shocks (Stiglitz 2000). It puts the medium-sized firm in a peculiar position and responding to turbulence with diversity by preserving a fair share of SMEs is more promising than any extreme constellation.

Although FSI has been raised across a number of different fields, there has been little research examining the factors that influence the SDOF over time or the consequences of FSI. The entrepreneurship literature puts the entrepreneur at the centre and suggests that as long as s/he can be identified, existing structures can be disrupted and FSI lowered. This assumption is accompanied by three complications: first, the conceptualisation of the entrepreneur itself, second, the identification of the entrepreneur, and third, the systemic forces at industry level constraining his/her success. Said forces are at the core of the literature on the SDOF and FSI, but these disregard the entrepreneur. Here, the entrepreneur is treated as a disturbance rather than an explanation. Recent applications of the LPE have revived the entrepreneur and by using the firm as the smallest unit of analysis – and taking into account its development –, they resolve the first two complications. These studies reveal that the contribution of the entrepreneur results in faster than average firm growth, but individual firm growth is accompanied by systemic forces leading to an increase in FSI. This eventually undermines entrepreneurial capital and structural change is no longer possible by simply focussing on the lower end of the SDOF without taking its properties into account.

It is the aim of this thesis to address these issues by considering the dynamics, determinants and implications of FSI. On the assumption that the SDOF is industry-specific, the first two RQs are: (RQ1) *to what extent has the SDOF changed*; and (RQ2) *what are the determinants of FSI?* Given the implications changes in the SDOF have on welfare, the third research question is: (RQ3) *what are the implications on welfare deriving from a change in FSI*? Before answering these questions, the next chapter presents the sample and methods used for the empirical analysis.

CHAPTER 4: METHODOLOGY

Regardless of the perspective taken in the previous chapters, be it the historical, theoretical or empirical perspective, there is a consensus that large firms continue to expand under stable conditions and that FSI increases unless radical innovations disrupt the process. But even then the diversified multinational is able to commercialise on disruptive innovations, because its sheer scale makes actions most visible, whereas the marginal firm is driven by environmental forces. It may grow faster than the large firm, but only in its early years and thus for sustainable economic growth it requires a continuous flow of entrepreneurially active firms. This makes diversity imperative, which results from the freedom that allows the seizure of opportunities for those in possession of skills and some form of assets, but it also requires commitment. Mainstream economic thought is proxied by *growth* and has been the primary interest throughout the reviewed literature. It attempts to identify and measure the key drivers of growth and is therefore skewed towards it. The entrepreneur's contribution was not taken into account until the 1980s and until the present day opportunities are assumed to exist at a constant rate.

Rather than focussing on growth, the formulated RQs suggest that it is diversity in firm size that should be the variable of interest. Despite the SDOF being the product of individual firm growth and influenced by aggregate growth, preserving a fair share of each firm-size class maintains a moderate degree of competition with positive implications on welfare. It does not contradict the assumption of a constant number of opportunities, but suggests that some opportunities cannot be seized because nature and properties of the large firm substantially differ from the small entrepreneurial unit. Yet, the large firm has the power to sustain itself at the expense of the middle; a process that starts anew with any newly emerging industry. Such dynamics are complex (Das and Pant 2006; Sutton 1997) and research carried out on the SDOF is no exception.

Even less explored continues to be the dynamic dimension (Gil 2010) and the determining factors that drive FSI.

The current chapter presents methodology and methods used to analyse the dynamics, determinants and consequences of FSI. Although this becomes most challenging for RQ3, operationalising the entrepreneur is required for all RQs. This cannot be Schumpeter's (1947) temporary entrepreneur nor Mises' (1951) pure entrepreneur, but Salerno's (2008) integral entrepreneur in the form of a legally registered firm (Acs 2006). It includes the potential of being an innovative unit, but the exceptional mind with which the entrepreneur is blessed, also imposes limitations and adds abstraction to the entrepreneurial firm. The entrepreneur becomes now Shane and Venkataraman's (2000) opportunist who competes with the managed firm and forms part of the industry that defines the degree of FSI, for which dynamics and determinants are assessed for the UK, Italy and Germany. The subsequent sections introduce these samples and the precautions taken to minimise potential bias, followed by the methodological choice taken to address the RQs. Before discussing the methodology of RQ1, ways to measure firm size and FSI are scrutinised. These gain importance for RQ2 aiming to identify the effect of observable firm and industry-specific factors. Due to the extensive discussion it requires the development of the models and an explanation of its components, which is the lengthiest part of this chapter. The last section outlines the approaches taken to address the implications of the SDOF on welfare, assumed to be influenced by innovative capacity, economic resilience, net job creation and sustainability.

4.1 Sample construction and measurement issues

The use of multiple samples and time spans are either defined by the scope of the RQ or imposed by the availability and transformation of accessible secondary quantitative data. While RQ1 and RQ2 share the same sample and data source at firm and industry level covering the three European countries, RQ3 demands a country-level approach. As the welfare analysis cannot be performed without the use of aggregate data, it requires the extension of the sample size to a statistically sufficient number of countries and hence the level of analysis changes to the EU27. This section comments on the peculiarities associated with the sources of data and justifies the choices made when constructing the samples. It includes a description of the necessary yet sensitive adjustments made to produce a viable dataset, which refers in particular to RQ2 and most notably to the treatment of outliers and firm-level records with consolidated accounts.

4.1.1 Sources of data

To ensure consistency across variables and firms, the data collection for RQ1 and RQ2 was limited to a single source. The *Bureau van Djik* offers a range of commercial databases, commonly updated and monitored by credit rating agencies, which makes them as accurate and reliable as commercial databases can be. *Orbis* was identified as the most comprehensive database enabling access to worldwide firm-level data with coverage of all firm-size classes across major industries for the last 10 years. A period of this length allows the observation of structural changes in firm size dynamics and the underlying forces regardless of short-term fluctuations, which RQ1 and RQ2 aim to examine. By offering detailed firm level data with regard to management composition, plant structure and performance data, the behaviour and development of individual firms and industries can be traced. The database also provides access to industry-specific summary tables, which enables the analysis of large datasets to draw a general picture. This can then be verified by detailed firm-level data.

It is assumed that national and institutional quality standards of the data provided are sufficiently harmonised, but the comprehensiveness of a cross-country dataset is bound to the national context. For instance, R&D expenditure in technology intensive industries is sensitive and the concealment thereof is legal in Italy and Germany (Hall and Oriani 2004). The comprehensiveness of the used database is achieved by consolidating the services provided by regional bodies, which imposes the risk that not every firm-size class is represented as one would expected it to be. The highly volatile environment small and micro firms are exposed to may lead to delays in recording firm birth and death rates and, due to differing legal forms across nations, may remain unnoticed. To reduce the risk of constructing a sample with unreliable entry and exit rates, the observations used for RQ1 and RQ2 are limited to active and surviving firms only, whereas firm demographics are reproduced in aggregate industry growth and life-cycle dummies.

The focus of RQ3, which links FSI to welfare, necessitates the use of unconventional and conventional country-level data from multiple data sources and the acceptance of restrictions in sample periods. To establish a correlation between FSI and welfare, the first part of the analysis is based on data from the most recent research. These are the levels of happiness and life satisfaction – still in their infancy – were obtained from the *European Social Survey* (round 4), publication *World Happiness Report 2012* (Helliwell *et al*. 2012). The indices refer to a scale from 0 to 10 and are limited to survey year 2008. Rankings of entrepreneurship and opportunity are provided by *The 2012 Legatum Prosperity Index* and refer to survey year 2012. These aspects have become central measures as they are most appropriate in reflecting the idea of welfare. But the absence of consistent and reliable longitudinal panels heavily constrains the establishment of a link with variables describing the degree of FSI. This requires going back to mainstream indicators, which are less accurate in the meaning RQ3 refers to, but benefit from significantly better data quality.

The World Bank database provided the Adjusted Net Savings (ANS) and its component data as far back as 1970 for most countries, while *Eurostat* offered comprehensive historical records of essential economic performance indicators. Accordingly, the second approach to analyse the interlink between FSI and welfare builds on conventional socio-economic measures. Besides the inclusion of ANS, these are GDP and derivatives thereof, patent applications made to the *European Patent Office* (EPO), the share of knowledge intensive services and the share of medium and high technology manufacturing firms, and unemployment rates. As prevalent indicators they illustrate to what extent different firm-size classes impact economic growth and resilience, innovative capacity, job creation and sustainability. These are the specific dimensions to be investigated in the third part of the analysis.

The data used for the said third part was retrieved from publications of the *SME Performance Review*, which is part of the enterprise and industry division of the European Commission (EC). The datasets cover the periods 2002-2008 and 2005-2012 and include the number of employees, the number of firms and the value added for each of firm-size class defined by the EC of non-financial firms, i.e. micro firms (<10 employees), small firms (10-49 employees), medium firms (50-249 employees) and large firms (≥250 employees). Accordingly, the term 'SMEs' refers to firms with a workforce between 10 and 249 employees. To maximise the consistency and accuracy, the newer dataset, ranging from 2005 to 2012, was added to the data of the years 2002-2004 from the earlier dataset. Changes in the industry classification from NACE Rev. 1.1 to NACE Rev. 2 in 2008 required verification for disruptive changes in employment share by firm-size class, country and simplified industry classifications (manufacturing/non-manufacturing) before merging the panels. Although minor deviations were observed, the comparison does not indicate a potential bias resulting from reallocations of economic activity and confirms the Wit and Kok (2014) examination of the same dataset.

4.1.2 Sample and data description: RQ1 and RQ2

A major issue of the cross-country analysis concerning the dynamics of the SDOF is the consideration of the national context, causing heterogeneity in firm growth patterns (Acs 2006; Audretsch and Elston 2006; Pagano and Schivardi 2003) that is influenced by institutions (Henrekson and Johansson 1999). The formation of independent samples consisting of the UK, Italy and Germany addresses said conditions. These countries are representative for central Europe and share a similar stage of economic development, but differ in their business demographics, which allows for better cross-validation. Restrictions in the availability of data apply to Germany and, to a lesser extent, to Italy. It classifies these countries as comparative samples to verify the findings obtained for the UK, which is one of the most advanced countries with a traditionally high degree of market concentration and a strong service sector (Booth 1995; Sawyer 1981). Italy is characterised by an industrialised north and less developed south, as well as low R&D expenditure, high unemployment rates and a high degree of small family-owned businesses (Lenihan *et al*. 2010a); attributes that are common for southern European economies. Finally, the German economy is shaped by the medium-sized firm structure, low stock market orientation, balanced power-relations between the 'representatives of capital' and employees, a higher degree of financial institution involvement with long-term investment strategies and cultural commitment quality (Dore 2000).

Given the maximum historical records of 10 years, the data collection was conducted during the last quarter of 2011, when records for 2001 were still available and those for 2010 up to date. Due to the macro-economic instability the financial crisis caused from 2008 onwards, it was crucial to maximise the number of pre-crisis years. This allows disruptive macro-economic shocks to be taken into account, whilst reducing the probability that these effects overshadow changes in FSI at times when certainty dominates. The resulting sample period is therefore 2001-2010 for the UK and Italy, and 2005-2010 for Germany, where earlier data records are either missing or of poor quality.

Two different samples are used to analyse the dynamics of FSI, i.e. RQ1. The first sample, henceforth referred to as the *extended sample*, originates from *Orbis'* database summary tables consisting of 20,857 firms for the UK, 27,729 firms for Italy and 21,118 firms for Germany across 18 main NACE Rev. 2 industry sections. The number of firms corresponds to the sum of all active firms allocated to a main industry section and with registered employee figures throughout the sample period. The said number of firms is constant over the sample period, but varies across main industries and firm-size classes. Due to organisational and structural inconsistencies of the public sector across countries and the different nature of non-industrial firms, such as financial firms, private equity firms etc., these categories were excluded. Only observations with no missing employee data and no missing primary NACE 4-digit industry code were considered as it would otherwise be impossible to transform firm-level data into industry-level observations. The 4-digit industry classification satisfies the need to perform an analysis at industry level (Adelman 1958; Dinlersoz and MacDonald 2009; Hart and Prais 1956; Marsili 2006; Peltoniemi 2011) and corresponds to the classification used by Kessides and Tang (2010), Sutton (1995; 1997) and Quandt (1966). It is sufficiently precise to avoid a conflation of specialised and non-specialised industries, whereas a narrower classification increases the probability that firms' activities are no longer independent from each other (Sutton 1997).

The second sample, called the *intermediate sample*, is a sub-sample of all active firms. To obtain an unbiased Gini-coefficient at the 4-digit industry level, used as proxy for FSI (see section 4.2.3), it was necessary to construct a constant number of firm-level observations. This required a random selection of firms out of the first sample with either 20, 30, 40, 50, 60, 75 or 100 firms for each 4-digit industry and excludes all 4-digit industries consisting of fewer than 20 firms. The reason for this is that industry dynamics decline with the number of firms due to a convergence towards contestable or monopolistic market conditions. Shifts in FSI are therefore less likely and the bias that such observations add is assumed to be greater than the additional information they add. It is further assumed that industries with fewer than 20 actors most likely operate in niche markets, regulated markets or in well-established sectors, which again indicates a weaker dynamism than in younger industries, especially for a sample period of no more than 10 years.

In addition, firms with fewer than five employees were excluded, because they showed unsatisfactory data quality and their legal status – which varies across countries – is a criterion for being listed in the database. Also, the disproportionately large number of micro firms would have resulted in the inclusion of fewer larger firms with more accurate records. This stems from the restriction imposed by the upper limit of firm-level observations that make up each 4-digit industry-level observation. It is worth noting that the exclusion of firms refers mainly to firms with a steady small number of employees despite carrying out an economic activity for at least six years. Thus, the respective firms maintain their marginal firm size because they are either restricted in their ambitions to grow or have been set up to perform tasks other than generating value added through manufacturing or the provision of services. Due to this steadiness, the said firm-size class is considered as a constant with negligible explanatory power. And, indeed, its employment share accounts for no more than a fraction of a percentage point of all firm-size classes. The resulting sample size for the intermediate sample, which takes into account the adjustments discussed in the section ‘Sample bias, missing values and outliers’, led to a total of 5,765 UK firms, 7,440 Italian firms and 7,550 German firms, which corresponds to 120, 172 and 168 4-digit industries respectively.

The intermediate sample also builds a foundation from which to estimate the coefficients responsible for changes in FSI. While for RQ1 the number of employees is sufficient to derive a FSI measure, the identification of its causalities – the purpose of RQ2 – demands the availability of a broader selection of variables. Since firm-level employment data is among the most comprehensive and reliable area of information, the unavailability of parameters explaining changes in employment cause a reduction in the number of observations. The sample used to address RQ2 is therefore termed *reduced sample* and comprises 96 4-digit industry-level observations (13 main NACE industries) consisting of 4,985 firms for the UK, 132 4-digit industries (12 main NACE industries) consisting of 6,070 firms for Italy and 146 4-digit industries (15 main NACE industries) consisting of 6,640 firms for Germany. These observations too were retrieved from *Orbis*, but no longer from summary tables as was the case for the extended sample. The vast majority of the difference in the number of 4-digit industry-level observations between the intermediate and the reduced model can be attributed to observations with excessively missing values for key variables, while only two observations had to be removed from the UK sample due to outlier behaviour – a restriction imposed by the regression estimators used. Yet it exceeds the number of industries considered in studies examining the industry life-cycle, which Peltoniemi (2011) quantifies between 20 and 50 and which are usually limited to ‘traditional manufacturing’ industries. The resulting panels remained strongly balanced, despite minor outlier and missing data issues having to be addressed at firm level (see next section).

4.1.3 Sample bias, missing values and outliers: RQ1 and RQ2

A number of precautions were taken to ensure the marginalisation of sample bias, such as for instance, the exclusion of subsidiaries from the sample due to the corporate parents' consolidated accounts. Especially ordinary least squares (OLS) estimations are sensitive to any kind of outliers. Missing values affect all estimators and were most common for Germany. Furthermore, the construction of representative observations for any 4-digit industry by using the mean, median or aggregate values of the respective firm-level observations bears an additional risk of biased results and warrants some attention. Most issues do not apply to the extended sample due to limited options for adjustment, but matter for the construction of the intermediate sample and the reduced sample.

Treatment of firm-level observations with consolidated accounts

When a mixture of firms with unconsolidated and consolidated accounts results in doubling up the figures, the exclusion of the few firms with consolidated accounts seems reasonable. It is, however, not as simple as that. Consolidated accounts include overseas activities that frequently outweigh the sum of domestic subsidiaries. Removing unconsolidated firm-level observations instead, implies that several subsidiaries, active in different industries and hence allocated to more precisely defined 4-digit industries, are replaced with a general – often even different in nature – core industry code that no longer reflects the economic activity of any subsidiaries. But subsidiaries are by nature less diversified than parent firms and fail to take into account the growth opportunities of the entire organisation with profits shifting to headquarters – Dischinger *et al*. (2014) estimated a gap of 25% – while consolidated accounts implicitly include information about subsidiaries. Furthermore, differing economic activities throughout the organisation remain in most cases traceable via secondary industry codes. This gives preference to eliminate subsidiaries with unconsolidated accounts that belong to firms with consolidated accounts included in the intermediate and reduced samples.

There was no possibility to take such bias into account when using data from summary tables. The dimension of the potential bias, i.e. the number of firms eliminated from the intermediate sample due to being classified as subsidiaries of a holding included in the sample, is significantly less than the sum of all firms with consolidated accounts and subsidiaries in the sample. For the UK the number of firms with consolidated accounts turned out to be less than 15.82% and shrinks to a minimum of 0.95% as firm-size classes become smaller. For Italy, the number of firms with consolidated accounts was just 0.47%, while Germany had 4.35%. Since the subsidiaries of some firms with consolidated accounts were not included in the sample, only 12.51% of subsidiary firms needed removing from the UK sample, 0.36% from the Italian sample and 3.64% from the German sample. This too suggests that most MNEs are located in the UK, with the least MNEs in Italy.

Missing values

According to Abrevaya and Donald (2011), 40% of empirical studies published in highly regarded journals suffer from missing data. Of the said studies, 70% used an estimator designed for complete information with the consequence that incomplete observations are simply dropped (Muris 2010). The estimation of the Gini-coefficient as the most sensitive element due to its derivation from micro-data and its scientific imperfection in describing FSI made it a precondition to restrict the sample to firms with no missing employee data. Although it is theoretically possible to estimate missing values when reliable regressors are available, missing employee data indicates even more missing non-employee data. Above all, estimating coefficients from questionable or unavailable regressors is a poor substitute for a complete observation. Since transparency and comprehensiveness of accounting information disclosure increases with size (Eng and Mak 2003; Inchausti 1997), sample selection bias cannot be excluded. However, capital is a scarce resource and SMEs rely most on external finance provided by banks (Booth 1995; Dore 2000; Eichengreen cited in Boltho 2013). And this encourages firms to mediate with fund providers through accounting information disclosure. As the probability of disclosure increases with the degree of owner-management (Eng and Mak 2003), such bias stays within reason for SMEs too.

The likelihood of meeting missing values increases with the number of variables assumed to affect FSI. Industry-specific requirements, preferences and accounting practices are accountable for systemic groups of missing data, which too applies to company accounts. Systemically missing data cannot be avoided, but in the best case occur randomly within industries. For the used sample, they are limited to time-variant variables that form part of the performance component *FPER* and do not apply to the basic model (these models will be explained in section 4.3.2). Also, randomly missing data generates less disturbances than a systemic absence of values (Jones cited in Verbeek 2012). On rare occasions, i. e. less than 5%, missing values were spread across the entire firm-level observation. As will be explained in more detail in section 4.3.2, for RQ2 firm-level data forms the basis to construct industry-level observations that enter into the regression analysis. Since said observations add more disturbance than information, maintaining them would have led to aggregate bias when pooled with the remaining observations. The randomness of the missing values allowed dropping the respective firms, which Cameron and Trivedi (2005) consider as the simplest and 'safest' way to preserve the remaining observations without adding further bias. For all other observations, which consist of complete information except for the *FPER* component, listwise deletion would have resulted in a disproportionate loss of information with a sample bias applying also to the basic model.

With regard to the *FPER* component, the estimated number of missing values was below 5% of all observations and at a level that legitimises the decision to interpolate missing values (Schafer cited in Cameron and Trivedi 2005). The time-variant nature of the respective variables allowed the reconstruction of values to preserve a maximum number of observations by applying the following conventions.

- One or two missing values within the sample period of a variable of firm *i* were replaced by the mean of adjacent or nearest available values of firm *i*.
- One or two missing values at the beginning or the end of the sample period of variable *i* was replaced by the last available value of firm *i*.
- If more than two values of a variable were missing in sequence, but the values for all other variables show less missing values, they were treated as missing values and replaced by the average of the respective subsample for each time period *t*.
- In all other cases a variable of firm *i* was treated as missing for the entire sample period. In this way it is not unsystematically considered in the industry-level observation and has the equivalent effect of listwise deletion, but without dropping the entire firm-level observation.

In addition, there are several mechanisms at work to minimise biasness whilst preserving information. Generating the mean or median of a series of *n* firms, of which some have missing values, still gives an industry-level observation without being affected by the missing data. The same applies to the aggregate value, which is a derivative of the mean. It is finally the separation of the extended from the basic regression model – both country-independent – that inhibits bias transmission from one model to the other and from country to country.

There are circumstances where not only mean substitution, but also a model-based approach, is ineffective. This refers to intangible assets, R&D and exports, which are of systematically poorer quality than any other variable and it remains unclear whether missing values suggest nil or are actually missing. For these three variables it was assumed that no data means no intangible assets, R&D expenditure or exports unless it was evident that values are not missing throughout the panel. Fairly consistent data for R&D and exports were only observed for the UK and resulted in the exclusion of these variables for Italy and Germany.

Outliers and leverage

While the term 'outliers' refers to abnormal values causing a high variance of the dependent variable, such abnormal fluctuations for independent variables are referred to as 'leverage points' (Rousseeuw and Zomeren 1990). There is no strict mathematical definition (Verbeek 2012), but the sensitive nature of OLS-based estimators results in a trade-off between preserving information and minimising bias. The identification of outliers took place at two stages: first at firm level and second at industry level – it was sufficient to identify leverage points at industry level only. The first step, i.e. the exclusion of outliers at firm level, is justified by the need to homogenise sample observations. Since the dependent variable is FSI, the underlying unit is firm size measured by the number of employees. The number of employees of firm *i* itself does not matter as much as its change from time *t* to time *t+1*, which, if divided by the number of employees at time *t*, gives the firm growth rate. Although it has been argued that smaller firms have a tendency to grow faster than large firms, there are limits to organic firm growth. These limits are exceeded when mergers or other organisational restructuring processes, causing a formal shift of employees from one firm to another, take place. Inconsistencies of this kind cause a marginalisation of other observations' growth rates and because the motivation for excessive growth rates cannot be modelled, such firm-level observations were eliminated from the sample. The table below illustrates extreme patterns in employee figures, the effect of which becomes even more evident when transformed to the annual firm growth rate.

Table 4.1: Patterns of abnormal firm growth

	Max. change in %	**No. of employees by year**									
		2010	2009	2008	2007	2006	2005	2004	2003	2002	2001
Firm 1	4,330	587	553	530	516	499	482	443	**10**	252	186
Firm 2	4,444	8	8	8	9	10	**409**	9	13	12	10
Firm 3	6,931	24	25	27	26	27	26	24	**1,828**	26	28
Firm 4	10,950	58	52	52	**3,491**	**2,300**	**1,974**	**1,989**	18	25	129
Firm 5	6,096	5,785	6,319	7,002	**113**	**104**	**106**	**107**	**260**	6,477	6,193
Firm 6	8,846	**1,238**	**1,185**	**1,120**	**1,163**	13	13	14	25	25	24

The limits defining abnormal annual growth or decline are sample specific and were defined as -80% and +80% for the UK and Italy, but, due to a considerably higher base growth rate, had to be extended to -80% and +100% for German firms. The argument that smaller firms grow faster than larger firms and result in a proportionally higher drop rate could not be observed. Although variations in outlier drop rates according to firm-size classes, as defined by the EC and extended by a class for a mean workforce of at least 1,000 employees (very large), the overall drop rate peaks at 8.7%. As the tables below show, for Germany the percentage of firms removed from each firm-size class is almost constant, while it increases with firm size for the UK and Italy, indicating that mergers or other organisational restructurings increase with firm size.

Thus, the underlying distribution maintains its right-skewed properties with no need for normalisation, because it is only the industry-level observations that enter into the regression model. Outlier and leverage point elimination at industry level are therefore justified by the assumption – although a weak one (Wooldridge 2013) – that observations should follow a normal distribution and that regressors containing extreme values do not cause abnormal changes of the dependent variable. *Stata* offers a range of diagnostic tools, which were used to identify critical observations with the result that such observations applied almost exclusively to 4-digit industries consisting of only 20 firm-level observations, wholesale or manufacturing firms. Since wholesale and manufacturing are the industries with the largest number of sub-industries, the deviating 4-digit industries are either highly specialised markets with distinct dynamics or the consequence of an insufficient number of firms to construct a reliable industry-level observation. Both cases require dropping problematic observations in order to come to generalised conclusions. The latter, however, is more likely to apply and bears less risk of aggregating bias by excluding observations. This leads to the final sample consisting of some 100 industry observations at the 4-digit level for each country. A summary is presented in Table 4.2.

Table 4.2: Sample properties of the reduced sample

	UK	Italy	Germany
No. of observations (4-digit industries)	96	132	146
No. of firms	4,985	6,070	6,640
Time period	2001-2010	2001-2010	2005-2010
Frequency of sub-sample size:			
20 firms	20 (20.8%)	36 (27.3%)	47 (32.2%)
30 firms	21 (21.9%)	22 (16.7%)	25 (17.1%)
40 firms	13 (13.5%)	21 (15.9%)	16 (11.0%)
50 firms	5 (5.2%)	11 (8.3%)	16 (11.0%)
60 firms	11 (11.5%)	15 (11.3%)	11 (7.5%)
75 firms	3 (3.1%)	12 (9.1%)	10 (6.8%)
100 firms	23 (24.0%)	15 (11.4%)	21 (14.4%)
No. of 4-digit Industries:			
Manufacturing	26 (27.1%)	82 (17.4%)	49 (33.6%)
Wholesale	19 (19.8%)	23 (62.1%)	45 (30.8%)
Other	51 (53.1%)	27 (20.5%)	52 (35.6%)

Industry classifications

Besides sample selection bias and distortions associated with the replacement of missing values and the removal of outliers, industry classifications also bear the risk of being biased. Managers are often unaware of their classification (Storey and Greene 2010) and highly diversified firms might find it difficult to unambiguously classify operational activities. Christensen (2013) scrutinised the ability of the NACE industry classification system with particular attention to the distinction between manufacturing and service firms. The analysis identified that 18% of all firms are misallocated at the 2-digit level due to managerial mistakes or inaccuracies, difficulties in allocating activities to a single primary industry code – being enhanced by increasing technological sophistication – and delays in classification system adjustments. On the one hand the bias originates from the firms' representatives unawareness or ignorance, and on the other hand are from systemic limitations of industry classification systems in providing sufficiently accurate options.

Moreover, most databases, including those provided by the *Bureau van Djik*, treat industry classifications as time-invariant records and hence impose limitations to long-term studies. Yet Christensen (2013) warns of over-interpreting his findings. Such bias is difficult to verify for large samples, but distortionary effects were reduced by using a single industry classification system without the need for conversion. Another precaution is the distinction between primary and secondary classification codes as it is unlikely that primary industry codes have changed, because most changes in corporate strategies comprise of the addition or removal of non-core activities. In addition, the relatively short time period reduces further bias, which, however, does not eliminate intentional or unintentional misallocations by firms' administrators.

4.1.4 Sample and data description: RQ3

It has been argued that the unconditional use of GDP as an indicator for welfare is insufficient and that alternative measures should be considered. The multi-dimensional approach required to address the consequences of FSI on well-being necessitates the reconstruction of the samples used for RQ1 and RQ2. While the first two RQs are addressed by using firm and industry-level observations, the availability of indicators measuring welfare is in most cases restricted to proxies at national level. The quantitative analysis the present work follows requires therefore the enlargement of the sample countries. The core membership of the UK, Italy and Germany of the EU gives preference to the extension of the sample countries to the EU27 over OECD countries. This allows access to statistical material, which has been widely homogenised by *Eurostat* and is less flawed by fluctuations of competing currencies. Furthermore, similarities in cultural context and social security systems are more likely to be found among EU member states than between the US and Japan.

Due to the differences in economic stage between East and West Europe, the EU27 countries are categorised in EU15 and non-EU15, which refers to countries that joined the EU from 2004 onwards. Croatia, which joined the EU27 in 2013, remained excluded, because data was incomplete. The maximum sample period is defined by the firm-size class share statistics available from the *SME Performance Review* unit, which is 2002 to 2012. The period shortens according to the availability of the respective welfare indicators under examination and shrinks to a minimum of a one year observation as it applies to happiness and life satisfaction levels as well as entrepreneurial opportunities retrieved from the *European Social Survey* and *The 2012 Legatum Prosperity Index*. Due to the variations in sample construction and examined periods, the sample periods will be recalled when discussing the methodology in detail.

Unlike the datasets used for RQ1 and RQ2, none of the datasets used for RQ3 suffered from missing data. The only exception is the ANS records in 2008 for Belgium, Germany, Luxembourg and Malta, where the missing values had to be estimated by extending the trend of the preceding three years. Outliers could be observed to a minor extent and were treated accordingly. Further details are discussed when constructing the model specifications.

4.2 Dynamics of firm size inequality

Before discussing the details of the method used to analyse shifts in FSI, two fundamental issues are clarified: the definition of firm size and the measurement of FSI. Both elements are strongly linked to the type, scale and quality of the data. As anticipated in the previous section, the number of employees has been considered as key in proxying firm size and that the resulting Gini-coefficient is used to measure FSI. The following sections justify these choices by reflecting on the alternatives under consideration. After examining the appropriateness and reliability of market concentration measures and the Gini-coefficient in particular, the final section presents the method used to identify shifts in FSI, based on the previously discussed samples.

4.2.1 Measuring firm size

The literature shows a wide disagreement on the appropriate measures for firm size with, as Dinlersoz and MacDonald (2009) state, limited knowledge “about the relationship among different measures.” Sales, the most intuitive measure and used by and Cassia and Colombelli (2010), is criticised for suffering from price fluctuations due to its property of being a function of changes in demand (Dinlersoz and MacDonald 2009). Prices are also sensitive to inflationary adjustments (*ibid*.) with substantial negative implications on longitudinal and cross-country studies. While Syverson *et al*. (cited in Dinlersoz and MacDonald 2009) argue that prices for products and services increase with firm size, Audretsch *et al*. (1999) and Bloch (1981) come to the conclusion that margins of small and large firms are at odds. Thus, sales as proxy for firm size is flawed and subject to market volatility.

Taking into account the impact of the industry life-cycle stage on the price-cost margin (Audretsch and Woolf 1986), sales figures may also contribute to the aggregate bias by pooling industries of different life-cycle stages. Coad (2009) and Hannah and Kay (1977) see economic value added as the ideal proxy, while Dinlersoz and MacDonald (2009) consider output as the only theoretically appropriate measure due to its consistency over the industry life-cycle. Such consistencies could not be guaranteed by the workforce employed when it changes with the introduction of new, more efficient means of production and heterogeneous life-cycle stages. Due to higher efficiency levels small firms are able to achieve, the number of employees could be misleading. However, the application of output in terms of shipment value as proxied by Bloch (1981) and Dinlersoz and MacDonald (2009) or global tonnage Deltas (2003) is limited to manufacturing firms and unsuitable for service providers. Equally industry-specific are the capital employed as used by Cirillo (2010) and the convenience of assets and its derivatives used by Adelman (1958), Collins and Preston (1961), Ghosh (1975) and Hart and Prais (1956).

In contrast, the number of employees is non-deflationary and most appropriate for cross-country comparison (Coad 2009), whilst easier to access. It is therefore among the most frequently used measures for firm size (Barbosa and Eiriz 2010; Lotti 2007) and has become part of the EC's (2003) definition of firm-size classes. Despite being strongly correlated with sales (Audretsch and Woolf 1986), employee figures are less volatile and biased than output, while better reflecting operational activities. There is a risk of overlooking fluctuations in output when using inert employee data to examine changes in firm size dynamics (Dinlersoz and MacDonald 2009), but structural changes demand the use of a measure insensitive to non-persistent fluctuations that occur in the very short term. Consistent with Simon and Bonini (1958), Coad (2009) emphasises the irrelevance of the definition of size due to similar results, whether size is defined in total assets, sales, employees or value added; also if used across industries. Nevertheless, the concerns expressed by previous research papers are taken into account and the cross-country and cross-industry nature of this work suggests that the number of employees is the best approach in measuring firm size.

4.2.2 Measuring market concentration and firm size inequality

A series of measures have been defined to measure market concentration, but once more with a contradicting debate on how to weight parameters (Davies 1980). Researchers, who consider market concentration in their analysis, show a tendency to compromise by using concentration ratios or the HHI due to the simplicity these measures offer (Bikker and Haaf 2000). The property of the concentration ratio to consider only the market share of the *n* largest companies allows the use of an unknown number of observations, as long as the total market share is known. Its popularity stems from the assumption that it reflects market power, which the US Federal Trade Commission (1992:2) *Horizontal Merger Guidelines* defines as the “ability profitably to maintain prices above competitive levels for a significant period of time”. By simplifying and universalising the measure in the form of the concentration ratio – and hence limiting the application to key players of the upper tail of an industry – the relationship between market concentration and market power becomes obscured. According to Barla (2000), it is U-shaped rather than J-shaped when associated with FSI and necessitates the consideration of measures that consider the entire distribution.

Bloch (1981) and Hariprasad (2011) use the variance in market shares as dependent variable to identify the determinants of FSI. This approach has a certain appeal and is less problematic in its valuation, but limited in the context of cross-industry analysis where the number of new entrants and established firms could be misleading if interpreted as FSI. It further demands a lognormal distribution, the condition of which cannot be met if applied to multiple industries (Clarke 1985), whereas the properties of the logarithm under-emphasise large firms (Hay and Morris 1991). It leaves the HHI, which is less restricted in its application, and allows the analysis of all sample observations as the only viable alternative. This fulfils the convention that "a good index of concentration must decline with the number of firms and increase with the level of inequality among firms" (Barla 1998:2). However, the HHI puts more emphasis on large firms and, by definition, marginalises changes affecting firms smaller in size.

Originally applied by Hart and Prais (1956), Collins and Preston (1961) and more recently by Barla (2000), the Lorenz-curve and Gini-coefficient (G) are less prone to the above noted concerns, but underestimate the market power of large firms due to their exponentially higher influence of competing market participants (Bikker and Haaf 2000). Since not all companies within a narrowly defined industry are necessarily competing with each other due to tacit co-existence and diversification strategies, which apply even more to industrialised countries and the necessity to export, the potential bias appears overestimated. Firms belonging to a cluster are especially likely to compete with outsiders rather than with their peers, as Porter and Stern (2001) find.

As a relative market concentration measure ($0 \leq G \leq 1$; 0 = firm sizes are evenly distributed, 1 = monopoly), the Gini-coefficient enables cross-industry and cross-country comparisons, with the option to directly compare national income inequalities at aggregate level. It satisfies the 'principle of transfer', which makes shifts of firm sizes within a quartile measurable, without imposing the requirement that the values of observations subject to the shift have to be larger than the mean as, for instance, demanded by the interquartile ratio (Deaton 1997). Due to the Gini-coefficient's emphasis on the degree of inequality rather than the number of firms and market share (Sawyer 1981), it qualifies for its application as firm inequality measure to represent the degree of polarisation of the SDOF. Although being "the most frequently used measure of inequality" and theoretically clearly defined as “twice the area between the 45-degree line and the empirical Lorenz curve” (Deltas 2003:227), adopted simplifications for its applications led to variations in its mathematical expression.

4.2.3 The Gini-coefficient and its reliability

In his paper, Barla (2000:698) defined the Gini-coefficient as $G = \frac{(n+1-2\sum_i il_i)}{n-1}$, where *n* is the number of observations and “firms are ordered by decreasing size (*i* = 1 is the largest firm, *i* = 2 is the second largest etc.).” The very small sample size used suggests that the estimated coefficients may be subject to small-sample bias, with limited importance for invariant sample sizes (Deltas 2003; Demuynck 2012). Based on three commonly used formulas to calculate the Gini-coefficient, Deltas (2003:226) performed a Monte Carlo simulation to demonstrate the significance of the small-sample bias, which means that “[t]he Gini coefficient of a large population estimated from a small sample will be substantially smaller than the Gini of the entire population”. The non-linear property of this bias means that “a reduction in the sample size leads to a reduction in apparent inequality” (Deltas 2003:227). Consequently, this issue becomes more severe when the number of observations in subsamples varies and leads to distorted coefficients and misinterpretations.

To remove a first order bias, Deltas (2003) suggests multiplying the obtained Gini-coefficient by $\frac{n}{n-1}$ with the consequence that it becomes unspecified whether the remaining bias has a positive or negative sign. The formation of an adjusted Gini-coefficient $G_{adj} = \frac{n}{n-1} G_n$ reduces the bias from “typically 15% of the true value for sample sizes between 5 and 10” to 3% for n = 10, 7% for n = 5 and “a maximum of 13% for [n]=2” with σ = 1.0 (Deltas 2003:230). The residual bias is called second order bias and is distribution-dependent, positively correlated with the standard deviation (*ibid*.) and requires the parameters of each 4-digit industry distribution. Consistent with the literature on the SDOF, Deltas (2003) notes that firm size distributions can generally be described by a lognormal distribution with 0.2 < σ < 1.0 and results in a significant bias for σ ≥ 0.5 and *n* ≈ 2. Since the estimation of each subsample's distribution and the selection of a distribution-specific adjustment approach for a large number of 4-digit industries is extremely time consuming, an extension of sample size is more efficient.

Whichever the sample size, "an upward-adjusted Gini … has been shown to reduce the bias" (Deltas 2003:234) and was used to estimate the degree of FSI for RQ1 and RQ2. For RQ3 the share of specified firm-size classes was also used. Deaton (1997:139) transformed the bias-adjusted expression $G = \frac{1}{\mu\, n(n-1)} \sum_{i>j} \sum_j |x_i - x_j|$ to the operational version $G = \frac{n+1}{n-1} - \frac{2}{n(n-1)\mu} \sum_{i=1}^{n} \rho_i x_i$, where *n* is the number of observations, *μ* the mean, *x* the value of the respective observation and ρ_i the rank (1 for the largest value). Based on this commonly used formula, the Gini-coefficients obtained from a test sample of 34 randomly selected UK 4-digit manufacturing industries, consisting of 15 firms each, showed that the unbiased, but upward-adjusted, Gini-coefficient is approximately 7% above the value obtained from the unadjusted formula. Its consistency is confirmed by Pearson's correlation coefficient for both biased and unbiased Gini-coefficient (r = 0.9998, p < 0.001), with a consistently lower value for the unbiased coefficient if the number of firms for each subsample would have varied. It underlines the need to use the adjusted coefficient, which corrects the first-order bias described by Deltas (2003). As noted earlier, the second order bias can be minimised by either using a constant number of observations or by controlling the bias originating from variations in the number of observations. The trade-off between sample bias and sampling flexibility led to the restriction that each 4-digit industry requires a minimum of 20 firms to qualify as measure for the degree of FSI.

4.2.4 Identifying shifts in firm size inequality

The purpose of analysing the dynamism of the SDOF is to get a general idea of the changes taking place across firm-size classes and the degree of FSI across industries and countries. The analysis is largely based on descriptive statistics and gives an understanding of the sample properties that lead to FSI measured by the Gini-coefficient, which is the dependent variable of RQ2.

Descriptive statistics are applied to analyse changes across industries according to the employment share of main NACE industry sections and changes across firm-size classes by country. This is complemented by an extended version of the procedure applied by Robson and Gallagher (1994). Their analysis is based on 20 firm-size classes, measured by the percentage of employees belonging to each defined firm-size class grouped into production and non-production firms. The NACE industry classification system suggests that a segmentation into manufacturing and non-manufacturing is more appropriate in categorising all major main industry sections, as is applied by Lotti (2007). To achieve a more detailed distribution of the middle and upper tail, the firm-size class range defined by Robson and Gallagher (1994) is extended to 30 with firm-size classes exponentially increasing in size. The addition of 10 size classes also enables the aggregation of firm-size classes according to the size classes defined by the EC (2003), applied in Barbosa and Eiriz (2010), Cassia and Colombelli (2010) and Wit and Kok (2014).

On the assumption that changes in FSI occur evolutionary with no sudden shocks, only even years are considered as observation points, i.e. 2002, 2004, 2006, 2008 and 2010. The unavailability of data for German firms before 2005 requires the use of 2006 as the first point of reference. This synthesizes the available data and is consistent with the two-year interval (1987, 1989) used by Robson and Gallagher (1994). As the used dataset consists of a constant number of firms, but variations in employment share, there are limitations in commenting on the mobility of firms across firm-size classes. This issue is readdressed when assessing the net job creation, for which the dataset consists of the population with firm entry and exits and also accounts for the size distribution fallacy discussed in section 4.4.3.

While the above analysis is based on summary tables (extended sample), the subsequent observations consist of the firm-level data used to generate the Gini-coefficient for each 4-digit industry (intermediate sample). Country-specific descriptive statistics, grouped into manufacturing and non-manufacturing firms, provide information on mean firm size and the higher moments over the sample period. These reflect the distribution properties that enter in the following distribution test. Due to the marginal differences between lognormal and Pareto distributions (Coad 2009; De Wit 2005) and the large share of service firms in West Europe, the low MES makes it satisfactory to limit the test to the lognormal distribution. To verify whether the size distributions of firms indeed follow a lognormal distribution, the normality test of D'Agostino *et al*. (1990) with Royston's (1991) error-adjustment, as suggested by Gould and Rogers (1991), was used.

Royston (1991) takes into account the fact that skewed distributions are more common than normal distributions, which fits with the nature of the SDOF as discussed in the literature review. In addition, his adjustment enables us to apply the test to small sample sizes, which would otherwise lead to an overly frequent rejection of the null-hypothesis, i.e. the tested distribution is normally distributed. Since the smallest groups of 4-digit NACE industries consist of 20 sample firms ($n_{min} = 8$), the application of the described test method can be considered as sufficiently accurate. The normality test was performed for main NACE industries and each 4-digit industry for each sample year. The rejection rate was used as an indicator to verify to how many 4-digit industries of each group the LPE applies. Industries are grouped according to manufacturing and non-manufacturing firms, and according to the number of firms making up each 4-digit industry-level observation.

A final set of descriptive statistics with the inclusion of higher moments was performed for the calculated Gini-coefficient for even years of the sample period. To exclude outliers, the median of the resulting FSI values is then used as an indicator for changes at main NACE industry level. In addition, the percentage of 4-digit industries showing an increase in FSI is reported. By using the difference rather than the absolute value of the FSI, the bias associated with the Gini-coefficient due to variations in the number of observations becomes negligible. However, with a decline in the number of 4-digit industries belonging to a main industry, the statistical significance of the change, expressed in the percentage of sub-industries moving in one or another direction, declines. The expectation is that traditional industries, i.e. those relying on heavy investments in tangible assets, show an increase in FSI.

4.3 Determinants of firm size inequality

This section develops a viable methodological approach to verify the impact of factors, which, according to the literature reviewed, are expected to affect the SDOF by either increasing or lowering FSI. The approach used by Ghosh (1975) – an early research paper on this matter – considers industry concentration of post-independent India as a dependent variable by regressing 4-firm (CR4) and 8-firm (CR8) concentration ratios on theoretically derived factors such as initial concentration, number of firms and industry growth rates. Given that concentration ratios contain information of just one tail, changes in market concentration do not necessarily imply a radical change in the SDOF, found to be stable over time. The use of data at national level cancels out differences among industries and ignores industry-specific characteristics, such as firm entry, exits and survival rates (Peltoniemi 2011) as a function of MES and potential growth. This limits interest and utility of industry structure related research studies at national or international level and might be one explanation why the vast majority focuses on not more than a few industries.

Due to its historical importance, the manufacturing industry still dominates in contemporary empirical research, partly because data is easier to access and is of good quality. The increasing share of service firms in advanced economies, however, has encouraged researchers to include non-manufacturing in the sample to provide a more comprehensive understanding of industry dynamics. As long as the number of industries that need controlling is manageable, dummy variables can be used to distinguish manufacturing from non-manufacturing and regional differences in time-variant panels. For instance, Teruel-Carrizosa (2010a) and Santarelli (2006b) use micro-level observations to analyse the influence of industrial district presence on SMEs' firm growth. By doing so, conclusions on the structural change of a given industry can be made, if the industry is sufficiently narrow. This results in a trade-off between the degree of industry refinement and the range of industries to be covered, unless the loss of the time dimension can be sacrificed.

Observations at firm level, as the smallest unit within the industrial economic paradigm, eliminate potential bias emerging from summarising *k* firm-level observations to one industry-level observation, but offer unsatisfactory possibilities when identifying the determinants of FSI. Since FSI is a measure obtained from *k* firm-level observations, which together portray a particular industry, its determinants have, by definition, to be brought to the same level. The cost of doing so is the generalisation of firm-specific parameters, but it offers the possibility to include a large number of 4-digit industries across a wide range of presumably incompatible industries. The number of dummy variables required to control for major industry-specific characteristics remains reasonable without running the risk of collinearity with independent variables of primary interest. Yet the consideration of generalised firm-specific characteristics, whether time-variant or time-invariant, is still feasible.

The nature of this approach brings the methodological choice closest to Ghosh (1975), Bloch (1981) and Hariprasad (2011), whose interests lie in the empirical identification of factors affecting FSI rather than theoretically modelling the distribution. The subsequent sections will first develop the theoretical model, which influences the choice of the estimation method, but is subject to the limitations imposed by the sample. This leads to an adjusted model specification, which takes into account relevant restrictions and is followed by an explanation of the variables considered in the specified model. Again, the model specification discussed herein refers to the reduced sample. To minimise the effects of sample bias, industry-level data of the model components *MAIN* and *FDIG* are derived from the extended and intermediate samples respectively. The reflections on model specification, such as the presence of heteroskedasticity and autoregressive disturbances presented thereafter, result from diagnostic tests of the adjusted empirical model applied to the final sample.

4.3.1 Model development and choice of estimators

From an econometric perspective, panel data is most comprehensive in processing information for each observation (Cameron and Trivedi 2005) with the possibility of analysing respective dynamics (Wooldridge 2010). It enables a time-variant measurement error (Gil 2010), but demands more attention on correlations between error terms over time (Cameron and Trivedi 2005). With regard to RQ2, the benefits of panel data outweigh a cross-section approach by better incorporating the dimensions required to establish a relationship between FSI and evolving industry structure parameters. This refers in particular to the fluctuations caused by macro-economic disturbances during the sample period. In practice, however, it occurs that records like firm-specific plant structure, management composition and industry-specific characteristics are treated as time-invariant variables as the dataset used herein. As a result, the inclusion of time-variant parameters is reduced to employee data, balance sheet and profit and loss account records. Although technically still considered as panel data, the model specifying the factors affecting FSI consists de facto of a combination of time variant and time invariant variables.

The relationship of FSI and its casual factors is assumed to be linear (Bloch 1981; Ghosh 1975; Hariprasad 2011). This gives a parametric regression model corresponding to the functional form $y_{it} = \alpha + \sum_{j=1}^{k} \beta_j x_{itj} + v_{it}$, which suggests a unique intercept for all individuals and hence omits heterogeneity. This so-called common constant model or pooled OLS model increases its accuracy with an increase in the number of observations – known as asymptotic efficiency – while potentially reducing omitted variable bias (Asteriou and Hall 2011). However, an OLS estimation imposes structural limitations and is only the best unbiased linear estimator when the Gauss-Markov assumptions are satisfied. It is unlikely that panel datasets comply with all conditions imposed, which occurs in particular when industries, different in their nature, are pooled together or when the dependent variable follows a trend (Verbeek 2012). Pooled OLS in its original form can therefore be classified as a hypothetical technique with estimates being subject to confirmation by an estimator taking into account these shortcomings unless the violation of individual assumptions can be addressed by an adjusted estimator.

To capture group specific heterogeneity, α has to be transformed into α_i, resulting in $y_{it} = \alpha_i + \sum_{j=1}^{k} \beta_j x_{itj} + u_{it}$ and complemented by time effects and unobserved heterogeneity. The former is necessary to allow for variations in macroeconomic conditions as it occurs in the event of economic shocks, while the latter is required to capture unobservable or unknown factors affecting the dependent variable, which in this context is FSI. Since every observation reflects an industry, each observation's FSI is the product of industry-specific dynamics that go beyond the generalisable parameters and hence makes it imperative to take the said unobserved heterogeneity into account. This can be achieved by splitting the error-component u_{it} into $\omega_i + \varepsilon_{it}$, which gives the generalised theoretical model $y_{it} = \alpha_i + \sum_{j=1}^{k} \beta_j x_{itj} + \varphi_t + \omega_i + \varepsilon_{it}$, where α_i are main industry-specific effects, x_{jit} the explanatory variables of primary interest, φ_t time-specific effects, ω_i unobservable heterogeneity and ε_{it} the random error-term with an expected mean of zero.

The functional form of the model is built on the foundations of the fixed effects (FE) and random effects (RE) models and is able to provide more accurate standard errors than a pooled OLS could. Also, OLS fails to distinguish between significant time-invariant unobservable heterogeneity and group-independent random effects, also called idiosyncratic error-term, and therefore generates inefficient estimates (Asteriou and Hall 2011; Wooldridge 2013). Since the primary interest does not lie in the estimation of the intercept α_i and the inclusion of time-invariant variables is essential, the RE model is the better alternative to OLS. Carrying out a Hausman test to verify whether the FE or RE model is more appropriate is therefore dispensable, but a Breusch and Pagan Lagrange multiplier test (Breusch and Pagan 1980) confirmed the superiority of the RE over the pooled OLS model. The discussed approach reflects the method adopted by Teruel-Carrizosa (2010a:32-33), who justifies it by arguing that "random effect models are more efficient since they incorporate information across individual firms as well as across periods." Wooldridge (2013) too argues that for time-variant regressors RE is more efficient and requires fewer parameters than FE, but the correlation of group-specific effects with any of the regressors leads to biased and inconsistent estimates and therefore requires particular attention.

In addition to the avoidance of multicollinearity, verifiable with the variance inflation factor, the absence of serial correlation – also known as autocorrelation – and heteroskedasticity, are necessary conditions to obtain efficient estimates (Wooddridge 2013). Both conditions were violated when performing the diagnostic tests. The presence of autocorrelation was identified by the inclusion of lagged residuals in the regression, showing a significant positive influence and was confirmed by the Wooldridge test for autocorrelation. Although no second order autocorrelation was identified, an RE GLS estimator accounting for AR(1) disturbances was applied to obtain reliable significance levels (Cameron and Trivedi 2010) and is consistent with Barla (2000). Ignoring AR(1) disturbances would result in an overestimation of significance levels. With regard to heteroskedasticity, the Breusch-Pagan/Cook-Weisberg test (Cameron and Trivedi 2005), which under H_0 assumes constant variance, diagnosed the presence of heteroskedasticity, implying the need for robust standard errors. Since such a test assumes a linear heteroskedasticity function and is biased when in combination with weighted least squares (WLS) estimations (Wooldridge 2013), the White test was applied on the pooled OLS estimation. This confirmed the outcome of the Breusch-Pegan/Cook-Weisberg test and hence demanded the use of robust standard errors.

Due to the presence of both autocorrelation and heteroskedasticity, the feasible GLS (FGLS) estimator developed by Greene (2012) – which is the operationalized GLS estimator and designed to address these violations – is used to validate the findings obtained from the random effects estimation with AR(1) disturbances. Both GLS and FGLS rely on a stronger exogeneity assumption than OLS and become inconsistent when strict exogeneity is violated, i.e. $E(y_{it}|x_{it}) = \beta x_{it}$ with no feedback from y_{it} to x_{it} (Wooldridge 2010). Despite being biased, in the event of moderate heterogeneity the FGLS estimator is more efficient than OLS and GLS if the heterogeneity function is unknown (*ibid*.). Since the latter is indeed the case and FGLS estimates become unreliable when heteroskedasticity is strong, Wooldridge (2013) recommends opting for GLS, because it is more accurate with its predictions, while still being more efficient than OLS. Since both the autocorrelation-adjusted RE estimator and FGLS estimator have their advantages, it makes sense to report both coefficients along with the unbiased OLS estimates with Newey-West standard errors, which also takes heteroskedasticity and AR(1) disturbances into account. Much the same has been applied by Baptista and Karaöz (2011), who favour FGLS in combination with the alternative Prais-Winsten OLS estimator.

Estimated fractional dependent variables

The utilisation of the Gini-coefficient as the suggested FSI measure imposes two econometric issues. The first is the property of a 'fractional response variable' as identified by Papke and Wooldridge (1996) and the second is the dependent variable being an estimated variable itself not free from sample bias. Since the Gini-coefficient moves between 0 and 1 inclusive, it can be classified as a fractional response variable and bears the risk that it does not follow a normal distribution as demanded by the OLS estimator. To achieve this distributional condition, Wooldridge (2010) suggests performing a log-odds transformation, which is to transform y_i to $w_i = \log\left[\frac{y_i}{1-y_i}\right]$. The limitations of this approach are twofold: as y_i moves towards the extreme interval values, w_i moves towards infinity ($-\infty$ for $y_i = 0$ and ∞ for $y_i = 1$), and interpreting β becomes challenging (Wooldridge 2010). The absence of empirically revealed Gini-coefficients consisting of extreme values relativises the importance of the first limitation and reduces the bias. Since the untransformed Gini-coefficient is close to a normal distribution for all sample countries, but with log-odds transformation showing an increase in significance levels, the latter will be included as an optional estimate to verify the untransformed dependent variable.

The second issue, which refers to the dependent variable being an estimate itself, is addressed by Lewis and Linzer (2005), resulting in two implications. The first is the underlying sample bias, resulting in heteroskedastic panels, and the second is the "random shock that would have [been] obtained even if the dependent variable [was] directly observed as opposed to estimated", not necessarily a source of heteroskedasticity (Lewis and Linzer 2005:346). According to Lewis and Linzer (2005), this leads to less efficient, and possibly also to inconsistent estimates. FSI as a function of a varying sample of firm-level observations results indeed in a bias of the estimated dependent variable and consequently also in heteroskedsastic panels. The intuitive solutions suggested by Lewis and Linzer (2005) are to ignore heteroskedasticity when using OLS or to use a heteroskedasticity-adjusted GLS approach, where the latter is superior for very high sampling errors only. However, according to Lewis and Linzer (2005:346), "[i]f sampling error comprises a larger share of the variation in the dependent variable and this uncertainty varies greatly across observations, appreciable gains in efficiency can be achieved through the use of … feasible generalised least squares (FGLS) estimators". This argument adds more value to the estimates obtained by the FGLS estimator, but its integrated bias in the heteroskedasticity function leaves substantial reliability attached to the coefficients estimated with the RE model.

4.3.2 Adjusted model specification

Country-specific peculiarities due to institutional effects (Audretsch and Elston 2006; Henrekson and Johansson 1999; Nelson cited in Peltoniemi 2011), differences in measurement (Gil 2010) and the disclosure of data restrict the application of the generalised model in its current form. This suggested it best to opt for independent country-specific regression models, consisting of a basic model – equally applicable to each sample country to ensure comparability – and an additional component, which covers factors varying across countries. Taking into account these aspects, the final model specification to identify the causalities of FSI can be expressed as:

$$FSI_{jt} = \beta_0 + \sum_{i=1}^{6} \beta_i SAMPLE_{ji} + \sum_{j=7}^{20} \beta_j MAIN_{jj} + \sum_{k=21}^{26} \beta_k FDIG_{jk} + \sum_{l=27}^{33} \beta_l FPRO_{jl} + \sum_{m=34}^{41} \beta_m FPER_{jtm} + \varphi_t + \omega_j + \varepsilon_{jt} \qquad (1)$$

Accordingly, FSI of industry j at time t is a function of the constant intercept β_0, the firm-level sample size adjustment dummies ($SAMPLE$), up to 13 main industry dummies and the main industry growth rate ($MAIN$), 6 industry characteristics at the 4-digit level ($FDIG$) and 7 firm-level properties ($FPRO$). The last component, $FPER$, represents the said country-specific element, which comprises firm-specific performance and structural characteristics and was affected by missing data. The terms φ_t, ω_j and ε_{jt} are consistent with the definitions provided for the generalised theoretical model, with φ_t consisting of three dummy-variables, identifying the crisis and post crisis years 2008, 2009 and 2010. It is evident that the right-hand side is dominated by time-invariant components except for the country-specific part resulting from restricted historical data records.

FSI is calculated at the 4-digit industry level and demands the transformation of all regressors from firm to industry level. Hence, j refers to the 4-digit industry-level observation at time t, obtained from n sample firms belonging to industry j. The table below shows the construction of observations applied for the specified regression model and is exclusively illustrative.

Table 4.3: Construction of observations

Industry (4-digit NACE)	**Firm**	**Dep. Var.** FSI	**Independent Variables** Industry growth	Indusry age	Part of a group	...	Intangible assets	Labour productivity
1011	1			*Firm Age*	*Yes = 1 x No. of Employees* *No = 0 x No. of Employees*	…	$\frac{Intangible\ Assets_t}{Total\ Assets_t}$	$\frac{Value\ Added_t}{EM_t}$
1011	2			…	…	…	…	…
Observation 1		***G of firms 1-2***	$\frac{\sum_{i=1}^{n} EM_t - \sum_{i=1}^{n} EM_{t-1}}{\sum_{i=1}^{n} EM_{t-1}}$	***ln[max (firm age)]***	$\frac{\sum_{i=1}^{n} EM}{Total\ EM}$	**…**	***mean of firms***	***ln(median of firms)***
1012	3			42	1	…	0.32219	1.09145
1012	4			32	0	…	0.53913	1.08179
Observation 2		0.62251	**-0.10877**	**3.7377**	**0.50**	**…**	**0.46307**	**0.08307**
j	*i*	***G of n firms***	…	…	…	…	…	…
Observation m			**…**	**…**	**…**	**…**	**…**	**…**

G = Gini-coefficient; *EM* = no. of employees; for simplicity, the time dimension *t* remained unconsidered

As noted earlier, the transformation into industry-level observations has distinct advantages. First, it enables the use of an extensive range of narrowly defined, but fundamentally diverse, industries in a single model. Second, the significance of industry-specific growth rates (Dinlersoz and MacDonald 2009; Teruel-Carrizosa 2010b) and the availability of certain parameters only at industry level – firm-level parameters are limited to the model components $FPRO$ and $FPER$ – contribute to conciseness. Apart from that, compressing detailed firm-level information into an industry-level observation inevitably contributes to a loss of information and requires the sensitive application of alternative calculations. With regard to the time-invariant firm-specific properties, consisting of dimensions with regard to about management, ownership and plant structure, two alternative measures were considered. Suppose the 'belongingness' of a firm to a group is represented by a dummy with value 1 for all firms that are part of a group and 0 otherwise, the first option is the calculation of the percentage of firms belonging to a group. This does not take into account the size of the firms and therefore very small firms account as much as very large firms. It represents the intensity of non-independent firms within a 4-digit industry. The second option is to add a weight to firm size by calculating the ratio of the sum of all employees belonging to firms which are part of a group and the total number of employees within an industry.

An intuitive way to generate industry-level observations out of the time-varying firm-level performance indicators is the arithmetic mean of n firms. However, given the distortionary effects outliers generate, the median is a better alternative as it does not require the elimination of firm-level observations that would alter the distribution. Restrictions result from variables with systemically poor values, such as intangible assets or R&D; characteristics reserved to the fairly large firm (Arrow 2000; Fishman and Rob 1999; Pagano and Schivardi 2003; Peltoniemi 2011; Schumpeter 1947). The resulting median underrepresents such assets as it treats the largest R&D expenditure or intangible asset as an outlier. Instead of considering the median ratio of intangible assets over total assets, the sum of all intangible assets for a particular industry over the sum of all total assets, i.e. aggregate intangible assets over aggregate total assets, is used. Aggregating these assets is expected to be a more efficient proxy for entry deterrence as they contain historical information in the sense that the intangible assets of one market player exerts positive effects on its peers. The aggregate value approach, which equates to the average intangible assets over the average total assets, has earlier been used by Ailawadi *et al*. (cited in Amato and Amato 2004) to achieve industry-level observations, and by Amato and Amato (2004) at firm-size class level. The considerations discussed give preference to the median and aggregate values for the firm-specific performance and structural characteristics with the restriction that the median is not applicable whenever firm-level data is poor and consequently results in an underestimation of the true value. These are the options considered to transform observations from firm-level to industry-specific and are commented on in more detail in the next section.

4.3.3 Variable formulation

Having discussed the choice of the dependent variable and potential alternatives, the preferential choices and peculiarities are now reconciled and aim to ensure clarity of the dependent variables used for RQ2. The remainder of the section is devoted to the definition and formulation of the explanatory variables embedded in the components of the adjusted model. The finite number of empirical research papers that considered the Gini-coefficient or its equivalents as measure for FSI induced some novelty in the adopted approach. Experimenting with alternative variables and variable combinations was therefore inevitable. To ease the differentiation of competing variables, they are classified as either core variables (denoted with c), which, according to theory and evidence, are expected to provide the best fit, or alternative variables (denoted with a), which are the next best option, based on the alternative reasoning. In addition, optional variables (denoted with o) are considered in the analysis, the background of which has been poorly discussed as this would go beyond the scope of this work, but may significantly influence FSI and hence provides an indication for future research. It is clear that the mechanics of a regression analysis imposes restrictions on the number of regressors and that some variables will need to be dropped during the process. Further limitations originate from the joint significance, where, for instance, the theoretically most appropriate variable may not lead to the econometrically best fit.

The selected independent variables affecting FSI are primarily based on previous papers in the field – in particular Bloch (1981), Ghosh (1975), Hariprasad (2011), Santarelli (2006b) and Teruel-Carrizosa (2010a) – and are gradually complemented by a selection of intuitive explanatory variables. The latter refer mainly to plant structure and management composition, but, in line with Hariprasad (2011) and Bloch (1981), all variables are assumed to be exogenous and in accordance with the strict erogeneity assumption. To retain the following discussion within legitimate boundaries, the focus is directed towards factors showing sufficient evidence in explaining the phenomenon of FSI. A summary with simplified mathematical definitions of the most relevant variables is provided in Appendix A.

Dependent variables

The primary measure for FSI is the Gini-coefficient calculated from the number of employees (G^c) and is backed by its log-odds transformation (GL^a). Although conceptually different, the Herfindahl-Hirschman Index (HHI^a) is expected to confirm the significance of the estimates obtained by the Gini-coefficient and its log-odds ratio. Since the HHI adds more weight to the largest firms, inconsistencies with the Gini-coefficient imply reverse effects for industries dominated by large firms.

The sample sizes of $n \geq 20$ led to the fixed number of firm-level observations for each composed 4-digit industry observation of either 20, 30, 40, 50, 60, 75 or 100 firms. Potential systemic bias originating from the second order bias (see discussion in section 4.2.3) is excluded by the use of dummy variables controlling the number of firm-level observations, noted as $SAMPLE$ in the model specification. The alternative use of a constantly fixed number of firm-level observations, say 50, would have excluded all 4-digit industries with fewer firms and resulted in the omittance of main industries with structurally large but limited firms, such as mining and quarrying. For the UK, this would have reduced the 4-digit industry observations to less than 50 even when summarising 4-digit industries with 20 to 30 observations to broader groups, while running the risk of merging dissimilar industries. Given the asymptotic efficiency of the estimators used, it was desirable to maximise the number of observations to avoid a loss in accuracy of the obtained estimates.

The problem of biased formulation does not apply to the HHI, but dummies controlling the number of firm-level observations might still be significant, because the HHI of a sample of 100 firms considerably differs from the HHI of 20 randomly selected firms out of the 100 firms. It is the sample bias which makes the sample size dummy variables significant, because large firms – in addition to squaring – gain even greater importance if included in a sample of 20 firms than in a sample of 100.

A more practical aspect to be considered is that the computational estimation of the Gini-coefficient requires the unique ranking of all firms. It is not unusual that different firms within a 4-digit industry have the same number of employees, which by definition results in the same rankings and therefore in distortions of the Gini-coefficient. To guarantee the uniqueness of firms having the same number of employees in a particular year, a random number between 0.0001 and 0.0100 was added to the number of employees. As the smallest number of employees is 5, the maximum bias of the original data is a negligible change of 0.2%.

Main industry characteristics

To capture fundamental industry-specific characteristics such as turnover, profitability, R&D and other factors that are industry-specific (Buigues and Sekkat 2009), dummy variables are used to identify the main NACE sections. In addition to the dimensions outlined by Buigues and Sekkat (2009), industries differ in technologies, short- and long-term cost functions (Quandt 1966; Viner 1932), technology and knowledge intensity (Audretsch and Elston 2006;

Barbosa and Eiriz 2010) and range in firm size (Pagano and Schivardi 2003). Industry dummies also capture a fair proportion of market distortions associated with industries subject to extensive regulation and government intervention, which vary across countries. Although art and entertainment industries account for a fraction of total employment and are largely free from such bias, the pattern is expected to diverge from mainstream industries (Peltoniemi 2011).

The most striking classification is the differentiation between manufacturing and non-manufacturing firms emphasised by Robson and Gallagher (1994). As the research interest in manufacturing industries suggests, it is the most dominant sector with the largest number of companies belonging to a single industry classification. 18% of all firms in the UK are classified as manufacturing and these account for 41% of all 4-digit classifications. The remaining share is spread across non-manufacturing industries. Such disproportions suggest a misrepresentation of other sectors, but it has no effect as long as corrective industry-dummies are included (Verbeek 2012). Hence, a larger share of manufacturing firms increases the efficiency of the estimation. Since not all countries allowed for a sample of at least 20 firms for each main industry, the number of dummies depends on the sample country, which applies in particular to industries with naturally large firms.

Main industry growth (GR_MAIN^{c}) is included as a time-variant explanatory variable and defined as $\frac{no.of\ empl._{kt} - no.of\ empl._{k.t-1}}{no.of\ employees_{k.t-1}}$, with $no.\ of\ employees_{kt}$ indicating the sum of employees of all firms belonging to the main industry section *k* at time *t*. As it lowers competition and decreases market concentration, main industry growth is associated with more opportunities for SMEs to expand their operations (Cassia and Colombelli 2010; Ghosh 1975). It further signals a premature industry stage where collective learning can take place (Jovanovic 1982; Peltoniemi 2011; Wennekers and Thurik 1999). FSI is therefore expected to decrease, but predictions by Bloch (1981) and Hariprasad (2011) indicate a positive effect, because large firms can better commercialise on the opportunities main industry growth offers. Translating it to the applicability of Gibrat’s Law, a positive coefficient confirms its applicability of the LPE, because the absolute number of employees increases faster for large firms than for smaller ones, even though at the same proportion. A negative coefficient rejects the LPE and firms of all size classes equally benefit from the main industry growth.

Industry characteristics at the 4-digit level

Firm growth and industry growth as an essential part of the economic literature cannot be ignored, but must not be treated in the same way. The industry-level approach favours limiting the variable at industry growth since the estimation of a mean or median firm growth rate would become detached from its sample. Drawing conclusions from a mean or median firm growth rate on other firms of the sample would only maintain the validity when the LPE holds. Rejecting this assumption due to the faster growth of small firms (Santarelli *et al*. 2006; Lambertini 2006) leads to the 4-digit industry growth (GR_FDIG^c) indicating aggregate growth opportunities and may significantly differ from main industry growth. The variable formulation corresponds to that of main industry growth and is consistent with Baptista and Karaöz (2011). It is defined as $\frac{no.of\ empl._{jt} - no.of\ empl._{j.t-1}}{no.of\ employees_{j.t-1}}$ with $no.\ of\ employees_{jt}$ indicating the sum of employees of all firms belonging to the 4-digit industry *j* at time *t*.

While main industry growth reflects the potential to increase the market share for all 4-digit industries with the expectation of lowering FSI, an increase in aggregate firm growth indicates the degree of competition. Since most firms within a narrowly defined industry compete with each other, they compete for the same resources and higher growth rates contribute to an increase of FSI resulting from a polarisation of efficient and inefficient firms (Cassia and Colombelli 2010; Peltoniemi 2011). The coefficient is negative if SMEs are able to outperform their large counterparts by successfully commercialising on basic R&D (Bruland and Mowery 2009; Pagano and Schivardi 2003; Acs *et al*. 1996), a superior responsiveness to changes in the market place (Cassia and Colombelli 2010) and an ability to absorb industry-specific knowledge (Buckley 2010; Jovanovic 1982; Liu 2008; Stöllinger 2013; Wang and Wong 2012).

Closely related to industry growth is the industry life-cycle stage and constitutes a structural indicator that reflects more than just industry-specific growth (Dinlersoz and MacDonald 2009; Teruel-Carrizosa 2010b). By representing an industry's attractiveness (McGahan 2004; Peltoniemi 2011), it reflects to some extent the business demography dynamics, i.e. firm birth, survival and exit rates. Audretsch and Woolf (1986) divided the industry life-cycle stage into two stages (growth and decline), observing changes in market share based on value added and Dinlersoz and MacDonald (2009) reduced Gort and Klepper's (1982) framework to three stages (growth, decline and maturity). All studies consider manufacturing firms, where inventories and shipping value are perfectly acceptable. Since these units are unsuitable for service industries, the changes in aggregate workforce were used to identify the life-cycle stage. Identifying these stages over a sample period of no more than 10 years – Dinlersoz and MacDonald (2009) examined a 35-year period – required the simplification of Gort and Klepper's (1982) life-cycle. The resulting variables were STAGE_G for growth or decline and STAGE_S^c for industries with negligible growth or decline. As the 4-digit industry growth rate (GR_FDIG) could not be omitted, it replaced STAGE_G with STAGE_S^c becoming the key variable of interest.

Dinlersoz and MacDonald's (2009) approach was modelled by assuming that for mature industries fluctuations in aggregate workforce do not exceed the interval of ±1% p.a. Although this is a sensitive limit, unrestricted variations at firm level are still possible, and further increases in aggregate output might be achieved by additional efficiency gains. The disturbances the macroeconomic shock in 2008 caused required the exclusion of years 2008 to 2010 from the determination of the industry stage. FSI is expected to increase if the process of polarisation continues, regardless of the shakeout, and implies uninterrupted dynamism. Since markets no longer grow, co-operation declines and competitive forces initiate a shift from product to process innovation where efficiency becomes an entry barrier that causes a redistribution of market share (Dinlersoz and MacDonald 2009; Peltoniemi 2011). The effect on FSI is negative if actors allow for co-operation and co-existence. Entry and exit rates have declined and strategic entry deterrents established by all surviving firms (Hariprasad 2011). Spill-overs are still possible (Pyka cited in Peltoniemi 2011) and enable SMEs to either compete with large firms or to specialise in niche markets (Audretsch *et al*. 1999; Drucker 1985; Lenihan *et al*. 2010a). It further implies that the shakeout contributed to a decrease in firm heterogeneity (Dinlersoz and MacDonald 2009).

Initial industry concentration is found to positively influence the process of firm size polarisation (Baptista and Karaöz 2011; Ghosh 1975; Wennekers and Thurik 1999). It is characteristic for developed economies with a large share of mature industries (Das and Pant 2006). Similar to Baptista and Karaöz (2011) and Ghosh (1975), initial industry concentration is measured by CR4 as core variable ($CR4EM^c$) and CR8 as alternative variable ($CR8EM^a$) on the basis of the number of employees. Both variables showed a better fit than concentration ratios based on turnover, which is more likely to vary across industries. High levels of initial concentration preserve established industry structures and accelerate the process of an emerging ‘missing middle’ (Ghosh 1975; Grass *et al*. 2012; Hariprasad 2011). It is the consequence of fewer innovations (Acs and Audretsch 1998), which reduces the possibility of spinoffs and spill-overs and offers less growth opportunities for SMEs. In contrast, lower initial concentration implies more competition (Baptista and Karaöz 2011) and has positive effects on a firm’s ability to go international and to stay open for future growth (Wennekers and Thurik 1999). But in the absence of domestic competition small firms lower their capabilities to compete in international markets. Larger firms are then more capable of commercialising on international trade, as indicated by Bloch (1981) and Hariprasad (2011). Although higher initial concentration suggests lower entry and exit rates, implying higher levels of FSI, there is a possibility that new entrants are allowed to co-exist (Baptista and Karaöz 2011), suggesting a negative coefficient. A decrease in FSI may also result from a convergence to contestable markets leading to homogeneous firm sizes, as predicted by Kessides and Tang (2010).

The consistent view that firm age is negatively correlated with the probability of failure and firm growth (Geroski 1995; Mansfield 1962; Rossi-Hansberg and

Wright 2007; Sutton 1997; Voulgaris *et al*. 2005), suggests that it affects FSI. Since industry age implies a higher mean in firm age, it too lowers the failure rate and attributes a competitive advantage to larger firms. Barbosa and Eiriz (2010) use mean firm age of a particular industry to analyse the spill-over effects of inward FDI, but with the consequence of ignoring the variation in firm ages and the special role the oldest firm may play. Firms founded more than fifty years ago may still hold a strong market position due to high initial concentration. Different proxies were considered to identify industry age: 1) the maximum firm age (AGE_MAX[c]), since an industry is as old as its oldest member and has since then accumulated market share and knowledge (Rossi-Hansberg and Wright 2007); 2) the minimum firm age (AGE_MIN[a]) indicating the youngest new entrant and hence the attractiveness of an industry; and 3) the standard deviation (AGE_STD[a]) as an indicator for the dispersion of firms' age.

A high standard deviation implies more competition and indicates a younger industry, still competing for resources and knowledge with decreasing effects on FSI. Processes and technologies no longer provide a competitive advantage as they have become disseminated and accessible to new entrants who can enter with the newest technology and catch up (Grass *et al*. 2012; Pagano and Schivardi 2003). Incumbents who stick to existing technology are required to rely on economies of scale. A low standard deviation may imply either an oligopolistic market structure or an industry in its early stage. Should industry age act as entry deterrent, it homogenises firm age (i.e. low standard deviation). As an industry ages, firms become more equal in size (Cabral and Mata 2003; Cirillo 2010; Collins and Preston 1961) and FSI decreases. However, increasing FSI results from a progressive increase in market concentration (Hart and Prais 1956; Lucas 1978; Rossi-Hansberg and Wright 2007; Dinlersoz and MacDonald 2009; Hariprasad 2011). Larger firms stick to their investment and delay technological change, whereas younger firms may have to deal with pre-mature technologies (Grass *et al*. 2012).

The existence of an MES (Bain 1956; Simon and Bonini 1958) indirectly regulates the number of new entrants and failure rates. It acts as an entry deterrent (Baptista and Karaöz 2011) and is lowest for service firms (Barbosa and Eiriz 2010; Teruel-Carrizosa 2010a). Both Barbosa and Eiriz (2010) and Teruel-Carrizosa (2010a) use mean firm size (MES_MEAN[c]) as proxy for MES. The minimum MES (MES_MIN[a]) is used as an alternative measure, because only firms operating for at least 10 years (at least 6 for Germany) are included in the sample and therefore testified an ability to compete. Accordingly, firm-level observations are determined by mean and minimum firm size over the sample period. An additional proxy, also based on the assumption that the sample is limited to surviving firms, is the median firm size relative to the largest player (MES_REL[a]) as used by Cassia and Colombelli (2010). Being a relative industry-specific measure, significance levels are expected to be higher than for the previous measures, which are distorted by the presence of industries different in their nature. Another peculiarity of the median firm size relative to the largest is that the median firm size is smaller than the mean and that the information it contains refers to the gap rather than the absolute size, enabling access to economies of scale. The higher the relative MES, the smaller the gap between the median firm size and the largest firm within a 4-digit industry, and the smaller the FSI.

The coefficient is expected to be positive for MES_MEAN, because it protects the incumbents' market position (Hariprasad 2011) with higher productivity levels being attributed to large firms (Acs *et al*. 1996; Gil 2010; Pagano and Schivardi 2003; Praag and Versloot 2007). The higher MES_MEAN, the harder it is for new entrants to compete on the basis of economies of scale. A low MES enhances FSI as it enables small firms to compete with larger ones (Barbosa and Eiriz 2010; Kessides and Tang 2010), such as in the service industry (Acs 2006; Barbosa and Eiriz 2010; Teruel-Carrizosa 2010a) and in southern European countries (Pagano and Schivardi 2003; Stenkula 2007), without forcing firms to exit (Lotti and Santarelli 2004). Yet, MES_REL is expected to be negative, because the smaller the gap, the easier it is for smaller firms to compete and hence FSI decreases (Cassia and Colombelli 2010; Kessides and Tang 2010). MES_REL tells more about the degree of competition, while MES_MEAN acts as proxy for barriers of entry and is found insignificant when all firms operate above the MES (Barbosa and Eiriz 2010; Bloch 1981; Simon and Bonini 1958).

Although the dataset offers limited possibilities to control for benefits firms can get from clusters, regional concentration is proxied by two variables: the logarithm of the number of political regions of a country (REG_N^c) across which firms belonging to one 4-digit industry are spread and the entropy of the number of regions (REG_ENT^a), taking into account the probability of each region. The coefficients are predicted to be insignificant if developments in ICT are able to bridge the lack of geographic concentration industry clusters offer (Audretsch and Thurik 2000; Santarelli 2006b), which is most likely the case when knowledge intensity is low (Audretsch and Feldman 1999; Iammarino and McCann 2006). More ambiguous is the coefficient when significant. Firms that are part of a cluster have significantly higher survival rates as they learn from each other or are spinoffs (Agrawal *et al*. 2012; Audretsch and Feldman 1999; Baptista and Swann 1998; Boschma and Wenting cited in Peltoniemi 2011; Iammarino and McCann 2006; Pagano and Schivardi 2003; Teruel-Carrizosa 2010a). They accelerate the speed of knowledge transfer (Buckley 2010), which implies that firms within a cluster face less competition (Porter and Stern 2001) and benefit from more entrepreneurial activity (Davidsson and Honig 2003; Iammarino and McCann 2006). Mutual gains and an indirect commitment to share resources motivate firms to allow for co-existence and equal growth opportunities which lower FSI. However, FSI increases with the presence of gazelles, which produce firm size heterogeneity (Henrekson and Johansson 2008; Picot and Dupuy 1998) or when firms compete in isolation and independently grow to an equal size.

Firm properties: management, ownership and plant structure

As has been extensively discussed, the entrepreneur is different from the manager and seen as irreplaceable, but is hard to identify when it comes to empirical work. Knowing that the firm is the vehicle on which to exercise his/her economic activity does not give assurance that all SMEs are led by entrepreneurs. Since the dataset does not distinguish between directors and managers and tasks in SMEs are less formalised (Estelyiova and Nisar 2012), the presence of an entrepreneur is assumed to be accompanied with managers who were either selected because they share the ambition of the entrepreneur or are efficient in executing it. To verify the value the entrepreneur adds, the dataset allowed the construction of two parameters. First is the composition of the top management team (TMT), i.e. directors and managers, consisting exclusively of individuals (TMTIND); second is the presence of TMT members, also being shareholders (TMTSH) to measure the degree of owner-managers.

The determination of whether TMTs consist of individuals only is based on a dummy variable with 1 for exclusively individuals for each firm and 0 otherwise. This gives a percentage of firms that have only individuals in their TMT ($TMTIND\_P^c$). An alternative measure is the dummy variable weighted by the number of employees and set in relation to the total workforce of the respective 4-digit industry ($DMIND\_EM^a$). TMTs are expected to perform better when consisting exclusively of individuals, because they make qualitatively better and faster decisions with regard to efficient resource allocation resulting from a higher degree of involvement (Arrow 2000). It increases their response rate to environmental conditions (Carree *et al*. 2002; Voulgaris *et al*. 2005; Drucker 1985). Since TMTs consisting of individuals are primarily installed in SMEs, it gives those firms an advantage and implies a decline in FSI. Such effects may be offset when relationships between banks and industry are close with the former being involved in the management, as occurs in Germany. It results in closer supervision and tighter control (Dore 2000), which enhances a firm’s ability to recognise environmental forces, but at the expense of entrepreneurial freedom. Accordingly, external board members enable access to additional resources (Carter *et al*., 2010) because they are predominantly installed in large firms, these pull ahead of smaller firms leading to an increase of FSI.

The determination of the impact of owner-managers on FSI is identical to the approach defined for DMIND_P and DMIND_EM. Value 1 is attributed to firms with at least one TMT member also being a shareholder and 0 otherwise. This gives the percentage of firms managed by owners ($DMSH\_P^c$) and the percentage weighted by the number of employees (DMSH_EM[a]). It too follows a similar logic and assumes that the decision-making process of owner-managed firms differs from non-owner-managed firms, with the former being more efficient and qualitatively superior (Arrow 2000; Casson 1987; Drucker 1985; Mises 1951; Praag 1999). Owner-managers are more likely to invest their own capital (Braga and Andreosso-O'Callaghan 2010), which increases entrepreneurial freedom (Marshall cited in Praag 1999). Decisions are made with a long-term view rather than in the interests of the capitalist's employee and although not all owners are entrepreneurs in the Misean and Schumpeterean theory, the dominance of owner-managers in SMEs (Neville 2011) suggests that behind most owner-managers stands an entrepreneur. As the entrepreneur imposes a limit to firm size (Knight cited in Praag 1999), s/he would need to be replaced by the less efficient manager with the expectation that owner-managed firms do better than managerial firms and hence lowers FSI.

An alternative approach to verify whether owner-managed firms perform better than non-owner-managed firms is to analyse the shareholder. According to the company independency index defined by the *Bureau Van Djik*, an independent company consists of shareholders with no more than 25% direct or total ownership each. Krämer and Lipatov (2011:16) use this index to "measure the easiness of managerial diversion". The determination whether a firm is entrepreneurial or not, is based on the allocation of the value 1 for at least one majority shareholder, i.e. 50% or more, and 0 otherwise. This gives the percentage of firms with majority ownership implying an autonomous decision maker (INDEP_P[a]) and the percentage weighted by the number of employees (INDEP_EM[a]). It should be considered that in using the independency index as proxy for agency problems within an industry-level context, it is difficult to distinguish a majority ownership, i.e. more than 50% of an SME from a subsidiary, fully owned by its holding. Due to this limitation, this approach is considered as an optional alternative. Assuming that the majority of independent firms are manager led, which is associated with more excessive consumption rather than investment, combined with suboptimal revenues (Ang *et al*. 2000), it produces inefficiencies for firms classified as 'independent'.

Nonetheless, the owner-managed firm is restricted in size, which is a function of entrepreneurial capacity (Casson 1987; Knight cited in Praag 1999) and hence attributes higher efficiency to non-owner (i.e. more independent) firms leading to an increase in FSI.

Among the entrepreneurship theorists only Casson (1982) attributed superior alertness to the foreigner in identifying market opportunities and makes foreign ownership deterministic to FSI. Consistent with the earlier variable formulations, value 1 is attributed to foreign-owned firms and 0 to all other firms. This gives the percentage of firms owned by foreign individuals or organisations ($FOROWN\_P^c$) and the percentage weighted by the number of employees ($FOROWN\_EM^a$). Since FDI is associated with technology spill-overs (Acs 2006; Barbosa and Eiriz 2010; Bellandi and Caloffi 2010; Buckley 2010; Stöllinger 2013) and an increase in efficiency of domestic firms (Liu and Li 2012) by lowering profit margins and hence encouraging competition (Nocke and Yeaple 2008; Pant and Pattanayak 2005), it ultimately lowers FSI. However, FSI increases when the technology gap between domestic firms and foreign-owned firms is too large and inhibits them from competing on the same technology (Barbosa and Eiriz 2010; Buckley 2010; Buckley 2010; Stöllinger 2013; Wang and Wong 2012). It favours the emergence of highly concentrated market structures and is confirmed by the exit of young domestic firms before the exit of foreign firms. The latter prefer industries with high entry barriers to gain from market imperfections (Mata and Portugal 2004) and recover faster from recessions and scaling down is less likely (Lawless 2012).

Despite being manager-led, firms belonging to a group may be able to offset the lack of entrepreneurial authority to some extent. The unweighted percentage ($GROUP\_P^c$) is obtained from attributing the value 1 to firms that are part of a group and 0 otherwise, whereas the weighted percentage ($GROUP\_EM^a$) takes into account the employee share. A large share of non-independent firms is predicted to increase FSI, because firms that are part of a group are more efficient in internal resource allocation with less restrictions to external funding, the benefits of which are assumed to offset the co-ordination activities thereof as the levels in the organisational hierarchy increase (Arrow 2000). It allows respective firms to access in-house support, while having more optimised organisational structures and processes in place (Santarelli 2006b). They too benefit from better skilled managers (Mata and Portugal 2004; Santarelli 2006b; Storey 1994) and hence grow faster (Teruel-Carrizosa 2010a). At operational level, they benefit from plant and product specialisation, which allows them to operate at higher efficiency levels and constitutes a barrier of entry (Baptista and Karaöz 2011). Accordingly, industries dominated by multi-plant structures are expected to polarise the SDOF more than singe-plant organisations.

Equally flexible are firms with control over subsidiaries, which includes those located in foreign countries. Again, the unweighted percentage ($SUBS\_P^{c}$) is obtained from attributing the value 1 to firms with subsidiaries and 0 otherwise, with the weighted percentage ($SUBS\_EM^{a}$) taking into account the employee share. As much as foreigner presence in domestic markets can drive competition and accelerate technological progress, so the presence of domestic firms in foreign markets contributes to it. Market intelligence obtained from subsidiaries active in other regional or foreign markets increases the competitive advantage (Santarelli 2006b) with plant and product specialisation resulting in higher efficiency and constituting an entry deterrent (Baptista and Karaöz 2011). It further allows more freedom in allocating resources (Arrow 2000; Sutton 1997), whilst being flexibile in exploiting the advantages of low wage and low tax countries. Since large firms are more likely to enter into foreign countries (Mata and Portugal 2004), they are the primary beneficiaries of said advantages, and this too contributes towards firm size polarisation.

Increasing macro-environmental uncertainty (Audretsch and Thurik 2000) and the positive correlation of firm growth with risk (Arrow 2000; Hardwick and Adams 2002) encourages firms to reduce their single market risk by diversifying their product portfolio. Since diversification is a function of firm size, it systemically influences FSI. Three alternative proxies are used to validate the significance of product or service diversity. The first approach is the percentage of firms within a 4-digit industry having registered at least one secondary industry ($DIVERS\_P^{oc}$) and the second being the median of secondary industry codes registered for each firm ($DIVERS\_D^{oa}$). A third way to control for diversity is noted by Gil (2010). It is the sum of all registered secondary industry codes divided by the number of firms. As the number of firm-level observations varies, it equates to the mean (DIVERS_A^{oa}). Apart from potential managerial misallocations (Storey and Greene 2010) the poor data quality for the sample countries Italy and Germany restrict the applicability to the UK. Nonetheless, intangible assets – discussed in the next section – is also associated with diversification (Hariprasad 2011), but by definition is an advantage of firms that have accumulated such assets.

Since smaller firms tend to operate in niche markets (Audretsch *et al*. 1999), the degree of diversification increases with firm size. It enables the systemic reduction of business risk, but comes at the cost of operational efficiency and innovative capacity (Arrow 2000; Drucker 1985). Yet its association with higher growth rates (Arrow 2000; Hardwick and Adams 2002) attributes a higher risk exposure to small firms and suggests that it increases rather than decreases FSI. Should the loss in operational efficiency be greater than its benefits (Nocke and Yeaple 2008) and small firms gain from larger profit margins (Audretsch *et al*. 1999), diversification increases the survival of the large firm, but does not increase FSI.

Firm performance and structural characteristics

Instead of using property as proxy for entry deterrent and firms' limitation to adjust to changing demands as applied by Cassia and Colombelli (2010), tangible and intangible assets are considered as separate dimensions. Both tangible and intangible assets are set in relation to total assets for each firm, which are then brought to industry level by taking the median for tangibles (TANTA_D^{c}). For intangibles, the median is replaced by the mean (INTTA_A^{c}) as it would otherwise underestimate the presence of intangible assets, because most sample firms do not show any such assets on their balance sheets. Alternatively, the aggregate measure is calculated, which is the sum of all tangible assets (intangible assets) within a 4-digit industry and divided by the sum of all total assets (TANTA_G^{a}; INTTA_G^{a}). Tangible assets in particular act as a barrier of entry by imposing a need to exploit economies of scale inaccessible to smaller firms (Acs *et al*. 1996; Ghosh 1975; Mata and Portugal 2004). The entry deterrent function applies also to intangible assets (Hariprasad 2011; Teece 1998) and hence protects the market position of incumbent firms. But whenever investments in equipment are high, it reduces the flexibility to instantaneously respond to new requirements. High switching costs encourage incumbents to continue producing at a technologically less efficient level, while late entrants do not face such switching costs and benefit from newer technologies permitting smaller lot sizes (Grass *et al.* 2012). This suggests that FSI is low for industries relying on investments in tangible assets, while high levels of intangible assets increase FSI.

A second type of entry deterrent identified by Hariprasad (2011) is the surplus of productive capacity, which too protects incumbents from new entrants by making it unattractive for them to enter into the particular industry or for existing firms to expand their operations. It is proxied as the median of stock to total assets ($STKTA\_D^c$) and the aggregate value ($STKTA\_G^a$), i.e. the sum of all inventories to the sum of all total assets within a 4-digit industry. As a deterrent, excess stock levels are expected to increase FSI. High stock levels indicate a shift from product to process innovation as it occurs in the late stage of an industry and is in favour of the most efficient firms (Dinlersoz and MacDonald 2009; Peltoniemi 2011). However, if excessive stock levels are the product of firms relying on economies of scale with a limited ability to adjust to changes in demand, medium-sized firms are more efficient in responding to it (Cassia and Colombelli 2010; Pinder 1998) by benefitting from efficient supply chain technologies.

It has been argued that the reallocation of resources is a privilege of the large firms, while small firms operate with less debt (Storey 1994; Larrea *et al*. 2010; Braga and Andreosso-O'Callaghan 2010), whether this choice has been made deliberately or not. For young firms though, cash flow matters before profits, especially when windows of opportunities are small (Drucker 1985). A lack of liquidity is assumed to restrict firms in responding to growth opportunities and absorbing macro-economic shocks with cash and cash equivalents acting as a buffer. Similar to the foregoing variables, liquidity is proxied by the median of cash and cash equivalents to total assets ($CCETA\_D^c$) and the aggregate value ($CCETA\_G^a$) for any 4-digit industry. Since SMEs face more constraints in accessing capital and have fewer possibilities to internally reallocate resources (Arrow 2000; Larrea *et al*. 2010; Löfsten and Lindelöf 2003; Storey 1994), FSI increases. However, there is also evidence that SMEs do not face any significant liquidity constraints compared to large firms as they prefer equity over debt (Watson 2010) and are less dependent on external finance (Braga and Andreosso-O'Callaghan 2010).

A number of studies, including Robson and Gallagher (1994), show that manufacturing and non-manufacturing industries follow different growth patterns. This distinction is taken into account by using labour intensity as key criteria to distinguish groups with different labour intensiveness. It is proxied by the median employee costs to operating turnover ($EMPTO\_D^c$) and the aggregate value ($EMPTO\_G^a$) for any 4-digit industry. Significantly lower requirements for tangible assets lower the entry barriers of service industries and increase competition. Hence, FSI is expected to be lower for labour intensive firms unless human capital accumulation takes place (Rossi-Hansberg and Wright 2007) and large firms are more committed to recruit and maintain skilled workforce (Storey 1994; Mata and Portugal 2004). Increasing FSI is enhanced by the presence of gazelles, but decreases if labour intensity implies lower rates of knowledge accumulation (Rossi-Hansberg and Wright 2007) and hence slower firm growth (Teruel-Carrizosa 2010a; Voulgaris *et al*. 2005).

The emergence of high-tech industries as a result of a shift towards the knowledge economy as proclaimed by Audretsch and Thurik (2001) alters existing industry structures by replacing economies of scale with knowledge intensity. To account for this shift, labour productivity is used to represent the degree of technological sophistication and distinguish between low-tech and high-tech industries. It is derived from the value added based productivity measures defined by the OECD (2001) and applied by Blomström and Kokko (cited in Buckley 2010), which is the value added over the number of employees. To reduce the marginal effects of excessive productivity, the natural logarithm is taken from the median firm-level labour productivity (VAEMP_D[c]) and the aggregate value (VAEMP_G[a]) for any 4-digit industry. Although large firms experience higher labour productivity growth (Acs *et al*. 1996; Gil 2010), industries with generally higher productivity levels are expected to offset the economies of scale previously necessary to remain competitive (Audretsch and Elston 2006; Voulgaris *et al*. 2005). This relativises the importance of firm size and results in a less polarised SDOF. A convergence towards more homogeneous firm sizes resulting from technology is also predicted by Bartelsman *et al*. (2005) and Pagano and Schivardi (2003) and increases the ability to absorb spill-overs (Buckley 2010; Stöllinger 2013; Wang and Wong 2012), which gives an additional advantage in staying competitive.

Competing on the basis of knowledge preconditions a commitment to R&D and makes it a relevant factor to be taken into account when examining FSI. It is determined by the mean of R&D to operating turnover (RNDTO_A[oc]) and the aggregate value (RNDTO_G[oa]). The large number of missing values would result in an underestimation of actual R&D commitment when based on the median. These may originate from the absence of formal R&D departments in SMEs and therefore produce a bias towards large firms. It is nonetheless the large firm that is more likely to carry out systemic R&D (Bruland and Mowery 2009; Fishman and Rob 1999; Pagano and Schivardi 2003; Peltoniemi 2011; Schumpeter 1947), giving it a competitive advantage over smaller firms. It is even argued that the size distribution is a function of technological R&D opportunities (Pavitt *et al*. 1987) and by being a sunk cost (Kessides and Tang 2010), it is an entry deterrent and therefore increases FSI (Hariprasad 2011). Yet, as an indicator of competition (Buckley 2010) and declining growth (Cassia and Colombelli 2010), R&D commitment may not produce the expected increase in FSI. The risk-averseness and inefficiencies of large firms attributes an innovation premium to small firms (Arrow 2000) and a critical number of firms with the capacity to produce radical innovations (Audretsch and Feldman 1999) may offset the increase in FSI.

An additional factor associated with the large scale firm is export orientation (Lenihan *et al*. 2010b), which, similar to the presence of subsidiaries, enables them to learn from foreign markets but also forces firms to engage with more intense competition (Buckley 2010; Santarelli 2006b). The determination of the export orientation is based on the mean export revenues to total operating turnover at firm level ($EXPTO\_A^{oc}$) and the respective aggregate value ($EXPTO\_G^{oa}$). Moreover, a significant proportion of firms do not appear to be engaged in any export activity, which requires using the mean rather than the median. The resulting coefficient is expected to be positive if large firms are the primary beneficiaries in accessing foreign markets (Becchetti and Trovato 2002; Hariprasad 2011; Lenihan *et al*. 2010b) and therefore benefit from faster firm growth (Teruel-Carrizosa 2010a). However, if export openness provides an opportunity to expand business operations by avoiding intense competition in domestic markets (Görg and Strobl cited in Buckley 2010; Larrea *et al*. 2010; Voulgaris *et al*. 2005) and simultaneously encourages firms to become more efficient (Nocke and Yeaple 2008; Santarelli 2006b; Zhou 2010), SMEs benefit equally from accessing foreign markets. Overall, export-oriented industries are more competitive than those focussing primarily on domestic markets, because they rely less on domestic demand, which ultimately lowers FSI.

Time effects

The economically hard times of 2008 were characterised by an initial macro-economic shock and subsequent abnormal fluctuations in demand for the vast majority of industries. What economists interpret as a process of *market adjustments* (Obstfeld *et al*. 2009) resulted in disruptive alterations of management accounts, which requires controlling for these time effects. The function of this component is not only for the sake of adjusting distortions over the sample period, but also acts as a macro-economic indicator reflecting the impact of crises on FSI. While Ghosh (1975) used dummy variables for periods with a different industry policy, the exceptional circumstances over the sample period are the years 2008 to 2010 with initial macro-economic turbulences, followed by uncertainty. The economic stagnation is expected to decrease FSI, because it causes diseconomies of scale for large firms (Picard and Rimmer 1999; Gaffeo *et al*. 2003) along with higher fluctuations in firm size (Acs *et al.*

1996). SMEs might experience more commitment from owners due to inflexible shareholder structures, but small firms especially are considered as vulnerable and specialised as they bundle their capabilities (Arrow 2000; Drucker 1985; Jovanovic 1982). In contrast, large firms benefit from public attention (Arrow 1962; Buigues and Sekkat 2009) and this ultimately suggests the reverse effect leading to more inequality (Collins and Preston 1961).

4.4 Implications on welfare

The attempt to consolidate and narrow the controversial views on welfare (see section 2.3.1) leads to epistemological difficulties originating from a seemingly straightforward noun. For empirical work the term ‘welfare’ has to be narrowed to measurable aspects, which includes traditional indicators as well as alternative approaches. It distances itself from the original dimension of primary interest and explains the trend increasing averseness to the use of proxies in the field of management studies (Birkinshaw *et al*. 2013). The eroding importance of GDP in determining welfare (Layard 2010; Ramanujam 2009; Stiglitz *et al*. 2010) supports the argument that “subjective measures of well-being would enable a welfare analysis in a more direct way” (Kahneman and Krueger 2006:22). However, its evaluation is difficult and there remains a high degree of idiosyncratic interpretation due to social adaptation. The *European Social Survey*, enquiring on happiness and life satisfaction levels, reflects such an approach, but comprehensive and consistent longitudinal data is not yet available. *Legatum* reports take a more holistic view and give a broad idea of country-specific economic prosperity levels deduced from a number of factors, including entrepreneurship and opportunities to be seized. Although these variables are set in correlation to the share of firm-size classes, the limited availability of appropriate representations of welfare allow for no more than a snapshot and are likely to be empirically flawed and incomprehensive.

The described quantification problem necessitates the use of proxies as a means of last resort with GDP itself being an approximation of a complex matter. Yet it increases the relevance of substitutes and complementary indicators to draw conclusions on welfare, whether directly or indirectly. It draws back to economic performance indicators monitored by international bodies, which, despite being imperfect when applied individually, are expected to give at least a more comprehensive understanding of the relationship between FSI and welfare. In addition to the fragile indicators, *happiness*, *life satisfaction*, *entrepreneurship and opportunity*, the analysis focusses on *innovative capacity*, *economic resilience*, *net job creation* and *sustainability*. The heterogeneity of these parameters has implications on the depth of analysis, but for all dimensions it is the contribution of the medium-sized firms that is focused on. Such effects are expected to be most dynamic when analysed at industry-level and tend to offset each other when brought to aggregate level. This applies in particular to sustainability, where the observable factors may become marginalised.

The subsequent sections present the specified regression models, which aim to confirm what the correlation analysis suggests and to explain what it cannot show, which are the underlying causalities. The regression models refer to innovative capacity, economic resilience and sustainability, whereas net job creation – third in the sequence – is based on a dynamic firm-size class approach. As it is beyond the scope of this thesis to develop comprehensive and optimised models for each dimension, simplifications are necessary, but without compromising on the reliable and valid indication in order to come to a final conclusion.

4.4.1 Innovative capacity

Taking economic growth and entrepreneurial opportunities into consideration gives a weak indication of future prosperity and undermines the contribution of each firm-size class on prosperity. Since innovative capacity and technological progress are necessary to ensure long-term growth and for the persistence of new opportunities to be seized, it is crucial to identify whether a moderate distribution of firm-size classes contributes to more innovative capacity than disproportionate shares of, for instance, large firms as occurs in the UK.

Restrictions in accessing the necessary data to remodel Porter and Stern's (2001) framework or Buesa *et al*.'s (2010) conception of knowledge production requires a more generic approach. Largely consistent with both studies, the number of patent applications made to the EPO is used as proxy for IP, because they have the advantage of being geographically accurate. They refer to the inventor's rather than the headquarter's residing nation (Buesa *et al*. 2010), but the use of patent applications as an indicator for innovative capacity is controversial. The patent application alone does not allow conclusions to be drawn on success rate, nor does it differentiate between process and product innovation. Buesa *et al*. (2010) underline that *patents* is a very general term and obscures firms' alternatives in protecting knowledge, which becomes unobservable, especially for firm-specific process innovations. As innovations of this kind increase with industry age, patent registrations are industry-specific. And because the concentration of industries varies geographically, they are also country-specific as demonstrated in Audretsch and Feldman (1996).

Yet patent registrations indicate that some sort of innovation is believed to exist, while ruling out the possibility that innovations cannot be patented due to legal restrictions. The non-patentability of IP does not by definition imply its irrelevance. It is rather the case that patent registrations underrepresent real innovations, but "guarantee a minimum level of originality … due to the high cost in time and money involved in the patenting process" (Buesa *et al*. 2010:724). Since IP emerges most likely in environments where knowledge and technology intensity are high, control variables representing the knowledge intensive services and medium and high technology manufacturing industries are incorporated. To address the differences in living standards, which are assumed to heavily affect patent applications (Buesa *et al*. 2010), a dummy differentiating between EU15 countries and those that joined the EU at a later stage is included. Due to the significantly lower patent application rate of Portugal and Greece compared to the rest of the EU15 countries and the high outperformance of Slovenia among the Eastern European countries, the inclusion of a country-specific dummy variable is necessary.

The independent variables are the employment share of medium and large firms, set in comparison to the employment share of large firms. In addition, the Gini-coefficient based on the employment share distribution of the firm-size classes defined by the EC (2003) is used and validated with the Gini-coefficient based on the value added by each firm-size class. Although similar in structure, the value added by each firm-size class is expected to lead to a better description as this is more closely associated with knowledge intensity than the workforce employed by a specific firm-size class. The structural form of the model is therefore:

$$P_{it} = \alpha_2 + \beta_2 C_i + \beta_3 K_{it} + \beta_4 H_{it} + \beta_5 S_{it} + \varphi_{1i} + \varepsilon_{2it} \qquad (2)$$

Where *P* is the natural logarithm of the number of patent applications *per million labour force* for country *i* at time *t*. *C* is a vector of country-dummies to control for member states of the EU15, Greece, Portugal and Slovenia. *K* represents the employment share of knowledge intensive services and *H* the employment share of medium and high technology manufacturing sectors, while *S* is the employment share of either medium, large or medium and large firms. These firm-size class share measures are complemented by the Gini-coefficient expressing the employment share distribution based on either the employment share per firm-size class or the value added per firm-size class. Since firm-size class share measured by value added is superior – compared to employment share – in describing innovative capacity, the significance levels are expected to be higher for value added. Due to the presence of heteroskedasticity and autocorrelation in a weak form, the coefficients are estimated by using pooled OLS with Newey-West standard errors and the RE estimator accounting for AR(1) disturbances. The results of the latter are verified by the FGLS estimates, which produces the heteroskedasticity function.

Although lower innovative capacity is attributed to entrepreneurs (Praag and Versloot 2007) and the large firm is superior in systemically innovating (Arrow 2000; Drucker 1985; Schumpeter 1947) and commercialising, the relative commitment of the large firm to innovate is not higher than of any smaller firm-size class (Pagano and Schivardi 2003). Nonetheless, existing firms mobilise new entrepreneurs who contribute to the emergence of novel sub-industries (Peltoniemi 2011; Wennekers and Thurik 1999), achieved by diversity (Agrawal *et al*. 2012; Audretsch and Thurik 2001; Wennekers and Thurik 1999). The process of collective learning, in particular in the premature stage of an industry (Jovanovic 1982; Peltoniemi 2011; Wennekers and Thurik 1999), allows firms to catch up and commercialise on these developments, but it requires the ability to absorb and commercialise such knowledge (Baptista *et al*. 2008). Since within-industry process innovations demand a high level of specialised expertise (Davidsson and Honig 2003; Drucker 1985) and windows of opportunity are smaller for knowledge-based innovations (Drucker 1985), it requires resources to commercialise on spill-overs. Consistent with Drucker (1985:132), who attributed the largest potential of innovative capacity to the “fair-sized” firm, a large share of medium-sized firms is expected to contribute to a higher degree of innovative capacity.

4.4.2 Economic resilience

While a high degree of innovative capacity ensures long-term prosperity and attracts most resources when certainty is high, economic resilience becomes relevant when uncertainty takes over. The model used to assess it is based on the approach of Carree and Thurik (1998), designed to verify the ability of medium-sized firms to absorb economic shocks and flexibility in periods of uncertainty. It incorporates the employment share of medium and large firms as independent variables in joined and separate models with production output as a dependent variable. The datasets published by the enterprise and industry division of the EC contain employment share and value added for each firm-size class and main industry section. Although GDP per capita remains a global measure in describing economic growth and recovery, the industry-level proxy to model the changes in output is the value added by each firm-size class. This is largely in line with the choice made by Pagano and Schivardi (2003), who use the average growth rate of value added per capita.

To minimise the endogeneity bias whilst selecting a period of economic decline, the production output of the years 2007 to 2010 is regressed on the employment share of 2005. Carree and Thurik (1998) examined the years 1993 and 1994, based on the employment share of 1990. They emphasise the importance of selecting a period that is long enough to avoid bias originating from the business cycle, but sufficiently short to ensure persistence of the SDOF. To address the latter, the findings are verified with the coefficients obtained from the employment share of 2006 and 2007 with the resulting model specification being defined as:

$$V_{ij} = \alpha_1 + \beta_1 S_{ij} + \gamma_i + \delta_j + \varepsilon_{1ij} \tag{3}$$

Where V_{ij} is the natural logarithm of value added as proxy for production output of country *i* and main NACE industry *j* in 2007, 2008, 2009 or 2010. *S* is the employment share of either medium firms, large firms or medium plus large firms at the base year 2005; base years 2006 and 2007 are used alternatively. The consequence of using absolute values to express the dependent variable is that most of the influence determining output is country and industry-specific. This leads to a consistently high R^2 and favours a focus on the F-statistics. Both Carree and Thurik (1998) and Pagano and Schivardi (2003) suggest the incorporation of dummies to control for significant variations in firm size across countries and industries. Accordingly, γ and δ represent country and industry dummies respectively, while ε denotes the error term and α the intercept. Carree and Thurik (1998) associate the large number of small businesses in Spain and Portugal with a backlog in economic development, while Pagano and Schivardi (2003) observe a deviating business cycle pattern for the UK. To ensure more homogeneity in economic stage, the sample is split into EU15 countries and non-EU15 countries, i.e. the EU27 countries without the EU15 countries. Also consistent with Carree and Thurik (1998) is the use of a WLS estimator. Compared to the traditional OLS estimator, it allows the addition of more weight to observations with large values, while still accounting for heteroskedasticity, found to be present in a weak form.

There are indications that large firms are argued to achieve higher productivity levels (Acs *et al*. 1996; Gil 2010; Pagano and Schivardi 2003; Praag and Versloot 2007) and that outperforming productivity growth of small firms is offset by weak productivity growth of less successful firms (Wong *et al*. 2005). However, when macro-economic conditions change, large firms are inflexible with negative implications on productivity (Carree and Thurik 1998). Proactive medium-sized firms perform better than large firms (Cassia and Colombelli 2010), small firms increase their employment share in times of recession, while large firms reduce it (Robson and Gallagher 1994), whereas entrepreneurial activity has positive effects on growth (Audretsch and Thurik 2001). Conditional on technological superiority of the relatively smaller firm, the presence of macro-economic uncertainty and liquidity constraints incentivises efficiency (Dhawan 2001) and makes SMEs crucial for economic stability and flexibility (Robson and Gallagher 1994). Economies with a larger share of medium-sized firms are therefore expected to be most resilient.

4.4.3 Net job creation

So far, models have been based on the absolute firm-size class share at time *t* with little attention being paid to the fact that firms close to the firm-size class limit at time *t-1* may belong to a different firm-size class at time *t*. Their full employment share is attributed to the firm-size class they belong to at time *t*, which is appropriate as long as the first difference remains unconsidered. However, when examining the change in employment share of size class *S* from time *t-1* to *t*, the bias introduced by Davis *et al*. (1996:301) as the “size distribution fallacy” emerges. To ensure that firms’ employment share is proportionally distributed to the respective firm-size class interval when firms cross the size class limit, Wit and Kok (2014) provide a general adjustment formula applicable to aggregate data. It assumes that the change in the number of firms belonging to firm-size class *S* is the result of an upward or downward shift from time *t-1* to *t* and that the number of employees of the respective firms was at the limit before the shift took place. Accordingly, they suggest a dynamic classification approach, which reduces the firm-size class (S_0) by the change in the number of firms (ΔN) times the lower firm-size class limit (L), plus the upper limit (U) times the change in the number of firms. This equates to the employment share before the change in firm-size class took place and can be expressed as:

$$S_{adjusted} = S_0 - L * (\Delta N)_{L\ or\ larger} + U * (\Delta N)_{U\ or\ larger} \qquad (4)$$

The adjustment formula contains the change in the number of firms from *t-1* to *t*, which reduces the sample period by one year. The negligible benefit for all previous applications – corrections account to a small single digit percentage – gave preference to the preservation of observations. However, for net job creation accuracy becomes most important as the effects of the adjustment increase in magnitude. According to Wit and Kok (2014), the dynamic classification method tolerates non-linear firm growth and has the advantage of avoiding the “regression fallacy”, also noted by Davis *et al*. (1996:297), which is in favour of lower firm-size classes leading to serious misinterpretations. Even though the absolute change in employment of competing firm-size classes cancels out the total employment growth, the change in absolute numbers affects the lower firm-size class more severely than the larger size class, the effect of which reverses when firms are allocated to firm-size classes according to their size at the end of the sample period (Wit and Kok 2014).

The described dynamic classification method is used for the descriptive evaluation of changes in employment from time *t-1* to time *t* of EU15 countries and non-EU15 countries, i.e. those countries belonging to the EU27, but not to the EU15. The resulting change in employment share of each firm-size class is then complemented by the manufacturing share, given that it represents the economic stage and allows conclusions to be drawn on economies rich in services and those relying more on the traditional manufacturing industry. A final analysis is devoted to the degree of entrepreneurial activity and positive effects originating from other firm-size classes. To examine these effects, the change in the number of micro firms from time *t-1* to time *t* is used as proxy for entrepreneurial activity, whereas only positive changes are considered. Although some newly established firms grow beyond a headcount of ten employees within a maximum period of twelve months, this is rather unlikely and suggests that it is part of a group and not a new independent firm. As it is expected that economies with a more diverse SDOF enable more opportunities and alternatives to establish and grow a business, FSI is expected to be negatively correlated with the number of new establishments.

The expectation is that net job creation is moderate for micro firms and somewhat larger for small firms (Davidsson *et al*. 1999; Davis *et al.* 1996; Picot and Dupuy 1998; Henrekson and Johansson 2010; Shane 2008; Storey 1994; Wong *et al.* 2005) unless gazelles contribute to outperformance (Henrekson and Johansson 2008). Since volatility decreases with firm size (Bartelsman *et al*. 2005; Lenihan *et al*. 2010b; Picot and Dupuy 1998; Praag and Versloot 2007; Voulgaris *et al*. 2005), but large firms create and destroy most jobs (Acs *et al*. 1996; Davis *et al*. 1996), high net job creation is expected to be most observable for countries with a large share of medium-sized firms. The importance of knowledge intensity in achieving positive net job creation (Baptista *et al*. 2008; Voulgaris *et al*. 2005) also puts medium-sized firms in a good position to increase net job creation. Nonetheless, high levels of entrepreneurial activity at a smaller scale are argued to produce positive effects (Audretsch and Thurik 2000; Praag and Versloot 2007; Voulgaris *et al*. 2005; Wennekers and Thurik 1999), but may be offset by the presence of gazelles emerging across all firm-size classes (Henrekson and Johansson 2008; Picot and Dupuy 1998).

4.4.4 Sustainability

The association of the marginal firm with a lack of environmental consciousness (Gray and Eid 2005), but a systemic exploitation of natural resources (Schumacher 1973), positions the medium-sized firm at the trade-off with the lowest contribution to environmental degradation. This signifies that a correlation between FSI and sustainability exists and that medium-sized firms are central to environmental sustainability. Against the belief of the post-war period, the efficiency at which they operate suggests that having a larger number of such firms is not in conflict with environmental goals. It is rather the imbalance in the SDOF that causes distress to sustainable growth. And whether any specific firm-size class indeed imposes a threat to sustainability is neither reflected in GDP nor is it observable from any previously discussed dimensions. Yet it has implications on life satisfaction in the long term as it reduces the resources available to future generations. The approach to estimate the impact of FSI on sustainability is based on the definition of the ANS rate provided by Bolt *et al*. (2002) and adopted by the United Nations (n.d.; 2007), which is:

$$ANS = \frac{GNS - CFC + EDE - \sum_{j=1}^{n} R_j - CD}{GNI} \tag{5}$$

GNS is gross national saving defined as gross national income (GNI) minus public and private consumption. CFC and EDE represent the consumption of fixed capital and education expenditure respectively, and CD the damages caused by carbon dioxide emissions. Gains obtained by the extraction of natural resources are denoted with R and estimated at market prices excluding extraction costs (Bolt *et al*. 2002:5) and consist of energy depletion (ED), metal and mineral depletion (MD) and net forest depletion (FD); all parameters relative to gross national income (GNI). This implies that ANS is a function of GNS, CFC, EDE, R and CD, where GNS is broadly the difference between total value added plus taxes and total consumption. Since the expectation of the idiosyncratic error term is zero, unobservable heterogeneity is expected to increase, because it reflects the influence of omitted variables. By substituting these with exogenous variables, such as the firm-size class parameters, unobservable heterogeneity diminishes with the magnitude of explanatory power of the newly added variables. In other words, the impact of firm-size class parameters on factors that are part of the ANS equation can be estimated by replacing the former with the latter. Although it might be more elegant to regress the variables of interest as, for instance, the rent from natural resources, on firm-size class parameters, which also avoids difficulties in interpreting the coefficients, the adoption of the described approach does not require further control variables. Furthermore, it permits the construction of a single dependent variable that incorporates all dimensions of resource depletion, while maintaining the ANS rate as dependent variable. This, by definition, requires the application of an estimator able to deconstruct the composite error-term into unobservable heterogeneity and idiosyncratic error-term. For natural resource depletion, including the damage caused by carbon dioxide, the model specification is therefore:

$$ANS_{it} = \alpha_3 + \beta_6 CV_{1it} + \beta_7 E_i + \beta_8 M_{it} + \beta_9 S_{it} + \varphi_{2i} + \varepsilon_{3it} \qquad (6)$$

For national net savings (NNS), defined by the *World Bank* as gross national savings minus consumption of fixed capital, i.e. “the replacement of value of capital used up in the process of production” (Bolt *et al*. 2002:5):

$$ANS_{it} = \alpha_4 + \beta_{10} CV_{2it} + \beta_{11} E_i + \beta_{12} M_{it} + \beta_{13} S_{it} + \varphi_{3i} + \varepsilon_{4it} \qquad (7)$$

Where ANS is the adjusted net savings rate excluding PM10 damages for country *i* at time *t*. CV_1 represents the control variables national net savings (NNS) and education expenditure (EDE), and CV_2 represents the control variables education expenditure (EDE), the rent on natural resources (R) and damages caused by carbon dioxide emissions (CD). Due to major differences in country-specific characteristics of the EU27, a dummy controlling for EU15 countries is included (*E* = 1 if EU15 member and 0 otherwise). Slovakia, which significantly deviates from the norm and causes a high correlation with the dependent variable, has to be removed from the sample for equations (6) and (7). Malta is excluded for equation (6) as it appears to run its economy at an extraordinary low level of environmental degradation and therefore adds a considerable proportion of noise. The economic stage is proxied by the employment share of manufacturing firms *M*, while *S* is the employment share of either medium, large or medium and large firms, complemented by the Gini-coefficient resulting from the firm-size class distribution.

4.5 Conclusions

The aim of this chapter was to present the way of analysing the changes in FSI, its determiannts and consequences for welfare. As the forces at work are numerous and the analytical framework comprehensive, methods and sample sizes change. RQ1 and RQ2, which refer to the changes and causes of FSI respectively, are addressed by looking at industry dynamics in the UK, Italy and Germany. These economies differ in industry structure and the historical path thereof, but best represent Europe's heterogeneity. To account for it, the country-specific samples are independent from each other and left as large as possible for as long as possible. By reducing unwanted noise and preserving information, the construction of extended, intermediate and reduced samples is justified.

The first part of RQ1, the objective of which is to analyse the changes in the SDOF across main industry sections and firm-size classes, is based on the extended sample. It allows for a trend analysis obtained from the largest number of firms the database offers. As the information the extended sample contains is narrow and unsuitable for anything more than descriptive statistics, the second part of RQ1 continues with firm-level observations that can be allocated to 4-digit industries and was introduced as the intermediate sample. According to the literature reviewed, the lognormal distribution is the most frequent pattern the SDOF follows when it reaches the natural stage. Testing each 4-digit industry for lognormality is therefore the most appropriate method to verify how many 4-digit industries within each main industry section have reached that stage. The observation of the distribution rejection rate also tells whether this trend increases over time. If it does, market forces push the SDOF to a natural equilibrium, which makes it increasingly difficult to alter existing structures by the mere presence of new entrepreneurs.

Since the lognormality test gives merely a yes-no output, the SDOF is then operationalised. This is done by calculating the Gini-coefficinet as a measure for FSI, which becomes the dependent variable of the model answering RQ2. When the data enters into the regression analysis, restrictions imposed by data, model and estimators narrow the dataset down to the reduced sample. The latter is the foundation on which to estimate the determinants of FSI. The underlying model is designed to make evident forces that act at economy, industry and firm level. These forces are either external or internal to the firm and are expected to increase or decrease the degree of FSI. They give an extensive understanding of industry forces and identify parameters with the capacity to delay the emergence of the missing middle. By using alternative dependent and independent variables, complimentary models and alternative estimators, the analytical method has become comprehensive. Yet it provides a solid foundation to cross-verify results, which too applies to the separate regression analyses for each country.

The analyses of both RQ1 and RQ2 are presented in the next chapter, while Chapter 6 begins with the analysis of RQ3. It examines the implication on welfare deriving from a change in FSI. The objective of RQ3 is to first examine the correlations between FSI and subjective measures of welfare in the context of the EU27 countries. As, from an empirical point of view, this approach is novel and the data is still in its infancy with a lack in consistency, the second step is to return to conventional proxies for welfare. This leads to four specific dimensions: innovative capacity, economic resilience, net job creation and sustainability. The rationale behind these dimensions is to diagnose the contribution of SMEs to welfare through technological progress, their responsiveness to change and ability to generate employment whilst ascerting that size does not by definition pose a threat to the environment. Said position is the core of Schumacher’s (1973) message, which makes the balance in the SDOF a precondition for sustainable socio-economic development.

CHAPTER 5: ANALYSIS

Based on the methodology described in sections 4.2 and 4.3, this chapter presents the analysis of the defined sample countries. The first part investigates the dynamics and the second part the determinants of FSI as inquired by RQ1 and RQ2 respectively. Because FSI was not the focus of the reviewed literature, identifying consistencies with earlier research becomes interpretative. This has come to surface when anticipating the expected sign of the factors determining FSI. Thus, where robust comparisons are possible, the findings are linked to the predictions set out in the methodology, however this does not by definition create inconsistencies with all others. It forms the foundation of the discussion in Chapter 6, which addresses the ambiguities that can only be clarified when brought into context and refers in particular to the theoretical debate presented in Chapter 2.

5.1 Employment share and firm-size class dynamics

The subsequent sections of this first part cover the changes in employment share across industries and firm-size classes, followed by the changes in FSI. Except for the analysis verifying the lognormality of the SDOF, the method is restricted to descriptive statistics and based on two samples. These are the *extended sample* retrieved from database summary tables consisting of the employment share by firm-size class and industry, and the *intermediate sample* containing the firm-level observations used to calculate the FSI at the 4-digit industry level. The former is used for a general indication of the dynamics across industries and size classes by looking at changes in employment share and firm size. The latter allows the determination of distribution properties and the degree of FSI, which serves as a core dependent variable for the regression analysis presented in the second part of this chapter.

5.1.1 Changes across industries

Tables 5.1, 5.2 and 5.3 summarise firm and employment share from 2002 to 2010[2] according to the main industry sections of the UK, Italy and Germany respectively. Since only surviving firms with available employee data are considered, the number of firms is constant over time, whereas the employment share varies and so too does the resulting mean firm size. The manufacturing industry accounts for the largest employment share, except for the UK, where wholesale and retail trade dominate and a much larger service industry has emerged than in Italy and Germany. It indicates the different economic stage the UK is in, which is also reflected in the declining employment share of the manufacturing industry and consistent with the trend emerging from the dataset of the *SME Performance Review*.

In accordance with Bartelsman *et al*. (2005) and Pagano and Schivardi (2003), the tables show that mean firm size varies across countries and industries, with Italy being among the countries with the smallest mean firm size. As expected, the UK is characterised by a large share of large scale firms for the majority of industries, except for *manufacturing*, *ICT*, *real estate*, *professional, scientific and technical activities* and *human health and social work activities*, where German firms tend to be twice as large. When comparing minimum and maximum mean firm size of all industries, the UK and Germany achieve a ratio of 1:32 and 1:31 respectively, while it is 1:14 for Italy. The mean firm size of Italy is indeed quite low across all industries with the highest mean for *mining and quarrying* which is less than a third of the equivalent mean firm size in the UK. The large variance in mean firm size of the manufacturing industry across countries suggests that applied technologies also differ as this would otherwise have resulted in less firm heterogeneity (Bartelsman *et al.* 2005; Pagano and Schivardi 2003).

[2] From 2006 to 2010 for Germany

Table 5.1: Firm and employment share – UK

Main industry	No. of firms (firm share)		Mean firm size (employment share) 2010		2008		2006		2004		2002	
Manufacturing	4,450	(21.3%)	493	(21.5%)	524	(22.3%)	493	(22.1%)	486	(22.5%)	503	(24.3%)
Wholesale and retail trade; repair services	3,932	(18.9%)	666	(25.7%)	651	(24.5%)	610	(24.2%)	575	(23.5%)	520	(22.2%)
Agriculture, forestry and fishing	198	(0.9%)	962	(1.9%)	987	(1.9%)	949	(1.9%)	1110	(2.3%)	1185	(2.6%)
Information and communication	1,303	(6.2%)	473	(6.0%)	494	(6.2%)	478	(6.3%)	430	(5.8%)	435	(6.2%)
Real estate activities	391	(1.9%)	96	(0.4%)	96	(0.4%)	99	(0.4%)	87	(0.4%)	77	(0.3%)
Professional, scientific and technical activities	925	(4.4%)	392	(3.6%)	389	(3.4%)	321	(3.0%)	272	(2.6%)	250	(2.5%)
Administrative and support service activities	2,401	(11.5%)	448	(10.5%)	471	(10.8%)	451	(10.9%)	422	(10.5%)	371	(9.7%)
Education	809	(3.9%)	125	(1.0%)	119	(0.9%)	114	(0.9%)	108	(0.9%)	101	(0.9%)
Human health and social work activities	986	(4.7%)	251	(2.4%)	242	(2.3%)	222	(2.2%)	195	(2.0%)	182	(1.9%)
Arts, entertainment and recreation	679	(3.3%)	242	(1.6%)	246	(1.6%)	241	(1.6%)	232	(1.6%)	211	(1.6%)
Mining and quarrying	162	(0.8%)	1823	(2.9%)	2050	(3.2%)	2559	(4.2%)	2799	(4.7%)	2534	(4.5%)
Electricity, gas, steam, air cond. supply	62	(0.3%)	2973	(1.8%)	2895	(1.7%)	2716	(1.7%)	2939	(1.9%)	2496	(1.7%)
Water supply; sewerage, waste management	77	(0.4%)	902	(0.7%)	886	(0.7%)	828	(0.6%)	816	(0.7%)	789	(0.7%)
Construction	1,802	(8.6%)	279	(4.9%)	299	(5.1%)	276	(5.0%)	256	(4.8%)	234	(4.6%)
Transportation and storage	857	(4.1%)	991	(8.3%)	1056	(8.7%)	955	(8.3%)	943	(8.4%)	912	(8.5%)
Accommodation and food service activities	526	(2.5%)	973	(5.0%)	933	(4.7%)	924	(4.9%)	1061	(5.8%)	1098	(6.3%)
Other service activities	1,297	(6.2%)	138	(1.7%)	138	(1.7%)	130	(1.7%)	124	(1.7%)	116	(1.6%)
	20,857	(100%)	489	(100%)	501	(100%)	475	(100%)	461	(100%)	441	(100%)

Source of data: Modified from Orbis

Table 5.2: Firm and employment share – Italy

Main industry	No. of firms (firm share)		Mean firm size (employment share) 2010		2008		2006		2004		2002	
Manufacturing	12,023	(43.4%)	89	(48.1%)	92	(48.9%)	88	(49.1%)	85	(48.5%)	92	(53.7%)
Wholesale and retail trade; repair services	7,070	(25.5%)	54	(17.2%)	52	(16.4%)	49	(16.2%)	46	(15.4%)	37	(12.7%)
Agriculture, forestry and fishing	439	(1.6%)	42	(0.8%)	35	(0.7%)	41	(0.8%)	42	(0.9%)	34	(0.7%)
Information and communication	943	(3.4%)	112	(4.7%)	140	(5.9%)	139	(6.1%)	146	(6.5%)	176	(8.0%)
Real estate activities	312	(1.1%)	39	(0.5%)	44	(0.6%)	43	(0.6%)	42	(0.6%)	146	(2.2%)
Professional, scientific and technical activities	1,102	(4.0%)	68	(3.4%)	67	(3.3%)	65	(3.3%)	62	(3.2%)	61	(3.2%)
Administrative and support service activities	696	(2.5%)	180	(5.6%)	171	(5.3%)	152	(4.9%)	146	(4.8%)	107	(3.6%)
Education	85	(0.3%)	35	(0.1%)	34	(0.1%)	35	(0.1%)	29	(0.1%)	24	(0.1%)
Human health and social work activities	467	(1.7%)	147	(3.1%)	134	(2.8%)	124	(2.7%)	120	(2.7%)	76	(1.7%)
Arts, entertainment and recreation	140	(0.5%)	64	(0.4%)	54	(0.3%)	63	(0.4%)	53	(0.3%)	73	(0.5%)
Mining and quarrying	162	(0.6%)	503	(3.7%)	505	(3.6%)	479	(3.6%)	470	(3.6%)	498	(3.9%)
Electricity, gas, steam, air cond. supply	103	(0.4%)	79	(0.4%)	69	(0.3%)	67	(0.3%)	65	(0.3%)	77	(0.4%)
Water supply; sewerage, waste management	294	(1.1%)	59	(0.8%)	55	(0.7%)	51	(0.7%)	49	(0.7%)	52	(0.7%)
Construction	2,082	(7.5%)	50	(4.7%)	50	(4.6%)	47	(4.6%)	62	(6.1%)	37	(3.8%)
Transportation and storage	1,205	(4.3%)	75	(4.1%)	76	(4.1%)	73	(4.1%)	68	(3.9%)	55	(3.2%)
Accommodation and food service activities	467	(1.7%)	100	(2.1%)	102	(2.1%)	97	(2.1%)	87	(1.9%)	52	(1.2%)
Other service activities	139	(0.5%)	61	(0.4%)	62	(0.4%)	62	(0.4%)	57	(0.4%)	50	(0.3%)
	27,729	(100%)	80	(100%)	81	(100%)	78	(100%)	76	(100%)	75	(100%)

Source of data: Modified from Orbis

Table 5.3: Firm and employment share – Germany

Main industry	No. of firms (firm share)		Mean firm size (employment share) 2010		2008		2006	
Manufacturing	4,767	(22.6%)	902	(49.5%)	916	(48.4%)	868	(44.1%)
Wholesale and retail trade; repair services	8,089	(38.3%)	201	(18.7%)	233	(20.9%)	324	(27.9%)
Agriculture, forestry and fishing	124	(0.6%)	48	(0.1%)	43	(0.1%)	44	(0.1%)
Information and communication	639	(3.0%)	861	(6.3%)	840	(5.9%)	832	(5.7%)
Real estate activities	815	(3.9%)	134	(1.3%)	130	(1.2%)	118	(1.0%)
Professional, scientific and technical activities	1,213	(5.7%)	630	(8.8%)	656	(8.8%)	622	(8.0%)
Administrative and support service activities	870	(4.1%)	231	(2.3%)	239	(2.3%)	212	(2.0%)
Education	43	(0.2%)	85	(0.0%)	186	(0.1%)	188	(0.1%)
Human health and social work activities	172	(0.8%)	665	(1.3%)	646	(1.2%)	569	(1.0%)
Arts, entertainment and recreation	135	(0.6%)	85	(0.1%)	80	(0.1%)	75	(0.1%)
Mining and quarrying	103	(0.5%)	131	(0.2%)	125	(0.1%)	115	(0.1%)
Electricity, gas, steam, air cond. supply	187	(0.9%)	1531	(3.3%)	1534	(3.2%)	1485	(3.0%)
Water supply; sewerage, waste management	192	(0.9%)	216	(0.5%)	214	(0.5%)	211	(0.4%)
Construction	1,884	(8.9%)	114	(2.5%)	114	(2.4%)	98	(2.0%)
Transportation and storage	1,339	(6.3%)	282	(4.3%)	281	(4.2%)	273	(3.9%)
Accommodation and food service activities	293	(1.4%)	121	(0.4%)	120	(0.4%)	117	(0.4%)
Other service activities	253	(1.2%)	133	(0.4%)	109	(0.3%)	102	0.3%
	21,118	(100%)	412	(100%)	427	(100%)	444	(100%)

Source of data: Modified from Orbis

In terms of firm size dynamics the overall mean firm size increased over time for most industries, but was subjected to higher volatility in 2008, which was confirmed by the *t*-test when validating the significance of the mean difference in absolute employment values. The question that remains unaddressed is whether the decline in mean firm size, where there is any, is the result of new entrants or overcapacity. The nature of the industries affected suggests the latter, except for ICT (Italy) and private education (Germany), where entry barriers tend to be lower than for mining and quarrying or the highly efficient British agriculture industry. Yet, the most notable change is the decline in the employment share of manufacturing in the UK and Italy, while Germany moved in the opposite direction, especially from 2006 to 2008, with the employment share of the manufacturing industry in absolute numbers increasing by 5.5%. Although variations in firm size across industries were expected, these vary considerably across sample countries and are an indication for a substantially different SDOF.

5.1.2 Changes across firm-size classes

The employment share by firm-size class presented in Table 5.4 – a summary of Appendix B – shows a stable size distribution over time with no dramatic changes as noted by Axtell (2001), Cabral and Mata (2003), Cirillo (2010), Cirillo and Hüsler (2009), Dinlersoz and MacDonald (2009) and Robson and Gallagher (1994). Employment share increases with rising firm-size class – the number of firms (not reported) decreases with an increase in firm-size class – and is highest for the firm-size class with 10,000 employees or more. This applies in particular to Germany, whereas Italy shows the smallest share, regardless of the nature of the industry. Although not reported, a similar pattern is observable from the population data of the *SME Performance Review*. However this shows a more evenly distributed employment share as firms larger in size are more likely to be listed in a commercial database.

Table 5.4: Employment share by firm-size class

Firm-size class*	2010		2008		2006		2004		2002	
	Manuf.	Non-manuf.	Manuf.	Non-manuf.	Manuf.	Non-manuf.	Manuf.	Non-manuf.	Manuf.	Non-manuf.
UK										
Micro	0.05%	0.17%	0.04%	0.17%	0.04%	0.18%	0.05%	0.20%	0.05%	0.22%
Small	1.14%	1.54%	0.98%	1.49%	1.03%	1.58%	1.05%	1.66%	1.06%	1.86%
Medium	12.48%	8.13%	12.07%	8.42%	12.99%	8.71%	13.11%	8.80%	12.23%	9.08%
Large	86.33%	90.16%	86.91%	89.92%	85.94%	89.53%	85.79%	89.34%	86.66%	88.84%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Italy										
Micro	0.95%	2.18%	0.88%	2.21%	0.92%	2.35%	0.92%	2.45%	0.83%	2.68%
Small	14.58%	14.39%	13.93%	14.32%	14.88%	15.16%	15.38%	15.50%	13.39%	17.33%
Medium	33.51%	23.26%	34.35%	23.68%	34.82%	24.50%	35.14%	23.25%	39.17%	28.17%
Large	50.96%	60.17%	50.84%	59.79%	49.38%	57.99%	48.56%	58.80%	46.61%	51.82%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Germany										
Micro	0.10%	0.74%	0.10%	0.70%	0.11%	0.63%	-	-	-	-
Small	0.66%	2.39%	0.64%	2.27%	0.69%	1.98%	-	-	-	-
Medium	4.39%	6.18%	4.33%	5.73%	4.44%	4.99%	-	-	-	-
Large	94.85%	90.69%	94.93%	91.30%	94.76%	92.40%	-	-	-	-
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	-	-	-	-

Source of data: Modified from Orbis

*) these firm-size classes refer to the EC (2003) and are defined as micro firms (up to 9 employees), small firms (10 to 49 employees), medium firms (50-249 employees) and large firms (250 employees or more)

Given the constant number of firms, it becomes evident that large firms are better able to maintain and expand their share, which applies to all sample countries and suggests that risk and market diversification have positive effects on firm growth. This phenomenon can best be observed in Italy, where large firms increase their relative employment share at a steady rate, especially in non-manufacturing industries and the cost of all other firm-size classes. Also in the UK large firms experience their largest increase in employment share when active in non-manufacturing, whereas the manufacturing industry is characterised by higher volatility. The employment share of SMEs gradually declines for non-manufacturing firms throughout the sample period. Although this also applies to firms within the manufacturing industry, the pattern is again more volatile. The dominance of large firm growth is less conclusive for Germany as earlier noted by Audretsch and Elston (2006). German SMEs, if active in non-manufacturing industries, outperform their larger counterparts, while SMEs operating in the manufacturing industry find it difficult to defend the achieved position. This suggests that overall FSI is increasing in both the UK and Italy, but not so for Germany.

5.1.3 Changes in firm size inequality

The preceding analysis provided some insights into firm-size class dynamics with a clear indication that patterns change across industries and countries. To facilitate a more detailed analysis of the changes taking place within main industry sections, the assessment continues with the *intermediate sample* for the reasons noted in the methodology chapter.

Consistent with the descriptive statistics presented earlier, the observations are categorised into manufacturing and non-manufacturing firms (industries). Tables 5.5, 5.6 and 5.7 summarise the sample properties of the firm-level observations belonging to the UK, Italy and Germany respectively. In comparison to Tables 5.1, 5.2 and 5.3, the mean firm size, measured by the number of employees, has declined and appears to stem from a few very large firms not being randomly selected. Furthermore, the exclusion of observations with missing data, other than employee figures, might have contributed to the difference in the mean. Given that Germany has by far the largest employment share for the firm-size class with more than 10,000 employees, it is not suspicious that its largest manufacturing firm exceeds the largest firm included in the UK sample by magnitude, while Italy's largest firm included in the sample is a fraction of the UK's.

However, the proportion of manufacturing firms is widely consistent with the share included in the extended sample. The trend of declining firm size within the manufacturing industry can be confirmed, whereas non-manufacturing firms have, on average, increased in size. Both tendencies are particularly strong for the UK. The standard deviation of the size of manufacturing firms has decreased in all sample countries implying a convergence in size. For non-manufacturing firms, the standard deviation increased only in Italy and Germany, suggesting more dynamism. Again, Italy's average firm size is by far the lowest and stems from the large share of very small and small share of very large firms relative to the UK and Germany (see Table 5.4). This too is consistent with the dataset of the *SME Performance Review*.

Table 5.5: Descriptive statistics of firm-level data – UK

Number of firms	Year	Mean firm size	Std. Dev.	Min	Max	Skewness	Kurtosis
ALL INDUSTRIES (120 4-digit industries, 15 main industries)							
5765	2010	367.64	1904.64	5	56056	15.7828	324.6541
5765	2008	385.35	2020.32	5	62629	16.6081	362.3439
5765	2006	369.34	1921.85	5	60158	16.4383	354.5389
5765	2004	364.78	2004.38	5	60473	17.5121	396.3941
5765	2002	357.78	1999.57	5	67612	17.7588	416.0050
Manufacturing (35 4-digit industries, 1 main industry)							
1500	2010	362.87	1499.23	5	35096	12.8975	232.1173
1500	2008	394.14	1599.71	5	38147	13.1847	245.3622
1500	2006	388.11	1569.77	5	36117	12.9943	230.8211
1500	2004	398.91	1642.84	5	36603	12.6907	214.9671
1500	2002	403.66	1645.69	5	36048	12.5009	206.8299
Non-manufacturing (85 4-digit industries, 14 main industries)							
4265	2010	369.31	2028.20	5	56056	15.8367	316.9310
4265	2008	382.25	2148.92	5	62629	16.7469	356.2788
4265	2006	362.74	2031.35	5	60158	16.7146	355.2197
4265	2004	352.77	2116.95	5	60473	18.0161	403.5394
4265	2002	341.64	2109.91	5	67612	18.3581	427.1341

Source of data: Modified from Orbis

Table 5.6: Descriptive statistics of firm-level data – Italy

Number of firms	Year	Mean firm size	Std. Dev.	Min	Max	Skewness	Kurtosis
ALL INDUSTRIES (172 4-digit industries, 12 main industries)							
7440	2010	61.71	163.10	5	7391	23.1024	845.1711
7440	2008	63.77	167.23	5	7476	22.2394	790.8130
7440	2006	62.14	167.43	5	7334	21.9910	755.6591
7440	2004	61.15	171.37	5	7886	24.6370	925.3218
7440	2002	68.81	162.98	5	5652	17.8248	478.2493
Manufacturing (101 4-digit industries, 1 main industry)							
4280	2010	67.26	151.51	5	6060	19.5787	635.2259
4280	2008	70.53	161.43	5	6045	17.8029	515.0214
4280	2006	69.12	162.40	5	6008	17.9843	508.7254
4280	2004	68.51	165.64	5	6611	20.2325	647.9677
4280	2002	79.20	179.14	5	5652	17.8815	457.3384
Non-manufacturing (71 4-digit industries, 11 main industries)							
3160	2010	54.20	177.36	5	7391	25.8181	967.8530
3160	2008	54.63	174.39	5	7476	27.0795	1065.4560
3160	2006	52.69	173.57	5	7334	26.5451	1015.0800
3160	2004	51.19	178.39	5	7886	29.5241	1206.6880
3160	2002	54.73	136.89	5	4611	16.3450	436.5802

Source of data: Modified from Orbis

Table 5.7: Descriptive statistics of firm-level data – Germany

Number of firms	Year	Mean firm size	Std. Dev.	Min	Max	Skewness	Kurtosis
ALL INDUSTRIES (168 4-digit industries, 15 main industries)							
7550	2010	458.16	6323.62	5	405000	42.4903	2381.1520
7550	2008	457.85	6475.94	5	427000	45.2094	2656.3720
7550	2006	432.58	6662.02	5	472500	52.5437	3453.9640
Manufacturing (56 4-digit industries, 1 main industry)							
2125	2010	783.70	10728.55	5	405000	29.3318	1006.6090
2125	2008	799.76	11107.02	5	427000	30.5099	1078.8070
2125	2006	787.85	11756.17	5	472500	33.1876	1258.0460
Non-manufacturing (112 4-digit industries, 14 main industries)							
5425	2010	330.64	3244.05	5	110254	21.4556	548.0973
5425	2008	323.92	3161.49	5	95703	21.3639	531.2060
5425	2006	293.42	2753.30	5	84128	21.8394	564.4998

Source of data: Modified from Orbis

It can further be concluded that all distributions are right-skewed as has been diagnosed by Gil (2010) and Lotti and Santarelli (2004), but with country and industry-specific variations as annotated by Stenkula (2007) and Hart and Prais (1956), Kessides and Tang (2010), Quandt (1966) and Simon and Bonini (1958) respectively. The skewness is strongest for Germany and shifts towards a more symmetric distribution for both manufacturing and non-manufacturing sectors, which is consistent with findings from Cabral and Mata (2003). The same applies to the UK non-manufacturing sector, whereas for Italy the distribution asymmetry increased until the beginning of 2008 due to an increase in the share of small firms. The tails of the distributions are largest for Germany and indicate a flatter distribution, which nevertheless moves towards a more peaked distribution for both manufacturing and non-manufacturing industries, suggesting a shift towards more firm size polarisation. The same trend can be observed for the British non-manufacturing industry, but not so much for its manufacturing sector. Once more, Italy differs as its SDOF flattens over time and implies a convergence towards more homogeneous firm sizes.

The normality test of the SDOF tends to be rejected when applied at main industry level and indicates the existence of a narrowly defined industry-specific distribution. When testing the normality of the log of firm sizes at the 4-digit industry level, the results indeed look quite different. The rejection rate of the null hypothesis, which is that ‘the SDOF is lognormally distributed’, is 37.3% for the UK, 25.6% for Italy and 30.5% for Germany. Accordingly, some two thirds of the industries follow an industry-specific lognormal distribution as found by Cabral and Mata (2003), Growiec *et al*. (2008), Hart and Oulton (1997), Hart and Prais (1956), Kaizoji *et al*. (2005) and Quandt (1966). Lognormal distributions are particularly frequent for industries operating at a high MES, such as mining and electricity, and applies to all sample countries. With regard to the manufacturing industry, Italy shows the highest rate of lognormality and hence the lowest rejection rate of the null hypothesis (12.9%), while the UK's has increased from 34.3% in 2001 to 48.6% in 2010 and is the most dynamic. In contrast, the rejection rate of non-manufacturing industries declines over time for both the UK and Germany and is mainly driven by the dynamics of the wholesale and retail industry – also by the construction industry for the UK. It means that these industries approach the lognormal distribution at a faster rate than manufacturing industries, which experience an upswing as the summary of manufacturing and non-manufacturing in Table 5.8 shows.

Table 5.8: Lognormality test rejection rate by industry

	No. of 4-digit industries	No. of firms	Rejection rate in %										
			2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	**Total**
UK													
Manufacturing	35	1500	48.6	48.6	48.6	40.0	34.3	40.0	40.0	37.1	34.3	34.3	**40.0**
Non-manufacturing	85	4265	30.6	32.9	34.1	35.3	36.5	36.5	37.6	40.0	40.0	37.6	**35.7**
Italy													
Manufacturing	101	4280	10.9	12.9	10.9	12.9	13.9	14.9	17.8	12.9	10.9	10.9	**12.9**
Non-manufacturing	71	3160	46.5	46.5	45.1	47.9	47.9	49.3	46.5	38.0	39.4	32.4	**43.7**
Germany													
Manufacturing	56	2125	26.8	23.2	25.0	23.2	25.0	25.0	-	-	-	-	**24.7**
Non-manufacturing	109	5425	50.5	51.4	53.2	54.1	55.0	55.0	-	-	-	-	**53.2**

Source of data: Modified from Orbis

An explanation of this is provided by the rejection rate according to the number of sample firms that make up a 4-digit industry (Tables 5.9, 5.10, 5.11). The result is that the frequency of a lognormal distribution increases as the number of firms allocated to one industry decreases. This pattern is strongest for Germany and appears to be the consequence of an evolving industry concentration as an industry matures. These findings are consistent with Adelman (1958), Cabral and Mata (2003), Hariprasad (2011) and Robson and Gallagher (1994), who advocate a natural equilibrium as the final stage of the sized distribution of firms, and Cirillo (2010) and Dinlersoz and MacDonald (2009) who associate increasing firm size homogeneity following the shakeout and with an increase in firm age. The consequence of a shift towards a lognormal distribution implies that growth becomes independent from firm size as has been emphasised by Hart and Prais (1956). Given that non-manufacturing industries approach the lognormal distribution at a faster rate than manufacturing industries, it confirms that in non-manufacturing industries firm growth is less dependent on size.

Table 5.9: Lognormality test rejection rate by sample size – UK

No. of sample firms*	No. of 4-digit industries	No. of firms	Share of manuf. firms	Rejection rate in %										
				2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	**Total**
20	33	660	36.4%	18.2	18.2	18.2	15.2	7.3	15.2	15.2	15.2	18.2	18.2	**16.4**
30	26	780	42.3%	38.5	38.5	38.5	38.5	34.6	38.5	38.5	42.3	38.5	38.5	**38.5**
40	16	640	18.8%	18.8	18.8	18.8	18.8	18.8	18.8	18.8	25.0	25.0	25.0	**20.6**
50	5	250	20.0%	80.0	80.0	100	80.0	80.0	80.0	80.0	80.0	80.0	60.0	**80.0**
60	11	660	27.3%	45.5	54.5	54.5	54.5	54.5	54.5	54.5	45.5	45.5	45.5	**50.9**
75	5	375	0.0%	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	40.0	20.0	**38.0**
100	24	2400	25.0%	54.2	54.2	54.2	58.3	62.5	62.5	66.7	66.7	62.5	62.5	**60.4**

Source of data: Modified from Orbis

Table 5.10: Lognormality test rejection rate by sample size – Italy

No. of sample firms*	No. of 4-digit industries	No. of firms	Share of manuf. firms	Rejection rate in %										
				2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	**Total**
20	52	1040	57.7%	11.5	13.5	13.5	15.4	13.5	15.4	15.4	13.5	13.5	11.5	**13.7**
30	33	990	57.6%	24.2	27.3	24.2	24.2	24.2	24.2	30.3	18.2	18.2	15.2	**23.0**
40	25	1000	72.0%	16.0	16.0	16.0	16.0	20.0	20.0	20.0	12.0	12.0	4.0	**15.2**
50	15	750	66.7%	40.0	33.3	40.0	33.3	40.0	60.0	33.3	26.7	26.7	26.7	**36.7**
60	16	960	56.3%	37.5	31.3	31.3	37.5	37.5	31.3	37.5	37.5	37.5	43.8	**36.3**
75	16	1200	37.5%	50.0	50.0	50.0	56.3	56.3	56.3	62.5	43.8	50.0	37.5	**51.3**
100	15	1500	60.0%	40.0	40.0	33.3	46.7	40.0	40.0	46.7	46.7	33.3	33.3	**40.0**

Source of data: Modified from Orbis

Table 5.11: Lognormality test rejection rate by sample size – Germany

No. of sample firms*	No. of 4-digit industries	No. of firms	Share of manuf. firms	Rejection rate in %										
				2010	2009	2008	2007	2006	2005	2004	2003	2002	2001	**Total**
20	54	1080	42.6%	18.5	16.7	16.7	16.7	18.5	16.7	-	-	-	-	**17.3**
30	30	840	39.3%	36.7	36.7	36.7	36.7	36.7	36.7	-	-	-	-	**36.7**
40	16	640	25.0%	25.0	25.0	31.3	31.3	37.5	43.8	-	-	-	-	**32.3**
50	17	850	35.3%	52.9	52.9	58.8	64.7	64.7	64.7	-	-	-	-	**59.8**
60	14	840	35.7%	35.7	35.7	42.9	42.9	42.9	35.7	-	-	-	-	**39.3**
75	12	900	41.7%	75.0	75.0	75.0	75.0	75.0	75.0	-	-	-	-	**75.0**
100	24	2400	8.3%	91.7	91.7	91.7	91.7	91.7	95.8	-	-	-	-	**92.4**

Source of data: Modified from Orbis

*) no. of sample firms that make up one 4-digit industry observation

In terms of Gini-coefficient, derived from the size distribution of each 4-digit industry, changes in FSI are negligible if considered at aggregate level. As Tables 5.12, 5.13 and 5.14 show, a noticeable change can only be observed for the UK manufacturing industry (from 0.677 in 2001 to 0.658 in 2010) and for Italy's non-manufacturing industry (from 0.540 in 2001 to 0.552 in 2010). Again, the magnitude changes when narrowing industry classifications as presented in Tables 5.15, 5.16 and 5.17.

Table 5.12: Descriptive statistics of firm size inequality – UK

Number of 4-digit industries	Year	Mean Gini-coef.	Std. Dev.	Min	Max	Skewness	Kurtosis
ALL INDUSTRIES (5767 firms, 15 main industries)							
120	2010	0.684841	0.135036	0.393249	0.975311	-0.007109	2.134424
120	2008	0.684301	0.135045	0.360954	0.975709	-0.063851	2.223910
120	2006	0.683326	0.133319	0.364978	0.975997	-0.034407	2.173981
120	2004	0.683852	0.133000	0.375877	0.973805	0.025900	2.151128
120	2002	0.686795	0.132494	0.386626	0.972207	0.028483	2.159460
Manufacturing (1500 firms, 1 main industry)							
35	2010	0.657713	0.150472	0.394211	0.902988	0.042803	1.851534
35	2008	0.658125	0.149308	0.360954	0.893882	-0.081091	1.961925
35	2006	0.660093	0.145133	0.364978	0.904839	-0.085654	2.083394
35	2004	0.667597	0.140125	0.375877	0.908162	-0.018510	2.103979
35	2002	0.672640	0.136185	0.386626	0.907780	-0.032902	2.130441
Non-Manufacturing (4265 firms, 14 main industries)							
85	2010	0.696012	0.127417	0.393249	0.975311	0.061193	2.194614
85	2008	0.695080	0.128100	0.379875	0.975709	0.033504	2.227317
85	2006	0.692893	0.127815	0.421419	0.975997	0.057410	2.086935
85	2004	0.690545	0.130217	0.415981	0.973805	0.070544	2.125709
85	2002	0.692623	0.131318	0.430867	0.972207	0.064343	2.140226

Source of data: Modified from Orbis

Table 5.13: Descriptive statistics of firm size inequality – Italy

Number of 4-digit industries	Year	Mean Gini-coef.	Std. Dev.	Min	Max	Skewness	Kurtosis
ALL INDUSTRIES (7440 firms, 12 main industries)							
172	2010	0.525691	0.110261	0.341410	0.915860	0.655916	3.171329
172	2008	0.525748	0.112515	0.342690	0.889390	0.747393	3.253828
172	2006	0.518738	0.115716	0.312650	0.907500	0.817292	3.498968
172	2004	0.517007	0.114625	0.322120	0.909010	0.897737	3.733355
172	2002	0.512743	0.104519	0.279440	0.832550	0.801134	3.601609
Manufacturing (4280 firms, 1 main industry)							
101	2010	0.506948	0.095665	0.351280	0.798640	0.920253	3.700648
101	2008	0.507456	0.102554	0.342690	0.882390	1.164818	4.539485
101	2006	0.501754	0.104511	0.335530	0.892670	1.230422	4.840982
101	2004	0.501107	0.103364	0.322120	0.889950	1.285428	5.169838
101	2002	0.495191	0.091760	0.343460	0.832550	1.455665	6.007926
Non-Manufacturing (3160 firms, 11 main industries)							
71	2010	0.552353	0.124086	0.341410	0.915860	0.258401	2.736707
71	2008	0.551770	0.121373	0.350730	0.889390	0.266223	2.557083
71	2006	0.542897	0.126879	0.312650	0.907500	0.349559	2.700534
71	2004	0.539626	0.126292	0.331620	0.909010	0.457559	2.805340
71	2002	0.537712	0.116537	0.279440	0.829300	0.151089	2.509666

Source of data: Modified from Orbis

Table 5.14: Descriptive statistics of firm size inequality – Germany

Number of 4-digit industries	Year	Mean Gini-coef.	Std. Dev.	Min	Max	Skewness	Kurtosis
ALL INDUSTRIES (7550 firms, 15 main industries)							
165	2010	0.703095	0.146991	0.378800	0.991550	0.159022	2.287161
165	2008	0.707024	0.146637	0.370530	0.992530	0.107270	2.259211
165	2006	0.706798	0.146363	0.366620	0.990310	0.098601	2.279475
Manufacturing (2125 firms, 1 main industry)							
56	2010	0.701163	0.131264	0.473270	0.981270	0.449678	2.658285
56	2008	0.708904	0.131121	0.470390	0.980840	0.385786	2.555021
56	2006	0.709931	0.129593	0.470650	0.983900	0.452093	2.612695
Non-Manufacturing (5425 firms, 14 main industries)							
109	2010	0.704087	0.155023	0.378800	0.991550	0.062183	2.131129
109	2008	0.706058	0.154575	0.370530	0.992530	0.025289	2.113559
109	2006	0.705189	0.154821	0.366620	0.990310	0.001836	2.113622

Source of data: Modified from Orbis

Table 5.15: Changes in firm size inequality – UK

Main industry	No. of 4-digit industries	No. of firms	Median change in FSI (Gini-coef.)					% change in median FSI				
			2010-08	2008-06	2006-04	2004-02	2010-02	2010-08	2008-06	2006-04	2004-02	2010-02
Manufacturing	35	1500	0.00267	-0.00390	-0.00788	-0.00398	-0.00785	-3.01%	0.67%	-0.07%	-1.82%	-4.21%
Wholesale and retail trade; repair services	29	1275	-0.00106	-0.00089	0.00065	-0.00296	-0.01056	-2.99%	-0.03%	0.07%	1.33%	-1.67%
Accommodation and food service activities	3	160	-0.00018	0.00198	-0.00294	-0.00205	-0.00023	-0.02%	-0.59%	-0.57%	-0.26%	-1.44%
Administrative and support service activities	6	390	0.00286	0.00982	-0.00141	0.00343	0.01943	-0.19%	2.23%	0.28%	0.12%	2.44%
Agriculture, forestry and fishing	2	40	0.02133	0.01070	0.00346	0.01925	0.05474	2.88%	1.46%	0.48%	2.72%	7.73%
Arts, entertainment and recreation	5	205	0.00527	0.01032	0.01139	0.00107	0.01808	0.73%	1.52%	1.18%	-1.41%	2.01%
Construction	7	350	-0.00661	0.00214	-0.00667	-0.01485	-0.00903	2.68%	-0.59%	-1.13%	-2.29%	-1.39%
Education	4	305	0.01370	0.00025	-0.00367	0.00107	0.01554	2.16%	-0.52%	-0.57%	1.39%	2.46%
Electricity, gas, steam, air cond. supply	1	20	0.00446	0.00290	-0.00048	0.00312	0.01000	0.56%	0.36%	-0.06%	0.39%	1.26%
Human health and social work activities	4	330	0.00448	-0.00305	0.00563	-0.00605	0.00250	0.61%	-0.32%	1.25%	-1.45%	0.07%
Information and communication	7	310	-0.00210	0.01479	0.00261	0.00441	0.00496	-1.97%	-0.81%	0.01%	-1.28%	-3.99%
Mining and quarrying	1	20	-0.03338	-0.00580	0.01637	0.02117	-0.00164	-4.39%	-0.76%	2.18%	2.90%	-0.23%
Professional, scientific and technical activities	5	315	0.01472	0.00149	0.00067	-0.01072	0.00395	2.19%	0.23%	-0.19%	-1.60%	0.59%
Transportation and storage	7	305	-0.00635	0.00161	0.00008	0.00401	-0.01361	0.79%	-2.48%	1.42%	0.94%	0.61%
Other service activities	4	240	0.00073	0.00262	0.00197	-0.01357	-0.00799	1.22%	0.40%	-0.63%	-0.57%	0.41%

Source of data: Modified from Orbis

Table 5.16: Changes in firm size inequality – Italy

Main industry	No. of 4-digit industries	No. of firms	Median change in FSI (Gini-coef.)					% change in median FSI				
			2010-08	2008-06	2006-04	2004-02	2010-02	2010-08	2008-06	2006-04	2004-02	2010-02
Manufacturing	101	4280	0.00286	0.00630	-0.00104	0.00585	0.00858	1.16%	2.04%	0.65%	0.57%	4.49%
Wholesale and retail trade; repair services	39	1815	0.00536	0.00658	-0.00020	-0.00801	0.01109	-0.36%	4.03%	0.41%	-1.48%	2.54%
Accommodation and food service activities	2	95	0.00133	0.01164	0.01888	-0.02449	0.00736	0.23%	2.08%	3.49%	-4.33%	1.30%
Administrative and support service activities	3	80	-0.00754	0.00730	-0.00419	0.03048	0.07497	-1.41%	3.59%	-0.82%	15.48%	16.97%
Agriculture, forestry and fishing	2	60	-0.01154	0.01263	0.01042	0.02288	0.03439	-2.02%	2.27%	1.90%	4.36%	6.56%
Construction	6	360	-0.00448	0.01507	0.01365	0.01542	0.04674	-0.35%	3.14%	2.80%	0.00%	5.67%
Human health and social work activities	1	60	0.01041	0.00301	0.00678	0.02972	0.04992	2.37%	0.69%	1.58%	7.45%	12.51%
Information and communication	4	175	0.00983	0.00518	-0.00217	-0.02726	-0.01218	1.65%	-0.19%	0.47%	-1.30%	0.61%
Mining and quarrying	2	60	0.00835	0.01130	0.00031	0.00166	0.02163	2.18%	3.04%	0.08%	0.45%	5.84%
Professional, scientific and technical activities	6	170	0.00615	0.00149	0.00177	0.00113	-0.01733	2.80%	2.30%	-3.62%	-6.22%	-4.96%
Transportation and storage	4	235	0.00066	0.01537	0.00164	-0.00958	-0.00573	0.11%	7.14%	-0.93%	1.63%	7.98%
Water supply; sewerage and waste management	2	50	-0.00109	0.00456	0.00957	0.00758	0.02062	-0.22%	0.93%	1.99%	1.60%	4.37%

Source of data: Modified from Orbis

Table 5.17: Changes in firm size inequality – Germany

Main industry	No. of 4-digit industries	No. of firms	Median change in FSI (Gini-coef.)					% change in median FSI				
			2010-08	2008-06	2006-04	2004-02	2010-06	2010-08	2008-06	2006-04	2004-02	2010-06
Manufacturing	56	2125	-0.00244	-0.00230	-	-	-0.00593	-2.56%	0.67%	-	-	-1.91%
Wholesale and retail trade; repair services	55	2815	0.00190	0.00225	-	-	0.00426	-0.10%	-0.92%	-	-	-1.02%
Accommodation and food service activities	2	160	-0.00113	-0.00008	-	-	-0.00122	-0.17%	-0.01%	-	-	-0.19%
Administrative and support service activities	9	270	-0.00180	-0.00515	-	-	-0.00775	0.61%	-0.75%	-	-	-0.15%
Agriculture, forestry and fishing	1	20	0.02642	0.02132	-	-	0.04775	6.81%	5.82%	-	-	13.02%
Arts, entertainment and recreation	1	30	-0.00266	0.01247	-	-	0.00981	-0.44%	2.12%	-	-	1.67%
Construction	11	785	-0.00108	0.00386	-	-	0.00003	-6.89%	2.10%	-	-	-4.93%
Electricity, gas, steam, air cond. supply	2	30	-0.00737	-0.00030	-	-	-0.00767	-0.81%	-0.03%	-	-	-0.84%
Human health and social work activities	2	70	0.00346	0.00670	-	-	0.01016	0.49%	0.96%	-	-	1.46%
Information and communication	9	260	0.00447	-0.00156	-	-	-0.00176	-3.65%	-0.54%	-	-	-4.17%
Mining and quarrying	2	60	-0.01779	-0.01134	-	-	-0.02912	-3.37%	-2.10%	-	-	-5.40%
Professional, scientific and technical activities	7	325	-0.00700	0.00562	-	-	-0.00139	2.44%	2.76%	-	-	5.26%
Transportation and storage	7	490	0.00009	-0.00144	-	-	-0.00249	1.39%	-2.94%	-	-	-1.59%
Water supply; sewerage and waste managem.	2	50	-0.01010	0.00212	-	-	-0.00798	-1.37%	0.29%	-	-	-1.09%
Other service activities	2	60	0.00056	-0.00122	-	-	-0.00066	0.08%	-0.17%	-	-	-0.09%

Source of data: Modified from Orbis

Please note that change in firm size inequality *(FSI) cannot be considered as statistically significant when the number of 4-digit industries is very low*

The median change in FSI of 4-digit manufacturing industries is consistent with the trend observed for the lognormal distributions. An increasing rejection rate of the lognormal distribution for the UK and Germany leads to a decline in FSI. However, FSI in the Italian manufacturing industry increases and considerable changes are observable from 2008 onwards, which suggests that macro-economic shocks reshape the SDOF as noted by Acs *et al.* (1996), Gaffeo *et al.* (2003) and Picard and Rimmer (1999). For Italy, increases in FSI are also observed across most non-manufacturing industries except for *professional, scientific and technical activities*, which is the only sector experiencing a decline of some 5% from 2002 to 2010. In the UK, *agriculture, forestry and fishing* leads among the non-manufacturing industries with the highest increase in FSI. Its steady rise may be the consequence of increasing market concentration, which in the *information and communication* industry is lower as it can otherwise not explain the largest change in the opposed direction. A similar yet more intense pattern is observed for Germany, where *construction* and *mining and quarrying* are among the sectors with a declining FSI if measured by the median change. Most notable however is the direction of the shift, which for Italy is different for nearly all main industry sections.

5.1.4 Conclusions

The indications the descriptive statistics provide confirm that the SDOF is country and industry-specific and barely changes when examined at aggregate level. Deindustrialisation, deliberate agglomeration and the attraction of foreign-owned firms noted by Booth (1995) and Bailey and Driffield (2007) explain the thin share of medium-sized firms in the UK. It is as persistent as Germany's strong *Mittelstand*, but Germany also has the largest share of firms with a workforce above 10,000 employees. The samples of both Germany and Italy show that nearly half of the workforce is employed in the manufacturing industry, which is about twice as large as the UK's and hence a sign for a different economic stage. Italy, however, has a much smaller average firm size than Germany and it is the only country with a decrease for manufacturing and non-manufacturing industries, with the most significant erosion of SMEs' employment share. Quite the opposite applies to Germany, while in the UK, only manufacturing industries experience a decline in average firm size and employment share.

The conclusions drawn from the database summary tables are consistent with the distribution analysis and the Gini-coefficient revealed from the final sample. About two thirds of each country's 4-digit industries follow a lognormal distribution and the frequency of detecting lognormality increases with mean firm size and market concentration. Where size distributions of firms follow a lognormal distribution and the MES is high, all firms operate above the MES and hence reflect a post-shakeout industry life-cycle stage. Accordingly, the lognormal distribution is a reasonably good description of the natural stage towards which the SDOF converges as an industry approaches maturity. Non-manufacturing firms grow faster and firm growth is less a function of firm size, but the more dynamic growth patterns imply that firms approach the lognormal distribution at a faster rate. As the SDOF comes closer to the natural stage, firm growth becomes independent from firm size and eventually leads to a decline in FSI. However, the latter also applies before the shakeout takes place and suggests that FSI is inversely U-shaped, at least for asset intensive industries.

There are indications that SMEs are able to compete with incumbent firms under certain circumstances. These yet unknown factors determine whether firms move upwards or downwards in the firm-size class hierarchy when the shakeout takes place. Macro-economic shocks play a role as they alter existing structures and seem to accelerate the process of increasing FSI. Overall, the expected increase in FSI in asset-rich traditional industries can be supported except for industries which have or are in the process of achieving oligopolistic or contestable market structures. These findings are most evident for Italy, where a large share of static small firms contributes to a lack of structural dynamics. The resulting question is, therefore, not whether a process of increasing FSI takes place, but how this change can be influenced, which is the purpose of the next section.

5.2 Determinants of firm size inequality

The next step is the identification of the impact of the factors revealed from the literature review on FSI, which refers to RQ2. The presence of distinct country-specific characteristics, commented in the first part of the analysis, confirm the need to perform a regression analysis for each sample country. Following the descriptive summary statistics of the variables included in the optimised regression models, a brief note on critical correlations among variables is presented. The analysis continues then with the regression output from OLS AR(1), RE AR(1) and FGLS AR(1) estimators for basic and extended models, aiming to address consistency and direction of the predicted impact. The final and most relevant part is devoted to the coefficients obtained from the reduced RE AR(1) regression model, which is then linked to the expectations suggested by previous literature. Since all regression models underwent optimisation loops, only relevant variables are presented. Alternative variables have been tested, but can be assumed to be insignificant or inferior to those reported. The most relevant exclusion is *diversification*, where proxies failed to deliver any meaningful insights for any sample country. It should finally be noted that the number of underlying firm-level observations are henceforth 4,985 firms (96 4-digit industry-level observations) for the UK, 6,070 firms (132 4-digit industry-level observations) for Italy and 6,640 firms (146 4-digit industry-level observations) for Germany.

5.2.1 Descriptive statistics

The summary statistics presented in Table 5.18 show the mean, standard deviation and range of values of the respective industry-level observations of dependent and independent variables. The dependent variable of primary interest is the Gini-coefficient (GINI), whose range is largest for Germany, but with a mean equal to the UK. Italy shows the smallest range and, on average, also the lowest degree of FSI. This becomes more visible when measured by the HHI, which covers a range of 0.678 for the UK, 0.191 for Italy and 0.940 for

Germany. The log-odds ratio is represented by GINI_L. As expected, the concentration ratio (CR4EM) is lowest for Italy, where regional dispersion (REG_N) is largest and home to the oldest firms (AGE_MAX). This may explain the negative 4-digit industry growth rate (GR_FDIG), which might be influenced by the largest industry-specific difference in relative firm size (MES_REL). It is however Germany that shows the largest share of stagnating 4-digit industries (STAGE_S).

Despite being the country with the largest share of firms managed by individuals (TMTIND_EM), the UK also shows the lowest share of owner-managed firms (TMTSH_EM), which is highest in Germany. The lack of owner-management in Britain might be influenced by it having the largest share of foreign-owned firms (FOROWN_EM), whose pattern differs from being part of a group. Firms belonging to a group (GROUP_EM) are most likely to occur in Germany, while the dominance of large firms in the UK brings the highest probability of subsidiaries (SUBS_EM) with it, which in turn is lowest for Germany. With regard to firm-specific assets, Italian firms rank lowest in tangible assets (TANTA_D) and can be explained by the relatively smaller firm size. Likewise, intangible assets (INTA_A) are lowest in Italy, while stock levels (STKTA_D) reach those of Germany. This might be due to the large manufacturing sectors, whereas the dominance of the service sector in the UK leads to lower stock levels, but higher employee turnover (EMPTO_D). However, employee turnover is largest for Germany when aggregating the data (EMPTO_G), while labour productivity (VAEMP_D) differs little across countries. Due to the absence of sufficient data on R&D and exports for both Italy and Germany, these dimensions cannot be considered in the analysis.

Table 5.18: Descriptive statistics of dependent and significant independent variables

	UK					Italy					Germany				
Variable*	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
GINI	960	0.688018	0.119625	0.379875	0.938633	1320	0.491269	0.083757	0.258998	0.776272	876	0.688249	0.136968	0.366415	0.992535
GINI_L	960	-0.582650	0.095839	-0.794993	-0.336321	1320	-0.725140	0.054687	-0.864041	-0.518440	876	-0.577468	0.119029	-0.802906	-0.202661
HHI	960	0.151084	0.122963	0.022557	0.701120	1320	0.065019	0.033008	0.017182	0.208603	876	0.176417	0.165817	0.025356	0.965532
GR_MAIN	864	0.016754	0.041246	-0.135118	0.292429	1188	0.006148	0.057023	-0.202844	0.494033	730	-0.005556	0.084419	-0.338932	0.596069
GR_FDIG	864	0.008548	0.048708	-0.232455	0.211721	1188	-0.006079	0.071257	-0.481717	0.241744	730	0.011106	0.062969	-0.482420	0.774043
STAGE_S	960	0.208333	0.406328	0.000000	1.000000	1320	0.250000	0.433177	0.000000	1.000000	876	0.452055	0.497980	0.000000	1.000000
CR4EM	960	0.501048	0.183035	0.124114	0.910875	1320	0.293061	0.125071	0.084164	0.654956	876	0.550093	0.207008	0.115087	0.994413
AGE_MAX	960	4.620030	0.270841	3.713572	5.049856	1320	4.341010	0.344241	3.663562	6.815640	876	4.671559	0.311862	3.663562	5.789960
MES_REL	960	0.775553	1.209612	-1.897120	3.131093	1320	2.264150	0.755759	0.289343	3.609441	876	0.830039	1.400942	-3.606072	3.068949
REG_N	960	12.10417	1.977344	5.000000	14.00000	1320	9.984848	3.310985	4.000000	18.000000	876	11.06164	2.547530	6.000000	16.00000
TMTIND_EM	960	0.920276	0.119315	0.327304	1.000000	1320	0.788986	0.146659	0.368413	0.999971	876	0.718681	0.215636	0.142124	0.999999
TMTSH_EM	960	0.379738	0.248662	0.005906	0.985434	1320	0.616872	0.209036	0.012375	0.943620	876	0.654596	0.276933	0.005239	0.999948
FOROWN_EM	960	0.284446	0.218185	0.000000	0.879676	1320	0.127766	0.145990	0.000000	0.560502	876	0.138369	0.172920	0.000000	0.703033
GROUP_EM	960	0.147342	0.176050	0.000000	0.748228	1320	0.207580	0.146618	0.000000	0.791946	876	0.305020	0.225368	0.000000	0.986728
SUBS_EM	960	0.725116	0.183532	0.025358	0.978838	1320	0.631902	0.138657	0.210586	0.951975	876	0.547728	0.292440	0.000000	0.996558
TANTA_D	960	0.252319	0.176619	0.018304	0.888314	1320	0.176003	0.105217	0.023653	0.789341	792	0.243123	0.174118	0.004858	0.813999
TANTA_G	960	0.276168	0.188409	0.025961	0.844432	1320	0.219492	0.100586	0.014916	0.690286	792	0.263349	0.182309	0.004858	1.178569
INTTA_A	960	0.023414	0.027046	-0.000348	0.238859	1320	0.022232	0.014693	0.001536	0.119162	792	0.037371	0.064040	0.000000	0.621763
INTTA_G	960	0.064898	0.111749	-0.022364	0.743355	1320	0.025060	0.026049	0.001924	0.306242	792	0.053415	0.099384	0.000000	0.666181
STKTA_D	960	0.101435	0.103003	0.000000	0.468609	1320	0.176413	0.100748	0.000000	0.564917	792	0.191259	0.155144	0.000000	0.787005
STKTA_G	960	0.104784	0.096797	0.000507	0.543499	1320	0.195501	0.091498	0.001025	0.537869	792	0.186754	0.155679	0.000000	0.845588
EMPTO_D	960	0.267477	0.138456	0.048389	0.767726	1320	0.169456	0.088224	0.020636	0.651125	774	0.250013	0.126922	0.002177	0.679009
EMPTO_G	960	0.230630	0.126913	0.019070	0.692390	1320	0.151420	0.083677	0.004106	0.669682	786	0.781447	1.067660	0.003948	8.001591
VAEMP_D	960	10.53609	0.449844	8.961109	13.38341	1320	10.59783	0.296293	9.875814	11.61941	786	10.72900	0.434139	7.253417	12.06897
VAEMP_G	960	6.966755	0.918247	3.931826	10.29404	1320	7.079057	0.661027	5.588618	10.71459	786	7.891290	1.132554	1.253992	10.78699
RNDTO_A	960	0.001817	0.012478	0.000000	0.210909										
RNDTO_G	960	0.001662	0.005731	0.000000	0.046825										
EXPTO_A	960	0.080210	0.091772	0.000000	0.410519										
EXPTO_G	960	0.080281	0.105499	0.000000	0.565313										

Source of data: Modified from Orbis

*) for full variable description see end of Appendix C3

5.2.2 Correlations with firm size inequality

The correlations of independent variables with dependent variables are reported in Table 5.19 in their most concise form. The weakest correlation of Gini-coefficient and HHI can be found for Italy and result from the weak presence of large firms. In terms of direction, correlations with the Gini-coefficient are consistent with those of the HHI, except for regional disparity (REG_N), affiliation with a group (GROUP_EM) and tangible assets (TANTA_G). For Italy and Germany, increasing regional disparity is associated with higher levels of FSI, but also with less market concentration. The same applies to Germany with respect to firms belonging to a group, whereas asset intensity increases market concentration in Italy, but lowers FSI and hence indicates a technology-driven convergence towards equal firm size. Main industry growth (GR_MAIN) matters only for Italy and has a negative effect on FSI, whereas 4-digit industry growth (GR_FDIG) has no significant effect for Italy, but lowers FSI in the UK and Germany. A higher share of stagnating industries (STAGE_S) too can be associated with decreasing FSI, but does not show any significant correlation for Italy.

For the UK alone, industry age (AGE_MAX), regional disparity (REG_N) and foreign ownership (FOROWN_EM) are negatively correlated with FSI, but are positively correlated for Italy and Germany. The presence of individual board members (TMTIND_EM) is negatively correlated with FSI in Italy only, and has the reverse effect for Germany. It is insignificant for the UK, where labour productivity (VAEMP_G) – in contrast to Italy and Germany – is negatively correlated with FSI and potentially lower market concentration. Uniform negative correlations are found for the MES (MES_REL) and stock levels (STKTA). Owner-management (TMTSH_P_EM) is linked to lower levels of FSI, but increases market concentration in the UK. Positive correlations can be attributed to the presence of subsidiaries (SUBSID_EM), intangible assets (INTTA_A/…_G), labour intensity (EMPTO_D/…_G), R&D (RNDTO_G) and export orientation (EXPTO_A), which all seem to reflect a competitive advantage.

Table 5.19: Correlations of independent variables with firm size inequality

	UK			Italy			Germany		
	GINI	GINI_L	HHI	GINI	GINI_L	HHI	GINI	GINI_L	HHI
GINI_L	0.9952***			0.9987***			0.9851***		
HHI	0.7376***	0.7713***		0.5222***	0.5352***		0.7526***	0.8238***	
GR_MAIN	-0.0169	-0.0235	-0.0857**	-0.0846***	-0.0848***	-0.0807***	-0.0196	-0.0210	-0.0140
STAGE_S	-0.1177***	-0.1258***	-0.0779**	-0.0382	-0.0429	-0.1837***	-0.1858***	-0.1773***	-0.1344***
CR4EM	0.6999***	0.7104***	0.7673***	0.5274***	0.5333***	0.8378***	0.7146***	0.7373***	0.8077***
GR_FDIG	0.1034***	0.0949***	0.0516	0.0000	-0.0014	-0.0127	0.1577***	0.1654***	0.1843***
AGE_MAX	-0.1209***	-0.1329***	-0.1952***	0.1479***	0.1613***	0.0249	0.0993***	0.1034***	-0.0253
MES_REL	-0.7522***	-0.7458***	-0.4550***	-0.6632***	-0.6616***	-0.1576***	-0.8252***	-0.8604***	-0.6816***
REG_N	-0.0987***	-0.1077***	-0.2852***	0.0962***	0.0953***	-0.4012***	0.1049***	0.0985***	-0.1741***
TMTIND_EM	0.0216	0.0120	0.0628*	-0.4990***	-0.5022***	-0.3157***	0.1880***	0.2073***	0.2471***
TMTSH_EM	-0.0132	0.0113	0.1569***	-0.5909***	-0.5988***	-0.4535***	-0.3644***	-0.3514***	-0.1736***
FOROWN_EM	-0.1550***	-0.1783***	-0.1270***	0.3994***	0.3995***	0.2140***	0.1245***	0.0882***	-0.0356
GROUP_EM	0.0185	0.0051	0.0281	0.4853***	0.4942***	0.3196***	0.1604***	0.1235***	-0.0660*
SUBS_EM	0.6075***	0.5950***	0.5187***	0.3701***	0.3706***	0.2500***	0.6047***	0.6023***	0.4633***
TANTA_D	0.1498***	0.1546***	0.2205***	-0.1667***	-0.1658***	0.0116	0.0189	0.0022	-0.0212
TANTA_G	0.0020	-0.0012	0.0391	-0.0608**	-0.0608**	0.0556**	0.0281	0.0015	-0.0322
INTTA_A	0.2384***	0.2397***	0.2027***	0.2425***	0.2490***	0.1795***	0.2812***	0.2732***	0.2703***
INTTA_G	0.4272***	0.4514***	0.5414***	0.2733***	0.2744***	0.1100***	0.3563***	0.3700***	0.3548***
STKTA_D	-0.1908***	-0.1846***	-0.1171***	-0.1140***	-0.1134***	-0.0893***	-0.2092***	-0.2017***	-0.0993***
STKTA_G	-0.2116***	-0.2039***	-0.1435***	-0.1584***	-0.1583***	-0.1660***	-0.2614***	-0.2441***	-0.1528***
EMPTO_D	0.1413***	0.1441***	0.1601***	0.0764***	0.0724***	0.0745***	0.1081***	0.0829**	0.0726**
EMPTO_G	0.1247***	0.1336***	0.1386***	0.1088***	0.1071***	0.1095***	-0.0129	-0.0007	0.1100***
VAEMP_D	0.0128	-0.0014	-0.0999***	0.0889***	0.0916***	0.0927***	0.1158***	0.1095***	0.1261***
VAEMP_G	-0.1086***	-0.1249***	0.0573*	0.0129	0.0206	0.6508***	0.1095***	0.1077***	0.2920***
RNDTO_A	0.0115	0.0052	0.0211						
RNDTO_G	0.1839***	0.1809***	0.1530***						
EXPTO_A	0.0870***	0.0924***	0.1412***						
EXPTO_G	-0.0290	-0.0318	0.0594*						

Source of data: Modified from Orbis *** p<0.01, ** p<0.05, * p<0.1

The most relevant correlations among independent variables are those linked to firm structure characteristics reported in Table 5.20. Italy stands out once more by showing the strongest correlation of industries with a large share of firms led by individuals (TMTIND_EM) and owner-management (TMTSH_EM), foreign ownership (FOROWN_EM) and group affiliation (GROUP_EM). It is intuitive that these correlations result from the large share of independent and small firms, most of them family owned – confirmed by the insignificance of subsidiaries. Where foreign firms are present, they frequently belong to a group and as technology holders affect the degree of FSI, the direction of which depends on SMEs' absorptive capacity.

Table 5.20: Intercorrelations of firm property variables

	UK			Italy			Germany		
	TMTIND~	TMTSH~	FOROWN~	TMTIND~	TMTSH~	FOROWN~	TMTIND~	DMSH~	FOROWN~
TMTSH_EM	0.1728***			0.5878***			-0.4802***		
FOROWN_EM	-0.3347***	-0.1882***		-0.6843***	-0.4922***		0..0955***	-0.3445***	
GROUP_EM	-0.1662***	-0.2625***	0.4946***	-0.5776***	-0.4576***	0.5278***	-0.1234***	-0.2288***	0.3871***
SUBS_EM	0.1492***	0.2287***	-0.0226	0.0040	-0.1957***	0.0125	0.2070***	-0.4228***	0.2837***

Source of data: Modified from Orbis *** p<0.01, ** p<0.05, * p<0.1

For Germany, an increase in owner-management leads to fewer individuals being appointed as board members, but labour productivity is higher when managers are individuals, i.e. not representatives of third party companies ($r=0.4188$, $p<0.01$). For Italy, this has negative effects on aggregate labour productivity ($r=-0.1401$, $p<0.01$) and declines further when the regional concentration of firms operating in the same industry decreases. This applies to all sample countries (UK: $r=-0.5046$, $p<0.01$; Italy: $r=-0.5020$, $p<0.01$; Germany: $r=-0.3966$, $p<0.01$). Hence, it appears that despite new communication technologies, geographical concentration still has an effect on productivity levels and this suggests process spill-overs that eventually lower FSI.

5.2.3 Regression results

Consistency of variables and estimators

Basic and extended regression models were estimated for each sample country using the OLS estimator with Newey-West standard errors (OLS) and the random effects estimator accounting for heteroskedasticity and first order autoregressive disturbances (RE), cross-validated with the equivalent coefficients obtained from the FGLS estimator (FGLS). Comprehensive regression tables can be found in Appendix C with the Gini-coefficient as the dependent variable of primary interest. Added footnotes show inconsistencies in the respective log-odds value and HHI. While the former is widely consistent with the Gini-coefficient, the latter results in fewer regressors being significant and indicates that the respective factors do not affect the market concentration where the large firms-size class dominates. Deviations between Gini-coefficient and HHI can also be noted for the sample size class dummies (S20/…/S75), where the Gini-coefficient demands a downward and the HHI an upward correction to account for the potential bias. As predicted, the bias declines as the number of firms that make up a 4-digit industry increases and is independent from the estimator applied. It also suggests that 50 firm-level observations are sufficient to obtain a FSI proxy with negligible bias.

The year-dummies show significance from 2008 onwards and indicate increasing FSI during periods of recession. The time effects are consistent for all estimators and point in the same direction for all countries. Industry-specific characteristics are most relevant for Italy and are least significant for the UK, but become less significant under RE, where differences in industries are absorbed by the unobserved heterogeneity term. However, for Germany and Italy manufacturing continues to be significant. Despite the relevance of a considerable proportion of industry dummies of the Italian sample, they all imply a lower degree of FSI regardless of the estimator used. The effect is positive for Germany, but varies for the UK under OLS and FGLS, and turns into insignificance under RE unless in combination with HHI. The sign of the coefficients of the explanatory variables controlling for industry, firm structure, ownership and performance properties are consistent for all model specifications and all estimators and, when significant, show relatively small variations in the magnitude. This applies in particular to OLS and RE, which deliver the most reliable coefficients. The only exception is the proxy for labour productivity in Italy, where the value added per employee has positive effects when measured by the median (VAEMP_D) and negative effects when measured at aggregate level (VAEMP_G). This suggests that knowledge intensive industries lower FSI, but it is mainly large firms that engage in these activities, the effect of which is much stronger.

In general, main industry growth (GR_MAIN), industry age (AGE_MAX), MES (MES_REL) and a large proportion of firms with individuals as board members (TMTIND_EM), owner-managers (TMTSH_EM) and foreign-ownership (FOROWN_EM) show an ability to lower FSI. Also, excess capacity (STKTA_D/…_G) and labour productivity (VAEMP_D/…_G) bear the capacity to lower FSI. Initial market concentration (CR4EM), 4-digit industry growth (GR_FDIG), the presence of subsidiaries (SUBS_EM) and intangible assets (INTTA_A/…_G) unconditionally contribute to an increase in FSI for all countries. Increased FSI also originates from stagnating industries (STAGE_S) in Italy, regional distance (REG_N) in the UK, group affiliation (GROUP_EM) for firms located in Italy and Germany, fixed tangible assets (TANTA_G) in Germany, labour intensity (EMPTO_A/…_G) in the UK and Germany and export orientation (EXPTO_A) in the UK. Findings for R&D are weak, but this also exerts positive effects on FSI. Country-specific negative effects result for stagnating industries (STAGE_S) in Germany and regional distance (REG_N) in Italy, whereas group affiliation (GROUP_EM) in the UK, fixed tangible assets (TANTA_D/…G) in the UK and Italy, and labour intensity (EMPTO_D/…_G) in Italy are inconclusive.

The largest share of unobserved heterogeneity in the UK sample is incorporated in 4-digit industry growth (GR_FDIG), intangible assets (INTTA_G), labour intensity (EMPTO_G) and labour productivity (VAEMP_D/…_G). In Italy it is main industry growth (GR_MAIN), intangible assets (INTTA_G), excess capacity (STKTA_D/…_G), labour intensity (EMPTO_D/…G) and labour productivity (VAEMP_G), where unobserved factors influence the coefficients. Industry growth at the 4-digit level (GR_FDIG), fixed tangible assets (TANTA_G), intangible assets (INTTA_G) and excess capacity (STKTA_D/…_G) are also the factors bearing the largest of unobserved heterogeneity in the German sample. The significant impact unobserved heterogeneity has on the explanatory power of the independent variables is confirmed by the Wald chi2, which is highest for the extended models when unobserved heteroskedasticity is taken into account. It therefore affects the coefficient of critical explanatory variables and is in support of the estimates obtained from the RE estimator discussed in more depth in the next section.

Findings from the final model

Reducing the commented regression models by excluding the sample size dummies S60 and S75, limiting the industry dummies to manufacturing only and dropping TMTIND_EM[3] due to its high positive correlation with DMSH_EM, imposes additional restrictions. Although the Wald chi2 shows a decline in overall explanatory power – mostly for Italy, where industry dummies were most significant – the confirmation of significance and predicted sign confirm the values obtained even under more restrictive assumptions. Accordingly, the extended models (D-A and G) provide the best explanation of the factors affecting FSI. A summary of the regression analysis using the RE estimator applied to all sample countries is presented in Table 5.21.

The sample size dummies (S20/…/S50) maintain the predicted significance levels, but with a stronger decline in the coefficient as sample size increases. The effect of the bias can be best observed for Italy and is weakest for the UK, and the result of firm heterogeneity. The increase in FSI initiated by the economic shock in 2008 is strongest for Italy and increases until the end of the sample period. In terms of economic significance, it explains 2% of Italy's annual increase in FSI. As the constant degree of FSI in the UK is higher, the impact declines to 0.5%. In Germany, this effect becomes visible in 2009 only and exclusively in combination with the variables added to the extended models. The insignificance of these coefficients for FSI measured by the HHI supports the view that large firms are more capable of absorbing uncertainty as argued by Arrow (2000), Collins and Preston (1961), Drucker (1985) and Jovanovic (1982). From this point of view it is inconsistent with Acs *et al.* (1996), Gaffeo *et al.* (2003), Picard and Rimmer (1999) and Robson and Gallagher (1994), who predict a decrease in FSI.

[3] As noted earlier, TMTIND_EM is highly correlated with TMTSH_EM and causes multicollinearity, but in the absence of TMTSH_EM, TMTIND_EM results insignificant for any sample country when in combination with the Gini-coefficient

Table 5.21: Coefficients of the reduced model affecting firm size inequality

	UK			Italy			Germany		
Model	**BASIC**	**D-A**	**G**	**BASIC**	**D-A**	**G**	**BASIC**	**D-A**	**G**
Dependent variable*	GINI	GINI	GINI	GINI	GINI	GINI	GINI	GINI	GINI
S20	-0.0298[d]	-0.0272[d]	-0.0202[d]	-0.0682***[d]	-0.0687***[d]	-0.0607***[d]	-0.108***[d]	-0.0991***[d]	-0.101***[d]
S30	-0.0265[d]	-0.0268[d]	-0.0222[d]	-0.0286**[d]	-0.0294**[d]	-0.0240*[d]	-0.0848***[d]	-0.0756***[d]	-0.0760***[d]
S40	-0.0351*[f]	-0.0317*[f]	-0.0255	-0.0372***[d]	-0.0382***[d]	-0.0342***[d]	-0.0523***[f]	-0.0480***[f]	-0.0501***[f]
S50	-0.00654	-0.00546	-0.00637	-0.0260*[d]	-0.0261*[d]	-0.0277*[f]	-0.0573***[f]	-0.0510***[f]	-0.0545***[f]
YR08	0.00145[d]	0.00146[ad]	0.00129[ad]	0.00495***[f]	0.000668[e]	0.00787***[f]	8.88e-05	0.00132	0.00126
YR09	0.00445***	0.00376***	0.00345**	0.00758***[f]	0.00508**[f]	0.00987***	0.00213[a]	0.00366**[f]	0.00336**[f]
YR10	0.00386***	0.00339**	0.00340**[f]	0.00903***	0.00573**[f]	0.0115***	-0.000578	0.00176	0.00215
I_MAN	0.0219*[f]	0.0215*	0.0175[a]	-0.0108	-0.00818	-0.0105	0.0240**	0.0161*	0.0175*
GR_MAIN	-0.0146*[f]	-0.0154**[f]	-0.0162**[f]	-0.0422***	-0.0380***	-0.0431***	0.00201	0.00517	0.00430
GR_FDIG	0.0679***	0.0685***	0.0639***	0.0489***	0.0552***	0.0460***	0.105***	0.120***	0.121***
STAGE_S	-0.0105	-0.00496	-0.00491	0.0195**	0.0197**	0.0201**	-0.00621	-0.00744	-0.00784
CR4EM	0.313***	0.310***	0.302***	0.296***	0.299***	0.296***	0.391***	0.380***	0.389***
AGE_MAX	-0.0479**[f]	-0.0478**[f]	-0.0450**[f]	0.000160	0.000224	0.00145	-0.0256	-0.00683	-0.00590
MES_REL	-0.0373***	-0.0375***	-0.0373***	-0.0384***	-0.0389***	-0.0365***	-0.0326***	-0.0281***	-0.0277***
REG_N	0.00654*	0.00680*	0.00583*[c]	-0.00253*[f]	-0.00251*[f]	-0.00252*[f]	0.00140	0.00144	0.000629
TMTSH_EM	-0.0783***[f]	-0.0666***[f]	-0.0758***[f]	-0.0482**	-0.0433*	-0.0559**	-0.0516***[f]	-0.0524***[f]	-0.0516***[f]
FOROWN_EM	-0.135***	-0.128***	-0.118***	0.0390	0.0357	0.0388	-0.0165[e]	-0.0298[be]	-0.0267[be]
GROUP_EM	0.0393	0.0366	0.0384	0.0694**	0.0661**	0.0654**	0.0493**[e]	0.0545***[e]	0.0533***[e]
SUBS_EM	0.191***	0.182***	0.184***	0.119***	0.117***	0.122***	0.0679***[f]	0.0745***[f]	0.0713***[f]
TANTA_D/…_G		0.00686	0.00272		-0.00641	-0.0212		0.00515	0.0219*[c]
INTTA_A/…_G		0.0835	0.0558***		0.0387	0.0939*[f]		0.0309	0.0419**
STKTA_D/…_G		-0.0559**	-0.0129		-0.0234	0.0269[d]		-0.0226**[f]	-0.0380***[f]
EMPTO_D/…_G		0.0125	0.0537***		0.00193	0.00701		0.00719	0.00455
VAEMP_D/…_G		-0.00309[e]	-0.00423**		0.0142***	-0.00594**[f]		-0.00481	-0.00562***
RNDTO_A/…_G		0.0101	0.0925						
EXPTO_A/…_G		0.0274*	0.00571						
Constant	0.638***[bf]	0.663***[bf]	0.648***[bf]	0.483***[bf]	0.334***[be]	0.510***[bf]	0.643***[bf]	0.604***[bf]	0.593***[bf]
Observations	864	864	864	1,188	1,188	1,188	730	645	655
4-digit industries	96	96	96	132	132	132	146	129	131
R-squared	0.843	0.846	0.856	0.751	0.749	0.751	0.871	0.877	0.880
Wald chi2	647.06***	705.14***	764.81***	569.35***	612.97***	601.95***	1263.94***	1393.56***	1408.51***

Source of data: Modified from Orbis

*** p<0.01, ** p<0.05, * p<0.1

*) for full variable description see end of Appendix C3

BASIC = basic model, which excludes variables related to firm performance (FPER); **D-A** = extended model consisting of basic model and FPER-variables based on either median (D) or mean (A), whichever is appropriate; **G** = extended model consisting of basic model and FPER-variables based on aggregate values

a = significant **positive** at p<0.1 with log-odds ratio of Gini as dependent variable
b = significant **negative** at p<0.1 with log-odds ratio of Gini as dependent variable
c = **not significant** at p<0.1 with log-odds ratio of Gini as dependent variable

d = significant **positive** at p<0.1 with HHI as dependent variable
e = significant **negative** at p<0.1 with HHI as dependent variable
f = **not significant** at p<0.1 with HHI as dependent variable

No footnote = sign and significance at p<0.1 consistent with log-odds ratio of Gini and HHI as dependent variable

The reduction of industry dummies intended to separate manufacturing from non-manufacturing industries shows positive effects on FSI at the 0.1 significance level for the UK and Germany, suggesting that technology homogenizes firm sizes within the manufacturing industry as noted earlier by Pagano and Schivardi (2003). Although the impact of a single industry dummy turns into insignificance for Italy, the significant negative effect it had when all industry dummies were included indicates an upward correction too. Main industry growth (GR_MAIN) shows the strongest effects and highest significance levels for Italy and marginal yet significant effects for the UK, while being insignificant for Germany. It implies that in Germany growth opportunities are equal for all firm-size classes, whereas in the UK and in particular in Italy, SMEs benefit most from less fierce competition as predicted by Cassia and Colombelli (2010) and Ghosh (1975). Since main industry growth is associated with the pre-shakeout stage, collective learning (Jovanovic 1982; Peltoniemi 2011; Wennekers and Thurik 1999) contributes to the decline in FSI.

The impact of industry growth becomes positive when considered at the 4-digit level (GR_FDIG) and is strongest for Germany, followed by the UK and Italy. Although the coefficient of the 4-digit industry growth is at least three times the coefficient of main industry growth, it does not reject the view that SMEs have more opportunities to expand their operations, but indicates a separation of efficient and inefficient firms within a narrowly defined industry as competition increases. This is consistent with predictions from Bloch (1981), Cassia and Colombelli (2010), Dinlersoz and MacDonald (2009), Hariprasad (2011) and Peltoniemi (2011). The superior responsiveness to change of medium-sized firms, noted by Cassia and Colombelli (2010), is insufficient in reversing the trend.

As observed in the first part of the analysis (Table 5.4), the share of the largest firms experiences continuous grow in Italy, which persists even in industries with little or no growth (STAGE_S). It is a clear indication that the large share of Italian small firms face physical constraints in implementing and commercialising on process innovation and are eventually outperformed by larger firms as the battle for market share intensifies and co-operation ceases: a pattern described by Peltoniemi (2011) and Dinlersoz and MacDonald (2009). Even though the share of stagnating industries is nearly twice as high in Germany, such effects do not apply to Germany and the UK. It appears that surviving SMEs operating in mature industries are still competitive or decide to operate in niche markets unattractive for large firms, which reduces competitive pressures (Drucker 1985; Lenihan *et al*. 2010a).

Initial industry concentration (CR4EM) plays a considerable role in explaining the degree of FSI and confirms the presence of competitive forces and the vanishing middle, as predicted by Acs and Audretsch (1998), Baptista and Karaöz (2011), Ghosh (1975), Grass *et al*. (2012), Hariprasad (2011) and Wennekers and Thurik (1999). It demonstrates the superiority of large and fast growing firms in strengthening their market position (Arrow 2000; Axtell 2001; Drucker 1985; Löfsten and Lindelöf 2003; Pagano and Schivardi 2003; Rossi-Hansberg and Wright 2007; Storey 1994) and rejects Baptista and Karaöz's (2011) argument that smaller firms are allowed to co-exist in highly concentrated industries.

Industry age (AGE_MAX) does not alter the degree of FSI in Germany and also loses its negative significance in Italy for the reduced model, but maintains the significant negative effect for the UK ($p<0.05$) unless the dependent variable is determined by the HHI. This means that firms become more equal in size as an industry ages, which is consistent with Cirillo (2010), Cabral and Mata (2003), Collins and Preston (1961), and Kessides and Tang (2010). According to Pagano and Schivardi (2003), it also indicates easier access to knowledge and human capital. Given the predominance of large firms in the UK in mature industries, this finding is not unexpected. It contradicts the notion of ever increasing FSI when initial concentration is high and hence disagrees with Lucas (1978), Rossi-Hansberg and Wright (2007), Dinlersoz and MacDonald (2009) and Hariprasad (2011), who predict a general increase in FSI.

A negative and highly significant ($p<0.01$) coefficient for the MES proxy (MES_REL) for all sample countries confirms that SMEs are more competitive when entry barriers are low. This is in line with Cassia and Colombelli (2010) and Kessides and Tang (2010) and, consistent with Lotti and Santarelli (2004), signals that firms are not forced to exit, but staying operative at a low MES also indicates more intense competition. The MES is also important for firms operating in mature industries, where gains from product and process innovation have become marginal. The significance of MES_MEAN (not reported) reveals that a higher mean firm size increases FSI and confirms that the MES acts indeed as an entry barrier in favour of the large scale firm, which is consistent with Hariprasad (2011). Accordingly, a low MES preserves the presence of SMEs and comes closer to the assumption that all surviving firms operate at or above the MES as stated by Barbosa and Eiriz (2010), Bloch (1981) and Simon and Bonini (1958). Nevertheless, the view that a high MES impedes smaller firms in achieving the productivity levels of large firms (Acs *et al*. 1996; Gil 2010; Pagano and Schivardi 2003; Praag and Versloot 2007), cannot be rejected.

In contrast to all other dimensions, the effect of regional industry concentration (REG_N) varies most across countries. Whilst being insignificant for Germany, it enhances FSI in the UK and lowers FSI in Italy. The reconciled predictions are more in favour of the UK, where firms either operate in isolation with little co-operation or regional concentration allowing them to mutually benefit from the advantages associated with clusters. The significance level shrinks to 0.05 when the logarithm of the number of regions is used and indicates that only for a few industries are British firms spread across many regions, while the majority are geographically concentrated. Hence, regional concentration offers a competitive advantage as argued by Audretsch and Feldman (1999), Buckley (2010), Boschma and Wenting cited in Peltoniemi (2011), Iammarino and McCann (2006), Pagano and Schivardi (2003), Porter and Stern (2001) and Teruel-Carrizosa (2010a). Due to additional growth opportunities (Baptista and Swann 1998), firms become more homogeneous in size.

The same phenomenon was expected for Italy, because everything else is in contradiction with its national context. Instead, coefficients are insignificant when FSI is measured by the HHI and it can be concluded that the observed effect originates from small rather than large firms. Compared to the UK, the variance in the number of regions is smaller with little regional specialisation. One explanation is that a large proportion of relatively small firms serve their local market, which would set a definite upper limit to firm size. An alternative explanation is that firms located in regional clusters produce a diverse firm population, including gazelles, which, according to Henrekson and Johansson (2008) and Picot and Dupuy (1998), emerge across all firm-size classes. By being outperformers, the presence of gazelles generates the observed degree of firm size heterogeneity, sustained by co-operation rather than competition. However, the low p-value of 0.1 supports Audretsch and Thurik (2000) and Santarelli (2006b), who predict a decline in the importance of clusters when combined with Audretsch and Feldman’s (1999) and Iammarino and McCann’s (2006) assumption of weak knowledge intensity.

The superiority of owner-managers (TMTSH_EM) in the context of SMEs applies to all countries, but significance levels are weaker for Italy, while for the UK and Germany the coefficients become insignificant when in combination with the HHI as a dependent variable. It suggests that owner-management is only efficient up to a critical level, which has been described as the firm size limit imposed by the entrepreneur capacity (Casson 1987; Knight cited in Praag 1999). Above this said level, the structured enterprise appears to operate as well as the owner-managed firm. However, as long as the owner-manager stays within the boundaries, owner-managed firms achieve the highest levels of managerial efficiency, which is in accordance with the theories of Arrow (2000), Casson (1987), Drucker (1985), Knight cited in Praag (1999) and Mises (1951), and the empirical work of Carree *et al*. (2002) and Voulgaris *et al*. (2005). Unlike in the UK and Italy, where the presence of owner-managers can be associated with individuals being appointed as board members, the correlation of non-individual board members and owner-managers in Germany [4] has rather positive effects on firm performance, leading to an additional advantage. Such findings are observed by Carter *et al*. (2010) and Dore (2000).

[4] The negative correlation of TMTSH_EM and TMTIND_EM was noted when assessing the correlations of firm-structure variables

FSI also declines with an increase in foreign-owned firm presence (FOROWN_EM), but varies across countries. The coefficients are highly significant ($p<0.01$) for the UK, where about a fourth of all sample firms are foreign-controlled, whereas it is about 7% in Italy and Germany. It might explain the insignificance for Italy and the weak significance for Germany, where coefficients are only significant when the dependent variable is either the log-odds ratio of the Gini-coefficient or the HHI. However, the direction in which FSI shifts when the share of firms owned by foreigners increases within an industry suggests that foreign-owned firms provide an incentive for domestic firms to grow and assimilate (Liu and Li 2012; Nocke and Yeaple 2008; Pant and Pattanayak 2005) and potentially benefit from positive spill-overs as predicted by Acs (2006), Barbosa and Eiriz (2010), Bellandi and Caloffi (2010), Buckley (2010) and Stöllinger (2013).

In accordance with expectation, firms that are part of a group (GROUP_EM) or controlling subsidiaries (SUBS_EM) contribute to an increase in FSI by being able to grow faster (Mata and Portugal 2004; Santarelli 2006b; Storey 1994; Teruel-Carrizosa 2010a) and are more efficient (Baptista and Karaöz 2011) and flexible (Arrow 2000; Sutton 1997) when specialised. The effect originating from the presence of subsidiaries generally exceeds the benefits firms get from being part of a group, but the latter does not apply to the UK and could be attributed to the headquarters effect, i.e. being the home of a large share of multinational firms does not give any additional advantage.

Variables related to structural assets and operational efficiency show less consistency across the different model formulations, but nevertheless allow some conclusions to be made. The implications of tangible assets (TANTA_D/…_G) on FSI are weak for all sample countries and merely show a positive effect for Germany at the 0.1 significance level when aggregate data is used, i.e. the sum of tangible assets of all firms within an industry over the sum of total assets of all firms. The efficiency of using tangible assets as an entry deterrent as argued by Acs *et al*. (1996), Ghosh (1975) and Mata and Portugal (2004) can therefore be questioned. Such effects may be offset by newer technologies (Grass *et al.* 2012; Pagano and Schivardi 2003), while market structures in investment-intensive industries in developed countries might have achieved the natural distribution. More significant is the positive effect that intangible assets (INTTA_A/…_G) have on FSI, but only when aggregated. This applies to all sample countries and is consistent with Hariprasad (2011) and Teece (1998), who identified intangibles as an effective entry deterrent. According to Hariprasad (2011), it also reflects the degree of diversification, which coefficients resulted insignificant, and for the same reason increases FSI. In contrast, excess capacity (STKTA_D/…_G) lowers firms size inequality and indicates a process of downscaling in the UK and Germany, while providing lean SMEs an opportunity to operate more efficiently. It is consistent with the flexibility Cassia and Colombelli (2010) and Pinder (1998) attribute to SMEs.

Labour intensity (EMPTO_D/…_G), which applies most to service industries and comprises the largest share in the UK, is more likely to cause an increase in FSI, but not so for Italy and Germany. For the latter, a significant negative impact was found before restricting the model. These results are in line with Rossi-Hansberg and Wright (2007), who argue that labour intensity is less scale dependent and therefore results in a lager variance in firm growth rates, where gazelles may cause the observed increase in FSI. The opposed effect results for labour productivity (VAEMP_D/…_G), implying a clear decline in FSI for the UK and Germany when aggregating the data. The result suggests that knowledge intensive industries are characterised by a more equal size distribution (Bartelsman *et al*. 2005; Pagano and Schivardi 2003), because economies of scale can be offset (Audretsch and Elston 2006; Voulgaris *et al*. 2005). Once more, Italy deviates from the norm by showing an increase in FSI when in combination with the median labour productivity. The resulting contradiction with the significant negative coefficient from the aggregate variable is an indication that, although knowledge intensity assists in offsetting economies of scale, not all firms are able to engage with and commercialise on technological sophistication. However, those who do are able to outperform the rest, and therefore produce an increase in FSI.

With regard to R&D (RNDTO_A/…_G) and export orientation (EXPTO_A/…_G) of British firms, a positive coefficient results only for mean export. Although the significance is rather weak for the Gini-coefficient ($p<0.1$), it increases to $p<0.05$ for log-odds ratio and HHI. The assumption that large firms benefit most from exporting as stated by Becchetti and Trovato (2002), Hariprasad (2011) and Lenihan *et al*. (2010b) can be confirmed. However, also SMEs engaged in exporting activities might add some weight to increasing FSI as this enables them to grow faster (Teruel-Carrizosa 2010a) than non-exporters. Consistent with Görg and Strobl cited in Buckley (2010), Larrea *et al*. (2010) and Voulgaris *et al*. (2005), it suggests that they are able to avoid competition in their home market, whilst increasing their efficiency, as argued by Nocke and Yeaple (2008), Santarelli (2006b) and Zhou (2010).

5.2.4 Conclusions

This chapter aimed to empirically analyse the extent to which the SDOF changed (RQ1) and to identify the determinants of FSI (RQ2). Among the analysed countries, i.e. the UK, Italy and Germany, the emergence of the missing middle is most visible for Italy. Its degree of FSI increased over the sample period in both manufacturing and non-manufacturing industries. For the UK and Germany, only marginal changes were observed, but a decrease in FSI in the UK's manufacturing industries suggests consolidation. The changes in FSI are amplified when breaking the analysis down into industry sections. Once more, increases occur most frequently in Italy across all industries, but the pattern is less clear for the UK and Germany. An explanation of the logic that industries follow is provided by the lognormality test. It revealed that the SDOF of industries follows a lognormal distribution when achieving the stage of consolidation. As this lifts the MES, firms below said scale become uncompetitive. In Italy, where the average firm is substantially smaller than in the UK or Germany, this leads to the observed increase in FSI and hence the emergence of the missing middle. In the UK and Germany, manufacturing industries are more dynamic than in Italy, but non-manufacturing industries approach the lognormal distribution quicker. This means that growth is less a function of firm size and that factors other than firm size drive the change in FSI.

The findings from the regression analysis, which addresses RQ2, confirm the industry and country-specific nature of the degree of FSI. In contrast to previous studies, macro-economic shocks increase rather than decrease FSI. This is because large firms are better able to withstand uncertainty and buffer shocks than SMEs and, therefore, have a higher chance of survival. Industry-specific parameters can be categorised as the pre-shakeout, shakeout and post-shakeout stage. Main industry growth, most likely to occur during the pre-shakeout stage, reduces competitive pressures and suggests that firms benefit from collective learning. Although competition dominates within narrowly defined industries and defines which firms move upwards and downwards in the firm-size class hierarchy when the shakeout takes place, export orientation provides additional growth opportunities, but is in favour of large firms. The findings suggest that only in Italy do small firms continue to shrink even after the shakeout. The static nature of the small business sector indicates a lack of engagement in new product development or an inability to commercialise on it, with firm size being a threat to benefit from economies of scale. It also appears that said firms fail to achieve a competitive scale or to find their niche market, which altogether accelerates the emergence of the missing middle.

Low entry barriers in terms of MES are in favour of SMEs, where those with lean structures may get a competitive advantage when a surplus of capacity emerges, but even more so if labour productivity is high, i.e. knowledge and technology intensive. Consistent with this argument is the replacement of tangible assets as an entry deterrent by intangible assets. The benefits of being in control of subsidiaries exceed those of being part of a group, but firms led by owner-managers operate at a higher efficiency level. In Germany, the presence of non-individuals in the boardroom contributes to firm growth. Positive effects also come from the presence of foreign-owned firms, as they contribute to less FSI and hence indicate positive spill-over effects and give domestic firms an incentive to compete and catch up. Finally, being part of a regional cluster pays off, however, to a smaller extent than would have been expected. There is also an indication of the presence of gazelles in said clusters. These add diversity rather than homogeneity to the firm population and might contribute to innovative capacity.

Not all dimensions that were expected to have a significant impact on FSI entered into the final analysis, while others were replaced by alternative variables leading to less noise and higher joint significance. The insignificance of all diversification proxy combinations was to some extent replaceable by intangible assets. Not so for the liquidity ratios, which remained insignificant and hence do not affect FSI. Despite being consistent with studies supporting the view that smaller firms do not face liquidity constraints, it also indicates a more complicated mechanism, the analysis of which is beyond the scope of this work. Nonetheless, the highly significant impact of 4-digit industry growth reflects the competition for resources, including the competition for financial resources. Thus, the observed increase in FSI resulting from said industry growth is not just the product of the shakeout, but also reflects the ability of firm-size classes in accessing the necessary resources for expanding their operations.

The insights the analyses of RQ1 and RQ2 demonstrate that the SDOF is determined by systemic and non-systemic factors, internal and external to the firm. The distribution it eventually follows is predetermined and turns firm growth into a random process. The entrepreneur is then subordinated and without being in possession of substantial resources s/he will be unable to disrupt existing structures. Hence, once the SDOF reaches this final stage, it cannot be reversed. By using FSI to monitor the evolution of the SDOF, the forces causing its change were identified. This allows for a systemic intervention in the evolution of industries and to delay the emergence of the missing middle. Even in mature industries, where knowledge and human capital is less distinct, operational efficiency increases as long as a minimum of competitive forces are active. However, competition is unlikely to persist when FSI converges to extreme levels and eventually tacit co-existence takes over. The resulting consequences do not end at the industry boundaries and have implications at a larger scale. On the assumption that extreme FSI is inferior to a moderate degree of FSI, it is hypothesised that the peripheral effect emerging from interactions of firms different in size has implications on welfare. These are evaluated in Chapter 6, which closes with a discussion on the issues that arose from the empirical findings.

CHAPTER 6: IMPLICATIONS

The hypothesised existence of a link between FSI and welfare has led to four key dimensions indirectly associated with it: innovative capacity, economic resilience, net job creation and sustainability. Before presenting the respective empirical work, the focus is directed on the association of FSI with conventional welfare indicators. This requires moving from industry to economy level and the extension of the sample size to the EU27. It is admittedly superficial, but gives a first idea of meaningful proxies associable with specific firm-size classes. The key variables are monitored by the EC, which gives policy makers clear direction, and also provides useful data for future research. It further assists in providing a more comprehensive discussion on the matter of FSI as a whole, which is covered in the second part of this chapter. In the context of contemporary challenges, it links empirical findings with the theoretical foundations of economic activity discussed in Chapter 2. This draws back to the origins and the motivation of the research, which is the interaction of FSI, innovation and sustainability.

6.1 Firm size inequality and welfare

The most intuitive variables identified as being associated with welfare in the broadest sense are happiness, life satisfaction and opportunities. In the context of the present work, the latter refers to opportunities related to entrepreneurial activity, which has indirect implications on the former two, as was noted in the literature review. The experimental stage of this data bears methodological inconsistencies. It adds to the large number of factors affecting subjective well-being and makes it difficult to interpret any statistically significant correlation.

The correlation coefficients presented in Table 6.1 do not show any eminent link between overall happiness levels and any of the defined firm-size classes.

However, life satisfaction is higher for countries with a larger share of large firms and lower for countries with many micro firms. Since these findings are not confirmed by the EU15 sample, the significant correlations are likely to be the result of different economic stages as indicated by Acs (2006). Nevertheless, economies – also those of the EU15 – with a large number of small businesses are characterised by fewer possibilities to seize opportunities and entrepreneurial activities. This refers in particular to southern European countries, where small and micro firms dominate, as identified in the previous chapter and stated by Pagano and Schivardi (2003) and Stenkula (2007).

Table 6.1: Firm size inequality, happiness, life satisfaction and opportunities

Median firm-size class employment share	**EU15**			**EU27**		
	Happiness	Life satisfaction	Entrep. & Opportunity	Happiness	Life satisfaction	Entrep. & Opportunity
Micro firms	-0.5156	-0.5574	-0.9419***	-0.2750	-0.3600	-0.4813**
Small firms	0.2772	0.2943	0.3065	0.0796	0.0433	0.1136
Medium firms	0.3181	0.4334	0.7590***	-0.1336	-0.0186	-0.0030
Large firms	0.4822	0.4924	0.8227***	0.3089	0.3841*	0.5220***
Gini-coefficient	-0.4755	-0.5154	-0.7560***	0.0969	0.0229	-0.1103

Sources of data: Modified from European Social Survey (round 4) and The 2012 Legatum Prosperity Index

*** p<0.01, ** p<0.05, * p<0.1

In contrast, a large share of medium and large firms can be associated with higher levels of entrepreneurship and opportunities, presumably originating from spill-overs and spinoffs. Despite neglecting institutional effects, the reported Gini-coefficient confirms the hypothesis that higher FSI leads to lower levels of entrepreneurial activity and opportunities. Given that large firms lead in advanced technology and knowledge accumulation (Drucker 1985; Pagano and Schivardi 2003; Rossi-Hansberg and Wright 2007), the presence of the next smaller scale of firm-size class is essential to absorb the resulting spill-over effects. The assumption that excessive gaps in technology and knowledge between firm-size classes impede any transfer, as found by Buckley (2010), Liu (2008), Stöllinger (2013) and Wang and Wong (2012), can therefore be supported.

When linking FSI with derivatives of GDP, knowledge, sustainability and unemployment, many more significant associations with firm-size classes emerge, as shown in Table 6.2. Material well-being, measured by GDP per capita at purchasing power standard, is lowest where a large share of micro firms dominates and reflects the inefficiencies Carree *et al*. (2002) observed in Italy. These effects are persistent for economic growth and recovery. In EU15 countries, medium-sized firms add most to GDP per capita, but in the event of a recession, the impact on GDP is highly influenced by the share of the largest firm-size class. In an EU27 context, medium-sized firms show the strongest ability to buffer economic shocks and can be associated with economic growth, which however, cannot be confirmed for the EU15.

Table 6.2: Firm-size classes, GDP, knowledge, sustainability and unemployment

Median firm-size class employment share	GDP per capita at purchasing power parity	GDP per capita at purchasing power parity in 2008	GDP growth rate	Patent applications	Share of medium and high-technology firms	Share of knowledge-intensive firms	ANS including CO_2 emissions	Unemploy-ment rate
	EU15							
Micro firms	-0.5004***	-0.6757***	-0.1659**	-0.6878***	-0.3029***	-0.7214***	-0.6380***	0.4772***
Small firms	0.2424***	0.3919***	-0.0134	0.1464*	0.1004	0.0101	0.2705***	-0.1908**
Medium firms	0.6623***	0.4503***	0.1404*	0.4727***	-0.0052	0.4723***	0.6475***	-0.4554***
Large firms	0.3107***	0.6355***	0.1644**	0.6699***	0.3765***	0.7547***	0.4816***	-0.3839***
Gini-coefficient	-0.4665***	-0.6031***	-0.1104	-0.5027***	-0.1405*	-0.4587***	-0.6716***	0.3863***
	EU27							
Micro firms	-0.2104***	-0.5295***	-0.1800***	-0.3756***	-0.2289***	-0.3136***	0.1632**	0.1777***
Small firms	0.1163**	0.2408**	-0.0231	0.0716	-0.3105***	0.0972*	0.2077***	-0.1402**
Medium firms	-0.0767	0.5116***	0.2658***	-0.1387**	-0.1218**	-0.1324**	-0.0912	-0.0530
Large firms	0.2404***	0.3148***	0.1002*	0.4878***	0.4652***	0.3992***	-0.2384***	-0.1293**
Gini-coefficient	0.0249	-0.4726***	-0.1077*	-0.0261	0.0946*	-0.0259	-0.3285***	0.1751***

Sources of data: Modified from Eurostat and World Bank *** p<0.01, ** p<0.05, * p<0.1

When looking at innovative capacity, a major contributor to long-term prosperity, it is not so surprising that patent application submissions increase with firm size. However, taking into account that independent medium-sized firms might be disadvantaged in protecting their IP (Praag and Versloot 2007; Santarelli 2006b), patent applications submitted by EU15 medium-sized firms are at a competitive level. This is unexpected, because the uncertainty involved in successful commercialisation increases as firm size declines, especially when process related (Buesa *et al*. 2010). In contrast, medium-sized firms in East Europe do not result as technology holders. In both manufacturing and service sectors, the technology and knowledge leaders are most likely large firms. Medium-sized firms struggle to keep pace with sophisticated manufacturing technologies, but those operating in service industries are able to benefit from knowledge intensity. This confirms the effectiveness of technological sophistication as a barrier of entry observed by Bruland and Mowery (2009) and the negligible importance of economies of scale in the service industry noted by Rossi-Hansberg and Wright (2007), enabling equal growth opportunities.

As Schumacher (1973) stated, the small business is by nature unable to systematically degrade the environment as much as the large firm can. For EU27 countries, it seems indeed that large firms contribute more to environmental degradation than any other firm-size class, but the correlation remains weak. The picture reverses for the EU15 sample, where micro firms are negatively correlated with ANS, while medium-sized firms contribute most to sustainability. As an indicator for sustainability, ANS is influenced by a number of issues and in particular national legislation, but there is no evidence that SMEs impose a threat to environmental goals. A special role is attributed to micro firms. The negative impact this size class causes suggests rather that the political agenda of countries with a large share of micro firms – an indication of economic backwardness – differs from those with a more balanced share across firm-size classes. Sustainability is less of an issue of primary interest and this too confirms Gray and Eid’s (2005) lack of environmental awareness of micro firms.

In fact, the share of micro firms is also positively correlated with the unemployment rate, while all other firm-size classes show significant correlations in the opposite direction. The resulting propositions are, therefore, that: 1) unemployment increases the number of micro-businesses with an increase in necessity entrepreneurship, which in many cases fail or results in low or no firm growth and hence also negligible net job creation as noticed by Davis *et al*. (1996); and 2) that the young, perhaps also less qualified workforce, is absorbed by the small and micro firm sector (Pinder 1998; Storey 1994), whereas large firms are in a position to ‘cherrypick’ the most talented. A more detailed analysis follows in the sequence outlined in the introduction of this chapter, which also comments on the exclusion of happiness, life satisfaction and entrepreneurial opportunities from further analytical examination.

It can however be concluded that the economic stage plays an important role in determining the extent to which SMEs contribute to an economy's performance. The magnitude of the share of medium-sized firms in West Europe adds to welfare, sustainability and unemployment, and outperforms all other firm-size classes in GDP per capita, while demonstrating competitiveness in innovative capacity and buffering economic shocks. The properties of small firms are closer to those of medium-sized firms than those of micro firms and hence are in a transitional stage. Although being an approximate measure for FSI and ignoring inter-industry effects, the Gini-coefficient supports these findings and indicates significant negative implications resulting from firm size polarisation across all dimensions.

6.1.1 Innovative capacity

The regression analysis presented in Appendix D shows the implications of FSI on innovative capacity. It is based on the regression model described in section 4.4.1 and confirms the high discrepancy in patent applications between EU15 countries and Eastern European countries summarised in Table 6.3. Although the application rate between these two groups converges, the mean of EU15 countries exceeds the mean of East European countries by the factor 11. This suggests that growth in industrialised countries relies indeed on technological sophistication as identified by Porter and Stern (2001), which might be influenced by the demand for higher living standards as hypothesised by Buesa *et al*. (2010). While Slovenia outperforms other Eastern European countries, Portugal and Greece are the underperformers among the EU15 group, followed by Spain. Although substantially different in firm-size class structure, the UK and Italy are characterised by similarly low levels of patent applications due to the large micro-business sector in Italy and the large service sector in Britain.

Table 6.3: Patent applications made to the EPO from 2002 to 2011 per million labour force

EU15					Non-EU15				
	Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
Austria	366.58	35.031	307.67	421.85	Bulgaria	4.89	1.722	2.21	7.94
Belgium	302.76	24.034	260.57	336.55	Cyprus	29.13	12.291	16.86	48.99
Denmark	384.91	34.631	323.31	437.57	Czech R.	26.50	9.159	12.99	39.73
Finland	500.89	28.843	458.35	554.12	Estonia	34.67	27.741	8.42	85.23
France	297.66	9.604	281.22	306.92	Hungary	36.66	6.840	24.09	44.69
Germany	558.90	17.243	526.93	584.06	Latvia	12.33	5.067	4.65	18.74
Greece	17.85	3.114	12.24	22.85	Lithuania	5.46	2.748	1.64	10.30
Ireland	140.55	16.087	118.09	169.65	Malta	39.20	12.374	25.06	70.09
Italy	180.80	15.348	154.14	204.50	Poland	10.19	6.138	2.51	21.07
Luxembourg	399.12	109.426	231.91	582.99	Romania	2.31	1.043	0.53	3.37
Netherlands	406.58	32.074	369.83	473.72	Slovakia	10.19	3.432	4.34	15.26
Portugal	14.56	5.446	7.60	22.17	Slovenia	100.30	27.899	52.24	133.79
Spain	59.14	8.440	45.69	70.57					
Sweden	504.93	40.465	444.76	571.15					
UK	182.19	15.723	157.10	210.52					

Source of data: Modified from Eurostat

The impact of knowledge intensive services on patent applications is substantially lower than the influence originating from medium and high-tech manufacturing firms and becomes stronger as firm size increases. Due to the low patent application rate of Eastern Europe, the coefficient for medium and large firms is negative, however would be positive if the sample consisted of EU15 countries only. Consistent with the theoretical prediction, adding medium-sized firms to the employment share of large firms lowers the negative impact on patent applications. But the positive influence of medium-sized firms loses strength when unobserved heterogeneity is taken into account.

The Gini-coefficient based on employment share confirms the observed pattern, but remains insignificant. Yet it becomes significant when replacing the firm-size class share measured by employment with value added, which takes knowledge intensity into account. The assumption that economies with a larger share of value added by small businesses is associated with more patent applications seems intuitive. Although not explicitly reported, the pattern is confirmed by the EU15 countries and large firms are the only group undertaking systematic R&D, which is much in support of Schumpeter (1947).

Neither impressive are East Europe's small and medium-sized firms with regard to innovative capacity. It is rather the micro firm, capable of generating a high degree of added value, which defines this pattern. The hypothesis that a higher degree of FSI lowers innovative capacity can therefore not be confirmed unconditionally. The conclusions that can be drawn are first that the economic stage has a considerable influence in determining the source of innovative capacity. This is consistent with the previous section. Second, in industrialised economies, large firms are the main contributors of patent applications, while it is the micro firm in transitional economies, where the negative effects of FSI on innovative capacity appear stronger. The latter confirms to some extent the benefit of entrepreneurial activity advocated by Audretsch and Thurik (2001).

However, it is worth noting that large, multinational firms in central Europe have an interest and the resources to contribute to a high number of patent applications. The limited contribution of medium-sized firms to innovate capacity suggests that they take on the role of a follower and that innovations are mainly delivered by outperformers. The superiority of large firms in achieving technological leadership is consistent with Pagano and Schivardi (2003) and Praag and Versloot (2007) and the significance of the Gini-coefficient demonstrates that firm size diversity increases innovative capacity as found by Agrawal *et al*. (2012), Audretsch and Thurik (2001) and Wennekers and Thurik (1999). These findings are further supported by taking into account the observed time-lag associated with spill-overs (Baptista *et al*. 2008).

6.1.2 Economic resilience

The estimates resulting from the regression model presented in section 4.4.2 attribute the most significant impact on production output to medium and large firms. Since the panel dimensions of the previous model, country and time, are replaced by industry and country, a regression analysis was performed for each year from 2007 to 2010. The UK, with an exceptionally large proportion of large firms, and Luxembourg and Greece who differ from their neighbours in economic activity and stage, had to be excluded from the analysis. However, the UK and Luxembourg are treated as a distinct sample, but with a considerably lower number of observations, which deflates the accuracy of the estimated coefficients.

Table 6.4: Firm size inequality and production output by value added

Employment share base year 2005	**Production output in …**			
	2007	2008	2009	2010
EU15				
Medium firm share	0.0361	-0.206	0.160	0.272
F-statistics	113.46***	100.69***	109.73***	105.99***
Medium & large firm share	0.914***	0.612***	0.478*	0.507*[d]
F-statistics	109.95***	139.05***	146.00***	141.81***
Large firm share	0.831***	0.778***	0.446[e]	0.462[eh]
F-statistics	120.21***	139.44***	142.49***	141.98***
EU15 without UK, Luxembourg and Greece				
Medium firm share	1.262*	1.157**	1.463***	1.724***
F-statistics	152.88***	133.75***	128.79***	118.04***
Medium & large firm share	0.995***	0.699**	0.711**	0.731**[d]
F-statistics	118.16***	176.49***	179.06***	168.00***
Large firm share	0.662**	0.493*[c]	0.356	0.324
F-statistics	103.46***	155.29***	156.15***	151.40***
UK & Luxembourg				
Medium firm share	-1.432	-4.030***	-3.316**[cg]	-3.543**[cg]
F-statistics	130.10***	100.97***	116.86***	115.88***
Medium & large firm share	2.553***	0.693[ae]	-0.0198	-0.00968
F-statistics	147.47***	139.17***	151.82***	150.94***
Large firm share	2.966***	1.906**	0.961	1.032
F-statistics	251.19***	193.62***	188.52***	191.05***
Non-EU15				
Medium firm share	-0.123	-0.146	-0.358	-0.289
F-statistics	131.11***	111.89***	144.74***	177.92***
Medium & large firm share	2.000***	1.983***	1.988***	2.000***
F-statistics	114.51***	81.20***	91.59***	88.12***
Large firm share	1.783***	1.675***	1.726***	1.706***
F-statistics	104.96***	82.58***	96.70***	87.68***

Source of data: Modified from EC SME Performance Review *** p<0.01, ** p<0.05, * p<0.1

a = significant positive at p<0.1 with base year 2006
b = significant negative at p<0.1 with base year 2006
c = not significant at p<0.1 with base year 2006
d = lowest value with base year 2006
e = significant positive at p<0.1 with base year 2007
f = significant negative at p<0.1 with base year 2007
g = not significant at p<0.1 with base year 2007
h = lowest value with base year 2007

No footnote = sign and significance at p<0.1 consistent with base years 2006 and 2007

The results presented in Table 6.4 confirm the heterogeneity of countries belonging to the EU27 when it comes to economic stage and industry composition. According to the EU15 sample, medium-sized firms do not have any significant impact on output unless merged with the large firm share. As one would expect, production output peaks in 2007 and drops in the following years. The magnitude by which output declines differs among size classes and becomes more evident when excluding the UK, Luxembourg and Greece from the EU15. The change in output is greater for the large firm share than for the medium firm share, with the lowest values in 2008, suggesting a higher job destruction rate originating from large firms when adjusting to new conditions as argued by Davis *et al*. (1996). However, in the years 2009 and 2010, medium-sized firms show a uniform and strong ability to recover from the recession, while large firms differ in their ability to respond to external forces.

The ability of smaller firms to increase efficiency (Dhawan 2001) and the inability of large firms to quickly address the resulting diseconomies of scale when abnormal changes in demand occur (Carree and Thurik 1998; Pinder 1998), attributes a particular function to the medium-sized firm class. Their role to act as a buffer for economic shocks enables economic resilience and prevents a decline in output as it would take place in the absence of a significant share of medium-sized firms. Especially in the UK, where the average employment share of large firms across industries exceeded 50% in 2005, output in production attributed to both large and medium firm share is significantly higher than in any other European country. The coefficients obtained from the sample of British and Luxembourgian industries support the hypothesis that medium-sized firms contribute to economic recovery as advocated by Audretsch and Thurik (2001) and Robson and Gallagher (1994), but also indicate that achieving pre-crisis output levels remains challenging.

One aspect of that might be the lack of attention medium-sized firms get from the public (Arrow 1962; Buigues and Sekkat 2009). Second, particularly in recessionary times, liquidity constraints are higher for SMEs, who also have little opportunity to reallocate their resources (Arrow 2000; Larrea *et al*. 2010; Löfsten and Lindelöf 2003; Storey 1994). Large firms are able to sell off and restructure inefficient business units, whereas medium-sized firms are limited in their ability to respond to growth opportunities (Drucker 1985). Third, the contribution to production output added by the said firm-size class is negative throughout the sample period, which suggests inefficiencies and an inability to compete with their larger counterparts. Since medium-sized firms find it difficult to outperform large firms, they may not wish to enter into the spiral of competition, as found by Audretsch *et al*. (1999). Quite different is the picture for member states that joined the EU since 2004. The medium-sized firm share is not as important as it is for more advanced economies, but contributes to a stable output in production and is further evidence that medium-sized firms buffer economic shocks and accelerate recessionary recovery. Hence, pre-industrialised countries rely more on large, potentially foreign-owned firms as they benefit from low labour costs at a larger scale than firms in industrialised countries. However, the latter can benefit from a flexible share of medium-sized firms.

6.1.3 Net job creation

To examine the relationship between firm-size classes and net job creation, the initially discussed unemployment rate is replaced by the firm-size class specific employment share using the dynamic classification approach discussed in section 4.4.3. Starting from the net job creation rates at the aggregate level, the values presented in Table 6.5 indicate that the EU27 generally follow the same trend of the EU15 community. Although the approach to calculate the net job creation rate is consistent with Wit and Kok (2014), the disruptive economic conditions cause considerable fluctuations over the sample period. It therefore makes little sense to consolidate the net job creation rates to an average figure, but to categorise the sample into pre- and post-crisis periods, i.e. 2004-2007 and 2010-2012 respectively. The years 2008 and 2009 are those with the greatest negative change and, where net job creation rates are still positive, rates are close to the mean of the pre-crisis period.

Table 6.5: Aggregate net job creation in percent by firm-size class

	Year	Manuf. share	Micro	Small	Medium	Large
EU15	2004	25.2	0.25	3.14	1.20	1.22
	2005	24.4	2.63	1.44	1.50	0.96
	2006	23.6	2.63	3.09	2.40	1.26
	2007	23.0	1.70	2.08	3.67	3.26
	2008	21.1	-2.57	-0.13	2.88	2.63
	2009	20.3	0.05	-0.45	-3.55	-3.75
	2010	19.9	-0.61	-2.14	0.36	-1.92
	2011	19.7	-0.36	-0.38	0.06	0.86
	2012	19.6	0.23	-0.09	-0.08	0.04
	Variance:	0.0484	0.0277	0.0324	0.0451	0.0472
	Mean 2004-2007:	24.1	1.80	2.44	2.19	1.67
	Mean 2010-2012:	19.7	-0.24	-0.87	0.11	-0.34
Non-EU15	2004	33.8	1.62	4.52	2.46	-2.01
	2005	32.8	1.17	2.65	2.35	0.07
	2006	32.0	2.23	4.59	4.13	1.33
	2007	30.8	3.82	5.05	4.37	2.77
	2008	28.6	3.33	5.84	3.00	2.18
	2009	27.3	-9.07	-6.10	-7.15	-5.30
	2010	27.1	2.19	-2.52	-1.61	-4.29
	2011	27.0	0.59	-1.26	-1.37	-0.29
	2012	26.9	-0.17	0.30	-0.35	-0.12
	Variance:	0.0777	0.1481	0.1681	0.1358	0.0766
	Mean 2004-2007:	32.4	2.21	4.20	3.33	0.54
	Mean 2010-2012:	27.0	0.87	-1.16	-1.11	-1.57
EU27	2004	29.1	0.51	3.35	1.48	0.65
	2005	28.2	2.35	1.63	1.68	0.80
	2006	27.3	2.55	3.32	2.79	1.27
	2007	26.4	2.11	2.56	3.83	3.17
	2008	24.4	-1.38	0.88	2.91	2.55
	2009	23.4	-1.66	-1.36	-4.33	-4.02
	2010	23.1	-0.07	-2.20	-0.06	-2.32
	2011	23.0	-0.18	-0.52	-0.25	0.67
	2012	22.9	0.16	-0.02	-0.14	0.01
	Variance:	0.0605	0.0242	0.0409	0.0598	0.0505
	Mean 2004-2007:	27.7	1.88	2.71	2.44	1.47
	Mean 2010-2012:	23.0	-0.03	-0.92	-0.15	-0.55

Source of data: Modified from EC SME Performance Review

The calculation of the net job creation rate is consistent with Wit and Kok (2014), i.e. net job creation to total employment. The manufacturing share is the mean manufacturing share of all countries belonging to a sample group.

The hypothesis that net job creation decreases with firm-size class as found by Wit and Kok (2014) can be confirmed for the pre-crisis period when micro firms are excluded. Although inter-industry dynamics remain hidden, low net job creation rates of micro firms may stem from their lack of ambition to grow larger or less opportunity recognition resulting from necessity entrepreneurship as noted by Baptista *et al.* (2006) and Block and Koellinger (2009). The described pattern becomes more evident for Eastern European countries, where the overall growth rates are significantly above those of the EU15, and SMEs heavily outperform large firms. While the small growth rates of large firms and their small variance can be interpreted as the replacement of obsolete structures by more efficient and economically flexible ones and hence indicates a process of Schumpeter Mark I, the strategic low-growth orientation micro firms adopt results in vulnerability.

Macro-economic shocks affect micro firms sooner than large firms, especially when located in advanced economies. However, they recover sooner and their variance in net job creation is the smallest. For EU15 countries the variance increases with firm-size class as predicted by Acs *et al*. (1996) and Davis *et al*. (1996), but the opposite applies to Eastern European countries. There, the variance declines with firm size, which is consistent with Bartelsman *et al*. (2005), Lenihan *et al.* (2010b), Picot and Dupuy (1998), Praag and Versloot (2007) and Voulgaris *et al.* (2005), and suggests a larger share of young firms compared to the firm population of EU15 countries. According to Figure 6.1, economies less dependent on the traditional manufacturing industry benefit from firm-size class specific patterns in net job creation. This reduces the negative impact of macro-economic shocks, which would otherwise occur simultaneously to all firm-size classes, as can be observed for East European countries (Figure 6.2).

Figure 6.1: Aggregate net job creation of EU15 countries

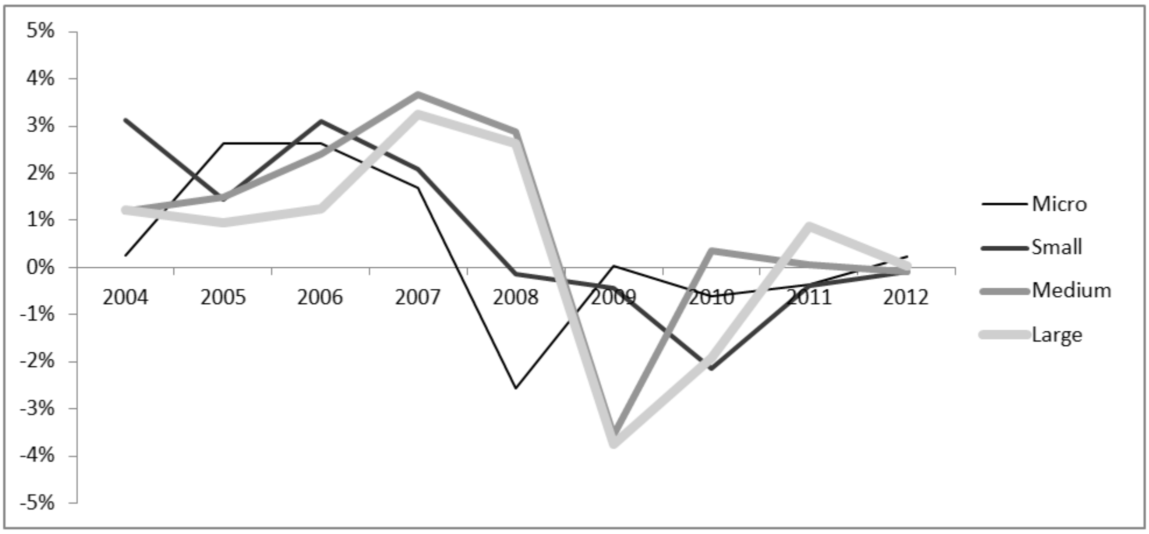
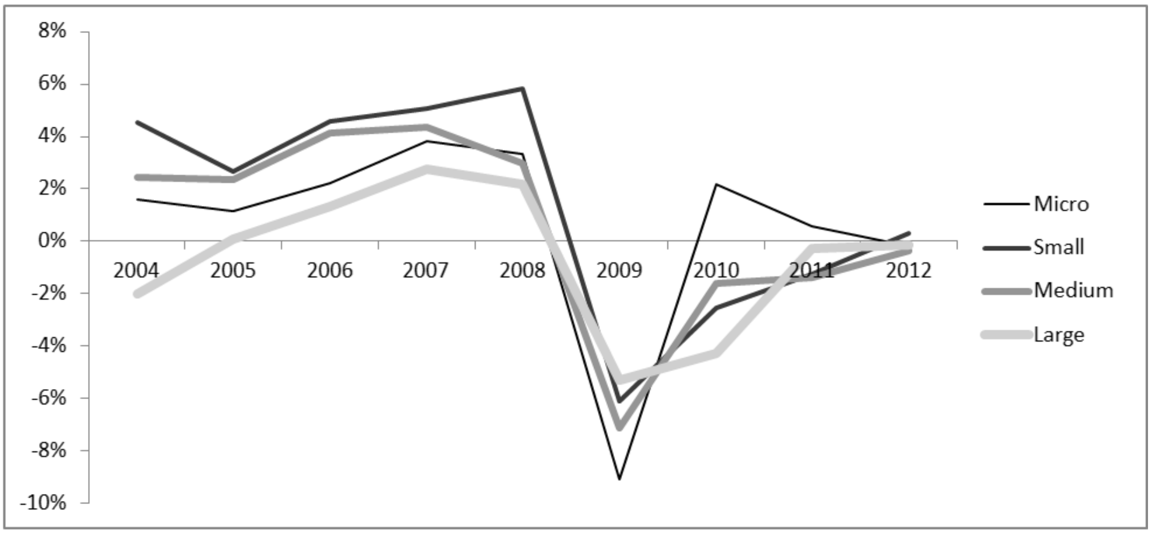


Figure 6.2: Aggregate net job creation of non-EU15 countries



When categorising the country-specific net job creation rates according to manufacturing share intensity (Table 6.6), EU15 countries belonging to the upper fiftieth percentile of the manufacturing share distribution show the most homogeneous net job creation rates across all firm-size classes. Since small firms in EU15 countries with a manufacturing share below 22% show the highest growth rate, industry structure indeed makes a difference. Non-manufacturing firms create more jobs as found by Baptista *et al*. (2008), whereas micro firms in general recover faster than any other firm-size class and even more so when the non-manufacturing sector is large. The influence of the manufacturing sector on jobs generated by SMEs in non-EU15 countries is considerably high and also robust when the median rather than the mean is used. According to Voulgaris *et al*. (2005), this can be attributed to technology intensive firms, which may be accompanied by the presence of gazelles as noted by Henrekson and Johansson (2008) and Picot and Dupuy (1998). Although large firms are better prepared for economic shocks, their contribution to net job creation during 2010-12 is negative and in most cases below the expectations of SMEs, indicating organisational inertia. These findings are consistent with those of Acs *et al.* (1996) and Davis *et al.* (1996), as discussed earlier. Hence, in times of certainty, the size of the manufacturing sector has a positive influence on the net job creation of micro and small firms, while a higher non-manufacturing share is most beneficial for the next largest firm-size class, i.e. SMEs.

Table 6.6: Net job creation rate in percent according to manufacturing intensity by firm-size class (see Appendix E for more details)

Country	Manuf. share	2004-2007 Micro	2004-2007 Small	2004-2007 Medium	2004-2007 Large	2010-2012 Micro	2010-2012 Small	2010-2012 Medium	2010-2012 Large
EU15 countries with a mean manufacturing share above 22% (Germany 31.4%, Finland 30.4%, Italy 29.2%, Sweden 27.2%, Portugal 25.6%, Austria 25.2%, France 24.0%, Belgium 23.9%)									
Variance	0.0860	0.0215	0.0170	0.0157	0.0079	0.0105	0.0183	0.0289	0.0070
Mean	27.1	2.05	2.43	2.08	2.08	0.01	-0.43	-0.07	-0.32
Median	26.4	2.19	1.98	1.93	1.73	-0.33	-0.01	-0.02	-0.14
EU15 countries with a mean manufacturing share below 22% (Denmark 21.6%, Ireland 19.2%, Spain 18.6%, UK 16.8%, Luxembourg 16.2%, Greece 15.7%, Netherlands 15.1%)									
Variance	0.0525	0.0406	0.0630	0.0285	0.0856	0.0262	0.0201	0.0456	0.0150
Mean	17.6	2.33	4.06	2.79	1.07	-0.19	-1.42	-1.81	-1.23
Median	16.8	1.87	3.42	2.96	2.04	0.27	-1.57	-1.65	-0.89
Non-EU15 countries with a mean manufacturing share above 30% (Slovakia 41.4%, Slovenia 37.5%, Czech Republic 36.9%, Romania 36%, Bulgaria 32.6%, Poland 31.0%)									
Variance	0.1370	0.2856	0.0869	0.0325	0.0748	0.0950	0.1111	0.0225	0.0090
Mean	35.9	4.10	4.83	3.36	0.12	1.01	-1.72	-1.01	-2.20
Median	36.5	2.52	4.93	2.60	0.61	0.09	-0.84	-0.56	-2.12
Non-EU15 countries with a mean manufacturing share below 30% (Hungary 29.8%, Estonia 29.6%, Lithuania 27.3%, Latvia 24.1%, Malta 23.6%, Cyprus 16.7%)									
Variance	0.2424	0.1904	0.0396	0.0510	0.1252	0.0639	0.0144	0.0476	0.0405
Mean	25.2	2.01	2.72	2.97	1.07	2.78	-0.10	-1.11	-1.36
Median	25.7	0.36	2.95	3.56	0.65	2.45	-0.09	-0.06	-1.04

Source of data: Modified from EC SME Performance Review

The net job creation rate is the mean net job creation rate over the respective sample period obtained from net job creation to total employment at t-1. The manufacturing share is the mean manufacturing share over the period 2003-2012.

When correlating the percentage of newly added micro firms as proxy for entrepreneurial activity with structural indicators, additional conclusions can be drawn. Entrepreneurial activity in EU15 countries is below the EU27 average and is positively correlated with the share of knowledge intensive services for EU15 countries, but negatively correlated with non-EU15 countries. The value added generated by manufacturing firms remains insignificant, but the employment share of manufacturing firms has a positive effect on entrepreneurial activity when considered at the EU27 level. Accordingly, countries with a larger share of manufacturing firms are more entrepreneurially active. While entrepreneurial activity in the EU15 is associated with knowledge intensity, technological sophistication in non-EU15 countries lowers entrepreneurial activity.

A large share of medium-sized firms results in more firm births with the coefficient being highest for non-EU15 countries during periods of economic stability (r=0.6148; p<0.001). In those countries, small firms either initiate or are the consequence of entrepreneurial activity, while in EU15 countries it is the large firm that shows a positive correlation with the emergence of new firms; most likely the result of technology spinoffs and outsourcing. This supports the view that existing firms contribute to the emergence of new firms discussed by Peltoniemi (2011) and Wennekers and Thurik (1999). The significance of the Gini-coefficient confirms that higher FSI results in less entrepreneurial activity throughout the EU27 and at all times.

6.1.4 Sustainability

A summary of the ANS – the adopted proxy for sustainability – of the EU27 is presented in Table 6.7 and shows a significantly higher mean for the EU15 countries. Greece and Portugal are the underperformers among EU15 countries and Slovenia and Estonia the outperformers among non-EU15 countries. Slovakia considerably deviates from the norm and its consistently large negative values required its exclusion form the regression analysis presented in Tables 6.8 and 6.9.

Table 6.7: Adjusted net savings rate from 2002 to 2008

	EU15				Non-EU15				
	Mean	Std. Dev.	Min	Max		Mean	Std. Dev.	Min	Max
Austria	14.053	1.9113	12.096	17.774	Bulgaria	3.496	1.7908	0.377	5.844
Belgium	13.694	2.5837	9.943	16.971	Cyprus	9.324	7.0372	-2.538	15.480
Denmark	13.311	0.6606	11.839	13.777	Czech R.	8.835	3.0678	4.863	13.452
Finland	16.268	0.9325	15.196	17.904	Estonia	12.345	1.9925	9.016	15.379
France	11.263	0.7393	9.801	11.895	Hungary	6.864	1.0872	5.039	8.137
Germany	12.583	3.3877	8.340	17.297	Latvia	8.308	3.4227	4.712	14.843
Greece	1.974	3.4830	-4.421	5.180	Lithuania	6.401	1.3191	4.775	7.995
Ireland	19.391	5.4393	7.487	22.969	Malta	7.277	0.6345	6.062	7.877
Italy	8.859	0.5888	8.081	9.913	Poland	8.113	2.1380	5.865	11.450
Luxembourg	19.165	3.4834	13.558	23.833	Romania	7.253	3.5136	4.135	13.713
Netherlands	13.329	6.6184	-0.985	18.868	Slovakia	-83.59	1.4812	-85.23	-81.06
Portugal	3.465	2.2026	0.621	6.087	Slovenia	17.710	1.2124	16.237	19.547
Spain	11.368	1.3614	9.808	13.163					
Sweden	19.425	1.7325	17.015	21.918					
UK	7.864	1.8765	3.908	9.252					

Source of data: Modified from World Bank

The correlation analysis of the EU27 (not reported) indicates that countries with a larger share of medium and large firms experience higher levels of gross national savings (GNS). This is supported by the negative Gini-coefficient, suggesting lower levels of GNS for economies with a higher unbalance in firm-size class shares. Given the insignificance of the manufacturing share, the effect does not stem from an economy's stage. The Gini-coefficient for fixed capital consumption (CFC) points in the same direction as GNS and hence permits the replacement of CFC and GNS with national net savings (NNS)[5]. Regressing the Gini-coefficient on ANS too results in a significant but weak ($p<0.1$) negative coefficient as reported in Table 6.8. The coefficients of the regression analysis also reveal that economic stage and differences between EU15 countries and non-EU15 countries matter in combination with the Gini-coefficient or the share of medium-sized firms. Regulatory differences among EU member states may be the reason for this, leading to the higher ANS in EU15 countries. Furthermore, the regression analysis confirms that the share of medium-sized firms accounts for the largest increase in NNS, where an increase in the share of medium-sized firms of 1% causes an increase of ANS by 0.59% ($p<0.01$). The effect remains positive, but drops to 0.20% when large firms are taken into account. Hence, a strong medium-sized sector maximises NNS and suggests higher efficiency levels for medium-sized firms.

[5] National net savings (NNS) is defined as Gross National Savings (GNS) minus consumption of fixed capital (CFC)

Table 6.8: Firm size inequality and sustainability

Independent variable	Employment share of … firms Medium	Medium and large	Large	Gini-coefficient
EDE	0.619	0.587	0.625	0.623
MID	-2.162	-1.460	-1.078	-2.083
END	-1.927***	-2.521***	-2.339***	-1.648**
NFD	-3.797	-2.683	-2.318	-3.502
CD	-3.858	-4.141*	-4.535*	-3.219
EU15	4.897***	1.598	0.879	3.737**
EMP_MAN	23.47***	10.98	13.05	22.66**
EMP_MED	59.05***			
EMP_ML		24.80***		
EMP_LAR			20.20**	
EMP_GINI				-12.80*
Constant	-10.32**	-5.467	0.383	4.165
Observations	182	182	182	182
Number of countries	26	26	26	26
R-squared	0.3878	0.4004	0.3091	0.3048
F-stat. / Wald chi2	38.13	39.65	28.93	27.49

Sources of data: Modified from World Bank and EC SME Performance Review *** p<0.01, ** p<0.05, * p<0.1

Estimator: random effects estimates accounting for heteroskedasticity and first order autocorrelation
Dependent variable: ANS = adjusted net savings
Control variables: EDE = education expenditure; MID = mineral depletion; END = energy depletion; NFD = natural resource depletion; CD = carbon dioxide emissions
Independent variables: EU15 = dummy for EU15 member states; EMP_MAN = employment share of manufacturing firms; EMP_MED = employment share of medium-sized firms; EMP_ML = employment share of medium and large firms; EMP_LAR = employment share of large firms; EMP_GINI = firm size inequality according to the Gini-coefficient resulting from the firm-size class shares
Omitted variable: NNS = national net savings

With regard to natural resource depletion, medium-sized firms no longer outperform their large counterparts. The correlogram indicates that medium-sized manufacturing firms account for the largest degree of environmental degradation. When controlling for EU15 countries, the regression output presented in Table 6.9 shows that the negative impact caused by medium-sized firms becomes insignificant and turns into a marginal positive effect when in combination with large firms. Accordingly, medium-sized firms do not by nature contribute to higher levels of resource depletion as Gray and Eid's (2005) findings suggest, but there are clear differences between EU15 countries and non-EU15 countries; the latter being characterised by higher levels of resource depletion. Such differences might also be responsible for the negative correlation of micro firms and ANS as initially discussed. It now results that it is the large firm that shows a consistent engagement in reducing resources available to future generations, which does not apply to medium-sized firms. The insignificance of the Gini-coefficient confirms that SMEs do not impose a threat to environmental goals, but also indicates some parallels with Gray and Eid (2005), i.e. an increase in firm size implies a higher probability of meeting environmentally conscious businesses, an effect particularly attributed to gazelles.

Table 6.9: Firm size inequality and natural resource depletion

Independent variable	Employment share of … firms Medium	Medium and large	Large	Gini-coefficient
NNS	1.016***	1.015***	1.015***	1.016***
EDE	1.041***	1.044***	1.043***	1.034***
EU15	0.632*	0.892***	1.114***	0.959***
EMP_MAN	-0.389	1.046	1.375	0.330
EMP_MED	-3.997			
EMP_ML		-4.267***		
EMP_LAR			-4.745***	
EMP_GINI				-1.465
Constant	-0.792	0.00290	-0.883*	-1.618***
Observations	175	175	175	175
Number of countries	25	25	25	25
R-squared	0.9790	0.9822	0.9818	0.9775
F-stat. / Wald chi2	23718.05	25007.28	24936.72	23914.81

Sources of data: Modified from World Bank and EC SME Performance Review

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Estimator: random effects estimates accounting for heteroskedasticity and first order autocorrelation
Dependent variable: ANS = adjusted net savings
Control variables: NNS = national net savings; EDE = education expenditure
Independent variables: EU15 = dummy for EU15 member states; EMP_MAN = employment share of manufacturing firms; EMP_MED = employment share of medium-sized firms; EMP_ML = employment share of medium and large firms; EMP_LAR = employment share of large firms; EMP_GINI = firm size inequality according to the Gini-coefficient resulting from the firm-size class shares
Omitted variables: MID = mineral depletion; END = energy depletion; NFD = natural resource depletion; CD = carbon dioxide emissions

6.1.5 Conclusions

The above analysis aimed to examine the implications on welfare deriving from a change in FSI as defined by RQ3. The findings confirm that SME presence positively influences welfare, but the empirical difficulties in measuring the multiplicity of factors affecting it left the causalities unexplained. Some of these were identified by assessing dimensions indirectly related to welfare, and this gives us an idea of how individual firm-size classes contribute to welfare. As it turned out, medium-sized firms in particular, and their presence is a precondition for low FSI, contribute to innovative capacity. Together with small firms they buffer economic shocks and accelerate economic recovery, which has a positive effect on net job creation. Also, SMEs do not impose a threat to sustainability, but there are differences in the role of firm-size classes and variations across regions.

A large share of medium-sized firms implies a higher firm birth rate, especially in East European countries. In West Europe it is mainly large firm presence that is associated with the birth of new firms in knowledge intensive sectors, which suggests the occurrence of spill-overs and spinoffs. But technological sophistication lowers firm birth rates in East Europe and indicates a reliance on the traditional manufacturing industry, which either survived ideological systems or is the product of FDI. Differences in economic stage between East and West Europe were also observable. Such differences are particularly strong when analysing the degree of innovative capacity and environmental sustainability. While East Europe benefits from the process of catching up, West Europe is approaching the knowledge economy. Although the importance of firm size declines as knowledge intensity increases, this prediction is limited to the service industry. At least in the most advanced European economies, large firms are knowledge and technology holders. They are most likely engaged with systemic research, whereas medium-sized firms stay followers. There is also evidence that knowledge intensive small firms bear a high growth potential and that FSI (in value added by firm-size class) supresses innovative capacity. In terms of environmental sustainability, considerable differences between Eastern and Western European countries exist. Medium-sized firms contribute most to resource preservation, but nevertheless there is a positive correlation between firm size and sustainability that applies for smaller firm-size classes.

Overall the pattern small firms follow is closer to medium-sized firms than to micro firms, with the latter being the inverse reflection of the effects observed for large firms. Small firms are therefore in a transitionary stage of growing firms and a firm-size class in its own right. In no other part of the empirical analysis has the distinct function of firm-size classes become so clear. They differ in their contribution to innovation and their response to change. These aspects are reconsidered in the subsequent discussion, which links the empirical findings to the theoretical predictions, as discussed in foregoing chapters. In combination with the historical perspective, the discussion closes with specific measures for policies aiming at rebalancing the SDOF and maintaining such a balance.

6.2 Discussion

6.2.1 Firm size inequality matters

The results that emerged from the empirical analysis strongly suggest that the SDOF is highly dynamic when analysed at the 4-digit industry level, and that FSI has negative implications on welfare. The data demonstrates that the SDOF converges to a natural stage, which comes close to the lognormal distribution and applies to about two thirds of the examined industries. Accordingly, the size distribution is industry-specific and country-specific, with the latter dependent on economic development and national context. When expressing the dynamism incorporated in FSI measured by the Gini-coefficient, it increases over time and is conditioned by initial market concentration, but declines when an industry has reached a critical age and the MES is high. In the event of low entry barriers, as occurs in the service sector, co-existence rather than competition among firms similar in size is the logical consequence.

The pattern reflects the simplified industry life-cycle, consisting of growth, maturity and decline. The shakeout preceding industry consolidation plays an important, if not the most important, role in weeding out inefficient firms from efficient firms. This selection process increases FSI and is part of the process leading to the natural stage of the SDOF. Given that most firms are multi-product firms and that diversification increases with firm size, the shakeout manifests itself in an increasingly polarised SDOF. Although average firm size continues to increase, the share of medium-sized firms declines as they move either up or down in the firm-size class hierarchy. The question is therefore not whether a missing middle will emerge – in the long run it will – but how it can be preserved over the short term so that the observed negative externalities can be minimised, whilst maintaining a balance at economy level.

The absence of lognormality until an industry has reached its final distribution implies that firm growth is *not* independent from size, because a given distribution can only persist when firm growth is random for all size classes.

This rejects the universal applicability of Gibrat’s Law and demonstrates that there are more growth opportunities for SMEs. Hence, there are circumstances under which SMEs can do better than large firms or are at least able to operate at a competitive level. Firm size matters least for non-manufacturing industries and partly explains its dynamism, whereas in manufacturing industries firm size is defined by MES and applied technology. Within these limits a range of efficient firm sizes exists, which lowers the degree of FSI. Firms operating below the MES are unable to compete when the shakeout takes place and the resulting negative growth combined with the presence of gazelles increases FSI. The thesis therefore shows that it is crucial that firms that are unable to compete on the basis of economies of scale seek specialisation at an early stage to attempt to achieve a level where diversification is possible.

A further implication of the shift towards a natural stage is the decline in the number of disruptive innovations as an industry grows older. This does not by definition reject the absence of Schumpeter’s (1947) creative destruction, but suggests that after the emergence of the dominant design as described by Peltoniemi (2011), radical innovations result in the emergence of new industries rather than existing ones being fully replaced. In accordance with Schumpeter (1947), this also supports the prediction that large firms take the lead in engaging with R&D, hence replacing SMEs in refining technologies. Both patterns apply to the industrial revolutions and confirm Schumpeter’s theoretical work. However, the nature of the analysed data, with its short time horizon that only includes surviving firms, does also contribute to this observed effect.

The importance of the entrepreneur is reflected in the negative impact of owner-manager presence on FSI. This means that SMEs perform better than divisionally-managed firms, but the importance of the entrepreneur declines with firm size as argued by Casson (1987), Knight (cited in Praag 1999) and Schumacher (1973). Accordingly, the contribution of the entrepreneur, be it as the innovator (Schumpeter 1947) or the efficient resource allocator (Mises 1951), is most relevant in the early stages of a firm and, if successful, the entrepreneurial role deteriorates as systemic management takes over. Firm survival is therefore directly linked to the qualities of the entrepreneur, whose ability to make decisions might be enhanced by the inclusion of outsiders who act as a partial substitute for the expert advice that firms part of a group have access to. Given the entrepreneur's properties to bear risk and uncertainty, a shift from the entrepreneurial firm towards the formally-managed firm leads by definition to increasing risk-averseness. The ability to foresee the future is then restricted and replaced with a systemic approach of risk diversification and draws back to the underinvestment in risky and experimental projects asserted by Arrow (1962). The results indeed show that a lower share of medium-sized firms reduces innovative capacity.

The consequence of this is outlined in Graeber (2012), who attributes a backlog in technological progress to the capitalists' preference for moderate innovations to maximise profits. The industrial revolutions demonstrated that entrepreneurs are able to initiate innovative processes by delivering radical innovations and that basic research can be commercialised by small businesses. Once radical innovations have been introduced and proved successful, gazelles emerge and fuel other firms with new industries and it is eventually the large firm that excels in accumulating knowledge and commercialising innovations. However, it also lies in the nature of capitalism that the most powerful firms attempt to preserve existing structures. The possibility to do so increases with a decreasing share of less influential, usually smaller, firms and eventually leads to the natural stage of the SDOF with irreversible imbalances.

If efficient medium-sized firms did not provide an incentive to run the multinational more efficiently, competitive forces would merely originate from its seemingly efficient (or inefficient) peers with little incentive to engage in radical innovations. By being efficient in allocating resources and responding to environmental changes, while at the same time being able to absorb technologically sophisticated information, medium-sized firms are crucial in extending the dynamism of the SDOF. It is irrelevant whether they are identified as followers since their positive contribution to innovative capacity, economic resilience and net job creation is sufficient to justify their status. Ignoring their contribution results in a suboptimal use of social energy and innovative capacity. Hence, the function of entrepreneurial SMEs substantially differs from the role of the large firm. The interactions taking place between firm-size classes define the performance at aggregate level with firms different in size being complementary rather than contradictory. But a continuum is better than polarisation, which is why consideration of FSI matters.

The consistent relevance of FSI in the empirical analysis supports Schumacher's (1973) proposition of a balanced SDOF. Its importance for sustainable economic and technological development was of little interest to classic and neo-classic economists and the entrepreneur remained unnoticed for quite a while as s/he is hostile to the equilibrium. In *Profit and Loss*, Mises (1951) introduced the entrepreneur as an analytical tool to explain economic progress and replaced statics with dynamism. Schumpeter (1947) equipped him/her with the power to alter existing structures and the concept fitted well in the opportunity-rich post-war period as it was conceptually appealing. As innovator and risk bearer s/he directly contributes to change and is essential in explaining social transformation. But the theoretical entrepreneur was also misunderstood and led to the assumption that capital and entrepreneurship can be separated. The Third Industrial Revolution has certainly offered more opportunities to men with negligible possessions than its predecessors did, but entrepreneurship and capital have remained sticky, as the presented theoretical and empirical discussion shows.

Equally overlooked were the restrictions that the evolving structures would impose. While the Austrian School continued to see the entrepreneur alongside the multinational as a means to achieve sustainable economic growth, Schumpeter (1947) concluded that a number of large firms exposed to moderate competition are a sufficient condition for technological progress. Consistent with Lucas' (1978) prediction of increasing FSI, there was no need to consider rebalancing the emerging structures. Only Drucker (1985) was among the few to argue that medium-sized firms are in a better position to recognise and seize opportunities than any other firm-size class. It was now the organisational entrepreneur who was viewed as being responsible for change. Regardless of the perspective, it was not dynamism and its source that went unrecognised, but the restrictions that evolving structures produce once the

SDOF has reached its natural stage. As Vaughn (1982:23) comments on Mises (1949), “human action may be free, but it is no[t] random” and yet “the consequences of [human beings’] actions are not always what they intend.”

The multinational – a product of capitalist ideology subject to an expansionary nature – is unlikely to show interest in maintaining a fair share of medium-sized firms as it puts its existence at risk. For much the same reason it has a tendency to either incorporate or supress anything that increases uncertainty and lowers predictability. It reduces the commercialisation of disruptive innovations with high potential start-ups – the next generation of SMEs – being acquired in their infancy. Failing to recognise the potential that diversity offers to welfare implies an increase in the gap in FSI. It is not the co-existence of small and large firms that imposes a threat, but the degree of polarisation resulting from it. Extreme FSI degrades the dialogue between firms different in size, be it in the form of spill-overs or competition, and leads to a co-existence or co-operation with unequal powers. If we believe in the virtue of moderation emphasised by the ancient Greeks (Salkever 2009), such a development is unlikely to be sustainable.

6.2.2 Policy implications

Looking through the lens of the SDOF, governmental inaction leads to the natural stage sooner, with meaningful innovations being unrealised or unnecessarily delayed if not in the interest of incumbent firms. Once the natural stage has been achieved, rebalancing the economy becomes unattainable without disruptive changes or governmental intervention. The observed dynamics reflect the logic that industries follow and the understanding thereof allows to decide on the nature of interventions aiming at rebalancing the SDOF. In order to achieve this, external and internal factors affecting the behaviour at firm level were identified. Since external factors like industry growth or economic downturns are beyond the control of the individual firm, it is obliged to respond. Internal factors, however, can be built and increase the firm’s flexibility in responding to those threats. Such factors are, for instance, an ability to continuously increase productivity levels, to access foreign markets or to accumulate intangible assets. While external factors increase the understanding of forces operating at industry and economy level and assist policy makers in deciding on the overall direction, internal factors represent specific measures to strengthen a firm's competitive position. They allow policy makers to systemically support specific firm-size classes and their inclusion in policies makes Europe more entrepreneurial, innovative and sustaining.

As the analysis on innovative capacity showed, economic growth cannot thrive when knowledge does not flow from one firm-size class to another. In the long term the creativity of the knowledge holders will cease, innovative capacity deteriorates and with it goes net job creation. Of primary interest are the dimensions leading to an increase in FSI. Above all, the increasing market volatility noted by Audretsch and Thurik (2000) demands flexibility and despite SMEs' contribution in buffering economic shocks, their existence is more fragile relative to large firms. The findings confirm the conclusions drawn from the discussion presented in Chapter 2, according to which Britain could do better with a less polarised SDOF and Italy with fewer very small firms. The SDOF is most balanced in Germany, but its FSI is increasing too as more industries mature and little has been done to revive a new *Gründerzeit*. So for Britain, the key issue is to rebalance the economy by strengthening its SME sector; for Italy it is to establish a competitive middle sized enterprise sector – especially in its South – and for Germany it is to increase entrepreneurial activity. Eastern Europe is catching up and benefitting from the impetus provided by FDIs. But it would also benefit from strong domestic firms able to absorb technological knowhow and seize opportunities before labour costs force foreign capital to exit its countries' economies. The subsequent sections outline implications for policy design that can be drawn from the empirical analysis presented herein.

The positive effect macro-economic shocks exert on FSI has been associated with an acceleration in approaching the natural stage of the SDOF by rewarding efficient firms and penalising less efficient firms. At aggregate level, it elegantly describes the dynamics taking place when the selective process begins. Macro-economic shocks are by definition uncertain and unpredictable and it is not just the inefficient firm that is penalised. The observed increase in FSI is an indication that unexpected disruptive events add a random multiplier to firm growth of all size classes with inflexible ones being disadvantaged. This might be described as Knightian uncertainty and adds Mazzucato's (2000) element of unpredictability to the shakeout. Some firms are prepared, some are not; others are lucky and some firms are clearly inefficient. Reducing business risk by stimulating artificial demand and encouraging the accumulation of overcapacities would be inappropriate, but reducing the operational risk of disadvantaged firm-size classes is desirable.

Unlike with large firms, the failure of the marginal firm has no immediate systemic implications and gaining political capital from saving it is disproportionally more difficult. From time to time, structural adjustments are necessary and exclude the weakest from participating in future growth. But in the absence of overcapacities and in the event of unjustified competitive pressures, enabling SMEs to access resources at fair conditions preserves their existence. This lowers the probability of underinvestment and, as the findings show, accelerates economic recovery. And although SMEs are operationally more efficient than large firms, they have fewer opportunities to reallocate resources and are less flexible in laying off staff when labour markets are rigid. Close interpersonal relationships and moral standards may even prevent it and put the very existence of the firm at risk. Assisting SMEs in temporarily lowering overhead costs when the effects of market failures affect the real economy increases firm survival. Italy is a prime example of this, but addressing the inefficiencies requires action too. To achieve this, a rise in average firm size is necessary so that firms become more capable of absorbing uncertainty. Entrepreneurs are the first movers and making the first move is associated with the highest level of risk.

As competition in developing industries increases and aggregate market shares are distributed, the SDOF becomes increasingly polarised. Firms part of a group or having established subsidiaries are advantaged by having access to networks and additional market intelligence or more choices in allocating resources. These are also the firms that are most likely to be engaged in exporting. To enable SMEs not in possession of such resources in accessing foreign markets, the Anglo-Saxon approach to industrial policy contributes more to firm growth than the mere provision of additional funds. As stated earlier, export openness allows firms to escape from competition in saturated domestic markets (Görg and Strobl cited in Buckley 2010; Larrea *et al.* 2010; Voulgaris *et al.* 2005), and assists in accumulating foreign market intelligence. The findings support Lenihan *et al*. (2010b), who identified knowledge-intensive and service industries as most promising. Here, geographic concentration to efficiently promote export orientation is an additional advantage that industrial clusters offer. This favours a regional approach to industrial policy with preference for decentralisation. As the results show, advances in ICT cannot undo the efficient knowledge transfer taking place when firms are geographically concentrated, but require knowledge intensity being present.

Particularly attractive is the involvement of foreign firms. Domestic firms, however, only benefit if the preconditions contribute to knowledge transfer, i.e. if the technology gap does not exceed a critical limit. This was confirmed by the decline in FSI when value added is high and the gap in MES is small. Countries with a large share of knowledge intensive industries are more likely to benefit from the presence of foreign-owned firms as they are able to absorb relevant knowledge. It eventually allows domestic firms to compete with foreign firms and, according to Lenihan *et al*. (2010b), results in less dependency on FDIs. Despite the contribution of FDIs to national economic growth and in assisting indigenous firms to catch up, there is also a risk that MNEs replace indigenous firms by incorporating their operations. This applies in particular to Eastern Europe where, according to Dischinger *et al*. (2014), foreign-owned subsidiaries have exceeded the number of parent firms. Thus, countries with a weak absorptive capacity are advised to follow a more moderate and selective approach in opening markets to foreign firms. This is because domestic structures need time to develop until achieving a sufficient absorptive capacity. Barbosa and Eiriz (2010) and Buckley (2010) recommend a regional industry-specific approach with emphasis on knowledge transfer rather than instant economic growth and the data in this thesis supports that suggestion. Further, for a sustainable and innovative society, Davis *et al*. (1996) also suggest a focus on job quality rather than the mere creation of employment opportunities, because they are too limited in scope. The analysis here also concurs with that assertion.

The entrepreneur plays a vital role in achieving lasting prosperity, but the minimisation of necessity entrepreneurship and the maximisation of opportunity entrepreneurship is required, as emphasised by Acs (2006). The analysis too demonstrates that entrepreneurial activity in the form of owner-management lowers FSI. Schumpeter (1947) suggested the pathway when describing the character to look for: it is the passion-driven genius that makes him/her an expert in the field. However, the tendency of seeing only the outstanding entrepreneur – blessed with extraordinary skills, ranging from specialist knowledge and management skills to emotional intelligence, and doubtlessly well connected – as the only source of growth is too idealistic and dismisses the reality. There is nothing wrong with the exceptional, but identifying it is disproportionally harder than meeting the 'average' entrepreneur many schemes are, and should be, targeting. And there is still the wealth of pseudo-entrepreneurs trying to make a living. One implication is that hoping for gazelles to emerge by increasing the number of start-ups is overly optimistic and misdirects social energy. A further consideration is that Europe's legal framework – the UK might be an exception – is not implicitly conducive to supporting entrepreneurship and makes it unattractive for the well-educated and experienced to take the risk.

Piergiovanni and Santarelli's (2006) call for a new generation of entrepreneurs, able to successfully implement their ideas, cannot be rejected, but expecting tremendous growth from unexperienced first time entrepreneurs is a risky bet. Equally speculative is the reliance on the large share of micro firms. Evidence suggests little entrepreneurial spirit, with most business owners having a limited (and therefore limiting) target income, which makes policies encouraging growth inefficient (Bridge and O'Neill 2012). The probability of approaching Salerno's (2008) integral entrepreneur is certainly higher for young firms, but focussing exclusively on new business venture creation is too simplistic and disregards the contribution of successful SMEs. The task is not just to identify entrepreneurs, but also SMEs with high growth potential (Teruel-Carrizosa 2010b) as has been practised in Scotland (Brown and Mason 2012). This work confirms this assertion and, due to the stickiness of entrepreneurial activity and capital, puts SMEs in a better position to innovate. They may also be a good place to find the next successful entrepreneurs. Spill-overs and spinoffs with positive peripheral effects follow from a dynamic SME sector (Praag and Versloot 2007) and help overcome the dependency of inward FDIs (Lenihan *et al*. 2010b). Encouraging entrepreneurship is a sensible strategy, but it is more fruitful when at least some resources are directed towards existing structures with the SDOF in mind.

As stated in the introductory section, in a world with living standards at a historical high, it seems at first that there is little left to be innovated; indeed the increase in private wealth provides few incentives to do so (Boltho 2013). It may also be that commercialising novel ideas has become more challenging. It is therefore crucial to reward the few who wish to engage in experimenting and who are willing to accept failure as part of the process. What are needed are serial entrepreneurs who responsibly capitalise on both failure and success. This requires the as yet poorly researched, but determining framework conditions (Klapper *et al*. 2012) to be in place and includes a legal framework that encourages rather than punishes such activities (Audretsch and Feldman 1999). Above all, the downward risk of experimenting has to be reduced if trial and failure is expected to deliver innovations. It too requires societal acceptance and a cultural change (Audretsch and Thurik 2000) with an awareness of the value entrepreneurial activity adds to society (Klapper *et al*. 2012). These factors apply equally to established firms, where entrepreneurial freedom to promote intrapreneurship is imperative. Entrepreneurs are needed, but the exact nature and 'make up' of these entrepreneurs is much more complex than the theoretical construct suggests. There needs to be the risk taker and the innovator alongside the intrapreneur and the entrepreneurial society. A larger range of entrepreneurial activity complements European firms' superiority in marginally improving existing products (Audretsch and Feldman 1999) with innovative capacity leading to disruptive innovations. Such activity opens windows of opportunity to rebalance the economy. Thus, one important conclusion from this research is that there are times when it makes sense to push start-up activity and times when it is more important to support existing firms. This is incompatible with general approaches to industrial policy.

Schumpeter's (1947) claim that hypercompetition is hostile to disruptive innovations should be taken seriously. Competition increases operational efficiency and is an incentive to do better than the average, but risky experiments are undermined because the opportunity cost is too high. The possession of capital or other tangible assets as a precondition to carry out most types of entrepreneurial activity slows down the most talented. To create space for entrepreneurial activity in an increasingly technology-rich environment, innovators require agents willing to provide the necessary infrastructure. Whether this comes from an existing firm or research institution, it will be rewarded by successful innovations that contribute to additional opportunities to expand its operations. Conducting basic research to compensate for the lack of systemic R&D observed for small businesses requires the involvement of intermediaries to bridge the knowledge and system gap of research institutions and small businesses willing to commercialise promising research output. As the researcher is likely to stay a researcher and the businessman a businessman, co-operation should be encouraged. For SMEs, it is a way to develop their portfolio of intangible assets. As the analysis reveals, they have replaced tangible assets as an entry barrier. Schemes helping SMEs to protect IP according to conditions that match their resources are worth considering. They reward smaller firms for their effort and give an incentive to accumulate knowledge before competitive forces erode it.

Conclusions

Market forces impose a limit to policy makers in rebalancing the economy, but this thesis demonstrates that some room for manoeuvre exists and gives a clear indication to what extent market forces can be influenced. The more disruptive the innovations, the more effective the act of rebalancing, because it is in harmony with industry dynamism. This matters most for the UK, where the contribution of the non-financial sector was underestimated for more than a decade and foreign-owned firms replaced a large part of the domestic industry. It not only exposes Britain to the goodwill of foreign MNEs, it also reduces the ability and speed of economic recovery when shocks occur. Although more entrepreneurial than continental Europe, the culture of treating young firms as a commodity inhibits the growth of independent firms before they are merged into an MNE. This needs to change if the objective is to build a strong SME sector. It is seemingly difficult for Italy, where the sheer number of micro and small firms cannot benefit from economies of scale. The resulting inefficiencies can hardly be removed without engaging with high-tech manufacturing and a knowledge intensive service sector, supported with intense R&D activities. A rigid labour market and a lack of funding opportunities systemically weaken the country's SMEs and impede regional development, as does the north-south divide. There is certainly a list of other issues that need addressing, but a regional approach to industrial policy with a focus on knowledge creation and selective FDI stimulus will contribute to a shift in the right direction.

Germany's *Mittelstand* is stable, but aging – as is its society – and relies on past success with limited scope for disruptive innovations. The latter alters existing structures, but without a new generation of SMEs, Germany is at risk of missing out on the technological leadership in emerging industries. Its current market leaders will increasingly compete in mature industries and at a global scale. It is the only way to compensate for the decline in the margin as the rest of the world is catching up. Without a serious commitment to developing a stream of young entrepreneurs, there will be a shortage of innovations coming from domestic firms. The service sector has not developed to its full potential yet, but achieving a level of sustainability requires a transition to the knowledge economy. Its precondition is the acceptance of failure as part of the development and an adjustment of critical framework conditions is the price for this. Even more exposed to the global markets is East Europe, where favourable production factors attract FDI. However, it should not miss the opportunity to capitalise on those assets. A development of national structures to absorb and geographically embed imported knowledge is required more quickly than was necessary for Europe half a century ago. In the long term it too needs to have a strong domestic industry upon which it can rely.

The pattern that emerges from the analysis reflects a specific function for each firm-size class and promotes Schumacher's (1973) 'balance' in terms of firm size. It is neither the entrepreneur nor the multinational alone that maximises welfare and sustainability. It is the combination of the two that makes a difference and induces the dynamism required to achieve a high degree of innovative capacity. We need the large firms to carry out large scale projects, to improve and disseminate innovations, and to enable spinoffs and spill-overs as a mechanism for technological progress. This may result in a feedback loop, as innovative developments are circulated from large firms to small firms, and then back to large firms for refinement. We need SMEs to efficiently carry out riskier projects at a systemic scale. Even when projects fail, job losses are most likely to stay within limits. We need young marginal firms to carry out experiments that enhance growth when successful or become part of the learning curve when unsuccessful. Whichever the outcome, an attempt to preserve knowledge serves technological progress and can be best achieved when the structural setting allows firms to absorb this knowledge. However, the old marginal firm also deserves appreciation. It is not outperforming its competitors in innovative capacity or net job creation, nor will it ever do so. Its objective is not to grow, but to serve its customers and too buffers economic shocks by maintaining the owner's income flexible.

CHAPTER 7: CONCLUSION

This thesis attempted to first analyse to what extent the SDOF, and with it FSI has changed and second to identify the determinants of such a change. As structural change affects socio-economic performance, the third objective was to scrutinise the implications on welfare deriving from the change in FSI. These associations are poorly addressed in classical writings, which focus either on individualism or collectivism, but rarely on the interplay of firms different in size and the implications thereof for society. The analogue pattern is reflected in entrepreneurship literature and research on the SDOF. The former assumes the presence of opportunities at a constant rate and barely questions the systemic force industry dynamics exert on entrepreneurial success, whereas the latter ignores the dynamism entrepreneurial activity initiates. It is the contribution of this work to consolidate these streams and to establish a link with welfare in the European context.

To address the first two issues, non-financial industries in the UK, Italy and Germany were analysed using advanced statistical methods. After applying descriptive statistics and lognormality tests to understand the dynamics of the SDOF, the Gini-coefficient was used as proxy for FSI to operationalise the information the SDOF contains. It is entered as the dependent variable in an econometric model capable of determining the forces of said dynamics. The constructed model allowed the pooling of heterogeneous industries at the 4-digit level and consists of components that use both firm and industry-level data. To cross-validate the estimates, an independent regression analysis for each sample country was performed and alternative dependent and independent variables were used. Since welfare indicators are only available at national level, the sample to analyse the implications of FSI on welfare was extended to the EU27. To control for the East-West divide, the sample was split into EU15 and non-EU15 countries. Following a correlation analysis of novel well-being measures and firm-size class shares, regression models were developed to estimate SMEs' contribution to innovative capacity and economic resilience. A dynamic firm-size class analysis was performed to examine their input to net job creation and once more regression models constructed to link firm-size classes to sustainability. The latter was measured by the adjusted net savings rate and aimed to investigate the compatibility of SMEs with environmental goals.

The next section reconciles the empirical findings and links them to the historical and theoretical perspectives presented in Chapter 2. As one of the contributions is to present a comprehensive understanding of the forces driving the SDOF, the findings of the first two research questions are merged. The next section then outlines the importance of this research, whose contributions to knowledge are restated. As for any academic work of this kind, there are restrictive conditions and assumptions. A reflection of such limitations is presented in the section thereafter. It builds the basis for the possibilities for future research, which provides directions to engage with the phenomenon discussed herein.

7.1 Empirical findings

The findings demonstrate that the SDOF is highly dynamic when analysed at industry level and influenced by systemic forces active at country, industry and firm level. It is more than the mere product of random firm growth resulting from advantageous environmental conditions. Since firms' contribution to innovation, economic resilience, net job creation and sustainability varies across size classes, the SDOF carries structural information with implications on welfare.

Chapter 5 reveals that the dynamism of the SDOF stems from entrepreneurial activity and industry life-cycle dynamics with the former being the source of radical change leading to new industries. When a new industry emerges, collective learning allows firms to mutually benefit from aggregate growth until the competition for resources intensifies and FSI increases. The following shakeout is accompanied by a shift from product to process innovation with the resulting efficiency gains raising the MES and hence average firm size. As firms age and initially simple products, technologies and processes become increasingly sophisticated, entry and exit rates decline and the SDOF becomes more symmetric and converges to a natural stage.

Firm growth is then randomly distributed across firm-size classes with the applied technology defining the degree of firm heterogeneity. As inefficient firms have been excluded by the market mechanism, all firms operate above the MES and follow the lognormal distribution. FSI in asset rich industries is therefore inverse U-shaped and unidirectional in industries with a low MES, because firms are not forced to exit. Since firm growth is less determined by technological factors, such industries are more dynamic and the speed at which firms approach the natural distribution occurs at a faster rate. With the vanishing share of medium-sized firms, diversity decreases and the enlarging discrepancy in technology and knowledge reduces the absorptive capacity of small firms. It disqualifies them from catching up, whereas incumbent firms are protected by high market concentration and flexible internal resource allocation. Exceeding a critical level of FSI impedes spill-overs and firms either co-operate by focusing on different tasks or allow tacit co-existence, but are no longer able to compete on the same ground.

Creative destruction leads in the first instance to new industries, while in mature industries the small firm is likely to stay small and the large firm's diversification strategy allows it to grow bigger with late entrants belonging to the former group. It implicitly contributes to firm size polarisation and, once achieved, rebalancing is almost impossible. Not only do small firms lack the resources necessary for achieving the technological sophistication large firms have accumulated throughout the life-cycle, the latter's self defence system has a tendency to supress any form of disruptive innovation that puts its existence at risk. It systematically erodes entrepreneurial activity and competition across firm-size classes. As the number of industries approaching maturity increases with economic development, encouraging self-employment with the objective to identify the real entrepreneurs is no longer a universal tool to increase aggregate growth. It might contribute to the birth of gazelles, but in contemporary Europe the risk of enlarging the share of necessity entrepreneurs is high and even counterproductive as it misdirects social energy.

The findings show that imbalances in the SDOF deflate innovative capacity, which results in weak economic growth and low levels of net job creation. Imbalances further lower the ability to respond to economic shocks, which paradoxically increase FSI unless overcapacities are present. For society it means that little more than marginal product and service improvements can be expected with continuous growth relying on large scale structures becoming unsustainable. It makes the large firm a poor substitute for a collection of small firms and attributes a special role to the medium-sized firm. Less event driven than the marginal firm – and hence more flexible – but more entrepreneurial than the large firm when owner-managed, the medium-sized firm is in a position to devote resources to systemic research without losing its ability to spontaneously recognise and seize opportunities. Medium-sized firms might not excel in sophisticated research and large scale projects, but their absorptive capacity makes them good followers that develop their own dynamics and ultimately contribute to technological progress.

Preserving a fair share of medium-sized firms is therefore desirable and yet is against the forces pushing the SDOF towards the natural stage. Since the act of rebalancing becomes disproportionately harder, the closer the distribution is to lognormality, extending the life of medium-sized firms within an industry can only be temporary, but essential to benefit from spill-overs and spinoffs. It is the equivalent effect that becomes visible from selective foreign firm presence, which prolongs within industry dynamism and opens the door to new industries that allow a new generation of young firms to emerge. Such occasions are windows of opportunities to rebalance the SDOF at aggregate level and their occurrence increases with opportunities available to existing firms. For entrepreneurial activity to succeed it requires an approach at different levels. To preserve the said dynamism, industry policy needs to be industry-specific with an ability to recognise windows of opportunity. These are central to the choice between encouraging start-up activity and support for existing firms. To create opportunities, it has to focus on SMEs' ability to accumulate intangible rather than tangible assets and encourage knowledge rather than labour intensity. When these conditions are met, clusters promote knowledge transfer and the resulting export opportunities increase small firms' ability to stay competitive without imposing a threat to environmental goals.

7.2 Contributions to knowledge

In *Small is Beautiful* Schumacher expressed his belief in diversity as the only means to achieve sustainability and was among the few to devote his intellect to the matter of firm size. This argument became the core of this work with the consolidation of the fragmented literature being the first, the empirical findings the second and the methodology leading to them the third contribution to knowledge.

For the relationship of firm size and welfare to be established, Chapter 2 reconciled the historical development back to the First Industrial Revolution to identify patterns and regularities. With reference to the Austrian School, it then inquired the contribution of the entrepreneur, followed by the restrictive factors to entrepreneurial activity. It led to FSI as the consequence of industrial dynamism and its implications for society. With evolutionary economists on the one side and neo-classic economists on the other, Chapter 3 reveals that the LPE was welcomed to model the complexity and led to new streams of research. These are the theoretical and empirical studies on the SDOF and a minority of empirical studies on FSI characterised by poor cross-referencing. The third stream is the validation of growth patterns across size classes and the underlying forces, whose emergence was the consequence of the limited applicability of findings on the SDOF for industrial policy. Merging said research areas became therefore a major contribution and assisted in identifying the dynamism of FSI, its determinants and implications for welfare.

The findings conclude that firms different in size are complementary, not contradictory. Innovations delivered by the entrepreneur differ from those emerging from any systemic approach. But as industries age and firm size increases, the entrepreneurial element decreases and is gradually replaced by the manager. The question is not whether the SDOF converges to a natural stage, but to what extent the speed of convergence can be influenced and how rebalancing might be possible. This makes FSI a relevant factor in determining welfare, because it is not growth at individual or aggregate level that leads to sustainability, but the diversity of firms in size. The empirical analysis presented in Chapter 5 brings together the factors that matter most in determining the selection of firms and the evolutionary pattern industries follow. By identifying the parameters that influence FSI, it enhances the effectiveness of policies aiming to induce structural change. The analysis also reveals that such change cannot succeed by encouraging self-employment without the contribution of SMEs. This makes the SDOF a relevant parameter in achieving sustainable growth, but has rarely been part of the discussion of contemporary entrepreneurship literature.

These findings are the product of a methodologically unconventional approach and required a choice between industry and firm-level analysis. Beside the use of sample data at economy level, the former is common in empirical work on the SDOF and the latter dominates in studies examining firm growth. Given the use of FSI as the operationalised coefficient of the SDOF, the industry-level analysis became by definition the lowest level of analysis. It nonetheless allowed the extension of the sample to a large number of industries, which in previous studies remained widely unconsidered as they focussed almost exclusively on manufacturing firms, and in some cases on service firms. In addition, the use of the Gini-coefficient and its log-odds ratio in combination with the HHI as proxies for FSI allowed cross-validation and a differentiation of patterns applicable to SMEs and large firms. Equally meaningful is the aggregation of firm performance components alongside the median or mean. It permits the interpretation of forces acting at industry level and those acting at firm level, which in some cases work in the opposed direction. With regard to welfare, four dependent variables that can be linked to FSI were identified. This allowed the verification that a balanced SDOF is beneficial for an economy, however this depends on the stage an economy is in. It too helped to verify whether large firm presence is sufficient in raising living standards and detecting the value the marginal firm adds to economic performance.

7.3 Limitations

The holistic approach demanded the engagement of a broad field of research areas and the consolidation of theories of entrepreneurship, firm and industry dynamics with reference to welfare. Simplifying the complexity in order to come to a generalised conclusion suitable for policy design was therefore unavoidable. There are debates that could have been extended and aspects that could have been addressed in more depth, but it is simply beyond the purpose of this work to go any further. The analysis too is bound to the methodological choice and therefore assumptions had to be made. As the welfare analysis has shown, not everything that is theoretically sound can be measured in the way demanded by the analytical tools chosen. Hence, more theoretical and empirical work, and more comprehensive datasets are required to verify what has been revealed and concluded. To assist in this, the following remarks give an account of the major limitations. These refer in particular to the conceptualisation of the entrepreneur, the restrictions imposed by methodology and data, and, finally, the scope of this thesis.

Classic and neo-classic economists developed their theories without regard for the contribution of the entrepreneur. Management strategists also ignored this rare character. However, the entrepreneur was essential for evolutionary economists as s/he was the missing link to the process of describing dynamism and technological progress. Evolutionary economists generated a theoretical construct that served their purpose, but which is difficult to operationalise when used for empirical work. For Mises (1951) the entrepreneur was the justification for everything that could otherwise not have been explained. He implies that the entrepreneur includes the small business owner who finds a way to co-exist next to the large firm. Since the possession of assets is secondary, Mises (1949, 1951) underestimates the importance of social interaction in fundraising, as noted by Casson (1982), Drucker (1985) and Knight (cited in Praag 1999).

For Kirzner (cited in Salerno 2008) seizing opportunities is even possible without the possession of assets. He assumes that opportunities do not vanish until the entrepreneur becomes active (Loasby 1982).

The findings show that windows of opportunity close as industries approach the stage of maturity and it is only Schumpeter's (1947) innovator with control over resources who might be in a position to alter existing structures. The temporary nature of the Schumpeterian entrepreneur, however, creates a conceptual problem for empirical work. Using the firm as the analytical unit conflates entrepreneurial leadership with systemic forces. An attempt to distinguish between these two factors was made by including the owner-manager as an influential factor in determining the degree of FSI. But when it comes to entrepreneurship, much rests on definitions and categorisations that evolve and change over time. Further, the multiplicity of forms that Casson's (1987) entrepreneur is associated with adds to the heterogeneity that quantitative approaches struggle to capture. The possibilities to implement what can theoretically be constructed are limited and even more so in quantitative work, where firm growth is in many cases the only criteria that separates success from failure.

Limitations also apply to the empirical part of the study, where factors that may affect the SDOF could not be included because the ability to quantitatively analyse the phenomenon depends on the measurability of dimensions and the availability of reliable data. Just as it is hard to transform the entrepreneur into a measurable format, so too is it difficult to analyse internal factors such as individuals' aspirations and motivations that explain why firms respond to change as they do. By distinguishing owner-manager from manager-led firms, the contribution of the entrepreneur to firm growth becomes observable, but nothing more. The mechanics of decision making remain unclear and although business and industry life-cycles play a vital role in firm survival, the inclusion thereof in the analysis says little about the selection process of specific firms. This leads to the determination of the industry life-cycle stage as another difficulty. Theoretically as clear as the definition of the entrepreneur, it reflects a system of firm entry and exit rates, competition and profit margins, and product and process innovation. The quantification of the life-cycle stage cannot but impose further restrictions.

Hence, the use of proxies to simplify abstract concepts to obtain estimates free from bias is an illusion. As the number of employees turned out to be the most appropriate proxy for firm size, it led to the Gini-coefficient as proxy for FSI of industry classifications allocated by administrators. The sample firms were retrieved from databases and official statistics with an unknown impact of institutional differences in evaluating and providing comprehensive and reliable datasets; none of it can be verified except the degree of underrepresentation of micro and small firms. There are, however, good proxies and not so good proxies and cross-validation gives some certainty that what has been found is valid. Using the Gini-coefficient as proxy for FSI is a surprisingly good proxy. The HHI showed consistency, as have alternative regression estimators, but with an element of uncertainty.

Said uncertainty stems from the availability and quality of the data. While the described construction of the Gini-coefficient was based on no missing data and a number of precautions were taken to minimise its bias, some independent variables were limited in applicability or were eventually omitted. The latter was the case for diversification, but, as the number of MNEs continues to rise, it becomes increasingly important for empirical work. Especially weak was the data on export orientation and R&D, whereas for regional dispersion it was the limitation in making sense of the available information that imposed a constraint. This applies in particular to Italy, where drawing conclusions on ‘inefficiencies’ due to its regional heterogeneity is challenging. Totally absent from the analysis remained mergers and acquisition and outsourcing activities, which contribute to venture aggregation and new venture creation. The used dataset did not allow such factors to be taken into account, but they are to some extent reflected in an industry’s age. In addition, sunk costs, for instance for advertisement, remained inaccessible, but might affect market concentration by protecting incumbent firms.

Additional limitations apply to the measures defined to examine the implications of FSI on welfare, each a dimension in its own right with much left to be investigated further. Accessible data on life satisfaction and happiness levels are too poor and too broad to establish any meaningful link between firm-size class shares and well-being. It is also clear that the latter is affected by many other factors, with the SDOF being among the most remote. Even though the alternative approach to assessing the implications on welfare results from general datasets, the findings are largely consistent with predictions. Yet another precaution taken was the use of population rather than sample data when estimating implications on welfare. The relevance of economic development and strong heterogeneity among EU countries in combination with proxies covering extensive parts of socio-economic aspects, such as ANS, require caution when interpreting the findings. Given the presence of aggregate bias, the accuracy of the coefficients is questionable and necessitated a focus on the direction of the dimensions rather than the magnitude of the estimated coefficients.

Also disregarded are legal, political, educational and labour market dimensions, which undoubtedly affect firm growth or results in preference for one firm-size class or another. Such tendencies are particularly strong for Italy, where financial institutions exert considerable power and, according to Beck *et al*. (2013), discourage firms from borrowing. The relevance of institutional factors is commented on by Henrekson and Johansson (1999) and Pagano and Schivardi (2003). Implications on firm growth and selection might also come from different tax regimes, leading to lower market concentration when resulting in higher costs. The single-country analysis with the inclusion of unobserved heterogeneity takes these issues into account, at least to some extent, but more efforts are needed to understand such correlations.

7.4 Possibilities for future research

In spite of the persisting difficulties in conceptualisation and measurement of the entrepreneur, the findings demonstrate that firm size is associated with entrepreneurial activity. Such activity declines as firm size increases and requires the acknowledgement that each firm-size class has a distinct function. The entrepreneurial element might be present in all size classes, but in a different form and with implications on welfare that differ from size class to size class. The Gini-coefficient condenses the structural information the SDOF contains and is a suitable operational measure to determine the degree of FSI. It is superior compared to the HHI, whose bias increases the larger the underrepresentation of small firms. Future research can build on these insights, but whether the empirical findings are consistent with the variance in firm size – Bloch (1981) and Hariprasad (2011) used the variance in market share – has yet to be verified.

Given the importance of SMEs and the creeping emergence of the missing middle, more work needs to be done to understand the factors that could not be addressed to a satisfactory extent. Export orientation, R&D, diversification and regional concentration are promising policy instruments, the effectiveness of which in lowering FSI needs further investigation. With regard to regional development, Larrea *et al.* (2010) suggest a narrow geographic scope of research projects and the findings indeed show that FSI is influenced by regional factors. Beyond regional peculiarities at national level, Europe's East-West divide matters when constructing samples of European countries. Of particular interest is the contribution of medium-sized firms to entrepreneurial activity in Eastern Europe. A country and industry-specific analysis would give an insight into policy requirements for transitional countries, which differ from measures appropriate for developed economies.

As industry life-cycles are long-term evolutionary patterns, a more extensive time horizon is recommended when examining their effects. Their influence is responsible for aggregate data being unsuitable in examining the dynamics of the SDOF, be it in the percentage of firm-size classes or FSI. Aggregating data is acceptable when limiting the analysis to large firms where commonalities exist: strategically and geographically well diversified with operations in established industries and none operating below the MES. But when extending samples to SMEs, industry-specific characteristics become increasingly important and need to be part of the analysis. This might require a clear distinction between ‘diversity’ (in industries) and ‘variety’ (in firm size) as advised by Mazzucato (2000). Here, these terms were used interchangeably, because the industry-specific approach chosen does no harm to clarity. Also, the inclusion of interaction terms would make sense to identify to what extent, for instance, industry age matters.

The variables were assumed to be exogenous – this was statistically confirmed – but approaches taking into account potential endogeneity should be considered for future research. As a structural indicator, FSI influences performance, as was confirmed when determining the impact of firm-size class shares on production output. The restrictive linearity assumption on which the specified models rely, are limited in their ability to reproduce the mechanics operating at and between firm and industries (Mazzucato 2000). This suggests the consideration of a non-parametric approach as the closest alternative. But no matter how sophisticated estimators are, without the inclusion of dimensions revealing processes occurring within the firm, interactions taking place between firms and industries cannot be grasped. For internal factors to be understood – and this refers primarily on the decision making process and the motivations behind it – the inclusion of qualitative data is vital and favours mixed methods. The *Global Entrepreneurship Monitor* database, for example, offers some of these dimensions and permits further examination of the implications of FSI on welfare.

Besides the need to validate the findings – ideally with more representative datasets for micro and small firms – in agreement with Pagano and Schivardi (2003), more research is also required to understand the mechanisms enabling technology and knowledge transfer and the consequences on innovation output. Micro and small firms especially are event-driven with little choice in allocating resources and are much more dependent on the environment. Their ability to commercialise on basic research is low, but knowing the necessary framework conditions is required to make such a firm-size class more innovative. A qualitative approach might be superior to any quantitative work in explaining the reasons for success and failure. Since most research is concerned with growth, a better understanding of failure is desirable in order to make policies more efficient. It may well be that, occasionally, failure contributes to more knowledge than success and it would be wasteful to leave it unused. The selective process the shakeout produces is associated with both unpredictability (Mazzucato 2000) and efficiency (Peltoniemi 2011) and both elements contribute to an increase in FSI. To validate the accuracy of the factors affecting FSI, a significant research effort is needed to understand the effects of industrial policies, which, according to Buigues and Sekkat (2009) is still weak. Measuring their efficiency is a commitment to complexity and demands long-term engagement and consistency, but is essential for regional and economic development.

Apart from its tendency to supress disruptive innovations, it has been assumed that capitalism is able to recognise the value of SMEs. Whether this is applicable or MNEs' acquisition strategies will incorporate innovative firms in their infancy and impede the development of a fair share of SMEs is a legitimate question with ideological character. Addressing it would assist in understanding MNEs' awareness of sustainability and whether capitalism is indeed able to learn. Yet another factor that remains unconsidered is state capitalism at an international scale, which is a new dimension of the large firm with serious long-term implications for welfare. With regard to the latter, there is a need to devote more energy to these factors. As additional well-being measures are under way and national statistic offices have started producing longitudinal records, new insights might be valuable. This would, for instance, allow the analysis of the extent to which a balanced SDOF offers more choice to both self-employed and non-self-employed activities, and the resulting implications on well-being.

Appendix A: Variable definition

Variable	Definition	Measurement at firm level and transformation to industry level
GINI[c]	Gini-coefficient as proxy for firm size inequality	The value is derived from the number of employees of each firm within a 4-digit industry according to the following formula: $$G_{jt} = \frac{n+1}{n-1} - \frac{2}{n(n-1)\mu_t} \sum_{i=1}^{n} \rho_{it} x_{it} \; ; \quad 0 \leq G_{jt} \leq 1$$ G_{jt} = Gini-coefficient of 4-digit industry j at time t n = no. of firms μ_t = mean at time t ρ = rank x = value of observation i
GINI_L[a]	Log-odds ratio of G	$$G'_{jt} = \ln\left[\frac{G_{jt}}{1-G_{jt}}\right]$$
HHI[a]	Herfindahl-Hirschman Index as alternative proxy for firm size inequality	$$HHI_{jt} = \sum_{i=1}^{n} s_{it}^2 \; ; \quad \frac{1}{n} \leq HHI_{jt} \leq 1$$ HHI_{jt} = Herfindahl-Hirschman Index of 4-digit industry j at time t n = no. of firms s = share of firm i
Second order adjustment adjustment		
SAMPLE[c]	Dummies controlling for second order bias due to variations in firm-level observations forming one industry-level observation	S20 = 1 for 20 firms; 0 otherwise S30 = 1 for 30 firms; 0 otherwise S40 = 1 for 40 firms; 0 otherwise S50 = 1 for 50 firms; 0 otherwise S60 = 1 for 60 firms; 0 otherwise S75 = 1 for 75 firms; 0 otherwise Industry-level observations that do not belong to any of the above categories consist of 100 firms
Main industry characteristics (MAIN)		
I_...[c]	Dummies controlling for main industry effects	I_ACC: Accomodation and food services I_ADM: Administrative and support services I_AGR: Agriculture, forestry and fishing I_ART: Arts, entertainment and recreation I_CON: Construction I_EDU: Education I_ELE: Electricity, gas, steam and air conditioning supply I_HUM: Human health and social work activities I_INF: Information and communication I_MAN: Manufacturing I_MIN: Mining and quarrying I_PRO: Professional, scientific and technical activities I_TRA: Transportation and storage I_WAT: Water supply; sewerage, waste management and remediation activities I_WHO: Wholesale and retail trade; repair of motor vehicles and motorcycles I_OTH: Other service activities

GR_MAIN[c]	Main industry growth measured by the percentage change from time *t-1* to time *t*	$$GR\_MAIN_k = \frac{no.of\ empl._{kt} - no.of\ empl._{k.t-1}}{no.of\ employees_{k.t-1}}$$ *k* = main industry section *t* = time
Industry characteristics at the 4-digit level (FDIG)		
GR_FDIG[c]	4-digit industry growth measured by the percentage change from time *t-1* to *t*	$$GR\_FDIG_j = \frac{no.of\ empl._{it} - no.of\ empl._{i.t-1}}{no.of\ employees_{i.t-1}}$$ *j* = 4-digit industry *t* = time
STAGE_S[c]	Dummy for mature industry-stage	1 for industries with fluctuations in employee numbers of no more or less than 1% per year; 0 otherwise
CR4EM[c] CR8EM[a]	Initial industry concentration, i.e. at the beginning of the sample period	$$CR4EM_j = \frac{\sum_{i=1}^{4} no.of\ employees_i}{\sum_{i=1}^{n} no.of\ employees_i}$$ $$CR8EM_j = \frac{\sum_{i=1}^{8} no.of\ employees_i}{\sum_{i=1}^{n} no.of\ employees_i}$$
AGE_MAX[c] AGE_MIN[a] AGE_STD[a]	Industry age based on the assumption that an industry is as old as its oldest firm (AGE_{max}), as young as its youngest firm (AGE_{min}) or defined by the dispersion of firms' age (AGE_{std})	$$AGE\_MAX_j = \ln[\max(firm\ age_i)]$$ $$AGE\_MIN_j = \ln[\min(firm\ age_i)]$$ $$AGE\_STD_j = \text{standard deviation}(firm\ age_i)$$
MES_MEAN[c]	Minimum efficient scale based on mean firm size	$$MES\_MEAN_j = \text{mean}(firm\ size_i)$$
MES_MIN[a]	Minimum efficient scale based on the smallest surviving firm	$$MES\_MIN_j = \min(firm\ size_i)$$
MES_REL[a]	Minimum efficient scale based on the median firm size relative to the largest firm	$$MES\_REL_j = \text{median}\left(\frac{firm\ size_i}{\max(firm\ size_i)}\right)$$
REG_N[c]	Regional concentration of firms belonging to the same 4-digit industry measured by the number of regions	$$REG\_N_j = \ln(no.of\ regions)$$
REG_ENT[a]	Geographic dispersion of firms belonging to the same 4-digit industry measured by the entropy of regions	$$REG\_ENT_j = -\sum_{r=1}^{z} p_r \ln(p_r)\ ;\quad 0 \le REG\_ENT_j \le \ln(z)$$ $$p_r = \frac{x_r}{n}\ ;\quad n = \sum_{r=1}^{z} x_r$$ REG_ENT_j = Entropy of 4-digit NACE industry *j* *z* = no. of regions p_r = probability of occurrence of region *r* *n* = no. of firms x_r = no. of firms in region *r*
Firm properties: management, ownership and plant structure (FPRO) – simplified formulation		
TMTIND_P[c]	% of firms exclusively managed by individuals	$$\frac{no.of\ firms\ managed\ by\ individuals_j}{total\ no.of\ firms_j}$$
TMTIND_EM[a]	% of employees belonging to firms exclusively managed by individuals	$$\frac{no.of\ employees\ of\ firms\ managed\ by\ individuals_j}{total\ no.of\ employees_j}$$

TMTSH_P[c]	% of owner-managed firms	$\frac{no.\,of\ firms\ with\ at\ least\ one\ TMT\ member\ also\ being\ a\ shareholder_j}{total\ no.\,of\ firms_j}$
TMTSH_EM[a]	% of employees belonging to owner-managed firms	$\frac{no.\,of\ employees\ of\ firms\ with\ at\ least\ one\ TMT\ member\ also\ being\ a\ shareholder_j}{total\ no.\,of\ employees_j}$
INDEP_P[a]	% of firms with a majority shareholder structure of at least 50%, i.e. owned by one shareholder	$\frac{no.\,of\ firms\ with\ majority\ shareholder_j}{total\ no.\,of\ firms_j}$
INDEP_EM[a]	% of employees of firms with a majority shareholder structure of at least 50%, i.e. owned by one shareholder	$\frac{no.\,of\ employees\ of\ firms\ with\ majority\ shareholder_j}{total\ no.\,of\ employees_j}$
FOROWN_P[c]	% of foreign owned firms	$\frac{no.\,of\ foreign\text{-}owned\ firms_j}{total\ no.\,of\ firms_j}$
FOROWN _EM[a]	% of employees belonging to foreign-owned firms	$\frac{no.\,of\ employees\ of\ foreign\text{-}owned\ firms_j}{total\ no.\,of\ employees_j}$
GROUP_P[c]	% of firms belonging to a group or holding	$\frac{no.\,of\ firms\ belonging\ to\ a\ group_j}{total\ no.\,of\ firms_j}$
GROUP_EM[a]	% of employees belonging to firms part of a group or holding	$\frac{no.\,of\ employees\ of\ firms\ belonging\ to\ a\ group_j}{total\ no.\,of\ employees_j}$
SUBS_P[c]	% of firms with domestic or foreign subsidiaries	$\frac{no.\,of\ firms\ with\ subsidiaries_j}{total\ no.\,of\ firms_j}$
SUBS_EM[a]	% of employees of firms with domestic or foreign subsidiaries	$\frac{no.\,of\ employees\ of\ firms\ with\ subsidiaries_j}{total\ no.\,of\ employees_j}$
DIVERS_P[oc]	% of firms with secondary industry codes	$\frac{no.\,of\ firms\ with\ secondary\ industry\ codes_j}{total\ no.\,of\ firms_j}$
DIVERS_D[oa]	Median number of secondary industry codes	$\mathrm{median}(no.\,of\ secondary\ industry\ codes\ registered)_j$
DIVERS_A[a]	Mean number of secondary industry codes	$\mathrm{mean}(no.\,of\ secondary\ industry\ codes\ registered)_j$
Firm performance and structural characteristics (FPER) – simplified formulation		
TANTA_D[c]	Tangible assets to total assets as proxy for entry deterrence and flexibility to respond to environmental changes	$\mathrm{median}\left(\frac{tangible\ assets_{it}}{total\ assets_{it}}\right)$
TANTA_G[a]		$\frac{\sum_{i=1}^{n} tangible\ assets_{it}}{\sum_{i=1}^{n} total\ assets_{it}}$

INTTA_A[c]	Intangible assets to total assets as proxy for entry deterrence	$\text{mean}\left(\frac{\textit{intangible assets}_{it}}{\textit{total assets}_{it}}\right)$
INTTA_G[a]		$\frac{\sum_{i=1}^{n} \textit{intangible assets}_{it}}{\sum_{i=1}^{n} \textit{total assets}_{it}}$
STKTA_D[c]	Stock to total assets as proxy for excess capacity	$\text{median}\left(\frac{\textit{stock}_{it}}{\textit{total assets}_{it}}\right)$
STKTA_G[a]		$\frac{\sum_{i=1}^{n} \textit{stock}_{it}}{\sum_{x=1}^{y} \textit{total assets}_{it}}$
CCETA_D[c]	Cash and cash equivalents to total assets as proxy for liquidity	$\text{median}\left(\frac{\textit{cash and cash equivalents}_{it}}{\textit{total assets}_{it}}\right)$
CCETA_G[a]		$\frac{\sum_{i=1}^{n} \textit{cash and cash equivalents}_{it}}{\sum_{i=1}^{n} \textit{total assets}_{it}}$
EMPTO_D[c]	Costs of labour to operating turnover as proxy for labour intensity	$\text{median}\left(\frac{\textit{cost of labour}_{it}}{\textit{operating turnover}_{it}}\right)$
EMPTO_G[a]		$\frac{\sum_{i=1}^{n} \textit{cost of labour}_{it}}{\sum_{i=1}^{n} \textit{operating turnover}_{it}}$
VAEMP_D[c]	Value added to no. of employees as proxy for labour productivity (technological sophistication)	$\ln\left[\text{median}\left(\frac{\textit{value added}_{it}}{\textit{no. of employees}_{it}}\right)\right]$
VAEMP_G[a]		$\ln\left(\frac{\sum_{i=1}^{n} \textit{value added}_{it}}{\sum_{i=1}^{n} \textit{no. of employees}_{it}}\right)$
RNDTO_A[oc]	R&D expenditure to operating turnover as proxy for R&D intensity and entry deterrent	$\text{mean}\left(\frac{\textit{R\&D expenditure}_{it}}{\textit{operating turnover}_{it}}\right)$
RNDTO_G[oa]		$\ln\left(\frac{\sum_{i=1}^{n} \textit{R\&D expenditure}_{it}}{\sum_{i=1}^{n} \textit{operating turnover}_{it}}\right)$
EXPTO_A[oc]	Export turnover to total operating turnover as proxy for export orientation	$\text{mean}\left(\frac{\textit{exports}_{it}}{\textit{operating turnover}_{it}}\right)$
EXPTO_G[oa]		$\ln\left(\frac{\sum_{i=1}^{n} \textit{exports}_{it}}{\sum_{i=1}^{n} \textit{operating turnover}_{it}}\right)$
Time effects		
YR08[c]	Sample year dummies	1 for year 2008; 0 otherwise
YR09[c]		1 for year 2009; 0 otherwise
YR10[c]		1 for year 2010; 0 otherwise

c = core variable, i.e. variable of primary interest a = alternative variable o = optional variable

Unless otherwise stated, variables are defined as follows:

i = firm-level observation
j = 4-digit NACE industry-level observation
k = main NACE industry-level observation
r = region
s = share
μ = mean
n = no. of firm-level observations
m = no. of 4-digit industry-level observations
l = no. of main NACE industry-level observations
z = no. of regions
p = probability
t = time period

Appendix B1: Employment share by firm-size class – UK

Firm-size class by number of employees	2010			2008			2006			2004			2002		
	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total
Up to 9	0.05%	0.17%	0.15%	0.04%	0.17%	0.14%	0.04%	0.18%	0.15%	0.05%	0.20%	0.16%	0.05%	0.22%	0.17%
Micro firms	0.05%	0.17%	0.15%	0.04%	0.17%	0.14%	0.04%	0.18%	0.15%	0.05%	0.20%	0.16%	0.05%	0.22%	0.17%
From 10 to 14	0.05%	0.15%	0.13%	0.04%	0.14%	0.12%	0.05%	0.15%	0.13%	0.05%	0.16%	0.14%	0.04%	0.17%	0.14%
From 15 to 19	0.08%	0.15%	0.13%	0.07%	0.15%	0.13%	0.08%	0.15%	0.14%	0.08%	0.16%	0.14%	0.08%	0.20%	0.17%
From 20 to 24	0.11%	0.17%	0.16%	0.10%	0.16%	0.15%	0.11%	0.17%	0.16%	0.12%	0.18%	0.17%	0.11%	0.20%	0.18%
From 25 to 29	0.14%	0.18%	0.17%	0.12%	0.17%	0.16%	0.11%	0.19%	0.17%	0.13%	0.21%	0.19%	0.11%	0.23%	0.20%
From 30 to 39	0.33%	0.42%	0.40%	0.28%	0.41%	0.38%	0.28%	0.45%	0.41%	0.28%	0.47%	0.42%	0.31%	0.49%	0.44%
From 40 to 49	0.43%	0.47%	0.47%	0.37%	0.46%	0.43%	0.40%	0.47%	0.45%	0.39%	0.48%	0.46%	0.41%	0.57%	0.53%
Small firms	1.14%	1.54%	1.46%	0.98%	1.49%	1.37%	1.03%	1.58%	1.46%	1.05%	1.66%	1.52%	1.06%	1.86%	1.66%
From 50 to 59	0.67%	0.55%	0.57%	0.57%	0.46%	0.48%	0.55%	0.51%	0.51%	0.60%	0.56%	0.57%	0.60%	0.60%	0.60%
From 60 to 69	0.76%	0.52%	0.57%	0.65%	0.51%	0.54%	0.75%	0.57%	0.61%	0.76%	0.58%	0.62%	0.75%	0.60%	0.63%
From 70 to 79	0.83%	0.52%	0.59%	0.78%	0.56%	0.61%	0.90%	0.58%	0.65%	0.81%	0.60%	0.65%	0.66%	0.62%	0.63%
From 80 to 89	0.83%	0.50%	0.58%	0.71%	0.55%	0.58%	0.81%	0.61%	0.66%	0.81%	0.58%	0.63%	0.83%	0.59%	0.65%
From 90 to 99	0.73%	0.52%	0.57%	0.84%	0.52%	0.59%	0.84%	0.56%	0.62%	0.77%	0.56%	0.61%	0.77%	0.56%	0.61%
From 100 to 124	1.88%	1.11%	1.28%	1.97%	1.19%	1.36%	1.88%	1.22%	1.37%	1.90%	1.25%	1.39%	1.79%	1.39%	1.48%
From 125 to 149	1.69%	1.08%	1.21%	1.47%	1.06%	1.15%	1.68%	1.15%	1.26%	1.82%	1.18%	1.32%	1.49%	1.09%	1.19%
From 150 to 199	2.73%	1.80%	2.00%	2.92%	1.92%	2.15%	2.82%	1.87%	2.08%	2.95%	1.87%	2.11%	2.99%	1.99%	2.25%
From 200 to 249	2.36%	1.53%	1.70%	2.16%	1.65%	1.77%	2.76%	1.64%	1.89%	2.69%	1.62%	1.87%	2.35%	1.64%	1.81%
Medium firms	12.48%	8.13%	9.07%	12.07%	8.42%	9.23%	12.99%	8.71%	9.65%	13.11%	8.80%	9.77%	12.23%	9.08%	9.85%
From 250 to 349	3.35%	2.48%	2.66%	3.70%	2.50%	2.77%	3.78%	2.50%	2.79%	3.85%	2.46%	2.78%	4.05%	2.69%	3.02%
From 350 to 499	3.89%	2.61%	2.89%	3.75%	2.70%	2.93%	4.02%	2.86%	3.12%	4.09%	2.88%	3.15%	3.84%	2.66%	2.95%
From 500 to 699	3.41%	2.83%	2.95%	3.77%	2.72%	2.95%	3.90%	2.72%	2.98%	4.36%	2.58%	2.98%	3.97%	2.67%	2.99%
From 700 to 899	2.93%	2.09%	2.27%	2.83%	2.27%	2.39%	3.69%	2.20%	2.53%	3.34%	2.21%	2.46%	3.49%	2.38%	2.65%
From 900 to 1199	3.13%	2.49%	2.63%	3.72%	2.48%	2.76%	3.93%	2.59%	2.88%	3.89%	2.51%	2.82%	4.15%	2.29%	2.74%
From 1200 to 1499	2.62%	1.74%	1.93%	1.89%	2.11%	2.06%	1.87%	1.79%	1.80%	3.23%	1.90%	2.20%	3.14%	2.28%	2.49%
From 1500 to 1999	3.52%	2.82%	2.97%	4.32%	2.82%	3.15%	4.60%	3.19%	3.50%	4.85%	2.79%	3.25%	4.57%	2.66%	3.13%
From 2000 to 2599	2.48%	3.03%	2.91%	2.94%	2.94%	2.94%	3.48%	2.84%	2.98%	3.34%	2.53%	2.71%	3.39%	3.29%	3.31%
From 2600 to 3499	3.45%	3.51%	3.50%	3.54%	3.81%	3.75%	3.79%	3.29%	3.40%	3.49%	3.95%	3.85%	3.71%	3.32%	3.41%
From 3500 to 4999	4.45%	4.90%	4.80%	4.05%	4.44%	4.35%	3.97%	5.02%	4.79%	4.39%	4.29%	4.31%	4.83%	4.09%	4.27%
From 5000 to 6999	4.01%	4.19%	4.15%	4.96%	3.77%	4.03%	4.34%	3.82%	3.94%	4.61%	4.76%	4.73%	3.90%	5.39%	5.02%
From 7000 to 9999	6.48%	4.64%	5.04%	5.10%	5.05%	5.06%	6.17%	5.26%	5.46%	5.84%	4.51%	4.81%	5.99%	5.05%	5.28%
10,000 or more	42.61%	52.83%	50.62%	42.34%	52.31%	50.12%	38.40%	51.45%	48.57%	36.51%	51.97%	48.50%	37.63%	50.07%	47.06%
Large firms	86.33%	90.16%	89.32%	86.91%	89.92%	89.26%	85.94%	89.53%	88.74%	85.79%	89.34%	88.55%	86.66%	88.84%	88.32%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Source of data: Modified from Orbis

Appendix B2: Employment share by firm-size class – Italy

Firm-size class by number of employees	2010			2008			2006			2004			2002		
	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total
Up to 9	0.95%	2.18%	**1.58%**	0.88%	2.21%	**1.55%**	0.92%	2.35%	**1.65%**	0.92%	2.45%	**1.70%**	0.83%	2.68%	**1.69%**
Micro firms	**0.95%**	**2.18%**	**1.58%**	**0.88%**	**2.21%**	**1.55%**	**0.92%**	**2.35%**	**1.65%**	**0.92%**	**2.45%**	**1.70%**	**0.83%**	**2.68%**	**1.69%**
From 10 to 14	1.54%	2.44%	**2.01%**	1.47%	2.39%	**1.94%**	1.53%	2.71%	**2.13%**	1.62%	2.76%	**2.20%**	1.07%	2.37%	**1.67%**
From 15 to 19	1.41%	2.02%	**1.73%**	1.46%	2.08%	**1.78%**	1.52%	2.06%	**1.79%**	1.64%	2.07%	**1.86%**	1.33%	2.46%	**1.85%**
From 20 to 24	1.53%	1.66%	**1.60%**	1.35%	1.55%	**1.45%**	1.61%	1.86%	**1.74%**	1.82%	1.89%	**1.86%**	1.50%	2.33%	**1.89%**
From 25 to 29	1.72%	1.73%	**1.72%**	1.72%	1.74%	**1.73%**	1.88%	1.86%	**1.87%**	1.81%	1.96%	**1.89%**	1.50%	2.09%	**1.77%**
From 30 to 39	4.01%	3.42%	**3.70%**	3.72%	3.39%	**3.55%**	3.95%	3.54%	**3.74%**	4.40%	3.73%	**4.06%**	4.36%	4.75%	**4.54%**
From 40 to 49	4.37%	3.12%	**3.72%**	4.21%	3.17%	**3.68%**	4.39%	3.13%	**3.75%**	4.09%	3.09%	**3.57%**	3.63%	3.33%	**3.49%**
Small firms	**14.58%**	**14.39%**	**14.48%**	**13.93%**	**14.32%**	**14.13%**	**14.88%**	**15.16%**	**15.02%**	**15.38%**	**15.50%**	**15.44%**	**13.39%**	**17.33%**	**15.21%**
From 50 to 59	3.88%	2.42%	**3.12%**	3.70%	2.63%	**3.15%**	3.98%	2.50%	**3.22%**	4.18%	2.51%	**3.32%**	3.59%	3.41%	**3.51%**
From 60 to 69	3.54%	2.11%	**2.80%**	3.61%	2.21%	**2.89%**	3.63%	2.64%	**3.13%**	3.66%	2.51%	**3.07%**	3.37%	2.61%	**3.02%**
From 70 to 79	3.16%	1.92%	**2.52%**	3.17%	1.89%	**2.52%**	3.27%	2.25%	**2.75%**	3.29%	2.12%	**2.69%**	3.55%	2.15%	**2.90%**
From 80 to 89	2.89%	1.84%	**2.35%**	3.07%	1.72%	**2.38%**	3.08%	2.03%	**2.55%**	3.22%	1.79%	**2.48%**	2.47%	2.03%	**2.27%**
From 90 to 99	2.36%	1.57%	**1.95%**	2.70%	1.52%	**2.10%**	2.60%	1.53%	**2.06%**	2.78%	1.56%	**2.15%**	2.84%	1.82%	**2.37%**
From 100 to 124	4.83%	3.57%	**4.18%**	4.90%	3.75%	**4.31%**	5.47%	3.41%	**4.42%**	5.38%	3.15%	**4.23%**	5.54%	3.78%	**4.73%**
From 125 to 149	3.79%	2.49%	**3.11%**	3.91%	2.48%	**3.18%**	3.70%	2.45%	**3.06%**	3.87%	2.57%	**3.20%**	4.06%	3.06%	**3.60%**
From 150 to 199	5.46%	4.11%	**4.76%**	5.57%	4.12%	**4.83%**	5.40%	4.31%	**4.84%**	5.10%	3.80%	**4.44%**	6.63%	4.95%	**5.85%**
From 200 to 249	3.60%	3.23%	**3.41%**	3.72%	3.36%	**3.54%**	3.69%	3.38%	**3.54%**	3.66%	3.24%	**3.44%**	7.12%	4.36%	**5.84%**
Medium firms	**33.51%**	**23.26%**	**28.20%**	**34.35%**	**23.68%**	**28.90%**	**34.82%**	**24.50%**	**29.57%**	**35.14%**	**23.25%**	**29.02%**	**39.17%**	**28.17%**	**34.09%**
From 250 to 349	4.74%	4.91%	**4.83%**	4.40%	4.73%	**4.57%**	4.76%	4.81%	**4.78%**	4.87%	4.68%	**4.77%**	5.80%	4.61%	**5.25%**
From 350 to 499	4.88%	5.40%	**5.15%**	5.18%	5.18%	**5.18%**	4.75%	5.12%	**4.94%**	4.23%	4.93%	**4.59%**	5.20%	5.95%	**5.54%**
From 500 to 699	4.06%	4.43%	**4.25%**	4.10%	5.16%	**4.64%**	4.33%	3.90%	**4.11%**	4.66%	3.34%	**3.98%**	3.03%	3.56%	**3.27%**
From 700 to 899	2.84%	3.02%	**2.93%**	2.83%	2.80%	**2.81%**	2.91%	2.87%	**2.89%**	2.68%	3.40%	**3.05%**	1.71%	1.81%	**1.75%**
From 900 to 1199	2.51%	4.17%	**3.37%**	2.49%	3.39%	**2.95%**	2.01%	3.94%	**2.99%**	1.80%	3.22%	**2.53%**	1.61%	2.28%	**1.92%**
From 1200 to 1499	1.73%	3.75%	**2.78%**	1.27%	4.49%	**2.92%**	1.50%	3.15%	**2.34%**	2.09%	2.75%	**2.43%**	1.42%	1.28%	**1.36%**
From 1500 to 1999	1.61%	3.15%	**2.41%**	1.99%	2.40%	**2.20%**	2.01%	2.72%	**2.37%**	2.21%	2.22%	**2.22%**	1.40%	2.90%	**2.09%**
From 2000 to 2599	2.49%	1.62%	**2.04%**	2.20%	1.02%	**1.60%**	2.15%	2.10%	**2.12%**	1.95%	2.95%	**2.46%**	1.38%	2.83%	**2.05%**
From 2600 to 3499	1.71%	3.55%	**2.67%**	2.10%	2.56%	**2.34%**	2.51%	2.15%	**2.33%**	2.98%	1.16%	**2.04%**	1.90%	0.36%	**1.19%**
From 3500 to 4999	1.91%	3.10%	**2.53%**	2.21%	3.64%	**2.94%**	3.73%	4.34%	**4.04%**	2.33%	4.35%	**3.37%**	1.13%	1.40%	**1.25%**
From 5000 to 6999	3.35%	4.07%	**3.72%**	2.14%	2.84%	**2.50%**	1.58%	2.10%	**1.84%**	2.31%	1.49%	**1.89%**	2.54%	0.63%	**1.66%**
From 7000 to 9999	0.81%	3.59%	**2.25%**	2.01%	3.72%	**2.88%**	0.72%	4.87%	**2.83%**	0.70%	3.95%	**2.38%**	1.45%	2.01%	**1.71%**
10,000 or more	18.32%	15.41%	**16.81%**	17.92%	17.86%	**17.89%**	16.42%	15.92%	**16.18%**	15.75%	20.36%	**18.13%**	18.04%	22.20%	**19.97%**
Large firms	**50.96%**	**60.17%**	**55.74%**	**50.84%**	**59.79%**	**55.42%**	**49.38%**	**57.99%**	**53.76%**	**48.56%**	**58.80%**	**53.84%**	**46.61%**	**51.82%**	**49.01%**
Total	100.0%	100.0%	**100.0%**	100.0%	100.0%	**100.0%**	100.0%	100.0%	**100.0%**	100.0%	100.0%	**100.0%**	100.0%	100.0%	**100.0%**

Source of data: Modified from Orbis

Appendix B3: Employment share by firm-size class – Germany

Firm-size class by number of employees	2010			2008			2006		
	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total	Manuf.	Non-Man.	Total
Up to 9	0.10%	0.74%	**0.43%**	0.10%	0.70%	**0.41%**	0.11%	0.63%	**0.41%**
Micro firms	**0.10%**	**0.74%**	**0.43%**	**0.10%**	**0.70%**	**0.41%**	**0.11%**	**0.63%**	**0.41%**
From 10 to 14	0.10%	0.46%	**0.28%**	0.10%	0.44%	**0.28%**	0.11%	0.39%	**0.27%**
From 15 to 19	0.10%	0.38%	**0.24%**	0.09%	0.36%	**0.23%**	0.09%	0.31%	**0.21%**
From 20 to 24	0.08%	0.33%	**0.21%**	0.07%	0.31%	**0.20%**	0.08%	0.28%	**0.20%**
From 25 to 29	0.08%	0.29%	**0.19%**	0.08%	0.27%	**0.17%**	0.07%	0.24%	**0.17%**
From 30 to 39	0.15%	0.53%	**0.33%**	0.15%	0.48%	**0.32%**	0.16%	0.41%	**0.30%**
From 40 to 49	0.15%	0.40%	**0.28%**	0.15%	0.41%	**0.28%**	0.18%	0.35%	**0.27%**
Small firms	**0.66%**	**2.39%**	**1.53%**	**0.64%**	**2.27%**	**1.48%**	**0.69%**	**1.98%**	**1.42%**
From 50 to 59	0.17%	0.46%	**0.32%**	0.17%	0.42%	**0.30%**	0.18%	0.38%	**0.29%**
From 60 to 69	0.20%	0.42%	**0.31%**	0.21%	0.37%	**0.29%**	0.23%	0.33%	**0.28%**
From 70 to 79	0.24%	0.41%	**0.32%**	0.23%	0.37%	**0.30%**	0.22%	0.32%	**0.28%**
From 80 to 89	0.22%	0.36%	**0.29%**	0.21%	0.37%	**0.29%**	0.26%	0.33%	**0.29%**
From 90 to 99	0.21%	0.36%	**0.28%**	0.23%	0.32%	**0.28%**	0.24%	0.25%	**0.25%**
From 100 to 124	0.64%	0.90%	**0.77%**	0.62%	0.85%	**0.74%**	0.66%	0.73%	**0.70%**
From 125 to 149	0.61%	0.74%	**0.68%**	0.55%	0.70%	**0.63%**	0.57%	0.60%	**0.59%**
From 150 to 199	1.15%	1.34%	**1.25%**	1.14%	1.24%	**1.20%**	1.08%	1.10%	**1.09%**
From 200 to 249	0.95%	1.19%	**1.07%**	0.97%	1.09%	**1.03%**	1.00%	0.95%	**0.97%**
Medium firms	**4.39%**	**6.18%**	**5.29%**	**4.33%**	**5.73%**	**5.06%**	**4.44%**	**4.99%**	**4.74%**
From 250 to 349	1.49%	1.78%	**1.64%**	1.50%	1.75%	**1.63%**	1.58%	1.49%	**1.53%**
From 350 to 499	2.23%	2.21%	**2.22%**	2.09%	2.03%	**2.06%**	2.13%	1.55%	**1.81%**
From 500 to 699	2.15%	2.34%	**2.25%**	2.22%	2.13%	**2.18%**	2.17%	1.83%	**1.98%**
From 700 to 899	1.44%	1.68%	**1.56%**	1.60%	1.50%	**1.55%**	1.86%	1.45%	**1.63%**
From 900 to 1199	1.88%	2.10%	**1.99%**	1.75%	2.13%	**1.94%**	1.62%	1.86%	**1.75%**
From 1200 to 1499	1.46%	1.61%	**1.54%**	1.37%	1.29%	**1.33%**	1.71%	1.09%	**1.36%**
From 1500 to 1999	1.63%	2.07%	**1.86%**	1.86%	2.06%	**1.96%**	1.55%	1.46%	**1.50%**
From 2000 to 2599	1.57%	2.51%	**2.05%**	1.15%	1.93%	**1.56%**	0.84%	1.77%	**1.36%**
From 2600 to 3499	1.61%	2.81%	**2.22%**	2.14%	3.33%	**2.75%**	2.47%	3.01%	**2.77%**
From 3500 to 4999	2.50%	4.12%	**3.32%**	2.37%	3.98%	**3.20%**	1.92%	3.45%	**2.78%**
From 5000 to 6999	2.26%	2.53%	**2.40%**	2.05%	2.06%	**2.06%**	2.05%	1.67%	**1.84%**
From 7000 to 9999	2.67%	2.69%	**2.68%**	2.78%	3.40%	**3.10%**	3.74%	2.75%	**3.19%**
10000 or more	71.96%	62.24%	**67.02%**	72.05%	63.71%	**67.73%**	71.12%	69.02%	**69.93%**
Large firms	**94.85%**	**90.69%**	**92.75%**	**94.93%**	**91.30%**	**93.05%**	**94.76%**	**92.40%**	**93.43%**
Total	100.0%	100.0%	**100.0%**	100.0%	100.0%	**100.0%**	100.0%	100.0%	**100.0%**

Source of data: Modified from Orbis

Appendix C1: Determinants of firm size inequality – UK

For decodification of abbreviations and variables please see end end of Appendix C3

Estimator (model)	OLS (BASIC)	OLS (D-A)	OLS (G)	RE (BASIC)	RE (D-A)	RE (G)	FGLS (BASIC)	FGLS (D-A)	FGLS (G)
Dependent variable	GINI	GINI	GINI	GINI	GINI	GINI	GINI	GINI	GINI
S20	-0.0499***[d]	-0.0530***[d]	-0.0165[d]	-0.0541*[d]	-0.0504*[d]	-0.0423[bd]	-0.0955***[d]	-0.125***[d]	-0.0852***[d]
	(0.0144)	(0.0141)	(0.0146)	(0.0292)	(0.0278)	(0.0272)	(0.0128)	(0.0128)	(0.0127)
S30	-0.0427***[d]	-0.0376***[d]	-0.0147[d]	-0.0451*[d]	-0.0450*[d]	-0.0388*[d]	-0.0674***[d]	-0.0674***[d]	-0.0591***[d]
	(0.0112)	(0.0110)	(0.0115)	(0.0242)	(0.0230)	(0.0225)	(0.00978)	(0.00975)	(0.0101)
S40	-0.0340***[f]	-0.0345***[f]	-0.00432[d]	-0.0344[b]	-0.0315[b]	-0.0238	-0.0663***	-0.0647***	-0.0386***[f]
	(0.0129)	(0.0131)	(0.0137)	(0.0243)	(0.0231)	(0.0225)	(0.0102)	(0.0101)	(0.0116)
S50	-0.0120	0.000302[d]	0.00138[d]	-0.0132	-0.0143	-0.0134	-0.0219**[f]	-0.0111	-0.0197*[f]
	(0.0101)	(0.00999)	(0.0108)	(0.0285)	(0.0271)	(0.0263)	(0.0106)	(0.0123)	(0.0105)
S60	-0.00830	-0.00411	0.00665	-0.00896	-0.0102	-0.00730	-0.0173**	-0.0154*[c]	-0.0294***
	(0.0100)	(0.0106)	(0.0107)	(0.0208)	(0.0198)	(0.0193)	(0.00814)	(0.00800)	(0.00800)
S75	0.0303***[f]	0.0412***[f]	0.0403***[f]	0.0314	0.0330	0.0342	0.0248***[f]	0.0313***[e]	0.0278***
	(0.00817)	(0.00796)	(0.00871)	(0.0313)	(0.0297)	(0.0288)	(0.00715)	(0.00561)	(0.00739)
YR08	0.00105	0.00548	0.00100	0.00145[ad]	0.00145[a]	0.001320[ad]	0.00141**[f]	0.000958	0.00131**[f]
	(0.00487)	(0.00473)	(0.00458)	(0.000926)	(0.000937)	(0.000931)	(0.000562)	(0.000609)	(0.000620)
YR09	0.00659	0.0118**[f]	0.00738	0.00447***	0.00378***	0.00350**	0.00505***	0.00404***[f]	0.00391***
	(0.00584)	(0.00565)	(0.00561)	(0.00134)	(0.00139)	(0.00137)	(0.000849)	(0.000934)	(0.000939)
YR10	0.00527	0.0103*[f]	0.00749	0.00387***	0.00347**	0.00351**	0.00480***	0.00415***[f]	0.00455***[f]
	(0.00569)	(0.00561)	(0.00550)	(0.00148)	(0.00156)	(0.00157)	(0.000992)	(0.00110)	(0.00110)
I_ACC	-0.0539***	-0.0772***	-0.0439**	-0.0588	-0.0663[e]	-0.0645	-0.0319[e]	-0.0729***	-0.0136[be]
	(0.0206)	(0.0223)	(0.0209)	(0.0467)	(0.0446)	(0.0435)	(0.0229)	(0.0205)	(0.0205)
I_ADM	0.0303*[f]	0.0305**[f]	0.0163	0.0301	0.0280	0.0211	0.0391***[e]	0.0692***[e]	0.0527***[ce]
	(0.0157)	(0.0152)	(0.0144)	(0.0342)	(0.0325)	(0.0316)	(0.0148)	(0.00965)	(0.0182)
I_AGR	0.0307[ad]	0.0167[ad]	0.000212	0.0303[d]	0.0324[d]	0.0245[d]	0.0590***	0.0815***	0.0455**[c]
	(0.0187)	(0.0211)	(0.0215)	(0.0436)	(0.0416)	(0.0404)	(0.0180)	(0.0113)	(0.0194)
I_ART	-0.00641[d]	-0.00807[d]	-0.0386**[f]	-0.00805[d]	-0.0163[d]	-0.0307	-0.0161	-0.0322**[cd]	-0.0562***
	(0.0154)	(0.0154)	(0.0158)	(0.0391)	(0.0372)	(0.0363)	(0.0151)	(0.0125)	(0.0184)
I_CON	-0.00117[e]	0.00843	-0.0109[e]	-0.00170	0.00449	0.00167	0.0328**[e]	0.0398***[e]	0.0121[e]
	(0.0145)	(0.0130)	(0.0143)	(0.0331)	(0.0315)	(0.0307)	(0.0165)	(0.0130)	(0.0182)
I_EDU	-0.0146[e]	-0.00818[e]	-0.0122[e]	-0.0156	-0.0185	-0.0270	-0.0361**[f]	-0.0518***[f]	-0.0409**
	(0.0132)	(0.0120)	(0.0137)	(0.0342)	(0.0326)	(0.0319)	(0.0146)	(0.00919)	(0.0170)
I_ELE	0.0602***[e]	0.119***[f]	0.114***[f]	0.0644	0.0719	0.0793	0.0730***[e]	0.139***[e]	0.102***[f]
	(0.0169)	(0.0172)	(0.0187)	(0.0591)	(0.0564)	(0.0547)	(0.0199)	(0.0137)	(0.0200)
I_HUM	0.0279**[cf]	0.0212*[ce]	0.0201*[cf]	0.0272	0.0223	0.0178	0.0316**[ce]	0.0148[e]	0.0367**[ce]
	(0.0133)	(0.0123)	(0.0114)	(0.0335)	(0.0320)	(0.0311)	(0.0151)	(0.0102)	(0.0170)
I_INF	0.0394***[f]	0.0561***	0.0292**[e]	0.0377	0.0355	0.0325	0.0356**[f]	0.0395***	0.0350**[ce]
	(0.0136)	(0.0133)	(0.0132)	(0.0334)	(0.0320)	(0.0309)	(0.0148)	(0.0104)	(0.0174)
I_MAN	0.0220*[f]	0.0251*	0.00917[af]	0.0192	0.0235	0.0140	0.0327**[f]	0.0340***[f]	0.00649
	(0.0129)	(0.0152)	(0.0137)	(0.0314)	(0.0301)	(0.0290)	(0.0145)	(0.0104)	(0.0171)
I_PRO	-0.0160[d]	0.00214[d]	-0.0437***[f]	-0.0137	-0.0182	-0.0266	-0.0108	-0.0140[d]	-0.0333*[f]
	(0.0146)	(0.0145)	(0.0138)	(0.0363)	(0.0346)	(0.0336)	(0.0157)	(0.0112)	(0.0182)
I_TRA	0.000841[e]	0.0107[e]	0.000147[e]	-0.000948	-0.00345	-0.00667	0.0158[ae]	0.0212[ae]	-0.0106[be]
	(0.0151)	(0.0151)	(0.0149)	(0.0337)	(0.0321)	(0.0312)	(0.0150)	(0.0136)	(0.0172)

I_WHO	-0.0131[e]	-0.0165	-0.0193[e]	-0.0168	-0.00219	-0.00830	0.00386[e]	-0.00107[e]	-0.0285*[f]
	(0.0135)	(0.0154)	(0.0133)	(0.0297)	(0.0290)	(0.0277)	(0.0151)	(0.0112)	(0.0171)
GR_MAIN	0.00261	-0.0110	-0.0255	-0.0146*[f]	-0.0150*[f]	-0.0160**[f]	-0.0116***	-0.0101*[f]	-0.0144***
	(0.0471)	(0.0415)	(0.0405)	(0.00781)	(0.00787)	(0.00784)	(0.00449)	(0.00530)	(0.00511)
GR_FDIG	0.0997**[cf]	0.148***	0.144***[f]	0.0681***	0.0688***	0.0642***	0.0653***	0.0646***	0.0624***
	(0.0409)	(0.0377)	(0.0353)	(0.00657)	(0.00662)	(0.00671)	(0.00405)	(0.00443)	(0.00453)
STAGE_S	-0.00254[e]	0.00259	-0.000282[e]	-0.00238	0.00114	0.00249	0.00216[e]	0.00231[e]	0.0139***[e]
	(0.00662)	(0.00616)	(0.00660)	(0.0136)	(0.0130)	(0.0126)	(0.00506)	(0.00523)	(0.00510)
CR4EM	0.362***	0.355***	0.345***	0.369***	0.365***	0.355***	0.443***	0.495***	0.453***
	(0.0281)	(0.0268)	(0.0291)	(0.0612)	(0.0582)	(0.0567)	(0.0239)	(0.0251)	(0.0268)
AGE_MAX	-0.0336***	-0.0215*	-0.0118[be]	-0.0334[be]	-0.0305[be]	-0.0241[e]	-0.0193[e]	0.000197[be]	0.0138[e]
	(0.0115)	(0.0110)	(0.0107)	(0.0242)	(0.0231)	(0.0224)	(0.0119)	(0.0116)	(0.0103)
MES_REL	-0.0323***	-0.0361***	-0.0296***	-0.0317***	-0.0323***	-0.0318***	-0.0194***	-0.0141***	-0.0173***
	(0.00392)	(0.00382)	(0.00428)	(0.00814)	(0.00776)	(0.00755)	(0.00295)	(0.00327)	(0.00342)
REG_N	0.00682***	0.00356	0.00386*	0.00702*[c]	0.00714*	0.00633[d]	0.00487***	0.00559***[c]	0.00818***
	(0.00244)	(0.00226)	(0.00205)	(0.00426)	(0.00407)	(0.00393)	(0.00156)	(0.00157)	(0.00178)
TMTIND_EM	-0.0580***[d]	-0.0681***[f]	-0.0832***[f]	-0.0569[d]	-0.0628[d]	-0.0726[bd]	-0.0182[cd]	0.0133[d]	-0.0209[bd]
	(0.0197)	(0.0196)	(0.0198)	(0.0483)	(0.0460)	(0.0446)	(0.0197)	(0.0179)	(0.0168)
TMTSH_EM	-0.0603***[f]	-0.0641***[f]	-0.0878***	-0.0607**[f]	-0.0581**[f]	-0.0685**[f]	-0.0771***[f]	-0.0828***[f]	-0.0583***[d]
	(0.0141)	(0.0139)	(0.0170)	(0.0299)	(0.0285)	(0.0278)	(0.0124)	(0.0115)	(0.0132)
FOROWN_EM	-0.117***	-0.101***	-0.0698***	-0.115***	-0.111***	-0.100***	-0.106***	-0.0973***	-0.0528***
	(0.0169)	(0.0180)	(0.0178)	(0.0342)	(0.0327)	(0.0317)	(0.0160)	(0.0140)	(0.0134)
GROUP_EM	0.0262[d]	-0.00542	-0.00357	0.0267	0.0204	0.0197	-0.0236[d]	-0.00730	-0.0397**[cd]
	(0.0171)	(0.0184)	(0.0174)	(0.0387)	(0.0368)	(0.0358)	(0.0186)	(0.0171)	(0.0171)
SUBS_EM	0.191***	0.191***	0.207***	0.191***[f]	0.192***[f]	0.198***[f]	0.189***	0.165***	0.204***
	(0.0199)	(0.0190)	(0.0186)	(0.0363)	(0.0345)	(0.0335)	(0.0164)	(0.0183)	(0.0160)
TANTA_D/..._G		-0.00280[d]	-0.0359*[f]		0.00808	0.00613		0.00360	-0.00582
		(0.0140)	(0.0189)		(0.00695)	(0.0106)		(0.00571)	(0.00629)
INTTA_A/..._G		0.0359[e]	0.105***		0.0625	0.0547***		-0.0120[e]	0.0502***
		(0.126)	(0.0248)		(0.0585)	(0.0168)		(0.0322)	(0.0112)
STKTA_D/..._G		0.00434	0.0765**		-0.0507**[f]	-0.00964		-0.00955	0.0191
		(0.0428)	(0.0348)		(0.0257)	(0.0227)		(0.0188)	(0.0158)
EMPTO_D/..._G		-0.0441	0.0947***		0.0166	0.0586***		0.0248**	0.0550***
		(0.0325)	(0.0230)		(0.0176)	(0.0158)		(0.0115)	(0.0104)
VAEMP_D/..._G		-0.0455***	-0.0192***		-0.00436[b]	-0.00440**		-0.0159***	-0.00689***
		(0.00662)	(0.00323)		(0.00338)	(0.00180)		(0.00230)	(0.00132)
RNDTO_A/..._G		0.433***	-0.149[e]		0.0116	0.0979		0.0672[ad]	0.112
		(0.129)	(0.496)		(0.0385)	(0.156)		(0.0444)	(0.120)
EXPTO_A/..._G		0.0220[d]	-0.0356[d]		0.0275*	0.00564[d]		0.00386[d]	0.00375[d]
		(0.0444)	(0.0287)		(0.0160)	(0.00724)		(0.0105)	(0.00593)
Constant	0.587***[b]	1.070***[b]	0.642***[b]	0.584***[bf]	0.611***[bf]	0.574***[bf]	0.489***[bf]	0.508***[b]	0.301***[bf]
	(0.0573)	(0.0979)	(0.0683)	(0.138)	(0.136)	(0.128)	(0.0702)	(0.0680)	(0.0663)
Observations	864	864	864	864	864	864	864	864	864
4-digit Industries	96	96	96	96	96	96	96	96	96
R-squared	0.866	0.880	0.887	0.866	0.867	0.878			
Wald chi2	233.60***	192.10***	205.66***	760.54***	842.07***	907.80***	10973.05***	19200.73***	13604.36***

Source of data: Modified from Orbis

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix C2: Determinants of firm size inequality – Italy

For decodification of abbreviations and variables please see end of Appendix C3

Estimator (model)	OLS (BASIC)	OLS (D-A)	OLS (G)	RE (BASIC)	RE (D-A)	RE (G)	FGLS (BASIC)	FGLS (D-A)	FGLS (G)
Dependent variable	GINI	GINI	GINI	GINI	GINI	GINI	GINI	GINI	GINI
S20	-0.0744***[d]	-0.0751***[d]	-0.0374***[d]	-0.0762***[d]	-0.0779***[d]	-0.0670***[d]	-0.0865***[d]	-0.0916***[d]	-0.0817***[d]
	(0.0101)	(0.0102)	(0.0137)	(0.0187)	(0.0185)	(0.0188)	(0.00928)	(0.00901)	(0.00973)
S30	-0.0425***[d]	-0.0440***[d]	-0.0136[d]	-0.0440***[d]	-0.0456***[d]	-0.0386**[d]	-0.0549***[d]	-0.0603***[d]	-0.0542***[d]
	(0.00827)	(0.00846)	(0.0106)	(0.0156)	(0.0156)	(0.0156)	(0.00743)	(0.00733)	(0.00801)
S40	-0.0398***[d]	-0.0388***[d]	-0.0171*[cd]	-0.0416***[d]	-0.0436***[d]	-0.0372**[d]	-0.0553***[d]	-0.0588***[d]	-0.0554***[d]
	(0.00838)	(0.00840)	(0.00997)	(0.0147)	(0.0146)	(0.0146)	(0.00717)	(0.00681)	(0.00762)
S50	-0.0407***[d]	-0.0407***[d]	-0.0248***[d]	-0.0409***[d]	-0.0420***[d]	-0.0398**[d]	-0.0480***[d]	-0.0524***[d]	-0.0560***[d]
	(0.00759)	(0.00783)	(0.00890)	(0.0158)	(0.0157)	(0.0155)	(0.00682)	(0.00689)	(0.00728)
S60	-0.00273[d]	-0.00592[d]	0.00830[d]	-0.00333[d]	-0.00430[d]	0.000314[d]	-0.00206[d]	-0.00410[d]	0.000122[d]
	(0.00647)	(0.00636)	(0.00711)	(0.0137)	(0.0136)	(0.0135)	(0.00466)	(0.00477)	(0.00484)
S75	0.00632[d]	0.00892[d]	0.0150**	0.00506[d]	0.00439[d]	0.00596[d]	0.00629[d]	0.00568[d]	0.00620[d]
	(0.00758)	(0.00719)	(0.00751)	(0.0132)	(0.0131)	(0.0129)	(0.00515)	(0.00486)	(0.00574)
YR08	0.00721**[f]	0.0174***[f]	0.0184***[f]	0.00498***[f]	0.000619[e]	0.00826***[f]	0.00455***	0.000786[e]	0.00525***
	(0.00340)	(0.00453)	(0.00433)	(0.00135)	(0.00198)	(0.00195)	(0.000864)	(0.00133)	(0.00136)
YR09	0.00914**[f]	0.0163***[f]	0.0163***[f]	0.00763***[f]	0.00552**[f]	0.0108***	0.00563***	0.00420***	0.00617***
	(0.00359)	(0.00439)	(0.00422)	(0.00168)	(0.00221)	(0.00224)	(0.00116)	(0.00155)	(0.00158)
YR10	0.00992***[f]	0.0170***[f]	0.0173***	0.00909***	0.00609***[f]	0.0122***	0.00796***	0.00555***	0.00861***
	(0.00378)	(0.00452)	(0.00426)	(0.00185)	(0.00229)	(0.00224)	(0.00137)	(0.00166)	(0.00165)
I_ACC	-0.0162	0.00452	-0.0299[b]	-0.0164	-0.0160	-0.0120	-0.0232	-0.0212	-0.0306
	(0.0177)	(0.0235)	(0.0184)	(0.0311)	(0.0323)	(0.0307)	(0.0334)	(0.0514)	(0.0377)
I_ADM	-0.0929***	-0.0862***	-0.104***	-0.0984***	-0.0972***	-0.0988***	-0.0800***	-0.0736***	-0.0678***
	(0.0188)	(0.0189)	(0.0187)	(0.0321)	(0.0321)	(0.0316)	(0.0216)	(0.0197)	(0.0213)
I_AGR	-0.0370	-0.00990	-0.0344	-0.0386	-0.0397	-0.0454	-0.0543**	-0.0500**	-0.0583**
	(0.0267)	(0.0284)	(0.0265)	(0.0373)	(0.0382)	(0.0368)	(0.0273)	(0.0249)	(0.0269)
I_CON	0.0168	0.0257*[cf]	0.0214	0.0129	0.0126	0.0105	0.0191	0.0232*[cf]	0.0216*[cf]
	(0.0151)	(0.0152)	(0.0153)	(0.0278)	(0.0277)	(0.0272)	(0.0130)	(0.0128)	(0.0124)
I_HUM	-0.0691***	-0.0487***	-0.0776***	-0.0758*[f]	-0.0741*[f]	-0.0736*[f]	-0.0624***	-0.0583***	-0.0540***
	(0.0141)	(0.0161)	(0.0144)	(0.0393)	(0.0394)	(0.0383)	(0.0109)	(0.0117)	(0.0119)
I_INF	0.0113	0.0139	0.0131	0.0111	0.0112	0.00289	0.0358***[f]	0.0399***[f]	0.0346***[f]
	(0.0142)	(0.0145)	(0.0138)	(0.0262)	(0.0263)	(0.0258)	(0.0120)	(0.0121)	(0.0124)
I_MAN	-0.0382***[f]	-0.0249**	-0.0424***[f]	-0.0399**[f]	-0.0395*[f]	-0.0436**[f]	-0.0290***[f]	-0.0276***[f]	-0.0319***
	(0.0107)	(0.0119)	(0.0114)	(0.0200)	(0.0204)	(0.0198)	(0.00819)	(0.00814)	(0.00936)
I_MIN	-0.0982***	-0.0822***	-0.106***	-0.0987***	-0.104***	-0.101***	-0.109***	-0.108***	-0.102***
	(0.0137)	(0.0146)	(0.0140)	(0.0316)	(0.0316)	(0.0309)	(0.0216)	(0.0171)	(0.0184)
I_TRA	0.0446**[f]	0.0538***[f]	0.0265	0.0460	0.0445	0.0486	0.0368	0.0333	0.0396*[f]
	(0.0174)	(0.0178)	(0.0177)	(0.0316)	(0.0316)	(0.0310)	(0.0230)	(0.0218)	(0.0239)
I_WAT	-0.0777***	-0.0711***	-0.0908***	-0.0818***	-0.0874***	-0.0806***	-0.0695***	-0.0733***	-0.0651***
	(0.0119)	(0.0128)	(0.0132)	(0.0308)	(0.0309)	(0.0302)	(0.00945)	(0.00944)	(0.0110)
I_WHO	-0.0345***	-0.0217*	-0.0367***	-0.0361*[f]	-0.0387*	-0.0438**	-0.0271***	-0.0278***	-0.0338***
	(0.0107)	(0.0125)	(0.0120)	(0.0204)	(0.0212)	(0.0207)	(0.00847)	(0.00904)	(0.0103)
GR_MAIN	-0.0620**	-0.0703***	-0.0710***	-0.0404***	-0.0365***	-0.0420***	-0.0497***	-0.0462***	-0.0502***
	(0.0260)	(0.0262)	(0.0256)	(0.00889)	(0.00894)	(0.00898)	(0.00698)	(0.00715)	(0.00722)

GR_FDIG	0.0623***	0.0572***	0.0548***[f]	0.0485***	0.0546***	0.0454***	0.0469***	0.0521***	0.0447***
	(0.0170)	(0.0172)	(0.0166)	(0.00593)	(0.00609)	(0.00607)	(0.00443)	(0.00469)	(0.00462)
STAGE_S	0.0210***	0.0210***	0.0219***	0.0210***	0.0209***	0.0223***	0.0193***	0.0182***	0.0213***
	(0.00345)	(0.00342)	(0.00346)	(0.00722)	(0.00718)	(0.00705)	(0.00294)	(0.00289)	(0.00297)
CR4EM	0.310***	0.322***	0.308***	0.319***	0.322***	0.323***	0.347***	0.361***	0.350***
	(0.0263)	(0.0270)	(0.0258)	(0.0471)	(0.0468)	(0.0459)	(0.0223)	(0.0221)	(0.0240)
AGE_MAX	-0.00925**[cf]	-0.00737*[cf]	-0.0102**[f]	-0.00934	-0.0103	-0.00699	-0.00972**[f]	-0.0119***[f]	-0.00631*[cf]
	(0.00414)	(0.00396)	(0.00403)	(0.00943)	(0.00937)	(0.00923)	(0.00378)	(0.00377)	(0.00375)
MES_REL	-0.0315***	-0.0311***	-0.0322***	-0.0303***	-0.0302***	-0.0281***	-0.0261***	-0.0230***	-0.0240***
	(0.00369)	(0.00378)	(0.00377)	(0.00666)	(0.00671)	(0.00657)	(0.00375)	(0.00369)	(0.00397)
REG_N	-0.00312***	-0.00313***	-0.00329***	-0.00287**[f]	-0.00292**[f]	-0.00286**[f]	-0.00346***	-0.00345***	-0.00381***
	(0.000636)	(0.000629)	(0.000610)	(0.00129)	(0.00128)	(0.00126)	(0.000600)	(0.000594)	(0.000622)
TMTIND_EM	-0.0491***[f]	-0.0476***[f]	-0.0332*[f]	-0.0523	-0.0501	-0.0498	-0.0571***[f]	-0.0675***[f]	-0.0592***[f]
	(0.0181)	(0.0178)	(0.0173)	(0.0371)	(0.0369)	(0.0363)	(0.0160)	(0.0159)	(0.0163)
TMTSH_EM	-0.0510***	-0.0453***	-0.0468***	-0.0468[e]	-0.0460[e]	-0.0551**	-0.0410***	-0.0440***	-0.0381***
	(0.0160)	(0.0157)	(0.0156)	(0.0286)	(0.0286)	(0.0281)	(0.0131)	(0.0133)	(0.0142)
FOROWN_EM	-0.0162	-0.0124	-0.00366	-0.0165	-0.0202	-0.0178	0.0101[e]	0.00221[e]	0.0240*[ce]
	(0.0148)	(0.0150)	(0.0150)	(0.0308)	(0.0306)	(0.0303)	(0.0143)	(0.0148)	(0.0141)
GROUP_EM	0.0786***	0.0794***	0.0851***	0.0797***	0.0775***	0.0775***	0.0770***	0.0695***	0.0737***
	(0.0133)	(0.0138)	(0.0135)	(0.0257)	(0.0255)	(0.0250)	(0.0132)	(0.0132)	(0.0135)
SUBS_EM	0.132***	0.140***	0.145***	0.128***	0.127***	0.129***	0.123***	0.117***	0.129***
	(0.0144)	(0.0144)	(0.0144)	(0.0269)	(0.0267)	(0.0263)	(0.0117)	(0.0138)	(0.0128)
TANTA_D /..._G		-0.0482**[f]	-0.00113		-0.000486	-0.0238		-0.0120[d]	0.00622
		(0.0220)	(0.0223)		(0.0185)	(0.0224)		(0.0116)	(0.0141)
INTTA_A/..._G		-0.129	0.135**[e]		0.0407	0.0983*[f]		-0.00549	0.0651*[f]
		(0.146)	(0.0603)		(0.115)	(0.0519)		(0.0802)	(0.0342)
STKTA_D/..._G		-0.0787***[f]	-0.0873***[f]		-0.0147	0.0177		-0.000773	0.0261*
		(0.0242)	(0.0248)		(0.0217)	(0.0236)		(0.0134)	(0.0154)
EMPTO_D/..._G		-0.0340	-0.0577*[f]		-0.0160	-0.0240		-0.00598[e]	-0.0256
		(0.0285)	(0.0298)		(0.0296)	(0.0337)		(0.0186)	(0.0224)
VAEMP_D/..._G		-0.0193***[f]	-0.0236***		0.0143***	-0.00658**[f]		0.0136***	-0.00392*[f]
		(0.00729)	(0.00584)		(0.00370)	(0.00293)		(0.00273)	(0.00228)
Constant	0.578***[b]	0.778***[bf]	0.730***[b]	0.576***[b]	0.435***[bf]	0.610***[b]	0.565***[b]	0.442***[bf]	0.566***[b]
	(0.0319)	(0.0842)	(0.0496)	(0.0614)	(0.0735)	(0.0631)	(0.0269)	(0.0395)	(0.0311)
Observations	1,188	1,188	1,188	1,188	1,188	1,188	1,188	1,188	1,188
4-digit industries	132	132	132	132	132	132	132	132	132
R-squared	0.814	0.819	0.824	0.813	0.811	0.814			
Wald chi2	126.46***	129.47***	120.75***	827.96***	858.95***	881.62***	6101.94***	6501.89***	7840.44***

Source of data: Modified from Orbis

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Appendix C3: Determinants of firm size inequality – Germany

Estimator (model) Dependent variable	OLS (BASIC) GINI	OLS (D-A) GINI	OLS (G) GINI	RE (BASIC) GINI	RE (D-A) GINI	RE (G) GINI	FGLS (BASIC) GINI	FGLS (D-A) GINI	FGLS (G) GINI
S20	-0.160***[d]	-0.135***[d]	-0.155***[d]	-0.160***[d]	-0.151***[d]	-0.150***[d]	-0.160***[d]	-0.152***[d]	-0.160***[d]
	(0.0187)	(0.0190)	(0.0188)	(0.0323)	(0.0294)	(0.0304)	(0.0105)	(0.0116)	(0.0130)
S30	-0.130***[d]	-0.113***[d]	-0.126***[d]	-0.130***[d]	-0.125***[d]	-0.123***[d]	-0.123***[d]	-0.126***[d]	-0.137***[d]
	(0.0172)	(0.0168)	(0.0170)	(0.0296)	(0.0263)	(0.0274)	(0.00938)	(0.00967)	(0.0116)
S40	-0.0902***[d]	-0.0832***[d]	-0.100***[d]	-0.0907***[d]	-0.0938***[f]	-0.0947***[d]	-0.0867***[d]	-0.0883***[f]	-0.0943***[d]
	(0.0145)	(0.0139)	(0.0140)	(0.0258)	(0.0227)	(0.0237)	(0.00665)	(0.00729)	(0.00918)
S50	-0.0965***[d]	-0.0802***[d]	-0.0935***[d]	-0.0956***[f]	-0.0901***[f]	-0.0916***[f]	-0.0979***[d]	-0.0975***[f]	-0.109***[d]
	(0.0153)	(0.0148)	(0.0144)	(0.0247)	(0.0218)	(0.0227)	(0.00786)	(0.00754)	(0.0101)
S60	-0.0312***[f]	-0.0221**[cf]	-0.0335***[d]	-0.0316	-0.0340*[cf]	-0.0322*[cf]	-0.0232***[f]	-0.0220***[f]	-0.0301***[f]
	(0.0105)	(0.00986)	(0.00989)	(0.0210)	(0.0181)	(0.0189)	(0.00713)	(0.00627)	(0.00660)
S75	-0.0526***[cd]	-0.0484***[cd]	-0.0498***[cd]	-0.0525**[cd]	-0.0497***[cd]	-0.0468**[cd]	-0.0489***[d]	-0.0431***[cd]	-0.0477***[cd]
	(0.0138)	(0.0126)	(0.0130)	(0.0212)	(0.0182)	(0.0189)	(0.00717)	(0.00629)	(0.00842)
YR08	-0.000505	0.000312	-0.000453	8.38e-05	0.00127	0.00125	0.000437[ae]	0.000512	0.000953*[f]
	(0.00439)	(0.00443)	(0.00432)	(0.00108)	(0.00136)	(0.00111)	(0.000448)	(0.000658)	(0.000493)
YR09	0.00251	0.00232	0.00333	0.00210[a]	0.00335**[f]	0.00315**[f]	0.00163**[f]	0.000948[a]	0.000565[a]
	(0.00549)	(0.00530)	(0.00527)	(0.00136)	(0.00153)	(0.00138)	(0.000643)	(0.000791)	(0.000674)
YR10	-0.000322	0.00173	0.00234	-0.000586	0.00161	0.00211	-0.000311[e]	7.04e-05	0.000190[a]
	(0.00537)	(0.00518)	(0.00517)	(0.00144)	(0.00165)	(0.00147)	(0.000805)	(0.000942)	(0.000830)
I_ACC	0.0548***[f]	0.00644	-0.00367	0.0557	0.00745	0.000193	0.0502**[e]	0.0416**[f]	0.000750[ae]
	(0.0188)	(0.0168)	(0.0164)	(0.0404)	(0.0374)	(0.0392)	(0.0213)	(0.0205)	(0.0422)
I_ADM	0.0234	-0.000653[d]	-0.00624[d]	0.0247	-0.000461[d]	0.00489[d]	0.0165*	0.0288***[f]	0.0241***
	(0.0165)	(0.0159)	(0.0125)	(0.0268)	(0.0282)	(0.0298)	(0.00853)	(0.00971)	(0.00659)
I_CON	-0.00222	-0.0323*[cf]	-0.0237[d]	-0.00302	-0.0319	-0.0290	-0.0210**[cf]	-0.0101	0.0107[a]
	(0.0184)	(0.0175)	(0.0150)	(0.0260)	(0.0277)	(0.0291)	(0.00930)	(0.00933)	(0.00830)
I_ELE	0.0337*[e]	0.0256[e]	-0.0129[e]	0.0342	0.00522[e]	0.00687	0.0125[ae]	0.0263**[ce]	0.0302***[ce]
	(0.0188)	(0.0182)	(0.0147)	(0.0531)	(0.0469)	(0.0495)	(0.00912)	(0.0109)	(0.00959)
I_HUM	0.0460	-0.0288[d]	-0.0205	0.0469	0.000984	-0.00357	-0.0458***[f]	-0.0684***[d]	-0.0567**[f]
	(0.0371)	(0.0452)	(0.0405)	(0.0399)	(0.0381)	(0.0398)	(0.0173)	(0.0180)	(0.0226)
I_INF	0.0322	6.38e-06	0.00225[d]	0.0347	0.0105	0.0113	0.0166[ad]	0.0510***[f]	0.0620***[f]
	(0.0197)	(0.0185)	(0.0162)	(0.0267)	(0.0287)	(0.0299)	(0.0112)	(0.0107)	(0.00982)
I_MAN	0.0583***	0.0158[ad]	0.0173[ad]	0.0577***[f]	0.0197[d]	0.0262[d]	0.0434***	0.0438***	0.0474***
	(0.0159)	(0.0158)	(0.0121)	(0.0212)	(0.0248)	(0.0260)	(0.00703)	(0.00860)	(0.00769)
I_PRO	0.0451**[e]	-0.00153	0.00148	0.0447	0.00294	0.00666	0.0209**[e]	0.0165**[f]	0.00263[e]
	(0.0203)	(0.0192)	(0.0178)	(0.0276)	(0.0292)	(0.0306)	(0.00831)	(0.00820)	(0.0154)
I_TRA	0.0268	-0.0463**[f]	-0.0630***[f]	0.0276	-0.0517*[f]	-0.0534*[f]	0.00959[e]	-0.0252***	-0.0633***
	(0.0246)	(0.0197)	(0.0194)	(0.0288)	(0.0299)	(0.0314)	(0.0101)	(0.00943)	(0.00895)
I_WAT	0.0362**[cf]	0.0126	-0.00358	0.0363	0.00275	0.00991	0.0133[a]	0.0319**[f]	0.0422***[f]
	(0.0173)	(0.0231)	(0.0167)	(0.0394)	(0.0368)	(0.0385)	(0.0101)	(0.0158)	(0.0120)
I_WHO	0.0449***[f]	0.0221[ad]	0.0103[d]	0.0456**[f]	0.0137	0.0207[d]	0.0258***[f]	0.0408***[f]	0.0366***[f]
	(0.0162)	(0.0169)	(0.0131)	(0.0213)	(0.0246)	(0.0258)	(0.00692)	(0.00880)	(0.00758)
GR_MAIN	0.00172	0.0111	0.00670	0.00255	0.00602	0.00508	-0.00209	0.00222[a]	0.00340
	(0.0232)	(0.0228)	(0.0233)	(0.00512)	(0.00640)	(0.00603)	(0.00225)	(0.00330)	(0.00253)

GR_FDIG	0.132***	0.143***	0.155***	0.105***	0.120***	0.121***	0.0861***	0.0854***	0.0760***
	(0.0394)	(0.0343)	(0.0348)	(0.00685)	(0.00786)	(0.00764)	(0.00510)	(0.00640)	(0.00590)
STAGE_S	-0.00896*[f]	-0.0101**[cf]	-0.0110**[cd]	-0.00965	-0.0129	-0.0130	-0.00249[d]	-0.0110***[ad]	-0.00890***[cd]
	(0.00526)	(0.00515)	(0.00544)	(0.00891)	(0.00812)	(0.00846)	(0.00314)	(0.00333)	(0.00289)
CR4EM	0.468***	0.409***[f]	0.430***[f]	0.467***	0.430***[f]	0.426***[f]	0.461***	0.429***	0.411***
	(0.0280)	(0.0308)	(0.0322)	(0.0562)	(0.0506)	(0.0529)	(0.0163)	(0.0199)	(0.0196)
AGE_MAX	-0.0203*	-0.000665	-0.00665	-0.0188	-0.000126	-0.00192	-0.0246***	0.00732	0.00352[e]
	(0.0105)	(0.00858)	(0.00905)	(0.0176)	(0.0155)	(0.0162)	(0.00640)	(0.00566)	(0.00542)
MES_REL	-0.0230***	-0.0232***	-0.0223***	-0.0233***	-0.0226***	-0.0229***	-0.0248***	-0.0233***	-0.0267***
	(0.00370)	(0.00346)	(0.00355)	(0.00740)	(0.00638)	(0.00669)	(0.00216)	(0.00269)	(0.00206)
REG_N	0.00116	0.00197	0.000651	0.00104	0.000505	-0.000330	0.00114[e]	0.000523[e]	-0.00260**[c]
	(0.00178)	(0.00164)	(0.00175)	(0.00298)	(0.00266)	(0.00279)	(0.000826)	(0.000994)	(0.00110)
TMTIND_EM	-0.0116	0.00274[d]	0.00272	-0.0135[d]	0.00435[d]	0.0101[d]	-0.0379***[cd]	-0.0246*[cd]	0.0178*[c]
	(0.0147)	(0.0153)	(0.0161)	(0.0225)	(0.0238)	(0.0242)	(0.00842)	(0.0134)	(0.00948)
TMTSH_EM	-0.0641***[d]	-0.0599***[f]	-0.0532***[f]	-0.0649***[f]	-0.0621***[f]	-0.0594***[f]	-0.0790***[d]	-0.0884***[d]	-0.0694***[d]
	(0.0114)	(0.0114)	(0.0125)	(0.0194)	(0.0181)	(0.0190)	(0.00618)	(0.00966)	(0.00818)
FOROWN_EM	-0.0274[be]	-0.0376**	-0.0402**	-0.0272[b]	-0.0462*	-0.0451*	-0.0304***	-0.0658***	-0.0683***
	(0.0185)	(0.0165)	(0.0186)	(0.0275)	(0.0240)	(0.0250)	(0.0111)	(0.0117)	(0.0114)
GROUP_EM	0.0439***[e]	0.0689***[e]	0.0704***[e]	0.0430**[f]	0.0716***[f]	0.0745***[f]	0.0450***[e]	0.0517***[f]	0.0747***[f]
	(0.0129)	(0.0129)	(0.0134)	(0.0203)	(0.0198)	(0.0211)	(0.00640)	(0.00927)	(0.00756)
SUBS_EM	0.0645***	0.0877***	0.0740***	0.0638***	0.0698***[f]	0.0737***	0.0803***	0.0831***[f]	0.0746***
	(0.0128)	(0.0124)	(0.0142)	(0.0196)	(0.0186)	(0.0195)	(0.00683)	(0.00987)	(0.00965)
TANTA_D/..._G		0.0263	0.0668***[f]		0.0104	0.0315**		0.0173***[cf]	0.0414***
		(0.0184)	(0.0192)		(0.0128)	(0.0132)		(0.00589)	(0.00630)
INTTA_A/..._G		0.126***	0.100***		0.0228	0.0372**		0.0299*[f]	0.0399***
		(0.0333)	(0.0289)		(0.0255)	(0.0177)		(0.0168)	(0.0116)
STKTA_D/..._G		0.0285	-0.0124[e]		-0.0244**[f]	-0.0391***[f]		-0.00425[bf]	-0.0236***
		(0.0219)	(0.0191)		(0.0116)	(0.0108)		(0.00500)	(0.00462)
EMPTO_D/..._G		0.119***	-0.000790[d]		0.0188	0.00750**		0.0640***[f]	0.00470***[c]
		(0.0238)	(0.00277)		(0.0162)	(0.00346)		(0.00892)	(0.00150)
VAEMP_D/..._G		-0.00645[bd]	-0.000444[b]		-0.00515*[cf]	-0.00570***		-0.00144[bf]	-0.00372***
		(0.00591)	(0.00317)		(0.00303)	(0.00138)		(0.00144)	(0.000685)
Constant	0.599***[bf]	0.542***[bf]	0.552***[bf]	0.596***[bf]	0.596***[bf]	0.584***[bf]	0.655***	0.516***[bf]	0.562***[b]
	(0.0659)	(0.0835)	(0.0584)	(0.112)	(0.108)	(0.108)	(0.0330)	(0.0361)	(0.0312)
Observations	730	645	655	730	645	655	730	645	655
4-digit industries	146	146	146	146	129	131	146	129	131
R-squared	0.887	0.905	0.902	0.886	0.896	0.899			
Wald chi2	215.73***	212.36***	167.24***	1390.22***	1581.92***	1570.57***	28142.10***	27030.24***	29709.89***

Source of data: Modified from Orbis

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

a = significant **positive** at p<0.1 with log-odds ratio of Gini as dependent variable
b = significant **negative** at p<0.1 with log-odds ratio of Gini as dependent variable
c = **not significant** at p<0.1 with log-odds ratio of Gini as dependent variable

d = significant **positive** at p<0.1 with HHI as dependent variable
e = significant **negative** at p<0.1 with HHI as dependent variable
f = **not significant** at p<0.1 with HHI as dependent variable

No footnote = sign and significance at p<0.1 consistent with log-odds ratio of Gini and HHI as dependent variable

Appendix C3 (*cont.*)

<u>Estimators and models:</u> OLS = ordinary least squares estimates with Newey-West standard errors accounting for heteroskedasticity and first order autocorrelation; **RE** = random effects estimates accounting for heteroskedasticity and first order autocorrelation; **FGLS** = feasible generalised least squares estimates accounting for heteroskedasticity and first order autocorrelation; **BASIC** = basic model, which excludes variables related to firm performance (FPER); **D-A** = extended model consisting of basic model and FPER-variables based on either median (D) or mean (A), whichever is appropriate; **G** = extended model consisting of basic model and FPER-variables based on aggregate values;

<u>Dependent variables:</u> GINI = firm size inequality proxied by the Gini-coefficient; **GINI_L** = firm size inequality proxied by the logarithm of the Gini-coefficient; **HHI** = firm size inequality proxied by the Herfindahl-Hirschman Index

<u>Independent variables:</u> S20/S30/S40/S50/S60/S75 = dummy variables controlling for the sample size of firm-level observations making up each 4-digit industry section (20, 30, 40, 50, 60 or 75 firms respectively) unless consisting of 100 firms; **I_ACC** = main NACE industry dummy for *Accomodation and food service activities*; **I_ADM** = main NACE industry dummy for *Administrative and support service activities*; **I_AGR** = main NACE industry dummy for *Agriculture, foster and fishing*; **I_ART** = main NACE industry dummy for *Arts, entertainment and recreation*; **I_CON** = main NACE industry dummy for *Construction*; **I_EDU** = main NACE industry dummy for *Education*; **I_ELE** = main NACE industry dummy for *Electricity, gas, steam and air conditioning supply*; **I_HUM** = main NACE industry dummy for *Human health and social work activities*; **I_INF** = main NACE industry dummy for *Information and communication*; **I_MAN** = main NACE industry dummy for *Manufacturing*; **I_MIN** = main NACE industry dummy for *Mining and quarrying*; **I_PRO** = main NACE industry dummy for *Professional scientific and technical activities*; **I_TRA** = main NACE industry dummy for *Transportation and storage*; **I_WAT** = main NACE industry dummy for *Water supply; sewerage and waste management*; **I_WHO** = main NACE industry dummy for *Wholesale and retail trade; repair services*; **I_OTH** = main NACE industry dummies for *Other service activities*; **YR08/YR09/YR10** = dummy variables controlling for inter and post-crisis years 2008, 2009 and 2010 respectively; **GR_MAIN*** = main NACE industry growth rate according to the number of employees; **STAGE_S** = dummy for industries in a mature stage with stagnating workforce; **CR4EM** = CR4 ratio proxied by the number of employees; **GR_FDIG** = industry growth rate according to the number of employees; **AGE_MAX** = industry age proxied by the logarithm of the age of the oldest firm; **MES_REL** = minimum efficient scale proxied by the logarithm of the median firm size relative to the largest firm size within the respective industry; **REG_N** = regional concentration proxied by the number of regions across which firms belonging to the same industry are spread; **TMTIND_EM** = percentage of firms with exclusively individuals in the top management team measured by employee share; **TMTSH_EM** = percentage of firms with at least one shareholder in the top management team measured by employee share; **FOROWN_EM** = percentage of foreign owned firms measured by employee share; **GROUP_EM** = percentage of firms belonging to a group or holding proxied measured by employee share; **SUBS_EM** = percentage of firms with subsidiaries measured by employee share; **TANTA_D** = tangible assets proxied by the median tangible assets to total assets ratio; **TANTA_G** = tangible assets proxied by the ratio of aggregate tangible assets to aggregate total assets; **INTTA_A** = intangible assets proxied by the mean intangible assets to total asset ratio; **INTTA_G** = intangible assets proxied by the ratio of aggregate intangible assets to aggregate total assets; **STKTA_D** = excess capacity proxied by the median stock to total assets ratio; **STKTA_G** = excess capacity proxied by the ratio of aggregate stock to aggregate total assets; **EMPTO_D** = labour intensity proxied by the median turnover to employees ratio; **EMPTO_G** = labour intensity proxied by the ratio of aggregate turnover to aggregate employees; **VAEMP_D** = labour productivity proxied by the logarithm of the median value added to employees ratio; **VAEMP_G** = labour productivity proxied by the logarithm of the ratio of aggregate value added to aggregate employees; **RNDTO_A** = R&D intensity proxied by the mean R&D expenditure to turnover ratio; **RNDTO_G** = R&D intensity proxied by the ratio of aggregate R&D expenditure to aggregate turnover; **EXPTO_A** = export orientation proxied by the mean exports to turnover ratio; **EXPTO_G** = export orientation proxied by the ratio of aggregate exports to aggregate turnover
*) except for *GR_MAIN*, the values for all variables are obtained from firm-level observations belonging to a 4-digit industry

Appendix D: Innovative capacity by firm-size class share

Estimates from firm-size class share by employment

VARIABLES	OLS	OLS	OLS	OLS	RE	RE	RE	RE	FGLS	FGLS	FGLS	FGLS
EU15	1.621***	1.615***	1.740***	1.729***	1.970***	2.034***	2.100***	2.160***	2.054***	1.989***	1.983***	2.091***
	(0.183)	(0.162)	(0.156)	(0.166)	(0.279)	(0.247)	(0.246)	(0.273)	(0.168)	(0.129)	(0.130)	(0.163)
D_POR	-1.107***	-1.293***	-1.324***	-1.064***	-1.596***	-1.768***	-1.746***	-1.591***	-1.407***	-1.542***	-1.365***	-1.429***
	(0.188)	(0.194)	(0.193)	(0.186)	(0.554)	(0.519)	(0.509)	(0.553)	(0.154)	(0.177)	(0.168)	(0.163)
D_GRE	-1.097***	-1.445***	-1.342***	-0.771***	-1.512***	-1.741***	-1.611***	-1.071*	-1.465***	-1.665***	-1.326***	-1.217***
	(0.201)	(0.197)	(0.187)	(0.255)	(0.574)	(0.540)	(0.514)	(0.576)	(0.148)	(0.198)	(0.169)	(0.160)
D_SLE	1.692***	1.691***	1.677***	1.657***	1.736***	1.769***	1.771***	1.718***	1.938***	1.696***	1.666***	1.748***
	(0.0946)	(0.0797)	(0.0804)	(0.0963)	(0.511)	(0.466)	(0.455)	(0.511)	(0.126)	(0.0709)	(0.0679)	(0.116)
K_SER	0.106***	0.113***	0.113***	0.103***	0.0780***	0.0813***	0.0816***	0.0724***	0.0916***	0.104***	0.113***	0.0880***
	(0.00989)	(0.00902)	(0.00859)	(0.00944)	(0.0142)	(0.0135)	(0.0133)	(0.0145)	(0.00713)	(0.00623)	(0.00574)	(0.00771)
MHT_MAN	0.0989***	0.125***	0.145***	0.113***	0.0984***	0.110***	0.116***	0.108***	0.0967***	0.156***	0.167***	0.111***
	(0.0216)	(0.0184)	(0.0190)	(0.0223)	(0.0305)	(0.0287)	(0.0288)	(0.0302)	(0.0153)	(0.0137)	(0.0128)	(0.0143)
EMP_MED	-1.416				-2.153				-3.070***			
	(1.650)				(2.199)				(1.019)			
EMP_ML		-2.514***				-1.837**				-2.745***		
		(0.503)				(0.827)				(0.453)		
EMP_LAR			-3.347***				-1.989**				-2.660***	
			(0.577)				(0.929)				(0.477)	
EMP_GINI				-0.777				-1.234				-0.267
				(0.727)				(0.756)				(0.410)
Constant	-0.294	0.325	-0.100	-0.485	0.530	0.836	0.441	0.367	0.179	0.379	-0.493**	-0.257
	(0.424)	(0.346)	(0.293)	(0.319)	(0.658)	(0.574)	(0.476)	(0.486)	(0.297)	(0.340)	(0.248)	(0.280)
Observations	270	270	270	270	270	270	270	270	270	270	270	270
Number of countries	27	27	27	27	27	27	27	27	27	27	27	27
R-squared					0.8878	0.8992	0.9011	0.8877				
F-stat. / Wald chi2	353.63***	447.38***	460.19***	356.77***	297.79***	363.01***	380.41***	299.39***	3572.48***	4636.31***	5356.27***	3291.35***

Sources of data: Modified from Eurostat and EC SME Performance Review   Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Estimators: **OLS** = ordinary least squares estimates with Newey-West standard errors accounting for heteroskedasticity and first order autocorrelation; **RE** = random effects estimates accounting for heteroskedasticity and first order autocorrelation; **FGLS** = feasible generalised least squares estimates accounting for heteroskedasticity and first order autocorrelation;

Dependent variable: **innovative capacity** proxied by the logarithm of the number of patent applications

Independent variables: **EU15** = dummy for EU15 member states; **D_POR** = dummy for Portugal; **D_GRE** = dummy for Greece; **D_SLE** = dummy for Slovenia; **K_SER** = share of knowledge-intensive service firms; **MHT_MAN** = share of medium and high-technology manufacturing firms; **EMP_MED** = employment share of medium-sized firms; **EMP_ML** = employment share of medium and large firms; **EMP_LAR** = employment share of large firms; **EMP_GINI** = firm size inequality according to the Gini-coefficient resulting from the firm-size class shares

Appendix D (*cont.*)

Estimates from firm-size class share by value added

VARIABLES	OLS	OLS	OLS	OLS	RE	RE	RE	RE	FGLS	FGLS	FGLS	FGLS
EU15	1.776***	1.591***	1.734***	1.716***	2.041***	1.954***	2.000***	1.994***	2.181***	1.671***	1.715***	1.585***
	(0.186)	(0.160)	(0.152)	(0.146)	(0.277)	(0.236)	(0.230)	(0.227)	(0.168)	(0.109)	(0.117)	(0.108)
D_POR	-1.142***	-1.161***	-1.248***	-1.505***	-1.562***	-1.546***	-1.560***	-1.698***	-1.455***	-1.128***	-1.070***	-1.174***
	(0.196)	(0.193)	(0.185)	(0.199)	(0.557)	(0.481)	(0.468)	(0.469)	(0.163)	(0.150)	(0.153)	(0.165)
D_GRE	-0.905***	-1.324***	-1.214***	-0.920***	-1.359**	-1.464***	-1.392***	-1.277***	-1.318***	-1.245***	-0.988***	-0.712***
	(0.181)	(0.189)	(0.173)	(0.165)	(0.552)	(0.486)	(0.467)	(0.458)	(0.143)	(0.165)	(0.144)	(0.121)
D_SLE	1.682***	1.476***	1.454***	1.300***	1.739***	1.669***	1.680***	1.590***	1.884***	1.478***	1.483***	1.364***
	(0.0941)	(0.0918)	(0.0995)	(0.106)	(0.511)	(0.440)	(0.425)	(0.424)	(0.127)	(0.0650)	(0.0612)	(0.0515)
K_SER	0.104***	0.103***	0.102***	0.0964***	0.0774***	0.0814***	0.0819***	0.0794***	0.0884***	0.101***	0.108***	0.106***
	(0.00923)	(0.00917)	(0.00856)	(0.00870)	(0.0143)	(0.0131)	(0.0129)	(0.0128)	(0.00710)	(0.00717)	(0.00673)	(0.00701)
MHT_MAN	0.114***	0.146***	0.165***	0.158***	0.102***	0.114***	0.117***	0.118***	0.101***	0.163***	0.169***	0.164***
	(0.0234)	(0.0180)	(0.0198)	(0.0176)	(0.0303)	(0.0281)	(0.0278)	(0.0272)	(0.0141)	(0.0132)	(0.0129)	(0.0104)
VA_MED	2.166				-0.276				0.00569			
	(2.167)				(1.722)				(1.010)			
VA_ML		-3.249***				-1.453*				-3.016***		
		(0.529)				(0.748)				(0.412)		
VA_LAR			-3.521***				-1.325*				-2.148***	
			(0.554)				(0.692)				(0.436)	
VA_GINI				-3.350***				-1.585***				-2.456***
				(0.514)				(0.578)				(0.360)
Constant	-1.123**	1.220***	0.530	0.182	0.120	0.796	0.388	0.339	-0.364	0.975**	-0.240	-0.358
	(0.562)	(0.427)	(0.337)	(0.312)	(0.587)	(0.610)	(0.479)	(0.430)	(0.311)	(0.390)	(0.299)	(0.253)
Observations	270	270	270	270	270	270	270	270	270	270	270	270
Number of countries	27	27	27	27	27	27	27	27	27	27	27	27
R-squared					0.8878	0.9027	0.9038	0.9088				
F-stat. / Wald chi2	386.49***	432.31***	491.19***	411.05***	296.44***	408.29***	436.06***	448.11***	3347.92***	3560.39***	3759.92***	4293.55***

Sources of data: Modified from Eurostat and EC SME Performance Review

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Estimators: **OLS** = ordinary least squares estimates with Newey-West standard errors accounting for heteroskedasticity and first order autocorrelation; **RE** = random effects estimates accounting for heteroskedasticity and first order autocorrelation; **FGLS** = feasible generalised least squares estimates accounting for heteroskedasticity and first order autocorrelation;

Dependent variable: **innovative capacity** proxied by the logarithm of the number of patent applications

Independent variables: **EU15** = dummy for EU15 member states; **D_POR** = dummy for Portugal; **D_GRE** = dummy for Greece; **D_SLE** = dummy for Slovenia; **K_SER** = share of knowledge-intensive service firms; **MHT_MAN** = share of medium and high-technology manufacturing firms; **VA_MED** = employment share of medium-sized firms; **VA_ML** = employment share of medium and large firms; **VA_LAR** = employment share of large firms; **VA_GINI** = firm size inequality according to the Gini-coefficient resulting from the firm-size class shares

Appendix E: Net job creation by firm-size class share

Net job creation rates in percent by firm-size class of EU15 countries with a mean manufacturing share above 23%

		2004-2007				2008-2009				2010-2012			
Country	**Manuf. share**	**Micro**	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**
Germany	31.4	1.08	2.31	2.60	1.33	6.30	6.74	3.71	2.33	-1.04	0.70	2.94	0.49
Finland	30.4	3.23	2.21	1.09	1.13	4.63	7.28	1.04	3.38	-0.53	0.16	-0.60	-1.36
Italy	29.2	1.50	1.75	2.16	2.24	-1.89	0.92	0.92	2.02	-0.39	-2.00	-1.76	-0.62
Sweden	27.2	-0.67	4.90	4.41	3.41	0.58	-1.05	-1.65	-1.88	-0.27	0.60	0.08	0.42
Portugal	25.6	4.12	3.93	3.00	3.43	-7.60	-3.50	-1.68	3.72	-1.15	-2.51	-2.60	-1.68
Austria	25.2	1.82	1.44	1.70	1.81	0.10	1.56	0.34	1.08	1.17	1.14	1.12	0.46
France	24.0	2.73	1.61	0.48	1.65	-0.05	-7.23	-7.13	-10.60	0.64	-0.18	-0.11	-0.25
Belgium	23. 9	2.55	1.28	1.21	1.62	0.29	-1.94	-0.16	-1.68	1.64	-1.35	0.34	-0.03
Variance	0.0860	0.0215	0.0170	0.0157	0.0079	0.1745	0.2432	0.0994	0.2204	0.0105	0.0183	0.0289	0.0070
Mean	27.1	2.05	2.43	2.08	2.08	0.30	0.35	-0.58	-0.20	0.01	-0.43	-0.07	-0.32
Median	26.4	2.19	1.98	1.93	1.73	0.20	-0.07	0.09	1.55	-0.33	-0.01	-0.02	-0.14

Net job creation rates in percent by firm-size class of EU15 countries with a mean manufacturing share below 23%

		2004-2007				2008-2009				2010-2012			
Country	**Manuf. share**	**Micro**	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**	**Micro**	**Small**	**Medium**	**Large**
Denmark	21.6	3.12	2.84	2.96	2.04	-6.01	3.73	9.89	4.81	0.81	-1.30	-1.65	-2.38
Ireland	19.2	6.26	8.19	4.03	2.48	-4.58	-1.70	-0.45	0.89	0.27	-2.70	-5.13	-1.99
Spain	18.6	2.69	3.42	3.65	5.26	-6.68	-14.56	-7.87	-2.42	0.56	-2.67	-3.03	-0.89
UK	16.8	0.09	0.71	1.20	0.14	-3.86	3.74	-0.80	-0.55	-0.10	-1.57	-0.54	-0.85
Luxembourg	16.2	1.11	2.32	0.52	-2.55	2.75	-1.65	3.44	1.64	1.84	1.43	0.02	0.29
Greece	15.7	1.15	6.01	5.29	-2.67	-0.45	0.21	-3.54	3.64	-2.85	-2.13	-3.31	-2.89
Netherlands	15.1	1.87	4.95	1.87	2.78	-1.35	1.62	4.29	5.19	-1.84	-1.01	0.95	0.11
Variance	0.0525	0.0406	0.0630	0.0285	0.0856	0.1135	0.3959	0.3330	0.0802	0.0262	0.0201	0.0456	0.0150
Mean	17.6	2.33	4.06	2.79	1.07	-2.88	-1.23	0.71	1.89	-0.19	-1.42	-1.81	-1.23
Median	16.8	1.87	3.42	2.96	2.04	-3.86	0.21	-0.45	1.64	0.27	-1.57	-1.65	-0.89

Source of data: Modified from EC SME Performance Review

Appendix E (*cont.*)

Net job creation rates in percent by firm-size class of non-EU15 countries with a mean manufacturing share above 30%

Country	Manuf. share	2004-2007 Micro	2004-2007 Small	2004-2007 Medium	2004-2007 Large	2008-2009 Micro	2008-2009 Small	2008-2009 Medium	2008-2009 Large	2010-2012 Micro	2010-2012 Small	2010-2012 Medium	2010-2012 Large
Slovakia	41.4	11.70	6.88	2.47	-1.01	-33.97	14.76	-0.69	-1.03	6.47	-6.00	0.30	-2.19
Slovenia	37.5	3.57	2.85	2.06	0.30	1.81	2.95	-0.76	-3.31	-1.86	-1.31	-0.97	-3.46
Czech Rep.	36.9	-0.30	0.88	2.72	1.10	-0.13	-2.57	-3.32	-3.69	0.21	0.61	-0.14	-1.97
Romania	36.0	9.48	7.70	2.26	-4.43	-3.57	-5.69	-6.08	-3.34	2.54	2.24	0.08	-2.06
Bulgaria	32.6	-1.34	7.68	6.81	0.91	5.38	2.17	0.27	-1.16	-1.29	-0.38	-3.69	-2.88
Poland	31.0	1.47	2.98	3.86	3.84	-2.41	6.73	1.45	1.15	-0.03	-5.49	-1.66	-0.66
Variance	0.1370	0.2856	0.0869	0.0325	0.0748	2.0483	0.5188	0.0747	0.0358	0.0950	0.1111	0.0225	0.0090
Mean	35.9	4.10	4.83	3.36	0.12	-5.48	3.06	-1.52	-1.90	1.01	-1.72	-1.01	-2.20
Median	36.5	2.52	4.93	2.60	0.61	-1.27	2.56	-0.73	-2.23	0.09	-0.84	-0.56	-2.12

Net job creation rates in percent by firm-size class of non-EU15 countries with a mean manufacturing share below 30%

Country	Manuf. share	2004-2007 Micro	2004-2007 Small	2004-2007 Medium	2004-2007 Large	2008-2009 Micro	2008-2009 Small	2008-2009 Medium	2008-2009 Large	2010-2012 Micro	2010-2012 Small	2010-2012 Medium	2010-2012 Large
Hungary	29.8	-0.20	2.37	1.36	-0.32	-4.25	-3.42	-2.36	-3.18	2.08	0.21	0.35	-1.14
Estonia	29.6	7.33	2.74	4.38	2.87	-10.29	-10.73	-7.65	-3.32	4.96	1.20	-0.47	0.58
Lithuania	27.3	7.40	4.71	4.33	1.18	-20.87	-8.70	-8.32	-5.05	2.83	-0.40	-3.81	-4.80
Latvia	24.1	0.03	4.25	2.79	0.13	-13.48	-11.42	-9.23	-7.20	6.30	-2.05	-3.93	-2.38
Malta	23.6	-3.21	-0.91	-0.57	-4.03	0.39	0.82	-0.24	2.77	1.19	1.02	0.82	0.49
Cyprus	16.7	0.69	3.16	5.52	6.60	2.68	-2.07	-1.85	7.36	-0.66	-0.61	0.39	-0.94
Variance	0.2424	0.1904	0.0396	0.0510	0.1252	0.7973	0.2553	0.1509	0.2959	0.0639	0.0144	0.0476	0.0405
Mean	25.2	2.01	2.72	2.97	1.07	-7.64	-5.92	-4.94	-1.44	2.78	-0.10	-1.11	-1.36
Median	25.7	0.36	2.95	3.56	0.65	-7.27	-6.06	-5.01	-3.25	2.45	-0.09	-0.06	-1.04

Source of data: Modified from EC SME Performance Review

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