ESSAYS ON THE WELFARE IMPACT OF ECONOMIC SHOCKS IN LOW-INCOME COUNTRIES

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Abstract

This thesis consists of three essays on the impact of unanticipated shocks on household welfare outcomes in sub-Saharan African countries. Paying particular attention to disaggregated shock pattern for seasonal rainfall measures, the first essay studies the effects of household shocks on the incidence of domestic violence using a unique set of micro data from the World Bank's Living Standard Measurement Survey for Tanzania. Coefficient estimates show that negative rainfall shocks increase the likelihood and severity of intimate partner violence in the household. More importantly, estimates from the disaggregated specification reveal that the overall effects are driven by droughts rather than floods.

The second essay examines the effect of mobile money adoption by households in Tanzania on welfare outcomes. Using an instrumented difference-in-difference methodology in addition to household and individual fixed effects for a panel of households and individuals, our results show that per-capita expenditure pattern for the extremely poor households is significantly smoothed in periods of negative idiosyncratic shock for mobile money adopter households. At the individual level, estimates reveal consistent welfare boost stories during negative shocks for human capital accumulation among children and; preventive health expenditure and financial subjective well-being in general.

The third essay investigates the impact of exogenous variation in early life rainfall patterns across localities on short-term nutritional health status and long-term welfare outcomes respectively. While our baseline results for children anthropometric measures reveal that negative rainfall deviation – at in-utero, in first and second years of birth respectively – leads to a resultant adverse effect on weight and height -for-age z scores for children, drought related shocks are estimated to be more persistent for disaggregated shock specifications. Regarding the long term outcomes, we find that female adults exposed to in-utero drought shock are more likely to be hospitalised and less productive relative to non-exposed group.

Dedication

I dedicate this thesis:

- To the Almighty GOD, for HIS grace and mercy; and ultimately for HIS unwavering love upon my life during the course of my research at the University of Leicester. *"Unless the LORD builds the house, they labor in vain who build it; unless the LORD guards the city, the watchman stays awake in vain"* Psalm 127:1 (NKJV)
- To my late father, Josiah Olushola Abiona; you set a precedence full of righteousness for us to build upon
- To my Mother, Esther Mogbonjubola Abiona; you prayed fervently for me to succeed in life
- To my brothers and sisters; for your warmth, love and support especially in periods of depression and ultimately
- To my wife, Folashade Alphonsen and son, Israel Temitayo for their unwavering love, support and patience through the difficult periods of my PhD

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Finally, I would like to thank GOD who is my source of encouragement throughout the PhD. For HIS grace and mercies that encompass my life, HIS praises shall continually be in my mouth forever and ever. Amen.

Declaration

The second and third chapters result from co-joint work with Dr Martin Foureaux Koppensteiner. I was responsible for the data analysis and the writing of the chapters was shared equally. The chapters of this thesis have been presented in major economics conferences. Full details of relevant conferences and workshops (ordered by date) are given below.

Chapter 2:

- 30th Annual Conference of European Society for Population Economics (ESPE) between 15th and 18th of June, 2016 in Berlin, Germany.
- DIW Workshop on "Analyzing the Impact of Extreme Weather Events from a Microeconomic Perspective" on the 27th of June, 2016 in Berlin, Germany.
- 28th Annual Conference of Economic Association of Labour Economists (EALE) between 15th and 17th of September, 2016 in Ghent, Belgium.

Chapter 3:

- 2016 NOVAFRICA Conference on Economic Development in Africa between 14th and 15th of July, 2016 in Lisbon, Portugal.
- 2016 International Conference on Shocks and Development: Shocks and Coping Strategies in Developing Countries between 6th and 7th of October 2016 in Dresden, Germany.
- 2017 Royal Economic Society (RES) PhD Meetings on 3rd and 4th of January 2017 in Westminster, United Kingdom.
- 2017 Centre for the Study of African Economies (CSAE) Conference between 19th and 21st of March, 2017 in Oxford, United Kingdom. Accepted.

Chapter 4:

- 2017 Centre for the Study of African Economies (CSAE) Conference between 19th and 21st of March, 2017 in Oxford, United Kingdom. Accepted.

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Chapter 1

1 Introduction

1.1 Background and motivation

This thesis is an empirical study on unanticipated economic shocks, welfare outcomes, and financial inclusion in developing countries. Chapter 2 analyses the effect of household shocks on domestic violence, paying particular attention to intra-household bargaining models to explain the theoretical underpinnings of intimate partner abusive relationships in Tanzania. Chapter 3 examines the effect of mobile money expansion, a quasi-formal financial inclusion strategy, in mitigating adverse shocks for various welfare outcomes such as poverty, health, children education, labour diversification and subjective well-being in Tanzania. Finally, chapter 4 re-examines the empirical question related to the relationship between early life shocks; short-term and long-term socioeconomic outcomes in rural Malawi using child anthropometric growth gradients and adulthood welfare outcomes.

In the remainder of the introduction, I summarise chapters 2, 3 and 4 as follows: Subsection 1.1.1 considers the impact of household shocks on the incidence of domestic violence: evidence from Tanzania; subsection 1.1.2 considers financial inclusion, household shocks and welfare: evidence from the expansion of mobile money in Tanzania; and lastly, subsection 1.1.3 considers adverse early life shocks and impacts on short term and long term outcomes: evidence from rural Malawi.

1.1.1 The impact of household shocks on the incidence of domestic violence: evidence from Tanzania

Different strands of theoretical literature differ on the underlying theoretical backgrounds for causative factors of the incidence of domestic violence. Notable among these, though in broad categories, are theories related to resources and exposure. The resource theory of domestic violence, which is often ascribed to Gelles (1976), asserts that women with more resources have better options outside of abusive partnership and are therefore better equipped to leave violent partners. This framework underpins intra-household bargaining models and has been useful in motivating intimate partner domestic violence dynamics. In the intra-household bargaining motivated intimate partner models, women with better outside options have higher threat points. Subsequent models that lend credence to this theory include Manser and Brown (1980); McElroy and Horney (1981); Bloch and Rao (2002); Anderson and Eswaran (2009); Aizer (2010); Eswaran and Malhotra (2011) and Bobonis *et al.* (2013).

A second prevailing theory explaining domestic violence is known as the exposure theory of abusive relationship. This theory posits that women are less likely to be abused if they spend less time with their partners. A strand of the opinion of exposure reduction model is a model that argues that an increase in male unemployment decreases the incidence of intimate partner violence, while an increase in female unemployment increases domestic abuse (Anderberg *et al.* 2015). Nevertheless, theoretical predictions of the models from the resource and exposure theories are mixed and substantially differentiated. Similarly, in an attempt to either validate or refute some of the theoretical predictions, different strands of empirical evidence have emerged over the years. The empirical results diverge hugely across studies which consider developed and developing countries. The causal effect of improved outside options of women on violence against women is equally, empirically ambiguous (Farmer and Tiefenthaler 1997; Panda and Agarwal 2005; Agarwal and Panda 2007; Garikipati 2007; Iyengar 2009; Jensen and Oster 2009 and Chin 2012).

Notwithstanding the discrepancies associated with the existing literature on the incidence of domestic violence, empirical literature identifies a unique underlying factor of domestic violence as unanticipated economic outcomes – economic shock (Sekhri and Storeygard 2014; Cools *et al.* 2015; Anderberg *et al.* 2015). Shocks – idiosyncratic or covariate – may have significant effect on the incidence and severity of domestic violence. More importantly, inadequate risk-coping strategies and lack of insurance mechanisms in developing countries may deteriorate the incidence of and cause repeat abuse in periods of unanticipated economic shocks. This prediction is also a reflection of substantial financial inclusion gaps across rural-urban dichotomies of households in the developing countries.

Recently, attention has shifted to the impact of exogenous shocks on the incidence of domestic violence in the developing countries (Cools *et al.* 2015; Sekhri and Storeygard 2014). These papers leverage the exogenous nature of precipitation patterns across districts to investigate the potential impact of resource shocks on aggregate measures of domestic violence indices in sub-Sahara African countries and India respectively. In this regard, lack of capacity to smooth covariate shocks in agricultural dependent households in developing countries is perceived as an important underlying cause of violence. However, empirical evidence in this regard is devoid of potential intra-household dynamics of intimate partner violence as it relates to teasing out mechanisms linking shock to the incidence of domestic violence. This argument suggests that the associated channel of shock to domestic violence is currently scarce. Empirical attention to understanding the underlying mechanisms of the link between business cycle shocks to domestic violence is relatively recent and limited to developed countries (van den Berg and Tertilt 2012). It would be interesting to verify similar evidence from other parts of the world, particularly from a resource scarce environment that is characteristically distinct from developed system.

Another limitation of the existing empirical evidence is that, they all focus on aggregate measures of domestic violence. There is, however, a firm belief that measures of domestic violence based on aggregated reports may actually be suitable for aggregate level shocks as adopted in most studies. Ability to capture individual level domestic violence indices would be very useful for more refined analytical framework part of which would be helpful in understanding the mechanism of transmission of shocks to domestic violence. Paying particular attention to the individual level domestic violence incidence reports, Chapter 2 of this thesis seeks to extend the literature on the aggregative evaluation of shocks on domestic violence by providing evidence from Tanzania, a potentially highly fragile environment with scarcity of resources and inadequate risk-coping mechanisms. This offers a new insight given that Tanzania presents a unique feature which has not been investigated in this context in the literature. Second, the chapter employs a disaggregated measure of shocks (negative and positive) in addition to the linear shock specification (Sekhri and Storeygard 2014). Negative and positive shock measures indicate drought and flood in some respect and results from this model helps to contextualise the impacts of shocks on domestic violence in sub-Saharan African countries for intervention purposes.

1.1.2 Financial inclusion, household shocks and welfare: evidence from the expansion of mobile money in Tanzania

Generally, an extensive body of literature has documented the role of remittance transfers play on welfare of relatives in the home country of migrants (Yang and Choi 2007; Acosta *et al.* 2008; Yang 2011; Adams and Cuecuecha 2010; Adams and Cuecuecha 2013). While some of the studies in the literature reveal some evidence of capital investment from remittance receipts, most of the evidence support a framework of remittance as an insurance mechanism in developing countries. However, the channel of transmission of this relation is ambiguous bordering on lack of the capacity to extend such insurance models to shock cushioning capacities for rural dwellers due to existing rural-urban financial inclusion gaps in developing countries. Hence, financial inclusion intervention programs in rural communities through access to savings services have proven to increase savings and enhance capital investments (Dupas and Robinson 2013a; 2013b). These findings particularly confirm important need for sustainable inclusive financial system for the unbanked to bridge the acute shortage of formal financial services in the developing countries.

In recent years, mobile money has emerged as a unique financial inclusion platform for rural and urban dwellers of developing countries. In this regard, mobile money has considerably bridged the financial inclusion gap among diverse sectors of the society making remittance easy and secure in adopter countries. Previous evidence from the literature portrays the efficacy of mobile money services for household consumption smoothing (Jack *et al.* 2013; Jack and Suri 2014; Munyegera and Matsumoto 2016; Aker *et al.* 2016; Riley 2016)[1]. Beyond the consumption smoothing capacities, more studies have revealed the use of mobile money as a substitute for formal financial platform for safety purposes (Economides and Jeziorski 2015). It is important to mention that mobile money as a wallet financial service is different from the existing culture of transfer of vouchers often undertaken in the developing countries for risk sharing purposes by friends and relatives. While this may help in consumption smoothing similar to evidence provided in Blumenstock

[1] Aker *et al.* (2016) is an exceptional literature among others in that it uses a RCT in Niger as against East African countries used as case studies for Jack *et al.* (2013), Jack and Suri (2014), Munyegera and Matsumoto (2016) and Riley (2016). Also, in addition to household welfare, Aker *et al.* (2016) study the cost implication for the agency involved in using mobile money compared to other intervention methods such as disbursement of cash.

et al. (2016), mobile money services have upgraded to encompass many other financial services in addition to remittance transfers.

Whilst the existing literature focuses on consumption smoothing outcomes of mobile money expansion, other household welfare components may be indirect beneficiaries of the novel financial inclusion. This is particularly relevant to shock cushioning capacities of the mobile money financial wallet (Jack and Suri 2014; Riley 2016)[2].

The main objective of this chapter is to extend previous literature on welfare impacts of mobile money to examining the role of mobile money in preserving human capital accumulation during unanticipated shocks. While our setting is relatively close to that of Jack and Suri (2014), Munyegera and Matsumoto (2016) and Riley (2016) our questions differ substantially[3]. The resultant short term welfare implication of mobile money adoption may play an important role in the understanding of long run benefits in resource scarce environments with inefficient insurance.

In chapter 3 of this thesis, we aim to complement the literature on consumption smoothing theoretical underpinnings of mobile money adoption with regards to exposure to idiosyncratic shocks. While consumption smoothing model in economics focus on the ability to smooth (per-capita) expenditure of vulnerable economic agents during shocks (Yang and Choi 2007, Jack and Suri 2014), the central feature of the study is to shift attention from general to per-capita expenditure smoothing for the most vulnerable households in periods of adverse shocks. The core research questions of this chapter are as follows. i) Does mobile money adoption help vulnerable households shield themselves from sliding into transient poverty? ii) What is the role of mobile money adoption in children's human capital accumulation – school attendance, afterschool learning activities and child labour? iii) Does the possession of mobile money within a household justify price effect revealed by Dupas (2009) in contrast to the anchoring effects of subsidy approach used in the past to drive

[2] With regard to commonly adopted informal insurance mechanisms in developing countries, the literature undermines sale of assets and livestock as inefficient and suboptimal for consumption smoothing among sub-Saharan African communities in periods of covariate shocks (Fafchamps *et al.* 1998; De Weerdt and Dercon 2006; Kazianga and Udry 2006; Islam and Maitra 2012).

[3] Also, the early majority stage of mobile money adoption in our setting – which helps showcase short-term dynamics of the effectiveness of mobile money – further differentiates our study from Jack and Suri (2014).

durable health investments in most Sub-Saharan African households (Dupas 2014)? and lastly iv) Is mobile money financial inclusion used by adults to complement or substitute[4] traditional non-farm labour diversification strategies during negative shocks?

1.1.3 Adverse early life shocks and impacts on short term and long term outcomes: evidence from rural Malawi

A growing body of literature documents evidence in support of both short term and persistent effects of early life shocks across developed and developing countries respectively. This includes the impact of early life disease environment (Almond 2006; Almond *et al.* 2009); natural disaster (Lehmann and Wadsworth 2011; Sotomayor 2013; Caruso and Miller 2015; De Vreyer *et al.* 2015; Deuchert and Felfe 2015); environment in general (Gould *et al.* 2011) and exposure to violence (Justino *et al.* 2014). Almond and Currie (2011b) attributes the impacts of the early life shocks to fetal programming period which is effectively triggered during in-utero. Findings from short term outcomes also consistently reveal the deleterious impacts of adverse early life shocks across children's short term health measures with focus on anthropometric measures of children between the ages of 0 to 60 months[5]; and incidence of diarrhoea among others (Rabassa *et al.* 2014; Thai and Falaris 2014).

On the other hand, only limited body of literature examines the role of intervention programs targeted at cushioning the deleterious impacts of early life shocks on both short term and long term outcome variables respectively (Maluccio *et al.* 2009; Hidrobo 2014). Whilst we acknowledge that the previous investigations are important in their own rights, it is important to highlight the importance of intervention programs targeted at cushioning adverse early life shocks on welfare having established the underlying insults to different facets of health and socioeconomic outcomes of individuals in later life. Most of the intervention programs are either conducted by governmental or non-governmental organisations to rescue affected cohorts from the effects of shocks. It may be equally necessary to examine potential intra-household dynamics in compensating for affected individual's welfare.

[4] This is majorly aimed at teasing out potential behavioural concerns of mobile money adoption in our study.
[5] Almond and Currie (2011a) highlights the importance of human capital accumulation before age five as an important component of socio-economic achievements of individuals at adulthood.

Chapter 4 of this thesis investigates the likelihood of adopting compensatory strategies for children exposed to adverse early life shocks compared to children predisposed to positive shock or not affected by any shock at all. The most relevant literature in this regard are papers by Maluccio *et al.* (2009) and Hidrobo (2014) which examine the influence of targeted nutritional programs on education achievements of adults in Guatemala; and cash transfers for age standardised height z and test scores in a panel of children in Ecuador respectively. The impact of improving nutrition during early childhood on education among Guatemalan adults, as revealed by Maluccio *et al.* (2009), indicates the importance of timely intervention towards children exposed to early life shocks. Hidrobo (2014) considers the role of accessing cash transfer on the effect of Ecuador's 1999 economic crisis on the age standardised z and test scores. Result shows compelling evidence in support of cushioning role for exposed children. A clear departure of our study is the investigation of the intra-household effort at compensating for damage caused in the early life of children. Second, different from interventionist nutrition program adopted in Maluccio *et al.* (2009), this paper considers nutritional rationing efforts to compensate for damage caused by exposure to shock around the period of birth. Our study examines the demonstration of the compensatory incentive within a multi-period shock framework i.e. exposure to shocks from in-utero to second year of birth.

Interestingly, as shown in Chapter 4 of this thesis, realisation of in-utero shocks' impact on contemporaneous adulthood health outcome attracts greater level of attention as characterised in the reversal of adverse effects of drought on average hospitalisation rate of individuals. This suggests that the persistent impact of drought shocks around the period of birth of children cohorts is cushioned by access to nutritional supplements associated with current welfare outcomes. This chapter further provides some suggestive evidence for potential gender dynamics to intra-household resource allocation of intervention. This chapter extends the literature by providing the first long term evidence of the role of compensatory effort to restore health and adulthood socio-economic outcomes to normalcy. The evidence helps to further strengthen the role of intervention programs and its multi-dimensional facet in addressing the impact of shocks.

1.2. Organisation of the thesis

The rest of the thesis is organised as follows: chapter 2 examines the impact of household shocks on the incidence and severity of intimate partner domestic violence in Tanzania, paying particular attention to intimate partner household bargaining model in economics. Combination of across and within community level variations in exogenous precipitation patterns; relating to negative and positive rainfall shocks from World Bank precipitation measures are exploited to examine the impact of disaggregated rainfall shocks on domestic violence at a disaggregated level. The chapter employs the use of probit model for incidence of domestic violence and ordered probit estimation approach for the categorical severity measures of domestic violence in the past year controlling for a large array of individual, household and community covariates respectively.

Chapter 3 investigates the effect of financial inclusion on welfare outcomes during household shocks in Tanzania. Employing instrumented difference-in-difference estimation approach, the chapter identifies this through community level mobile money agent distribution that created exogenous variation in access to mobile money adoption across households. Hence, agent availability and distance to the nearest agent are used as instruments for mobile money adoption within households. This variation in agent distribution is combined with exogenous distribution of inter-community rainfall shocks for an instrumented difference-in-difference identification approach in this chapter. The choice of variables borders on previously ignored welfare variables beyond per-capita income used for consumption smoothing models in the existing literature. These include poverty, schooling outcomes, after school learning, subjective well-being and labour supply.

Chapter 4 re-examines the effect of early life shocks on short term and long term welfare outcomes in Malawi, taking into account the disaggregation of shocks for policy perspectives regarding mitigating welfare consequences of early life shocks. The identification strategy used in this study borders on exposure of similarly aged children to differential shocks across different communities from in-utero stage to second year of birth. This may be categorised as non-exposed to exposed comparison or simply comparing groups’ exposure to different magnitudes of shocks.

Finally, section 5 concludes the thesis, considers some relevant policy implications, acknowledges certain limitations inherent in the study, and offers some direction for future research.

Chapter 2

2 The impact of household shocks on the incidence of domestic violence: evidence from Tanzania

2.1 Introduction

Violence against women – in particular intimate partner violence – is a major public health issue which has attracted increased attention in economics lately (Aizer 2010; Carrell and Hoekstra 2010; Card and Dahl 2011; van den Berg and Tertilt 2012; Bobonis *et al.* 2013; Hidrobo and Fernald 2013, Sekhri and Storeygard 2014; Anderberg *et al.* 2015). A recent analysis by the WHO, based on existing data from over 80 countries, found that 35% of women worldwide have experienced either physical intimate partner violence or non-partner physical violence in the past (WHO 2014), with the majority of these incidences being related to intimate partner violence. Besides the direct welfare concerns for victims of domestic violence (DV), the costs of violence against women related to policing, health expenditure, lower intra-household productivity and distorted investment incentives are substantial (Walby 2004, Doepke *et al.* 2012; Duflo 2012). Walby (2009) estimates the cost of DV at approximately 6 billion pounds a year for the United Kingdom. This figure includes estimates for lost economic output due to time off work related to injury and cost estimates for public services used including criminal justice, social services, housing and health care. Health care costs associated with DV account for approximately 1.5 percent of public health expenditure in the UK in 2008.[6] In Chile, women's lost earnings as a result of DV cost US$1.56 billion which is above 2 percent of the country's GDP in 1996 while in Nicaragua an estimate of US$29.5 million which translates to 1.6 percent of the national GDP in 1997 was reported (Morrison and Orlando 1999). More recent cost estimates for other countries, in particular developing countries, are very rare, probably because of limited information on the incidence of DV.

In addition to the cost borne by the victim, the negative externalities of DV extend to children in households of victims and the unborn children of victims. Aizer (2011)

[6] Own calculation based on estimates on health care costs from Walby (2009) and official health care expenditure data from the Office for National Statistics (2011).

documents the cost of exposure to DV in utero on newborn health in the US and finds that hospitalization for DV leads to a reduction in birth weight of about 160 grams. Rawlings and Siddique (2014) find that children exposed to DV in utero across 30 low- and middle-income countries have worse health at birth and an increased child mortality rate.

The main motivation for the study of domestic violence in economics is clearly the potential association between income or economic fundamentals of anger leading to abuse. Evidence from the existing literature has sharpened background knowledge in this respect further giving important insight into policy directions to reduce domestic violence to the barest minimum across diverse settings. Main theories underpinning the incidence or repeat occurrence of domestic violence among intimate partners are exposure theory, resource theory and backlash hypothesis. The resource theory has gained prominence among these within the economics literature. In this direction, a strand of the literature focuses on examining possible socioeconomic characteristic and their intrahousehold distribution as determinants for intimate partner violence. Early work by Gelles (1976) uses a simple household bargaining model to explain the intra household use of violence.[7] In bargaining models, women with better outside options have higher threat points and lower reference points for abuse leading to lower incidence of DV in these households. A number of empirical papers have demonstrated how income or relative income between partners influence prevalence of DV incidence through shifting bargaining powers (Tauchen *et al.*1991; Tauchen and Witte 1995; Farmer and Tiefenthaler 1997; Bowlus and Seitz 2006; Srinivasan and Bedi 2007; Chin 2012). In a recent paper by Aizer (2010) using exogenous changes in the demand for labour in female-dominated industries, she estimates the effect of the male-female wage gap on the incidence of DV and provides evidence consistent with a household bargaining model. Anderberg *et al.* (2015) show for the UK how a shift in male and female unemployment have opposite-signed effects on domestic abuse, where female unemployment leads to a weakening in the bargaining position of females and to an increase in DV.

[7] Subsequent household bargaining models include Manser and Brown (1980), McElroy and Horney (1981), Bloch and Rao (2002), Srinivasan and Bedi (2007), Anderson and Eswaran (2009), Aizer (2010), Eswaran and Malhotra (2011) and Bobonis *et al.* (2013).

Rather than focusing on the relative bargaining position of females in high-income countries, we are interested in the effect of exogenous shocks to the economic position of a household in a resource-scarce environment, namely Tanzania, one of the poorest countries in the world. To learn about the effect of these shocks on DV we make use of a unique dataset that provides very detailed information about the incidence and the severity of domestic abuse, including categories of physical, severe physical and sexual abuse, for 2,606 households. We then combine this information with household level information on exogenous rainfall shocks for households whose main income depends on agricultural production to estimate the causal effects that household resource shocks have on domestic abuse.

Our paper is closest to two recent papers by Sekhri and Storeygard (2014) and Cools *et al.* (2015). Sekhri and Storeygard (2014) study the effect of rainfall shocks on dowry deaths in India. Using district level data from 583 Indian districts, they find that a one standard deviation decline in annual rainfall from the local mean increases reported dowry death by 8 percent explaining their results with the use of dowry to smooth consumption during negative rainfall shocks. Cools *et al.* (2015) investigate how weather shocks affect violence against women using rainfall variation across selected African countries. They find that droughts lead to an increase in the risk for first abuse in relationships where only the woman and not her husband works in agriculture.

We contribute to this literature with estimates of rainfall shocks on DV using household level variation in precipitation and making use of an extraordinarily rich dataset providing a rich set of controls and a unique set of measures of DV not available in other datasets. We provide evidence that rainfall shocks have a significant effect on the incidence of DV in Tanzania. A one standard deviation negative rainfall shock (approximately 15% decrease in precipitation from the long-run mean) increases the probability of DV by 3.2 percent. These effects translate to approximately 18.8 percentage point increase in DV compared to the mean incidence for wives. An important contribution in this regard is the establishment of purely economic link between rainfall shock and domestic violence after eradicating all other potential types of mechanisms including emotional cue and house structure.

We furthermore show that rainfall shocks have an effect on physical violence (with a magnitude similar to the combined DV specification). We do not find an effect on severe physical or sexual abuse, findings consistent with the strategic use of violence in household bargaining models. Estimates from disaggregated shock model reveal that the overall effects are driven by dry shocks (droughts) rather than wet shocks (floods). The result indicates that droughts are more impactful on household resource and that wet shocks may be managed by smallhold farmers. This evidence of asymmetric impacts particularly offers policy makers direction for intervention policies targeted at cushioning shocks for agricultural dependent households. We also show that effects are much stronger for poorer households (as measured by quartiles of the non-agricultural assets in the household). More importantly, we provide evidence that female empowerment mitigates the impact of rainfall shocks.

The remainder of this paper is organized as follows. In section 2.2, we describe the data and the variables used in the analysis. Section 2.3 discusses the rainfall shock measures. Section 2.4 introduces the identification strategy. Section 2.5 presents and discusses the main results. In section 2.6, we explore possible underlying mechanisms and we conclude in section 2.7.

2.2 Data

We use data from the Tanzanian Household National Panel Survey, which is part of the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) for this paper. The LSMS-ISAs are collaborative initiatives between the World Bank and national bureaus of statistics (or similar) in selected developing countries providing researchers with nationally representative high quality micro data for agricultural-dominant economies. Tanzania first participated in the survey in 2008/2009 and we use this wave in the analytical framework of this paper. Individual and household level data is complemented by extensive community level data drawing on a variety of sources. For households engaging in agricultural practices additional very detailed plot-level information about agricultural inputs and outputs are also collected. The Tanzanian LSMS follows 3,265 households over the three waves including information on 16,711 household members. Attrition rates are low due to the extraordinary effort being made to track households and individuals moving households or villages etc. Figure 2.1 shows a map of the 386 randomly selected enumeration areas (EA) for which data has been collected, where red dots denote the randomised settlements.

We restrict the data on households for which the agricultural questionnaire has been completed and for which data on rainfall on the household level is available, restricting the sample to 2,606 households. The sample of households for which plot-level rainfall data is available in this regard is plausibly random resulting from the underlying randomisation of the enumeration areas from the population of enumeration areas for the survey and random selection of households from each enumeration area.

Household summary statistics are reported in Table 2.1**.** Average household size is just above seven, 82 percent households have a male household head with 69 percent of these households being located in the rural areas. Individuals are on average 21 years old reflecting high fertility rates in Tanzania. The sample comprises of 47 percent males and 53 percent adults are married. Educational attainment is generally low among adults, with the vast majority reporting primary education as the highest attainment (80 percent), 19 percent have a junior or senior high school qualification with only 0.6 percent having a college degree. The large majority of the adults work either in agriculture or in mining sector (67 percent), while sizeable adults are self-employed (15 percent) with a smaller fraction having employment in the private sector or in NGOs (7 percent). The remainder either works as civil servant in local or regional government (5 percent) or as domestic worker or unemployed (6 percent).

Information on violence towards female household members is available only in the 2008/2009 Tanzanian LSMS-ISA wave. DV questions were administered to women within 15 – 50 years of age and great care has been taken when collecting this information. Women were interviewed for these questions in separate rooms ensuring that the conversation could not be overheard by anyone else. The questions were administered by specially trained female interviewers and interviewees were instructed that the interview could be ended at any point at their request. Out of 3,182 women eligible for the DV section, 2,933 individuals answered these questions, so the response rate is 92.2 percent.

Questions on DV were repeated for two timescales, reporting the incidence over the past 12- month period and over the entire life of the interviewees. Eight separate questions were asked about the incidence of domestic abuse for these timescales and their frequency was recorded including whether the respondent was subjected to either hitting, pushing, beating, slapping, choking, burning, the use or the threat to use a weapon, and forced and unwanted sexual intercourse. As is standard in the literature we categorized these questions into physical abuse including the first four questions, severe-physical abuse comprising of choking, burning and the use of a weapon, and a category including sexual violence. From these categories, we created indicator variables for the incidence of physical, severe physical and sexual violence, as well as a general indicator variable covering any of the three categories as the focus outcome variable.

Further questions from the domestic violence section reveal the number of repeat abuse individual observations experience in the past twelve months or lifetime[8]. We construct an index of domestic violence using the frequency of occurrence available in the questionnaire, each for the 12-month and lifetime exposure. The domestic violence index conveys the severity of domestic violence over the 12- month period and over the entire life of the interviewees similar to the indicator variable. We also construct severity index of domestic violence for the categories highlighted above. We denote domestic violence index as 3 for women who experienced abuse several times, 2 for women who experienced abuse a few times, 1 for women who experienced abuse only one time and zero for women who were not abused within the timescales. Different to the indicator variable of domestic violence, these indices further expands the severity of the repeat occurrence of violence as revealed from higher numerical values for several and few occasions of abuse. While we use the probit model in estimating the indicator outcomes, ordered probit model is used for the severity indices.

In addition, females were asked about their perception of the acceptability of violent acts by their partner. The question asked whether a husband would be justified in hitting or

[8] This is apparently restricted to the observations that have reportedly experienced any domestic violence within the stipulated period.

beating his wife in a range of scenarios.[9] The survey also included questions on whether victims have ever sought help after physical violence with either family, hospital or health centre, village or community leaders, an NGO, religious leaders or the police, which provides very helpful information on the reliability of statistics of DV incidences based on reported incidences with any of these agencies.

While twenty-three percent of women in the sample report having experienced at least one form of physical or sexual violence over their lifetime, twelve percent report to being victimized in the last twelve months (Table 2.2, Chart A) indicating that a considerable proportion of females suffer from repeat incidences of domestic violence. Within the previous twelve months, roughly 10 percent report having experienced some form of physical violence, 1 percent severe-physical violence, and 5 percent sexual violence. The figures are slightly higher for wives within the household. 31 percent have experienced abuse in their entire life while 17 percent have been abused in the last twelve months. These figures are 8 percentage points and 5 percentage points higher than general reports of female-targeted DV respectively for lifetime and twelve months. Chart B of Table 2.2 reports the findings on the perception of the acceptability of violence for female respondents. Going out without permission, child neglect, argument with male partner and refusal of sex are named equally frequently as acceptable justification of violence by a husband with on average just above 30 percent of women accepting these as justification. Problems with the families of either the respondent or their partner, financial problems and lack of food are much less frequently being accepted as justification, with 3, 2, and 6 percent respectively.

Chart C of Table 2.2 shows that 7 percent of respondent victims have ever been to hospital or to a health clinic as a result of abuse; 5 percent ever reported an incident to the police and 1 percent state that they turned to an NGO, demonstrating the likely degree of underreporting of DV using official data from health institutions or the police and explaining the discrepancy when comparing the incidence of DV across such datasets. In combination with the attention by the trained survey teams to ensuring privacy the information on DV is

[9] These include 'if she goes out without telling him', 'if she neglects the children', 'if she argues with him', 'if she refuses to have sex with him', 'if there are problems with his or her family', 'if there are money problems', 'if there is no food at home', 'other'.

likely among the most reliable data on the incidence of DV minimizing potential measurement error, in particular when comparing to official statistics based on reporting to public services.

2.3 Measuring Rainfall Shocks

We use annual and seasonal rainfall shocks to investigate the effect of these economic shocks on the incidence of DV for households where agricultural income is a major component. To create measures of household rainfall shocks we use the data provided in the LSMS-ISA for Tanzania using information from the georeferenced agricultural plot locations on the household level. After information on precipitation has been merged by household ID, georeferenced data is removed to preserve the confidentiality of the households. Different from many other datasets though, the precipitation is available on the plot level rather than at the enumeration area or regional level, so that we have available variation in precipitation not only across regions or villages, but even within the village as individual plots are often spread out over a larger area[10]. This also helps us to reduce measurement error in precipitation compared to weather shocks based on regional precipitation data. In the same vein, this helps with concerns more recently raised about spatial correlation of rainfall data (Lind 2015). One way to address these concerns is the link to the units of observation. Because of the absence of georeferenced household data in many studies precipitation data is observed only at the district level.

When constructing rainfall shocks we follow closely the previous literature (Maccini and Yang 2009; Björkman-Nyqvist 2013; Rocha and Soares 2015[11]), and we adopt the conventional measure of shocks as a deviation of a given year's rainfall from historical average for the same locality. The relevant year's rainfall in our case relates to the total yearly rainfall from July 2007 till June 2008 to capture the relevant rainfall for the main planting season prior to the 2008/2009 LSMS-ISA, while the historical rainfall average is the mean value of the yearly rainfall for the period 2001 to 2008 as measured for the July to June

[10] See details of World Banks' formation of plot level geo-referenced precipitation estimates from both weather stations and multiple meteorological satellites in Appendix A.

[11] Although, Rocha and Soares (2015) has alternative shock specification in terms of drought dummy, estimates from the rainfall shock specification adopted by our study is the focus for the general interpretation of results in their paper.

periods. Hence, we construct the rainfall shock variable as log-deviation from historical average as follows[12]:

$$\text{rainfall shock}_\text{h} = ln\, R_{ht-1} - ln\, \overline{R_h} \tag{2.1}$$

where R_{ht-1} indicates the yearly rainfall in household *h* for 2007/2008 planting season, $\overline{R_h}$ is the average historical yearly rainfall in household h. Thus, $\text{rainfall shock}_\text{h}$ is defined as the deviation between the natural logarithm of the total rainfall in the 12 months prior to the 2008/2009 survey and the natural logarithm of the average yearly historical rainfall in household h. The rainfall deviation implies a percentage deviation from mean rainfall (Maccini and Yang 2009). Rainfall shock summary statistics in Table 2.1 indicates an average of 0.3 percent decrease in plot-level (and community) precipitation from the mean for the 2007/2008 agricultural season. In addition to the plot-level rainfall measures, we construct village level long-term rainfall shock measures. We use the GPS information provided for each village in the Tanzania LSMS to access the University of Delaware's rainfall repository by matching each village to the four closest weather stations for historical rainfall data between 1978 and 2007. The data which is compiled and made available by Matsuura and Willmott (2012) has been used in many empirical studies in economics.

2.4 Identification Strategy

The difficulty of estimating the effect that the household socioeconomic background or a shock to household income has on the incidence of DV in a household arises from the fact that confounding factors that are related to these socioeconomic conditions and to the propensity to using violence or being the victim of violence may be unobservable to the econometrician and their omission may then lead to biased estimates.

To circumvent this problem we propose to use plausibly exogenous variation in rainfall on the plot-level to estimate the effect of unanticipated economic shocks on the incidence or repeat occurrence of DV. We used exogenous variation in rainfall shocks to capture the economic shocks faced by households in this region. The economic shock fundamentally measures shock to resource availability to households that may be routed

[12] We repeat the same exercise for wet season (agricultural season) rainfall shocks and dry season (out-of-planting season) shocks respectively.

through shock to income or food insecurity. We rely on differential magnitudes in the deviation of recent agricultural season to the local historical norm in the same location for the identification of the impact of shocks on domestic violence. This approach has been widely used to capture shocks in the literature. Identification assumption is that in the absence of variation in shocks through plot levels rainfall patterns, incidence of domestic violence and repeat occurrence will not differ across households.

In line with a rich literature using rainfall variation in place of socioeconomic shocks, we estimate the following reduced form model:

$$DV_{ih} = \alpha + \beta \text{rainfall shock}_h + X_{ih}' \nu_x + Z_c' \upsilon_z + \varepsilon_{ih} \qquad (2.2)$$

where DV_{ih} is the domestic violence measure for an individual respondent *i* (measured as an indicator variable or severity index within 12 months of abuse) in household h. β is the parameter on the variable of interest rainfall shock_h. $\boldsymbol{X}$ and $\boldsymbol{Z}$ are vectors of controls to enhance the precision of our estimation. $\boldsymbol{X}$ is an array of individual and household level covariates including household demographic characteristics such as household size, number of children, indicator variable for gender of household head, average household age, an indicator for rural households, proxies for household wealth, indicators for household savings group membership and whether the household has taken out a loan previously. Individual controls mainly consist of individual demographic characteristics including individual's age, gender, education, occupation categories and marital status. $\boldsymbol{Z}$ is a vector of relevant community level controls including community level infrastructure facilities such as bank, birth and death registration centre, court, government health facilities and hospitals, government primary and secondary schools, daily and weekly market facilities, police station, post office, nursery care facility, savings and credit cooperative (SACCO), private health facilities and hospitals, private primary and secondary schools and veterinary clinics. In addition, community level controls include the proximity of community of residence to district or regional headquarters. We also include annual community level temperature because an existing literature argues that high temperature contributes to the propensity for violence (Anderson 2001; Burke *et al.* 2013). The error is ε_{ih} are assumed to be iid between households but correlated within households so that the standard errors are clustered at the household level. As a sensitivity test for our baseline estimates, the standard errors are clustered at the village level.

To further investigate the differential role of negative and positive rainfall shocks namely dry shock and wet shocks respectively we propose to separate these effects following practice in the literature (Sekhri and Storeygard 2014) and we modify equation 2.2 to accommodate the two potential categories of shocks in a disaggregated fashion as follows:

$$DV_{ih} = \alpha + \beta_1 \text{dry shock}_h + \beta_2 \text{wet shock}_h + X'_{ih}\nu_x + Z'_c\upsilon_z + \varepsilon_{ih} \qquad (2.3)$$

where dry shock_h connotes negative rainfall shocks and is constructed as absolute value if the deviation of the previous season's rainfall from historical average is negative; zero otherwise. Analogously, wet shock_h connotes a positive rainfall shock and constructed as actual value if the deviation of the previous season's rainfall from historical average is positive; zero otherwise.

Because rainfall shocks are constructed in a manner that reflects previous agricultural season's farm harvest, they determine the economic resource availability at that period. We also repeat the estimation procedure of equation (2.2) for the planting season and out-of-season using the seasonal breakdown data to shed more light on the precise relationship between rainfall shocks and DV incidence.

2.5 Results

2.5.1 Main Results

Table 2.3 presents the main estimates of equation (2.2) by reporting marginal effects from probit estimates for a binary outcome model. We find that a negative rainfall shock (drought) leads to an increase in the incidence of DV. The inclusion of controls reduces the estimates significantly, while remaining statistically significant (Columns 2 and 3). Focusing on the model including community and individual/ household level controls, estimates in column 3 indicate that a one standard deviation[13] positive (negative) rainfall shock reduces (increases) the likelihood of DV targeted towards female in a typical household by a probability of 0.10

[13] Summary statistics of rainfall shock in Table 2.1 indicates that a standard deviation shock indicates a 15% movement in actual rainfall measure.

statistically significant at the 5 percent level[14]. The impact of rainfall shock on DV is 1.5% inverse response of DV incidence to a one standard deviation movement in rainfall. This effect corresponds to a 12.1 percentage point movements in DV incidence given the baseline. Results are very similar in magnitude to linear probability model estimates of the impact of rainfall shock on DV incidence (see Appendix Table A8).

Shifting our attention to the different categories of DV, results from Table 2.4 indicate that the overall effect is driven by the effect on physical violence, while we do not find any effect for severe physical or sexual violence. A one standard deviation negative rainfall shock increases the likelihood of physical abuse by 0.097 (Column 1) – a very similar magnitude to the main overall effect. On the contrary, the estimate from severe-physical DV (Column 2) indicates a negligible response (β = 0.005) to rainfall shocks, while the coefficient for sexual abuse (Column 3) is -0.031 and not statistically significant. We estimate equation (2.2) for the crude DV categories in the questionnaire. Estimates reported in Appendix Table A9[15] show that rainfall shock estimates for categories of DV under physical DV – which includes slapping, pushing, hitting and beating – all reveal a very similar effect to the head category namely physical DV, while the individual variables for severe physical abuse are very small and not significant, except the estimate for forced sex.

Not surprisingly, the effect is driven by violence towards spouses of the household head (Appendix Table A1). We find no effect on children in the household and a much smaller effect on other females in the household who are not spouses (Table 2.9). Interpreting the rainfall shock estimate of -0.21 from Appendix Table A1, results in 3.2% inverse response of DV incidence to a standard deviation rainfall shock. Given the sample average 0.17 DV incidence for wives, the effect implies approximately 18.8 percentage point impact for wives.

We then turn our attention to the severity of DV using the information on the frequency of abuse. This exercise follows the literature for consistency check for results obtained from the use of binary variable as an indicator for victim of DV (see Hidrobo and

[14] Appendix Table A10 presents similar community level rainfall shock estimate.
[15] Section I of the 2008 Tanzanian LSMS Questionnaire for the Domestic Violence is presented in Appendix A.

Fernald 2013). Table 2.5 and Appendix Table A2 report rainfall shock estimates for general and abuse against wives respectively for DV severity measures.

Results on Table 2.5 show that there is a similar inverse relationship between rainfall shock and DV intensity/severity. Using the marginal effects on Table 2.5 in column 2, the physical abuse reports a more predominant rainfall shock estimate among existing categories with a magnitude similar to that of the overall abuse reported in column 1 (-0.031 and -0.035 respectively for physical and overall abuse outcomes[16]). While the magnitude for the sexual abuse is considerably smaller, the severe-physical abuse reports an even smaller estimate, indicating that severe-physical and sexual assaults are not necessary driven by rainfall shocks relative to physical abuse. While rainfall shock estimates for all DV and physical DV category specifications are significant at 5%, rainfall shock estimates for severe-physical DV and sexual DV specifications are not significant at any traditional t values. This shows that the emerging patterns conform to results earlier reported for DV incidence estimated across diverse categories. Estimates of rainfall shock for wives' DV indices in Appendix Table A2 present similar trend.

2.5.2 Household Level Outcomes

We also estimate the effect of rainfall shocks on additional outcomes related, including separation of partners and the incidence of divorce within the household in the past twelve months. Results in Appendix Table A3 indicate that a negative rainfall shock leads to an increase in the likelihood of separation among partners. In particular, a one standard deviation negative rainfall shock increases the likelihood of separation by 6 percentage points (Column 2 of Appendix Table A3). Likewise, though surprising, we find an effect on the probability of divorce.

2.5.3 Community Level Outcomes

We can repeat the exercise using additional information on the number of disputes at the village level, which include information on community disputes brought to the village elders. Administrative data on monthly community level disputes resolved by the tribunal avails us

[16] While the marginal estimates for rainfall shocks in DV index specifications do not directly replicate marginal estimates for DV incidence, the DV index specification are mainly useful as a check for a consistent pattern of DV categories with those in the DV incidence.

the opportunity to explore relevant outcomes from community level variables on rainfall shock. Results in Appendix Table A4 reiterate the relevance of rainfall shock with respect to marriage cases reported to the tribunal relative to others. A one standard deviation negative rainfall shock increases the number of marriage cases reported to the tribunal. Rainfall shock estimate for natural logarithm of the number of marriage cases is -1.97(Column 1 of Appendix Table A4). Apart from smaller rainfall shock estimates for other tribunal cases namely money dispute, land dispute and inheritance dispute, these are insignificant at the traditional levels as with marriage cases which is significant at 1% (Columns 2 – 4 of Appendix Table A4).

2.5.4 Non-linear Impacts of Rainfall Shocks and Timing of Shocks

Estimates from the regression of equation (2.3) reported in Table 2.6 allow us to investigate simultaneously the impact of dry shock and wet shock on the incidence of DV. This exercise helps us to disentangle the main components of rainfall shocks as it relates to agricultural crop production. The estimates in Table 2.6 show that the overall effects are driven by dry shocks, while wet shocks have a much smaller impact and are not statistically significant at the conventional levels. Importantly, across different phases, dry shocks are very robust and the coefficients are considerably stable when controlling for a large array of community and individual controls, diminishing any concerns raised from Table 2.3. A one standard deviation increase in dry shock increases the incidence of DV targeted towards female in a typical household by a probability of 0.22 and the effect is precisely estimated at the 1 percent level of significance[17]. Table 2.7 presents rainfall shock estimates of regression outcomes for *planting-season* and *out-of-season* shocks respectively related to agricultural practices from equation (2.2). Estimates show that rainfall shock within planting season displays a stronger impact (Column 1) on DV than out-of-season effects (Column 2). These estimates send a strong signal that the timing of our shock is primarily driven by shocks to harvests as it relates to changes to weather pattern during crop cultivation.

2.5.5 Robustness Checks

To be able to interpret the estimates of rainfall shocks as the consequence of economic shocks to the household, we would like to rule out that the rainfall leads to an increase in DV directly,

[17] Regressions linked to both linear and disaggregated specifications in equations 2.2 and 2.3 above are clustered at the community level for sensitivity tests of the main results.

i.e. even in the absence of an underlying economic shock. For example, more rainfall could lead families to spend more time in limited living space increasing tensions between household members. Likewise, dry shocks could be associated with excessively high temperatures directly leading to an increase in violence, even in the absence of economic shocks to the household. Although we do not find that including temperature influences the estimates of dry shocks, and while we do find that violence is specifically targeted at the spouse rather than any female in the household in Table 2.9, we would like to test if the inclusion of relevant controls does make a difference to the estimates. Table 2.8 reports robust rainfall estimates by including measures of household living conditions, which may potentially cause tensions and household violence (e.g in alignment with exposure theory), as controls. Column 1 repeats our rainfall shock estimate for baseline specification while columns 2 - 6 reports rainfall shock estimates after sequentially including potentially confounding variables such as household living conditions and water scarcity respectively.

Intra-household exposure can be determined by the number of rooms available in the house. Column 2 includes number of rooms available in the house as an additional control to our main model (equation 2.2). Our rainfall shock estimate remains largely unchanged in magnitude to the baseline rainfall shock estimate in column 1. Also, the differences in household roofing type used for covering the house may indicate that the impact of rainfall shock is not credibly channelled through income shocks since wet rainfall shock can permeate most of the roofing materials used in Tanzania. Column 3 includes different types of roofing materials used for building as a control. Resulting rainfall shock estimate is exactly the same as the baseline estimate in column 1. This indicates that leakage caused by some roofing material is not a driver of the impact of rainfall shock on the incidence of DV. Columns 4 and 5 include type of water access used during rainy and dry seasons as controls respectively to investigate the role of access to water in the effect of rainfall shocks on the incidence of DV. Rainfall shock estimates for respective specifications is -0.09. While this effect is slightly weaker compared to our baseline rainfall shock effect in column 1, the margin is not wide and does not imply any threat on the robustness of our baseline rainfall shock estimate. Column 6 includes water shortage shock experience of household within the last 12 months as a control. Rainfall shock estimate for this specification is -0.10 which indicates that the impact of rainfall shock on DV is not driven by water shortage shocks.

Overall, all the robustness check specifications from columns 2 – 6 present rainfall shock estimates that are not substantially different from our baseline rainfall shock estimate in column 1. More importantly, the rainfall shock estimates from columns 2 – 6 are statistically significant at 5 percent following the baseline rainfall shock estimate which indicates a robust rainfall shock estimate for our baseline result[18].

We also would like to rule out that the estimates are driven by spatial correlation of rainfall shocks. Although we make use of plot-level variation in rainfall, we want to make sure that village level rainfall shocks are not correlated with the village level long-run incidence of DV. For this purpose we regress incidence of DV on the community level on long term rainfall variability (measured as the standard deviation of 30-year historical rainfall pre-empting the 2008-09 agricultural season). Appendix Table A7 presents the results using both 12 month and life-time DV incidence. We do not find any significant or sizeable effect of long-term rainfall variability on these measures, reducing any remaining concerns around spatial correlation of rainfall in our cross-section.

2.6 Potential Mechanisms and Heterogeneous Effects

An in-depth understanding of rainfall shock effects along diverse heterogeneous classifications is important to understand potential mechanism of DV incidence attributable to response to shocks in Tanzania. Educational background of females and level of financial independence are commonly explored to capture the prevalence of intimate partner violence (Aizer 2010; Bobonis *et al.* 2013; Hidrobo and Fernald 2013). Outcomes associated with rainfall deviation are commonly affiliated with agricultural practices and agricultural associated shocks may be cushioned using non-agricultural assets at the household level.

2.6.1 Gender of Household Head

An empowerment story can be built around the catering responsibility and headship status of females involved in an intimate relationship. Table 2.10 splits the spousal specification by female headship and male headship categories of the household. The estimates of rainfall shock impact on DV for male headed and female headed households are -0.26 and 0.04

[18] It is important to equally emphasize that dry shock impact resonates for the disaggregated model on all the battery of tests conducted on the main results in Table 2.8 (results available from authors upon request).

respectively (including all controls). This indicates that a one standard deviation negative rainfall shock increases the probability of DV incidence by 0.26 for households with male head. This estimate is slightly higher than the baseline spousal specification where rainfall shock estimate is -0.21. Whereas, households with female head reports 0.04 rainfall shock estimate on DV. Since most Sub-Saharan African (SSA) communities attribute household headship to responsibility, we perceive that ex-ante bargaining power play an important role in moderating the impact of rainfall shock on DV.

2.6.2 Female Empowerment

Previous papers have pointed out the importance of female empowerment as a mediating factor for economic shocks. We investigate this by using information on the inheritance policy at death of husband, as proxy for female empowerment. We estimate equation (2.2) including an interaction term for both rainfall shock and empowerment dummy (1 if women and children are allowed to inherit husband when husband is dead and zero otherwise)[19]. Results reported in Table 2.11 shows that the empowerment interaction mitigates the effect of rainfall shock on DV. While the rainfall shock estimate remains negative as expected, interaction of rainfall shock and empowerment dummy is positive. Importantly, the positive interaction estimate negates and substantially diminishes the negative rainfall shock effect on DV incidence. Combining the rainfall shock estimate and the interaction estimate indicates a weakened effect of rainfall shock on DV for females within the empowered community[20]. This is not the case for the measure of rainfall shock impact on DV for females that belong to communities where wives or children are not legally allowed to inherit the man's wealth after death as the shock effect persists.

2.6.3 Non-agricultural Household Assets

Table 2.12 reports result of baseline estimations by asset valuation quartiles for the household. We adopt the 2012/2013 household asset valuation since the actual values of assets are not available within the 2008/2009 survey. Using the average valuation of household asset for both purchase price and current price respectively, our results reflect that

[19] Appendix Table A11 shows that inheritance customs in our sample favours widows in 45.9 percent of the communities and children of deceased in 32.3 percent.

[20] More details on the orthogonal nature of rainfall patterns to our inheritance measure can be found in the appendix. Appendix Table A13 shows a 0.00 correlation between historical rainfall pattern and inheritance empowerment status for women and children across communities.

both first and second quartiles have considerable rainfall shock estimates of -0.17 and -0.20 respectively. These are significant at 10% and 5% respectively. The third and fourth quartiles yield relatively weak and statistically insignificant rainfall shock coefficient estimates of -0.01 and -0.00. While pattern of coefficient estimates across quartiles seems to be largely similar for other asset values, using purchase or current worth, the most obvious trend is the small magnitudes of rainfall shock within the third and fourth quartiles under all the wealth definitions. Hence, we have suggestive evidence of cushioning shock through household assets, as this is one viable channel through which the impact of rainfall shock on DV can be mitigated.

The heterogeneous rainfall shock estimates from the above indicate that inter-household resource distribution dynamics play a crucial role in the strength of the effect of rainfall shock on the incidence of DV. The households in the lower half of the non-agricultural asset valuation are disproportionately more affected than the upper half of our sample. This is suggestive evidence of cushioning drought effect on households using asset sale as consumption smoothing strategy which incidentally weakens the effect of rainfall shock on DV. Our result is consistent with Cools and Kotsadam (2015) which unveil resource inequality as a viable source of intimate partner violence both within household and at the aggregate level.

2.6.4 The Effect of Employment Outside of Agriculture

Appendix Table A5 shows a stronger rainfall shock effect when both partners[21] belong to the agricultural sector than for any other[22] combination of sectors between partners. Rainfall shock estimate for both partners being engaged in agricultural sector is -0.30 while the estimate for other occupational sector combination is -0.09. Rainfall shock estimate for both spouses in agricultural sector is significant at 1 percent level contrary to the combination identifying at least a spouse outside the agricultural sector. The agricultural spouses' rainfall shock effect is stronger than the spousal baseline estimate in Appendix Table A1, which

[21] We restrict our analysis in this section to spousal relationship with 1,665 observations in total. Estimates from this regression are technically comparable to estimates in Appendix Table A1.
[22] Others in this case is a combination of either spouse belonging to a mixed of agricultural and non-agricultural occupational sectors or both belonging to non-agricultural occupational sector.

indicates that agricultural dependent families suffer higher level of intimate partner DV in times of drought, which affects agricultural harvests.

2.6.5 Age Gap

The role of differential age gap between intimate partners has not been explored in the DV literature. This can be attributed to the aggregate framework for the economic dynamics of DV within the existing literature. It is unclear how age differentials will influence the underlying effect of shocks on DV particularly in the developing country setting where partner's age difference matters – especially in sub-Saharan Africa. Appendix Table A6 shows a differential in the estimates across age gap between partners. Rainfall shock estimate of the sample of older male spouses reported in the table is similar to that of overall spousal specification (β = -0.21) while the estimate in the group for older female spouses unveils a negligible magnitude (β = 0.01). These results indicate that age gap in favour of women in a marital relationship is a deterrent to abusive acts with respect to economic shock consequences.

2.7 Discussion and Conclusion

The primary objective of this paper is to estimate the relationship between transitory shocks and female targeted DV in Tanzania using unique micro level data in Tanzania. It contributes to the DV literature by investigating different mechanisms when investigating the impact of income shock on DV incidence – through exogenous weather shocks. In addition, given the inherent limitations poised by aggregate impact evaluation in the literature, our analysis is based on precise micro-level empirical framework as deemed fit to highlight specific channels of the shocks to DV.

Our estimation exploits exogenous variation in rainfall and finds that rainfall shock has a significant effect on domestic abuse of females by males. We consistently find that rainfall shock has an inverse and considerable impact on the likelihood of DV incidence. A one standard deviation negative rainfall shock increases the likelihood of abuse by 18.8 percentage points for female spouses. Also, the most prominent part of the evidence is linked to physical abuse category (which includes beating, hitting, slapping and pushing) and not severe-physical abuse (such as choking or use of weaponry) or sexual abuse (forced sex or unwanted sex) respectively. Marginal effects of rainfall shock estimates from the use of severity indices of DV constructed by the authors provide similar evidence for the impact of rainfall shock on DV incidence.

Our main results are robust to sequentially controlling for household living conditions, which may confound our rainfall shock's impact on DV. We find that the main rainfall shock estimate is driven by a negative rainfall shock – dry shocks or droughts – while the impact of wet shock is generally muted in our disaggregated model. In addition, while DV incidence is more responsive to rainfall shock during planting seasons, we find no evidence for the impact of out-of-season shocks. Further findings reveal an asymmetric effect along asset valuation quartiles with poorer household disproportionately affected. Lastly, our results provides a supporting evidence of consistent patterns of outcomes from partner's separation and reported marriage cases along household and community levels, respectively, to complement our individual level results.

We show that female empowerment through female household headship and female inheritance rights play an important role in mediating the relationship between rainfall shocks and DV. The latter is illustrated from localized empowerment measure derived from community level inheritance policy for women and their children which considerably weakens the impact of rainfall shock on DV incidence while communities with no such gender-equality policy continues to exhibit significant effects of rainfall shock on DV. Our results provide unique framework in favour of the effectiveness[23] of female empowerment to cushion the impact of shock on DV.

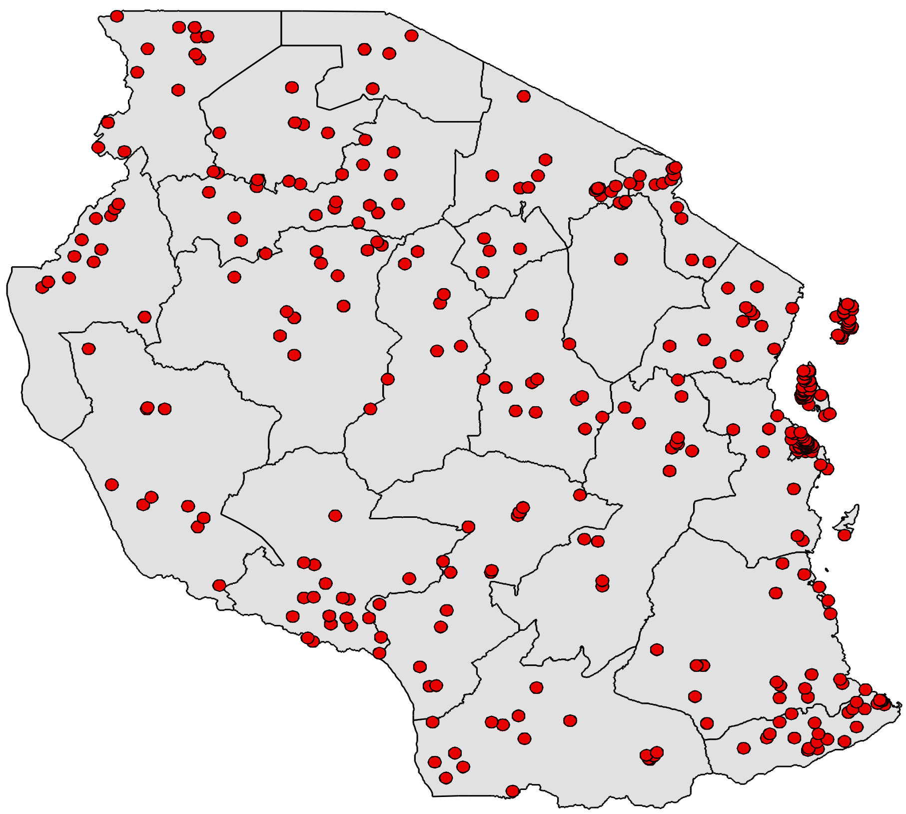
The estimated effect of rainfall shocks on DV is also important for the understanding of the total costs of rainfall shocks, in particular droughts, on individual welfare. As we demonstrate in this paper, droughts significantly increase the incidence of DV in rural households where agriculture is the main source of income. The results in this paper may therefore contribute to the understanding of the persistent high incidence rates of DV in Sub-

[23] Female empowerment does not always lead to relatively higher bargaining power as argued in the literature. Chin (2012) explores male backlash as a potential threat for women employment status in India, while Bobonis *et al.* (2013) considers instrumental use of further abuse targeted at uncooperative spouses in Mexico.

Saharan African countries subject to frequent droughts. The findings are also important for an understanding of the possible consequences of an increase in the variability of rainfall in the context of climate change. There is a general consensus that productivity of rainfed agriculture predominant in Sub-Saharan African will suffer with the increase in the prevalence of droughts linked to climate change (Kurukulasuriya *et al.* 2006; IPCC 2012). There is a risk that climate change may lead to an increase in the incidence of DV in affected countries and the findings contribute with household level evidence to a literature linking more generally weather variability and climate change to violent conflict in Africa (Hsiang *et al.* 2011; O'Loughlin *et al.* 2012; Burke *et al.* 2013).

Chapter 2: Figures and Tables

Figure 2.1: Map of the United Republic of Tanzania (Depicting the Enumeration Areas of LSMS Survey).



Notes: The map depicts the 26 regions of Tanzania with the red dots representing the Enumeration Areas in the LSMS-ISA used in this paper.

Table 2.1:Summary Statistics: Households and Individuals

Variables	Mean	Std. Dev.
Household Characteristics		
Rural	0.688	0.463
Household size	7.166	3.947
Female head	0.183	0.387
No. of children	4.190	2.903
Asset (ln)	4.136	0.693
SACCO membership	0.065	0.246
Rainfall shock (household)	-0.003	0.151
Rainfall shock (community)	-0.003	0.150
Individual Characteristics		
Age	21.141	17.772
Male (indicator)	0.471	0.499
Married (indicator)	0.529	0.499
Education(Adults)		
None	0.004	0.064
Primary	0.797	0.402
Junior high	0.178	0.382
Senior high	0.016	0.124
College	0.006	0.076
Sector of employment (Adults)		
Agricultural and Extractive	0.674	0.468
Self-employed	0.150	0.357
NGO and private	0.068	0.251
Unemployed and Domestic work	0.061	0.240
Civil servant	0.047	0.211

Notes: Number of observations are 2,933. SACCO stands for Savings and Credit Co-operative. Rainfall shock is measured as the deviation of natural logarithm of approximate household/community rainfall measure from the natural logarithm of the historical rainfall mean.

Table 2.2: Summary Statistics of Domestic Violence (DV) Incidence for Females Aged 15-50.

Variables	All		Wife only		Other females in HH	
Chart A: Prevalence of DV	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
DV (lifetime)	0.231	0.421	0.309	0.462	0.129	0.335
DV (12-months)	0.124	0.330	0.168	0.374	0.066	0.249
Categorised DV (12-month):						
Physical	0.099	0.299	0.137	0.344	0.050	0.217
Severe Physical	0.013	0.112	0.015	0.122	0.009	0.097
Sexual	0.053	0.224	0.070	0.256	0.030	0.171
Chart B: Perspective on justification for DV						
DV incidence is generally justified if (there is):						
A woman goes out without permission	0.332	0.471	0.386	0.487	0.284	0.451
A woman neglects children	0.366	0.482	0.406	0.491	0.324	0.468
A woman argues with him	0.301	0.459	0.344	0.475	0.275	0.447
A woman refuses sex	0.311	0.463	0.393	0.489	0.255	0.436
Household problems	0.029	0.169	0.040	0.195	0.027	0.162
Financial problems	0.015	0.123	0.026	0.159	0.007	0.084
No food	0.060	0.238	0.075	0.264	0.058	0.235
Chart C: Reporting of incidence of DV to:						
Family	0.485	0.500	0.500	0.501	0.434	0.497
Hospital	0.069	0.254	0.075	0.263	0.053	0.224
Community Leaders	0.202	0.402	0.214	0.410	0.164	0.372
NGO	0.009	0.096	0.010	0.100	0.007	0.081
Religious Leader	0.037	0.189	0.034	0.182	0.046	0.210
Police	0.052	0.223	0.046	0.210	0.072	0.259

Notes: Total number of observations for All is 2,933. This is divided into 1,665 observations for wives and 1,268 observations for other household females respectively. Categorised DV by Physical DV, Severe Physical DV and Sexual DV presents mutually non-exclusive events of 12 months DV incidence in Chart A. Chart B reports fraction of women that accept outlined conditions as justification for DV incidence.

Table 2.3: The Impact of Rainfall Shock on DV Incidence.

	Dependent Variable: DV Incidence		
Variables	(1)	(2)	(3)
Rainfall shock	-0.217***	-0.137***	-0.101**
	(0.045)	(0.048)	(0.046)
Constant	-1.168***	-1.282***	-0.476
	(0.032)	(0.301)	(0.392)
R^2	0.012	0.053	0.129

Notes: The table above presents marginal effect coefficients of probit regression for 2,933 observations. Each column represents a separate regression. Outcome variable is DV incidence where 1 indicates an affirmative response for being a victim of aggression in the previous 12 months and 0 otherwise. Columns (1) – (3) each represents estimation without controls, with community level controls and all controls respectively. Community level controls include mainly infrastructural facilities at the community level as these portray access to facility for residential households. Infrastructures include bank, court, district headquarters, government primary and secondary schools, government hospital and/or other government health facilities, private primary and secondary schools, private hospital and/or other private health facilities, daily and weekly market stores, post office facility, police station and SACCO group. All controls include household controls and individual level controls with the community level controls. Household controls include household characteristics such as household size, gender of household head, number of children, urban dummy and wealth base measured by asset possession of household. Lastly, the individual controls mainly consist of individual demographic characteristics including individual's age and education, marital status, education and occupational categories. Robust standard errors (clustered at the household level) are reported in parentheses.

***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.4: The Impact of Rainfall Shock on DV Incidence (By Categories).

Variables	Dependent Variables: Categories of DV Incidence		
	Physical	Severe Physical	Sexual
	(1)	(2)	(3)
Rainfall shock	-0.097**	-0.005	-0.031
	(0.041)	(0.014)	(0.032)
Constant	-0.911**	-10.451***	-0.478
	(0.454)	(0.554)	(0.460)
R^2	0.128	0.206	0.129

Notes: The table above presents marginal effect coefficients of probit regression for 2,933 observations. Each column represents a separate regression for physical DV, severe physical DV and sexual DV respectively. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.5: The Impact of Rainfall Shock on DV Index

Variables	Dependent Variable: DV Index			
		Categories of DV Index		
	Overall	Physical	Severe Physical	Sexual
	(1)	(2)	(3)	(4)
Rainfall shock	-0.498**	-0.615**	-0.135	-0.322
	(0.243)	(0.257)	(0.516)	(0.319)
Marginal effect	-0.035**	-0.031**	-0.001	-0.012
	(0.017)	(0.013)	(0.005)	(0.012)
R^2	0.096	0.098	0.177	0.101

Notes: The table above presents both actual and marginal effect coefficients of ordered probit regression for 2,933 observations. Each column represents a separate regression for all DV, physical DV, severe physical DV and sexual DV index respectively. Categories are hierarchically ranked from highest to lowest for many times, a few times and one time respectively; while 0 indicates none. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.6: The Impact of Dry Shock and Wet Shock on DV incidence.

	Dependent Variable: DV Incidence		
Variables	(1)	(2)	(3)
Dry shock	0.285***	0.240***	0.218***
	(0.081)	(0.088)	(0.085)
Wet shock	-0.141	-0.026	0.023
	(0.088)	(0.082)	(0.078)
Constant	-0.555	-1.359***	-1.209
	(0.389)	(0.302)	(0.053)
R^2	0.013	0.054	0.130

Notes: The table above presents marginal effect coefficients of probit regression for 2,933 observations. Wet and dry shock each indicate quantified positive and negative rainfall shocks as exogenous explanatory variables respectively. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.7: The Effects of Planting Season and Out-of-Season Rainfall Shocks on DV Incidence.

	Seasonality of rainfall shock	
Variables	Planting Season Shock	Out-of-season Shock
	(1)	(2)
Rainfall shock	-0.066*	-0.018
	(0.038)	(0.025)
Constant	-0.454	-0.488
	(0.396)	(0.397)
R^2	0.129	0.127

Notes: The table above presents marginal effect coefficients of probit regression for 2,933 observations by seasons of rainfall shock. Each column represents a separate regression for overall DV incidence. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.8: Robustness Check on the Impact of Rainfall Shock on DV Incidence.

	Dependent Variable: DV Incidence					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall shock	-0.101**	-0.102**	-0.101**	-0.093**	-0.093**	-0.100**
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Constant	-0.476	-0.428	-0.438	-0.587	-0.589	-0.486
	(0.392)	(0.395)	(0.398)	(0.402)	(0.400)	(0.394)
No. of rooms		-0.008				
		(0.005)				
Roofing material			-0.002			
			(0.005)			
Water (rainy season)				0.003		
				(0.002)		
Water (dry season)					0.004*	
					(0.002)	
Water shortage (dummy)						0.018
						(0.023)
R^2	0.129	0.131	0.130	0.130	0.131	0.130

Notes: The table above presents marginal effect coefficients of probit regression for 2,933 observations. While column 1 presents the baseline rainfall shock coefficient of eq. 2.2, columns 2 – 6 add number of rooms, roofing materials used for the house, water source in rainy season, water source in dry season and a dummy for water shortage in the past year. The coefficients presented follow table 2.3 column 3 with all controls in addition to the household level variables inputted as controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.9: Rainfall Shocks and Targeting of DV Incidence

Variables	Wives	Children (18 years old and younger)	Others
Rainfall shock	-0.211***	0.005	0.057
	(0.067)	(0.045)	(0.070)
Constant	-0.014	0.092	-4.713***
	(0.469)	(0.139)	(0.871)
Observations	1,665	336	932
R^2	0.103	0.111	0.197

Notes: The regressions for the table above repeat estimation in table 2.3 column 3 by household membership dichotomy for 2,933 observations. Others indicate female household residents who are neither wives nor children within the household. Each regression is carried out with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.10: The Impact of Rainfall Shock on DV Incidence by Household Head Gender.

Variables	Male household head	Female household head
Rainfall shock	-0.259***	0.037
	(0.072)	(0.174)
Constant	-0.083	-3.509***
	(0.503)	(1.339)
Observations	1,449	216
R^2	0.113	0.312

Notes: The regressions for the table above splits observations in table 2.9 column 1 by household head gender. Each regression is carried out with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.11: Community Inheritance Rights and the Impact of Rainfall Shock on DV Incidence.

Variables	Wives' inheritance right	Wives and children's inheritance right
Rainfall shock	-0.138**	-0.441***
	(0.066)	(0.166)
Inheritance dummy	0.022	0.074***
	(0.014)	(0.023)
Rainfall shock * Inheritance	0.112	0.399**
	(0.092)	(0.171)
Constant	-4.912***	-5.093***
	(0.367)	(0.433)
R^2	0.133	0.140

Notes: The table above reports marginal effect coefficients of probit regression for 2,872 observations with the addition of community inheritance rights for wives and their children with interaction terms to baseline specification. This is short of 61 observations from the baseline observations due to non-reported inheritance right for some communities. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Table 2.12: The Impact of Rainfall Shock on DV Incidence by Household Asset Valuation Quartiles.

Variables	quartile1: 0-25%	quartile2: 25-50%	quartile3: 50-75%	quartile4: 75-100%
Rainfall shock	-0.172*	-0.198**	-0.015	-0.003
	(0.099)	(0.093)	(0.081)	(0.090)
Constant	-0.423	-4.876***	-0.429	0.323
	(0.848)	(0.724)	(0.975)	(0.839)
Observations	733	734	733	733
R^2	0.208	0.206	0.208	0.217

Notes: The table above presents marginal effect coefficients for probit regression. The coefficients presented follow table 2.3 column 3 with all controls by household non-agricultural asset quartiles referenced by the average of purchase and current price. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses.***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Chapter 3

3 Financial inclusion, household shocks and welfare: evidence from the expansion of mobile money in Tanzania

3.1 Introduction

Mobile money as financial innovation has in recent years transformed financial services in many sub-Saharan African countries and helped to overcome gaps in financial inclusion of the unbanked poor in these countries (Jack and Suri 2011).[24] Mobile money – a financial innovation that allows individuals to store and transfer funds using short message services – has transformed mobile phones from simply being a communication tool to enabling low-cost financial services and has seen unprecedented growth in these countries. While in Europe and North America mobile money services are practically inexistent, with less than 1 percent of the population having an active mobile money account, in sub-Saharan Africa there are now close to 25 mobile money accounts per 100 adults (Aron *et al.* 2015). In early adopter countries, such as Kenya, as little as four years after the introduction more than 75 percent of households have at least one active mobile money account and in June 2014 the monthly value of transactions was about US$2 billion, about 60 percent of average monthly GDP (Aron *et al.* 2015). The dramatic expansion of mobile money in sub-Saharan Africa is likely driven by very limited available financial services (in 2011 there were only 850 bank branches in Kenya, but 28,000 mobile money agents) and the already prevailing popularity of mobile phone services as compared to landline telephone services. Tanzania, the country of interest in this paper, has seen similar increases in the use of mobile money since its introduction in 2009. Mobile money led to a dramatic decrease of the transaction cost of transferring funds between users, in particular across large distances allowing individuals to send and receive remittances much more cheaply than before the introduction of the service.

[24] One of the first and to date most successful examples of mobile money is M-PESA in Kenya, which launched its service in 2007.

Jack and Suri (2014) show for Kenya that mobile money has changed risk sharing by allowing users to send and receive remittances in cases of negative shocks to the household. They find that while shocks reduce consumption for non-users, the consumption of user households is unaffected. The authors argue that these effects are partially due to improved risk sharing facilitated by reduced transaction costs from mobile money. With this paper we contribute to the literature on mobile money by focusing on the welfare consequences of mobile money access beyond consumption smoothing. We follow Jack and Suri and make use of the rapid expansion of the mobile money agent network in Tanzania over the period from 2011 to 2013 during which the mobile money uptake by households has increased from 13 to 41 percent lending for an instrumental variable identification strategy while employing household and individual fixed effects. Our econometrics framework include the use of agent proximity measures such as the availability of agent within locality, distance and cost to the nearest agent as appropriate instruments to identify the impact of mobile money on outcome variables.

We are particularly interested in how mobile money protects the welfare outcomes of households that are subject to household shocks. To circumvent the endogeneity problem of household shocks we focus on rainfall shocks to households that depend on rain-fed agricultural production. Different from Jack and Suri, we use deviation in seasonal rainfall measure from the historical mean for households to capture the economic resource available across households. Apart from the granularity and exogenous nature of our rainfall shocks, this approach to the measure of economic shock provides the exact magnitude of shock realisation to households thereby projecting there shock cushioning requirements. Besides consumption smoothing, we are particularly interested in understanding the effects of mobile money on the poorest households through extreme poverty index. In addition, our major contribution to the literature borders on the potential shock cushioning role of mobile money on human capital investments – education and health – and the overall effect of mobile money on subjective wellbeing and labour diversification of adults during shocks.

We find that while per-capita expenditure is not significantly smoothed within our baseline specification, per-capita expenditure of the most vulnerable households is smoothed in periods of negative idiosyncratic shock for mobile money adopter households. Our results indicate that mobile money adopter households are less likely to slide into transient extreme poverty while non-adopter households are more likely to be classed as poor after being subjected to rainfall shocks. At the individual level, the effect on children's absenteeism from school as a result of rainfall-driven income short fall is cushioned for mobile money adopter households. This is complemented by more time for school homework as against engaging in household chores. Similarly, reduction in preventive health expenditure (e.g. treatment of insecticide bed nets) as a result of negative household shock is compensated for mobile money adopter households. We also provide evidence that adults in mobile money adopter households indulge in non-diversification of labour activities to cushion agricultural shocks.

The remainder of the paper is organised as follows. Section 3.2 provides financial inclusion and mobile money expansion background in Tanzania. Section 3.3 discusses the data sources and summarizes important variables at the individual and household levels. Section 3.4 presents the empirical strategy for identification. Sections 3.5 presents first stage results, the main results and some heterogeneous results respectively. Section 3.6 discusses the results and concludes.

3.2 Background: Tanzania, Mobile Money and Financial Inclusion

Tanzania is a sub-Saharan African country with a population of 48 million in 2012. The country remains among the poorest in the world with about 28 percent of the population being classified under the $1.25 poverty line in 2011/12.[25] Current per-capita GNI is $570 in 2012 and more recently Tanzania has been described as a development success story with average growth rate of 7 percent between 2000 and 2011 (World Bank 2013). The Tanzanian economy is still – to a large extent – based on agriculture production with about 27 percent of GDP and about 80 percent of employment related to the agricultural sector. With its vast landmass, the country is sparsely populated and predominantly rural creating additional

[25] World Bank (2015).

challenges for economic activity, the provision of services, including telecommunication and access to financial services, including banking.

According to the 2012 World Bank Financial Index in Tanzania, only 17 percent of individuals 15 years and older have a bank account, compared to 97 percent in the United Kingdom for the same age group. Also, on average there are 1.56 commercial bank branches and 2.22 ATMs per 100,000 population between 2004 and 2011 in Tanzania. [26] These contrast sharply with 26.4 and 123 respectively in the United Kingdom. These figures indicate the very weak provision of formal financial services in Tanzania resulting in a financial inclusion gap, especially for the rural population. This is evidenced by the very low position of Tanzania in financial inclusion rankings, even among other sub-Saharan African countries (World Bank 2014).

Tanzania emerged as one of the early adopters of mobile money services. Likely due to the acute shortage of formal financial services, the introduction of mobile money in Tanzania has been extremely successful since its introduction in 2009. The proximity to Kenya, where mobile money has been first introduced very successfully, also contributed to the quick adoption of the services and Tanzania is currently catching-up with its neighbour in terms of the number of users and the volume of mobile money transactions (CGAP 2016). Currently there are four mobile money services on the market: Vodacom's M-Pesa, Tigo Pesa, Airtel Money and Ezy Pesa. The national microfinance bank completes the market with their own mobile money services pressing for a competitive mobile money market and lower transaction prices than in Kenya. The Financial Inclusion Insights Surveys (CGAP 2016) shows that in 2015, 38 percent of adults in Tanzania have a mobile money account. The household survey data we introduce in the next section, shows that in 2014 41 percent of households have at least one mobile money account, while this number was only 13 percent in 2011, revealing the sharp increase of households with access to the technology. In 2012 36 percent of all money transfers in Tanzania are made through mobile money transfer services (World Bank 2016).

[26] Given the vast geographic expansion of the country this equates to 0.41 and 0.60 commercial banks and ATMs respectively for every 1,000km^2 in Tanzania (IMF 2012).

3.3 Data

This paper uses data from the World Bank's Living Standard Measurement Studies (LSMS) for Tanzania. We use two waves of the panel LSMS for 2010/11 and 2012/13 and focus our analysis on this two-period panel.[27] The data contains very detailed information on individuals and households followed over the two periods and provides detailed community level information.

The map presented in figure 3.1 depicts the enumeration areas of the survey showing the broad geographic coverage of the data collection, and confirming the representative nature of the survey[28]. From 3,924 households in the 2010/11 survey, 3,776 households were successfully re-interviewed in the 2012/13 survey amounting to an attrition rate of less than 4 percent between the two waves. The panel nature of the survey allows us to follow 18,669 individuals over time from these households.[29]

The LSMS survey collects very detailed information on individual and the households they live in. These include information on age, gender, marital status, education levels and occupation. Household level characteristics include gender of household head, household size, average household age, household location (rural/urban), a very detailed description of basic household assets, household membership of a Savings and Credit Cooperative (SACCO) group, household membership of any other credit and savings society, household access to loan, bank account possession, number of mobile phones the household possesses, value of voucher the household purchases in recent times.

There is also an abundance of information on educational decisions, including school enrolment, school absenteeism, individual's schooling expenditure, number of after-school hours children spend on homework and domestic work.

[27] The 2008/09 wave is part of the panel LSMS for Tanzania, but does not contain yet information on mobile money. Because we cannot rule out that some households nevertheless were already early adopters in 2009, we cannot use the 2008/09 wave of the LSMS, by assuming that no household had access to mobile money.
[28] The original 26 regions across Tanzanian geographical map at the inception of the National Panel Survey in 2008/09 survey are retained over the three waves for consistency.
[29] The attrition rate in our study is comparable to what is obtainable in most field experiments with follow-up survey for a panel data analysis (see Dupas and Robinson 2013a).

Very detailed itemised information on household expenditure allows us to investigate total household and per capita expenditure.[30] Focusing on real total expenditure, rather than a single category for food expenditure, allows us to investigate household poverty, rather than food security only, in addition to a number of other expenditure categories including expenditure on health and education. In addition to the detailed expenditure data, the LSMS provides information on the frequency of visits to health clinics, the acquisition of mosquito bed nets, and self-reported satisfaction along a number of dimensions.

Tables 3.1 and 3.2 present summary statistics of the household and individual characteristics, respectively. On average households consist of just above 5 members, with most children below the age of 18. Average age of the individuals surveyed in the data is 26 years showcasing the low population age in Tanzania. 72 percent of the households live in rural areas. 22 percent of the households have a member that belongs to a SACCO group while only 16 percent have a formal bank account. Agricultural activities dominate the household labour supply with 63 percent of adults engaging in such activities. 13 percent of adults are self-employed, and 6 and 4 percent working in the private and public sector, respectively. 14 percent of individuals in the survey are unemployed.

Table 3.3 reports summary statistics for the use of mobile money over the two survey waves. The reported dominant reason for mobile money use in both survey rounds was sending and receiving money, accounting for roughly 80 percent of the responses. Around 8 percent of respondents buy airtime for themselves as the most important use of mobile money, and around 5 percent and 3 percent report to predominantly use it for daily expenses and emergency savings, respectively. About 60 percent report to use mobile money only occasionally, in line with the less frequent use for sending and receiving remittances and for emergency use only. Only a small number report to use mobile money on a weekly or daily basis, a pattern consistent with the low reporting of mobile money predominantly being used for daily expenses. The data nevertheless reveals a shift towards more frequent use of mobile

[30] The World Bank's LSMS team reports 12 month nominal and real household expenditure total for different expenditure classes ranging from necessity expenditure (e.g. food) to luxury expenditure (such as on sporting items). The timing of the 12 months household expenditure figures coincides with the period following the rainfall shock variable extracted from the geographical variable file which reports 12 months household (plot level) rainfall patterns.

money. Together with the expansion of mobile money across households this shows an increase in both, the extensive and intensive margin, of mobile money use in these households.

3.4 Empirical Strategy

In this paper, we are primarily interested in the effect of mobile money on consumption smoothing and welfare outcomes for households during periods of shocks[31]. For this purpose, we exploit rainfall variation, as measured by deviations from the long-term rainfall, using a very fine partitioning of rainfall data available to us across vast geographic space and over time. We then interact these measures of household shocks with the availability of mobile money accounts in the household to understand the impact mobile money has on our set of household and individual outcomes. Deviation in rainfall from the long-run means provide a credible source of variation for unanticipated economic shocks to the household and are, given the large dependence of households on smallhold agricultural practices in Tanzania, indeed the most important source of shocks these households face to their resources[32]. By using this variation, we investigate whether mobile money adoption plays a role in coping with the consequences of negative transitory shocks. In our empirical framework, we focus on the shock-cushioning role of mobile money for bottom of the pyramid income group in Tanzania using extreme poverty measure. We estimate the following econometric model:

$$Y_{ht} = \alpha_h + \delta_t + \boldsymbol{\beta_1}(\mathrm{MM_{ht}}) + \boldsymbol{\beta_2}(\mathrm{Rainshock_{ht-1}}) + \boldsymbol{\tau}(\mathrm{MM_{ht}}\ \mathrm{X}\ \mathrm{Rainshock_{ht-1}}) + X'_{ht}\boldsymbol{\beta}_3 + Z'_{ht}\boldsymbol{\beta_4} + \varepsilon_{ht} \qquad (3.1)$$

where Y_{ht} represent the set of outcome variables at the household and individual level. $\boldsymbol{\beta_1}$ represents the impact of household mobile money usage, while the coefficient $\boldsymbol{\beta_2}$ represents the direct effect of rainfall shocks on the outcome variables. $\mathrm{MM_{ht}}\ \mathrm{X}\ \mathrm{Rainshock_{ht-1}}$ is the interaction term for mobile money and rainfall shock measure; $\boldsymbol{\tau}$ *is* the coefficient of interest in our model. Comparing the coefficient estimates for $\boldsymbol{\tau}$ relative to $\boldsymbol{\beta_4}$ will provide us with the overall effect that mobile money access has on the set of outcome variables in response

[31] A conceptual framework specifically for the relative consumption smoothing for a two-period shock dynamics is presented in Appendix B.

[32] In a similar framework for another East-African country – Uganda, Björkman-Nyqvist (2013) demonstrated the importance of rainfall patterns as an important determinant of the household economic resources including income.

to rainfall shocks. α_h and δ_t are household/individual and year fixed effects. To control for time-varying household and individual characteristics and to increase the precision of our estimates we include individual (X_{ht}) and household level controls (Z_{ht}) in some specification. Error term (ε_{ht}) is clustered at the community/household level for household/individual level estimations, respectively.

Because the adoption of mobile money in households is potentially endogenous[33], we make use of the rapid expansion of the mobile money agent network between the two LSMS waves and follow Jack and Suri (2014) by combining household shocks with an instrumental variable strategy in an instrumented difference-in-difference (DiD) strategy. We explore exogenous distribution of mobile money agents across communities over two periods to measure the level of exposure of households to mobile money service. Two main variables that qualify for excellent determinant of mobile money use in this regard are agent availability and proximity. Mobile money availability is depicted using an indicator variable for the presence of mobile money agent within the locality where the household resides. Proximity is measured by the distance/ associated cost to the nearest agent. Agent proximity measures help to capture intense accessibility to mobile money service not captured by the availability measure. Rather than relying on self-reported recall of household shocks as in Jack and Suri (2014) we use exogenous and objective measures for household shocks, namely deviation from mean rainfall. Because (3.1) includes an interaction term ($\mathrm{MM_{ht}}$ X $\mathrm{Rainshock_{ht-1}}$) we interacted the two instruments for mobile money adoption with rainfall shocks and we follow Jack and Suri (2014) in the choice of instruments by using the presence of a mobile money agent in the village and distance (or cost) to agent as instruments for mobile money adoption. The first stage of the estimation is specified as follows.

$$\mathrm{MM_{ht}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c}) + \xi_{ht} \tag{3.2}$$

$$\mathrm{MM_{ht}} * \mathrm{Rainshock_{ht-1}} = \boldsymbol{\varphi_1}(\mathrm{Agent_c} * \mathrm{Rainshock_{ht-1}}) + \boldsymbol{\varphi_2}(\mathrm{Agent\_dist_c} * \mathrm{Rainshock_{ht-1}}) + \varsigma_{ht} \tag{3.3}$$

[33] For instance, using remittance as an outcome variable in the econometrics specification from equation 3.1 above could lead to biased results. Mobile money use may be determined by the likelihood or frequency of remittance received by the households leading to a simultaneous bias in coefficient estimates.

where Agent_c represents an indicator variable for mobile money availability while $\mathrm{Agent\_dist}_c$ represents the distance (in kilometres) to the nearest agent. Identification for the instrumented DID strategy relies on the exclusion restriction to hold, namely that agent availability and proximity over time to affect poverty (and other outcomes) only through the use of mobile money. Identification assumption for this strategy entails that, in the event of shock the outcomes between user and non-user households would maintain the same trajectory in the absence of mobile money service. In addition, we assume that deviations in rainfall are exogenous.

3.4.1 Construction of Rainfall Shock Measure

To construct our measure of rainfall shocks we use precipitation data provided by the World Bank (along with the LSMS data) that is available on the plot level.[34] We follow the literature in constructing rainfall shocks and create measures of deviations in rainfall from the long-run mean rainfall for an area by constructing shocks in the following way:

$$\mathrm{Rainshock}_{\mathrm{ht-1}} = ln\, R_{ht-1} - ln\, \overline{R_h} \qquad (3.4)$$

where $\mathrm{R}_{\mathrm{ht-1}}$ indicates the yearly rainfall in household *h* for the preceding year's planting season and $\overline{R_h}$ represents the average historical yearly rainfall in household *h*. Thus, the $\mathrm{Rainshock}_{\mathrm{ht-1}}$ above is equivalent to the shock measure used for deviation of the natural logarithm of the total rainfall in the 12 months prior to the 2010/2011 and 2012/2013 periods and the natural logarithm of the average yearly historical rainfall in the household *h* prior to the corresponding years. The lag nature of equation 3.4 above ensures that rainfall shock realisation is a measure of current economic resource within households. The approach is similar to prominent economic literature. The rainfall deviation basically implies a percentage deviation from mean rainfall (Maccini and Yang 2009).[35]

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[34] In the Appendix we provide a full description of the source of rainfall data used in this paper alongside detailed information on the technicalities involved in creating agricultural cycle rainfall measures. Yearly rainfall is adopted due to household's freedom of choice to either cultivate short or long rainy seasons for agricultural yields. However, it is noted from the agricultural data in Tanzanian LSMS that households partake in the long rainy seasons' agricultural activities perhaps due to higher certainty of agricultural yields from the long rainy season between December and February as against short rainy seasons in June and July cultivation.

[35] A substantial number of papers in the economics literature has adopted this procedure. Recent examples include Maccini and Yang 2009; Björkman-Nyqvist 2013; Rocha and Soares 2015.

3.4.2 First Stage Results

Table 3.4 reports coefficient estimates of the first stage regression of our IV model and the diagnostic tests. The first stage outcomes, for mobile money usage and interaction with rainfall shock refer to equations 3.2 and 3.3 above. Estimates are reported for agent availability indicator and distance to the nearest agent in Panel A[36]. Estimates of mobile money usage indicator in Panel A of Chart A gives a clear indication that household mobile money usage is significantly related with the availability of agent within communities. Availability of mobile money agent increases the likelihood of mobile money usage for households by 10 percent. Unexpectedly, a positive correlation exists between mobile money usage and the distance to the nearest agent. However, this trend is rectified in the interaction segment (Panel B) of the first stage results[37]. Also, a negative relationship between smoothened mobile money usage indicator and natural logarithm of distance to the nearest mobile money agent, depicted in figure 2.2 below, relieves us of concerns regarding the wrongly signed correlation[38]. Interaction term estimates reported in Panel B of Chart A reveals stronger correlation coefficients between mobile money usage and agent proximity by showing that in periods of shock, availability of mobile money agent increases the likelihood of adoption of mobile money by 30 percent. Also, there is a negative relationship between distance to mobile money agent and the probability of usage as expected. This indicates that reduction in the distance to agent distribution by 1km increases the households' usage rate for mobile money within the community by 5.6 percent. These estimates are significant at 1 percent.

Diagnostic tests of the first stage results are reported in Panel B. Panel A reports a R-squared of 0.23 and F-statistics of 13.27 for mobile money usage regression with controls. Panel B reports a R-squared of 0.53 and F-statistics of 21.90 for the model conveying the interaction of mobile money usage with rainfall shock. Associated F-statistics for the

[36] Please note that we changed 0s to 1s before taking log transformation of distance and costs to mobile money agents similar to the approach used in Jack and Suri (2014).

[37] The reason for positive signed relationship between mobile money usage and distance to agent in Panel A is unclear. However, the establishment of negative correlation between these two variables in Panel B could be attributed to the shock component of the regression indicating the requirement for agent proximity for accessibility of mobile money services in periods of shock.

[38] A similar negative trend is demonstrated for the existing relationship between household mobile money usage and natural logarithm of the associated cost to the nearest mobile money agent.

excluded instruments are 5.98 and 55.16 with probability value of 0.00 respectively for mobile money usage and the interaction term respectively. In Table 3.4 Chart B, the under identification tests for the first stage results show that the first stage instruments competently identify the impact of the household mobile money adoption on poverty and other welfare outcomes. However, the weak identification tests[39] across endogenous variables show that the interacted mobile money model demonstrates more resilience and displays stronger identification relative to mobile money adoption model.

3.5 Results

3.5.1 Main Results: Households

3.5.1.1 Poverty and Consumption Smoothing

We present the results for the impact of mobile money and household shocks on household poverty in Table 3.5. In detail, this table contains the coefficients from equation (3.1) where we use our exogenous measure for household shocks, namely rainfall deviations, and instrument mobile money adoption for both, the separate inclusion of mobile money adoption and in the interaction term with shocks in equation (3.1). We estimate equation (3.1) using simple OLS in a linear probability framework.[40] As a first observation from Table 3.5 we find that the coefficients for the direct effect of mobile money are positive as expected, but not significant at any conventional level of significance. This result shows that mobile money may not necessarily enhance remittance transfers outside the context of consumption smoothing framework in the period of shocks.

Next we are interested in direct effect of shocks and the interaction term. We find that a one standard deviation negative (indicating less than mean rainfall) rainfall shock raises the probability of extreme poverty among affected bottom of the pyramid income

[39]We adopt the Angrist-Pischke (AP) first-stage F statistics test for weak identification of each endogenous regressor.

[40] We adhere to linear probability models since probit and logit fixed effects models yield bias slope coefficient estimates resulting from the incidental parameter problem explained in Greene (2003). Although, we can obtain consistent slope estimates can with the use of conditional fixed effects in the logit model, yielding similar results (qualitatively and statistically) as the corresponding linear probability model. However, magnitude of estimates requires cautious comparison in the absence of substantial knowledge of the distribution of fixed effects (Wooldridge 2010). The main weakness of conditional fixed effects for logit models is that estimates do not converge when including year fixed effects in our regressions. This is a fundamental problem which is associated with maximum likelihood estimators of coefficients in nonlinear models as elaborated in Greene (2004).

group by around 3.8 percentage points. This indicates an impoverishment rate of approximately 5.4 percent of the sample of observations compared to sample mean rate of poverty. This result is in line with findings in the literature on the negative consequences of rainfall shocks and droughts on household poverty (Harttgen *et al.*, 2016). The coefficient on the interaction between shocks and mobile money adoption is negative and statistically significant at the 5 percent level. A one standard deviation negative rainfall shock interacted with the mobile money indicator leads to a 10 percentage point decrease in the probability of sliding below the poverty line. This translates to a decrease in the percentage of observations living below the poverty line by 15 percent relative to the mean value of poverty ratio. Interestingly, when combined with the direct effect of rainfall shocks, this more than counteracts the negative consequences of rainfall shocks. One possible interpretation to explain this unexpected outcome is related to the way households in need receive remittances and seems to suggest that these households possibly receive more remittances than the negative rainfall shock would require. This type of overcompensation is more likely in a framework where remittance transfers are easier because of lower transaction costs. Riley (2016) finds similar evidence for overcompensation in a related framework. This suggests that very poor households with access to mobile money are able to smooth their consumption to protect them from the negative consequences of resource shocks and avoid sliding into extreme poverty and may benefit from a diverse set of senders of remittances and the lower transaction costs enabled by mobile money.

We also estimate equation (3.1) for total per capita household expenditure to test for general consumption smoothing. The results are presented in Appendix Table B1. While we find quantitatively similar results and very similar patterns compared to the outcomes for poverty in Table 3.5, none of the coefficients are nevertheless significant at conventional levels. This indicates that access to a low-cost financial transaction technology may be most important for the poorest households that are most vulnerable to shocks. Using even more extreme poverty indicators, for example using a definition based on $US 1, reveals very similar results compared to a standard $US1.25 definition (results available from the authors upon request).[41]

As a first robustness check we estimate equation (3.1) using two alternative sets of instruments. The estimates for the coefficients are very similar when using either *distance to agent* (Table 3.5 chart A) or *cost to agent* (Table 3.5 chart B) as instrument.

More recently, concerns regarding potential spurious correlation of weather events have been raised in the literature when using rainfall variation as exogenous source of variation (Lind 2015). While the panel nature of our data allows us to hold constant fixed household characteristics, the very fine partitioning of the data does not limit us to the use of across-village variation in rainfall, but allows us to use additional variation of rainfall within geographically spread-out villages and agricultural plots and this additional variation helps us to alleviate some of these concerns. Nevertheless, remaining inter-spatial correlation of rainfall and household expenditure patterns for spatially proximate households may still lead to spurious inference when using rainfall shocks in our framework. Lind (2015) proposes two solutions to address spurious weather correlation concerns in studies focussing on weather variability as the variable of interest. The first is to conduct a placebo test using an out-of-context rainfall variation on outcome variable of interest while the second pivots around the adoption of spatially varying time trend in rainfall pattern as additional control variable to de-trend the rainfall data. Following Fujiwara *et al.* (2016), we adopt three locality-specific trends for the purpose of de-trending the spatial correlation of rainfall shocks in our estimation of equation (3.1). We implement a linear, quadratic and cubic community-specific trends respectively in the regression of extreme poverty index. Estimates reported in Appendix Table B3 Columns 3 – 5 present the de-trended rainfall shock and interaction term estimates for the corresponding time trends. The estimates vary only very

[41] Using information on the amount of welfare support received by households during the survey years as outcome in the same framework yields an interesting insight in the use of mobile money during shocks (Appendix Table B2). Access to mobile money reduces significantly the amount of welfare received by households; remittances available through mobile money may provide a partial substitute to welfare transfers. Rainfall shocks do not seem to have a significant impact on welfare transfers in a specification including controls (and have the ‘wrong’ sign), the interaction term is significant and reveals a positive effect on welfare transfers as response to negative rainfall shocks. This result could be due some welfare transfers received through mobile money.

slightly as a result of inclusion of diverse spatially varying time trends and do not differ from the baseline results in Column 2, reducing remaining concerns related to spatial correlation of rainfall shocks further.

3.5.1.2 Duration between Harvest Season and Interview Date

Most of the households in the Tanzanian LSMS rely on agricultural smallhold farming as source of income and own consumption. Planting in Tanzania revolves around two major rainy seasons; the long and the short rainy seasons, which last from February – May and September – October, respectively. This leads to planting for the long rainy season taking place around December (previous year) to February to be harvested from May to July each year. Coinciding with harvest period for the long rainy season is planting for the short rainy season which takes place between June and July with harvesting taking place between November and December.[42] In addition to the timing patterns of planting and harvesting, households can to some extent store produce from the previous harvest for own consumption, so that their consumption will not necessarily deteriorate instantaneously after a bad harvest manifests. Our data provides the exact date of the survey of the households and we are able to exploit this information to disintegrate our sample into observations nearer and farther away from the previous harvesting seasons in Tanzania to investigate when exactly household expenditure is impacted after the realization of the rainfall shock. Each survey round takes place between October of the starting year and ends in November of the subsequent year and we split the sample in households observed up to six month after the shock and households observed 6-12 months after the shock.

Table 3.6 Panel A reports the estimates for the households nearer to the harvest season, i.e. first six months from October (starting year) to March (following year) while Panel B reports estimates of the regression for second half of the survey year, April to September of the current year. The estimates for the sample observed 6-12 month after the shock are much more pronounced, while the overall pattern of the estimates is preserved in both samples. In particular, the estimates for the rainfall shocks are also smaller for the within

[42] The vast majority of agricultural activities take place within the long rainy season in Tanzania. This is consistent with the nature of rainfed agricultural practices in most sub-Saharan African communities due to low adoption of irrigation technology for the purpose of crop cultivation.

six month sample, suggesting that the differences in the estimates of the interaction terms are not driven by a time gap in the receipt of remittances. These results are consistent with shocks initially absorbed through the consumption of remaining stocks.

3.5.2 Main Results: Individuals

In addition to household outcomes and the effect of shocks contemporaneously on poverty, information from individual household members in the LSMS survey allow us to investigate a number of additional outcomes. In particular, we are interested in understanding the potential of mobile money to mediating the effect of shocks for long-term outcomes and the intergenerational transmission of poverty. Shocks to poor households may for example impact health investments of adults in the household and subsequently their labour supply. Shocks to household resources may also impact the ability of households to invest in the human capital of children in the household through investments in health and education. In addition, we are able to investigate the direct effect mobile money has on a number of subjective wellbeing measures.[43] For educational outcomes we restrict observations to children aged five – 18 and examine individual education expenditure and school enrolment of children for this age bracket. Also, we use an indicator for absenteeism and the number of hours spent on homework outside school hours as outcome variables. Lastly, we investigate children's likelihood to partake in household chores. This is because after school learning and household chores are mutually exclusive events for children and the latter helps to unravel potential shock cushioning role of mobile money for human capital investments as it relates to optimal choice of parents for after-school activities of their children.

3.5.2.1 Children

3.5.2.1.1 Schooling Outcomes

We start to investigate individual outcomes by looking at schooling outcomes of children, including log school expenditure, school enrolment, school absenteeism and number of daily hours dedicated to homework. Unfortunately, some of these measures may not properly capture human capital investments by households. For example, outside of school supplies and school uniforms – which often are bought at the beginning of the school year – within

[43] Subjective wellbeing are categorically ranked self-reported wellbeing in general or with reference to base period used as benchmark for unfolding events in the current period. Questions on subjective wellbeing are conducted on a number of areas including health, finance, spouse and life in general.

public schools are free.[44] Similarly, school enrolment is completed at the beginning of the school year in January and therefore may not be affected by events during the calendar year (or for that sake by the realization of rainfall shocks during the long rainy season). We report the instrumented DiD estimates for schooling outcomes separately by gender in Table 3.7. Indeed we do not find significant effects on school expenditure and school enrolment for either girls or boys. Looking at school absenteeism, we find that a negative rainfall shock leads to a significant increase in absenteeism for boys and girls. This could for example be the result of children engaging in child labour activities. While the interaction term for boys is not statistically significant, the sign is as expected. For girls the coefficient on the interaction term is significant at the 10 percent level. A similar pattern emerges for school absenteeism as did for household poverty, the coefficient on the interaction term of mobile money with shocks reveals an 'overcompensation' of the direct effect of rainfall shocks on absenteeism. During shocks, mobile money protects school attendance of children in affected households. A one standard deviation negative rainfall shock increases the rate of absenteeism by 8 and 6 percentage points for boys and girls, respectively. These effects correspond to 31.8 percent and 21.9 percent relative to average rate of school absenteeism. The interaction effects for mobile money adopters show a reduction of 21 and 26 percentage points (80.3 percent and 96.4 percent relative to mean absenteeism rate) for boys and girls, respectively. The results in column (4) on the daily number of hours dedicated to homework reveal some interesting heterogeneous effects by gender. While we estimate small and insignificant effects for rainfall shocks and the interaction term for boys (chart A) we find substantially larger effects (significant at the 10 percent level) for girls. Mobile money shields girls' time dedicated to homework from the negative effect of rainfall shocks.[45]

3.5.2.1.2 Participation in Unpaid Household Chores

The heterogeneous effects by gender reported for hours dedicated to homework are matched by similar heterogeneous effects for household chores. Two major household chores in the Tanzanian context involve water fetching and firewood gathering. Table 3.8 Columns 1 to 3

[44] Tuition fees in primary schools were abolished in 2002.

[45] Joint estimates for boys and girls are provided in Appendix Table B4, with overall similar results to Table 3.7.

report estimates for a combined indicator for any of these two categories as the dependent variable restricted to children between 5 and 18 for all children, and boys and girls separately.

While none of the rainfall shock estimates are significant, the coefficient on the interaction term for children is positive, revealing that a negative rainfall shock is mediated by the availability of mobile money accounts in the household. These results are almost completely driven by the effects for girls. A one standard deviation negative rainfall shock leads to a 22 percentage point decrease in the likelihood of girls engaging in household chores such as water fetching. Given the rate of household chores participation for girls, this coefficient estimate indicates that mobile money mediates approximately 57 percent impact of shock, which is apparently more than compensates the negative impact of shock. Access to mobile money may therefore be particularly important when there are girls in the household, which are generally more exposed to these activities and our results are consistent with findings in the literature on the relationship between remittances and child labour, especially as it related to gender differences (Acosta 2011).

3.5.2.2 Health Outcomes

In the sub-Saharan African context, private health expenditure is an important component of human capital investment at the household level. The inefficiencies of the public health system force households to often rely on private investments in health behaviour. This is exemplified by the role of private purchases of treated malaria bed nets as an effective measure against the disease, particularly for children (Dupas 2014). Dupas (2009) reports cost as the most important factor in households' decisions to invest in treated bed nets in Kenya. In the absence of subsidies, liquidity constraints faced by households may substantially limit investment in bed nets and the recurring treatments with insecticides to maintain the effectiveness of the protection. To investigate the impact of shocks and mobile money accounts on health outcomes we use individual level data on the use of treated bed nets and preventive health expenditures. The question on individual preventive health expenditure reports the amount spent on preventive health expenditure relating to the past four weeks prior to the survey date. Table 3.9 reports estimates on preventive health expenditure outcomes. This category relates to expenditures made for privately paid pre-natal visits, check-ups, insecticide treatment of bed nets, repellents etc. Column (1) reports the results for an indicator variable (of any such expenditure over the past four weeks in the household) and column (2) report estimates for log real expenditure, both including the full set of controls. For both, the indicator and log health spending, we find effects for the rainfall shocks as expected, and for the interaction term, both significant at the 1 percent level.

In Table 3.10 we present the estimates of equation (3.1) for bed net use. Columns (1) presents the findings for whether a household member slept under a bed net the night prior to the survey and column (2) reports the estimates for whether an individual specifically used treated bed nets. We find that a one standard deviation negative rainfall shock decreases the use of insecticide treated bed net by 8 percentage points while the interaction term shows an increase of 25 percentage points for mobile money adopters, confirming previous results on 'overcompensation' for shocks for mobile money users. Given the mean likelihood of the usage of treated bednets, the estimates correspond to a 16 percent decrease in treated bednets use resulting from negative shock and a corresponding compensation of around 49 percent for this effect with mobile money use. We find similar, but less accentuated effects for all bed net uses (regardless of insecticide treatment status).

3.5.2.3 Self-Reported Well Being

Next we investigate whether the above results on the mediating effect of mobile money during shocks also translate into improvements of subjective wellbeing. We focus on self-reported satisfaction with the financial situation of the household, satisfaction with life overall and satisfaction with health status. Satisfaction levels are evaluated using rank system ranging from very unsatisfied to very satisfied. We construct a satisfaction indicator assigned "satisfied" if satisfaction level is above average level and "unsatisfied" for below average level category.

Table 3.11 reports the estimates on diverse self-reported adult satisfaction outcomes for finance, life and health respectively. Estimates on the satisfaction with the financial situation reveal the expected (negative) impact of negative rainfall shocks on the financial situation in the households. In line with the previous findings, the magnitude of the interaction term exceeds the coefficient estimate for rainfall shock. The simple availability of mobile money does not seem to have a significant effect on financial satisfaction (although the magnitude is relatively large and the estimates are noisy). We do not find significant effects on either life satisfaction or health satisfaction.

3.5.2.4 Labour Supply

As a final outcome for individuals we investigate the effect of shocks and mobile money on labour supply in the household. The existing literature points out the role of labour supply diversification into the non-agricultural sector during rainfall shocks that help to mitigate the impact of these shocks. This strategy is usually aimed at smoothing income to enhance consumption smoothing in periods of shock (Morduch 1995; Kochar 1999). Kochar (1999) specifically reveals that members of rural households diversify hours of labour into non-agricultural activities to compensate for the shortfall in agricultural income by earnings from other wage activities outside the agricultural sector in rural India.[46] As showcased by Kijima *et al.* (2006), the low wage diversification strategy tends to be more effective to adapt to negative agricultural shocks among the more vulnerable units – asset poor segment of the community. However, the diversification of labour activities between agricultural and non-agricultural sectors hinges strongly on the availability of non-agricultural opportunities in the rural area.

Table 3.12 reports estimates of rainfall shocks and its interaction with mobile money on non-agricultural wage labour in the seven days prior to the survey.[47] Columns 1 and 2 of Table 3.12 respectively present regression estimates for participation in non-agricultural wage labour for adults and children, respectively. We are particularly interested in understanding the potential effect shocks and mobile money may have on child labour. Focusing on adult labour supply first, estimates from column (1) show that a one standard deviation decrease in rainfall increases the likelihood of off-farm labour participation of adults by 2 percentage points (10 percent of mean off-farm labour supply in the current sample). The interaction term indicates that this effect is counteracted by a 7 percentage points' decrease in the likelihood of non-agricultural wage labour activities by an adult. The interaction term estimate corresponds to a 27 percent decrease in non-agricultural wage

[46] In another context, other studies demonstrate how nonfarm employment can help rural dwellers oust sliding into poverty during agricultural shocks in Africa and Asia (Kijima et al. 2006; Otsuka and Yamano 2006).

[47] We focus the estimates using wage labour in the most recent seven days. Whilst wage labour in the previous twelve months is available in the data, the effect of shocks cannot be attributed using data stretching over such long periods.

labour in the current context. While it is difficult to interpret this effect from a welfare point of view, the fact that mobile money may decrease engagement in non-agricultural activities in periods of shocks may also indicate a possible perverse effect that access to an effective remittance mechanism may have on labour supply. Although results for child labour are qualitatively very similar, pointing to a positive role mobile money may play in reducing child labour, because of the small number of observations the coefficients are not significant at conventional levels.

3.5.3 Transmission Channel

Numerous papers in the mobile money literature have linked consumption smoothing mechanism by adopters to remittance receipts to cushion the effect of shocks (Jack and Suri 2014; Riley 2016). Similar to these papers, we also investigate the role of remittances in the context of mobile money and shocks. In particular, we are interested in understanding the effect on the likelihood and the amount of remittance received by households in the past twelve months.[48] Naturally we would prefer remittance measures related to a much shorter time frame, but unfortunately this data is not available. Having previously reported summary statistics on the most common uses of mobile money services – sending and receiving of remittances – it is less likely that savings from electronic money receipts would be a major factor to the impact of mobile money adoption especially in periods of shocks. To establish the role of remittance, Table 3.13 reports the impact of mobile money adoption, rainfall shock and interaction term on remittance indicator and natural logarithm of amount received in our focus cross-section data.

Our results indicate that mobile money adopter households are more likely to receive domestic remittance transfers and indeed receive greater amounts relative to non-adopters. Negative rainfall shocks increase the likelihood and amount of remittances received by households, but the estimates are noisy. The sign of the interaction effect points to greater

[48] Natural logarithm of the amount of remittance received in Tanzanian Shillings is used in the estimation of amount of remittance received in the past twelve months. To ensure that zero remittance values are kept in the regression process, they are converted to ones before computing the logarithmic values of the remittance amounts. Also, we restrict our regression to the last wave owing to the inappropriateness of remittance receipt questionnaire which focuses on remittance from abroad in the first wave. Hence, our estimation strategy borders on cross sectional instrumental variable estimation for observations in the last wave of our data. Our result in this regard should be representative of the use of remittance as a cushioning mechanism against shock on welfare conditional on the representation of the panel data structure in the two waves.

chance for remittance transfers and the greater amount received in periods of negative shocks for adopter households relative to non-adopters, but the coefficients are not significant. This provides complementary evidence in support of appropriate allocations of remittance income for welfare enhancing outcomes revealed in sections 3.5.1 and 3.5.2 above. While the welfare results obtained earlier on reflect welfare enhancing distribution of remittance income, this should not be interpreted as consequences of income in general but as an welfare enhancing alternative to income in periods of shocks.

3.6 Discussion and Conclusion

Financial exclusion remains an important issue in many developing countries. The rural poor are particularly affected by financial exclusion because of the reliance on rainfed agricultural practices and their related vulnerability to rainfall shocks. There is a well-established literature in economics on the consequences of financial exclusion at the macro level, and an emerging literature providing credible evidence on the welfare effects of financial exclusion using micro evidence. In this paper we provide evidence on the effect of a financial innovation – mobile money – on households and the individuals living in these households.

For this purpose we use a national representative household panel data set from Tanzania to estimate the role of the household adoption of mobile money in cushioning the welfare consequences of rainfall shocks to predominantly rural smallholder farmers. We combine information on rainfall variation on the household level with an instrumental variable strategy capable of addressing the potential endogeneity of the decision of individual households to adopt mobile money in an instrumented DiD framework.

We find that mobile money access prevents households from sliding into extreme poverty during periods of negative rainfall shocks. Our evidence suggests that the poorest households may benefit most from access to mobile money, as they are also particularly vulnerable to shocks. The findings from the poverty outcome is consistent with the consumption smoothing hypothesis in the existing literature. Jack and Suri (2014) demonstrates the consumption smoothing role of mobile money in Kenya by showing that consumption declines for non-user households by 7 percent during shocks while there is no such evidence for user households. This pattern is replicated for the most important segment of household consumption, which is expenditure on food items. Riley (2016) shows that while household users smoothed their consumption with the help of mobile money services, there is no smoothing pattern for the aggregate consumption at the community level including non-users. The result demonstrates lack of perfect risk sharing hypothesis for the expansion of mobile money services. Our result shows that a one standard deviation negative rainfall shock increases the likelihood of living under poverty index by 5.4 percent while mobile money compensates for this by a reduction of 15 percent. Our findings in this regard is uniquely different from the literature by virtue of the overcompensation for the negative impact of shocks. While there exists behavioural explanation for the above pattern, it could be perceived as access to more remittance payments over and beyond the shock effects.

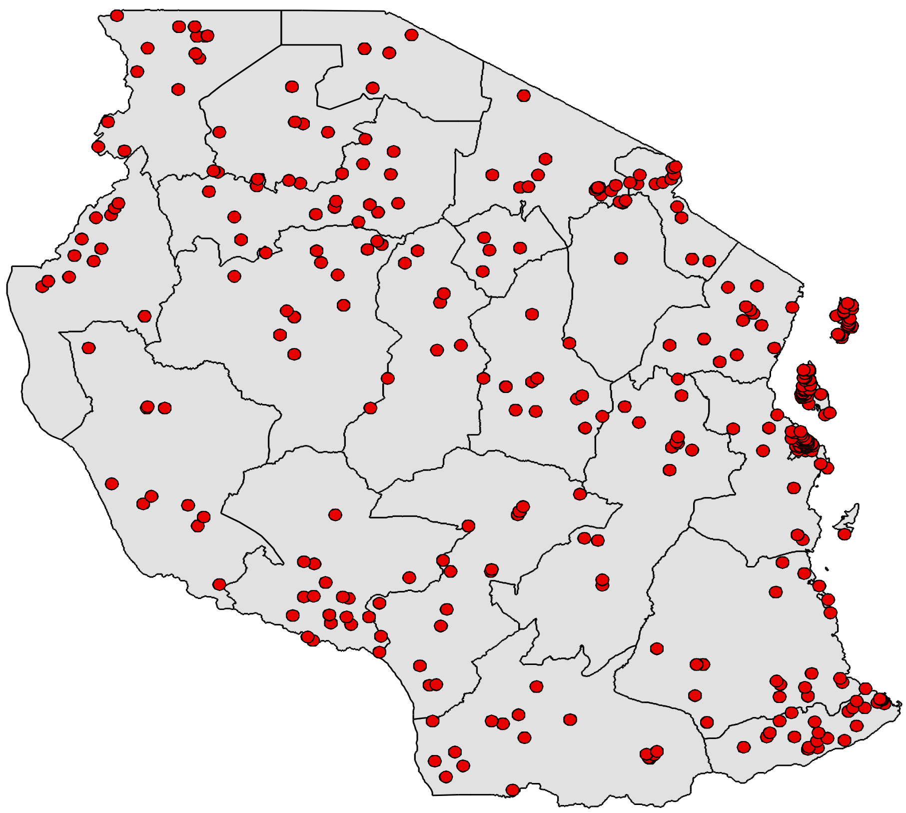
We further provide evidence for the potential long-run effects financial inclusion may have – in the form of access to mobile money – for human capital accumulation. We find that access to mobile money helps smoothing of preventive health expenditure and increases the fraction of individuals in households sleeping under treated malaria bed nets.

While – not surprisingly – we do not find that mobile money improves school expenditure or enrolment, we provide evidence that mobile money helps to reduce school absenteeism in the aftermath of rainfall shocks and increases the number of hours dedicated to homework compared to households without mobile money access. This effect is particularly strong for girls. Similarly, we find that mobile money shields girls from spending time fetching water and collecting fire wood in response to shocks.

Lastly, our results also point to potential perverse effects of access to mobile money on non-agricultural labour supply, but without a better understanding of the consequences of moving away from small-hold farming towards other sources of income, the interpretation of the findings on labour supply is inconclusive and beyond the scope of this paper.

Chapter 3: Figures and Tables

Figure 3.1: Map of the United Republic of Tanzania (Depicting the Enumeration Areas of LSMS Survey).



Notes: The map depicts the 26 regions of Tanzania with the red dots representing the Enumeration Areas in the LSMS data used in this paper.

Figure 3.2: The Graphical Illustration of the Correlation between Mobile Money and Distance to Agent

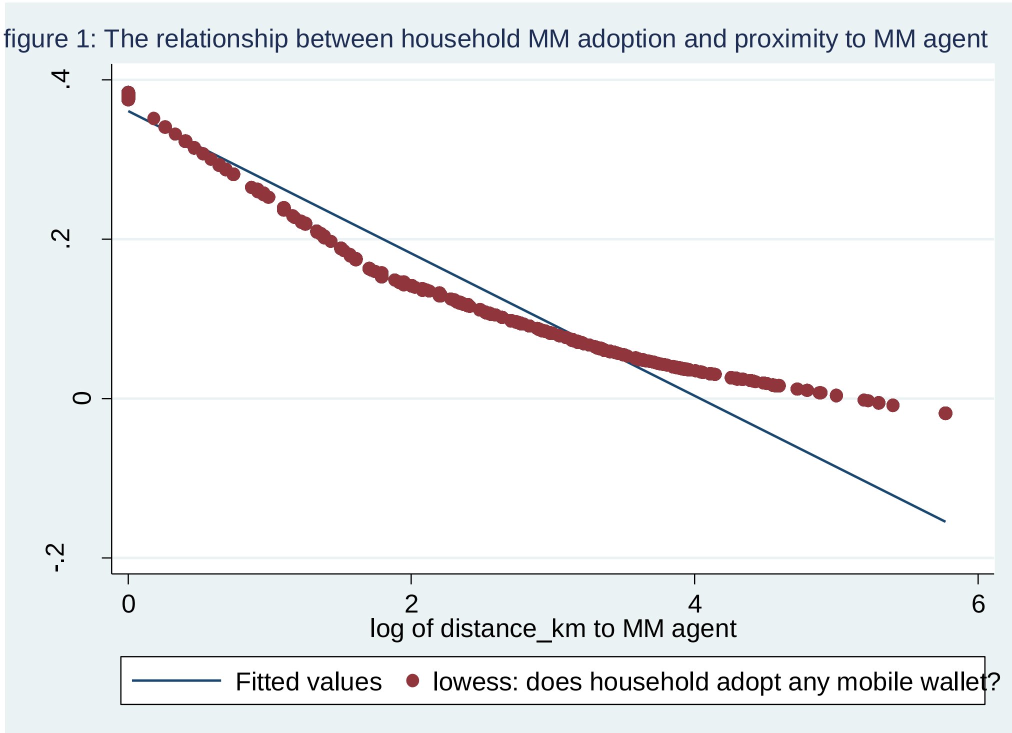


Table 3.1: Household Summary Statistics.

Variable	Mean	Standard Deviation
Household Size	5.197	2.697
No. of Children	2.745	2.124
Wealth Measure	73.644	58.528
Female Head	0.251	0.433
Rural	0.717	0.450
HH Phone Possession	0.629	0.483
SACCO Membership	0.219	0.413
Mobile Money	0.213	0.410
Bank Account Ownership	0.159	0.365
Self-Reported Shock	0.361	0.480
Household Head		
Married	0.833	0.373
Formal School	0.762	0.426
Occupational Categories		
Agriculture	0.632	0.482
Self-Employed	0.162	0.369
Private	0.089	0.285
Unemployed	0.063	0.243
Public	0.054	0.226

Notes: The summary statistics reported in Table 3.1 above are for the focus household sample. Female Head, Rural, HH Phone Possession, SACCO Membership, Mobile Money, Bank Account Ownership and Self-Reported Shock are all indicator variables. Self-Reported Shock is an indicator variable measured as 1 for an incidence of shock in the past twelve months within the households; and 0 otherwise. Shock components for Self-Reported Shock indicator includes drought, crop pest infestation, livestock deaths, business collapse, loss of paid job, sale price decrease, food price increase, input price increase, water shortage, land slide, illness, death of breadwinner, death of any member, HH break up, jail sentence for any member, fire incidence, robbery attack on HH, HH damage and other negative shocks.

Table 3.2: Individual Summary Statistics.

Variable	Mean	Standard Deviation
Age	26.200	19.739
Male	0.489	0.500
Married	0.832	0.374
Formal School	0.730	0.444
Occupational Categories		
Agriculture	0.629	0.483
Unemployed	0.139	0.346
Self-Employed	0.132	0.339
Private	0.062	0.241
Public	0.039	0.194

Notes: The summary statistics reported in Table 3.2 above are for our focus individual of panel observations. Male, married and formal school are all indicator variables. Married, formal school and occupation categories of individuals above are restricted to adult individuals.

Table 3.3: Service Preference and Frequency of Use of Mobile Money by Adopters in Tanzania Between 2011 and 2013.

Chart A : Service Preference	2011	2013
Buy Airtime	0.082	0.076
Send Airtime	0.008	0.004
Send Money	0.384	0.306
Receive Money	0.425	0.502
Receive Payment for Sales	0.008	0.020
Save for Emergency	0.029	0.028
Daily Expense	0.057	0.044
Large Purchase	–	0.008
Chart B : Frequency of Use		
Occasional (Emergency)	0.625	0.570
Half-Yearly	0.016	0.020
Quarterly	0.090	0.048
Monthly	0.147	0.178
Fortnightly	0.049	0.045
Weekly	0.057	0.092
Daily	0.016	0.044

Notes: Chart A of Table 3.3 above for service preference reports the overall most important use to which mobile financial service is put by adopters as a fraction of entire adopter households by year in the Tanzanian Living Standard Measurement Study from the World Bank data. Please note that "large purchase service use" category is unavailable for the 2010/2011 wave. Chart B presents the frequency of use of mobile financial service by adopters as a fraction of entire adopter households over two waves in the same survey.

Table 3.4: First Stage Results of Instrumental Variable Regressions and Diagnostic Tests.

	Dependent Variables:			
	Panel A: Mobile Money Indicator		Panel B: Mobile Money Indicator X Rainfall Shock	
Variables	(1)	(2)	(1)	(2)
Chart A: Estimates				
Agent Availability (X Rainfall Shock)	0.090**	0.100***	0.282***	0.299***
	(0.037)	(0.033)	(0.060)	(0.059)
Agent Distance (X Rainfall Shock)	0.023*	0.027**	-0.060***	-0.056***
	(0.014)	(0.013)	(0.017)	(0.017)
R-squared	0.187	0.233	0.523	0.533
F-stat	48.260	13.270	75.450	21.900
F-stat (4, 291)	2.660	5.980	52.560	55.160
Chart B: Diagnostic Tests				
Under Identification Test - Chi-Sq (4, 291)	–	10.170 (0.017)	–	187.810 (0.000)
Weak Identification Test - F (3, 291)	–	3.35	–	61.89
Household Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: Table 3.4 above presents first stage estimates for the main result presented in Table 3.5 below. Total number of observations for the regression is 3,590 households. Chart A reports the first stage estimates for agent availability (indicator) and agent distance (alongside their interaction with rainfall shocks) respectively for the first stage results of mobile money usage indicator and its interaction with rainfall shock. See notes in Table 3.5 for a list of all controls used in the regression process. Each regression is clustered at the community level. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.5: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock for Poverty Index.

	Dependent Variable: Extreme Poverty Incidence	
Variables	(1)	(2)
Chart A: Distance to Agents		
Mobile Money	0.299	0.238
	(0.272)	(0.264)
Rainfall shock	0.038**	0.038**
	(0.017)	(0.016)
Interaction	-0.103**	-0.104**
	(0.047)	(0.043)
Chart B: Cost to Agents		
Mobile Money	0.245	0.128
	(0.378)	(0.412)
Rainfall shock	0.040**	0.041***
	(0.017)	(0.016)
Interaction	-0.105**	-0.105**
	(0.052)	(0.047)
Household Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	No	Yes

Notes: Table 3.5 above reports the linear probability model (LPM) estimates of mobile money adoption, rainfall shock and their interaction term. Extreme Poverty Incidence is measured as 1 for real per-capita expenditure above US$1.25; and 0 otherwise. Mobile Money indicates mobile wallet adoption at the household level. Interaction implies an interaction term between mobile money adoption and rainfall shock measures (household shocks). Each column is a separate regression for 3,590 observations. Columns (1) – (2) each represents estimation without controls and with controls respectively. The controls used in the estimation of column (2) include an array of household level controls. These are gender of household head, education and occupation categories of household head, household size, average household age, household residential place (rural/urban), household asset valuation, household membership of a SACCO group, household membership of any other credit and savings society, household access to loan, bank account possession within the household, number of mobile phones the household possesses, value of voucher the household purchases in the past month. Each regression is clustered at the community level. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.6: Instrumental Variable Estimates of Mobile Money and Interaction Term on Poverty Considering the Timing of Planting Seasons

	Dependent Variable: Extreme Poverty Incidence			
	Panel A: Within six months of harvest		Panel B: After six months of harvest	
Variables	(1)	(2)	(3)	(4)
Mobile Money	0.034	0.027	0.615	0.399
	(0.288)	(0.329)	(0.504)	(0.403)
Rainfall shock	0.026	0.019	0.055	0.054*
	(0.020)	(0.018)	(0.035)	(0.031)
Interaction	-0.045	-0.050	-0.155*	-0.141*
	(0.057)	(0.060)	(0.092)	(0.074)
Observations	1,702	1,702	1,905	1,905
Household Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes

Notes: Table 3.6 above reports the linear probability model (LPM) estimates of mobile money adoption, rainfall shock and their interaction term on extreme poverty index from Table 3.5. Panel A conveys estimates for households surveyed in the first six months of harvest while Panel B reports estimates for households surveyed after six months of harvest. Mobile Money indicates the mobile wallet adoption at the household level. Interaction implies an interaction term between mobile money adoption and rainfall shock measures (idiosyncratic shocks). See notes in Table 3.5 for a list of all controls used in the regression process. Each regression is clustered at the community level. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.7: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Children School Outcomes by Gender.

	Dependent Variables:			
	School Expenditure (Tanzanian shilling)	School Enrolment (indicator)	School Absenteeism (indicator)	Homework (Hours/Day)
Variables	(1)	(2)	(3)	(4)
Chart A : Boys				
Mobile Money	303.301	0.073	-0.785	-0.801
	(208.711)	(0.353)	(1.201)	(1.611)
Rainfall shock	7.456	-0.001	-0.084**	0.023
	(9.578)	(0.017)	(0.040)	(0.050)
Interaction	-8.087	0.026	0.212	-0.037
	(34.997)	(0.050)	(0.148)	(0.217)
Observations	1,898	1,898	1,492	1,492
Chart B : Girls				
Mobile Money	-16.631	-0.158	-0.501	1.702
	(55.969)	(0.205)	(0.694)	(1.065)
Rainfall shock	3.068	0.003	-0.060*	0.098*
	(3.333)	(0.016)	(0.037)	(0.056)
Interaction	0.286	0.019	0.264*	-0.409*
	(14.620)	(0.053)	(0.137)	(0.219)
Observations	2,042	2,042	1,678	1,676
Individual Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Table 3.7 above reports the estimates of mobile money adoption, rainfall shock and their interaction term. Column 1 displays estimates for natural logarithm of children school expenditure while column 2 reports estimates from linear probability for school enrolment indicator. School enrolment indicator is measured as 1 if a child aged 5 to 18 is currently attending school; and 0 otherwise. On the other hand, school absenteeism indicator in column 3 indicates 1 if an enrolled child missed school in the last two weeks; and 0 otherwise. Column 4 engages in the daily hours used for school homework at home. Mobile Money indicates the mobile wallet adoption at the household level. Interaction implies an interaction term for mobile money adoption and rainfall shock measures (idiosyncratic shocks). Charts A and B reports estimates for boys and girls respectively. Each column follows column 2 of Table 3.5 above in reporting estimates of the regression which includes relevant household controls. In addition to household level controls, age and gender of children are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.8: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Children Household Chores.

	Dependent Variables: Household Chores		
	Children	Boys	Girls
Variables	(1)	(2)	(3)
Mobile Money	-0.473	-0.622	-0.506
	(0.332)	(0.554)	(0.417)
Rainfall shock	-0.015	0.007	-0.045
	(0.020)	(0.025)	(0.029)
Interaction	0.116*	0.029	0.217**
	(0.066)	(0.083)	(0.106)
Observations	6,956	3,494	3,462
Individual Fixed-Effect	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table 3.8 above reports the estimates of mobile money adoption, rainfall shock and their interaction term. Household Chores in columns 1 – 3 is a union of water fetching and firewood gathering duties. This is measured as 1 if a child fetches water or gathers firewood at home; and 0 otherwise. Mobile Money indicates the mobile wallet adoption at the household level. Interaction implies an interaction term for mobile money adoption and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 of Table 3.5 above in reporting estimates of the regression which includes relevant household controls. In addition to household level controls, age and gender of children are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.9: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Preventive Health Expenditure Measures.

	Dependent Variables:	
	Preventive Health Exp. Indicator	Real Preventive Health Expenditure
Variables	(1)	(2)
Mobile Money	-0.001	-0.023
	(0.015)	(0.214)
Rainfall shock	0.003***	0.047***
	(0.001)	(0.018)
Interaction	-0.016***	-0.235***
	(0.006)	(0.085)
Individual Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	Yes	Yes

Notes: Table 3.9 above reports the estimates of mobile money adoption, rainfall shock and their interaction term. Preventive Health Expenditure Indicator in column (1) is measured as 1 if an individual spends any amount on preventive health in the past four weeks; and 0 otherwise. Real preventive health expenditure in column (2) is calculated as the natural logarithm of real preventive health expenditure in thousand Tanzanian shillings. Mobile Money indicates the mobile wallet adoption at the household level. Interaction implies an interaction term for mobile money adoption and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 of Table 3.5 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.10: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Bed Net Adoption and Treatment.

	Dependent Variables:	
	Bed Net Use Indicator	Treated Bed Net Indicator
Variables	(1)	(2)
Mobile Money	0.824*	0.926*
	(0.427)	(0.510)
Rainfall shock	0.038	0.084***
	(0.025)	(0.029)
Interaction	-0.198**	-0.254**
	(0.096)	(0.114)
Individual Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	Yes	Yes

Notes: Table 3.10 above reports the estimates of mobile money adoption, rainfall shock and their interaction term. Bednet Use Indicator in column (1) indicates 1 if an individual uses mosquito bednet during sleep; and 0 otherwise while Treated Bednet Indicator in column (2) indicates 1 if an individual specifically uses treated bednet; and 0 otherwise. Mobile Money indicates the mobile wallet adoption at the household level. Interaction implies an interaction term for mobile money adoption and rainfall shock measures (idiosyncratic shocks). Each column is a separate regression for 13,350 observations. Each column follows column 2 of Table 3.5 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.11: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Subjective Well-Being.

	Dependent Variables:		
	Finance Satisfaction (indicator)	Life Satisfaction (indicator)	Health Satisfaction (indicator)
Variables	(1)	(2)	(3)
Mobile Money	0.350	0.410	-0.364
	(0.319)	(0.318)	(0.253)
Rainfall shock	0.035*	0.019	-0.015
	(0.019)	(0.022)	(0.017)
Interaction	-0.131*	-0.105	0.088
	(0.069)	(0.071)	(0.058)
Observations	5,880	5,870	5,878
Individual Fixed-Effect	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Notes: Table 3.11 above reports the estimates of mobile money adoption, rainfall shock and their interaction term. Satisfaction indicators in columns (1) – (3) is measured as 1 if an individual if satisfied beyond average reported satisfaction index from the questionnaire; and 0 otherwise. Mobile Money indicates the mobile wallet adoption at the household level. Interaction implies an interaction term for mobile money adoption and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 of Table 3.5 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the estimation. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.12: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Wage Labour Supply

	Dependent Variable : Weekly Wage Participation Indicator	
	Adults	Children
VARIABLES	(1)	(2)
Mobile Money	0.204	-0.034
	(0.191)	(0.329)
Rainfall shock	-0.020**	-0.037
	(0.010)	(0.026)
Interaction	0.069**	0.070
	(0.029)	(0.059)
Observations	6,326	1,176
Individual Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	Yes	Yes

Notes: Table 3.12 above reports the estimates of mobile money adoption, rainfall shock and their interaction term. Weekly Wage Participation Indicator is measured as 1 if an individual engaged in a wage rewarding labour activity in the last seven days; and 0 otherwise. Column 1 reports estimates for adults over 18 years while column 2 reports estimates for children aged 5 – 18. Mobile Money indicates the mobile wallet adoption at the household level. Interaction implies an interaction term for mobile money adoption and rainfall shock measures (idiosyncratic shocks). Each column follows column 2 of Table 3.5 above in reporting estimates of the regression which includes necessary controls respectively. In addition to household level controls, age, gender, marital status, educational and occupational categories of individuals are used as additional individual controls for the adult estimation in column 1 while age and gender are used as additional controls in column 2. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Table 3.13: Instrumental Variable Estimates of Mobile Money and Interaction Term on Remittance

	Dependent Variable: Remittance			
	Panel A: Remittance Indicator		Panel B: ln (amount)	
Variables	(1)	(2)	(3)	(4)
Mobile Money	0.378***	0.951***	4.353***	9.718***
	(0.083)	(0.279)	(0.935)	(2.870)
Rainfall shock	-0.038	-0.029	-0.269	-0.147
	(0.034)	(0.035)	(0.377)	(0.375)
Interaction	0.006	-0.013	-0.009	-0.184
	(0.075)	(0.076)	(0.844)	(0.832)
Observations	1,809	1,809	1,809	1,809
Controls	No	Yes	No	Yes

Notes: Table 3.13 above reports the estimates of mobile money adoption, rainfall shock and their interaction term on remittance receipts by observation households. Panel A and Panel B report estimates for indicator and natural logarithm of remittance receipts (in Tanzanian Shillings) by households respectively. See notes in Table 3.5 for a list of all controls used in the regression process. Each regression is clustered at the community level. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Chapter 4

4 Adverse early life shocks and impacts on short-term and long-term outcomes: evidence from rural Malawi

4.1 Introduction

A large portion of the empirical evidence in favour of persistent impacts of early life shocks on long-term socioeconomic outcomes focus on nutrition as an important transmission mechanism (Alderman *et al.* 2006; Yamauchi 2008; Alderman *et al.* 2009; Maluccio *et al.* 2009; Neelsen and Stratmann 2011; Ampaabeng and Tan 2013; Dercon and Porter 2014 and Bertoni 2015). Most of the literature focus on health and education outcomes as the mainstream human capital outcomes. Commonly used health variables include height, weight, frequency of sickness, health expenditure and chronic illness of individuals in the data (Maccini and Yang 2009; Dercon and Porter 2014). Additional outcome variables, such as cognitive development, labour market proficiency, life achievements and satisfaction levels, are equally used for broader understanding of the impact of early life shocks. The consensus for childhood welfare outcomes for children between the ages of 0 to 60 months are anthropometric health measures captured by standardised Z-scores in weight-for-height (WHZ), weight-for-age (WAZ) and height-for-age (HAZ) (Hidrobo 2014; Rabassa *et al.* 2014; Thai and Falaris 2014). In a low-income setting, many authors use variability in weather patterns to capture the vulnerability of agricultural dependent households – usually smallholder farmers – for an understanding of food security dynamics in these households. These include Hoddinott and Kinsey (2001), Maccini and Yang (2009), and Thai and Falaris (2014).

Recent studies extend the analysis by studying other unconventional outcomes to provide evidence on mental health and death. Adhvaryu *et al.* (2014)[49] study the origins of adult mental health using early life income variations originating from exogenous cocoa price fluctuation in Ghana. Using variation in cocoa prices around the time of birth, the paper shows that a rise in the price of cocoa for cohorts born around the same time significantly decreases the likelihood of severe mental distress in adulthood (by around

[49] This literature is closely related to a growing body of work that has established critical period programming through evidence from early life malnutrition or famine and natural disaster on adulthood mental health in the medical field (Barker and Clark 1997; Huang *et al.* 2013b; Maclean *et al.* 2016; Xu *et al.* 2016).

half of the average prevalent rate). Comfort (2016) finds that exposure to early life adverse shock increases the likelihood of maternal mortality for women. She examined this hypothesis in 14 African countries by relating rainfall when a woman was in-utero with her maternal survival in adulthood. Her results indicate that sufficient levels of rainfall, representing better in-utero conditions, decrease the probability of maternal death by 1.1 percentage points, a 58% decrease from a mean of 1.9%. Better rainfall while in-utero also reduces the probability of anemia during pregnancy, a risk factor for postpartum hemorrhage. Although the rapidly expanding body of literature regarding the welfare impact of exposure to early life shocks consistently reveals the adverse impact of negative shocks, an important strand of this literature studies the impact of intervention programmes on the devastating effect of these shocks on welfare (Maluccio *et al.* 2009; Yamano *et al.* 2005; Hidrobo 2014). None of the existing literature has considered the interaction effects of exposure to early life shocks and gender resource allocation.[50]

This paper estimates the impact of rainfall shocks at the developmental stages of life on short-term children's anthropometric health measures and long-term welfare outcomes, paying particular attention to welfare outcomes important to rural livelihood in Malawi.[51] The contribution of this paper is in the use of disaggregated extreme rainfall shock measures to examine the symmetric or asymmetric impact that rainfall shocks – drought and wet shocks – may have on welfare outcomes. This approach will provide an in-depth understanding of the prevailing mechanisms at work when studying the impact of rainfall shocks in the Sub-Saharan African region. We also use multiple shock exposure around the time of birth of individuals, covering three separate agricultural seasons from in-utero to the second year rainfall shocks to examine the comprehensive impact of shocks around birth on welfare outcomes.[52] Lastly, we contribute to the

[50] This argument is valid within the context of a large body of literature that reveals discriminatory intra-household resource allocation for boys (Masterson 2012; Zimmermann 2012; Azam and Kingdon 2013) and girls (Himaz 2010).
[51] While health and labour market outcomes have been extensively investigated in the literature, as highlighted above, this study pays particular attention to the elements of health and labour market outcomes that directly inform the livelihood of rural households in a developing country framework.
[52] The closest literature in this regard is Thai and Falaris (2014) on Vietnam. A distinguishing feature of our paper is the emphasis placed on disaggregated extreme rainfall shock specification in our analytical framework and the consideration of more salient welfare outcomes to reflect livelihood and sustenance of individuals in the rural areas of the sub-Saharan African region. Also, this study takes on a broader perspective to investigate the intra-household dynamics of gender-based differential welfare outcomes of early life shocks in Malawian individuals.

understanding of some additional pathways of early life rainfall shocks on children's anthropometric health measures.

Our baseline results for rainfall deviation specifications regarding child anthropometric health measures indicate that negative (positive) rainfall shocks in early life – in-utero period inclusive – decrease (increase) WAZ and HAZ. We focus on a disaggregated extreme shock econometric specification for the interpretation of results. An incidence of drought shock leads to a decrease of 15%, 17% and 43% in WAZ for shock exposure at the in-utero stage, in the first and second years respectively. Correspondingly, the impacts of drought shock on HAZ are 14%, 15% and 27%. The impact of wet shocks on both variables deteriorates across early life reference periods. Additional results from various alternative indicators, such as underweightness or moderate and severe stunting, corroborate our standardised score results. We also find that the impact of drought shocks at the in-utero stage persists for hospitalisation and hours of informal labour outcomes. More importantly, we find that this evidence pertains to women only, while no substantial evidence is reported for men. In the paper, we provide evidence suggesting that the use of nutritional intervention programmes reveal that the gender-specific asymmetric results could potentially be linked to intra-household resource allocation between males and females in Malawian households.

The remainder of the paper is organised as follows: Section 4.2 provides a country background, while section 4.3 describes the household data and summarises the main variables. Section 4.4 describes the construction of the rainfall deviation and the disaggregated extreme rainfall shock measures. Section 4.5 unveils the conceptual framework and empirical strategy for evaluating the impact of rainfall shock on infant and other welfare measures. Section 4.6 presents the main results for children, highlights potential pathways, presents overall welfare results and examines the role of access to intervention nutrition programmes. Section 4.7 discusses the findings and provides the concluding remarks.

4.2 Country Background

The context for our study is Malawi, a sub-Saharan African country located on the south-eastern part of the continent. This country shares borders with Zambia, Mozambique and Tanzania. The total area of the country is 118,484 km² by land mass, and it had a population of approximately 17 million people in 2014 (World Bank, 2014). According to World Bank statistics Malawi was rated among the world's poorest countries in 2014. The country is predominantly made up of rural communities, which play host to smallholder farmers. There is a seasonal rainfall pattern across the various Malawi regions, with the rainy season continuing from November to April in the following year. Most crop cultivation takes place during this season, while the rainfall pattern for the dry season, between May and October, is unreliable for crop cultivation.

Malawi's agricultural sector contributes about 29 percent to the country's GDP and accounts for around 85 percent of the export revenue of the economy. Small holder farmers rely mostly on seasonal rainfall for their crop cultivation and other agricultural activities. As a result, weather patterns have a profound effect on agricultural harvests and Malawi's GDP. Furthermore, the Malawian diet is overwhelmingly dominated by maize consumption, which relies on the seasonal precipitation of agricultural seasons. Not only are rural livelihoods affected by the severe weather pattern on the agricultural sector, nonfarm rural and poor urban sectors are equally vulnerable given the strong production and price linkages between the agricultural sector and the rest of the economy in Malawi.

The landlocked African country suffers from frequent droughts and floods. Flooding leads to destruction, which, in effect, damages infrastructure and housing – occasionally leading to displacement of population – and droughts to severe crop failure and, hence, malnutrition. However, more attention is usually paid to their effect on agricultural production and national food security issues in this context. Malawi has been hit by a series of devastating droughts over its history. The adverse weather shocks that have had substantial impacts on agricultural outputs and food security in Malawi include droughts in 1999, 2002, 2009 and 2012-2013. Whenever a drought affects agricultural yields, the national food security of the country is threatened due to low crop production and storage. Children often suffer disproportionately from drought events, and a nutritional pathway of critical programming hypothesis (for children developmental stages) has been widely established in the literature.

4.3 Data and Summary Statistics

We used three rounds of Malawian household survey data collected by the World Bank, which are made up of the Malawi Integrated Household Survey (IHS) and Malawi Living Standard Measurement Study-Integrated Survey on Agriculture (LSMS-ISA), hereinafter called the Malawi Household Surveys (MHS) in this paper. The first wave is from 2004 to 2005, while the last waves, between 2010 and 2011, and 2013, are for a panel of observations. The number of observations matched with rainfall data from the household survey for the surveys are 11,280, 3,246 and 4,000 households, comprising 49,066, 15,582 and 20,076 individuals respectively. We pooled the different household survey rounds for repeated cross-section data to investigate the impact of weather variation around the time of birth on children's short-term anthropometric health status and other welfare outcomes. We estimated the impact of weather shocks on the health status of children using observations between six and 59 months in the data. We used children born before the first round of the survey and in between the surveys. We made use of an important component of the MHS, which documents the locality of the births of the individuals interviewed. We constructed rainfall shocks for individuals around their period of birth by place of birth to examine the impact of childhood agricultural weather shocks on welfare outcomes. The assumption here is that individuals' place of birth is the place of early life shock exposure.

To measure local rainfall shocks, we relied on rainfall data from terrestrial precipitation: the 1900 to 2010 gridded monthly time series from the University of Delaware's (UDel) Center for Climatic Research (version 3.01). The dataset provides estimates of monthly precipitation on a 0.5° by 0.5° grid covering terrestrial areas across the globe for the period 1900 to 2010.[53] Rainfall estimates are based on the climatologically-aided interpolation of available weather station information. The data have been compiled and made available by Matsuura and Willmott (2012). We used the GPS information provided for each local community in the MHS by matching each community to the four closest weather stations in order to obtain rainfall data for the years spanning 1900 to 2010. We weighed the four closest weather stations by the distance to GPS supplied in the MHS in obtaining the rainfall data.

[53] The University of Delaware (UDel) rainfall data repository is well cited in the economics literature and is commonly used for empirical studies. Recent papers that have used the UDel rainfall data for the purpose of empirical investigation include Chaurey (2015), Rocha and Soares (2015), and Foureaux Koppensteiner and Manacorda (2016).

4.3.1 Children's Anthropometric, Health and Labour Market Outcomes

This paper uses anthropometric measures for children between the ages of six and 59 months in the MHS. These data consist of the height[54] and weight of each observed child in this category. The combination of the anthropometric data with the age of children in months was used for calculating the nutritional anthropometric outcomes in line with standard child growth trajectory measures of the World Health Organization (WHO). Stata code for the WHO children growth trajectories by nutritional health standard was used for constructing the WAZ and HAZ scores for child health outcomes (Leroy 2011). Using anthropometry measures and the monthly ages of children over the three rounds, in addition to community weather shocks around the periods of births, we were able to identify the community level average effect of weather shocks on the nutritional health status of children born within a community using community-fixed effects and year dummies.

We also examine hospitalisation rates in addition to health expenditure and the likelihood of chronic ailment as indicators of health wellbeing. Similarly, we focus our attention on hours committed to various labour activities within the previous week as a determinant of individual level labour productivity in the repeated cross-sectional MHS data. The likelihood of hospitalisation captures the health wellbeing of all the observations in the data, while labour market activities are restricted to individuals above five years of age. We investigate the effect of early life shocks on health and labour market variables by the respondents' gender.

4.3.2 Summary Statistics

Our analysis focuses on rural Malawi. The summary statistics in Table 4.1 Section A can be compared to the international reference group, which has an expected mean z-score of 0 for all normalised growth indices. In general, z-scores that are two standard deviations below the reference are associated with growth retardation in the case of WAZ and HAZ,[55] referring to underweight and stunting respectively. The standardised distribution of WAZ and HAZ for children between six and 59 months of age in our sample is displayed in figures 4.1 and 4.2 below. Each distribution is highly skewed to the left,

[54] Note that height or length indicates standing or lying measurement positions in the data. This helps in the construction of the child nutritional health measures, which are HAZ and WAZ scores.
[55] WAZ and HAZ are obtained using a STATA command developed by Leroy (2011).

implying that growth retardation is prevalent among children of this category in rural Malawi. Section A further provides the summary statistics for WAZ and HAZ in focused observations of 6,422 and 6,695 children by gender and age in months. An average child in our sample is 0.6 standard deviations underweight and 1.6 standard deviations shorter than the international reference mean of 0. Using relative indices, approximately 9% and 39% of children are underweight and stunted respectively. Boys are more likely to suffer from growth retardation than girls, with a stunting ratio of 42% to 36%. This gender-specific pattern is consistent with the observed pattern of growth gradients for boys and girls in Nigeria (Rabassa *et al.* 2014). By age group, stunting is more prevalent among children in their third and fourth years, with 49% and 43% respectively exhibiting stunting. This is followed by 39% and 38% stunting rates for children in their fifth and second years respectively. Children in their first year are the least stunted, with an 18% stunting rate.

Table 4.1 Section B presents the individual and household baseline characteristics used as controls in our estimations. The average age of children in our sample is slightly above two years. Around 51% of the sample are girls while 49% are boys. The average value of non-agricultural assets for a typical rural household in Malawi is approximately 18,000 Malawian Kwacha, which comes to US$90, giving an idea of the prevalence and severity of the poverty levels in these households. Households in our sample comprise on average six individuals, with two children between the ages of six and 18 years. The average household age across the households in the sample is 17 years while the mean age of the head of household is 37 years. Most of the households, around 84%, are headed by males. Lastly, only 22% of the heads of household have ever had any formal school tuition in their lifetimes.

4.4 Constructing Rainfall Deviation and Shocks

We aggregate the rainfall measure for each community by agricultural season, which is November to October of the following year. We reference a year by the agricultural season's rainfall measure in this context and derive the yearly rainfall deviation as the deviation of the local rainfall from the 30-year historical rainfall average in the locality. Similar to Maccini and Yang (2009), Björkman-Nyqvist (2013) and Rocha and Soares

(2015),[56] amongst others, rainfall deviation is constructed as the natural logarithm of the current agricultural season minus the historical average for the same locality.

$$\text{Rainfall Deviation}_{ct} = ln\ \text{Rainfall}_{ct} - ln\ \overline{\text{Rainfall}_c} \qquad (4.1)$$

where Rainfall_{ct} indicates the yearly precipitation for the current agricultural year within the locality for community *c*, and $\overline{\text{Rainfall}_c}$ is the average historical yearly precipitation of the community over 30 years. Thus, $\text{Rainfall Deviation}_{ct}$ is defined as the deviation between the natural logarithm of the total precipitation in the 12 months of the agricultural season and the natural logarithm of the corresponding average seasonal historical precipitation at the community level. This measure of locality precipitation dynamics essentially denotes a percentage deviation from mean and is measured in log-points deviation (Maccini and Yang 2009).

Based on equation (4.1) above, we construct measures of drought and flood shocks for the yearly agricultural cycle within a locality and then match individuals to one of the measures depending on the month of birth. We follow the literature on the creation of drought or flood shock by using a long-term time series of rainfall observations to fit a gamma distribution of rainfall within each community. We then assign each agricultural season's rainfall realisation in that location to its corresponding percentile in the historical distribution of rainfall at the community. We define a drought (flood) shock as a rainfall realisation that is in the bottom (uppermost) 25th percentile of that location's rainfall distribution over the past 30 years. As a robustness check, we calibrate with standard deviation bins below and above 30-year historical rainfall for an understanding of shock patterns below and above historical average (Comfort 2016).

We construct the disaggregated shock components for extreme precipitation measures (drought and flood shock incidence) for localities in the following way:

$$\text{Drought Shock}_{ct} = \begin{Bmatrix} 1 \text{ if rainfall within locality is below 25th percentile of norm} \\ 0 \text{ if rainfall within locality is above 25th percentile of norm} \end{Bmatrix} \quad (4.2)$$

[56] Although Rocha and Soares (2015) consider alternative shock specification in terms of drought dummy, estimates from the linear rainfall deviation in equation (4.1) are used for the general interpretation of the results in their paper.

$$\text{Flood Shock}_{ct} = \begin{cases} 1 \text{ if rainfall within locality is above 75th percentile of norm} \\ 0 \text{ if rainfall within locality is below 75th percentile of norm} \end{cases} \quad (4.3)$$

4.5 Empirical Strategy

4.5.1 Conceptual Framework

The potential channels for the impact of rainfall shock on welfare outcomes in the literature include agricultural income shock, disease environment and malnutrition (Almond and Currie 2011a). Our framework on the impact of shock on both short-term and long-term welfare outcomes provides a unique opportunity to evaluate these existing channels on diverse welfare outcomes in agricultural dependent households. While many welfare outcomes have been explored in the literature, additional outcome variables of hospitalisation rates and levels of productivity in our context elaborate the potential mechanisms for the welfare impacts of early life shock in an agricultural dependent setting. The agricultural income channel is mostly explored for outcomes on contemporaneous weather conditions through agricultural yields and livestock production (Bengtsson 2010; Fichera and Savage 2015) while the disease environment link between weather and welfare outcomes is theoretically plausible for both early life and contemporaneous shocks. Lastly, the malnutrition channel for the impact of rainfall shock is widely explored in the medical literature as being determined by caloric intake of individuals as much as by the composition of the nutrients. In this framework, food insecurity problems associated with drought shocks can independently affect any of the above components of nutritional intake of individuals. It is important to note that while contemporaneous drought shocks could be the major contributing factor to nutritional deficiencies, growing evidence on the welfare impact of the first 1,000 days of exposure to shocks presents us with a framework on which to base our estimation strategy.

4.5.2 Empirical Strategy

The main identification problem in the estimation of impacts of early life shocks on both the short- and long-term social and economic outcomes of individuals is the potential endogeneity of household shocks. In this paper, we exploit the variation of early life precipitation measures as exogenous shock events to overcome this identification problem. As a result, we provide unique evidence on both the short- and long-term effects of the early childhood environment on children’s anthropometric, health and labour market outcomes, including age standardised weight and height scores, and an array of health variables and labour productivity. Our empirical strategy is to exploit the exposure to shocks at different stages of early life (focussing on the first 1,000 days) relating to harvests from agricultural seasons for agricultural dependent households to identify the causal effects of children's exposure to nutritional shocks on their childhoods and on adult welfare outcomes. We follow the literature that investigate the impact of shocks on anthropometric indices of children's nutritional health status (e.g. Hidrobo 2014; Rabassa *et al.* 2014; Thai and Falaris 2014) using a reduced form specification for the impact of early life rainfall shock on WAZ and HAZ, as presented in equation (4.4) below.

In our pooled cross-section data, the effect of early life shocks is identified by comparing the average difference in child growth across communities whose children are born the same number of months apart. This is measured as the average outcome differences of a particular locality for a certain agricultural season as compared to the average differences of the same locality in another season. Identification occurs through children of similar age across these periods in the same community, which may constitute shock-exposed and non-exposed cohorts, or in other words, groups that may be exposed to differential magnitudes or extreme shock events in our disaggregated framework. Insofar as the variables in the error term are orthogonal to an individual child's early life exposure to rainfall shock, the estimates of the effect of rainfall shock on child outcomes will be unbiased. This identification strategy is similar to the differential exposure to months of crisis in alignment with the month of birth in Hidrobo (2014). The identification assumption is that in the absence of rainfall deviation or shocks within a village, health and productivity outcomes are likely to be similarly distributed across periods within the same community. This means that in the absence of a shock, the average difference in outcomes for children with a similar age gap would be the same within the same community. In order for this assumption to hold, the time trends in early outcome variables must be linear.

4.5.2.1 Linear Rainfall Deviation

$$\text{Child Health}_{ict} = \alpha_c + \gamma_t + \phi_a + \sum_{p=k-1}^{k+1} \varphi_p \,\text{Rainfall Deviation}_{c,p} + X_i' \,\theta_x + Z_{ct}' \,\theta_z + \varepsilon_{ict} \tag{4.4}$$

where $\text{Child Health}_{ict}$ represents WAZ and HAZ for children aged six to 59 months for an observation *i* in community *c* for a survey round t. The subscript t indicates the survey year in which the child was measured. The z-score measures for each child differ across surveys in the case of the panel survey. $\text{Rainfall Deviation}_{c,p}$ ranges across the agricultural season prior to the year of birth, denoted by subscript *k-1*, first year of birth by k and second year of birth by *k+1*. We also consider additional child health outcome variables for the linear rainfall deviation measure in our empirical analysis using underweight, moderate and severe stunting indicators. α_c in equation (4.4) is the community fixed effect and γ_t is the interview season and the year of interview fixed effect.[57] We use the age (in years) fixed effect ϕ_a in our model to rectify concerns about the inter-age group effect in our regression. φ_p is the parameter of interest, namely the coefficient on community rainfall variation around the time of birth ($\text{Rainfall Deviation}_{c,p}$). φ_p measures the rainfall dynamics of the agricultural season around a child's birth, hence directly linking shocks around the period of birth to malnutrition, which may be triggered by critical-period programming of shocks on short-term and general welfare outcomes.

We also use seasonal temperature at the community level as a control due to the adverse effect of excess heat on foetal health, which may impact the child's growth gradients in the short term and their welfare in adulthood (Hancock *et al.* 2007; Martinez *et al.*, 2011; Huang *et al.* 2013a; Wilde *et al.*, 2014; Barreca *et al.*, 2015; Isen *et al.*, 2015). The temperature measure enters into the regression of our preferred model as a deviation from the historical average.[58] X is a vector of household and individual level covariate, namely household non-agricultural asset valuation, household size, the gender of the head of household, average household age and the education and occupational categories of the head of household. Individual controls mainly consist of individual demographic characteristics, namely the child's age and gender. Z is a vector of community level controls to enhance precision in our estimation.[59] The error term (ε_{ict}) accounts for

[57] It is important to note that a variation namely the month of interview by year fixed effect is used during the estimation process with no apparent difference to the estimates of the preferred model.

[58] Linear use of seasonal temperature in the regression gives the same results as the temperature deviation measure.

[59] This includes indicator variables for access to roads, measured by year-round road usability, and quality of road infrastructure, measured by ease of road passage, the presence of a daily market within the community, the presence of a weekly market within the community, the presence of a phone call centre within the community, the presence of chemists within the community, the presence of a government-run health clinic within the community, the availability of a medical practitioner in the government medical centre, sales of subsidised bed nets within the community, the presence of a bank within the community, a representative from the community at the parliament, and school quality. Other community level controls include the average number of months roads are usable for buses and lorries in a year, number of teachers in government primary schools, number of teachers in government secondary schools, number of pupils in government primary schools, number of pupils in government secondary schools, number of private

unobserved time-variant community characteristics not captured by the trend and unobserved individual characteristics. The error term of the model is assumed to be identically and independently distributed (iid) across localities but correlated within localities; hence, standard errors are clustered by locality.

4.5.2.2 Disaggregated Extreme Weather Shocks: Drought and Flood

In general, variety of deviation shock measures have been used to capture shocks in the literature. We use indicator variables, in addition to these, for extreme precipitation namely drought or flood shock to complement the existing knowledge of the impact of early life shock dynamics in this paper. We regress child health outcomes on early life drought and flood shock incidences in equation (4.5) below.

$$\text{Child Health}_{ict} = \alpha_c + \gamma_t + \phi_a + \sum_{p=k-1}^{k+1} D_p \text{ Drought Shock}_{c,p} + \sum_{p=k-1}^{k+1} F_p \text{ Flood Shock}_{c,p} + X_i' \theta_x + Z_{ct}' \theta_z + \varepsilon_{ict} \quad (4.5)$$

where coefficients D_p and F_p capture the differential impacts of drought and flood shocks from in-utero to second year of birth on child anthropometric health outcomes. Also, general welfare effects of extreme rainfall shocks are examined using equation (4.6) below.

$$\text{General Welfare}_{ict} = \alpha_c + \gamma_t + \Gamma_a + \sum_{p=k-1}^{k+1} D_p \text{ Drought Shock}_{c,p} + \sum_{p=k-1}^{k+1} F_p \text{ Flood Shock}_{c,p} + X_i' \theta_x + Z_{ct}' \theta_z + \varepsilon_{ict} \quad (4.6)$$

where Γ_a is the year-of-birth fixed effect (similar to the identification approach in Maccini and Yang 2009 and Adhvaryu *et al.* 2014).

4.6 Results

4.6.1 Anthropometric Health Outcomes

4.6.1.1. The Impact of Early Life Rainfall Deviation on WAZ and HAZ

We first present estimates of the regression of WAZ and HAZ on linear rainfall deviation. Results show that rainfall around the period of birth substantively affects average growth trajectories of children between the ages of six and 59 months in Malawi. Coefficient estimates of the linear rainfall deviation around period of birth on anthropometric health measures in Tables 4.2 and 4.3 reveal that negative (positive) rainfall movement decreases (increases) WAZ and HAZ respectively. Columns (1) to (5) of Table 4.2 report

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primary schools, number of private secondary schools, distance to community health clinic, community industry, and the number of churches and mosques.

the effect of rainfall deviation on the age standardised weight scores of children within the community by systematically controlling for outlined covariates and fixed effects respectively.

In column (1), we present the coefficient estimates of a regression which includes a community-level temperature measure (deviation from the 30-year historical average) as well as a community fixed effect, a year fixed effect and a month-of-birth fixed effect. Column (2) adds community, household and individual covariates as control variables to the model. Column (3) includes an interview month-by-year fixed effect to control for discrepancies associated with weather conditions in different months of the year, while column (4) analogously includes interview season by year fixed effect to ensure seasonal variations do not drive our estimates of rainfall deviation on WAZ. Lastly, column (5) additionally includes an age cohort fixed effect to purge our estimates of the inter-age variation of the impact of shocks on WAZ among children.

The richest specification in Table 4.2 Column (5) reports in-utero, first and second year-of-birth rainfall shock estimates of 1.068, 0.695 and 1.018 respectively, and are significant at the 1 percent level. Rainfall shocks are measured in log-ratio; hence, each measure percentage deviation while WAZ is in standard deviation units of children health scores. A 10% lower than the norm rainfall indicates a negative rainfall shock of approximately 0.1 log-point. Hence, the impact of such a negative shock on WAZ is a reduction of 0.107, 0.070 and 0.102 standard deviation units in average weight for shocks during in-utero, year of birth and year after birth respectively. Given that the average WAZ from our summary statistics is -0.607 standard deviation, a 0.1 log-point in-utero rainfall shock translates to an approximately 18% decrease in the average standardised weight measure for children. The shock effects for birth year and the year after are equally 12% and 17%. The effects are extremely robust across different specifications.

Table 4.3 reports the coefficient estimates of rainfall shocks around the period of birth on the average age standardised height scores as an alternative measure of child development. As expected, rainfall shock estimates are not significantly different across specifications from Columns (1) to (5) of Table 4.3. We focus our attention on the standard model in column (5) for the purpose of the interpretation of results. Coefficient estimates of column (5) indicate that a 0.1 log-point negative rainfall shock reduces average standardised height scores by 0.236, 0.176 and 0.160 standard deviation units respectively for in-utero to year-after-birth periods. The impact of these estimates with respect to mean HAZ of -1.594 is an average decrease of 15%, 11% and 10% in HAZ for exposures at in-utero, birth year and year after respectively. Our results, in this case, imply an interpretation consistent with an adverse (positive) health effect of negative (positive) rainfall deviations. We investigated this further by examining our main results in a disaggregated framework, using extreme shocks to highlight the potential mechanisms along the types of shock in this context. This allowed us to complement linear rainfall deviation specifications explored for the impact of precipitation patterns in the literature (Maccini and Yang 2009; Rabassa *et al.* 2014; Rocha and Soares 2015).[60]

4.6.1.2. The Impact of Early Life Rainfall Deviation on Alternative Child Health Measures

Motivated by the literature on nutritional health effect of shocks (Giles and Satriawan 2015), we examine the impact of early life shocks on indicators for underweightness and stunting. The stunting measure examines two critical indices – moderate and severe stunting. Table 4.4 Columns (1) to (3) present point estimates of rainfall shocks around the time of birth on underweightness and stunting indicators. The use of underweightness and stunting indicators in this paper help us to gain further insights into the depth of early life malnutrition and child health nexus. While coefficient estimates reveal that underweight and moderate stunting outcomes in columns (1) and (2) are affected by in-utero and year-of-birth rainfall shocks only, the results from column (3) reveal a result consistent with the baseline effects in Tables 4.2 and 4.3.

The point estimates of column (1) show that in-utero and year-of-birth rainfall deviation measures have a considerable impact on the proportion of underweight children

[60] We would also like to rule out that the results are driven by spatial correlation of rainfall shocks, as elucidated by Lind (2015). Although we make use of less aggregated rainfall data compared to district level measures common in the literature, we want to make sure that village level rainfall shocks are still not serially correlated with the average health outcomes of the children. For this purpose, we regress children nutritional health measures on the village level long-term rainfall variability (measured by the standard deviation of 30-year historical rainfall around the season of birth). Appendix Table C1 in the appendix reports the results using both WAZ and HAZ measures of children's nutritional health outcomes. While long-term village level rainfall variability devised for in-utero period marginally affects WAZ and HAZ respectively, the magnitude of the coefficient estimates are not comparable to corresponding standard model rainfall shock coefficient estimates in Tables 4.2 and 4.3. In other words, we do not find any sizeable effect of long-term rainfall variability on these measures, reducing any remaining concerns around spatial correlation of rainfall in our repeated cross-section framework.

at the community level. Rainfall deviation estimates are -0.119 and -0.078 respectively (significant at 1 and 5 percent levels). For the purpose of the interpretation of the results, we adopt a benchmark of 0.1 log-point negative rainfall shock for each reference period, as adopted earlier. A 0.1 log-point negative rainfall shock during the pregnancy of a child and the first year translate to an increase in the likelihood of having lower than expected weight by 0.012 and 0.008 percentage points. Given the sample ratio of underweight children of 0.090 in our sample, these estimates indicate a 13% and 9% increase in the average likelihood of underweight children in the event of a 10% decrease in rainfall level relative to normal rainfall at the local level.

With regard to stunting indicators, in-utero and first-year rainfall shock coefficient estimates present -0.337 and -0.235 respectively for moderate stunting outcome in column (2) – both significant at the 1 percent level. This shows that a 0.1 log-point negative rainfall shock during the pregnancy of a child and the first year lead to a corresponding increase in the likelihood of stunting by 0.034 and 0.024 percentage points. In reference to the baseline mean of 0.391, the estimates correspond to an average of a 9% and 6% increase. Also, in-utero, first-year and second-year rainfall deviation coefficient estimates are -0.192, -0.177 and -0.104 for severe stunting outcomes in column (3). A 0.1 log-point negative rainfall shock between the pregnancy period and second year after birth increases severe stunting ratio by 0.019, 0.018 and 0.010 respectively. Given a baseline mean for severe stunting of 0.174, the in-utero rainfall deviation estimate leads to an 11% average increase in the severe stunting rate; while 10% and 6% average effects are associated with first and second-year impacts.

4.6.1.3. The Impact of Drought and Flood Shocks on WAZ and HAZ

Table 4.5 repeats the regression of the baseline models on Tables 4.2 and 4.3 using drought and flood shocks constructed from equations (4.2) and (4.3) respectively. Columns (1) and (2) of Table 4.5 report coefficient estimates of drought and flood shocks from the in-utero period until the second year of birth on WAZ and HAZ respectively. Coefficient estimates of shocks for WAZ in column (1) show that an incidence of in-utero drought shock decreases WAZ by 0.089 standard deviations while wet shock increases it by 0.194 standard deviations. While the in-utero wet shock is significant at the 1 percent level, the drought shock counterpart is only marginally significant at 10 percent. In contrast, drought shocks for the first and second years of birth correspondingly decrease the standardised weight measure of children by 0.105 and 0.263 standard deviations units (respectively significant at 5 and 1 percent levels), while wet shocks are insignificant.

The coefficient estimates of drought and wet shocks within the baseline mean of -0.607 standard deviations mean that an incidence of in-utero drought shock decreases the average WAZ by 15%, while wet shock increases it by 32%. Drought shocks in the first and second years further decrease average WAZ at the locality by 17% and 43%. Our results do not show any discernible impact for the wet shock component as the coefficient estimates weaken and turn insignificant.

The in-utero drought shock incidence decreases HAZ by 0.223 standard deviations while the wet shock counterpart increases it by 0.416 standard deviations – both estimates are significant at 1 percent level. First year drought shock incidence significantly decreases HAZ by 0.247 standard deviations while the wet shock counterpart significantly increases it by 0.203 standard deviations. While the drought shock incidence of the second year decreases HAZ by 0.435 standard deviation units, wet shock incidence has no impact. Given the mean HAZ in our sample, in-utero drought and wet shock incidences lead to a corresponding decrease and increase in standardised height scores of 14% and 26%. Also, a first-year drought shock incidence induces a decrease in standardised height scores measure by 15%, while the wet shock component increases it by 13%. Lastly, the second year drought shock incidence decreases the standardised height score by 27%, while the wet shock incidence has no apparent effect.

An important trend in the above results is the apparent asymmetric effects of second year drought and wet shocks on age standardised weight and height scores. Secondly, while both in-utero drought and wet shocks affect our health measures, the drought shock estimates strengthen from the in-utero to second year periods, while the wet shock estimates fade away and become insignificant. The asymmetric pattern in the magnitudes of the coefficient estimates of drought and wet shocks on WAZ outcome – the weight component of child growth trajectory – starting from the first year of birth suggests some evidence to support nutrition as an important transmission mechanism from exogenous rainfall shock to children's growth status in developing countries. However, the positive impact of in-utero wet shocks supports the potential benefits of sufficient rainfall and not necessarily an excessive dimension in terms of floods (Comfort 2016).

As a robustness check, we use standard deviation movements of precipitation measures above and below a 30-year historical average, similar to Comfort (2016). The results from this exercise show that the asymmetric impacts of negative and positive shocks are more visible for birth year and year after birth respectively (results available from the author upon request). This is similar to the use of bins of rainfall shock to understand the underlying mechanisms of shock on outcomes variables (Sekhri and Storeygard 2014). Contrasting evidence of negative and positive shock patterns between Sekhri and Storeygard (2014) and Comfort (2016) may be attributed to differential contexts and outcome variables. Our findings align with the literature on the adverse impact of drought shocks and the positive, but fading, impact of wet shock on welfare outcomes. Also, we conducted a sensitivity analysis on all the main results by estimating the impact of rainfall deviation and shocks on health using a sample of children aged between six and 35 months, similarly to some studies (Rabassa *et al.* 2014). We did not find significantly different coefficient estimates across samples (Appendix Table C2 and Appendix Table C3).[61]

4.6.1.4. Heterogeneous Impacts of Early Life Rainfall Deviation (Boys and Girls)

Charts 1 and 2 of Table 4.6 present the coefficient estimates of the impact of rainfall deviations on children health measures. Panel A of each chart focuses on weight-related outcomes while Panel B centres on height-related health outcomes. The results from Chart 1 for boys show that estimates of rainfall deviation are important for WAZ and HAZ, which are the priority children's health outcomes in this paper. Also, indicators for underweight, moderate and severe stunting particularly show the effects for in-utero and first year exposure to rainfall deviation for boys. Similarly, Chart 2 presents rainfall deviation measures that have a significant impact on girls' growth trajectories for WAZ and HAZ. Deviation estimates by time reference for girls are marginally stronger relative to boys for the same outcome variables.[62] While only in-utero shock affects the underweight measure, all shock references impact the moderate and severe stunting indicators for the girls. In summary, the above results do not reveal any substantial difference in the response of growth trajectories for boys and girls. This is an indication

[61] While the shock estimates slightly reduces for the new focus sample of observations, a pairwise Wald test of the equivalence of coefficient estimates shows that corresponding rainfall shock estimates are not significantly different across sample estimations.

[62] A Wald test of equality of estimates indicates no significant difference among boys and girls.

that nutritional health measures between boys and girls do not differentially respond to early life rainfall shocks in our sample.

4.6.1.5. Other Explanations for the Impact of Rainfall Deviation on Child Health

In addition to potential pathways for the impact of rainfall shocks on health, there could be transmission of health directly from the environmental factors potentially through mothers to foetuses during pregnancy. This perspective negates widely acclaimed nutritional basis for WAZ and HAZ measures. We test if children's health may be directly linked to disease environment of early life rainfall deviation rather than harvest from the weather patterns. To investigate this pathway, we use a non-season rainfall variation as measures of rainfall deviations for a non-nutritional explanation of rainfall effects on WAZ and HAZ. This approach closely follows Rocha and Soares (2015) in constructing shocks for a newer perspective and to investigate other mechanisms of early life rainfall impact beyond nutrition. Panels A and B of Table 4.7 present coefficient estimates of environmental-oriented rainfall deviations for WAZ and HAZ respectively. We observe that the adoption of non-seasonal rainfall deviation reveals smaller point estimates when compared to coefficient estimates reported for corresponding outcome variables in Tables 4.2 and 4.3 respectively. However, the significance of associated pre in-utero rainfall deviation coefficient estimates in columns (2) and (4) of Table 4.7 may signal some environmental-driven shock impacts for growth trajectories of rural children in Malawi.

4.6.2 Health and Labour Market Outcomes

4.6.2.1. Chronic Ailments, Health Expenditure and Rate of Hospitalisation

In this section, we focus on the impact of early life rainfall shocks on basic health outcomes of individuals in rural Malawi. The variables of interest in this regard consist of chronic health outcomes and individual level health expenditures. We explore the rich health data in the household survey to create an indicator variable for chronic ailment[63] for individual respondents in our sample, and we use recent four-week health expenditure in various dimensions[64] for the typical health expenditure of individuals in our sample. We also explore the previous year's individual level hospitalisation indicator as an important health outcome to investigate the impact of exposure to early life extreme shock events on the average rate of hospitalisation for concerned groups. Since health outcomes above are demand driven, we include community-level, supply-side health facilities as controls in our estimation to account for differences in availability and access to health facilities across communities.

The results for recent health expenditure and chronic disease indicator are reported in Appendix Table C4 in the appendix. We did not find any unique pattern for the impact of early life extreme rainfall shocks on health expenditure patterns or on the average number of people currently suffering from a chronic ailment due to exposure to early life extreme weather events. On the other hand, we found an impact of in-utero rainfall deviation on the average hospitalisation rate of exposed individuals (Table 4.8). Our result shows that this effect is specific to early life drought shock, while the wet shock component did not have any effect. Table 4.8 Columns (1) to (3) present the coefficient estimates of the two extreme rainfall shock components of all individuals. We focus our attention on the preferred model in column (3), which includes temperature shock, community of birth, season and year-of-birth fixed effects, and community linear trends, similarly to the approach used for broader health outcomes in the literature (Adhvaryu *et al.* 2014). Lastly, we include individual, household and community level controls. The coefficient estimate for in-utero drought shock

[63] We focus on the potential chronic health conditions that may be related to early life shocks in our sample where 1 represents individual affected by a chronic health disease; 0, otherwise.

[64] The health expenditures are reported in *Tanzanian Shillings* for the recent four weeks. The components of the health spending from the questionnaire include medical, prescription and non-prescription health expenditures in the recent four weeks. The natural logarithm of the health expenditure is used in the regression in line with the common practice in the literature.

shows an average increase of a 0.8 percentage points hospitalisation rate for individuals exposed to drought shock. The estimate is significant at the 5 percent level. The in-utero wet shock estimate is a 0.01 percentage points increase in the hospitalisation rate, with no significance at any level. The coefficient estimates for drought and wet shocks for first and second year are equally weak and insignificant at the traditional levels. The impact of the incidence of drought shock on the hospitalisation rate is measured at 23.5 percent.

We separate the impact of extreme early life shocks on hospitalisation rates by gender difference. Columns (1) to (2) of Table 4.9 present the coefficient estimates of the extreme rainfall shock events on the hospitalisation rates for male and female samples respectively. Each regression refers to the preferred model in Column (3) of Table 4.8. In column (1), both in-utero drought and wet shock estimates are weak and insignificant for male respondents whilst the in-utero drought shock estimate is stronger and significant at 1 percent compared to the in-utero wet shock for the female observations in column (2). The in-utero drought shock estimate for females is 0.014. Given the mean hospitalisation rate for females, this coefficient estimate corresponds to a 35 percent impact for the in-utero period drought shock on the hospitalisation rate for females. This heterogeneous result establishes the predominance of the impact of in-utero drought shock on hospitalisation among females.

We investigated the role of intervention programmes on the impact of early life shocks on the rate of hospitalisation. We focused on food intervention programmes or supplementary feeding arrangements for malnourished individuals in the MHS data using the last two waves of the survey with identical social safety net questions. These included questions on free food and supplementary feeding intervention programmes for households. Of the 40,394 observations reported in Table 4.8, the last two waves comprise 16,026, for which household level social safety net and intervention programme questions are the same and match the hospitalisation context in our data.[65] We formally tested the role of supplementary feeding programmes in an econometric framework using the modified

[65] The wording of the safety net section for the 2004-2005 wave refers to recent years of household access while the same question in the 2010-2011 and 2013 surveys refers to access in the previous 12 months which matches the hospitalisation question timeframe. Inconsistencies across these waves may lead to variable mismatch and reporting and measurement errors, which may bias the interactive term estimates in our model.

version of equation (4.6), where drought shock for each reference time was interacted with an indicator of household supplementary feeding in the past twelve months.[66] While the drought shock parameters convey the established impact of adverse early life shocks on the rate of hospitalisation, the interaction term depicts the role of the feeding programme in that regard. The results presented in Table 4.12 suggest a gender-specific asymmetric effectiveness of food intervention on the impact of early life droughts. Column (1) reveals that the incidence of in-utero drought shock increases the likelihood of hospitalisation by 1.3 percentage points while the interaction term presents a counteractive effect of a reduction in the hospitalisation rate by 2.1 percentage points. This result indicates that households' access to food intervention mediates the impact of in-utero drought shock reported earlier in Table 4.8. We observe that this pattern holds for the male observations for whom an increased hospitalisation rate for individuals exposed to in-utero drought shock is counteracted by more than a compensatory reduction in the hospitalisation rate for individuals who have access to food intervention (Column 2). On the other hand, while the in-utero drought shock estimate remains roughly the same for female observations, the interaction term is weak and insignificant at the conventional levels.

4.6.2.2 Labour outcomes: Hours of Productivity

Next we report the coefficient estimates of various productivity hours of our regression in columns (1) – (5) of Table 4.10[67]. Table 4.10 Column (1) presents the shock estimates for hours spent in agricultural labour in the past seven days. The result shows an estimate of -0.417 for in-utero drought shock (significant at 5 percent). Although the in-utero wet shock coefficient of -0.202 is large, it is not significant at the traditional levels. On the other hand, the coefficient estimates for first and second years indicate weak impacts of shocks linked to

[66] $\text{General Welfare}_{ict} = \alpha_c + \gamma_t + \Gamma_a + \sum_{p=k-1}^{k+1} D_p \text{ Drought Shock}_{c,p} + \sum_{p=k-1}^{k+1} I_p \text{ Drought Shock}_{c,p} * \text{Feeding Program}_h + X_i' \theta_x + Z_{ct}' \theta_z + \varepsilon_{ict} \qquad (4.7)$

[67] We use the number of hours spent on each economic activity as a more accurate measure of productivity at the individual level. We use the hours of economic engagement from both the formal and informal sectors, which include agricultural, informal business, household chores, paid formal labour and unpaid apprenticeship programmes (as expected, more individuals partake in the agricultural sector and informal business activities while an insignificant fraction of the sample takes part in formal jobs and unpaid apprenticeship programs). The sample size of observations that fall within each category are 30,585; 30,585; 30,590; 30,589 and 13,172 respectively (observations investigated are restricted to individuals above five years of age who report hours worked on specific economic activity in the previous seven days).

those time references on agricultural productivity. Similarly, column (2) reports an in-utero drought shock estimate of -0.238 for informal business while all other shock estimates including in-utero wet shock are insignificant. The impacts of in-utero drought shock on agricultural and informal business productivity levels given the respective baseline mean are a 5.25 percent and 22 percent decrease. The results for the impact of shocks on other labour market engagements – reported in columns (3) to (5) – do not show a significant effect.

In Table 4.11, we split the sample observations by gender of respondents for agricultural and informal business engagements. We restrict our analysis to these two outcomes due to the established impact of in-utero drought shock on them. Columns (2) and (4) reveal stronger and significant in-utero drought shock coefficient estimates[68] in the productivity hours of female within the agricultural and informal business sectors respectively, similar to findings in the overall sample, while estimates for males are generally weak and insignificant. The impacts of the in-utero drought shock on agricultural and informal business engagements are 9 percent and 38 percent relative to the baseline mean for females. This heterogeneous pattern is generally consistent with previous results on hospitalisation rates in Table 4.9.

4.7 Discussion and Conclusion

This paper re-examines the dynamics of early life weather shocks on the anthropometric health measures of children and later life welfare outcomes of rural households in Malawi. The study contributes to the literature in four major ways. First, the paper emphasises disaggregated extreme weather events with respect to drought and wet shocks. This exercise directly extends the context of numerous linear rainfall deviation models used in the existing literature for both the short-term and long-term impacts of weather patterns (Maccini and Yang 2009; Rabassa *et al.* 2014, Thai and Falaris 2014). Second, the paper contributes to the literature with estimates on welfare outcomes, such as productivity and hospitalisation rates, which have been previously ignored due to the lack of adequate data to capture these in the literature. Third, the paper provides evidence for both the short-term and medium-term

[68] For the agricultural sector, our estimates also reveal that in-utero wet shock has a deleterious effect on the productivity of females of a similar magnitude as drought shock – significant at the 5 percent level.

impact of extreme early life weather events in a developing country setting. Lastly, the paper provides a gender specific differential impact of early life shocks on later life welfare.

Using repeated cross-section data from the World Bank household surveys in Malawi, we find that early life rainfall deviation and extreme shock events affect age standardised weight and height scores of children aged six to 59 months. Coefficient estimates from our disaggregated extreme shock model reveal that the effect of extreme early life shock events is prominent for drought shocks. The results from the linear rainfall deviation specification regarding children's standardised growth status reported in Tables 4.2 and 4.3 show that negative (positive) rainfall shock decreases (increases) standardised weight and height scores of children. Specifically, estimates show that a 0.1 log points adverse (positive) rainfall shock at the in-utero, first and second years of life decreases (increases) the age standardised weight scores of children by 18 percent, 12 percent and 17 percent respectively. Corresponding effects of the shocks on age standardised height scores are 15 percent, 11 percent and 10 percent. This finding is consistent with results from prominent papers in related literature. While the interpretation of the linear shock framework is unambiguous, this study focuses more on disaggregated extreme weather shock dynamics. The disaggregated extreme shock model reveals that drought shock leads to a resultant average decrease of 15%, 17% and 43% in WAZ for shocks experienced at the in-utero stage, the first year and the second year respectively. Also, the impacts of an incident of drought shock on HAZ are 14%, 15% and 27% respectively. While the impacts of drought shock strengthen progressively from in-utero to the second-year period and remain significant, the impact of wet shock deteriorates and becomes insignificant. Our findings on disaggregated shocks impacts are robust for alternative shock specifications, such as standard deviation movements below and above the historical rainfall norm.

We look at the long-term outcomes for all individuals given that we have access to information on the place of birth of individuals in the MHS data. The results from long-term outcomes show an impact of drought shocks on welfare indicators as measured by the hospitalisation rate and hours of work in informal economic activities. Our findings in this regard show that in-utero drought shock increases the hospitalisation rate and reduces the productivity level of females while no effect is found for males. Also, there is no evidence of an impact of the incidence of drought or wet shocks on the hospitalisation rate and productivity level for the first and second years of birth respectively. The gender-specific heterogeneous findings align with the long-term impact of shocks at the time of birth on adult socioeconomic, outcomes as revealed in Maccini and Yang (2009). Also, our generalised results are consistent with the findings by Adhvaryu *et al.* (2014) and Majid (2015), which investigate the adulthood impact of early life shocks in other developing settings. We investigate the role of food intervention programmes on the adverse effects of drought shock on the hospitalisation rate. Our result in this regard reveals that access to nutrition intervention programmes mediates the persistent impact of in-utero drought shock on the hospitalisation rate. While our result documents the cushioning effect for the male observations, we did not find the food intervention programme to be useful in mediating the adverse effect of early life drought shock for females.

Our results for children's anthropometric health measures do not reveal any gender-specific heterogeneous response of children growth progression to early life rainfall. This short-term health results corroborate the findings in Rabassa *et al.* (2014) for Nigeria. Although multiple agricultural cultivation reference to rainfall shocks in their paper do not correspond to periods of birth shocks, our findings complement this literature by specifically linking the effects of rainfall shock to the incidence of drought shock in the early life period as a way of formulating a vibrant policy to cushion nutrition shocks at the early stage of life, which is an important component of child growth. The persistent widening of gender specific in-utero drought shock estimates for other welfare outcomes in the absence of differential short-run evidence should not be mixed as the sample of observations are from entirely different cohorts.

Lastly, this paper contributes to a small, but growing, evidence on the vulnerability of rural households to exogenous weather patterns and how this imposes short-term and long-term future costs on welfare of individuals. While momentary effects persist due to a lack of a consumption smoothing capacity outside the agricultural sector in these areas, indirect long-term effects of exposure to early life shocks seem to be similarly prevalent. As revealed in our results, drought shock may be relatively more impactful on welfare outcomes than wet shock since irrigation systems used to mitigate the impact of drought can be quite expensive to manage and technical to handle, while excess rainfall can be easily channelled in such a manner that will not adversely affect agricultural outputs in rural areas. Given that the most important potential pathway of our effect is nutrition at the early life period, more attention is required to address the malnutrition of pregnant mothers and babies in the Sub-Saharan African countries during extreme weather conditions – especially drought. In this context, our paper further strengthens the stance of the economics literature in alignment with the established biomedical background of the welfare effect of in-utero nutritional deficits (Wu *et al.* 2004; Zhu *et al.* 2006; Abu-Saad and Fraser 2010). Actions in this direction will help stabilise women during pregnancy periods and reduce the high rate of maternal mortality cases, as revealed by Comfort (2016). Similarly, this step will be helpful for protecting childhood and adulthood welfare outcomes of foetuses and new-borns.

Chapter 4: Figures and Tables

Figure 4.1: Weight-for-age Z Scores Distribution for Children in Malawi (2004 – 2013).

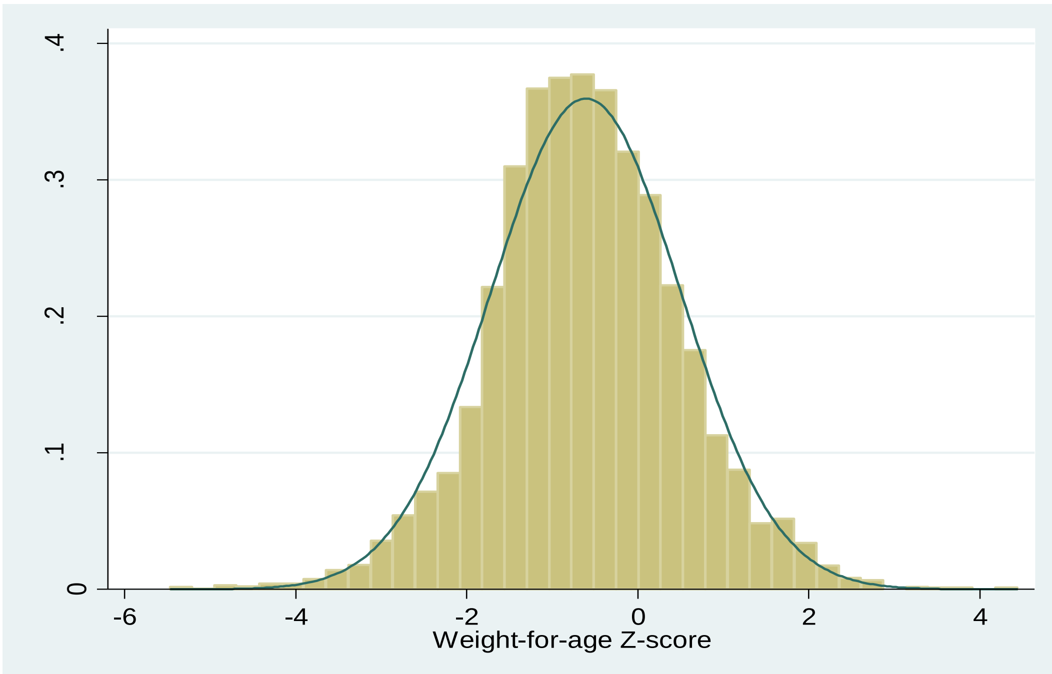

Figure 4.2: Height-for-age Z Scores Distribution for Children in Malawi (2004 – 2013).

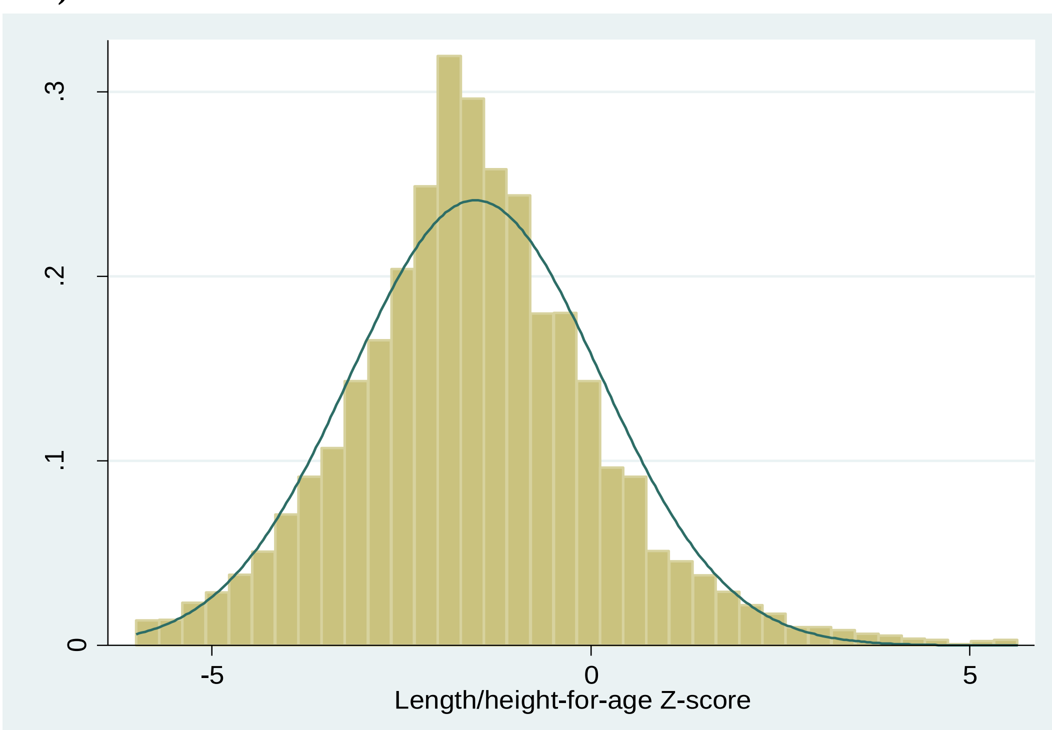

Table 4.1: Summary Statistics for Children Aged 6 to 59 Months and Household Covariates.

Variables	Mean	Std. Dev.	Obs.
Section A: WAZ and HAZ			
Total Sample			
WAZ	-0.607	1.109	6,422
HAZ	-1.594	1.623	6,695
Boys			
WAZ	-0.666	1.120	3,159
HAZ	-1.680	1.644	3,300
Girls			
WAZ	-0.549	1.095	3,263
HAZ	-1.510	1.600	3,395
6 – 11 months			
WAZ	-0.136	1.297	742
HAZ	-0.536	1.865	784
12 – 24 months			
WAZ	-0.538	1.186	1,419
HAZ	-1.494	1.721	1,493
25 – 36 months			
WAZ	-0.628	1.096	1,330
HAZ	-1.884	1.554	1,391
37 – 48 months			
WAZ	-0.680	0.990	1,589
HAZ	-1.812	1.401	1,646
49 – 59 months			
WAZ	-0.831	0.965	1,342
HAZ	-1.750	1.425	1,381
Section B: Ind and HH characteristics			
Age (in years)	2.195	1.315	
Female (indicator)	0.507	0.500	
Total value of household assets ('000 Malawi Kwacha)	17.847	377.304	
Household Size	5.889	2.333	
Number of children	2.042	1.727	
Average household age	16.568	4.679	
Age of the head of household	37.494	12.363	
Male head of household (indicator)	0.839	0.367	
Head of household educated (indicator)	0.220	0.414	

Notes: Table 4.1 above reports the summary statistics of WAZ and HAZ in Section A; and individuals and household characteristics in Section B. Observations are restricted to those living in rural areas of Malawi. Total value of household assets in Panel B is measured in thousands of Malawian Kwacha.

Table 4.2: The Impact of Early Life Rainfall Deviation on Weight-for-Age Z-Scores of Children In Malawi.

	Dependent Variable : WAZ				
Variables	(1)	(2)	(3)	(4)	(5)
In-utero deviation	0.979***	0.973***	0.992***	0.979***	1.068***
	(0.143)	(0.142)	(0.142)	(0.142)	(0.142)
First year deviation	0.692***	0.685***	0.693***	0.688***	0.695***
	(0.124)	(0.125)	(0.125)	(0.125)	(0.124)
Second year deviation	0.876***	0.873***	0.904***	0.882***	1.018***
	(0.139)	(0.137)	(0.137)	(0.136)	(0.142)
Temperature deviation	Yes	Yes	Yes	Yes	Yes
Community FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	-
Month of birth FE	Yes	Yes	Yes	Yes	Yes
Controls (Ind, HH and Comm)	No	Yes	Yes	Yes	Yes
Interview month X Year FE	No	No	Yes	No	-
Interview season X Year FE	No	No	No	Yes	Yes
Cohort FE	No	No	No	No	Yes
Observations	6,422	6,422	6,422	6,422	6,422
R-squared	0.232	0.244	0.252	0.244	0.257

Notes: Table 4.2 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on WAZ for 6,422 observations of children aged 6 to 59 months. All estimations focus on observations resident in rural areas in line with the literature on the impact of weather shocks on welfare outcomes in developing countries. Rainfall deviation for each period is constructed as the deviation of the natural log of the community level rainfall from the corresponding 30-year historical average. Yearly precipitation measures refer to the agricultural season's rainfall for a locality, measured as the total precipitation for wet and dry seasons, corresponding to November-April and May-October respectively. All estimations are clustered at the community level, with a total of 590 communities comprising the focus sample. Community level controls include indicator variables for access to roads, measured by year-round road usability, and quality of road infrastructure, measured by ease of road passage, the presence of a daily market within the community, the presence of a weekly market within the community, the presence of a phone call centre within the community, the presence of chemist within the community, the presence of a government-run health clinic within the community, the availability of a medical practitioner in the government medical centre, sales of subsidised bed nets within the community, the presence of a bank within the community, a representative at the parliament from the community, and school quality. Other community level controls include average number of months roads are usable for buses and lorries in a year, number of teachers in government primary schools, number of teachers in government secondary schools, numbers of pupils in government primary schools, number of pupils in government secondary schools, number of private primary schools, number of private secondary schools, distance to community health clinic, community industry, and the number of churches and mosques. Household controls include household non-agricultural assets in Malawi Kwacha and household demographic characteristics, such as household size, gender of the head of household, average household age, and the education and occupational categories of the head of household. Individual controls mainly consist of individual demographic characteristics, namely child's age and gender. Robust standard errors (clustered at the community level) are reported in parentheses. ***,**,* represent significance at the 1 percent, 5 percent and 10 percent levels respectively.

Table 4.3: The Impact of Early Life Rainfall Deviation on Height-for-Age Z-Scores for Children In Malawi.

	Dependent Variable : HAZ				
Variables	(1)	(2)	(3)	(4)	(5)
In-utero deviation	2.244***	2.281***	2.303***	2.282***	2.357***
	(0.213)	(0.214)	(0.213)	(0.214)	(0.216)
First year deviation	1.768***	1.764***	1.775***	1.764***	1.762***
	(0.176)	(0.175)	(0.175)	(0.175)	(0.172)
Second year deviation	1.497***	1.508***	1.540***	1.511***	1.601***
	(0.208)	(0.207)	(0.208)	(0.207)	(0.212)
Temperature shock	Yes	Yes	Yes	Yes	Yes
Community FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	-
Month of birth FE	Yes	Yes	Yes	Yes	Yes
Controls (Ind, HH and Comm)	No	Yes	Yes	Yes	Yes
Interview month X Year FE	No	No	Yes	No	-
Interview season X Year FE	No	No	No	Yes	Yes
Cohort FE	No	No	No	No	Yes
Observations	6,695	6,695	6,695	6,695	6,695
R-squared	0.299	0.309	0.317	0.309	0.318

Notes: Table 4.3 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on HAZ for 6,695 observations of children aged 6 to 59 months. See Table 4.2 above for more notes and a list of additional controls. Robust standard errors (clustered at the community level) are reported in parentheses.
*** indicates significance at 1 percent level
** indicates significance at 5 percent level
* indicates significance at 10 percent level

Table 4.4: The Impact of Early Life Rainfall Deviation on Children Underweight and Stunting Indicators In Malawi.

	Dependent Variables :		
	Underweight	Moderate Stunting	Severe Stunting
Variables	(1)	(2)	(3)
In-utero deviation	-0.119***	-0.337***	-0.192***
	(0.034)	(0.060)	(0.047)
First year deviation	-0.078**	-0.235***	-0.177***
	(0.030)	(0.049)	(0.041)
Second year deviation	-0.041	-0.031	-0.104**
	(0.034)	(0.055)	(0.045)
Temperature shock	Yes	Yes	Yes
Community FE	Yes	Yes	Yes
Month of birth FE	Yes	Yes	Yes
Controls (Ind, HH and Comm)	Yes	Yes	Yes
Interview season X Year FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Observations	6,422	6,695	6,695
R-squared	0.256	0.202	0.174

Notes: Table 4.4 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on stunting and underweight indicators for 6,695 and 6,422 observations of children aged 6 to 59 months. Moderate stunting and severe stunting indicators are the ratio of children with HAZ below -2 and -3 standard deviations respectively while underweight indicator measures the ratio of children below -2 standard deviation WAZ. Baseline mean of underweight, moderate stunted and severe stunted children are 0.090, 0.391 and 0.174 respectively. Each column is a separate regression of the preferred model of Tables 4.2 and 4.3 presented above. Linear Probability Model is used in the estimation process for each column. See Table 4.2 above for more notes and a list of additional controls. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 4.5: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on WAZ and HAZ In Malawi.

	Dependent Variables :	
	WAZ	HAZ
Variables	(1)	(2)
In-utero drought shock	-0.089*	-0.223***
	(0.053)	(0.069)
In-utero flood shock	0.194***	0.416***
	(0.046)	(0.064)
First year drought shock	-0.105**	-0.247***
	(0.052)	(0.079)
First year flood shock	0.045	0.203***
	(0.047)	(0.064)
Second year drought shock	-0.263***	-0.435***
	(0.053)	(0.077)
Second year flood shock	0.034	-0.040
	(0.049)	(0.068)
Temperature shock	Yes	Yes
Community FE	Yes	Yes
Month of birth FE	Yes	Yes
Controls (Individual, Household and Community)	Yes	Yes
Interview season X Year FE	Yes	Yes
Cohort FE	Yes	Yes
Observations	6,422	6,695
R-squared	0.255	0.313

Notes: Table 4.5 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's extreme rainfall shocks on WAZ and HAZ for 6,695 and 6,422 observations of children aged 6 to 59 months. Each column is a separate regression of the preferred model of Tables 4.2 and 4.3 presented above. Drought shock is an indicator variable measured as 1 for locality rainfall measures below 25th percentile of 30-year historical rainfall distribution; and 0 otherwise. Analogously, flood shock is an indicator variable measured as 1 for locality rainfall measures above 75th percentile of 30-year historical rainfall distribution; and 0 otherwise See Table 4.2 above for detailed notes and a list of additional controls. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 4.6: The Impact of Early Life Rainfall Deviation on Children Health Trajectories In Malawi by Gender.

	Panel A:		Panel B:		
	WAZ	Underweight	HAZ	Moderate Stunting	Severe Stunting
Variables	(1)	(2)	(3)	(4)	(5)
Chart 1: Boys					
In-utero deviation	0.917***	-0.115*	2.321***	-0.392***	-0.230***
	(0.218)	(0.062)	(0.322)	(0.090)	(0.075)
First year deviation	0.553***	-0.086	1.672***	-0.209***	-0.197***
	(0.198)	(0.055)	(0.274)	(0.081)	(0.066)
Second year deviation	0.843***	-0.034	1.428***	0.048	-0.105
	(0.215)	(0.053)	(0.314)	(0.089)	(0.068)
R-squared	0.336	0.284	0.384	0.330	0.303
Observations	3,159	3,159	3,300	3,300	3,300
Chart 2: Girls					
In-utero deviation	1.388***	-0.134***	2.616***	-0.337***	-0.171***
	(0.208)	(0.047)	(0.319)	(0.088)	(0.066)
First year deviation	0.871***	-0.057	1.931***	-0.291***	-0.185***
	(0.180)	(0.044)	(0.245)	(0.076)	(0.060)
Second year deviation	1.325***	-0.047	1.922***	-0.144*	-0.131*
	(0.218)	(0.052)	(0.299)	(0.086)	(0.069)
R-squared	0.343	0.249	0.384	0.335	0.284
Observations	3,263	3,263	3,395	3,395	3,395

Notes: Table 4.6 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on health trajectories of children between 6 to 59 months by gender. Charts A and B respectively presents results for boys and girls. Each column is a separate regression of the preferred model of Tables 4.2 and 4.3 presented above including temperature shock and controls. The regressions also include community fixed effect, year fixed effect, month of birth fixed effect, interview month by year fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Tables 4.2 and 4.4 above for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 4.7: The Impact of Direct Rainfall Deviation Measures on WAZ and HAZ

	Panel A: WAZ		Panel B: HAZ	
Variables	(1)	(2)	(3)	(4)
Rainfall deviation measures				
12 – 24 months before birth		0.359**		0.491**
		(0.145)		(0.206)
0 – 12 months before birth	0.244**	0.418***	0.066	0.241
	(0.105)	(0.142)	(0.153)	(0.209)
1 – 12 months after birth		0.138		-0.352
		(0.147)		(0.216)
Constant	71.832	179.544*	42.974	68.025
	(110.205)	(104.411)	(153.897)	(160.603)
R-squared	0.247	0.261	0.295	0.309

Notes: Table 4.7 above presents estimates of rainfall deviation with reference to the exact month of birth of children. This is different from the use of agricultural cycle for deviation computations. Deviations are constructed as log-deviation from norm exactly as constructed in Rocha and Soares (2015). Each column is a separate regression of the preferred model of Tables 4.2 and 4.3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Table 4.2 for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 4.8: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Rate of Hospitalisation In Malawi.

	Dependent variable: Hospitalisation indicator		
Variables	(1)	(2)	(3)
In-utero drought shock	0.009**	0.009**	0.008**
	(0.003)	(0.003)	(0.003)
In-utero flood shock	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
First year drought shock	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)
First year flood shock	-0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.003)
Second year drought shock	0.005	0.005	0.004
	(0.003)	(0.003)	(0.003)
Second year flood shock	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
R-squared	0.039	0.039	0.043
Observations	40,394	40,394	40,394
Temperature deviation	Yes	Yes	Yes
Community of birth fixed effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Year of Birth Fixed Effect	Yes	Yes	Yes
Community of Birth Linear Trend	No	No	Yes
Controls	No	No	Yes

Notes: Table 4.8 above presents linear probability model coefficient estimates of the impact of early life extreme rainfall shocks on hospitalisation rate of individuals. See notes in Tables 4.2 and 4.5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.
*** indicates significance at 1 percent level
** indicates significance at 5 percent level
* indicates significance at 10 percent level

Table 4.9: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Rate of Hospitalisation In Malawi by Gender.

	Dependent variable: Hospitalisation indicator	
	Males	Females
Variables	(1)	(2)
In-utero drought shock	0.003	0.014***
	(0.004)	(0.005)
In-utero flood shock	0.003	0.001
	(0.004)	(0.005)
First year drought shock	0.002	0.007
	(0.004)	(0.005)
First year flood shock	-0.001	0.000
	(0.004)	(0.004)
Second year drought shock	0.002	0.007
	(0.004)	(0.005)
Second year flood shock	0.006	-0.003
	(0.004)	(0.005)
R-squared	0.064	0.065
Observations	20,113	20,281

Notes: Table 4.9 above presents linear probability model coefficient estimates of the impact of early life extreme rainfall shocks on hospitalisation indicator of individuals. Each column is a separate regression of the preferred model in Table 4.8 column 3 above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 4.2 and 4.5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.
*** indicates significance at 1 percent level
** indicates significance at 5 percent level
* indicates significance at 10 percent level

Table 4.10: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Productivity in Malawi.

	Dependent Variables (hours per week):				
	Agriculture	Informal business	HH chores	Formal jobs	Apprentice
VARIABLES	(1)	(2)	(3)	(4)	(5)
In-utero drought shock	-0.417**	-0.238**	0.028	-0.130	0.017
	(0.203)	(0.115)	(0.037)	(0.128)	(0.039)
In-utero flood shock	-0.202	0.102	0.013	-0.015	-0.036
	(0.211)	(0.124)	(0.034)	(0.121)	(0.033)
First year drought shock	-0.047	-0.060	-0.036	0.000	0.036
	(0.186)	(0.120)	(0.032)	(0.129)	(0.043)
First year flood shock	-0.092	-0.167	0.047	-0.007	-0.017
	(0.205)	(0.110)	(0.045)	(0.122)	(0.013)
Second year drought shock	-0.012	0.105	0.016	-0.151	0.014
	(0.199)	(0.118)	(0.027)	(0.128)	(0.034)
Second year flood shock	0.071	-0.083	0.032	-0.055	0.021
	(0.199)	(0.120)	(0.052)	(0.119)	(0.038)
R-squared	0.447	0.100	0.095	0.071	0.030
Observations	30,585	30,585	30,590	30,589	13,172

Notes: Table 4.10 above presents coefficient estimates of the impact of early life extreme rainfall shocks on weekly productivity hours of individuals aged 5 years and above for diverse labour outcomes. Each column is a separate regression of the preferred model in Table 4.8 Column (3) above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 4.2 and 4.5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 4.11: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Productivity in Malawi by Gender.

	Dependent Variables (in hours per week):			
	Agriculture		Informal business	
	Males	Females	Males	Females
Variables	(1)	(2)	(3)	(4)
In-utero drought shock	-0.274	-0.684***	-0.175	-0.317**
	(0.275)	(0.261)	(0.179)	(0.143)
In-utero flood shock	0.211	-0.657**	0.123	-0.076
	(0.290)	(0.281)	(0.198)	(0.139)
First year drought shock	0.036	-0.178	-0.044	-0.112
	(0.281)	(0.258)	(0.195)	(0.147)
First year flood shock	0.248	-0.385	-0.449**	0.050
	(0.285)	(0.278)	(0.188)	(0.130)
Second year drought shock	-0.062	0.114	0.227	-0.063
	(0.288)	(0.255)	(0.210)	(0.138)
Second year flood shock	0.257	-0.256	-0.016	-0.232*
	(0.303)	(0.260)	(0.196)	(0.126)
Observations	15,238	15,347	15,239	15,346
R-squared	0.466	0.465	0.139	0.123

Notes: Table 4.11 above presents coefficient estimates of the impact of early life extreme rainfall shocks on weekly productivity hours of individuals aged 5 years and above for agricultural and informal business engagements by gender. Each column is a separate regression of the preferred model in Table 4.8 Column (3) above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 4.2 and 4.5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 4.12: Nutrition Intervention and Gender Asymmetric Impact on Hospitalization Rate.

	Dependent variable: Hospitalisation indicator		
	Total sample	Male	Female
Variables	(1)	(2)	(3)
In-utero drought shock	0.013***	0.013**	0.013*
	(0.004)	(0.006)	(0.007)
In-utero drought shock X Food intervention	-0.021*	-0.027*	-0.017
	(0.012)	(0.014)	(0.019)
First year drought shock	-0.002	0.003	-0.006
	(0.005)	(0.006)	(0.008)
First year drought shock X Food intervention	0.008	-0.011	0.035
	(0.021)	(0.022)	(0.029)
Second year drought shock	0.002	-0.003	0.007
	(0.005)	(0.006)	(0.007)
Second year drought shock X Food intervention	0.007	0.044	-0.027
	(0.017)	(0.028)	(0.023)
Observations	16,026	7,935	8,091
R-squared	0.038	0.064	0.062

Notes: Table 4.12 above presents coefficient estimates of the impact early life drought shocks and interaction terms with access to food intervention program on hospitalisation rate. Columns (2) and (3) separate the sample observations by gender of respondents. Each column is a separate regression of the preferred model in Table 4.8 Column (3) above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 4.2 and 4.5 above for a list of all controls and additional information on the construction of drought shock. Robust standard errors (clustered at the community level) are reported in parentheses.
*** indicates significance at 1 percent level
** indicates significance at 5 percent level
* indicates significance at 10 percent level

Chapter 5

5 Conclusion

This thesis examined three dynamic topics with a common feature, unanticipated economic shocks and welfare outcomes. Foremost, exploring the World Bank individual level domestic violence data, the shock-domestic violence nexus is re-examined for intra-household behavioural pattern within resource scarce and volatile environment in chapter 2 using plot-level precipitation variation for household specific shocks on agricultural yields. Second, given the acute shortage of formal financial service provision[69] and the associated implications for welfare outcomes within Africa, innovative financial inclusion technology – mobile money – is investigated as being effective remittance platform for risk coping mechanism in periods of unexpected shock in chapter 3. Finally, given the lack of active social security systems and formal insurance markets; along with financial inclusion gaps in Africa, an examination of the effects of exposure to early life shocks on short and long term outcomes is presented in chapter 4. The notable features of this study is examining the impact of disaggregated extreme shock framework and expansion of shock horizon to early life seasonal harvest shocks to investigate critical programming period hypothesis.

Using a cross-section dataset of Tanzanian households in the 2008-2009 World Bank LSMS-ISA survey, result in chapter 2 suggests that rainfall shocks have a significant impact on the incidence and severity of female-targeted DV. The results further suggest that the impact is concentrated in dry shocks while wet shocks have no apparent effect on DV indices within a household. This asymmetric effect indicates that linear shock specification may project misleading symmetric interpretation for both decreasing and increasing levels of precipitation deviations. The disintegrated analysis suggests that the effect of shock on DV remains strong for physical violence against females while coefficient estimates of shock for severe physical and sexual violence across the sample of observations are weak and insignificant. The results are found to be robust to inclusion of potential confounding and non-economic mechanisms of rainfall shock. Given that coefficient shock estimate for female intimate partners becomes stronger and more significant, targeted mechanism

[69] This is the main precursor for financial inclusion gap in most developing countries.

associated with bargaining model of DV in periods of unanticipated economic shock is upheld as against emotional cue. Similarly, there is no clear evidence in support of bad match hypothesis. More importantly, using household head gender and community level inheritance rights as empowerment proxies in a predominant patriarchal environment, we find that the impact of shock is mediated for female headed households and communities with female (and children) inheritance rights.

Using an instrumented difference-in-difference methodology to identify the impact of innovative financial inclusion service on welfare outcomes similar to Jack and Suri (2014), the findings in Chapter 3 suggest that mobile money remittance service is useful as an insurance mechanism in periods of economic shocks in Tanzania. The findings reported in this chapter corroborate those reported for consumption smoothing model, particularly as it relates to mobile money financial inclusion in Kenya (Jack *et al* 2013; Jack and Suri 2014) and Tanzania (Riley 2016). Beyond the main estimates from poverty index, results from this chapter highlights support for schooling outcomes for children, preventative health expenditure and subjective financial well-being for individuals in periods of shocks. Trends in the result show overcompensation for the adverse impacts of shocks in a framework linked to unlocked remittance access from broader network. Results in this regard show higher likelihood of receiving remittance and larger sums of remittance as mechanisms of transmission of the welfare effects of mobile money. On the contrary, our results contradict labour diversification attempts as would be expected for compensating income during adverse shocks in rural areas. This perverse finding suggests that mobile money financial inclusion technology may pose a *"free-rider"* behavioural threat due to asymmetric information between senders and receivers of remittance in our context. The kind of impact that this may have on overall welfare is currently unclear in the literature, however it is worth emphasising that the behavioural attitude may jeopardise overall welfare equilibrium. Whilst policy implications could be drawn from this paper for countries currently embracing mobile money in Sub-Saharan African countries because of the possible link with risk coping tendencies, behavioural hazards need be considered as well to avoid negative consequences. The findings from this chapter may serve as a benchmark against which to measure the success of quasi-formal financial inclusion against existing (informal and formal) financial service platforms in Africa.

Finally, motivated by the severe impact of contemporaneous malnutrition on health outcomes in most developing countries, Chapter 4 examines the impact of exposure to early life shocks – for the first three agricultural seasons– on short and long term welfare outcomes in Malawi. This chapter embraces a holistic focus of early life shock impacts on welfare outcomes of children and adults in alignment with critical programming hypothesis in medical literature. More importantly, the study models welfare outcomes as a function of disaggregated extreme weather shocks – using extremely low and high rainfall shocks respectively – as potential sources of early life malnutrition in a fashion that diverges from the existing literature (Maccini and Yang 2009; Rabassa *et al.* 2014; Thai and Falaris 2014). Results from this chapter suggest that incidence of drought shocks during in-utero to second year of life periods persistently halt children growth progression as measured by age standardised weight and height z-scores. On the contrary, the effect of wet shocks weakens over the same period. The chapter, however, notes that the alteration in health indices arising from extremely low rainfall shock decreases with age of children across 6 to 35 months and 36 – 59 months in a fashion that suggests potential compensatory framework. Whilst there is no evidence to support the impact of early life shocks on most health outcomes, our results indicates that in-utero drought shock increases the hospitalisation rate and level of productivity of individuals. The distortionary effects of in-utero drought shock are particularly associated with the female observations while males are completely exonerated from the impact of similar in-utero drought shock. It is also implied from this chapter that the effectiveness of intervention nutrition programs is flawed by embedded intra-household gender allocation which "favours" males – a common feature of intra-household resource allocation in developing countries.

Limitations and Further Research

The main limitations of this thesis relate to the data used and results from the empirical analysis. Although the individual level domestic violence data in Chapter 2 helps with more intense analysis of shocks on domestic violence and particularly better exposition compared to aggregate level analysis in the literature, this is only available in the first wave of the

Tanzanian Panel Survey from the LSMS-ISA. Lack of panel data in the domestic violence section of the survey limits potential shock and intra-person analysis over time. Also, empirical findings in Chapter 3 uses magnitudes of economic shock components from precipitation level computed as a deviation from seasonal less aggregated precipitation patterns from the historical norm. While this is an important strength of the chapter, the welfare results indicate that mediating response of mobile money to extreme shocks are potentially similar to those of mild shocks. Lack of annual precipitation patterns with similar disaggregated nature limits our capacity for this analysis. We attempt to use aggregate shock measures similar to existing literature but unable to find results consistent with compensating welfare results in periods of shocks. This result is premised on lack of sufficient variation to capture shocks at a more specific level for compensation effects from households' use of mobile money services.

Our results for children anthropometric health measures and adulthood welfare outcomes in Chapter 4 do not reflect results for the same cohorts of individuals and should not be interpreted as lifelong impacts of early life shocks. Hence, the persistent widening of gender specific in-utero drought shock estimates for generalised welfare outcomes in the absence of differential short-run evidence should not be mixed up as the sample of observations are entirely from different cohorts. An avenue for future research is to examine the gender dynamics of short-term to long-term welfare impacts of early life shock events for the same cohorts of individuals. Also, it will be interesting to study potential resilience impact of exposure to early life extreme shock events and how it helps individuals to cope with future shocks in life. Evidence from these research questions will be useful for understanding a holistic impact of early life shock events in developing countries.

Appendix

Appendix A

Weather Data: Rainfall Data from the LSMS-ISA

The main rainfall data used in this paper are obtained from the National Oceanic and Atmospheric Administration Climate Prediction Centre (NOAA CPC) African Rainfall Estimation Algorithm Version 2.0. The rainfall dataset from Rainfall Estimate (RFE) v2.0 is a valuable component of geographical variables because it provides a standardized time-series for all of the LSMS-ISA countries. Toté *et al.* (2015) provide a validation of the RFE rainfall measure relative to other measurement methods. The RFE outperforms Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) and TAMSAT African Rainfall Climatology and Time-series (TARCAT) v2.0 products, especially in drought detection for Mozambique.

It is important to understand that RFE is a merged product using data from multiple meteorological satellites and rainfall stations. The remote sensing data provide a continuous surface, at a specific resolution, measuring rainfall estimates. According to a sourced technical document from the World Bank's LSMS team, station data are essentially used to calibrate the merged satellite surfaces. The apparent granularity of the plot-level measure comes from the RFE modelling, as well as the method used to extract the data. Rainfall values are extracted at household locations using a bilinear interpolation or distance-weighted average of 4 nearest grid cell values as used in practice.

Seasonal precipitation data gathered from the Tanzanian meteorological weather stations are used in the interpolation of the global positioning system (GPS) of surveyed Tanzanian households[70]. These data include annual and wet season precipitation measures respectively. While the household level GPS are withheld for confidentiality reasons, these are engaged to capture household specific approximates of precipitation measures outlined above. Spatial distribution of households included in the LSMS-ISA survey for Tanzania

[70] Due to spatial distribution of household observations in the survey data, enumerators were provided with a technological device that helps to capture exact GPS location of the respondent household and its immediate environs. Households close to each other have exactly the same GPS while households farther away may have different GPS measurements.

enhances the credibility of the rainfall variation at the Enumeration Area (EA) level with additional variation achievable within the EA – engaging the household level approximations of the precipitation measures. Preliminary analysis shows that rainfall measures within the same locality are actually correlated but different in absolute terms. It is important to reiterate that while this unique data displays more variation of precipitation measures between EA compared to within EA, availability of such sophisticated level of precipitation augments rainfall shock driven inquiries in the literature.

Furthermore, specific nature of the rainfall data helps to address inter-spatial correlation of rainfall data with broader geographical precipitation variation, such as the district level, commonly used in the literature. Other weather parameters captured are geophysical characteristics at the landscape level including rainy season parameters and soil fertility conditions for agricultural production. While the unmodified household GPS measured are not released for confidentiality of survey observations, modified EA level GPS are released as part of the survey data.

Descent Tracing (Patrilineal and Matrilineal) and Inheritance Patterns: The Tanzanian Context

Various succession laws guide inheritance in Tanzania. These range from customary, Islamic to statutory laws. Ethnicity and religious affinity are the major underlying factors in the decision for the appropriate inheritance legal system applicable in each Tanzanian community. However, in rural communities, the customary laws play a predominant role in guiding inheritance sharing. Given that most deceased persons in the sub-Saharan Africa die intestate, the intent of the deceased may not be a feasible way for property sharing.

Islamic law somewhat contends with the customary laws with inheritance procession concerning Muslims due to diverging views on inheritance sharing in the community and Quran. In the case of conflict of customary and Islamic laws, the court of law is resorted to; to engage in the mode of life test of the deceased[71]. In essence, customary laws overrule Islamic laws on distribution of estates except otherwise proven unacceptable to the deceased

[71] The mode of life test investigates the more accustomed of either the religious or customary affiliation that an individual engages in before demise and decides which of the two dominates his/her life. The outcome determines the premise upon which the estate of the deceased is shared among beneficiaries.

through means of official documents (testate succession category) or mode of life test. Statutory law is generally applicable to most of the other population in the rural communities (Christians and Traditional rulers) and this consists of the use of codified egalitarian principles of inheritance sharing among survivors/dependants. However, it is rarely applied in the rural communities since upholding customs lead to preference for customary laws compared to others laws.

The laws that generally apply to the majority of people in inheritance are the Customary Law and Probate Administration Ordinance. Importantly, the codified customary law, contained in the Customary Law Declaration Order (CLDO) 1963 (Government Notice No. 436 of 1963) applies to diverse patrilineal ethnic groups (constituting about 80 percent) of Tanzania communities. On the contrary, the unmodified customary law rules remain the guiding rule for the matrilineal communities (20 percent of the communities) subject to proof of authenticity from groups relying on them (Rwebangira, 1996).

There is historical evidence that women are marginalized in sub-Saharan African countries when it comes to inheritance. Household resources are generally not equally owned by married partners by virtue of the belief that domestic contribution to the ownership of household property is not suitable enough for women to claim equality of household assets. The undervaluation of domestic work, contributed mainly by women, further inhibits their rights to inheritance after the deaths of their husbands. This form of gender inequality may contribute to the prevalence of DV in the communities where these beliefs are upheld. For instance, complexity surrounding widow’s inheritance rights eludes the Marriage Act and thus solely relies on Customary Laws for resolution of widow’s inheritance matters.

Custom of the parties’ community prevail in the treatment of widows over the inheritance rights that should be adopted after a deceased husband irrespective of patrilineal or matrilineal descent tracing in such communities (Rwebangira, 1996). This is contrary to a clearer pattern of children’s inheritance rights following closely with patrilineal or matrilineal structure practised within the community. In addition to descent tracing for individuals in each village (Appendix Table A12), the 2008/2009 Tanzania World Bank Household data extracts information on the inheritance patterns of widows (Appendix Table A11). This sheds light on female empowerment status across various Tanzanian communities, which we use in the estimation of heterogeneous effects by widows' inheritance status. Because the spousal inheritance status may be endogenous for the purpose of our exercise, we investigate the orthogonality of the local inheritance practice (the practice adopted at the village level) with historic rainfall patterns.

Appendix Table A11 below shows that inheritance customs in the sample communities favour widows in 45.9 percent of the communities. Also, descent is commonly traced to the father in a majority (81.9 percent) of the communities as sole patrilineal societies while 11.7 percent others are shared with the matrilineal societies (Appendix Table A12).

Historical Rainfall and Inheritance Rights

It is important that historical rainfall pattern is orthogonal to inheritance practice to ensure the heterogeneous effect across inheritance practice is not driven by historic rainfall variability. A positive relationship between inheritance customs and historic rainfall shocks would invalidate the findings for heterogeneous effects using inheritance rights. In order to examine the orthogonality of female inheritance customs to rainfall pattern, we regress female inheritance practice indicator on historical rainfall.

Appendix Table A13 reports the estimates of this exercise. We basically find a zero relationship between historic rainfall pattern and the predominant inheritance rule on the community level (please note that historical rain coefficients in Appendix Table A13 are multiplied with 10,000) removing any concerns one may have about the use of inheritance practice for the interaction term estimates in Table 2.11.

Appendix Table A1: The Impact of Rainfall Shock on DV Incidence for Wives

	Dependent Variable : DV incidence			
		Categories of DV incidence		
Variables	All	Physical	Severe Physical	Sexual
	(1)	(2)	(3)	(4)
Rainfall shock	-0.211***	-0.184***	-0.013	-0.082*
	(0.067)	(0.062)	(0.022)	(0.046)
Constant	-0.014	-0.710	-0.019	0.043
	(0.469)	(0.532)	(0.023)	(0.534)
R^2	0.103	0.103	0.035	0.117

Notes: The table above presents marginal effect coefficients of probit regression for 1,665 married women. Each column represents a separate regression for all DV, physical DV, severe physical DV and sexual DV respectively. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A2: The Impact of Rainfall Shock on DV Index for Wives

	Dependent Variable : DV index			
		Categories of DV index		
Variables	All DV index	Physical	Severe Physical	Sexual
	(1)	(2)	(3)	(4)
Rainfall shock	-0.073***	-0.057***	-0.001	-0.033*
	(0.027)	(0.020)	(0.008)	(0.020)
R^2	0.074	0.078	0.252	0.086

Notes: The table above presents the marginal effect coefficients of ordered probit regression for 1,665 married women. Each column represents a separate regression for all DV, physical DV, severe physical DV and sexual DV index respectively. Categories are hierarchically ranked from highest to lowest for many times, a few times and one time respectively; while 0 indicates none. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A3: The Impact of Rainfall Shock on Household Divorce and Separation

Variables	Dependent Variable: Divorce Indicator	Separation Indicator
	(1)	(2)
Rainfall shock	-0.097***	-0.057**
	(0.033)	(0.029)
Constant	-5.284***	-1.476***
	(0.534)	(0.542)
R^2	0.220	0.173

Notes: The table above presents the marginal effect coefficients of probit regression for 2,930 observations. Each column represents a separate regression for twelve months household incidence of divorce and separation respectively. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A4: The Impact of Community Rainfall Shocks on Community Dispute Cases

Variables	Dependent Variables: Community Disputes			
	Marriage (ln)	Money (ln)	Land (ln)	Inheritance (ln)
	(1)	(2)	(3)	(4)
Community rainfall shock	-1.969***	-1.180*	-0.638	-0.928
	(0.614)	(0.674)	(0.678)	(0.677)
Constant	1.013	1.605*	0.654	1.428**
	(0.777)	(0.879)	(0.624)	(0.598)
Observations	2,610	2,618	2,610	2,608
R^2	0.368	0.325	0.276	0.333

Notes: The table above presents coefficients of ordinary least square regression for four major dispute categories in Tanzanian communities. Each column represents a separate regression for the natural logarithm of the number of reported disputes (by type) on community rainfall shock respectively. The coefficients presented follow table 2.3 using only community level controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A5: The Heterogeneous Impact of Rainfall Shock on DV Incidence By Occupational Sector Of Partners

Variables	Both spouses in agricultural sector	At least one spouse outside agricultural sector
Rainfall shock	-0.302***	-0.090
	(0.088)	(0.119)
Constant	-0.944	-0.024
	(0.815)	(0.778)
Observations	1,048	599
R^2	0.117	0.163

Notes: The regressions for the table above split the observations in Appendix table A1 column 1 above by occupational sector mix of spouses. Please note that 18 spouses for which occupational categories were not specified in the data are exempted from this regression. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A6: The Impact of Rainfall Shock on DV Incidence For Wives (By Age Gap Between Partners)

Variables	Husband Age > Wife Age	Husband Age ≤ Wife Age
Rainfall shock	-0.266***	0.009
	(0.074)	(0.157)
Constant	-0.100	-3.920***
	(0.521)	(1.296)
Observations	1,360	305
R^2	0.114	0.226

Notes: The regressions for the table above split the observations in Appendix table A1 column 1 above by age difference of spouses. The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A7: The Impact of Long-term Rainfall Variation on Aggregate DV

	Dependent Variable: Aggregate Domestic Violence	
Variables	12 months	Life-time
	(1)	(2)
Long-term shock	-0.009	-0.030
	(0.019)	(0.023)
Constant	4.071	10.522
	(7.103)	(8.858)
R-squared	0.269	0.284

Notes: The table above presents coefficient estimates of linear regression for our focus sample observations. Estimations are carried out by aggregating DV cases at the community level and weighed by number of observations by community. Long-term shock is computed as the standard deviation of 30-year historical rainfall distribution at the community level from UDel precipitation data. The standard deviation measure adopted centralizes drought and flood over the years. Coefficients presented follow table 2.3 column 2 with community level controls. See table 2.3 above for a list of community level controls. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A8: The Impact of Rainfall Shock on DV Incidence (Linear Probability Model)

	Dependent Variable: DV Indicator		
Variables	(1)	(2)	(3)
Rainfall shock	-0.212***	-0.129***	-0.102**
	(0.043)	(0.047)	(0.047)
Constant	0.124***	0.106*	0.381
	(0.006)	(0.059)	(0.271)
R^2	0.009	0.037	0.085

Note: The estimated coefficients above are from a linear probability model of the impact of rainfall shock on DV incidence. See table 2.3 in the main text for a list of all controls. Number of observation is 2933. Robust standard errors are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A9: The Impact of Rainfall Shock on DV Incidence (By Questionnaire DV Categories)

	Dependent Variable: DV Indicator							
	Slapped	Pushed	Hit	Beat	Burnt	Use weapon	Forced sex	Unwanted sex
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall shock	-0.087**	-0.089**	-0.082**	-0.083***	-0.006	-0.001	-0.060**	-0.013
	(0.035)	(0.035)	(0.032)	(0.028)	(0.009)	(0.011)	(0.029)	(0.025)
Constant	-4.745***	-0.804	-3.655*	-0.742	-1.212	-11.084***	1.587	2.298
	(1.772)	(1.717)	(2.041)	(2.121)	(4.086)	(3.772)	(1.793)	(1.981)
R^2	0.150	0.118	0.153	0.150	0.379	0.269	0.134	0.173

Note: Each column is a separate regression for different types of DV dummy for 2933 observations. The estimation uses a probit model. The estimated coefficients reported above include all controls. See table 2.3 in the main text for a list of all controls. Robust standard errors are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A10: The Impact of Community Rainfall Shock on DV Incidence

Variables	DV Incidence
Community rainfall shock	-0.112***
	(0.046)
Constant	-0.480
	(0.392)
R^2	0.130

Notes: The table above presents marginal effect coefficients of probit regression for 2,933 observations. The community rainfall shock coefficient presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table A11: Inheritance Custom for Deceased Husbands in Tanzanian Communities

Custom	Freq.	Fraction
Wife of Deceased	177	0.459
Children	125	0.323
Clan	14	0.036
Extended Family	62	0.161
Unknown	8	0.021
Total	386	100

Source: 2008/2009 LSMS Tanzanian Data.

Appendix Table A12: Descent Tracing in Tanzanian Communities

Descent	Freq.	Fraction
Father	316	0.819
Mother	17	0.044
Both	45	0.117
Unknown	8	0.021
Total	386	100

Source: 2008/2009 LSMS Tanzanian Data.

Appendix Table A13: Women's Inheritance Rights and Historical Rain Pattern in Tanzania

Variables	Wives' inheritance right	Wives' and children's inheritance right
Historical rain	0.503	0.206
	(0.517)	(0.300)
Constant	5.871***	7.693***
	(0.469)	(0.813)

Notes: The table above presents coefficients of probit regression for 2,872 observations. Each column represents a separate regression of inheritance rights for wives and children respectively. Estimates for historical rain above are reported in multiple of ten thousands (x10,000). The coefficients presented follow table 2.3 column 3 with all controls. See table 2.3 above for a list of all controls. Robust standard errors are reported in parentheses. ***, ** and * represent significance at 1 percent, 5 percent and 10 percent levels respectively.

Domestic Violence Questions (Page 29, 2008 Tanzania LSMS Questionnaire)

SECTION I: VIOLENCE AGAINST WOMEN **1. ENTER THE HOUSEHOLD ROSTER ID OF THE RESPONDENT:**

THIS SECTION SHOULD BE ASKED TO EVERY WOMAN, AGE 15-50. QUESTIONS SHOULD BE ASKED IN PRIVATE. REMIND RESPONDENT THAT SHE IS FREE TO STOP AT ANY TIME.

2. Sometimes a husband is annoyed or angered by things that his wife does. In your opinion, is a husband justified in hitting or beating his wife in the following situations: YES…1 NO…2

A. If she goes out without telling him?		E. If there are problems with his or her family	
B. If she neglects the children?		F. If there are money problems	
C. If she argues with him?		G. If there is no food at home	
D. If she refuses to have sex with him?		H.Other (specify)	

	3. Has your current partner, or any partner ever ……[….]	**4. Has this happened in the past 12 months?**	**5. In the past 12 months would you say this has happened once, a few times or many times?**	**6. Before the past 12 months would you say this has happened once, a few times or many times?**
			NEVER………….0	NEVER………….0
	YES…1	YES…1	ONE TIME………1	ONE TIME………1
	NO…2	NO…2	A FEW TIMES….2	A FEW TIMES….2
	►NEXT ROW	►NEXT ROW	MANY TIMES….3	MANY TIMES….3
A. Slapped or thrown something at you that could hurt you?				
B. Pushed you or shoved you?				
C. Hit you with his fist or with something else that could hurt you?				
D. Kicked you, dragged you, or beaten you up?				
E. Choked or burnt you on purpose?				
F. Threatened to use or actually used a gun, knife or other weapon against you?				
G. Physically forced you to have sexual intercourse when you did not want to?				
H. Did you ever have sexual intercourse you did not want because you were afraid of what he might do?				

7. DID RESPONDENT REPORT 'YES' TO ANY ITEM IN QUESTION 3? YES…1 PROCEED TO 8; NO….2 ► END

8. After any of the incidents of physical violence, did you ever go to […] for help? YES…1 PROCEED TO OPTIONS NO….2

A. Family		D. NGO	
B. Hospital/health centre		E. Religious leader	
C. Village/community leaders		F. Police	

Appendix B

Weather Data: Rainfall Data from the LSMS-ISA

The main rainfall data used in this paper are obtained from the National Oceanic and Atmospheric Administration Climate Prediction Centre (NOAA CPC) African Rainfall Estimation Algorithm Version 2.0. The rainfall dataset from Rainfall Estimate (RFE) v2.0 is a valuable component of geographical variables because it provides a standardized time-series for all of the LSMS-ISA countries. Toté *et al.* (2015) provide a validation of the RFE rainfall measure relative to other measurement methods. The RFE outperforms Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) and TAMSAT African Rainfall Climatology and Time-series (TARCAT) v2.0 products, especially in drought detection for Mozambique.

It is important to understand that RFE is a merged product using data from multiple meteorological satellites and rainfall stations. The remote sensing data provide a continuous surface, at a specific resolution, measuring rainfall estimates. According to a sourced technical document from the World Bank's LSMS team, station data are essentially used to calibrate the merged satellite surfaces. The apparent granularity of the plot-level measure comes from the RFE modelling, as well as the method used to extract the data. Rainfall values are extracted at household locations using a bilinear interpolation or distance-weighted average of 4 nearest grid cell values as used in practice.

Seasonal precipitation data gathered from the Tanzanian meteorological weather stations are used in the interpolation of the global positioning system (GPS) of surveyed Tanzanian households[72]. These data include annual and wet season precipitation measures respectively. While the household level GPS are withheld for confidentiality reasons, these are engaged to capture household specific approximates of precipitation measures outlined above. Spatial distribution of households observed in the LSMS-ISA survey for Tanzania enhances the credibility of the rainfall variation at the Enumeration Area (EA) level with additional variation achievable within the EA – engaging the plot-level approximations of the precipitation measures. Preliminary analysis shows that rainfall measures within the same locality are actually correlated but different in absolute

[72] Due to spatial distribution of household observations in the survey data, enumerators were provided with a technological device that helps to capture exact GPS location of the respondent household and its immediate environs. Households close to each other have exactly the same GPS while households farther away may have different GPS measurements.

terms. It is important to reiterate that while this unique data displays more variation of precipitation measures between EA compared to within EA, availability of such sophisticated level of precipitation augments rainfall shock driven inquiries in the literature.

Furthermore, specific nature of the rainfall data helps to address inter-spatial correlation of rainfall data with broader geographical precipitation variation, such as the district level, commonly used in the literature. Other weather parameters captured are geophysical characteristics at the landscape level including rainy season parameters and soil fertility conditions for agricultural production. While the unmodified household GPS are not released for confidentiality of survey observations, modified EA level GPS are released as part of the survey data.

Conceptual Framework

The response of a risk-averse household within the insurance and risk-sharing models aftermath of shock is unambiguous as described in Yang and Choi (2007) and Jack and Suri (2014) respectively. However, our model considers an aggregate economic framework where some households are exempted from the negative shock and can support with remittance transfers to affected households. Assuming the same basic assumption of the existence of pareto-efficient allocation of risk across households, as in Yang and Choi (2007), in different states of shock[73] hold, welfare state for negative income shock households may vary in different dimensions and under varying circumstances. Consider a network consisting of at least two households, indexed by $h \in \{1,2,\ldots n\}$. We assume that at least one of the network household is faced with a different state of shock S^i from that experienced by our focus household mainly from a subset where $i \in \{+,-\}$. S_t^+ and S_t^- represent positive and negative states of shock at period t respectively[74]. One important component of our model is the acquisition of innovative financial technology for the purpose of fund transfers back and forth across network of households in diverse states of nature. While asset and livestock sales continues to play

[73] A set of positive and negative shock exposed network of households, in a risk sharing arrangement, are able to smooth consumption perfectly. This is driven by different but complementary states of household financial positions within a network in different regions of the country with differing rainfall patterns at a point in time.

[74] Positive and negative states of shock respectively refers to quantified positive and negative deviation of household plot level rainfall measure associated with the recent agricultural season from the average historical rainfall pattern.

consumption smoothing role, reduced transaction costs[75] associated with the emancipation of mobile money facilitates the consumption smoothing process through accessibility to wider network in periods of emergency (Jack and Suri, 2014).

Along the two major states of shock stated above, households (and individuals therein) face uncertain income in each period t, following Yang and Choi (2007). Similarly, household *h* consume $c^h_{s_t^+}$ or $c^h_{s_t^-}$ in either time period, leading to four potential combinations for each household across shock faced and time frame[76]. However, we deviate from Yang and Choi (2007) with a consideration of welfare ratio of the same household across periods (facing the same or different states of shock). If the utility derivable from household consumption ($U_h^t c^h$) is separable over time, and each instantaneous utility is twice differentiable with $U_h' > 0$ and $U_h'' < 0$. The ratio of welfare status of households across time periods can be written as:

$$\frac{U_h^{1'}(c^h_{s_1^i})}{U_h^{2'}(c^h_{s_2^i})} = \frac{\mathrm{W}_1^h}{\mathrm{W}_2^h}, \quad \text{for all } h \text{ and } i. \qquad (1)$$

Where W_1^h and W_2^h are welfare status of household across two periods; first and second periods respectively. In an ideal state, where consumption is perfectly smoothed over the two periods, the right hand side segment of the equation is equivalent to 1, indicating that negative idiosyncratic shock faced by a household does not affect its consumption pattern across time. This is particularly relevant for households with negative income shock in the second period irrespective of their first period state of shock.

$$\frac{\mathrm{W}_1^h}{\mathrm{W}_2^h} = 1, \text{ for all types of } h. \qquad (2)$$

[75] It is important to note that exorbitant transaction costs continues to be charged in traditional/antiquated remittance platforms alongside lots of associated risk and time requirements for delivery of remittance to households. Apart from cost issues with traditional remittance in Tanzania, most of the traditional remittance platforms are not suitable for meeting household emergency demands.

[76] First, a household may be exposed to a positive income shock in periods 1 and 2 respectively. Second, a household may as well experience negative income shock in the consecutive periods. While this seems to be representative of a static model of household shock disposition, the magnitude across these consecutive periods may play a dynamic role in affecting household welfare. Third, a household may be exposed to negative income shock in the first period and consequently have a positive income shock in the second period. The last case is the case where a household experiences a positive income shock and then is faced with a negative income shock in the second period.

On the other hand, an inequality may exist between the current welfare state of a household relative to its previous welfare state. This is illustrated by eq. (3) below.

$$\frac{\mathrm{W}_1^h}{\mathrm{W}_2^h} \lesseqgtr 1\ , \quad \text{for all types of } h. \qquad (3)$$

Disintegrating the above equation to two welfare ratios where the first is less than unity and the other is greater than unity gives us an idea of the dynamics of less than full consumption smoothing (Fafchamps *et al.* 1998) and greater than full consumption smoothing respectively – overcompensation for the impact of shocks.

While the use of mobile money has replaced traditional mechanisms as a result of the efficiency of the use of the remittance services in periods of emergency (shock), sales of household assets/livestock and access to existing formal and informal financial system within East African communities may aid smoothing in excess of the impact of shock. More so, a broader network of households, across the different regions of the country, avails the household the tendency of getting more than required funds to cushion shock.

Our main objective in this paper is to empirically establish the welfare dynamics of mobile money insurance that play out between equations (2) and (3) above using the sparsely distributed Tanzanian population. For this purpose, we will engage household and individual welfare outcomes – including poverty and human capital investments – to understand consumption smoothing priorities in the use of mobile money for shock affected households.

Appendix Table B1: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Per-capita Expenditure.

	Dependent Variable: Per-capita Expenditure (ln)	
Variables	(1)	(2)
Chart A: Distance to Agent		
Mobile Money	-0.1154	-0.2843
	(0.3921)	(0.4133)
Rainfall shock	0.0076	0.0130
	(0.0195)	(0.0190)
Interaction	0.0092	0.0048
	(0.0582)	(0.0542)
Chart B: Cost to Agent		
Mobile Money	0.1419	-0.1948
	(0.4613)	(0.4947)
Rainfall shock	0.0082	0.0156
	(0.0189)	(0.0188)
Interaction	-0.0175	-0.0116
	(0.0615)	(0.0561)
Household Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	No	Yes

Notes: Appendix Table B1 above reports the estimates of mobile money adoption, rainfall shock and their interaction term for the natural logarithm of per-capita expenditure. Controls used in column 2 are outlined in the notes of table 3.5 above. Robust standard errors (clustered at the community level) are reported in parentheses.
***, ** and * represent significance at 1, 5 and 10 percent respectively.

Appendix Table B2: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Household Welfare Support.

	Dependent Variable: ln amount	
Variables	(1)	(2)
Mobile Money	-0.8739*	-0.9995*
	(0.5103)	(0.5806)
Rainfall shock	0.0365*	0.0283
	(0.0219)	(0.0225)
Interaction	-0.1969*	-0.2049*
	(0.1171)	(0.1117)
Household Fixed-Effect	Yes	Yes
Year Fixed-Effect	Yes	Yes
Controls	No	Yes

Notes: Appendix Table B2 above reports the linear probability model (LPM) estimates of mobile money adoption, rainfall shock and their interaction term on the natural logarithm of the amount of funds solicited from welfare support societies in the past one year. See table 3.5 for additional notes and controls. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Appendix Table B3: Spatial Correlation Consideration for Poverty Results.

	Dependent Variable: Extreme Poverty Indicator				
Variables	(1)	(2)	(3)	(4)	(5)
Mobile Money	0.2991	0.2381	0.3198	0.3386	0.3399
	(0.2723)	(0.2639)	(0.3519)	(0.3538)	(0.3443)
Rainfall shock	0.0381**	0.0380**	0.0376**	0.0374**	0.0377**
	(0.0168)	(0.0158)	(0.0161)	(0.0162)	(0.0161)
Interaction	-0.1030**	-0.1042**	-0.1052**	-0.1038**	-0.1036**
	(0.0466)	(0.0425)	(0.0432)	(0.0428)	(0.0427)
Household Fixed-Effect	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Community Varying Linear Trend X Time	No	No	Yes	No	No
Community Varying Quadric Trend X Time	No	No	No	Yes	No
Community Varying Cubic Trend X Time	No	No	No	No	Yes

Notes: Appendix Table B3 above reports the linear probability model (LPM) estimates of mobile money adoption, rainfall shock and their interaction term with community varying trends by time to control out for spatial correlation. See table 3.5 for additional notes and controls. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Appendix Table B4: Instrumental Variable Estimates of Mobile Money and Interaction With Rainfall Shock on Children School Outcomes.

	Dependent Variables:			
	School Expenditure (Tanzanian shilling)	School Enrolment (indicator)	School Absenteeism (indicator)	Homework (Hours/Day)
Variables	(1)	(2)	(3)	(4)
Mobile Money	76.3315	-0.2027	-0.2884	1.2409
	(56.1424)	(0.1965)	(0.7384)	(1.0065)
Rainfall shock	6.0651*	-0.0035	-0.0610**	0.0668*
	(3.4078)	(0.0133)	(0.0289)	(0.0398)
Interaction	-11.8226	0.0364	0.1695	-0.2938*
	(13.4400)	(0.0417)	(0.1090)	(0.1603)
Observations	4,242	4,242	3,374	3,372
Individual Fixed-Effect	Yes	Yes	Yes	Yes
Year Fixed-Effect	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Appendix Table B4 above reports the estimates of mobile money adoption, rainfall shock and their interaction term for children school outcomes. See Table 3.7 for additional notes. Each regression is clustered at the household level. Robust standard errors (clustered at the household level) are reported in parentheses. ***, ** and * represent significance at 1, 5 and 10 percent respectively.

Appendix C

Appendix Table C1: Spatial Correlation between Rainfall and Children Growth.

	Dependent Variable :	
	WAZ	HAZ
VARIABLES	(1)	(2)
Long-term rainfall variation		
In-utero shock	-0.006*	-0.020***
	(0.004)	(0.005)
First year shock	0.001	0.004
	(0.002)	(0.003)
Second year shock	-0.005	0.010
	(0.005)	(0.006)
Observations	6,422	6,695
R-squared	0.247	0.298

Notes: Appendix Table C1 above presents coefficient estimates of the regression of WAZ and HAZ on long term rainfall shocks around the period of birth. Long-term shocks are computed as the standard deviation of 30-year historical rainfall distribution at the community level from UDel precipitation data. Each column is a separate regression of the preferred model of Tables 4.2 and 4.3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Table 4.2 for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table C2: The Impact of Early Life Rainfall Deviation on Children Health Trajectories In Malawi (6 – 35 months).

	Panel A:		Panel B:		
	WAZ	Under weight	HAZ	Moderate Stunting	Severe Stunting
Variables	(1)	(2)	(3)	(4)	(5)
In-utero deviation	0.832***	-0.063	2.630***	-0.440***	-0.213***
	(0.198)	(0.046)	(0.336)	(0.082)	(0.059)
First year deviation	0.406**	-0.083*	1.787***	-0.260***	-0.165***
	(0.191)	(0.048)	(0.267)	(0.074)	(0.059)
Second year deviation	0.604**	-0.006	1.670***	-0.086	-0.093
	(0.268)	(0.062)	(0.426)	(0.101)	(0.082)
Observations	3,491	3,491	3,668	3,668	3,668
R-squared	0.365	0.267	0.405	0.323	0.273

Notes: Appendix Table C2 above reports coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviations on health trajectories of children between 6 to 35 months. Each column is a separate regression of the preferred specifications of Tables 4.2 and 4.3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Tables 4.2 and 4.4 above for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table C3: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on WAZ and HAZ In Malawi by Age Divisions.

	Panel A: 6 – 35 months		Panel B: 36 – 59 months	
	WAZ	HAZ	WAZ	HAZ
Variables	(1)	(2)	(3)	(4)
In-utero drought shock	-0.147**	-0.395***	-0.047	0.014
	(0.074)	(0.099)	(0.089)	(0.117)
In-utero flood shock	0.081	0.433***	0.082	0.129
	(0.093)	(0.123)	(0.101)	(0.146)
First year drought shock	-0.185**	-0.478***	0.142*	0.111
	(0.082)	(0.121)	(0.084)	(0.121)
First year flood shock	-0.090	0.134	0.023	0.109
	(0.085)	(0.115)	(0.122)	(0.162)
Second year drought shock	-0.348***	-0.843***	0.004	0.086
	(0.120)	(0.180)	(0.076)	(0.101)
Second year flood shock	-0.090	-0.144	0.170**	0.118
	(0.096)	(0.129)	(0.075)	(0.109)
Constant	-0.017	-3.486**	-0.083	-1.183**
	(0.830)	(1.433)	(0.392)	(0.569)
Observations	3,491	3,668	2,931	3,027
R-squared	0.367	0.406	0.322	0.399

Notes: Appendix Table C3 above reports coefficient estimates for the impact of early life 1,000 days rainfall shocks on WAZ and HAZ of children by age divisions. Panels A and B reports disaggregated shock estimates for WAZ and HAZ for children aged 6 to 35 months and children aged 36 – 59 months respectively. Each column is a separate regression of the preferred specifications of Tables 4.2 and 4.3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Table 4.2 above for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

Appendix Table C4: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Health Expenditures and Chronic Illness In Malawi.

	Dependent variables:			
	Illness expenditure	Prescription expenditure	Preventative expenditure	Chronic illness (indicator)
Variables	(1)	(2)	(3)	(4)
In-utero drought shock	0.023	-0.000	-0.001	0.002
	(0.018)	(0.007)	(0.026)	(0.004)
In-utero flood shock	0.022	-0.000	-0.005	0.000
	(0.017)	(0.005)	(0.024)	(0.004)
First year drought shock	0.005	-0.001	0.055**	0.001
	(0.016)	(0.005)	(0.023)	(0.004)
First year flood shock	-0.003	-0.003	0.001	-0.009**
	(0.017)	(0.006)	(0.023)	(0.004)
Second year drought shock	0.010	-0.007	0.043*	-0.004
	(0.015)	(0.007)	(0.025)	(0.004)
Second year flood shock	0.024	-0.006	0.001	-0.003
	(0.017)	(0.006)	(0.024)	(0.004)
Observations	40,376	40,389	40,253	40,385
R-squared	0.069	0.058	0.116	0.126

Notes: Appendix Table C4 above presents coefficient estimates of the impact of early life disaggregated extreme rainfall shocks on the natural logarithm of diverse categories of health expenditure from Column (1) – (3) and indicator variable for chronic illness of individuals in Column (4). Each column is a separate regression of the preferred model in Table 4.8 Column 3 above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 4.2 and 4.5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

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