

University of Leicester
Department of Economics

GENERALIZED ADDITIVE MODELS IN THE CONTEXT OF SHIPPING ECONOMICS

by

Sebastian Köhn .:

M.Sc. Economics, University of Leicester, 2005

Dipl.-Math.oec., Universität Hamburg, 2006

Supervisor: Prof Dr Wojciech Charemza

Internal Examiner: Dr Barbara Roberts

External Examiner: Prof Dr Kevin Cullinane

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Abstract

This thesis addresses three current issues in maritime economics by the application of semi-parametric estimations within a generalized additive model framework.

First, this thesis shows that there are vessel and contract specific differences in time charter rates for dry bulk vessels. The literature on microeconomic factors of time charter rates could show the emergence of a two-tier tanker market during the post-OPA90 period. However, previous results do not allow for any safe conclusions about the existence of a two-tier dry bulk market. This thesis extends the results of previous research by showing that a good part of the variation in physical time charter rates is due to microeconomic factors. It empirically proves the existence of a two-tier dry-bulk market. Controlling for a variety of contract specific effects as well as vessel specific factors the presented model quantifies quality induced differences in physical dry bulk charter rates.

Second, the literature on the formation of ship prices focuses exclusively on rather homogeneous shipping segments, such as tankers and dry bulk carriers. Due to the comparatively low number of sales and the complexity of the ships, vessel valuation in highly specialised and small sectors, such as chemical tankers, is a much more challenging task. The empirical results of this thesis confirm the findings in recent literature that ship valuation is a non-linear function of size, age and market conditions, whilst other parameters that are particular to the chemicals market also play a significant role.

The third topic addresses the recent increase in operational expenses of merchant vessels (opex). The available literature cannot explain the development nor provides information on vessel individual level. This thesis considers a quantitative model of opex that is particularly successful in explaining the variation in opex across vessels of different type, size, age and specification. The results confirm that differences in opex are due to the behaviour of a vessel's operator and to regulatory requirements. Furthermore, it shows that there are significant differences in opex due to earnings and employment status of a vessel.

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Wie das Kind die Worte nur in ständigem Wechselspiel von Handeln, Sprechen und Erfahren lernen kann, so entwickelt sich die Wissenschaft in unmittelbarem Zusammenhang mit der praktischen Anwendung, und diese bleibt letzten Endes der eigentliche Maßstab für die Richtigkeit der gewonnenen Erkenntnis.

Heisenberg (1942)

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1 Introduction

As one of the key factors to the globalization, the shipping industry has changed the shape of the world economy. Planned industrial shipping and highly competitive markets have made this segment of the world economy to one of the exponents of the perfect competition model. Maritime shipping is the most important mean of international transport activity. Hence, it is of utter importance for international trade of all kinds of commodities and products. At the same time the market depends and affects industrial production and international trade. Due to its cyclicity it is characterized by a high degree of uncertainty. Large distances and increasing cargo volumes demand for very large ships e.g. Emma Maersk, Jahre Viking or Berge Stahl as the largest representatives for the container, tanker and bulker markets, respectively. Due to the necessarily large assets, shipping is a very capital intensive business. This puts an enormous pressure for positive cash flows onto operators and owners. The cyclical pattern of the shipping markets, depends on whether shocks to demand are anticipated or not. In most cases shocks are unexpected, having a fixed fleet size in the short/mid term and only limited possibilities to reduce supply through low steaming and/or early dry-docking, results in strong short/mid term impacts on freight markets and subsequently on second-hand, shipbuilding and demolition markets. The demand for hedging opportunities to protect against any imponderabilities has strongly increased during the last couple of years. Thus, informational advantages can be of crucial importance for the success of any investment into merchant vessels. As a natural result the maritime business has developed an information industry which provides data, analyses and forecasts to the "real"

industry, generating considerable profits. Scientific research delivers much of the knowledge to this branch of the shipping industry. Unfortunately, in most cases this knowledge finds its way into the practice rather later than sooner, resulting in suboptimal decision making, and hence, a large amount of avoidable costs and losses to the entire economy.

To sum up, freight and asset markets can be characterized as capital intensive, very volatile and competitive, resulting in a need for rather complex contractual agreements, valuation and modelling tools with respect to financing and operation of vessels. This thesis addresses the above issues within two of the four classical shipping markets which are the freight and the second-hand market. Additionally, it analyses one of the most neglected segments which can be considered as the buying market where operators obtain all they need to operate a vessel e.g. manning or insurance service.

1.1 Shipping economics and quantitative methods

Shipping economic theory distinguishes between four shipping markets. First, the freight market where operators and charterers trade transportation service as spot, time charter or forward contracts. Second, asset trading takes place on the second hand market. Third and fourth, the shipbuilding and the scrapping market are the cradle and the grave for any merchant vessel. The major external factor, among steel price, exchange & interest rates, to this structure is the demand for transport services driven by the volume of trade and the status of the world economy. At the same time supply of transportation service is the bottle neck for international trade and economic growth during times of full fleet utilization. The main indicators for the general status of the market are freight rates and second hand prices, i.e. the

first two shipping markets. Hence, those variables have been the subject of most scientific investigations and academic publications in shipping economics. However, ideas to extend this basic four-market theory to five, six or even seven basic shipping markets e.g. the shipping finance market or the shipping buying market, for all supplies necessary for the operation of a vessel or the shipping labour market, directly affecting the operating costs, have been proposed.

Determining freight rates as a function of supply and demand dates back to Koopmans (1939) and Zannetos (1966). Excellent information on the current size of the fleet and the order book available today, makes it relatively easy to forecast supply on a short to mid term basis depending on the length of the order book¹. However, detailed predictions for demand for transportation on specific trade routes is a very difficult task and rather a problem of commodity research. Most models implemented in practice, bypass the difficulty of demand prediction by assuming it being exogenous. They are focused on the prediction of earnings in form of spot and charter rates given certain demand scenarios.

Following Glen (2006) the recent history of quantitative modelling of the shipping markets can be characterized through four trends.

1. Reduced form rather than structural modelling
2. Greater focus on modelling the volatility rather than the levels of freight rates
3. Introduction of models of financial derivatives and their application to shipping markets
4. The use of segmented models of different ship types and higher frequency data.

¹Length of the order book refers to the quantity of vessels on order and the average delivery lag.

Building up on the work of Shimojo (1979) and Charemza & Gronicki (1981), Beenstock & Vergottis (1989b, 1992, 1993) present a fully specified integrated (wet and dry bulk) structural econometric model of the shipping market. However, despite its importance, this is the last appearance of a full structural model in the maritime literature. What follows is the development of the new econometric technique of cointegration analysis as the second important event for quantitative work in shipping economics. Thereafter, the unifying theme of many empirical studies is reduced form and vector autoregressive (VAR) modelling, see for instance Glen (1997), Veenstra (1999), Kavussanos & Alizadeh (2002a) or Wright (2003). This can be interpreted as the rejection of structural models as published in Beenstock & Vergottis (1993). The second mainstream of research is the use of GARCH and EGARCH models to examine price dynamics with respect to its volatility e.g. Kavussanos (1996a, 1996b, 1997), Glen & Martin (1998) or Chen & Wang (2004). The introduction of models of financial derivatives has been pushed forward through the work of Koekebakker & Adland (2004) and Adland, Jia & Koekebakker (2004). Due to improved data availability, mostly through commercial channels which have been made available to academics, a trend towards segmented models and high frequency data can be observed. Prominent examples for this development among many others are Tsolakis, Cridland & Haralambides (2003) and Adland & Koekebakker (2007).

Maritime policy research is largely concerned with solving problems in the maritime industry and advancement of industry specific knowledge. Despite all success and advances made in the scientific modelling of the shipping markets and its practical implications and solutions to "real world" problems, there is a strong feeling between those involved in shipping business that any sort of formal analysis plays a secondary or even tertiary role compared to other qualities such as the gut feeling

for the market. Many quantitative models seem obscure and too theoretical for the industry. On the contrary one might also suspect some lack of literacy and interest with respect to quantitative methods. If the use of quantitative methods would become more widespread, for instance, among shipping banks as a mean for the estimation of default probabilities as currently enforced through the introduction of the Basel II framework for capital adequacy, it would find (or even force) its way to owners, operators and charterers. Decision making and investment based on inter-related factors, thus defining future supply, must be based on a sound information basis taking into account all individual characteristics an investment might have. This necessarily leads to a certain degree of complexity of the methods and models applied. Selection and application of the appropriate methodology is an integral part of scientific progress. As Panayides (2006) put it: *"The selection and adoption of appropriate methodology and methods for empirical investigation is the linchpin for success..."*. The academic scene aims for a more concerted effort towards more empirical investigations, including increase in the application of quantitative methods simultaneous to an increased recognition of maritime research on a higher level of acceptance of research implications in practice.

Having those issues in mind, in much of the work of the younger history and recent papers the authors themselves put forward the argument of practical relevance as a parameter for justifying the significance of their work, whereas special sections of the papers or entire papers are devoted to practitioner implications and recommendations for solutions to investigated problems. Despite this applied nature of the academic research in maritime economics, a lowering of the standards of the application of scientific methods cannot be observed. Practical implications and problem solving is based on valid and generalizable scientific methodology.

To conclude this section I like to quote Goss (2002) who analysed the future of maritime economics with respect to the use of quantitative methods and its acceptance among practitioners and policy makers in the shipping industry:

”Some good work has already been done...but there is a rich field waiting for econometricians. ...

...there are many opportunities for good research in this field, probably more by way of practical application, comparison and examples of 'best practices' than by the development of new theory. A good deal of future effort may well turn out to consist of gaining acceptance amongst those who operate maritime services, in ships and ports, for ideas which are already common ground within the profession.”

1.2 Motivation and objectives of this thesis

From the above it becomes clear that macroeconomic and time series properties have been extensively analysed. However, from an microeconomic perspective it is very important how a specific vessel will perform in under general market conditions. Moreover, the question of whether general market conditions are representative for any given vessel is raised. It can be shown that with respect to forecasting performance we do not need to expect major and significant differences. However, we experience a complex of problems related to any individual value to be assigned to a given vessel on the microeconomic level.

Specifically, the following hypotheses are going to be empirically tested.

1. There are vessel individual differences in physical time charter rates. Especially the quality of a vessel does affect its earnings potential, i.e. there is a two-tier²

²Charter markets which are split into a sub-market for quality vessels and another sub-market

- Panamax dry bulk market. (Chapter 3)
2. The financial incentives implied by the two-tier market are sufficient for the renewal of the fleet and additional investments in security and safety of vessels. (Chapter 3)
 3. The functional form of second hand chemical tanker prices are non-linear with respect to vessel individual characteristics such as size and age as well as market factors such as charter rates and newbuilding prices. (Chapter 4)
 4. Cargo- and cargo handling diversity do have larger effects on second hand prices of chemical tankers than specialisation. (Chapter 4)
 5. Apart from the fact that operational expenses (opex) function as lower boundary for physical charter rates there is no independence of earnings and opex as assumed in most extant research (see Section 5.3). Moreover, the employment status does affect the level of maintenance and hence operating costs. (Chapter 5)
 6. In addition to regulatory requirements as a source for differences in opex, the operators economic behaviour and operating policies are a significant factor to differences in opex. (Chapter 5)

While the evaluation of the hypotheses is primarily of theoretical interest, the quantitative results are important for the modelling and valuation of any cash flow driven monetary claim. Moreover, they are relevant to practical decision making. As can be shown, the application of semi-parametric methods are of large potential in commercial and academic sense. The exact evaluation of rates and prices and the influence of opex predictions do affect practical decisions and theoretical implications.

for non-quality vessels are known as "two-tier markets".

1.3 Non- and semi-parametric methods in shipping economics

Thinking about the issues discussed above, it does not surprise that there are (literally) only a handful of published papers applying non- and semi-parametric methods to model the shipping markets or to test shipping specific hypotheses. A first attempt to introduce non-parametric methods in shipping economics can be found in Adland (2003). In his PhD thesis Adland builds a non-parametric one-factor model of freight rates and a non-parametric non-Markovian discrete-time model of freight rates. Using kernel regressions it can be shown that, consistent with maritime economic theory, spot rates are mean reverting and exhibit a stochastic trend i.e. are integrated of order one. Additionally, through an extension of this model to a non-Markovian model which captures lag effects in the conditional mean and volatility it can be shown that with respect to magnitude and dynamics of the volatility there are significant differences among the bulk shipping sectors. This research has subsequently been extended to the tanker markets and similar results have been published in Adland & Cullinane (2006).

Another branch of non-parametric modelling has been applied to shipping economics and published in 2004. Two papers using artificial neural networks (ANNs) analysed Suez canal traffic and the tanker market, respectively. Lyridis, Zacharioudakis, Mitrou & Mylonas (2004) aim to show the benefits of artificial neural networks in forecasting VLCC spot freight rates. Identifying a set of explanatory factors they predict 1, 3, 6, and 12 month periods. Those forecasts are then compared to a model in which forecasts are simply the last observed spot rate. Using spot rates for the route Ras Tanura - Rotterdam for the period 1979 to 2003 they find that short term

forecasts do not outperform the simple model. Increased forecast horizons show a better performance. However, the chosen benchmark can be questioned since time charter rates of respective length are readily available and represent a much more realistic benchmark when interpreted as the markets expectation of the level of average spot rates. Despite the fact that artificial neural networks seem to show some advantages the presented results are not entirely convincing.

A second attempt to establish the use of artificial neural networks in shipping economics is Mostafa (2004). Comparing the performance of ANNs and a simple ARIMA process in forecasting the Suez canal traffic flow he finds that the appropriate selection of network inputs and architecture are crucial to the forecasting performance. Despite using the model with the best fit which does introduce a good amount of subjectivity to the model selection process, he concludes that small advantages of ANNs are insignificant and do not justify the efforts compared to those involved in ARIMA modelling.

Adland & Strandenes (2006) revise the efficiency hypothesis in the wet bulk freight market. Using a kernel smoothing of the spot freight rate history they are able to show that it would be possible to archive significant profits from trading information on identified peaks and troughs in the freight market cycle. Hence they reject the efficient market hypothesis.

As the most recent and promising application of non-parametric modelling in the context of shipping economics Adland & Koekebakker (2007) depart from the use of time series analysis and static econometric market models and propose to model ship prices in a cross sectional framework using actual ship sales data. They use a

cross sectional dataset of sales and purchases of Handysize dry bulk vessels for the period 1993-2003. Applying a multivariate density estimation approach they estimate a two- and a three-factor model of second hand prices. They propose to use non-parametric multi-factor models of generic pricing variables (ship size, age and freight rate) and find that the resulting value surfaces can be non-linear. However, they note that, despite the relative homogeneity of Handysize dry bulk vessels, a three factor model is not capable of sufficiently explaining the observed vessel prices in the market. This is due to the remaining factors that an experienced ship broker will take into account, e.g. engine make, fuel consumption building yard or cargo gear. Their non-parametric approach suffers from being data intensive and unable to cater for the multitude of ship-specific technical specifications that may affect ship values, in particular for highly specialised and sophisticated ships.

1.4 Generalized additive models

This thesis comes as the natural extension of the above string of research in two ways. First, it focuses on the microeconomic aspects in shipping economics using high density cross sectional data rather than the macroeconomic aspects of time series properties of the market. Secondly, it broadens the range of econometrics tools applied in shipping economics in a systematic way to non- and semi-parametric approaches. Generalized additive models are applied to a set of issues relevant to academics and practitioners of the maritime sector.

Generalized Additive Models (GAMs) provide enough flexibility to take non-linear relationships into account without making any specific assumptions about the functional form of these relations. At the same time it is possible to combine non-parametric components with parametric components such as in our case dummy

variables for vessel types and other vessel specific factors. Another positive aspect of using a semi-parametric framework instead of a fully non-parametric is that it provides reliable results in samples of moderate size. This, so called, curse of dimensionality in the context of ship valuation is discussed in Adland & Koekebakker (2007).

A generalized additive model is the extension of a generalized linear model to a combination of a linear predictor and the sum of smooth functions of explanatory variables. The flexibility of those models allows the user to incorporate variables that are suspected to have a non-linear relationship to the respective dependent variable. However, this flexibility comes at the cost of two necessities. The question of how to represent the smooth terms needs to be answered and the degree of smoothing has to be chosen.

The bases for our estimations are thin plate regression splines (TPRS) in combination with a general cross validation procedure (GCV). Standard bases for regression splines such as cubic splines, cyclic cubic splines or p-splines require the user to choose knot locations, i.e. the basis dimension. Furthermore, they allow only for the representation of the smooth of one predictor variable and it is not clear to what extent these bases are better or worse than others. TPRS surmount these problems and are in a limited sense optimal with respect to these problems. A detailed explanation of GAMs its advantages and disadvantages can be found in Chapter 2.

1.5 Summary of contributions

1.5.1 Chapter 3: Evaluation of physical dry bulk time charter rates

The literature on microeconomic factors of time charter rates could show the emergence of a two-tier³ tanker market during the post-OPA90 period. Being a main indicator for the quality of a vessel, the age of a tanker seems to make a significant difference for physical time charter rates, i.e. the older a vessel the more likely are accidents and a loss of reputation for the charterer. The idea of a two-tier charter market has subsequently been extended to the dry bulk segment. Those risks should require a discount on the charter rate to establish the necessary financial incentives for improved safety and environmental security. However, previous results do not allow for any safe conclusions about the existence of a two-tier dry bulk market. Chapter 3 extends the results of previous research by using generalized additive models to explain vessel and contract specific differences in time charter rates. This way, it can be shown that a good part of the variation in physical time charter rates is due to microeconomic factors. Moreover, it empirically proves the existence of a two-tier dry bulk market (Hypothesis 1). Controlling for contract specific effects such as place of delivery, charter length and number of days forward to delivery as well as vessel specific factors such as size and consumption, the chapter quantifies quality induced differences in physical dry bulk charter rates. However, the financial incentives implied by the two-tier market do not seem to be sufficient for the renewal of the fleet and additional investments in security and safety of vessels (Hypothesis 2).

³Charter markets which are split into a sub-market for quality vessels and another sub-market for non-quality vessels are known as "two-tier markets".

1.5.2 Chapter 4: Second hand chemical tanker price determination

The literature on the formation of ship prices focuses exclusively on shipping segments such as tankers and dry bulk carriers, that are fairly liquid and homogeneous with respect to technical specifications of the vessels. Vessel valuation in the highly specialised and small sectors such as chemicals, gas or reefers, is a much more challenging task but no less important for the market players and financial institutions involved. This challenge arises because of the comparatively low number of sales and the complexity of the ships, where certain technical features may be critical for a ship's attractiveness in an illiquid second-hand market. In Chapter 4 we sidestep the lack of time series price data in these sectors and adapt a semi-parametric approach to the cross-sectional "desktop" valuation of chemical carriers. The empirical results of this chapter confirm the findings of the recent literature that ship valuation is a non-linear function of main drivers such as ship size, age, and market conditions (Hypothesis 3), whilst other parameters that are particular to the chemicals market such as IMO grade and cargo diversity also play a significant role (Hypothesis 4).

The contributions from Chapter 4 are twofold. Firstly, it applies, for the first time, a semi-parametric generalized additive model to the task of ship valuation. Secondly, it extends research outside of the comfort zone of tankers and bulkers and analyses ship price formation in what is probably the most sophisticated of shipping sectors, that is, chemical carriers. This enables us to draw conclusions on the, possibly non-linear, impact of pricing variables that are not necessarily easy to quantify a priori, such as the effect of cargo diversification through the number of cargo tanks and pumps.

1.5.3 Chapter 5: The economic determinants of opex

The recent increase in operational expenses of merchant vessels (opex) has stimulated interest in explaining its determinants. However, the available literature cannot explain the development nor provides information on a level of necessary detail. Chapter 5 considers a quantitative model of opex that is particularly successful in explaining the variation in opex across vessels of different type, size, age and specification. Using a generalized additive model framework to analyse the determinants of opex, the results confirm that differences in opex are due to the behaviour of a vessel's operator and to regulatory requirements (Hypothesis 6). Furthermore, it can be shown that there are significant differences in opex due to earnings and employment status of a vessel (Hypothesis 5).

1.6 Structure of the thesis

This thesis consists of three separately written articles which are presented in Chapters 3, 4 and 5 preceded by a comprehensive explanation of the methodology in Chapter 2. Chapter 6 provides a summary of the results and connects the conclusions of each chapter and their interrelating implications.

2 Generalized additive models

2.1 Introduction to GAMs

A generalized additive model⁴ is the extension of a generalized linear model to a combination of a linear predictor and the sum of smooth functions of explanatory variables. In general a model may look like

$$g(\mu_i) = \mathbf{X}_i^* \boldsymbol{\theta} + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \dots \quad (2.1)$$

where $\mu_i \equiv \mathbb{E}(Y_i)$, Y_i is the response variable, Y_i follows some exponential family distribution, \mathbf{X}_i^* is a vector of explanatory variables that enter the model parametrically, $\boldsymbol{\theta}$ is a corresponding parameter vector and the f_j are smooth functions of the variables that are modelled non-parametrically. Assuming $\epsilon_i \sim \text{i.i.d. } N(0, \sigma^2)$ normal errors and $g(\mu_i) = \mu_i$, Equation 2.1 could be written as

$$Y_i = \mathbf{X}_i^* \boldsymbol{\theta} + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \dots + \epsilon_i$$

This framework allows for a very flexible model specification. Instead of determining detailed parametric relationships we specify the model in terms of smooth functions. This flexibility allows for the incorporation of non-parametric components for all explanatory variables that are expected to have a non-linear relation to the dependent variable. However, this flexibility comes at the cost of two necessities. First, we

⁴The foundations of generalized additive models can be found in Hastie & Tibshirani (1990, 1993). An introduction to GAMs can be found in Wood (2006b).

need to answer the question of how to represent the smooth terms. Secondly, we need to choose the degree of smoothing.

The remainder of this section will show how to estimate GAMs by penalized regression splines, and how to use cross validation to determine an appropriate degree of smoothing for f_j . The following section will provide the necessary details on the theory of GAMs. Section 2.3 will summarize the advantages and shed critical light on the assumptions and shortcomings of GAMs.

2.1.1 The cubic regression spline

Considering a simplified version of (2.1) with one smooth function of one regressor

$$y_i = f(x_i) + \epsilon_i, i = 1 \dots n \quad (2.2)$$

where y_i is a response variable, x_i a regressor, f a smooth function and $\epsilon_i \sim$ i.i.d. $N(0, \sigma^2)$. Moreover, suppose the x_i to lie in $[0, 1]^5$. Estimating f by standard estimation techniques (e.g. OLS or Maximum Likelihood) requires f to be represented such that (2.2) becomes a linear model. To achieve this we need to choose a space of functions from which f shall be an element, so called "spline-basis".

$$f(x) = \sum_{j=1}^q b_j(x) \beta_j \quad (2.3)$$

Equation 2.3 shows the representation of f where $b_j(x)$ is the j^{th} basis function with unknown parameters β_j . Substituting (2.3) into (2.2) yields a linear model which can be estimated easily.

⁵We will come back to this in Section 2.2.1.

A cubic spline is a continuous curve constructed from sections of cubic polynomials such that the curve is continuous in first and second derivatives. The points at which the polynomials join are known as *knots*. For regression splines, other than for conventional splines, the knot locations $\{x_i^* : i = 1, \dots, q - 2\}$ must be chosen. Knots may be placed at quantiles of the distribution of the x values or can be evenly spaced through the interval of observed x values.

Given the knot locations there are many ways of writing down a basis for a cubic spline. However, all possible alternatives are equivalent with respect to the spline estimation. Wahba (1990) and Gu (2002) provide a very general approach to splines. A simple spline basis which has been derived in Gu (2002, p.37) is shown in (2.4). For this basis $b_1(x) = 1$, $b_2(x) = x$ and $b_{i+2} = R(x, x_i^*)$ for $i = 1 \dots q - 2$ where

$$R(x, z) = \frac{[(z - \frac{1}{2})^2 - \frac{1}{12}][(x - \frac{1}{2})^2 - \frac{1}{12}]}{4} - \frac{[(|x - z| - \frac{1}{2})^4 - \frac{1}{2}(|x - z| - \frac{1}{2})^2 + \frac{7}{240}]}{24} \quad (2.4)$$

Using this spline basis f becomes $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \epsilon$, where the i^{th} row of the model matrix is $\mathbf{X}_i = [1, x_i, R(x_i, x_1^*), R(x_i, x_2^*), \dots, R(x_i, x_{q-2}^*)]$. The model can then be estimated by OLS.

2.1.2 Degree of smoothing - penalized regression spline

The basis dimension q is crucial for the degree of smoothing of any regression spline. However, simply choosing the basis dimension through backward-selection and hypothesis testing is problematic. First, a model based on $k - 1$ knots is not necessarily nested within a model based on k knots. Secondly, the estimation results depend strongly on the knot locations since uneven knot spacing can lead to poor model performance (see Wood (2006b), p.128).

There are alternatives to controlling the smoothness by changing the basis dimension. One possibility is to fix the basis dimension at a size which is slightly larger than it would reasonably be necessary and control the smoothness by adding a "wiggleness" penalty. Instead of fitting the model by minimizing $\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2$, one would minimize

$$\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda \int_0^1 [f''(x)]^2 dx$$

where $\lambda \int_0^1 [f''(x)]^2 dx$ penalizes models which are too "wiggly". Between model fit and smoothness is a trade off that now can be controlled through smoothing parameter λ . Obviously, $\lambda = \infty$ results in a straight line estimate whereas $\lambda = 0$ leads to an un-penalised estimate. Since f is linear in parameters β_i the integral can be calculated as $\boldsymbol{\beta}^T \mathbf{S} \boldsymbol{\beta}$. Gu (2002, p.34) shows that $S_{0,0} = S_{1,1} = 0$ and $S_{i+2,j+2} = R(x_i^*, x_j^*)$. Therefore, we have to minimize

$$\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2 + \lambda \boldsymbol{\beta}^T \mathbf{S} \boldsymbol{\beta} \tag{2.5}$$

and the penalized least squares estimator is given by

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X} + \lambda \mathbf{S})^{-1} \mathbf{X}^T \mathbf{y} \tag{2.6}$$

Neither the exact choice of basis dimension q nor the precise selection of knot locations has a lot of influence on the model fit as long as q has been chosen larger than necessary to represent the complexity of $f(x)$. Now, the choice of smoothing parameter λ is of crucial importance to the flexibility and the estimated shape of $\hat{f}(x)$. The problem of determining the smoothness has now become the problem of estimating the smoothing parameter λ .

2.1.3 Smoothing parameter λ - cross validation

If λ has been chosen too large or too small, the data will be under- or over-smoothed. In any case the spline estimate \hat{f} will not show the desired approximation to f . This can be expressed in the following criterion

$$M = \frac{1}{n} \sum_{i=1}^n (\hat{f}_i - f_i)^2$$

where $\hat{f}_i \equiv \hat{f}(x_i)$ and $f_i \equiv f(x_i)$. Since f is unknown M cannot be calculated directly. Nonetheless, it is possible to derive an estimate, $\mathbb{E}(M) + \sigma^2$ which is the expected mean square error while predicting a new variable.

Let $\hat{f}^{[i-]}$ be the model fitted to all data except y_i and define the *ordinary cross validation* score as

$$\mathcal{V}_o = \frac{1}{n} \sum_{i=1}^n (\hat{f}_i^{[i-]} - y_i)^2. \quad (2.7)$$

To obtain this score we leave out each datum in turn, estimate the spline with the remaining data and calculate the squared difference between the missing datum and its predicted value then we average over all single scores.

Substituting $y_i = f_i + \epsilon_i$ in (2.7) gives

$$\begin{aligned} \mathcal{V}_o &= \frac{1}{n} \sum_{i=1}^n (\hat{f}_i^{[i-]} - f_i - \epsilon_i)^2 \\ &= \frac{1}{n} \sum_{i=1}^n (\hat{f}_i^{[i-]} - f_i)^2 - (\hat{f}_i^{[i-]} - f_i)\epsilon_i + \epsilon_i^2 \end{aligned}$$

Since $\mathbb{E}(\epsilon_i) = 0$ and ϵ_i and $\hat{f}_i^{[-i]}$ are independent, taking expectations results in

$$\mathbb{E}(\mathcal{V}_o) = \frac{1}{n} \mathbb{E} \left(\sum_{i=1}^n (\hat{f}_i^{[-i]} - f_i)^2 \right) + \sigma^2$$

Given $\hat{f}^{[-i]} \approx \hat{f}$ it holds that, $\mathbb{E}(\mathcal{V}_o) \approx \mathbb{E}(M) + \sigma^2$ with equality in the large sample limit. Thus, if it would be desirable to minimize M in order to choose an optimal λ it is reasonable to minimize \mathcal{V}_o . Choosing λ by minimizing \mathcal{V}_o is known as *ordinary cross validation* (OCV).

Choosing a model in order to maximize the ability to predict data to which the model was not fitted, does not suffer from the problem that will be experienced in estimations where the data to be predicted is included in the fitting data sample. More complicated models will always be preferred over simpler ones. This is not the case with OCV. It can be shown that

$$\mathcal{V}_o = \frac{1}{n} \sum_{i=1}^n \frac{(y_i - \hat{f}_i)^2}{(1 - A_{ii})^2}$$

where $\mathbf{A} \equiv (\mathbf{X}^\top \mathbf{X} + \lambda \mathbf{S})^{-1} \mathbf{X}^\top$, the influence matrix from (2.6). Using this set-up has computational advantages over the calculation of \mathcal{V}_o by leaving out one datum at a time.

The weights $1 - A_{ii}$ can be replaced by the mean weight, $tr(\mathbf{I} - \mathbf{A})/n$ without altering the large sample properties. This leads us to the *generalized cross validation* (GCV) score

$$\mathcal{V}_g = \frac{n \sum_{i=1}^n (y_i - \hat{f}_i)^2}{[tr(\mathbf{I} - \mathbf{A})]^2}$$

Clearly this simplification results in further computational advantages. However, even more important are the invariance properties (Wahba 1990, p.53) which will be explained in Section 2.2.8.

2.1.4 Penalized regression spline basis for a generalized additive model

Assume that a dependent variable y can be sufficiently well described by two explanatory variables x and z by a simple additive model of the following form

$$y_i = f_1(x_i) + f_2(z_i) + \epsilon_i \quad (2.8)$$

where f_1 and f_2 are smooth functions and the ϵ_i are *i.i.d.* $N(0, \sigma^2)$.

Please note that the assumption of additive effects, $f_1(x_i) + f_2(z_i)$, is a quite restrictive special case of the general smooth function of two variables, $f(x, z)$. Moreover, since the model contains more than one function, this introduces an identifiability problem. The f_i are each only estimable within an additive constant. Any constant could be simultaneously added to f_1 and subtracted from f_2 without changing the model outcome. Thus, identifiability constraints have to be imposed on the model. Once the identifiability problem has been solved the model can be fitted with penalized least squares and the smoothing parameter can be chosen by cross validation as explained above.

Each function in (2.8) can be represented by a penalized regression spline basis.

Using the spline basis given in (2.4) we obtain,

$$f_1(x) = \delta_1 + x\delta_2 + \sum_{j=1}^{q_1-2} R(x, x_j^*)\delta_{j+2}$$

$$f_2(z) = \gamma_1 + x\gamma_2 + \sum_{j=1}^{q_2-2} R(z, z_j^*)\gamma_{j+2}$$

where δ_j and γ_j are the unknown parameters, q_1 and q_2 are the number of unknown parameters and x_j^* and z_j^* are the knot locations for f_1 and f_2 respectively.

The identifiability constraint in this set-up is defined so that the two constants δ_1 and γ_1 are confounded. However, restricting one of them to zero resolves the issue. Let $\gamma_1 = 0$ allows us to write the model in linear form $\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$ where the i^{th} row of the model matrix now is

$$\mathbf{X}_i = [1, x_i, R(x_i, x_1^*), R(x_i, x_2^*), \dots, R(x_i, x_{q_1-2}^*), z_i, R(z_i, z_1^*), R(z_i, z_2^*), \dots, R(z_i, z_{q_2-2}^*)]$$

$$\text{and } \boldsymbol{\beta} = [\delta_1, \delta_2, \dots, \delta_{q_1}, \gamma_1, \gamma_2, \dots, \gamma_{q_2}]^T.$$

The penalty functions can now be written exactly as for the univariate case explained above

$$\int_0^1 [f_1''(x)]^2 dx = \boldsymbol{\beta}^T \mathbf{S}_1 \boldsymbol{\beta} \text{ and } \int_0^1 [f_2''(z)]^2 dz = \boldsymbol{\beta}^T \mathbf{S}_2 \boldsymbol{\beta}$$

where \mathbf{S}_1 and \mathbf{S}_2 are equal to zero except for $\mathbf{S}_{1i+2, j+2} = R(x_i^*, x_j^*)$ for $i, j = 1, \dots, q_1 - 2$ and $\mathbf{S}_{2i+q_1+1, j+q_1+1} = R(z_i^*, z_j^*)$ for $i, j = 1, \dots, q_2 - 2$. The above holds independent of the basis. Once a basis has been chosen, model and penalty matrices can be obtained immediately. The parameter estimates of (2.8) are calculated by

minimizing the penalized least squares objective function

$$\|y - \mathbf{X}\beta\|^2 + \lambda_1 \beta^\top \mathbf{S}_1 \beta + \lambda_2 \beta^\top \mathbf{S}_2 \beta \quad (2.9)$$

where λ_1 and λ_2 are the smoothing parameters chosen by GCV to control the smoothness of the f_i .

Defining $\mathbf{S} \equiv \lambda_1 \mathbf{S}_1 + \lambda_2 \mathbf{S}_2$, the OLS estimator is eventually given by

$$\hat{\beta} = (\mathbf{X}^\top \mathbf{X} + \mathbf{S})^{-1} \mathbf{X}^\top \mathbf{y}.$$

2.2 Theory of GAMs

The purpose of this section is to theoretically justify the methods introduced in the previous section. Moreover, distribution theory will be added to facilitate confidence interval calculation and hypothesis testing.

The methods discussed in this chapter build up on penalized regression smoothers based on splines as introduced by Wahba (1980) and Parker & Rics (1985). Hastie & Tibshirani (1990) suggested to represent GAMs by penalized regression smoothers similar to splines. This work has been extended by Marx & Eilers (1998).

2.2.1 Cubic regression splines

We want to smooth the data rather than interpolating it. Thus, instead of setting $g(x_i) = y_i$ we could treat $g(x_i)$ as n free parameters of the cubic spline in order to

estimate them by minimizing

$$\sum_{i=1}^n \{y_i - g(x_i)\}^2 + \lambda \int g''(x)^2 dx$$

where λ controls the conflicting goals of matching the data and smoothness of the fitted curve g . For all functions f that are continuous on $[x_1, x_n]$, $g(x)$ is the function minimizing

$$\sum_{i=1}^n \{y_i - f(x_i)\}^2 + \lambda \int f''(x)^2 dx. \quad (2.10)$$

Given some other function $f^*(x)$ that minimizes (2.10) we could interpolate $\{x_i, f^*(x_i)\}$ using a cubic spline $g(x)$. By the properties of interpolating splines, first, the sum of squares of $g(x)$ and $f^*(x)$ must be equal and secondly, the integrated squared second derivative of $g(x)$ must be smaller than for $f^*(x)$. Thus, $g(x)$ results in a lower value for (2.10) which is a contradiction unless $g(x) = f^*(x)$.

The basis used in the previous section was one way of defining a cubic regression spline basis. However, there are different ways of defining cubic regression spline bases. The following definition of a cubic spline basis can be found in Lancaster & Salkauskas (1986).

Let $f(x)$ be a cubic spline function with k knots x_1, \dots, x_k . In addition let $\beta_j = f(x_j)$ and $\delta_j = f''(x_j)$. The spline can then be written as

$$f(x) = a_j^-(x)\beta_j + a_j^+(x)\beta_{j+1} + c_j^-(x)\delta_j + c_j^+(x)\delta_{j+1} \text{ if } x_j \leq x \leq x_{j+1} \quad (2.11)$$

where $a_j^-(x) = (x_{j+1} - x)/h_j$, $a_j^+(x) = (x - x_j)/h_j$, $c_j^-(x) = [(x_{j+1} - x)^3/h_j - h_j(x_{j+1} - x)]/6$, $c_j^+(x) = [(x - x_j)^3/h_j - h_j(x - x_j)]/6$ and $h_j = (x_{j+1} - x_j)$ are the basis functions. Since the spline is continuous up to the second derivative at x_j and

has zero second derivatives at x_1 and x_k it can be shown that

$$\mathbf{B}\boldsymbol{\delta}^- = \mathbf{D}\boldsymbol{\beta} \quad (2.12)$$

where $\boldsymbol{\delta}^- = (\delta_2, \dots, \delta_{k-1})^\top$, $\delta_1 = \delta_k = 0$ and \mathbf{B} and \mathbf{D} are defined as $D_{i,i} = 1/h_i$, $D_{i,i+1} = -1/h_i - 1/h_{i+1}$, $D_{1,1+2} = 1/h_{1+1}$, $B_{i,i} = (h_i - h_{i+1})/3$ for $i = 1 \dots k - 2$ and $B_{i,i+1} = h_{i,i+1}/6$, $B_{i+1,i} = h_{i+1,i}/6$ for $i = 1 \dots k - 3$.

Let $\mathbf{F}^- = \mathbf{B}^{-1}\mathbf{D}$ and $\mathbf{F} = [\mathbf{0}, \mathbf{F}^-, \mathbf{0}]^\top$ it follows that $\boldsymbol{\delta} = \mathbf{F}\boldsymbol{\beta}$. Thus, the spline can be entirely expressed in terms of $\boldsymbol{\beta}$

$$f(x) = a_j^-(x)\beta_j + a_j^+(x)\beta_{j+1} + c_j^-(x)\mathbf{F}_j\boldsymbol{\beta} + c_j^+(x)\mathbf{F}_{j+1}\boldsymbol{\beta} \text{ if } x_j \leq x \leq x_{j+1}$$

which can, implicitly defining new basis functions $b_i(x)$, be further simplified to

$$f(x) = \sum_{i=1}^k b_i(x)\beta_i.$$

Moreover, Lancaster & Salkauskas (1986) show that

$$\int_{x_1}^{x_2} f''(x)^2 dx = \boldsymbol{\beta}^\top \mathbf{D}^\top \mathbf{B}^{-1} \mathbf{D} \boldsymbol{\beta},$$

i.e. $\mathbf{S} \equiv \mathbf{D}^\top \mathbf{B}^{-1} \mathbf{D}$ is the penalty matrix.

Please note that this basis does not require to re-scale the regressors to $[0, 1]$. However, it is still necessary to choose knot locations.

2.2.2 P-splines

P-splines have been developed by Eilers & Marx (1996) building up on B-splines (see de Boor, (1978)). P-splines are low rank smoothers using a B-spline basis, commonly defined on evenly spaced knots. To control the wiggleness a *difference penalty* is directly applied to the parameters β_i .

The B-spline basis can be used to represent cubic splines. The B-spline basis functions are strictly local, i.e. each basis function is only non-zero over the intervals between $m + 3$ adjacent knots, where $m + 1$ is the order of the basis. A k parameter spline basis is defined by $k + m + 1$ knots $x_1 < x_2 < \dots < x_{k+m+1}$ where the spline is evaluated over the interval $[x_{m+2}, x_k]$. Thus, the first and last $m + 1$ knot locations are arbitrary. A spline of order $m + 1$ can be written as

$$f(x) = \sum_{i=1}^k B_i^m(x) \beta_i$$

where the basis functions are recursively defined

$$B_i^m(x) = \frac{x - x_i}{x_{i+m+1} - x_i} B_i^{m-1}(x) + \frac{x_{i+m+2} - x}{x_{i+m+2} - x_{i+1}} B_{i+1}^{m-1}(x), i = 1, \dots, k$$

and

$$B_i^{-1}(x) = \begin{cases} 1 & x_i \leq x \leq x_{i+1} \\ 0 & \text{otherwise.} \end{cases}$$

The penalty function is then defined as the squared difference between adjacent β_i values

$$\mathcal{P} = \sum_{i=1}^{k-1} (\beta_{i+1} - \beta_i)^2.$$

P-splines are easy to set up and allow for a decent amount of flexibility by the ability to combine any order of penalty with any order of B-spline basis. However, when using uneven knot spacing this advantage diminishes. Furthermore, the penalties are less easy to interpret than other penalties, in terms of the properties of the fitted smooth.

2.2.3 Thin plate regression splines

Given the problem of estimating $g(\mathbf{x})$ such that $y_i = g(\mathbf{x}_i) + \epsilon$, thin plate regression spline smoothing estimates $g(x)$ by finding the function \hat{f} minimizing

$$\|\mathbf{y} - \mathbf{f}\|^2 + \lambda J_{md}(f) \quad (2.13)$$

where \mathbf{y} is the vector of y_i data, $\mathbf{f} = [f(\mathbf{x}_1), f(\mathbf{x}_2), \dots, f(\mathbf{x}_n)]$, $J_{md}(f)$ is a penalty function measuring the "wiggleness" of f and λ is a penalization parameter. The wiggleness penalty is defined as

$$J_{md} = \int \dots \int_{\mathbb{R}^d} \sum_{\nu_1 + \dots + \nu_d = m} \frac{m!}{\nu_1! \dots \nu_d!} \left(\frac{\delta^m f}{\delta x_1^{\nu_1} \dots \delta x_d^{\nu_d}} \right)^2 dx_1 \dots dx_d \quad (2.14)$$

If $2m > d$, it can be shown that (2.13) has the form

$$\hat{f}(\mathbf{x}) = \sum_{i=1}^n \delta_i \eta_{md}(\|\mathbf{x} - \mathbf{x}_i\|) + \sum_{j=1}^M \alpha_j \theta_j(\mathbf{x}) \quad (2.15)$$

where $\boldsymbol{\delta}$ and $\boldsymbol{\alpha}$ have to be estimated subject to the constraint $\mathbf{T}^\top \boldsymbol{\delta} = 0$ ($T_{ij} = \theta_j(\mathbf{x}_i)$)

and

$$\eta_{md}(r) = \begin{cases} \frac{(-1)^{m+1+d/2}}{2^{2m-1} \pi^{d/2} (m-1)! (m-d/2)!} r^{2m-d} \log(r) & d \text{ even} \\ \frac{\Gamma(d/2-m)}{2^{2m} \pi^{d/2} (m-1)!} r^{2m-d} & d \text{ odd.} \end{cases}$$

Defining \mathbf{E} by $E_{ij} \equiv \eta_{md}(\|\mathbf{x}_i - \mathbf{x}_j\|)$, the thin plate spline fitting problem reduces to

$$\text{minimize } \|\mathbf{y} - \mathbf{E}\boldsymbol{\delta} - \mathbf{T}\boldsymbol{\alpha}\|^2 + \lambda\boldsymbol{\delta}^\top\mathbf{E}\boldsymbol{\delta} \text{ subject to } \mathbf{T}^\top\boldsymbol{\delta} = 0, \quad (2.16)$$

with respect to $\boldsymbol{\delta}$ and $\boldsymbol{\alpha}$.

The idea of thin plate regression splines is to truncate the space of the components with parameters $\boldsymbol{\delta}$ of the thin plate spline. Given that $\mathbf{E} = \mathbf{U}\mathbf{D}\mathbf{U}^\top$ is the eigen-decomposition of \mathbf{E} , where \mathbf{D} is a diagonal matrix of eigenvalues of \mathbf{E} with $|D_{i,i}| \geq |D_{i-1,i-1}|$ and columns of \mathbf{U} are the corresponding eigenvectors. Define \mathbf{U}_k being a matrix consisting of the first k columns of \mathbf{U} and let \mathbf{D}_k denote the top right $k \times k$ sub-matrix of \mathbf{D} . Restricting $\boldsymbol{\delta}$ to the column space of \mathbf{U}_k by writing $\boldsymbol{\delta} = \mathbf{U}_k\boldsymbol{\delta}_k$ implies that (2.16) becomes

$$\text{minimize } \|\mathbf{y} - \mathbf{U}_k\mathbf{D}_k\boldsymbol{\delta}_k - \mathbf{T}\boldsymbol{\alpha}\|^2 + \lambda\boldsymbol{\delta}_k^\top\mathbf{D}_k\boldsymbol{\delta}_k \text{ subject to } \mathbf{T}^\top\mathbf{U}_k\boldsymbol{\delta}_k = 0 \quad (2.17)$$

w.r.t $\boldsymbol{\delta}_k$ and $\boldsymbol{\alpha}$. Incorporating the constraints yields the unconstrained minimization problem:

$$\text{minimize } \|\mathbf{y} - \mathbf{U}_k\mathbf{D}_k\mathbf{Z}_k\tilde{\boldsymbol{\delta}}_k - \mathbf{T}\boldsymbol{\alpha}\|^2 + \lambda\tilde{\boldsymbol{\delta}}_k^\top\mathbf{Z}_k^\top\mathbf{D}_k\mathbf{Z}_k\tilde{\boldsymbol{\delta}}_k \quad (2.18)$$

w.r.t $\tilde{\boldsymbol{\delta}}_k$ and $\boldsymbol{\alpha}$.

2.2.4 Choosing the basis dimension

As mentioned above, the basis dimension needs to be chosen when using penalized regression splines. This, in relation to full spline methods, reduces the computational effort substantially. Moreover, it underlines the fact that something must be seriously wrong if a statistical model requires as many coefficients as there is data. At the cost of a slightly artificial assumption that the "truth" is in the spanned

space, it eases the demonstration of large sample properties of smoothing methods.

Based on simulation Kim & Gu (2004) have shown that, given a sample size of n the size of the spline basis dimension should be approx. $n^{2/9}$. Wood (2006a) suggests also to include the number of regressors in addition to the sample size. However, how can one really know what the constant proportionality is as long as you don't know the truth to be estimated?

In practice the choice of the basis dimension is a part of the model specification. However, it is important to keep in mind that the exact size of the basis dimension is not of critical importance. It only sets an upper limit to the flexibility of any smooth term. The smoothing parameter is actually controlling the effective degrees of freedom. Thus, the model to be fitted is insensitive to the basis dimension as long as it is not too small.

2.2.5 Variable coefficient models

A variable coefficient model, as introduced by Hastie & Tibshirani (1993) may look like

$$g(\mu_i) = \mathbf{X}_i^* \boldsymbol{\theta} + f_1(x_{1i})x_{2i} + f_2(x_{3i})x_{4i} + f_3(x_{5i}, x_{6i})x_{7i} + \dots$$

This kind of model can include interaction terms of smooth terms with other regressors. The only modification to the GAM framework presented in this section, is that the formal expression for the model matrix for the term $f_1(x_{1i})x_{2i}$ becomes $diag(\mathbf{x}_2)\mathbf{X}_1$ where \mathbf{X}_1 is the model matrix for $f_1(x_{1i})$ and $diag(\mathbf{x}_2)$ is a diagonal matrix with x_{2i} at the i_{th} position on its diagonal.

2.2.6 P-IRLS

To estimate a model as given by Equation 2.1 we specify a basis for the smooth components and define a term to control the wiggleness. Each function can then be represented as

$$f_j(x_j) = \sum_{i=1}^{q_j} \beta_{ji} b_{ji}(x_j)$$

where x_j may be a vector and the b_{ji} are the coefficients of the smooth to be estimated. Having chosen a basis one can write down the model matrix $\tilde{\mathbf{X}}_j$, for each smooth function. If \mathbf{f}_j is a vector with elements $\mathbf{f}_{j_i} = f_j(x_{j_i})$ and $\tilde{\boldsymbol{\beta}}_j = [\beta_{j1}, \beta_{j2}, \dots, \beta_{jq_j}]^\top$ then

$$\mathbf{f}_j = \tilde{\mathbf{X}}_j \tilde{\boldsymbol{\beta}}_j$$

where $\tilde{\mathbf{X}}_{j_{ik}} = b_{jk}(x_{j_i})$, and in case the regressor x_j may be a vector. Unless each smooth is subject to a centering constraint, (2.1) is an unidentifiable model in most cases. One possible remedy is to constrain the elements of \mathbf{f}_j to sum up to zero which can be written as

$$\mathbf{1}^\top \tilde{\mathbf{X}}_j \tilde{\boldsymbol{\beta}}_j = 0.$$

This constraint can be incorporated by re-parameterization. Defining matrix \mathbf{Z} of which $q_j - 1$ columns are orthogonal and it holds that

$$\mathbf{1}^\top \tilde{\mathbf{X}}_j \mathbf{Z} = \mathbf{0}.$$

Re-parameterizing the smooth components in term of $q_j - 1$ new parameters $\boldsymbol{\beta}_j$ such that $\tilde{\boldsymbol{\beta}}_j = \mathbf{Z}\boldsymbol{\beta}_j$ we obtain a new model matrix for the j^{th} term $\mathbf{X}_j = \tilde{\mathbf{X}}_j \mathbf{Z}$ such that $\mathbf{f}_j = \mathbf{X}_j \boldsymbol{\beta}_j$.⁶

⁶ \mathbf{Z} is never formed explicitly since it can be represented by a single Householder matrix

Given the new model matrices for the smooth terms, (2.1) can now be written as

$$g(\mu_i) = \mathbf{X}_i \boldsymbol{\beta}$$

where $\mathbf{X} = [\mathbf{X}^* : \mathbf{X}_1 : \mathbf{X}_2 : \dots]$ and $\boldsymbol{\beta}^\top = [\boldsymbol{\theta}^\top, \boldsymbol{\beta}_1^\top, \boldsymbol{\beta}_2^\top, \dots]$.

It is now easy to write down the likelihood $l_p(\boldsymbol{\beta})$ and to estimate the model. However, given a large number of knots and estimating the parameters by ordinary maximum likelihood we run into overfitting issues. Therefore GAMs are estimated by penalized likelihood maximization.

The penalties can be expressed in quadratic form of the smooth functions parameters. The wiggleness of the j^{th} function can be measured $\tilde{\boldsymbol{\beta}}_j^\top \tilde{\mathbf{S}}_j \tilde{\boldsymbol{\beta}}_j$ where $\tilde{\mathbf{S}}_j$ is a matrix of known coefficients. The re-parameterization would transform this to $\boldsymbol{\beta}_j^\top \bar{\mathbf{S}}_j \boldsymbol{\beta}_j$ where $\bar{\mathbf{S}}_j = \mathbf{Z}^\top \tilde{\mathbf{S}}_j \mathbf{Z}$. For notational convenience we write the penalty in terms of the full coefficient vector $\boldsymbol{\beta}^\top \mathbf{S}_j \boldsymbol{\beta}$ where \mathbf{S}_j is $\bar{\mathbf{S}}_j$ filled up with zeros. Thus, $\mathbf{S}_j \equiv \bar{\mathbf{S}}_j$.

The penalized likelihood function is then given by

$$l_p(\boldsymbol{\beta}) = l(\boldsymbol{\beta}) - \frac{1}{2} \sum_j \lambda_j \boldsymbol{\beta}^\top \mathbf{S}_j \boldsymbol{\beta} \quad (2.19)$$

where λ_j are the smoothing parameters. However, finding $\hat{\boldsymbol{\beta}}$ by maximization of l_p requires us to estimate λ_j first. Practically, the GAM penalized likelihood (2.19) can be maximized by penalized iteratively re-weighted least squares. Let $\mathbf{S} = \sum_j \lambda_j \mathbf{S}_j$

and assume λ_j are known. We can rewrite (2.19)

$$l_p(\boldsymbol{\beta}) = l(\boldsymbol{\beta}) - \frac{1}{2} \boldsymbol{\beta}^\top \mathbf{S} \boldsymbol{\beta}.$$

To maximize l_p we set the derivatives w.r.t. β_j to zero

$$\frac{\delta l_p}{\delta \beta_j} = \frac{\delta l}{\delta \beta_j} - [\mathbf{S} \boldsymbol{\beta}]_j = \frac{1}{\phi} \sum_{i=1}^n \frac{y_i - \mu_i}{V(\mu_i)} \frac{\delta \mu_i}{\delta \beta_j} - [\mathbf{S} \boldsymbol{\beta}]_j = 0$$

where $[\cdot]_j$ denotes the j^{th} row of a vector. These equations are the same that would have to be solved to maximize the penalized non-linear least squares problem

$$\mathcal{S}_p = \sum_{i=1}^n \frac{(y_i - \mu_i)^2}{\text{var}(Y_i)} + \boldsymbol{\beta}^\top \mathbf{S} \boldsymbol{\beta}$$

assuming the $\text{var}(Y_i)$ terms are known, Wood (2006b, pp.169) shows that in the neighbourhood of some parameter vector $\hat{\boldsymbol{\beta}}^{[k]}$

$$\mathcal{S}_p \simeq \left\| \sqrt{\mathbf{W}^{[k]}} (\mathbf{z}^{[k]} - \mathbf{X} \boldsymbol{\beta}) \right\|^2 + \boldsymbol{\beta}^\top \mathbf{S} \boldsymbol{\beta}. \quad (2.20)$$

Given a model's link function g , $\mathbf{z}^{[k]}$ is a vector of pseudo-data and $\mathbf{W}^{[k]}$ is a diagonal matrix with diagonal elements $\omega_i^{[k]}$, then

$$\omega_i^{[k]} = \frac{1}{V(\mu_i^{[k]}) g'(\mu_i^{[k]})^2} \text{ and } z_i = g'(\mu_i^{[k]}) (y_i - \mu_i^{[k]}) + \mathbf{X}_i \hat{\boldsymbol{\beta}}^{[k]}.$$

Thus, given smoothing parameters, the maximum likelihood estimates, $\hat{\boldsymbol{\beta}}$, can be estimated by iterating the following two steps to convergence

1. Given the current $\hat{\boldsymbol{\mu}}^{[k]}$, calculate $\mathbf{z}^{[k]}$ and $\omega_i^{[k]}$
2. Minimize (2.20) w.r.t. $\boldsymbol{\beta}$, to find $\hat{\boldsymbol{\beta}}^{[k+1]}$. Calculate the linear predictor $\boldsymbol{\eta}^{[k+1]} \mathbf{X} \hat{\boldsymbol{\beta}}^{[k+1]}$,

and fitted values $\mu_i^{[k+1]} = g^{-1}(\eta_i^{[k-1]})$. Repeat from step 1.

The *iteratively re-weighted least squares* method has been introduced by Nelder & Wedderburn (1972) in the context of generalized linear models. Building up on this work, O’Sullivan, Yandall & Raynor (1986) developed *penalized* likelihood maximization for smooth models. An introduction to the method of *penalized iteratively re-weighted least squares (P-IRLS)* in the context of GAMs can be found in Wood (2006b).

2.2.7 EDF and residual variance

The question to be answered in this section is: How many degrees of freedom does a fitted GAM have? To this end define the *effective degrees of freedom* as $tr(\mathbf{A})$ where \mathbf{A} is the influence matrix ($\hat{\boldsymbol{\mu}} = \mathbf{A}\mathbf{y}$). It can be shown that the maximum of $tr(\mathbf{A})$ is the number of parameters less the number of constraints. The minimum is $rank(\sum_i \mathbf{S}_i)$ less the maximum. Given that the smoothing parameters vary from zero to infinity the effective degrees of freedom vary continuously between these limits.

Since the effective degrees of freedom are reduced by the application of penalties and the penalties are different for each smooth term we want to calculate the effective degrees of freedom for each smooth term. Since each element of $\hat{\boldsymbol{\beta}}$ is penalized differently, one might even want to break the effective degrees of freedom down into effective degrees of freedom for each element $\hat{\beta}_i$ of $\hat{\boldsymbol{\beta}}$.

Let $\mathbf{P} \equiv (\mathbf{X}^\top \mathbf{X} + \mathbf{S})^{-1} \mathbf{X}^\top$. Thus, $\hat{\boldsymbol{\beta}} = \mathbf{P}\mathbf{y}$ and $tr(\mathbf{A}) = tr(\mathbf{X}\mathbf{P})$. Define \mathbf{P}_i^0 to be \mathbf{P} with all rows except the i^{th} set to zero. Therefore $\mathbf{P}_i^0 \mathbf{y}$ has $\hat{\beta}_i$ as i^{th} element

and is zero for the rest. Thus,

$$tr(\mathbf{A}) = \sum_{i=1}^p tr(\mathbf{X}\mathbf{P}_i^0).$$

Hence, $tr(\mathbf{X}\mathbf{P}_i^0)$ can be interpreted as effective degrees of freedom for the i^{th} parameter. Since $tr(\mathbf{X}\mathbf{P}_i^0) = (\mathbf{P}\mathbf{X})_{i,i}$, the vector of effective degrees of freedom for all model parameters is given by the leading diagonal of

$$\mathbf{F} = \mathbf{P}\mathbf{X} = (\mathbf{X}^T\mathbf{X} + \mathbf{S})^{-1}\mathbf{X}^T\mathbf{X}.$$

In case of normal errors and identity link function, σ^2 can be estimated by the residual sum of squares divided by the residual degrees of freedom

$$\hat{\sigma}^2 = \frac{\|\mathbf{y} - \mathbf{A}\mathbf{y}\|^2}{n - tr(\mathbf{A})}. \quad (2.21)$$

For the *generalized* additive model the error variance is estimated by

$$\hat{\phi} = \frac{\sum_i V(\hat{\mu}_i)^{-1}(y_i - \hat{\mu}_i)^2}{n - tr(\mathbf{A})}.$$

It can be shown that (2.21) is biased since

$$\mathbb{E}(\|\mathbf{y} - \mathbf{A}\mathbf{y}\|^2) = \sigma^2[n - 2tr(\mathbf{A}) + tr(\mathbf{A}^T\mathbf{A})] + \mathbf{b}^T\mathbf{b} \quad (2.22)$$

where $\mathbf{b} = \boldsymbol{\mu} - \mathbf{A}\boldsymbol{\mu}$ represents the smoothing bias. Thus, an alternative estimator for $\hat{\sigma}$ can be easily derived. However, \mathbf{b} still needs to be estimated, hence even the new estimator is still biased. Due to this and the complexity of (2.22) Wood (2006b, pp.172) suggests to work with (2.21).

2.2.8 Smoothing parameter selection - UBRE, CV & GCV

As explained above, P-IRLS estimates model coefficients β given smoothing parameters λ . This section introduces different criteria of smoothing parameter selection and theoretically justifies the use of generalized cross validation as introduced in Section 2.1.3.

One way of selecting smoothing parameters would be to choose them in order to minimize the mean square error of the model, i.e. to keep $\hat{\mu}$ as close as possible to the true $\mu \equiv \mathbb{E}(\mathbf{y})$.

Wood (2006b, pp.51) shows that

$$\mathbb{E}(M) = \mathbb{E} \left(\|\mu - \mathbf{X}\hat{\beta}\|^2/n \right) = \mathbb{E} \left(\|\mathbf{y} - \mathbf{A}\mathbf{y}\|^2/n - \sigma^2 + 2tr(\mathbf{A})\sigma^2/n \right) \quad (2.23)$$

where M is the mean square error of the fitted model and the right hand side depends on λ through \mathbf{A} . Thus, a reasonable approach would be to minimize the *unbiased risk estimator (UBRE)* of the mean square error w.r.t. λ . The UBRE approach has been developed by Craven & Wahba (1979). An equivalent to this is Mallows's C_p as introduced by Mallows (1973). As long as σ^2 is known, selecting λ through minimizing $\mathcal{V}_u(\lambda)$

$$\mathcal{V}_u(\lambda) = \|\mathbf{y} - \mathbf{A}\mathbf{y}\|^2/n - \sigma^2 + 2tr(\mathbf{A})\sigma^2/n \quad (2.24)$$

works well. However, since in our case σ^2 has to be estimated we do experience problems. Substituting (2.21) into (2.23)

$$\hat{M} = \mathbb{E} \left(\|\mu - \mathbf{X}\hat{\beta}\|^2/n \right) = tr(\mathbf{A})\hat{\sigma}^2/n \quad (2.25)$$

shows that a 2-parameter model has to reduce $\hat{\sigma}^2$ to less than half the value of the 1-parameter model before being identified as a better model. Thus, in our case UBRE is not suitable for the selection of $\boldsymbol{\lambda}$.

To surmount this problem we could use the mean square *prediction* error, $P = \sigma^2 + M$ (MSPE), instead of the mean square error.

As explained in Section 2.1.3, the MSPE is obtained by fitting the data omitting one data-point at a time. In doing so, we arrive at the ordinary least squares estimate of P

$$\mathcal{V}_o = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{\mu}_i^{[-i]})^2$$

where $\hat{\mu}_i^{[-i]}$ is the prediction error of $\mathbb{E}(y_i)$ obtained from the model fitted to the data excluding y_i .

However, it is not necessary to perform n model fits to calculate \mathcal{V}_o . Given the penalized least squares objective which could be minimized to find the i^{th} term in the OVC score

$$\sum_{j=1, \forall j \neq i}^n (y_j - \hat{\mu}_j^{[-i]})^2 + \text{penalties.}$$

Adding $(\hat{\mu}_i^{[-i]} - \hat{\mu}_i^{[-i]})^2$ yields

$$\sum_{j=1}^n (y_j^* - \hat{\mu}_j^{[-i]})^2 + \text{penalties.} \quad (2.26)$$

Minimizing this, we obtain the i^{th} prediction $\hat{\mu}_i^{[-i]}$ and the influence matrix \mathbf{A} . Let $\mathbf{y}^* = \mathbf{y} - \bar{\mathbf{y}}^{[i]} + \bar{\boldsymbol{\mu}}^{[i]}$ and $\bar{\mathbf{y}}^{[i]}$ & $\bar{\boldsymbol{\mu}}^{[i]}$ are zero except for their i^{th} element it follows

that

$$\hat{\mu}_i^{[-i]} = \mathbf{A}_i \mathbf{y}^* = \mathbf{A}_i \mathbf{y} - A_{ii} y_i + A_{ii} \hat{\mu}_i^{[-i]} = \hat{\mu}_i - A_{ii} y_i + A_{ii} \hat{\mu}_i^{[-i]}$$

where μ_i is from the model fitted to the whole dataset. Subtracting of y_i and rearranging shows

$$y_i - \hat{\mu}_i^{[-i]} = \frac{y_i - \hat{\mu}_i}{1 - A_{ii}}.$$

As result the OCV score becomes

$$\mathcal{V}_o = \frac{1}{n} \sum_{i=1}^n \frac{(y_i - \hat{\mu}_i)^2}{(1 - A_{ii})^2} \quad (2.27)$$

which can be obtained from the initial model fit to the full dataset. Interestingly it can be shown (see Stone, (1977)) that asymptotically OCV is equivalent to the Akaike Information Criteria.

OCV seems to be a reasonable approach to smoothing parameter selection. However, there are two problems with this approach. First, it is computationally expensive in the additive model case. Secondly, Golub, Heath & Wahba (1979) show that OCV is not invariant to transformation of $\mathbf{y} - \mathbf{X}\boldsymbol{\beta}$.

Consider the additive model fitting objective. Given $\boldsymbol{\lambda}$ all inferences about $\boldsymbol{\beta}$ are made on the basis of minimizing

$$\|\mathbf{y} - \mathbf{X}\boldsymbol{\beta}\|^2 + \sum_{i=1}^m \lambda_i \boldsymbol{\beta}^\top \mathbf{S}_i \boldsymbol{\beta}.$$

Given any orthogonal matrix \mathbf{Q} of appropriate dimension. Since pre-multiplication with an orthogonal matrix is merely a matrix rotation, i.e. all angles and vector

length stay the same, $\mathbf{y} - \mathbf{X}\boldsymbol{\beta} = \mathbf{Q}\mathbf{y} - \mathbf{Q}\mathbf{X}\boldsymbol{\beta}$. Hence, inferences based on

$$\|\mathbf{Q}\mathbf{y} - \mathbf{Q}\mathbf{X}\boldsymbol{\beta}\|^2 + \sum_{i=1}^m \lambda_i \boldsymbol{\beta}^\top \mathbf{S}_i \boldsymbol{\beta}$$

are not different from those made from the previous set-up.

Despite the invariance of parameter estimates, effective degrees of freedom and expected prediction error to rotation of $\mathbf{y} - \mathbf{X}\boldsymbol{\beta}$, those problems arise from the fact that the diagonal elements A_{ii} of the influence matrix \mathbf{A} change with rotation of $\mathbf{y} - \mathbf{X}\boldsymbol{\beta}$. Thus, (2.27) changes.

The concept of *generalized cross validation* solves this problem by choosing a \mathbf{Q} to make all A_{ii} equal. Thus rotation does not affect the validation score. Given \mathbf{A} as the influence matrix of the initial problem, the influence matrix of the rotated problem is

$$\mathbf{A}_\mathbf{Q} = \mathbf{Q}\mathbf{A}\mathbf{Q}^\top.$$

Let \mathbf{B} be a matrix such that $\mathbf{B}^\top \mathbf{B} = \mathbf{A}$ we can write the influence matrix as

$$\mathbf{A}_\mathbf{Q} = \mathbf{Q}\mathbf{B}\mathbf{B}^\top \mathbf{Q}^\top$$

If \mathbf{Q} has been chosen such that each row of $\mathbf{Q}\mathbf{B}$ has the same euclidean length all elements on the leading diagonal of $\mathbf{A}_\mathbf{Q}$ have the same value. Since $tr(\mathbf{A}_\mathbf{Q}) = tr(\mathbf{Q}\mathbf{A}\mathbf{Q}^\top) = tr(\mathbf{A}\mathbf{Q}^\top \mathbf{Q}) = tr(\mathbf{A})$, $A_{ii} = tr(\mathbf{A})/n$; $\forall i$. Thus, (2.27) can be written as

$$\mathcal{V}_g = \frac{n\|\mathbf{y} - \hat{\boldsymbol{\mu}}\|^2}{[n - tr(\mathbf{A})]^2}. \quad (2.28)$$

This *generalized cross validation score (GCV)* has been developed by Golub et al. (1979).

To apply this to the *generalized* additive model, the fitting objective can be written in terms of the model *deviance*, which is minimized w.r.t. $\boldsymbol{\beta}$

$$D(\boldsymbol{\beta}) + \sum_{j=1}^m \lambda_j \boldsymbol{\beta}^\top \mathbf{S}_j \boldsymbol{\beta}.$$

Wood (2006b) shows that this objective can be quadratically approximated by

$$\left\| \sqrt{\mathbf{W}}(\mathbf{z} - \mathbf{X}\boldsymbol{\beta}) \right\|^2 + \sum_{j=1}^m \lambda_j \boldsymbol{\beta}^\top \mathbf{S}_j \boldsymbol{\beta} \quad (2.29)$$

which is essentially the same as (2.9) for the two-variable case.

The GCV score for the smoothing parameter selection now becomes

$$\mathcal{V}_g^\omega = \frac{n \left\| \sqrt{\mathbf{W}}(\mathbf{z} - \mathbf{X}\boldsymbol{\beta}) \right\|^2}{[n - \text{tr}(\mathbf{A})]^2} \quad (2.30)$$

Only locally to the $\boldsymbol{\lambda}$ used to find \mathbf{z} and \mathbf{W} this is a good approximation. However, Hastie & Tibshirani (1990) show that a globally applicable approximation is given by

$$\mathcal{V}_g = \frac{nD(\hat{\boldsymbol{\beta}})}{[n - \text{tr}(\mathbf{A})]^2}. \quad (2.31)$$

2.2.9 Distributional results and the Bayesian model

Given that the parameter estimates can be represented by

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \mathbf{S})^{-1} \mathbf{X}^\top \mathbf{W} \mathbf{y}$$

where the data have covariance matrix \mathbf{W}_ϕ^{-1} , it follows that

$$\mathbf{V}_e = (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \mathbf{S})^{-1} \mathbf{X}^\top \mathbf{W} \mathbf{X} (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \mathbf{S})^{-1} \phi$$

is the covariance matrix of the estimators $\hat{\boldsymbol{\beta}}$ and approximately $\hat{\boldsymbol{\beta}} \sim N(\mathbb{E}(\hat{\boldsymbol{\beta}}), \mathbf{V}_e)$. If $\boldsymbol{\beta} = \mathbf{0}$ then $\mathbb{E}(\hat{\boldsymbol{\beta}}) = \mathbf{0}$ the results can be used for testing model terms for equality to zero. However, since $\mathbb{E}(\hat{\boldsymbol{\beta}}) \neq \boldsymbol{\beta}$ generally, there are problems calculating confidence intervals.

Using a Bayesian approach has been shown to be a good alternative to parameter uncertainty estimation. The Bayesian posterior covariance matrix is given by

$$\mathbf{V}_\beta = (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \mathbf{S})^{-1} \phi$$

with corresponding posterior distribution

$$\boldsymbol{\beta} \sim N(\hat{\boldsymbol{\beta}}, \mathbf{V}_\beta).$$

A very good introduction to Bayesian econometrics can be found in Koop (2003). A more theoretical framework is presented in Poirier (1995).

Prior

Having selected smoothing bases and penalties a model can be written as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}, \text{ with } \boldsymbol{\epsilon} \sim N(\mathbf{0}, \mathbf{W}^{-1}\sigma^2). \quad (2.32)$$

Assuming the model has been re-parameterized to eliminate identifiability constraints, it can be estimated by minimization of the penalized least squares objective

$$\|\mathbf{W}^{1/2}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})\|^2 + \sum_{i=1}^m \lambda_i \boldsymbol{\beta}^\top \mathbf{S}_i \boldsymbol{\beta}. \quad (2.33)$$

Define the prior for $\boldsymbol{\beta}$ as

$$f_{\boldsymbol{\beta}}(\boldsymbol{\beta}) \propto e^{-\frac{1}{2}\boldsymbol{\beta}^\top \sum \mathbf{S}_i / \tau_i \boldsymbol{\beta}}$$

where τ_i are parameters to control the dispersion of the prior. Following Wahba (1983) and Silverman (1985) this prior explicitly presents our belief that smooth models are more likely than wiggly ones but gives same odds to all models of similar smoothness.

From the initial model specification the conditional distribution of \mathbf{y} given $\boldsymbol{\beta}$ is

$$f(\mathbf{y}|\boldsymbol{\beta}) \propto e^{-\frac{1}{2}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^\top \mathbf{W}(\mathbf{y} - \mathbf{X}\boldsymbol{\beta}) / \sigma^2}.$$

Applying Bayes rule this can be rearranged to

$$\begin{aligned} f(\mathbf{y}|\boldsymbol{\beta}) &\propto e^{-\frac{1}{2}(\mathbf{y}^\top \mathbf{W} \mathbf{y} / \sigma^2 - 2\boldsymbol{\beta}^\top \mathbf{X}^\top \mathbf{W} \mathbf{y} / \sigma^2 + \boldsymbol{\beta}^\top (\mathbf{X}^\top \mathbf{W} \mathbf{X} / \sigma^2 + \sum \mathbf{S}_i / \tau_i) \boldsymbol{\beta})} \\ &\propto e^{-\frac{1}{2}(-2\boldsymbol{\beta}^\top \mathbf{X}^\top \mathbf{W} \mathbf{y} / \sigma^2 + \boldsymbol{\beta}^\top (\mathbf{X}^\top \mathbf{W} \mathbf{X} / \sigma^2 + \sum \mathbf{S}_i / \tau_i) \boldsymbol{\beta})}. \end{aligned}$$

Defining $\boldsymbol{\alpha} \sim N([\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i]^{-1} \mathbf{X}^\top \mathbf{W} \mathbf{y}, [\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i]^{-1} \sigma^2)$, the probability density function for $\boldsymbol{\alpha}$ is

$$\begin{aligned} f_{\boldsymbol{\alpha}}(\boldsymbol{\alpha}) &\propto e^{-\frac{1}{2}(\boldsymbol{\alpha} - (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i)^{-1} \mathbf{X}^\top \mathbf{W} \mathbf{y})^\top (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i) (\boldsymbol{\alpha} - (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i)^{-1} \mathbf{X}^\top \mathbf{W} \mathbf{y}) / \sigma^2} \\ &\propto e^{-\frac{1}{2}(-2\boldsymbol{\alpha}^\top \mathbf{X}^\top \mathbf{W} \mathbf{y} / \sigma^2 + \boldsymbol{\alpha}^\top (\mathbf{X}^\top \mathbf{W} \mathbf{X} / \sigma^2 + \sum \lambda_i \mathbf{S}_i / \sigma^2) \boldsymbol{\alpha})}. \end{aligned}$$

Comparing $F_\alpha(\boldsymbol{\alpha})$ and $f(\boldsymbol{\beta}|\mathbf{y})$, and choosing $\tau_i = \sigma^2/\lambda_i$ it follows that

$$\boldsymbol{\beta}|\mathbf{y} \sim N([\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i]^{-1} \mathbf{X}^\top \mathbf{W} \mathbf{y}, [\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i]^{-1} \sigma^2)$$

$$\boldsymbol{\beta}|\mathbf{y} \sim N(\hat{\boldsymbol{\beta}}, (\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i)^{-1} \sigma^2)$$

The prior on $\boldsymbol{\beta}$ has been chosen to give a convenient form for the distribution of $\boldsymbol{\beta}|\mathbf{y}$. Please note that the prior is equivalent to the assumption that each wiggleness component of the model $\boldsymbol{\beta}^\top \mathbf{S}_i \boldsymbol{\beta}$ is an *i.i.d* random variable with $\mathbb{E}(\boldsymbol{\beta}^\top \mathbf{S}_i \boldsymbol{\beta}) = \tau_i$. In the case of the GAMs used in this thesis, it holds that $\sum \mathbf{S}_i$ is block-diagonal. Therefore, the assumption of independence comes quite naturally from the non-overlapping nature of the penalties.

Posterior

Consider a GAM $g(\mu_i) = \mathbf{X}_i \boldsymbol{\beta}$, $\mu_i \equiv \mathbb{E}(Y_i)$, $Y_i \sim$ some exponential family where g is a known link function, and it is estimated by the minimization of

$$-l(\boldsymbol{\beta}) + \frac{1}{2} \sum_{i=1}^m \lambda_i \boldsymbol{\beta}^\top \mathbf{S}_i \boldsymbol{\beta} \quad (2.34)$$

with respect to $\boldsymbol{\beta}$ where $l(\boldsymbol{\beta})$ is the log-likelihood of the model. Problem (2.34) is minimized by solving

$$\text{minimize} \left\| \sqrt{\mathbf{W}^{[k]}} (\mathbf{X} \boldsymbol{\beta} - \mathbf{z}^{[k]}) \right\| + \sum_{i=1}^m \lambda_i \boldsymbol{\beta}^\top \mathbf{S}_i \boldsymbol{\beta}$$

where k is the iteration index, $\mathbf{z}^{[k]} = \mathbf{X} \boldsymbol{\beta}^{[k]} + \mathbf{G}^{[k]}(\mathbf{y} - \boldsymbol{\mu}^{[k]})$, $\mu_i^{[k]}$ is the current model estimate of $\mathbb{E}(Y_i)$, $\mathbf{G}^{[k]}$ is a diagonal matrix such that $G_{ii}^{[k]} = g'(\mu_i^{[k]})$ and \mathbf{W} is a diagonal matrix where $W_{ii} = \left[G_{ii}^{[k]2} V(\mu_i^{[k]}) \right]^{-1}$.

Working in terms of the random vector as suggested by the iterative least squares approach

$$\mathbf{z} = \mathbf{X}\boldsymbol{\beta} + \mathbf{G}(\mathbf{y} - \boldsymbol{\mu})$$

shows that $\mathbb{E}(\mathbf{z}|\boldsymbol{\beta}) = \mathbf{X}\boldsymbol{\beta}$ and $\mathbf{W}^{-1}\phi$ is the covariance matrix of $\mathbf{z}|\boldsymbol{\beta}$. Now let $\mathbf{v} = \mathbf{X}^\top \mathbf{W} \mathbf{z}$. Therefore, $\mathbb{E}(\mathbf{v}|\boldsymbol{\beta}) = \mathbf{X}^\top \mathbf{W} \mathbf{X} \boldsymbol{\beta}$ and $\mathbf{X}^\top \mathbf{W} \mathbf{X} \phi$ is the covariance matrix of $\mathbf{v}|\boldsymbol{\beta}$. Furthermore, it can be shown (Wood (2006b, p. 193) that asymptotically

$$\mathbf{v}|\boldsymbol{\beta} \sim N(\mathbf{X}^\top \mathbf{W} \mathbf{X} \boldsymbol{\beta}, \mathbf{X}^\top \mathbf{W} \mathbf{X} \phi). \quad (2.35)$$

Using this large sample approximation the posterior can be written as

$$\boldsymbol{\beta}|\mathbf{v} \sim N([\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i]^{-1} \mathbf{v}, [\mathbf{X}^\top \mathbf{W} \mathbf{X} + \sum \lambda_i \mathbf{S}_i]^{-1} \phi) \quad (2.36)$$

where the ϕ can be estimated as $\hat{\phi} = \|\mathbf{W}^{1/2}(\mathbf{y} - \hat{\boldsymbol{\mu}})\|^2 / \text{tr}(\mathbf{I} - \mathbf{A})$.

Bayesian confidence intervals

For non-linear functions of parameters Bayesian confidence intervals can be obtained though simulation of the posterior distribution of $\boldsymbol{\beta}$. If $G(\boldsymbol{\beta})$ is the approximate posterior cumulative distribution function, $\hat{F}(g)$ for G can be calculated by sampling random vectors $\{\boldsymbol{\beta}^* : i = 1, \dots, N\}$ from the multivariate normal posterior for $\boldsymbol{\beta}$, thus

$$\hat{F}(g) = \frac{1}{N} \sum_{i=1}^N H(g - G(\boldsymbol{\beta}_i^*))$$

where H is the Heaviside function which is 1 for values $\geq g$ and 0 for values $< g$. From the quantiles of this distribution, Bayesian confidence intervals can be obtained easily. Interestingly, in cases where the evaluation of G is computationally cheaper, the costs of calculating confidence intervals this way will be about the same as the

cost of performing one bootstrap replicate (see Wood, 2006b).

P-values

The question of significance of one smooth term of an estimated GAM is the question of significance of a subset β_j of β . Thus, if $\beta_j = 0$ then $\mathbb{E}(\hat{\beta}_j) \approx \mathbf{0}$. If the covariates of a given smooth are uncorrelated with those of other smooths of the model it even holds that $\mathbb{E}(\hat{\beta}_j) = \mathbf{0}$.

Separating the covariance matrix of $\hat{\beta}_j$, $\mathbf{V}_{\hat{\beta}_j}$ from \mathbf{V}_e it holds that under the null hypothesis $\beta_j = 0$, and hence,

$$\hat{\beta}_j \sim N(\mathbf{0}, \mathbf{V}_{\hat{\beta}_j}).$$

It follows that if $\mathbf{V}_{\hat{\beta}_j}$ is of full rank that under the null hypothesis

$$\hat{\beta}_j^T \mathbf{V}_{\hat{\beta}_j}^{-1} \hat{\beta}_j \sim \chi_d^2$$

where $d = \dim(\beta_j)$. However, usually penalization suppresses some dimensions of the parameter space. Hence, $\mathbf{V}_{\hat{\beta}_j}$ is not of full rank. Therefore, testing is performed using

$$\hat{\beta}_j^T \mathbf{V}_{\hat{\beta}_j}^{r-} \hat{\beta}_j \sim \chi_r^2$$

where $r = \text{rank}(\mathbf{V}_{\hat{\beta}_j})$ and $\mathbf{V}_{\hat{\beta}_j}^{r-}$ is the rank r pseudoinverse of the covariance matrix.

The p-value for the test $\beta_j = 0$ is $Pr[X > \hat{\beta}_j^T \mathbf{V}_{\hat{\beta}_j}^{r-} \hat{\beta}_j]$ where $X \sim \chi_r^2$ and r is determined numerically or with reference to the effective degrees of freedom of the smooth term.

If \mathbf{V}_e and therefore $\mathbf{V}_{\hat{\beta}_j}$ include an unknown scale parameter ϕ p-value calculations can be based on the approximate result

$$\frac{\hat{\beta}_j^T \mathbf{V}_{\hat{\beta}_j}^{-1} \hat{\beta}_j / r}{\hat{\phi} / (n - edf)} \sim F_{r, edf}.$$

2.3 Summary and concluding remarks

From the above it becomes clear that there are various possibilities to make use of generalized additive models in combination with a spline basis. However, the choice of the basis is crucial. Standard bases for regression splines such as cubic splines, cyclic cubic splines or p-splines require the user to choose knot locations, i.e. the basis dimension. Furthermore, they allow only for the representation of the smooth of one predictor variable. Given the fact that splines are the smoothest interpolators (see Green & Silverman (1994)) it can be shown that cubic splines (see Section 2.2.1) turn out to be an ideal basis for statistical regressions. The only drawback is that there are as many free parameters as there are data. Dealing with more than one regressor this becomes very expensive with respect to computational efficiency. We can overcome those issues by using penalized regression splines. However, the problem of choosing the basis dimension remains (see Lancaster & Salkauskas (1986)). P-splines overcome those issues for the price of less easy interpretation of the properties of the fitted smooth (see Section 2.2.2). Therefore, the bases for our estimations are thin plate regression splines (TPRS) in combination with a GCV procedure. TPRS surmount the mentioned problems and are in a limited sense 'optimal' with respect to these problems. TPRS avoid the problem of knot-placement and are relatively cheap to compute.

One disadvantage of using GAMs with any spline basis is that hypothesis testing

is only approximate and that satisfactory interval estimation requires a Bayesian approach. Using the Bayesian posterior covariance matrix and a corresponding posterior distribution allows us to calculate p-values and confidence intervals. Typically the p-values calculated this way will be somewhat too low, because they are conditional on the smoothing parameter, which is usually uncertain. Therefore, we will be quite restrictive while interpreting the data and talking about significance.

3 Evaluation of physical dry bulk time charter rates

3.1 Introduction

This chapter aims to identify vessel and contract specific determinants of physical dry bulk time charter rates. Furthermore, in quantifying the effect of the quality of any given vessel on period rates it seeks to prove the hypothesis of a two-tier⁷ Panamax dry bulk market. These questions arise due to, first, increased interest in modern financial instruments for hedging purposes such as FFAs and forward pricing options. These instruments require a sound validation of the underlying fundamentals, i.e. freight and time charter rates. Second, increased public perception about environmental issues and seafarer safety have been the reason for the introduction of stricter maritime legislation in Australia during early 90's which nowadays affect almost the entire Pacific region (see HORSCOTCI (1992) and BTCE (1994)). Differences in allocation of quality vessels in the Atlantic and Pacific require the creation of incentives to renew the fleet and increased standards of vessel maintenance (Timmermann & McConville (1996) and Rowlinson (1996)). Hence, we raise the question of whether the financial incentives are sufficient for owners and operators to increase standards of safety and security in the Panamax dry bulk segment.

The objectives of this chapter are achieved by applying semi-parametric estimation techniques, which are capable of describing all non-linear relations between

⁷Charter markets which are split into a sub-market for quality vessels and another sub-market for non-quality vessels are known as "two-tier markets".

time charter rates and the factors. For the first time, this chapter applies the semi-parametric class of generalized additive models (GAM) to a dataset of actual Panamax dry bulk fixtures over the period 2003-2007. Previous studies on the existence of two-tier markets required to make crucial assumptions about how to define quality. For instance, the questions of whether the cut-off point⁸ for quality vessels is 10, 15 or even 20 years of age had to be subjectively answered in all studies of this kind. This is because other measures of quality like flag or classification society proved to be bad approximations or entirely irrelevant. Semi-parametric models in general allow for a very flexible model specification which sidesteps those issues. GAMs in particular do not require to choose any functional form apart from additivity of the factors under consideration.

The existing literature addressing the first issue offers insight into most macroeconomic relations and a variety of volatility, risk and time series related analyses of different markets (see for instance, Kavussanos & Alizadeh (2002b) or Koekebakker, Adland & Sodal (2007)). However, on the microeconomic level freight and charter rates did not receive much attention. Regarding the existence of two-tier markets one can find studies analysing the post OPA90 tanker markets presenting ambiguous results (Tamvakis (1995) or Strandenes (1999)). With respect to the dry bulk segment, however, studies mostly concentrate on factors of casualties than determinants of individual time charter rates, despite the intersection to be expected (Tamvakis & Thanopoulou (2000) and Roberts & Marlow (2002)).

This chapter extends the results of previous research by using generalized additive models to explain vessel and contract specific differences in time charter rates.

⁸The "cut-off point" is an artificially chosen threshold which divides two-tier markets according to the age of the vessels into the quality and non-quality segment for the purpose of statistical investigations.

This way, it can be shown that a good part of the variation in physical time charter rates is due to microeconomic factors. Controlling for contract specific effects such as place of delivery, charter length and number of days forward to delivery as well as vessel specific factors such as size and fuel consumption this chapter quantifies quality induced differences in physical dry bulk charter rates. The results of this chapter are important in two different aspects. First, it extends previous research with respect to the microeconomic modelling of time charter rates on the contract and vessel specific level. It underlines the importance of vessel and contract specific factors to time charter rates. Secondly, it empirically proves the existence of a two-tier Panamax dry bulk market and thus, leads to important insights and implications for environmental safety and the security of cargo and seafarers.

The remainder of this chapter is structured as follows. Section 3.2 reviews the related literature on spot and time charter rates with a focus on vessel and contract specific factors. Section 3.3 provides an introduction to the Panamax dry bulk freight and charter market. A description of the identified factors and the available data can be found in Section 3.4. The presentation of the different models and a discussion of the results can be found in Section 3.5. Finally, Section 3.6 summarizes and concludes.

3.2 Literature review

As the main indicators of the shipping market condition spot⁹ and time charter rates have attracted a lot of academic attention on the macroeconomic level. Starting with the classical work of Koopmans (1939) and Tinbergen (1959), continuing with

⁹Please note that the words "spot rate" are used as synonym for "voyage rate" throughout the thesis

the extensive structural integrated market models of Charemza & Gronicki (1981), Beenstock & Vergottis(1989a, 1989b, 1989c, 1992, 1993) and Veenstra (1999) finding its latest results in option pricing and research on FFAs, e.g. Kavussanos & Alizadeh (2002b), Koekebakker & Adland (2004) and Koekebakker et al. (2007). However, on a microeconomic level charter rates have not been analysed in great detail. One can find two strings of research. First studies on the volatility of charter rates with respect to the size of a vessel, see Kavussanos (1996a) and second, papers investigating the vessel-quality and age effect on charter rates as in Tamvakis (1995), Strandenes (1999) and Tamvakis & Thanopoulou (2000).

Kavussanos (1996a) concentrates on charter rates with respect to volatility as a central element of business decision-making. The paper describes spot freight rates as a function of industrial production, price of bunkers and size of the existing fleet. Using an ARCH-model and monthly data from 1973 to 1992 for Handysize, Panamax and Capesize vessels the analysis shows that risks in the charter market vary over time and those risks differ dependent on vessel size. Comparing time vs. spot charter it can be shown that with respect to the risks involved the spot market has to be preferred. The paper argues that due to the element of changing expectations in time charter rates they tend to show a higher risk as reflected by a relatively high variation. With respect to vessel size the paper can show that generally the variation of rates decreases with vessel size, i.e. operating smaller vessel tends to be a less risky business. According to the author the economic reasoning behind this is the higher flexibility of smaller vessels in terms of cargo and port restrictions.

The first paper to investigate vessel specific differences in charter rates is Tamvakis (1995). Following the introduction of the Oil Pollution Act in 1990 (OPA90)

the paper addresses the question whether there is a two-tier spot freight market for crude oil carriers, i.e. does the market pay a premium for employing younger, high quality vessels? The study uses two-sample t-tests to compare a variety of sub-samples from a dataset of approximately 12,000 fixtures from 1989 to 1993. Sub-samples are differentiated with respect to US-bound fixtures, size in dwt, hull, age and pre-or post-OPA90 period. The results of the analysis do somewhat vary. On one hand a difference between non-US-bound and US-bound fixtures can be shown. On the other hand, apart from some cases, there is no consistent difference between younger, double-hull and older single-hull vessels. As some of the flaws of the study the author mentions weak market conditions which disfavour freight rate discrimination. Moreover, due to the lack of data, not all relevant vessel characteristics could be included into the study.

Strandenes (1999) builds upon the Tamvakis (1995) idea of a two tier tanker market. The paper develops a computable equilibrium model which is used to simulate freight determination in tanker markets segmented with respect to quality restrictions. The model is calibrated to the market conditions in the second half of 1991. Four different scenarios are simulated: (a) rise in US-imports, (b) reduction in quality tanker tonnage, (c) restrictions on the use of old tankers in European ports, (d) replacement of low quality tankers in the case of restrictions on the use of low quality tankers in Europe. The main results of this study are that it requires substantial changes in the markets to induce two-tier freight rates. Moreover, increasing demand must come at the cost of demand for standard tankers. Furthermore, it can be shown that a situation with a two-tier market is not a lasting one. The paper concludes that given the difficulties of assessing the quality of a vessel it is possible that quality tankers may obtain marginally higher returns due to the greater

flexibility. This in combination with the assumption of a preference of high quality vessels indicates shorter idle periods i.e. a higher utilization of quality vessels.

One of the most recent papers analysing vessel specific differences in charter rates is Tamvakis & Thanopoulou (2000). After Strandenes (1999) having established the the idea of a two-tier tanker market theoretically, Tamvakis & Thanopoulou (2000) extended the 1995-idea to the Panamax and Capesize dry bulk market. Theory suggests that due to new environmental requirements and due to the loss of image, also dry bulk charterers prefer to employ younger and high quality vessels and are willing to pay a higher price for this increased environmental safety. Grouping the available data on voyage fixtures into fixtures for vessels younger and older than 15 years the paper finds empirical evidence for the two-tier market hypothesis during the recent history for the Panamax segment. However, without controlling for other relevant vessel and contract specific factors, there seems to be no evidence in the Capesize segment for a two-tier market in the older history.

3.3 The formation of time charter rates

The Panamax dry bulk freight market is said to be an almost perfect market in the sense that there is a huge number of buyers and sellers, and prices i.e. freight rates are purely determined by supply and demand for transportation. From an economists point of view this is a very desirable condition since it eases the modelling and forecasting of the market. The freight market is split up into two parts defined by the type of transaction traded. Under voyage charter contract the shipper buys transport from the shipowner at a fixed rate per ton of cargo to be transported. Under the time charter contract a ship is hired for a fixed rate per day and the charterer gets full operational control over the vessel.

A time charter contract involves risk for both parties. Whereas the shipowner pays the operational costs, the charterer has to pay for all voyage costs. Hiring a vessel can be a somewhat difficult thing since any problems that are likely to happen have to be considered to save the costly process of arguing about the financial responsibility in case something unusual happens. The details of a time charter contract are set out in the charter-party. A thought-through charter-party will provide clear agreements on the legal responsibility in any event. In the charter-party the shipowner states the vessel's speed, consumption and cargo capacity. Additionally, the charter party contains information on the conditions of lay-up and off-hire and any kind of termination agreement. The terms of hire will be adjusted if the vessel does not perform according to these standards. Those factors are expected to influence the charter rate, i.e. an increasing charter rate with speed and capacity and a decreasing rate with respect to consumption. Under time charter contract the charterer takes the risk of changes in bunker costs. Hence, any charterer might not be willing to pay as much for a vessel with high consumption. Moreover, it needs to be considered that consumption and speed are highly correlated.

Charter rates are freely negotiable. However, since the starting point for the charter negotiations is the "last done", i.e. the last fixture, there is a strong interest in reports of recent transactions. A typical dry cargo market report as nowadays available through a variety of sources, includes a commentary on the general market conditions followed by a listing of all recent transactions which are typically divided into the different dry bulk cargoes and period charter fixtures. A unifying measure for the current and past market conditions is the Baltic Freight Index (BFI). The BFI is a statistical index set up in 1985, covering freight rates for eleven trade routes

of which four are grain routes, three coal routes, one iron ore and three time charter routes. The index is calculated as a weighted average of actual rates on the different trade routes. If no fixtures are available, a panel of brokers independently estimates what the charter rate would have been.

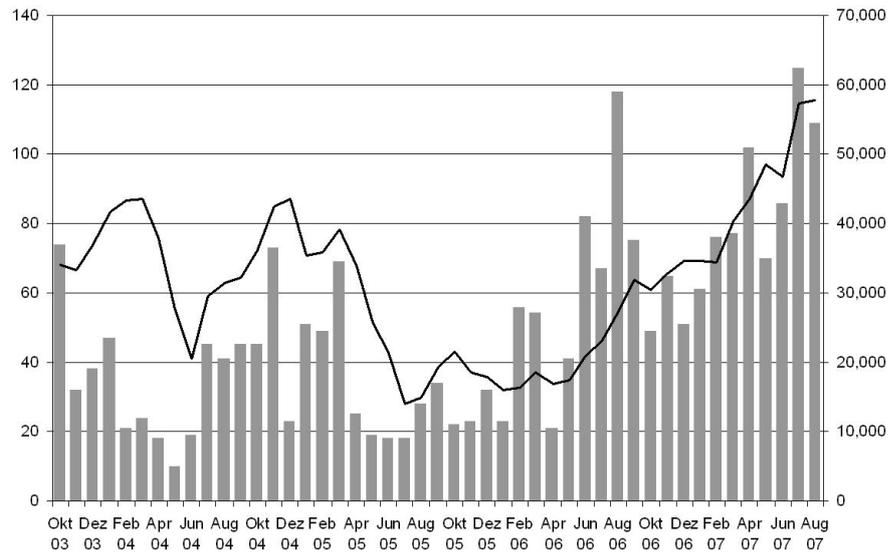


Figure 3.1: The dry bulk Panamax market, source: Clarksons Research

Figure 3.1 shows the development of the Panamax dry bulk market for the period from October 2003 to August 2007. The bars reflect the level of market activity as number of fixtures on the primary axis. The line shows the average of the four Panamax TC routes of the Baltic Panamax Index measured in USD/day on the secondary axis¹⁰. As can be seen the level of market activity is positively correlated to the level of time charter rates. The period under consideration covers a full cycle beginning with the market peaks in 2003/04 through the market downturn of 2005/06 reaching another peak in 2007.

Another important factor to the determination of time charter rates is the element

¹⁰Clarkson Research Ltd.: Monthly time series number 43444.

of expectations in time charter and forward contracts. An owner closes a time charter contract if he is not willing to bear the risk of varying spot rates. The rate on which the owner and the charterer agree, can therefore be interpreted as the average market's expectations for the charter period. Any shipowner closing a time charter contract does not expect the market to show higher average spot rates (incl. risk adjustment). Otherwise he would expect to be better off in the spot market. However, the charterer expects the market to show higher average spot rates than the rate agreed upon. Another important point to be considered with respect to market expectations is, how many days or month in advance the contract has been closed. Since the market rate will change until the transportation service is provided, some adjustment to the rate agreed upon compared to fixtures with immediate delivery have to be expected. Since the term structure is typically backward-dated, deliveries further into the future will have a lower period rate¹¹.

However, in practice things get more complex. Due to environmental safety legislation the charterer bears the costs of having an unsafe and/or old vessel employed. In case of damage the operator faces e.g. the loss of the cargo, costs of re-establishing the environment, a loss of corporate image and increased operating cost due to higher insurance premiums. Therefore, one might expect a charterer be willing to pay higher rates for vessels which do not bear those risks. Given such preferences the market exhibits necessary incentives for operators to aim for more environmental safety while operating their vessels.

¹¹For more details on the time-varying risk premium and forward freight rate dynamics see Kavusanos (1997), Adland (2002) and Koekebakker & Adland (2004).

3.4 Determinants of physical dry bulk time charter rates

Factors influencing physical time charter rates can be divided into three factor groups. First, there are macroeconomic measures reflecting the general state of the market. Second, there are microeconomic factors accounting for contract and, third, vessel specific effects. To capture the general market movements we use the Baltic Panamax Index, which is the average of the four Panamax routes from the Baltic Freight Index. Moreover, due to the speculative element of forward and time charter contracts we need to consider the timing of the contracts in terms of how many days forward to delivery has the contract been closed and for what time period. Together with the place of delivery these factors account for the contract specific effects on period rates. Vessel specific but somewhat unsurprising the size is the most crucial individual factor which influences the charter rate. However, much of the size effect is redundant since we analyse Panamax bulker. Hence, we will observe relatively small size differences only, which do not necessarily make a difference with respect to cargo and port flexibility. If the hypothesis of the two-tier market stands, age as the most important indicator of a vessels quality, has a significant impact on rates. Other vessel specific factors expected to affect time charter rates are speed, consumption, horsepower, flag and classification society.

The dataset used in this analysis has been provided by Clarksons Research. It contains 2,328 observations on Panamax dry bulk TC-fixtures from October 2003 to August 2007. Full information is available for the time charter rate, Baltic Panamax Index, and the size of the vessels contracted. For the charter length, the number of days forward, age and fuel consumption only limited information is available.

Table 3.1: Summary statistics

Variable	Unit	N	Mean	Std.Dev.	Min	Max
Charter rate	USD/day	2,328	32,629	11,203	10,000	72,500
Baltic Panamax Index	USD/day	2,328	34,764	11,576	15,055	59,490
No. of days forward	Days	1,754	8.83	9.86	0	59
Charter length	Days	1,597	244.72	169.49	30	730
Size	dwt	2,328	70,393	7,677	50,149	79,900
Age	years	1,824	6.28	5.38	0	25
Consumption	tonnes/day	637	32.50	2.77	25.50	39.90

Table 3.1 shows the summary statistics of the dataset after 5% from the boundaries of the sample have been dropped¹². It can already be seen that minimum and maximum charter rates for individual fixtures deviate by several thousand USD per day from the market average, 10,000 USD/day and 72,500 USD/day vs. 15,055 USD/day and 59,490 USD/day, respectively. This is more than we would expect those differences to be from simple arbitrage. On average, fixtures are closed about 9 days prior to delivery with a natural minimum of 0 and a maximum of about 2 month. The charter length varies between 1 month and 2 years.¹³ The vessel size ranges from about 50' dwt to 80' dwt having an age between 0 and 25 years.¹⁴ Information about fuel consumption given in metric tonnes per day is only available for 637 observations in the dataset.¹⁵

In addition to the variables presented in Table 3.1 the dataset includes information about the place of delivery (PoD) for each fixture. Place of delivery, especially

¹²Low data-density in the boundaries of the sample leads to broad confidence intervals and inconclusive results in the regression to come in Section 3.5. Therefore we dropped 5% of the observations from each variables low data density regions.

¹³Please note that the dataset includes longer charter periods of up to 5 years. However, those have been dropped due to low data density.

¹⁴Please note here that it is necessary to bear in mind that younger vessels tend to be larger. This issue and the correlation of the dependent variables in general will be addressed below.

¹⁵The following regressions have been carried out with different numbers of observations and general model comparison can only be of limited scope.

Atlantic or Pacific delivery are expected to make a difference to the charter rates since market equilibria in these two basins can deviate by several thousand USD per day (see Timmermann & McConville (1996) and Rowlinson (1996) for more details on the issue of allocation of quality tonnage). All delivery places have therefore been grouped into Atlantic, Pacific and worldwide delivery according to geographic vicinity. As a result, 29.1% of the dataset are Atlantic deliveries, 63.7% Pacific deliveries and 7.2% unspecified worldwide deliveries.

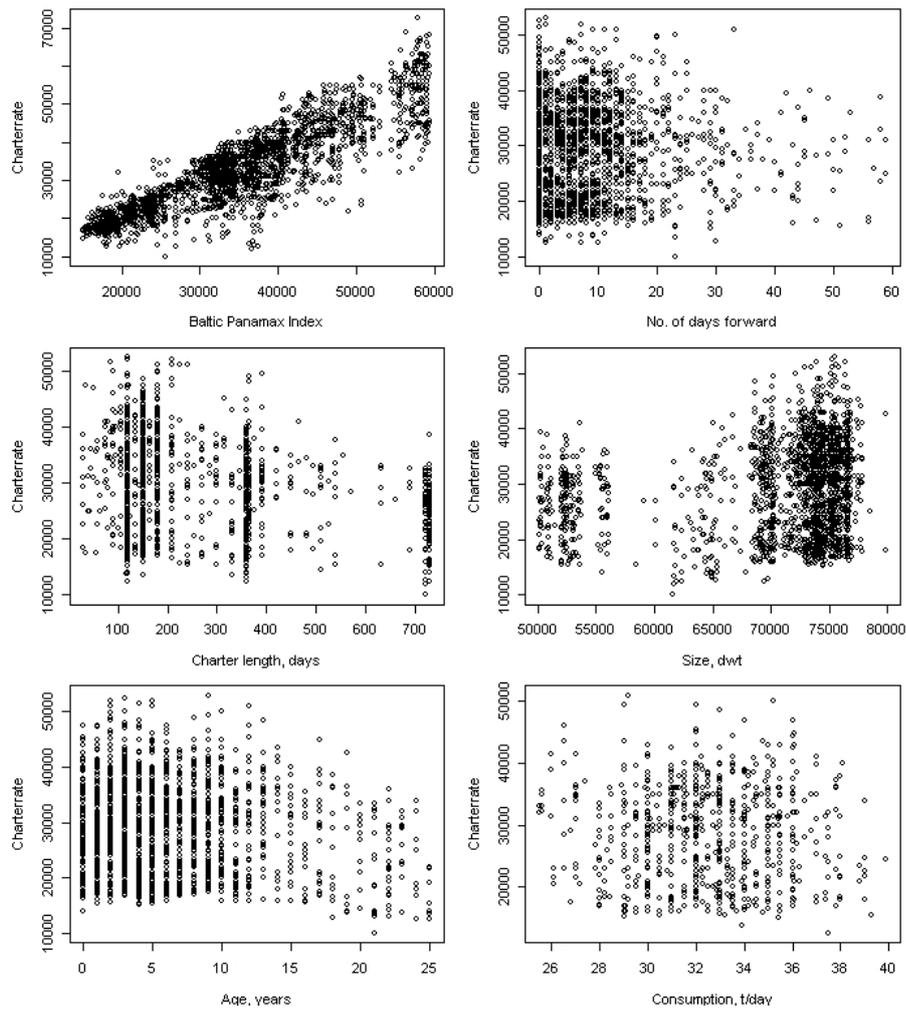


Figure 3.2: Timecharter rates - market, contract and vessel-factors

Figure 3.2 presents an graphical overview of the data. The upper left panel presents the obviously linear relation of single fixture rates to the general market level. Of

same obviousness is the large and increasing variation around the market average, indicating heteroscedasticity with respect to the Baltic Panamax Index. The top-right panel shows the time charter rate against the number of days forward to delivery a contract has been fixed. The data density decreases with forward days and there seems to be no visible nexus to charter rates. By contrast, the charter length in the mid-left panel shows a negative relation with time charter rates and cluster points at around 6, 12 and 24 month, which on one hand shows the habitualness of those charter length and on the other hand that there are many fixtures with "non-standard" charter length. The mid-right and the bottom-left panel show the scatterplot of charter rate against size and age respectively. The first shows two size clusters at around 49' to 56' dwt and 67' to 78' dwt, corresponding to the small and large standard Panamax sizes. Moreover, the low density data area at around 57' dwt to 67' dwt indicates that non-standard sized vessels seem to receive lower time charter rates than the former standard sized vessels. The later of the two panels shows a slight negative nexus to charter rates from the age of about 10 to 15 years¹⁶. As mentioned above and confirmed through the correlation analysis below, size and age are negatively correlated. Thus, while analysing any age specific effect to rates we necessarily need to control for size. The last panel shows that consumption seems to be completely unrelated to time charter rates.

To complement the graphical analysis Table 3.2 presents the pairwise correlations between all factors of physical time charter rates under consideration. Following the graphical analysis above we can identify relevant correlations¹⁷ (highlighted in bold numbers). The number of days forward and charter length are negatively correlated to charter rates with an insignificant correlation coefficient for days forward.

¹⁶As age is measured in years as integer we do observe a peculiar shape of the scatterplot.

¹⁷Please keep in mind that correlation coefficients as a measure for any linear nexus lack the ability to detect most multivariate and/or non-linear relations between two or more variables.

Table 3.2: Correlation

	Charter rate	BPI	No. of days forward	Charter length, days	PoD Pacific	PoD Atlantic	PoD world-wide	Size, dwt	Age, years	Consumption, t/day
Charter rate	1									
BPI	0.7828	1								
Days forward	-0.0614	0.0843	1							
Charter length	-	0.1831	0.2906	1						
	0.2271									
PoD Pacific	-0.0736	-0.0983	-0.0932	-0.0787	1					
PoD Atlantic	0.1080	0.0811	-0.0717	-0.0304	-	1				
PoD worldwide	-0.0619	0.0430	0.3359	0.2238	-	-	1			
Size	0.1620	-0.0562	0.0394	-0.0401	-0.0532	0.0536	0.0039	1		
Age	-	0.0487	-0.0167	0.0036	-	0.1024	0.0198	-	1	
	0.2112				0.1075			0.1941		
Consumption	-0.0758	0.0479	0.0285	-0.0045	0.0030	0.0080	-0.0221	0.0489	0.1575	1

The dummy for Atlantic delivery is positively correlated to the dependent variable. Same holds for the size of a vessel. Age is negatively correlated to charter rate with a correlation coefficient of -0.21. Supporting the graphical analysis, consumption shows a very low correlation coefficient of -0.08. As expected age and size are negatively correlated. Age is also negatively related to Pacific delivery and positively correlated to Atlantic delivery. Thus, following the argument of Timmermann & McConville (1996) there seems to be some preference for younger Panamax vessels in the Pacific basin. Charter length is also positively correlated to BPI and number of days forward, i.e. in a strong market, participants seem to prefer longer fixture periods which in turn reflects increased time charter market activity during strong market periods as shown in Figure 3.1. At the same time number of days forward and charter length seem to be positively related. Unsurprisingly, worldwide delivery and the number of days forward and charter length are positively correlated. This is due to the fact that long-term contracts are usually fixed long before the actual place of delivery is known.

3.5 Quantitative models of time charter rates

In Section 3.4 all factors to physical time charter rates have been divided into three factor groups. First, there are measures of the general state of the market. Secondly, there are factors which can describe the specific contract that has been closed and third, there are vessel specific factors. According to those factors group we classified "market models", "market-contract models", "market-vessel models" and "market-contract-vessel models".

3.5.1 The market factor model

The market model shown in Equation 3.1 tries to explain any contract specific time charter rate merely by the general state of the market. Where $RATE_i$ is the time charter rate of fixture i , the state of the Panamax market is measured by the average of the four Panamax TC routes of the Baltic Panamax Index measured in USD/day, BPI as explained above and $g(\cdot)$ is the link function¹⁸.

$$g(E(RATE_i|\cdot)) = \gamma_0 + s(BPI_i) \quad (3.1)$$

Table 3.3 presents the regression results for Model 3.1. The upper panel shows the results for the parametric terms which, in this case, is just the constant term of the regression. The lower panel presents the results for the smooth component $s(BalticPanamaxIndex)$. The effective degrees of freedom of 8.4 indicate a clear non-linearity (see Section 2.2.7). Moreover, the smooth term is highly significant. The R^2 is 78.9%. Thus about 79% of the variation in charter rate fixture is due to the general market level. More interestingly, it follows that 21% of the differences are due to other sources of charter rate determination.

¹⁸The natural logarithm, $ln(\cdot)$ has been used as link function for all models.

Table 3.3: Results for the market factor model

Parametric terms			
	Estimate	p	sig.
Intercept	10.333	0.000	***
Smooth terms			
	Effective DF	p	sig.
s(Baltic Panamax Index)	8.422	0.000	***
R^2	78.9%		
GCV score	0.026214		
N	2328		

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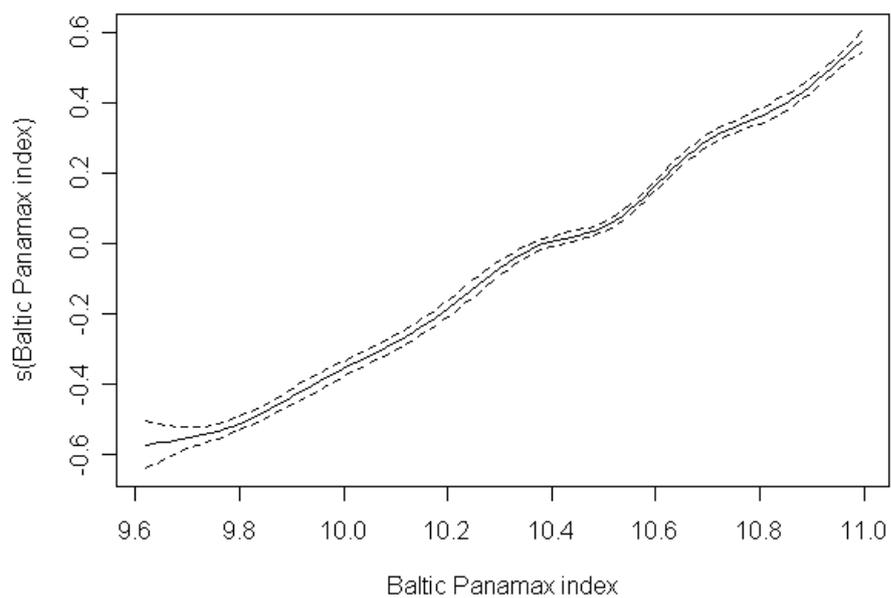


Figure 3.3: Smooth of Baltic Panamax Index

Looking at Figure 3.3 shows that despite the technically high non-linearity, as expected the dependence of individual fixtures to the general market level is almost linear and semi-parametric modelling should not make much of a difference for the analysis. However, extending the framework justifies the use of non-linear estimation techniques.

3.5.2 The market-contract model

Equation 3.2 presents the model setup including the contract specific factors, number of days forward $FORWARD_i$, charter length $LENGTH_i$ and place of delivery I_i^{pod} as dummy variables.

$$g(E(RATE_i|\cdot)) = \gamma_0 + s(BPI_i) + s(FORWARD_i) + s(LENGTH_i) + \sum_{pod} \gamma_{pod} I_i^{pod} \quad (3.2)$$

Supporting the results of the correlation analysis, Pacific delivery tends to lead to a lower charter rate than Atlantic delivery while the worldwide delivery dummy is insignificantly negative. Compared to the pure market factor model the effective degrees of freedom of the smooth for BPI slightly decreased. The number of days forward to delivery and the charter length are highly significant with 3.5 and 5.6 effective degrees of freedom, respectively.

Please note that the number of observations used to estimate this model is 1,597 compared to 2,328 observation in the previous model. Thus, the increased R^2 of 82.8% is not necessarily due to increased explanatory power of the model including contract specific factors.

The upper right panel of Figure 3.4 presents the smooth of $FORWARD$. The number of days forward to delivery seem not to make a difference between 0 and 20

Table 3.4: Results for the market-contract model

Parametric terms			
	Estimate	p	sig.
Intercept	10.264	0.000	***
PoD Pacific	-0.019	0.005	**
PoD worldwide	-0.016	0.398	
Smooth terms			
	Effective DF	p	sig.
s(Baltic Panamax Index)	5.317	0.000	***
s(No. of days forward)	3.451	0.000	***
s(Charter length)	5.571	0.000	***
R^2	82.8%		
GCV score	0.015229		
N	1597		

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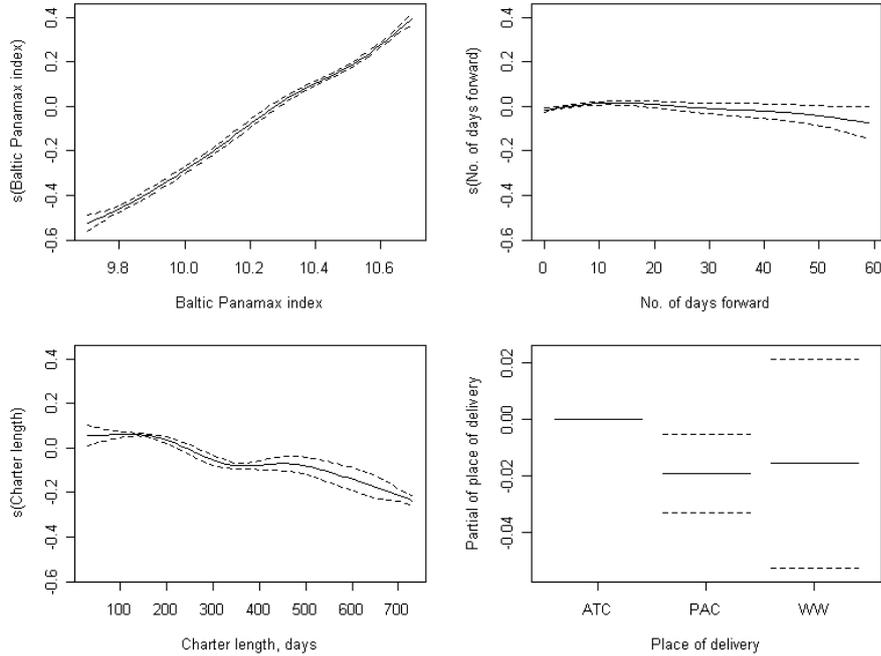


Figure 3.4: Smooths and partials of market-contract model

days. However, for 20 and more days forward to delivery charter rates seem to receive a discount. Same holds for the charter length presented in the bottom-left panel of Figure 3.4. Due to the data density the confidence band shows very narrow parts at 6, 12, and 24 month as expected. Furthermore, we observe decreasing charter rates with increasing contract periods. The bottom-right panel shows the partials of $g(E(RATE_i|.))$ with respect to the PoD dummy variables. Pacific delivery results in a lower period charter compared to Atlantic delivery with worldwide delivery being insignificant.

3.5.3 The market-vessel model

Equation 3.3 presents the market-vessel model which, contrary to the above, assumes independence of contract specific factors and aims to explain time charter rates by vessel specific factors age, size and consumption.¹⁹

$$g(E(RATE_i|.)) = \gamma_0 + s(BPI_i) + s(SIZE_i) + s(AGE_i) + s(CONSUMPTION_i) \quad (3.3)$$

As can be seen from Table 3.5, size, age and consumption are significant factors to Panamax dry bulk charter rates. However, they exhibit different degrees of non-linearity as expressed through effective degrees of freedom of 2.6 and 2.2 for *SIZE* and *AGE* as well as 5.8 for *CONSUMPTION*. The number of observations included in the regression further reduced due to only 637 observations for the vessels' consumption (see Table 3.1). Despite this the R^2 did not change significantly.

¹⁹In addition to the factors included in (3.3) we also ran regressions considering flag, grain capacity, draft, speed, horsepower and engine type. None of those variables turned out to be significant or altered the estimation results of the above model setup significantly. Contrary to our expectation flag as indicator for quality and the design speed did not add additional power. Substituting consumption by speed did show the expected significant effect. However, adding consumption to this model design made the speed variable redundant.

Table 3.5: Results for the market-vessel model

Parametric terms			
	Estimate	p	sig.
Intercept	10.237	0.000	***
Smooth terms			
	Effective DF	p	sig.
s(Baltic Panamax Index)	5.472	0.000	***
s(Size)	2.642	0.000	***
s(Age)	2.199	0.000	***
s(Consumption)	5.846	0.000	***
R^2	82.6%		
GCV score	0.015015		
N	637		
Signif. codes: 0'***'0.001'***'0.01'*'0.05'.'0.1"1			

Figure 3.5 shows that, compared to Model 3.1 and 3.2, the behaviour of the BPI smooth does not change significantly. The smooth of size exhibits a slight s-shaped nexus to charter rates. Age and consumption are monotonic negatively related to charter rates. From the age of 10 years vessels seem to achieve lower period rates. Consumption does not seem to have any effect in the range of 30 mt/day to 35 mt/day. However, vessels with a very low or clearly sub-standard consumption receive a premium/discount, respectively. We observe a negative slope between 26 mt/day & 30 mt/day and an even more pronounced negative slope between 35 mt/day & 40 mt/day.

3.5.4 The market-contract-vessel model

Given the above results and as natural extension of the simple market factor model we set up the market-contract-vessel model. This comprehensive model version aims to accommodate all relevant factors of physical Panamax dry bulk charter rates as identified above. Moreover, given the GAM model structure it includes all relevant

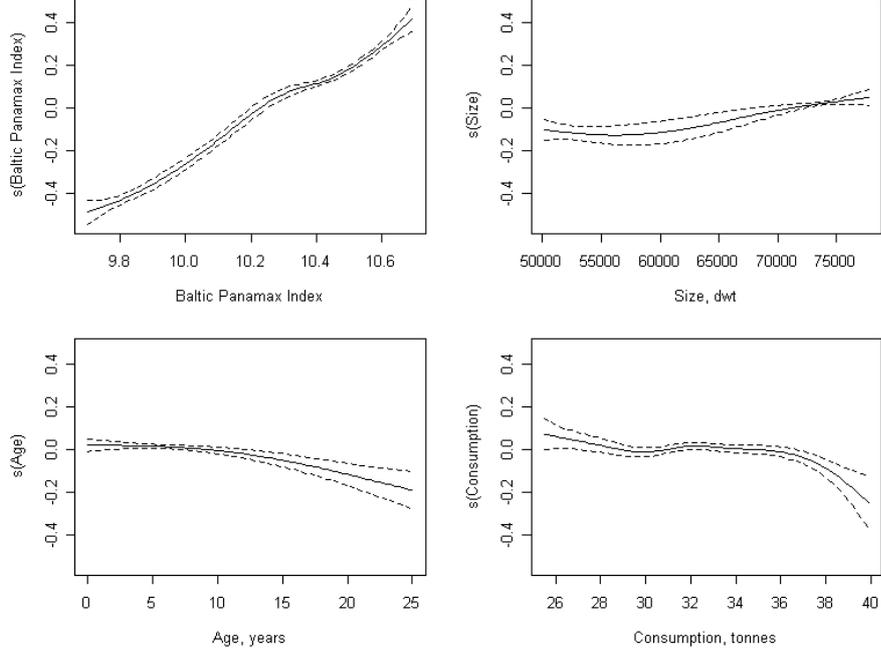


Figure 3.5: Smooths of market-vessel model

information without making specific assumptions about the functional form of any of those relations apart from additivity of the model terms.

$$\begin{aligned}
 g(E(RATE_i|\cdot)) &= \gamma_0 + s(BPI_i) + s(FORWARD_i) + s(LENGTH_i) \\
 &+ \sum_{pod} \gamma_{pod} I_i^{pod} + s(SIZE) + s(CONSUMPTION_i) + s(AGE_i) \quad (3.4)
 \end{aligned}$$

Table 3.6 presents the results of Model 3.4. Compared to the market-contract model the parametric components did not change. Pacific delivery can be expected to result in a 2% lower period rate than Atlantic delivery. Worldwide delivery does not make a difference. The smooth term of BPI is still significant with an EDF of 8.4. Number of days forward and charter length show the same significant and non-linear effect as in the market-contract model. Contrary to Model 3.3 the smooth of size shows a significant and almost linear behaviour with EDF of 1.5. The effect of consumption to charter rates also is less pronounced than in the previous model.

Table 3.6: Results for the market-contract-vessel model

Parametric terms			
	Estimate	p	sig.
Intercept	10.250	0.000	***
PoD Pacific	-0.020	0.010	*
PoD worldwide	-0.001	0.9649	
Smooth terms			
	Effective DF	p	sig.
s(Baltic Panamax Index)	8.350	0.000	***
s(No. of days forward)	2.799	0.002	**
s(Charter length)	4.820	0.000	***
s(Size)	1.532	0.000	***
s(Consumption)	3.807	0.009	**
s(Age)	8.871	0.000	***
R^2	90.9%		
GCV score	0.0083034		
N	637		

Signif. codes: 0'***'0.001'**'0.01'*'0.05'.'0.1"1

However, we still observe a non-linear and significant smooth of consumption. The most interesting effect can be observed for the smooth of age which now has 8.9 EDF compared to 2.2 EDF in Model 3.3 on a highly significant level. The full model shows high explanatory power with an R^2 of 91%.

Figure 3.6 shows the smooths and partials of the market-contract-vessel model. Compared to previous model setups the smooth of all but one variable did not change significantly despite the use of sub-samples of significantly different size. Therefore, all effects seem to be reasonably robust against the inclusion of additional variables and alternation of model setup. Furthermore, there are no indications of model over-fitting which could have resulted in unexpected and drastic changes in the functional form of the single smooths. Most interesting is the resulting shape of the smooth of age.

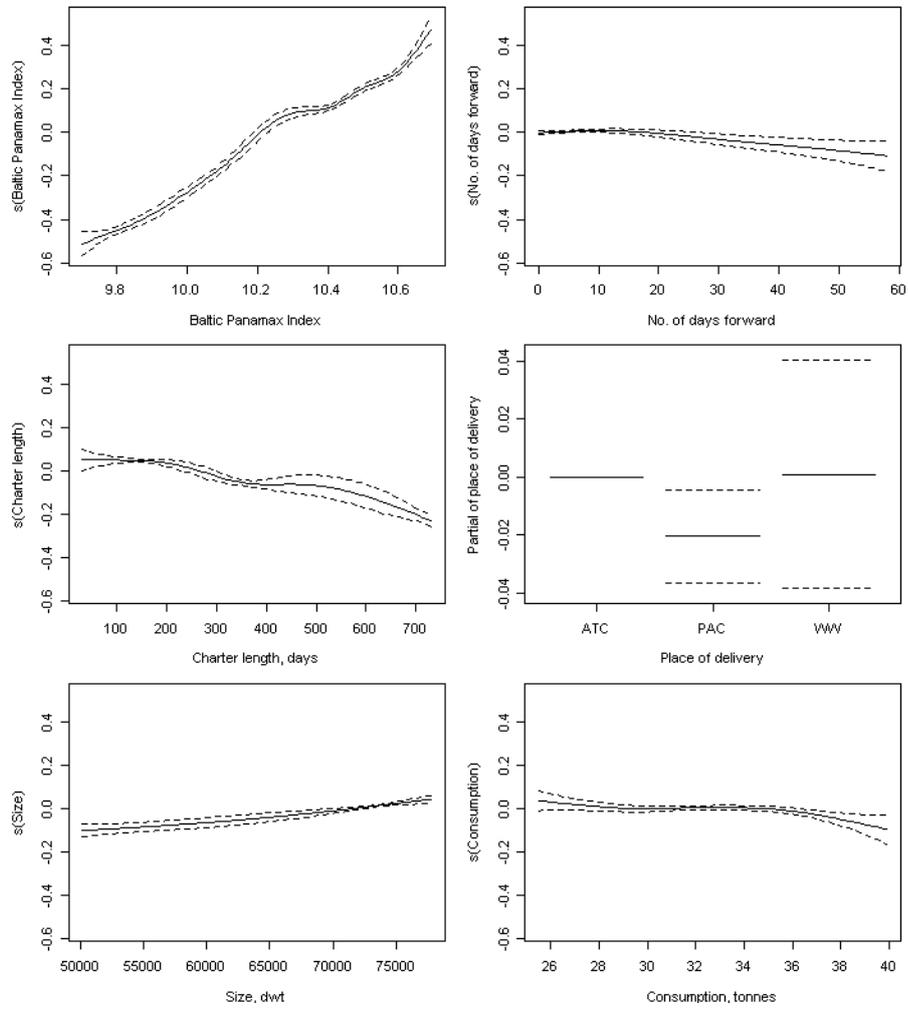


Figure 3.6: Smooths and partials of market-contract-vessel model

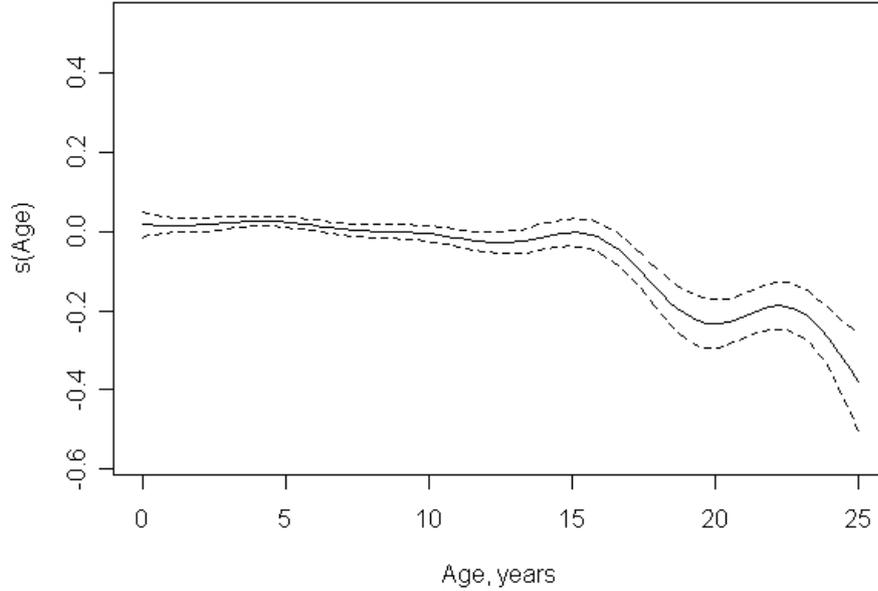


Figure 3.7: Smooths of age from market-contract-vessel model

Comparing Figure 3.7 to the lower left panel of 3.5 where charter rates seemed to decrease almost linear from the age of 7 years, the smooth now shows a straight and constant line until the age of 15 years. Starting almost exactly at the age of 15 years, vessels seem to receive a discount in charter rates until the age of 25 with a plateau at around 20 to 22 years. However, despite 5% truncation of low data density areas, the confidence bands get considerably large at the right hand side. The confidence band is large enough to allow for a monotonic shape of the smooth of age. Additionally, as there is not theoretical justification, we conclude that the plateau must be data driven.

To sum up, there seems to be a very pronounced two-tier market where the first tier is relevant for vessel being 15 years or younger. All vessels in the second tier being older than 15 years do not just receive a fixed discount, the charter rates rather seem to be discounted depending on the actual age, $15 + x$.

3.6 Summary and concluding remarks

In evaluating vessel and contract specific effects to physical dry bulk charter rates the contributions of this chapter are twofold. While applying semi-parametric GAMs to a cross sectional dataset of actual Panamax dry bulk fixtures it can present strong empirical evidence for the existence of a two-tier dry bulk time charter market. Secondly, this chapter presents a quantitative model which is of potentially great use and importance for the valuation of FFAs and freight rate options. Controlling for all relevant effects it is capable of quantifying differences due to the quality of any given vessel.

Other than in the tanker markets where a couple of prime charterers have strong influence on the markets, in the bulk segment there are hardly any to the end consumer known brand names which could experience a loss of corporate image. Thus it is questionable if there are incentives to renew the fleet. Differences in rates for old and modern vessels, not just in depressed markets as opposed to the results of Tamvakis & Thanopoulou (2000), turn out to be significant. However, the questions of whether those differences are big enough remains unanswered, since they would need to compensate for higher capital costs and cash flow risks in volatile markets. Moreover, any new investment runs a risk of appropriate timing, thus running an older fleet might still seem more profitable to the operator/investor. The risk-adjusted incentives to demonstrate more than the minimum required sensitivity for safety issues do not seem to exist in the markets.

Despite this and contrary to the expectations of Tamvakis & Thanopoulou (2000) that a two-tier market is unlikely in the near future, the results of this chapter indicate the existence of a trend towards a stronger differentiation of quality tonnage in

the dry bulk segment. Therefore, it is very well possible to create a two-tier market which provides the necessary incentives to increased safety. However, for the time being the given financial incentives do not seem to fulfil the condition of sufficiency to show the effects in desired extent to dry bulk safety.

For future research it would be interesting to find out whether the trend towards stronger discrimination of "risky" tonnage is persistent. The existence of a three-tier or even n -tier market would extend the validity of the two-tier market theory and its implications.

4 Second hand chemical tanker price determination

The contents of this chapter are based on "A multivariate semi-parametric approach to chemical tanker desktop valuations" resubmitted to *Transportation Research Part E* written in co-authorship with Dr Roar Adland.

4.1 Introduction

The second hand market, also known as the sale and purchase or S&P market, facilitates easy entry and exit of investors from the shipping industry but also allows investors to switch between the various sub-sectors of the market. The volume of ships transacted varies substantially, both with the state of the relevant freight market and between segments, but is of course largely proportional to fleet size. This means that activity is focused in the large and homogeneous tanker and bulk carrier sectors, where price discovery functions sufficiently well in the presence of a large number of buyers and sellers. For shipping sub-sectors with smaller fleets and a higher degree of specialisation, which typically leads to a wider variation in technical ship specifications, the market is much less liquid and deals may be concluded privately. The resulting lack of price transparency and difficulties in comparing transactions can render time series of vessel values either impossible to compile or of dubious quality, which creates challenges for both researchers and financial institutions that attempt to manage the risk in ship mortgage portfolios.

According to Stopford (1997), there are four main factors driving second hand prices in shipping: freight rates, age, inflation, and expectations. Peaks and troughs in the

freight market tend to quickly work their way through into the S&P market, and freight rates are relatively highly correlated with vessel values. As far as the effect of aging goes, brokers who value ships tend to assume linear depreciation down to scrap value over the expected economic life of the vessel (around 20 - 25 years for bulk ships). However, in addition to these generic factors that influence ship values, there are several important ship-specific factors that will influence the actual price a vessel will obtain in the market. These typically include the yard and country of build, the ship's cargo capacity relative to its peer group, hull type (single versus double hull for tankers), the ship's cargo-handling gear (e.g. the number of cargo pumps and their capacity), and its speed and fuel consumption. Such ship-specific characteristics generally become more important in the small and highly specialised sectors of the shipping industry such as the reefer, chemical carrier and gas carrier markets.

Research into the formation of second hand ship prices has hitherto been based on time series of values for generic vessels in the tanker or dry bulk sectors (see, for instance, Tsolakis et al., 2003; Veenstra, 1999; Glen, 1997; Kavussanos, 1996a, 1996b, 1997). This chapter proposes an extension of the work of Adland & Koekebakker (2007) who propose a non-parametric ship valuation model that is based on data from actual vessel sales in the bulk carrier market. By using the raw sales data directly, they sidestep the potential empirical problems induced in the literature by the use of time series based on shipbrokers' estimates. However, a pure non-parametric model allows only a limited number of dimensions and, thus, Adland & Koekebakker are unable to incorporate factors other than the size and age of the ship and the state of the relevant freight market.

This chapter extends this research and sidesteps the data-issue by using a semi-parametric generalized additive model which, under the assumption of separable factors, allows for a much greater number of pricing variables. By applying this methodology to the chemical tanker second hand market it can be shown that the effects of several variables which have been expected to influence second hand prices can be correctly quantified. This is the first academic work to use semi-parametric models for vessel valuations, thereby facilitating the study of vessel valuation at the microeconomic (vessel-specific) level. The methodology of generalized additive models (GAM) is relatively new to maritime economics and, while it has been successfully applied in the modelling of operational expenses of merchant vessels (see Koehn, (2008)), this is the first academic work to model the prices of physical assets in a GAM framework.

A vessel valuation model that can account for generic market factors as well as vessel-specific characteristics is of potentially great use and importance for shipowners, brokers and shipping banks alike, in particular when performing "desktop valuations"²⁰ of specialised ships where reliable brokers estimates are costly or perhaps not available. Additionally, it could be a tool in producing forecasts of vessel values conditional on freight rate forecasts, and could be used for the pricing of derivatives based on second hand values.

The remainder of this chapter is structured as follows. Section 4.2 provides a review on the existing literature on the modelling of second hand ship prices. Section 4.3 examines the determinants of second hand prices for chemical tankers. A description of the dataset and the methodology can be found in Section 4.4 and 4.5, respec-

²⁰Valuations are referred to as "desktop-valuations" if the price assessment does not include a physical inspection of the ship. Most brokers' valuations are desktop valuations, with inspections being the responsibility of the buyer prior to contact signing.

tively. The estimation results are presented in Section 4.6. Section 4.7 summarizes and contains concluding remarks.

4.2 Literature review

There are two distinct lines of research on the formation of second hand values in shipping. The recent literature, starting with Hale & Vanags (1992), focuses on the analysis of the time series properties of vessel prices. Glen (1997) tests for efficiency in the second hand market for bulk ships using the Johansen cointegration approach. He concludes that the existence of cointegration does not necessarily imply market inefficiency, if the factors that create the common trends are stochastic in nature, and argues that the empirical evidence is consistent with market efficiency in the long run. Kavussanos (1996a, 1996b, 1997) uses ARCH models to describe the dynamics of volatilities in the second hand market for bulkers and tankers. He finds that the nature and magnitude of the volatility varies across vessel sizes. Veenstra (1999) finds that second hand values are integrated $I(1)$ and seeks to find a cointegrating relationship between the second hand price, the newbuilding price, the time charter rate, and the scrap value. Veenstra distinguishes between replacement sales and speculative sales by the age of the vessel.

The second line of research focuses on econometric models of the market structure in shipping. Charemza & Gronicki (1981) propose equations where ship prices are determined by freight rates and activity rates. Beenstock (1985) argues that supply and demand analysis is not sufficient for the modelling of ship prices and that ships should be considered as just another capital asset available to the global investor. Based on traditional portfolio theory, Beenstock proposes a framework where the share of ships in the world's total wealth varies directly with the ex-

pected return on ships as capital assets and is inversely related with the expected return on alternative investments. This implies that asset prices depend on expectations. Beenstock & Vergottis (1989a, 1989b, 1992, 1993) develop this idea further in subsequent papers. Strandenes (1984, 1986) regards second hand values as a weighted average of short and long-term profits, adjusted for the real rate of depreciation. The short-term profit is determined by the current time charter equivalent (TCE) spot freight rate, while long-term profits depend on the expected long-run equilibrium TCE. In Strandenes (1986) the second hand market is integrated with the newbuilding market by relating the long-run equilibrium rate to the newbuilding price. For analytical convenience, Strandenes assumes infinite economic life. However, Kavussanos & Alizadeh (2002a) show that this assumption can have a significant impact on the empirical results. Tsolakis et al. (2003) attempt to bridge the gap between the structural and time series approach to second hand price modelling. They develop a vector error correction model (VECM) with a structure that is based in maritime economic theory. Their main finding is that the second hand prices in different subsectors react differently to the underlying fundamental factors.

Adland & Koekebakker (2007) depart from the use of time series analysis and static econometric market models and propose to model ship prices in a cross sectional framework using actual ship sales data. They use a cross sectional dataset of sales and purchases of Handysize dry bulk vessels for the period 1993-2003. Applying a multivariate density estimation approach they estimate a two- and a three-factor model of second hand prices. They propose to use non-parametric multi-factor models of generic pricing variables (ship size, age and freight rate) and find that the resulting value surfaces can be non linear. However, they note that despite the relative homogeneity of Handysize dry bulk vessels a three factor model is not ca-

pable of sufficiently explaining the observed vessel prices in the market. This is due to the remaining factors that an experienced shipbroker will take into account e.g. engine make, fuel consumption building yard or cargo gear. Their non-parametric approach suffers from being data intensive and unable to cater for the multitude of ship-specific technical specifications that may affect ship values, in particular for highly specialised and sophisticated ships. In light of the literature reviewed here, the contribution from the present chapter is primarily twofold. First, we apply, for the first time, a semi-parametric generalised additive model to the task of ship valuation. Second, we step outside of the comfort zone of tankers and bulkers and analyse ship price formation in what is probably the most sophisticated of shipping sectors, that is, chemical carriers. This enables us to draw conclusions on the, possibly non-linear, impact of pricing variables that are not necessarily easy to quantify a priori, such as the effect of cargo diversification through the number of cargo tanks and pumps.

4.3 Determinants of chemical tanker second hand prices

There is a broad range of factors that might influence the second hand price of a vessel and chemical tankers in particular. Among them are measures for the current state of the market and the market participants' expectations, specifications of the vessel such as size, hull, tanks coatings, measures for the quality of a vessel like for instance yard and country of build, as well as regulatory factors like for instance the IMO class. This section compiles a variety of factors and shows the different effects that have to be expected. It does not claim to be complete but includes the most important specifications and configurations of chemical tankers. The first and

most important factor to the formation of second hand prices for any type of vessel is the current state of the market in terms of current and expected earnings. As mentioned above there have been a couple of papers which use investment theory to explain this relationship. The nexus is intuitively clear, empirically well established and widely accepted among theorists and practitioners.

The literature on the formation of second hand prices for generic vessels could establish an intuitively correct and empirically robust relation between newbuilding and second hand prices, see for instance Tsolakis et al. (2003). Another naturally important factor is the size of the vessel. However, there is the question of which measure is the best to use. For chemical tankers we can choose between dead weight tonnes, cubic meters or gross registered tonnes or a combination of these. Of the same natural importance for the formation of second hand prices for any given vessel is the age. Given a vessels life expectancy any buyer is willing to pay a price which enables the investor to gain some given desired profit over the rest of the vessels lifetime. Clearly this also relates to the buyers expectations with respect to the earnings for this period, as explained above. Especially for tankers and therefore for chemical tankers, the hull type is another important price determinant. Since international safety regulations restrict the transport of certain goods with single hull, double sides and double bottom vessels, any potential buyer is willing to pay more for a full double hull tanker.

The carriage of chemicals can be a somewhat complicated affair. Different chemicals require different tanks and coatings. Since the cargo lots are smaller than in dry bulk or crude oil transportation, it is often necessary to carry different chemicals on one trip to make it economically worthwhile. It is, however, very difficult to

say which coating is worth more than another since some chemicals require epoxy coating and some might require steel or zinc coatings.

Table 4.1: Suitability of coatings, Source HSH Nordbank AG

Coating	Suitability	Comments
Epoxy	Alkalis, glycols, seawater, animal fats, vegetable oils	Can pick up product traces. Unsuitable for benzene, toluene, ethanol and methanol.
Stainless steel	Sulphuric acids, nitric acids, Phosphoric acid, caustic soda, wine	Corrosion has to be monitored. Seawater is especially corrosive.
Polyethane	Alkalis, glycols, seawater, animal fats, vegetable oils	Cleans easier than epoxy.
Zinc	Aromatic hydrocarbon, benzene, toluene, alcohols, ketones	Moisture in tank can result in some halogenated compounds reacting with cargo to produce acids which damage coating. Unsuitable for acids, seawater, most vegetable oils and animal fats.

Table 4.1 gives an overview of different coatings and their compatibility with different chemicals. However, not having any coatings or the wrong coatings should decrease any vessels value, and vice versa. The same holds for the number of tanks and cargo separations. Ideally any vessel should have an optimal number of cargo tanks and separations with different coatings. A certain degree of diversification among coatings and number of tanks and cargo separations should make the vessel worth more since it is more flexible with respect to the cargoes which can be transported. The same holds for the ability of any vessel to handle the cargo i.e. to loading and unloading. For a chemical tanker the most important means of cargo handling are the pumps. However, having one powerful pump on-board enables the operator to load and unload only one cargo type at a time. Having many but not so powerful pumps enables the operator to load and unload different cargoes but

it'll need more time. As will be shown below it is possible to quantify this effect by using the idea of diversification and an optimal combination of number of pumps and pump capacity. Apart from the ability of a vessel to carry certain chemicals there are a different number of safety regulations which may apply to the transport of certain chemicals. The IBC code defines three types of chemical tankers called IMO1, IMO2 and IMO3. These codes relate to the ability of vessels of a given size to survive an assumed damage in certain parts of their length and to the location of the cargo tanks for the most dangerous goods to be carried. IMO1 type vessels must be able to survive assumed damage anywhere their length and cargo tanks for the most dangerous goods should be outside the extent of the assumed damage and at least 760mm from the vessels shell. Other cargoes which present a lesser hazard can be carried in tanks next to the hull. The same holds for IMO2 type vessels larger than 150m with one exception, vessels less than 150m should survive an assumed damage anywhere their length except when it involves the bulkheads bounding machinery spaces located aft. IMO3 type vessels larger than 125m should survive an assumed damage anywhere their length except it involves the bulkheads bounding machinery spaces. Vessels smaller than 125m should be able to survive an assumed damage anywhere their length, except it involves machinery spaces. There is no requirement for cargo tank location for IMO3 type vessels. Regarding the physical quality and status of maintenance of any vessel the country of build and the classification society may provide some information with respect to the second hand price which may be achieved during a sale. Potential buyers are willing to pay more for vessels built at yards in countries which are known to deliver good quality. Not just for subjective reasons but for the expectation of lower operating costs during the time of operation (see Chapter 5). Similar the classification society may provide information on the status of maintenance since some classification societies are stricter with respect to

the current physical state of any vessel. Comparably high standards are set out by the International Association of Classification Societies (IACS). Getting the classification for a vessel from a non-IACS classification society not complying to IACS rules might be easier than getting the class for the same vessel from an IACS society. Other factors that will influence the economic efficiency or attractiveness of a chemical carrier could include engine make, engine horsepower, vessel speed, ice notation and the availability of cargo heating coils or an inert gas indicator. Especially for chemical tankers, these factors are almost countless. This chapter uses all information the dataset provided without claiming to be complete but taking the most important factors into account.

4.4 Sale & purchase data for chemical tankers

The dataset obtained from Clarkson Research includes 842 observations of chemical tanker sales between October 1990 and March 2005. It provides information on price achieved in the sale, a variety of vessel characteristics such as age, size measured as dwt, grt and cubic meters, number of cargo separations, tanks and pumps, the pump capacity, engine type, speed and horsepower, hull type, IMO type, ice class, classification society, country of build and coatings. Furthermore, the current newbuilding prices measured in USD/cgt and the earnings at the date of sale have been included. From the list of 842 we removed vessels that were sold under unusual circumstances. This included damaged vessels, vessels sold at auction, and judicial sales. In addition we excluded transactions of vessels sold with attached time charter commitments as this is known to influence the price obtained in the market. We also excluded en-bloc transactions as it is difficult to attribute a price to the individual vessel in the sale. This leaves us with 736 observations.

Table 4.2 provides a first overview of the data available. We observe prices between

Table 4.2: Data overview

Variable	Min	Average	Max
Price (Mio. USD)	0.25	11.09	100.00
NB Price (USD/cgt)	829	1,012	1,315
Earnings (USD/day)	6,054	17,205	40,984
Age	0	12	25
Size (dwt)	1,032	17,485	50,600
No. tanks	4	17	43
No. pumps	2	12	43
Pump capacity	150	2,890	8,670
Speed	10.5	13.5	17.0
Horsepower	600	6,719	17,400

0.25 Mio. USD and 100 Mio. USD with an average of 11.09 Mio. USD. The data set includes all kind of prices from scrapping to resale value. The newbuilding prices and earnings range from 829 USD/cgt to 1,315 USD/cgt and 6,054 USD/day to 40,984 USD/day with an average of 1,012 USD/cgt and 17,205 USD/day, respectively. The size of the vessels ranges from 1,032 to 50,600 dwt with an average of 17,485. The average age is 12 years ranging from 0 to 25 years. The number of tanks, pumps, pump capacity, speed and horsepower reflect the market average and show a large variance. Overall the continuous variables in the dataset seem to provide enough variation to provide good explanatory power to the model of prices.

Table 4.3 shows the data distribution for country of build, classification society and engine type. Almost half of the chemical tankers sold between October 1990 and March 2005 were built in Japan (44.9%) followed by South Korea (10.7%) and Croatia (7.9%). The majority of vessels have been classed by Det Norske Veritas with 24.9%. Second and third most important classification societies are Nippon Kaiji Kyokai (18.8%) and Lloyds Register (17.7%). B.&W., Mitsubishi and Sulzer are the three most used engine types on chemical tanker vessels. They make 67.2% of the whole sample.

Table 4.3: Data distribution - country of build, class and engine type

Country	%	Classification society	%	Engine type	%
Belgium	1.0	American Bureau of Ship.	3.3	Akasaka	3.3
China P.R.	0.6	Bureau Veritas	9.3	B. & W.	35.5
Croatia	1.3	China Classification Soc.	1.8	Deutz	1.9
Denmark	4.3	Det Norske Veritas	24.9	Hanshin	5.8
Finland	1.3	Germanischer Lloyd	5.6	M.a.K.	7.5
France	1.7	Korean Register	7.0	M.A.N.	3.0
Germany	3.8	Lloyds Register	17.7	misc.	7.2
Italy	1.7	Nippon Kaiji Kyokai	18.8	Mitsubishi	20.6
Japan	44.9	Polski Rejestr Statkow	0.8	Pielstick	1.4
Netherlands	2.7	Register Italiano	3.2	Sulzer	11.1
Norway	5.6	Russian Maritime Register	1.8	Wartsila	2.7
Poland	0.9	misc.	6.0		
South Korea	10.7				
Spain	2.4				
Sweden	3.0				
Turkey	2.3				
United Kingdom	1.3				
misc.	2.2				

Table 4.4: Data distribution - coating, hull and IMO

Coating	%	Hull	%	IMO	%
Epoxy	46.5	D/Bottom	46.3	IMO1	29.2
S.Steel	6.4	D/Hull	29.4	IMO2	46.6
S.Steel, Epoxy	6.0	D/Sides	2.7	IMO3	3.9
S.Steel, Epoxy, Zinc	6.4	S/Skin	8.0	na	20.2
S.Steel, Poly	11.1	na	13.7		
S.Steel, Zinc	7.1				
Zinc	4.1				
misc.	12.6				

Table 4.4 presents the data distribution with respect to coating, hull and IMO type. Most of the vessels in the sample have tanks with epoxy coating which reflects the compatibility of epoxy coating with many chemicals in seaborne trade. Almost half of the vessels in the sample have a double bottom hull, 29.4% are full double hulled. Single skin and double sided vessels represent 10.7% of the dataset.

Table 4.5 shows the correlation of the variables in the dataset. The correlation measures the degree of any linear relation between two variables. Therefore, the purpose of the correlation analysis in this section is twofold. First, it is thought to give a first indication of possible relations between our variables and second, in the later analysis the importance of non-linear modelling will be shown as some of the variables which despite showing a low correlation to the second hand price have a significant impact on prices. All correlations above and equal to 0.39 are shown in bold numbers. Looking at the first column of Table 4.5 we can see that, as expected, there is a strong negative correlation of prices and age. Moreover, size, pump capacity, horsepower and the double hull dummy variable are positively correlated to the second hand price. The strongest correlation exists between horsepower and size which is not surprising since the bigger a vessel the more engine power is required for a given design speed. The number of tanks and pumps are also positively correlated. The same holds for different measures which relate to size as speed and horsepower. Interestingly, we also observe some positive correlation between the IMO2 notation, zinc- and steel dummy variables and number of tanks & pumps. Furthermore, there is some positive correlation between the IMO2 notation, Zinc- and steel dummy variables, while negative correlation can be observed between the epoxy- and the steel dummy variables. This analysis gives us a first hint as to the relation among the variables. However, there are existing relations which cannot be found by a simple correlation analysis as will be seen later.

Table 4.5: Correlation

	Price (Mio. USD)	NB Price (Mio. USD)	Ear- nings (USD/ day)	Age	Size (dwt)	No. tanks	No. pumps	Pump capacity	Speed	Horse- power	Double Bot- tom	Double Hull	Double Sides	Single Skin	IMO1	IMO2	IMO3	Epoxy	Poly	Zinc	Steel		
Price (Mio. USD)	1																						
NB Price (USD/ ctg)	0.11	1																					
Earnings (USD/ day)	0.06	-0.27	1																				
Age	-0.53	-0.11	0.10	1																			
Size (dwt)	0.55	0.03	0.13	-0.11	1																		
No. tanks	0.03	0.08	-0.07	0.28	0.20	1																	
No. pumps	0.22	0.07	0.00	0.05	0.19	0.72	1																
Pump capacity	0.56	0.04	0.15	-0.23	0.74	0.16	0.36	1															
Speed	0.37	0.02	0.09	0.05	0.61	0.39	0.38	0.51	1														
Horsepower	0.50	0.04	0.11	-0.06	0.91	0.36	0.36	0.69	0.73	1													
Double Bottom	-0.20	0.12	-0.12	0.26	-0.08	0.33	0.17	-0.12	-0.06	-0.03	1												
Double Hull	0.40	-0.13	0.18	-0.42	0.15	-0.22	0.08	0.27	0.12	0.14	—	1											
Double Sides	0.08	-0.04	-0.01	0.01	0.27	-0.11	-0.13	0.14	0.16	0.16	—	—	1										
Single Skin	-0.07	0.01	-0.03	0.12	0.07	-0.02	-0.13	-0.02	0.13	0.07	—	—	—	1									
IMO1	-0.03	0.04	-0.03	0.14	-0.02	0.22	0.25	-0.02	0.08	0.06	0.03	0.06	-0.04	-0.04	1								
IMO2	0.01	0.05	0.02	0.13	-0.15	0.46	0.53	-0.02	0.11	-0.06	0.28	0.08	-0.19	-0.08	—	1							
IMO3	0.17	-0.01	0.06	-0.04	0.17	0.17	0.25	0.16	0.18	0.19	0.34	0.20	0.09	-0.09	—	—	1						
Epoxy	0.11	0.04	0.00	-0.05	0.28	-0.08	-0.19	0.18	0.03	0.21	0.05	-0.17	0.10	0.06	-0.09	-0.25	-0.05	1					
Poly	-0.06	-0.03	0.02	0.08	-0.06	0.07	0.01	-0.05	0.01	-0.05	-0.03	-0.09	-0.03	0.16	-0.03	0.01	-0.03	-0.12	1				
Zinc	-0.13	0.11	-0.07	0.33	-0.05	0.50	0.44	-0.02	0.11	0.05	0.39	-0.23	-0.13	-0.13	0.17	0.45	0.19	-0.27	0.05	1			
Steel	-0.09	0.04	-0.01	0.07	-0.30	0.26	0.40	-0.14	0.03	-0.19	0.08	0.04	-0.11	-0.12	0.15	0.41	0.09	-0.48	-0.02	0.02	1		

4.5 Methodology

Equation 4.1 shows the basic setup. It includes the intuitively most important variables: newbuilding price (NB), earnings ($EARN$), size (measured in dwt) and age.

$$g(E(PRICE_i|.\)) = \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) \quad (4.1)$$

Equation 4.2 extends the base-model by hull-type. For tankers of any kind the hull-type is expected to have an important impact on the second hand price. It is included as a dummy variables indicating double hull, double bottom, double sides and single hull.

$$g(E(PRICE_i|.\))\gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) + \sum_{hull} \gamma_{hull} I_i^{hull} \quad (4.2)$$

In addition to the hull, the coating and the number of tanks are expected to influence the price a potential buyer is willing to pay. This is shown in Equations 4.3 and 4.4. Coating is included as dummy variables for epoxy-, polyurethane-, zinc-, and stainless steel-coating. The number of tanks is given by $NOTANK$.

$$g(E(PRICE_i|.\)) = \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) + \sum_{hull} \gamma_{hull} I_i^{hull} + \sum_{coat} \gamma_{coat} I_i^{coat} \quad (4.3)$$

$$g(E(PRICE_i|..)) = \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) \\ + \sum_{hull} \gamma_{hull} I_i^{hull} + \sum_{coat} \gamma_{coat} I_i^{coat} + s(NOTANK_i) \quad (4.4)$$

Following the argument of the advantage of versatility in the chemical tanker business, as explained above, Equation 4.5 shows a model including the interaction term *CARGODIV* as product of number of different coatings available and number of tanks instead of coating and *NOTANK*.

$$g(E(PRICE_i|..)) = \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) \\ + \sum_{hull} \gamma_{hull} I_i^{hull} + s(CARGODIV_i) \quad (4.5)$$

The same argument of versatility is then used to further augment the model to include a measure for the ability and flexibility of any vessel to handle the cargo. This is done by including the interaction term between number of pumps and pump capacity, *PUMPDIV* as shown in Equation 4.6.

$$g(E(PRICE_i|..)) = \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) \\ + \sum_{hull} \gamma_{hull} I_i^{hull} + s(CARGODIV_i) + s(PUMPDIV_i) \quad (4.6)$$

As mentioned above its not just the ability of a vessel to carry certain chemicals but also security aspects have to be taken into account. Not every vessel which is able to carry a cargo is also allowed to do so. The allowance is achieved by having an appropriate IMO type vessel. Equation 4.7 includes the IMO type of any given vessel as dummy variables.

$$\begin{aligned}
g(E(PRICE_i|.\)) &= \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) \\
&+ \sum_{hull} \gamma_{hull} I_i^{hull} + \sum_{coat} \gamma_{coat} I_i^{coat} + s(CARGODIV_i) \\
&+ s(PUMPDIV_i) + \sum_{imo} \gamma_{imo} I_i^{imo} \quad (4.7)
\end{aligned}$$

In addition to the variables introduced. We want to add some measures for the efficiency and quality of any given vessels. Therefore, we include speed as smooth variable and country of build as dummy variables. This is shown in Equations 4.8 and 4.9 below.

$$\begin{aligned}
g(E(PRICE_i|.\)) &= \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) \\
&+ \sum_{hull} \gamma_{hull} I_i^{hull} + \sum_{coat} \gamma_{coat} I_i^{coat} + s(CARGODIV_i) \\
&+ s(PUMPDIV_i) + \sum_{imo} \gamma_{imo} I_i^{imo} + s(SPEED_i) \quad (4.8)
\end{aligned}$$

$$\begin{aligned}
g(E(PRICE_i|.\)) &= \gamma_0 + s(NB_i) + s(EARN_i) + s(SIZE_i) + s(AGE_i) \\
&+ \sum_{hull} \gamma_{hull} I_i^{hull} + \sum_{coat} \gamma_{coat} I_i^{coat} + s(CARGODIV_i) \\
&+ s(PUMPDIV_i) + \sum_{imo} \gamma_{imo} I_i^{imo} + s(SPEED_i) + \sum_{country} \gamma_{country} I_i^{country} \quad (4.9)
\end{aligned}$$

All regressions are carried out using $g(\cdot) = \log(\cdot)$ as link-function and assumes that second hand prices follow a Gamma distribution, $PRICE_i \sim G(\alpha, \beta)$.²¹

²¹As this model of second hand prices is rather data-driven than from a theoretical background with respect to these parameters, experiments with different specifications (Normal distribution and different link-functions) suggested this setup. These specifications showed the best fit and model performance.

4.6 Results

The regression results for Equation 4.1 to 4.8 are shown in Table 4.6. Since we estimated models which consist of parametric and non-parametric components Table 4.6 is divided in two panels. The upper panel shows the results for the non-parametric components as effective degrees of freedom (edf) which reflects the degree of non-linearity present the regressors nexus to second hand prices and the significance of this explanatory factor. Since the effect of any non-parametric component differs with respect to the magnitude we do not include measures for the slope coefficient. The lower panel provides information on the parametric components given as point estimate and its significance which can be interpreted directly.

Table 4.6: Regression results for Model 4.1 to 4.8

Model	(4.1)		(4.2)		(4.3)		(4.4)		(4.5)		(4.6)		(4.7)		(4.8)	
	edf	Sig	edf	Sig	edf	Sig	edf	Sig	edf	Sig	edf	Sig	edf	Sig	edf	Sig
NB Price	6.102	***	6.060	***	6.270	***	6.107	***	5.871	***	5.865	***	5.566	***	5.438	***
Earnings	5.454	***	5.519	***	5.411	***	5.934	***	5.383	***	5.872	***	3.197	*	3.019	*
Size	8.373	***	8.649	***	8.619	***	8.225	***	8.110	***	8.272	***	7.607	***	6.701	***
Age	7.413	***	7.743	***	7.690	***	6.109	***	3.258	***	6.875	***	6.723	***	6.962	***
No. tanks	—	—	—	—	—	—	8.356	**	—	—	—	—	—	—	—	—
Cargo diversity	—	—	—	—	—	—	—	—	7.856	***	8.198	***	8.230	***	7.884	***
Pump diversity	—	—	—	—	—	—	—	—	—	—	1.001	***	1.000	***	1.000	***
Speed	—	—	—	—	—	—	—	—	—	—	—	—	—	—	7.228	***
Hull	pe	Sig	pe	Sig	pe	Sig	pe	Sig	pe	Sig	pe	Sig	pe	Sig	pe	Sig
D/Bottom	—	—	-0.252	***	-0.244	***	-0.260	***	-0.313	***	-0.268	***	-0.217	***	-0.164	***
D/Sides	—	—	-0.386	***	-0.317	**	-0.418	***	-0.352	**	-0.274	*	-0.181	*	-0.207	*
D/Skin	—	—	-0.471	***	-0.395	***	-0.427	***	-0.410	***	-0.371	***	-0.298	***	-0.244	***
Coating																
Steel	—	—	—	—	0.145	—	0.131	—	—	—	—	—	—	—	—	—
Poly	—	—	—	—	0.076	—	0.042	—	—	—	—	—	—	—	—	—
Epoxy	—	—	—	—	0.162	—	0.261	—	—	—	—	—	—	—	—	—
Zinc	—	—	—	—	0.054	—	0.062	*	—	—	—	—	—	—	—	—
IMO																
IMO2	—	—	—	—	—	—	—	—	—	—	—	—	0.254	***	0.257	***
IMO3	—	—	—	—	—	—	—	—	—	—	—	—	0.299	**	0.303	***
Intercept	2.049	***	2.263	***	2.092	***	2.041	***	2.266	***	2.252	***	2.066	***	2.04	***
N	736		736		736		736		736		736		736		736	
Adj. R^2	81,9%		83,7%		84,0%		84,7%		85,2%		85,2%		85,7%		86,3%	

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The results for the base Model 4.1 show that the relationships are of non-linear nature and are highly significant. As expected, second hand prices vary with new-building prices and earnings. Furthermore, prices increase with size and decrease with age. Model 4.2 which in addition to Model 4.1 includes the hull type shows that vessels not having a double hull achieve a lower price at sale. The highest discount has to be expected with single skin vessels (approx. -47%) followed by double sides and double bottom vessels with around -39% and -25% respectively. Taking the coating into account as shown by Model 4.3 gives a surprising result at first sight. All kind of coatings under consideration show a positive sign. However, none of the coefficients is significantly positive. The same holds for Model 4.4 which also includes the number of tanks. The number of cargo tanks is a significant factor while explaining the second hand price. Nevertheless, coatings are still of low significance. Using the idea of versatility and diversity with respect to the possible cargoes a vessel can take aboard leads to Model 4.5. Including the interaction term between number of cargo tanks and number of different available coatings gives a significant and highly non-linear explanatory factor to second hand prices of chemical vessels. Moreover, all variables from the base model (4.1) stay significant and do not change with respect to non-linearity. At the same time the R^2 increases from 81.9% (Model 4.1) to 85.2% (Model 4.5). Model 4.6 extends Model 4.5 by additionally including a measure of cargo handling versatility, pump diversity. This factor seems to be related to the price significantly. However, using a non-linear model seems not to be necessary with this factor since its effective degrees of freedom are near one indicating a linear nexus. Apart from its ability a vessel needs to have a certain IMO type to be allowed to carry a given cargo. Including the IMO type dummies leads to an unexpected result as shown by Model 4.7. Despite IMO1 type vessels being the vessels which are allowed to carry the most dangerous cargoes, they seem not to be

the vessels which archive the highest prices in the second hand market. Compared to IMO1 type vessels, IMO2 and IMO3 vessels receive a premium of around 25% and 30% respectively. A possible explanation that has been suggested on this point is the importance given to quality by charterers in the higher tier of the market - and consequently by prospective buyers of tonnage - to the age of the vessel as a proxy of quality, as charterers are in need to secure quality warranties due to the nature of cargoes transported in this tier (see Chapter 3). The last column of Table 4.6 shows the regression results for Model 4.8 which extends Model 4.7 by including speed as a smooth component. As expected, speed is a significant factor while explaining the second hand price.

Table 4.7: Regression results for Model 4.9

Model 4.9						
	edf	sig		pe	sig	
NB Price	5.902	***	Country of Build			
Earnings	3.514	***				
Size	4.114	***		Belgium	0.342	*
Age	5.871	***		China	0.134	
No. tanks	—			Croatia	0.045	
Cargo diversity	7.412	***		Denmark	0.448	***
Pump diversity	1.001	**		Finland	0.282	*
Speed	7.785	***		France	-0.130	
				Germany	0.402	***
Hull	pe	sig		Italy	0.227	*
D/Bottom	-0.113	*		Netherlands	0.232	*
D/Size	-0.413	***		Norway	0.307	***
S/Skin	-0.200	**		Poland	-0.114	
IMO				South Korea	-0.054	
IMO2	0.166	***	Spain	0.172	*	
IMO3	0.218	*	Sweden	0.149	*	
			Turkey	0.232	*	
Intercept	1.938	***	Ukraine	-0.381	**	
			UK	0.056		
N	736		other	0.039		
Adj. R^2	88,0%					

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Table 4.7 presents the regression results for the final model setup (4.9). Including country of build to measure the quality of any given vessel increases the explanatory power of the model to 88%. In comparison to Japan built chemical tankers 11 of 17 countries show a significant difference. Most of the countries with a positive sign are Western-European countries whereas vessels from Ukraine seem to have a lower quality reflected by second hand prices. Vessels from other Asian countries such as South Korea and China as well as vessels from France, Croatia, Poland and the UK do not differ significantly in second hand prices. Figure 4.1 presents the smooth of

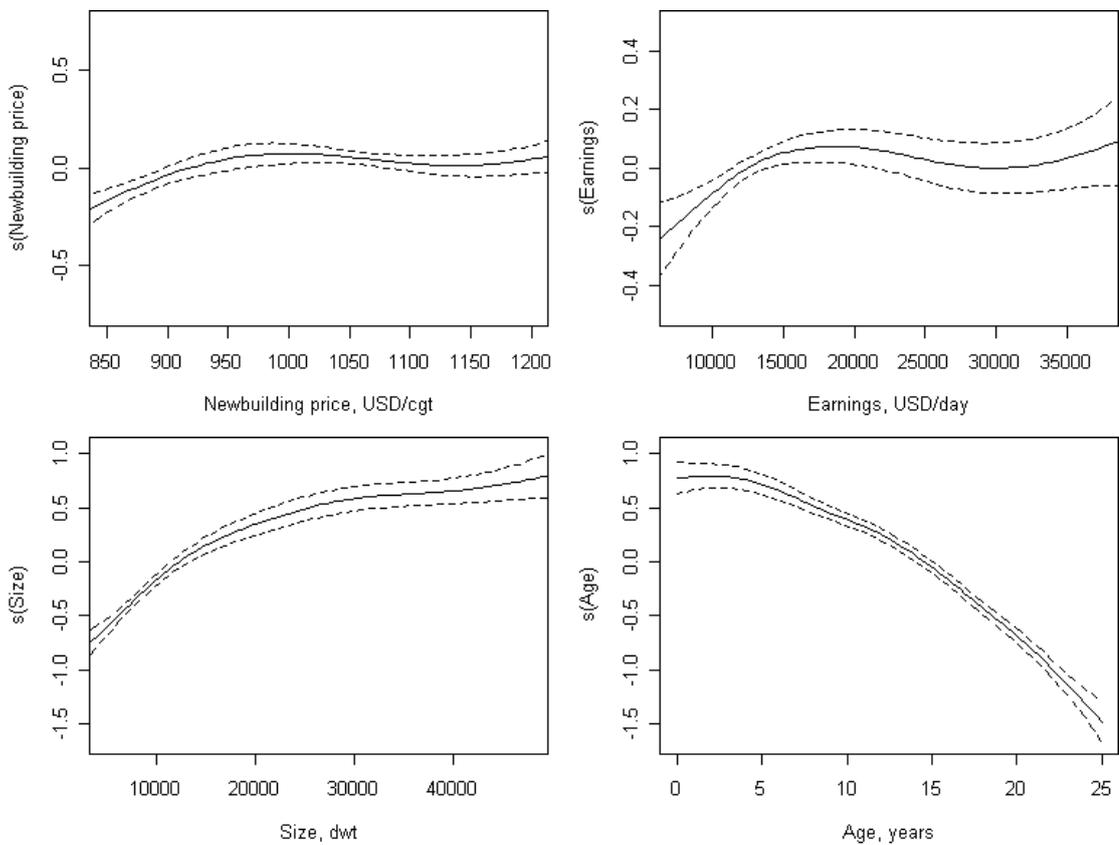


Figure 4.1: NB price, earnings, size and age

newbuilding prices, earnings, size and age to second hand prices. The top left panel shows the relationship of newbuilding to second hand prices. Between 850 USD/cgt and 1,000 USD/cgt the smooth shows a positive slope. Between 1,050 USD/cgt and

1,200 USD/cgt the smooth shows a slight negative slope. However, the confidence bands allow for the conclusion that second hand prices might not react to changes in newbuilding prices between 1,050 USD/cgt and 1,200 USD/cgt. The top right panel of 4.1 shows the relationship between earnings and second hand prices. Within the range of 5,000 USD/day and about 17,000 USD/day second hand prices increase with earnings. Above 20,000 USD/day the effect to second hand prices becomes somewhat undefined. The confidence band in this area is too large to draw any safe conclusions. The lower two panels show the effect of size and age to second hand prices. As expected, second hand prices increase with size and decrease with age. The confidence bands are satisfactory small. As can be seen from the graph the relationships of the different factors are strongly non-linear, which underlines the importance of non-linear modelling of second hand prices. Therefore, we conclude that linear modelling of second hand prices with respect to these factors cannot be appropriate. The relationship of second hand prices of chemical tankers to vessel

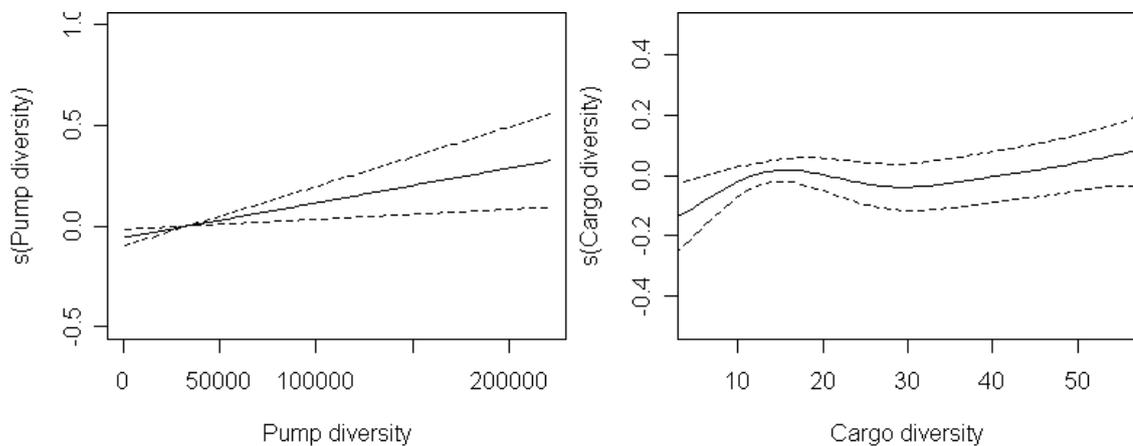


Figure 4.2: Pump- and cargo diversity

characteristics such as number of pumps, pump capacity, number of cargo tanks and coatings is shown in Figure 4.2. As mentioned above we chose to measure the versatility of any given vessel with respect to its ability to carry and handle different cargoes given as interaction terms between number of pumps & pump capacity and

number of cargo tanks & number of available coatings. The relationship between second hand prices and pump diversity seems to be of a linear nature. The smooth shows a significantly positive slope for the whole interval of pump diversity. The nexus between cargo diversity and the second hand price is non-linear. Overall, second hand prices seem to increase with cargo diversity. However, between 20 and 30 the smooth shows a negative slope with a broad confidence interval. Since there is no theoretical reason for this we conclude that this is due to the data used. In ad-

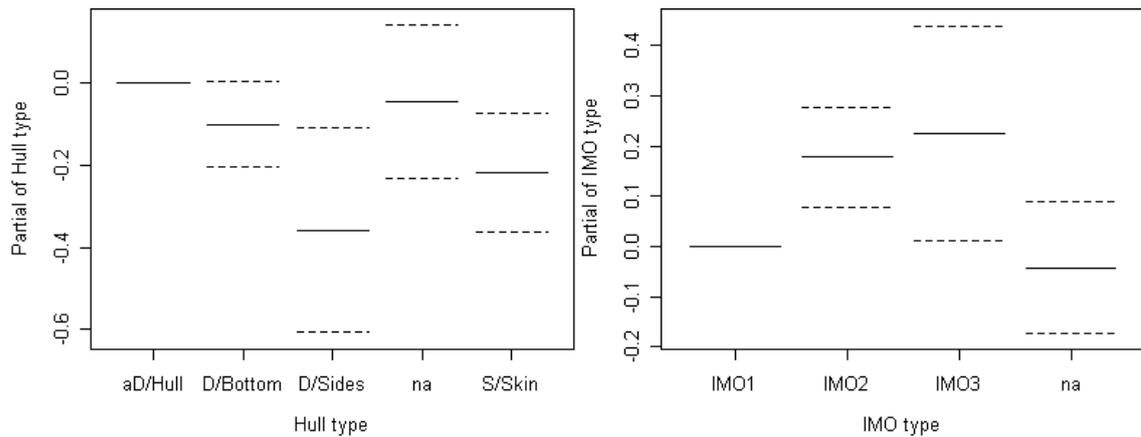


Figure 4.3: Hull type and IMO vessel type

dition to the non-parametric terms, the model includes different explanatory factors as parametric components. Figure 4.3 shows the partials of hull- and IMO vessel types. As expected single hull type vessels show a negative effect to second hand prices. Surprisingly IMO2 and IMO3 type vessels are significantly more expensive than IMO1 type vessels. Figure 4.4 is thought to give an overview of the behaviour of second hand prices with respect to size and age. It is important to note the non-linear behaviour of prices with respect to these two variables, which actually belong to the "easy to quantify"-factors. These findings support the conclusion in Adland & Koekebakker (2007) that non-linearity is an important feature of vessel valuation. Coming back to the correlation analysis it can be seen that some of the explanatory variables seemed to have little or no influence on second hand prices.

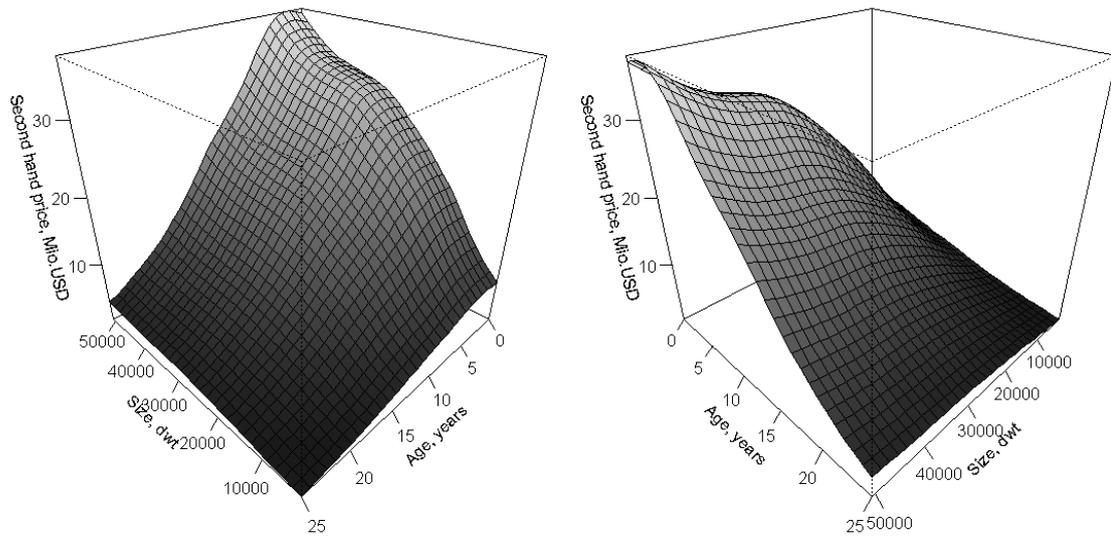


Figure 4.4: 3D plot of second hand prices against size and age

As can be seen now, it is important to consider non-linear connections between the variables to come up with some reasonable results. Correlation analysis gave a good hint but did not show all important factors.

4.7 Summary

Vessel valuation in the highly specialised and small sectors such as chemicals, gas or reefers, is challenging task but is perhaps even more important in the face of lower liquidity. This challenge arises because of the comparatively low number of sales and the complexity of the ships, where certain esoteric technical features may be critical for a ship's attractiveness in the second hand market. This chapter developed a comprehensive multivariate semi-parametric framework for the estimation of chemical tanker second hand prices. Previous attempts at ship valuation using purely non-parametric models have shown that non-linear modelling is an appropriate method to estimate second hand prices. However, those studies suffered from the curse of

dimensionality in non-parametric estimations. The model presented here surmounts these issues and extends the existing literature by applying semi-parametric GAMs to a cross sectional dataset of actual sale and purchase transactions of chemical tankers. Even the heterogeneous nature of chemical tankers and the high variation in chemical tanker second hand prices could be modelled with this framework. It has been shown that ship specific factors which have not been included in previous models have a significant impact on prices and the explanatory power of this model appears to outperform linear methods of estimation. Most of the factors turned out to show the expected effects on prices. However, IMO1 type vessels seem to achieve lower prices than IMO2 type vessels due to quality related considerations during the price determination. Furthermore, classification society and ice class do not have any significant effect on the prices of chemical tankers. In addition it could be shown that factors reflecting the degree of flexibility of the vessel with respect to cargo- and cargo handling diversity have a larger effect on second hand prices as opposed to measures of specialisation. To sum up, semi-parametric methods - especially GAMs - seem to provide an appropriate framework to model second hand prices even in a very heterogeneous segment of the shipping industry. The major implication is that, from an investors point of view the application of non-linear models for asset valuation allows for a more efficient capital allocation through a much more precise price estimation. This, in turn, reduces the risk of misinvestments and the risk of overestimation of recovery rates and losses in case of investment defaults.

5 The economic determinants of opex

The contents of this chapter are based on: Koehn, S. (2008), "The economic determinants of vessel operating expenses: a semi-parametric approach", *Maritime Economics and Logistics* **10**, 275-294.

5.1 Introduction

"SURVEY REVEALS BOXSHIP COSTS TradeWinds - 13.10.2006 The first ever mass study of operating costs for German-owned boxships has revealed major fluctuations for smaller units and a 30% increase across the board in 2000-2004"

"INSURANCE SURVEY REVEALS COST LEAP TradeWinds - 20.10.2006 Real numbers show an average rise of 10% for hull and P&I cover. A big increase in shipowners' insurance costs reported by...Moore Stephens is raising market eyebrows"

It is well known that operational expenses (opex) play an important role for the financial success of a vessel. Interestingly, over the last couple of years the interest in opex and opex themselves increased simultaneously. The above mentioned articles from TradeWinds are just two recent examples on how the industry tries to get hold of opex and their development. In fact the mentioned surveys do not provide a lot more than a simple description of the year-on-year development of opex across certain subtypes of predefined vessels and markets.

There is an extensive literature on the behaviour of the shipping market in general and for certain sub markets such as dry bulk, tanker or container. The second hand market has received a lot of attention and a huge number of papers applied investment theory to the shipping markets. Beginning with Koopmans (1939) and Tinbergen (1959), followed by Hawdon (1978), Charemza & Gronicki (1981), Beenstock & Vergottis (1993), and more recently Adland (2002), Kavussanos & Alizadeh (2002a), Adland, Jia & Strandenes (2006) and Adland & Koekebakker (2007), opex have always been a building block of theoretical and empirical models in shipping economics. Although, opex are an extremely important factor, in scientific work they are typically ignored, badly approximated and treated as exogenous. The lack of sufficient data and the low variation in opex during the past might be reasons for the fact that opex have never been the subject of a scientific investigation on their own right, although they play an important role in theoretical models and might even alter the conclusions of some empirical papers.

This chapter aims to analyse the determinants of opex and the type of relationship to opex. We use a generalized additive model framework (GAM) to be able to incorporate the possible non-linear relationships between opex and their determinants. The advantage of this method is that we do not need to make assumptions about the functional form of these relationships. We utilise a panel-dataset which includes data on aggregated opex, vessel characteristics as type, age and size, as well as information about the earnings and employment status for 241 vessel from 2000 to 2005. The estimation results show that, opex depend on the factors in a non-linear way. We find several different effects which alter opex significantly in a non-trivial fashion. We show that opex increase with age and size although with a decreasing slope. In addition, the results suggest different effects due to the behaviour of ship oper-

ators and regulatory requirements at the boundaries of the sample. Additionally, we find that opex increase with earnings from time charter contracts during periods of low to intermediate market levels. As a by-product, the quantitative framework developed in this chapter can be used to construct customized benchmark opex for a variety of vessel types with a qualitative level that has not been achieved until today.

The chapter is structured as follows. Section 5.2 provides a detailed explanation of opex in practice. Section 5.3 discusses the literature where opex have been a relevant factor to the process of modelling and for the conclusions that were drawn. Section 5.4 discusses the determinants of opex and the type of relationship between these factors and opex. Section 5.5 provides an overview of the data used. The modelling and estimation results are presented in Section 5.7 and 5.6. Finally, Section 5.8 concludes.

5.2 Opex in practice

According to Stopford (1997) there are four main factors that determine the total cost of running a vessel: capital costs and repayments²², voyage costs, periodic maintenance and operating costs. Following this definition operating costs are connected with the day-to-day running of the vessel, excluding voyage costs and major dry dockings. This study deals with opex according to a slightly different definition. We explicitly exclude voyage cost of any kind and define opex²³ to be the sum of daily operating costs plus a periodic maintenance provision per day to cover the major dry docking costs. The operating cost structure depends on the size and nationality

²²Strictly speaking, repayments are not costs. However, they account for a large part of the break-even of any bank-financed vessel.

²³Please note that the terms "operating expenses" and "operating costs" are used synonymously throughout this thesis.

of the crew, maintenance policy and the age and insured value of the vessel, as well as the administrative efficiency of the operator, i.e. owner or management-company. In many cases the day to day management is sub-contracted to a management company for a pre-determined fee, mostly connected to the current charter rates.

Manning costs include all costs incurred by the crewing of the vessel: salaries/wages, social insurance, pensions, victuals and repatriation costs. The level of manning costs for a vessel running under a particular flag depends on two factors: the size of the crew and the employment policies adopted by the operator or the vessels flag state. According to Stopford (1997) about 50% of the operating costs are manning costs, although it should be noted that this relation changes over time. The minimum number of crew on a vessel is given by the regulations due to the flag of registration. These regulations may include rules connected to the nationality of the captain, the number and nationality of officers and the number of engineers on board. Under some flags manning scales govern the numbers of personnel required on the various types and sizes of ships, and any reductions must be agreed between the operator's organization and the seamen's union. Crew wages on merchant vessels are very difficult to handle. Even though there are international guidelines, e.g. the minimum monthly wages given by the International Transport Workers Federation ITF, they are not generally accepted and applied. Vessels running under Liberia or Panama flag can reduce their manning cost by 50% compared to vessels running under some European flag, especially German flag. Shipowners have the opportunity to flag out their vessel by choosing a flag different from the one of the country of their origin. This opens the world labour market to the ship operators. They can hire their crew in any country of convenience. Crew costs are the sum of actual wages, travel costs, manning and support, medical insurance and victualling.

According to Stopford (1997) insurance costs account for 15% to 40% of operating expenses. The necessary insurances are hull and machinery (H&M), insurances against war risks and a third-party liability insurance, the so called Protection & Indemnity (P&I), whereas H&M and P&I are compulsory and the most expensive insurances. They protect the operator against physical loss or damage and provide cover against third party liabilities. Price determinants for H&M are the operators claims record and the value of the ship. The costs for P&I depend on the claims record, trading route, cargo, flag and nationality of the crew. Additional voluntary insurances might be taken to protect for instance against war risk, strikes or loss of earnings.

Costs for maintenance include general maintenance, spares, navigation and communication services. Repairs and maintenance include routine maintenance and repairs due to unexpected breakdowns/failures. Since classification societies require a certain standard, the owner has to keep the ship up to these requirements. Routine maintenance like engine maintenance, steel renewals and painting are carried out while the ship is at sea. The costs for repairs due to breakdowns are significantly higher. Usually these repairs have to be carried out at shipyards, which leads to a substantial loss of trading time. The necessary repair and maintenance costs increase with age because more spares and staff are needed to handle this work.

General costs include overhead costs, communications, costs for shore based administrative and management costs as well as additional miscellaneous costs. General stores include spare parts, deck and engine room equipment. These costs increase significantly with the age of the ship.

As mentioned above, to maintain a certain standard (class) for insurance purposes all vessels must undergo regular surveys. Every ship has to be dry-docked every two years and has to undergo a special survey to certify the necessary standard²⁴ every four years. These surveys include inspection of machinery and the thickness of the steel is measured and compared with the standard requirements. Regular surveys often lead to substantial repairs. Especially for old ships, these costs can be extraordinarily high. Vessels near their scrapping age might be taken into lay-up because it's not worth carrying out these repairs. Costs for periodic maintenance include dry-dock charges, port charges, charges for tug, agency, general services, hull blast clean and painting, dry-dock paint, steel replacement, cargo spaces, ballast spaces, hatch covers, deck fittings, main engine, propulsion, auxiliaries, piping and valves, navigation and communications, accommodation, surveyors and spare parts.

5.3 Opex in theory

As it is intuitively clear, the financial success of a ship operator depends mainly on three factors: income in the form of daily charter rates, interest and capital repayments as well as opex. There is an extensive literature on the behaviour of the shipping market in general and for certain sub markets, e.g. dry-bulk, tanker or container. The second hand market was analysed heavily and a huge number of papers applying investment theory to the shipping markets was published. Koopmans (1939) analysed the behaviour of taker freight rates. He assumes that the ton-miles supply is directly proportional to the fleet size while the supply created by a unit of capacity depends on the ratio of freight rates to an index of bunker prices and operating expenses. Thus, the effect of opex was indeed suspected but

²⁴There are regulations that these surveys can be postponed for some time.

not thoroughly investigated. Tinbergen (1959) investigated the sensitivity of freight rates to changes in the level of demand and factors affecting supply. Among others, opex were also specified to influence freight rates but since opex remained more or less unchanged during the period under investigation they were assumed to be constant. As will be shown later this assumption does not hold for the period 2000 to 2006. Hawdon (1978) investigates tanker freight rates. He does not include opex directly but finds that labour costs, which are a major component of opex, are an insignificant factor to explain freight rates over the period from 1950 to 1973. One of the first papers to develop an econometric model of the world shipping market is Charemza & Gronicki (1981). They constructed a permanent disequilibrium model to describe and analyse supply and demand balances in the world shipping and shipbuilding markets. However, their model does not include opex, although they play a relevant role in determining investment decisions and - consequently - supply. A more general econometric model developed by Beenstock & Vergottis (1993) includes opex as an exogenous factor in a variety of relationships, e.g lay-up ratio and profit in the dry bulk and tanker market. Their aim is similar to the objective of Charemza & Gronicki (1981) - analysing and describing the behaviour in world shipping. Additionally, they carried out scenario analyses and forecasts by simulation. Although opex appear in some of their most important relationships they were limited by the availability of opex data. Therefore they constructed an opex index given by the ratio of the "industrialized countries wholesale price index" published by IFS²⁵ and the US-Dollar SDR²⁶ exchange rate. More recent studies also include opex in their theoretical model but use poor indicators of opex due to the lack of data. For instance, Adland (2002) analyses the expectation hypothesis of the term structure of freight rates and argues that the risk premium in the freight

²⁵IFS: International Financial Statistics published by the International Monetary Fund, IMF.

²⁶SDR: special drawing right of the International Monetary Fund, IMF.

market should be time varying and depend on the state of the current spot freight market. He estimates the risk premium from dry bulk using a non-parametric spot freight rate model and finds that the risk premium varies around zero and that it is a decreasing function of the spot freight rate level. One important assumption of his model is that opex are independent of the ship operators charter policy, i.e. time charter or spot employment but he suggests that in practice a time charter may result in better maintenance i.e. higher opex. Therefore, it is possible that future opex are lower due to the high level of maintenance from previous periods under time charter contract. This could alter his results. Kavussanos & Alizadeh (2002a) analyse the efficient market hypothesis in conjunction with rational expectations in the formation of dry bulk ship prices over the period from 1976 to 1997. They use a variable called operational profits defined as charter income less repayments, interests and opex. However, they do not provide any information about the sources of the data on opex or how they approximated it. Adland et al. (2004) analyse a stochastic extension of the classical partial equilibrium models of the spot freight market. In their model, supply is based on the microeconomic analysis of the supply characteristics of a given fleet and order book as well as stochastic demolition and ordering behaviour. The model is used to simulate scenarios for the future very large crude oil carrier (VLCC) spot freight rate. The freight rate is determined by the marginal costs of any vessel (i.e. opex) that satisfies the demand for transportation. They conclude that when almost all vessels are employed (that was the case in 2002 to 2005) the only possibility to increase supply are higher speed, reduced port time, shorter ballast legs and delaying regular maintenance. Therefore, opex change during times of full employment. Periods of excess supply will force less cost efficient vessels to withdraw from the market. As there are switching costs, the threshold rate must be slightly lower than opex minus daily lay-up costs. For lay-up ever to

make economic sense, daily lay-up costs must be lower than opex. Therefore, time charter equivalent spot rates are bounded from below as a function of opex and lay-up costs. To underpin these theoretical results they estimate a supply function and simulate a model assuming opex to be 7,000 USD/day increasing by 1.5% per year of age. Although 1.5% seems to be a reasonable ageing factor for opex, other factors like the size of a vessel are ignored despite the fact that they use a dataset of 431 vessels with a size of 200,000 dwt and bigger. The biggest VLCC in use in 2003 was 460,000 dwt which suggests a large variation in size and opex in addition to the variation due to the age. The most recent empirical analysis is Adland et al. (2006). They investigate the supercycle in the dry bulk market between 2003 and 2005. The aim of this chapter is to evaluate whether there was a significant deviation of asset values from their fundamentals in the dry bulk market. Using a vector error correction model (VECM) they find that there was no asset bubble in the Capesize dry bulk sector. They assume opex to be constant at 5,500 USD/day, although it can be seen from the data that this was not the case. Even the fact that their time series data exhibits a break in terms of the size of the quoted vessels (120,000 dwt and 170,000 dwt) they use the same opex for the whole series even though it is obvious that bigger ships require more maintenance and manning i.e. higher opex.

From this review it is clear that opex play an important role as input in general shipping models, testing the expectations hypothesis of the term structure of freight rates, the freight market equilibrium theory or second hand ship valuations and investment decisions. Although opex are such an important factor in most of the economic models for the maritime sector they are often ignored, badly approximated and treated as exogenous.

5.4 Determinants of opex

Given the definition of opex, it is clear that opex increase with age and size, and that considerable differences can be expected due to vessel type and vessel characteristics. In addition, some specific effects due to the behaviour of shipowners have to be taken into account. During the first two or three years of a vessels lifetime, opex are considered to be significantly lower compared to vessel ages between 5 to 20 years, even when accounting for the general aging effect on opex. This is due to the fact that the vessel is brand new and the first regular drydocking, special class or survey, has to be done after the first two years of operation. Furthermore, these are not as costly as they are later during the operating span. This leads to the expectation that opex increase very quickly during the first couple of years compared to the rest of the lifetime. Another effect is that, given a vessel life expectancy and that the vessel is near its scrapping age, the owner will not spend much effort in maintaining the ship nor doing any drydockings. He will simply run the vessel as long as still profitable while saving money on opex. This process usually takes 3 to 5 years depending on the vessels maintaining status at the end of the last maintaining period. As we will see later, it might even be the case that, after a period of zero or low maintenance, the charter rates are overwhelmingly high and far above the cost of "catching up"-maintenance plus the costs of a regular classification (25 year class) owners will decide to take these costs and make the vessel running another couple of years.

As mentioned above, Adland (2002) suggests that the status of employment, i.e. spot or time charter, might alter the operator's behaviour with respect to maintenance. That means that vessels running under a time charter contract might have higher opex due to the behaviour of the operator. As will be shown later, this sug-

gestion seems to be valid. Including net earnings as an explanatory factor shows that higher earnings are associated with higher opex. Using information about the employment status shows that this effect is even stronger for vessels running under time charter contract and diminishes for those in the spot market.

In addition to the factors discussed above there are many other factors that might influence opex. However, the dataset used does not provide information on all of these. To overcome these problems and to increase the explanatory power, the following model uses the panel structure of the dataset and includes previous years opex as explanatory factor. The idea is straightforward and similar to estimating fixed effects in a linear panel data framework.²⁷ If unknown factors alter the level of opex independent of time, current differences in opex between similar vessels (same type, age and size) can be explained by past differences in opex in case the model controls for general time specific effects. For example, Vessel A and B are of same type, age, size and employment status. Assuming, last year vessel A had higher opex than vessel B due to a time invariant factor X, Vessel A should have higher opex than vessel B this year, too. In fact, it can be shown that including last years opex as an indicator for the unknown factors (X), the explanatory power of the model increases by approx. 5% including all other opex determinants such as age, size, employment status and time as control variables.

5.5 Data

The utilized data is provided in anonymous form on confidentiality agreement by Commerzbank AG Hamburg - Global Shipping Research. The unbalanced panel contains 783 observations on aggregated opex for 241 vessels over the years 2000 to

²⁷This issue will be adressed in Section 5.6 of this chapter.

2005. Additionally information on employment status, vessel type, age, earnings, size (dwt) is provided. Table 5.1 provides an overview of the data. Most of the

Table 5.1: Data distribution over type, year and employment status

Type	Share	Year	Share	Status	Share
Bulker	25.3%	2000	12.8%	Spot	48.0%
Container	23.4%	2001	14.1%	TC	52.0%
Tanker	23.4%	2002	14.1%		
Chemical	12.5%	2003	16.1%		
Product Carrier	4.5%	2004	20.1%		
LPG Carrier	4.0%	2005	22.7%		
(Other)	6.8%				

sample is composed of bulker, container and tanker vessels. These types make 72% of the whole dataset, whereas the remaining 28% are due to chemicals, product carriers, LPG carriers, car carriers and reefer. The density of the data grows with time. The year 2005 represents 22.7% of the data, i.e. most recent data has a larger weight in the following analysis. The ratio between spot and time charter employment is almost 1:1 with 48%:52% respectively. The vessels tracked over time are the same for the whole period, supplemented by additional vessels over time. Therefore, the panel dataset is unbalanced. However, there are no significant changes in the relative composition of vessels with respect to type, age, size and employment status. Table 5.2 shows the development of opex and earnings by ship type over time for bulker, container and tanker. From 2000 to 2005 the average earnings of bulker increased by 268% and average opex increased by 60%. Similarly, opex and earnings for container increased by 53% and 77%, respectively. For tankers the increase in opex is somewhat smaller(32%). This shows that the development of the markets during the last 6 years is reflected by the dataset in use. At the same time we already observe some positive correlation between opex and earnings for the vessels under consideration.

Table 5.2: Opex and earnings by type and year

Type by year		Opex			Earnings		
		Mean	Min	Max	Mean	Min	Max
Bulkер	2000	3,146	2,425	4,500	8,333	3,750	19,200
	2001	3,365	2,400	5,200	7,895	4,000	14,950
	2002	3,550	2,700	4,850	7,230	5,225	12,200
	2003	4,435	3,250	6,400	15,221	7,700	23,650
	2004	4,815	3,500	7,400	33,575	12,200	57,000
	2005	5,079	4,000	7,000	30,742	12,200	53,750
Container	2000	3,586	2,900	4,200	12,333	6,275	15,800
	2001	3,892	3,000	4,700	13,717	8,000	19,500
	2002	3,880	2,800	4,750	13,567	4,700	24,300
	2003	4,630	3,150	6,100	15,073	6,600	24,300
	2004	5,005	3,300	8,500	19,504	11,500	30,500
	2005	5,475	3,900	7,200	21,788	13,750	38,500
Tanker	2000	5,496	4,120	9,280	20,322	9,325	37,799
	2001	5,384	1,153	8,859	20,382	9,148	30,318
	2002	5,638	4,165	8,100	15,899	7,680	37,145
	2003	6,502	4,850	9,170	22,993	12,550	37,040
	2004	6,742	4,950	9,450	42,933	11,675	95,200
	2005	7,250	4,950	11,500	36,910	12,650	69,450

Table 5.3: Size and age by type

Type	dwt			Age		
	Mean	Min	Max	Mean	Min	Max
Bulkер	102,355	19,000	210,000	15	0	30
Container	50,280	14,000	80,000	6	0	25
Tanker	146,388	39,000	340,000	13	0	31

To complete the picture Table 5.3 provides the mean, min and max for tanker, container and bulker for the whole time span of the sample. We do observe even more than the regular life expectancy (25 years) for each vessel type. In addition the dataset includes observations for newbuildings and a broad spectrum of vessel sizes ranging from 19,000 dwt to 210,000 dwt for bulker, 14,000 dwt to 80,000 dwt for container and 39,000 dwt to 340,000 dwt for tanker. The top left panel of Figure 5.5

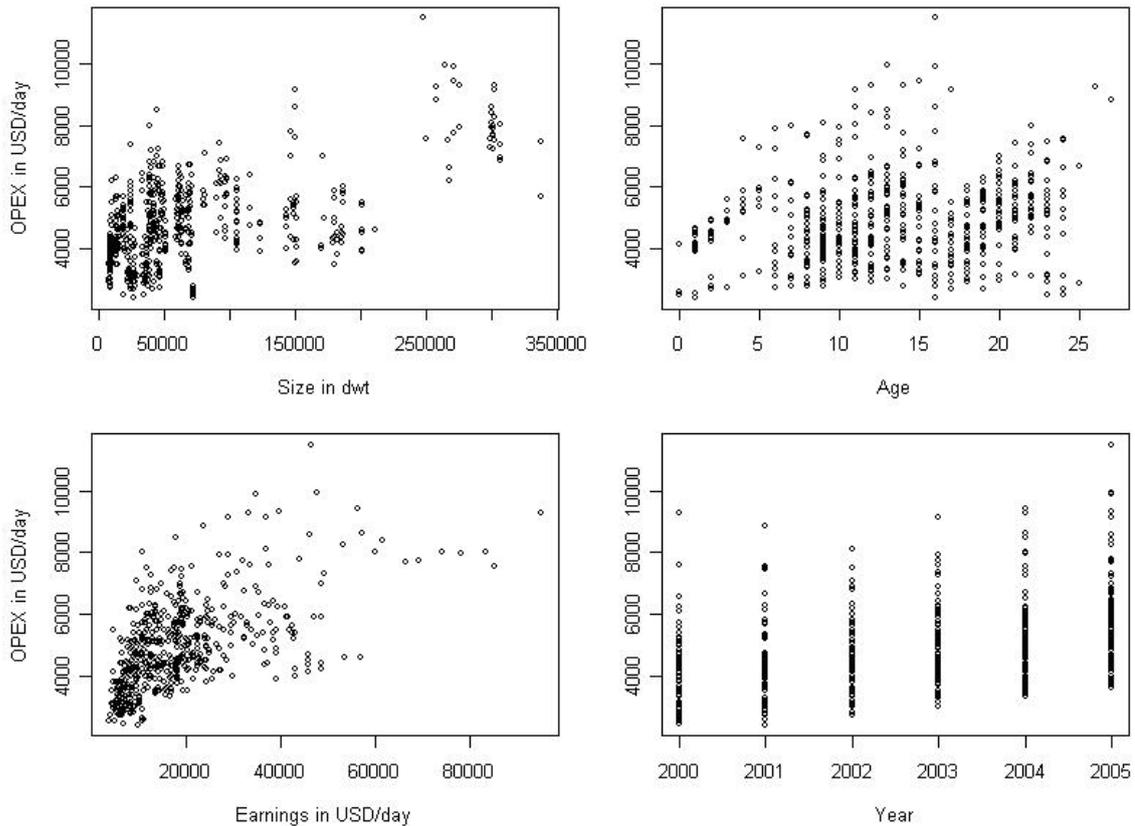


Figure 5.1: Opex - size, age, earnings and year

shows a scatterplot of opex against the size of the vessel measured in dwt. As can be seen there seems to be a positive dependence of opex on the size of the vessel. However the variation due to other factors is very large. Unlike the nexus between size and opex the relationship between age and opex (ignoring other factors) seems to be not as obvious. The top right panel of Figure 5.5 shows that the dataset

contains some observations for vessels younger than 5 years and few for vessels older than 25. The largest amount of observations lies within the age range of 5 to 24 years. As can be seen from the graph, there is a break in opex around the 16th year of operation. This break reflects the crucial role of maintenance for vessels with that age. At this age, the 15-year classification is due and operators which failed to do good maintenance to keep the vessel up to all security standards have to catch up to the get the certificate. Due to the tight markets that have been observed during the period under consideration, the level of maintenance and consequently opex drop after passing the classification. The relation between earnings and opex as shown in lower left panel is quite clear. Finally, the lower right panel shows the development of opex over time. It suggests a general increase of opex during the years 2000 to 2005.

To summarize, the dataset seems to provide relevant information on a variety of vessel types and all variables appear to be important to explain the variation in opex.

5.6 Methodology

As the data set under consideration is a panel, one might consider estimating a dynamic fixed effects or random effects model of the form

$$OPEX_{it} = \gamma_0 + \gamma_1 SIZE_{it} + \gamma_2 AGE_{it} + \gamma_3 OPEX_{i,t-1} + \dots + \epsilon_{it} + v_i$$

However, given the large number of vessels in the dataset the fixed/random effects model would require too many dummy variables for the model specification. Moreover, the error terms might be correlated with the individual effects. Assuming group

effects being uncorrelated with the regressors, even in a parametric framework, it is better to employ a more parsimonious model (see Greene (2003) or Baltagi (2001)). Thus, we expect no significant advantages from linear or quasi-linear fixed/random effects modelling. In addition to this, the unbalancedness of the dataset would need special treatment as for instance proposed by Bruno (2005). Most importantly, we do want to show the non-linear behaviour of opex with respect to its determinants without making too strict assumptions about the functional form as for instance through quasi-linear modelling with monotonically transformed variables. As mentioned above, there are many factors influencing opex and many reasons suggesting a non-linear nexus between opex and their determinants. To be able to correctly account for the possible non-linearities we use semi-parametric methods for our empirical model of opex. Having the advantages of GAM in mind and given the above issues this chapter also makes use of a GAM framework. However, we do not want to leave the panel properties unconsidered as will be explained below.

Unlike other attempts in the past, we try to explain the huge variation in opex across and within the existing submarkets and vessel-types represented by the dataset in use. To be able to extract the general effects of the determinants of opex independently of vessel type and time of observation, and to increase the explanatory power of the model by increasing the number of observations while using the dataset as a pooled panel in one regression framework, we need to take the differences due to vessel types and years into account.²⁸ At the same time the consideration of temporal effects by inclusion of year-dummies rules out any effects from general inflation. This is done by using the ability to incorporate parametric terms into the model by

²⁸Please note that it is quite unconventional to talk about opex in aggregated form and to use observations from different vessel types in one regression framework. However, this chapter follows a different approach to show the general behaviour of opex with respect to the determinants that are relevant to all different types of vessels.

introducing dummy variables according to type and year. Furthermore, we include three smooth terms depending on size, age and earnings, respectively. This setup is shown in Model 5.1.

$$g(E(OPEX_{it}|\cdot)) = \gamma_0 + \sum_{type} \gamma_{type} I_i^{type} + \sum_{year} \gamma_{year} I_{it}^{year} + f(SIZE_i) + f(AGE_{it}) + f(EARN_{it}) \quad (5.1)$$

To show the specific effect of time charter earnings we employ a variable-coefficient-model (see Hastie & Tibshirani (1993)). Model 5.1 is extended by an interaction term of the smooth of earnings and a employment status dummy which equals 1 if the vessel was under time charter contract during the year or 0 if it was employed in the spot market.

$$g(E(OPEX_{it}|\cdot)) = \gamma_0 + \sum_{type} \gamma_{type} I_i^{type} + \sum_{year} \gamma_{year} I_{it}^{year} + f(SIZE_i) + f(AGE_{it}) + f(EARN_{it}) + f(EARN_{it}) I_{it}^{Status} \quad (5.2)$$

As mentioned above, there are unknown factors which have effect on opex. Using the idea of indicating time invariant unknown factors by last periods opex, leads to the last model extension.²⁹ Model 5.3 shows the final regression setup.

$$g(E(OPEX_{it}|\cdot)) = \gamma_0 + \sum_{type} \gamma_{type} I_i^{type} + \sum_{year} \gamma_{year} I_{it}^{year} + f(SIZE_i) + f(AGE_{it}) + f(EARN_{it}) + f(EARN_{it}) I_{it}^{Status} + f(OPEX_{i,t-1}) \quad (5.3)$$

²⁹Please note that we do not introduce lagged opex to capture variation over time. Time effects are captured by year dummies. In connection with these year dummies it is possible to extract time invariant effects of unknown factors on opex.

All regressions are carried out using $g(.) = \log(.)$ as link-function and assumes that opex follow a Gamma distribution, $OPEX_{it} \sim G(\alpha, \beta)$.

5.7 Results

The following regression analysis was done, using a subset of the existing dataset. First, we had to exclude all observations for which we did not have information on all of the explanatory variables. Secondly, to achieve a necessary degree of confidence for the estimation results we trimmed the dataset by excluding 5% of all observations from the low density data regions. And thirdly, to be able to compare the different models with respect to the explanatory power we run all regression on the data from 2001 onwards.

Table 5.4: Regression results for Model 5.1, 5.2 and 5.3

	(5.1)			(5.2)				(5.3)				
	Estimate	Std. Error	Sig.	Estimate	Std. Error	Sig.	Estimate	Std. Error	Sig.			
Intercept	8.04	0.02	***	8.04	0.02	***	8.14	0.02	***			
Car Carrier	0.29	0.04	***	0.29	0.04	***	0.16	0.04	***			
Chemical	0.51	0.02	***	0.51	0.02	***	0.38	0.03	***			
Container	0.27	0.02	***	0.26	0.02	***	0.21	0.02	***			
LPG Carrier	0.42	0.03	***	0.43	0.03	***	0.31	0.03	***			
Product C.	0.34	0.03	***	0.35	0.03	***	0.27	0.03	***			
Reefer	0.28	0.04	***	0.31	0.04	***	0.23	0.04	***			
Tanker	0.36	0.02	***	0.36	0.02	***	0.27	0.02	***			
2002	0.06	0.02	***	0.06	0.02	***	0.05	0.02	***			
2003	0.15	0.02	***	0.15	0.02	***	0.12	0.02	***			
2004	0.19	0.02	***	0.19	0.02	***	0.14	0.02	***			
2005	0.25	0.02	***	0.25	0.02	***	0.19	0.02	***			
	AD	edf	p-value	Sig	AD	edf	p-value	Sig	AD	edf	p-value	Sig
s(Size)	0.01	7.33	0.00	***	0.01	7.18	0.00	***	0.01	6.91	0.00	***
s(Age)	62.86	8.56	0.00	***	60.00	8.61	0.00	***	44.37	8.55	0.00	***
s(Earnings)	0.01	1.55	0.01	**	0.01	1.00	0.33		0.01	1.57	0.27	
s(Earn.)*TC		—	—	—	0.03	1.76	0.00	***	0.02	2.57	0.00	***
s(Opex(t-1))		—	—	—		—	—	—	0.24	1.00	0.00	***
adj. R^2	81,4%				84,3%				86,3%			
GCV	0.0116				0.0104				0.0098			
n	454				454				454			

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Table 5.4 presents the regression results for Equations 5.1, 5.2 and 5.3. The upper panel shows the coefficient estimates and the standard errors for the parametric

part of each model. The lower panel presents average marginal effects (AD)³⁰, effective degrees of freedom (edf) and p-values for the non-parametric components of the models. The results for Model 5.1 show that there are considerable differences between the different vessel types. All coefficients on the type-dummy variables differ positively from the base type bulk. The time specific effects show the development of opex during the last couple of years. On average opex in 2005 have been approx. 25% higher than in 2001. The positive differences between opex in 2001 and the following years are highly significant. The smooth term of size is highly significant and shows a large degree of non-linearity. The number of effective degrees of freedom is 7.3. Furthermore, the AD has a positive sign, indicating an increase in opex of about 0.01 USD/day per additional dwt on average. Similarly, the smooth term of age exhibits 8.6 effective degrees of freedom and a highly significant AD of about 63 USD/day per year, i.e. if any vessel gets one year older, opex increase by 63 USD/day on average, in case all other factors are assumed to be constant. The effect of earnings on opex is still strong with significance on a 1% level, an AD of 0.01 and 1.5 effective degrees of freedom. Model 5.2 has the same setup as Model 5.1 but in addition it incorporates an interaction term of earnings and the TC-contract dummy. The parametric components and the smooth terms for size and age show the same behaviour as in Model 5.1 but interestingly the general smooth term for earnings gets insignificant and the earnings-TC interaction smooth becomes significant below the 1% level. Thus, we can conclude that the general effect of earnings that was suggested by Model (5.1) disappears, while the effect of earnings seems to be due to vessels which ran under TC-contract during 2001 to 2005. Furthermore the adj. R^2 increased from 81.4% to 84.3%. Introducing lagged

³⁰AD is the shortcut for "average derivative". Since we cannot present slope coefficients for every point of interest we calculated the linear slope coefficient of the fitted values, i.e. the average marginal effect. For interpretational convenience we present them in terms of the response variable, USD/day.

opex (opext-1) into this regression as shown by Model 5.3 increases the adj. R^2 to 86.3%. All parametric terms are significant below the 0.1% level apart from the coefficient on the 2002 dummy which is significant on the 1% level. The smooth terms for size and age are still highly significant. The general smooth for earnings is left being insignificant on all relevant levels with 1.6 effective degrees of freedom.

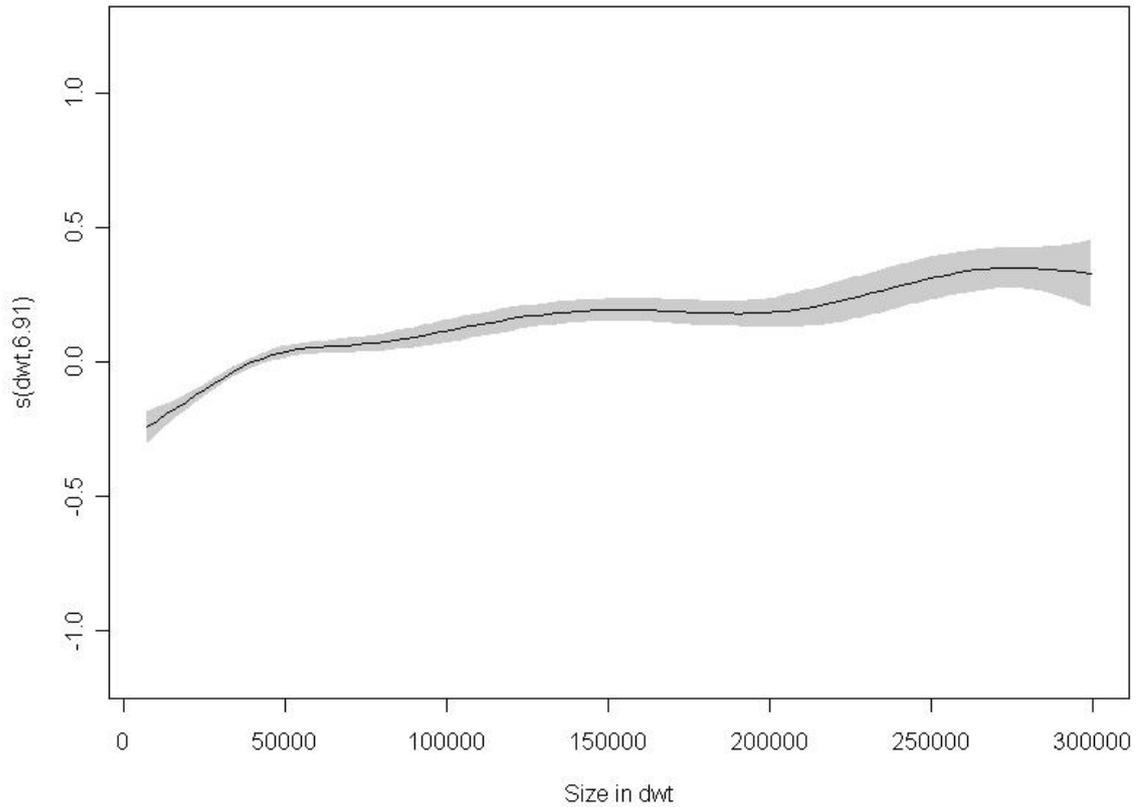


Figure 5.2: Smooth of size in dwt

Figure 5.2 presents the estimate smooth component of size in dwt and the Bayesian confidence band on a 95% level. As expected, opex increase with size. In addition we observe a steeper increase of opex for smaller vessel sizes between approx. 10,000 dwt and 50,000 dwt. As shown in the graph, the confidence intervals for these sizes are satisfactory small. For sizes larger than 50,000 dwt the average increase in

opex due to size develops with a smaller positive slope and with growing confidence intervals. One reason for the wave-like behaviour is that certain vessel types are built near standard sizes, e.g. 170,000 dwt for Capesize bulk vessels. These vessels near standard size might have lower opex due to the routine that these vessels can be handled with. This can explain the slight downward slope between 160,000 dwt and 170,000 dwt. Although we trimmed the data, the confidence interval at the right boundary of the sample gets considerably large. Thus, we conclude that the downward slope at this end is due to the sample and does not necessarily represent the actual behaviour.

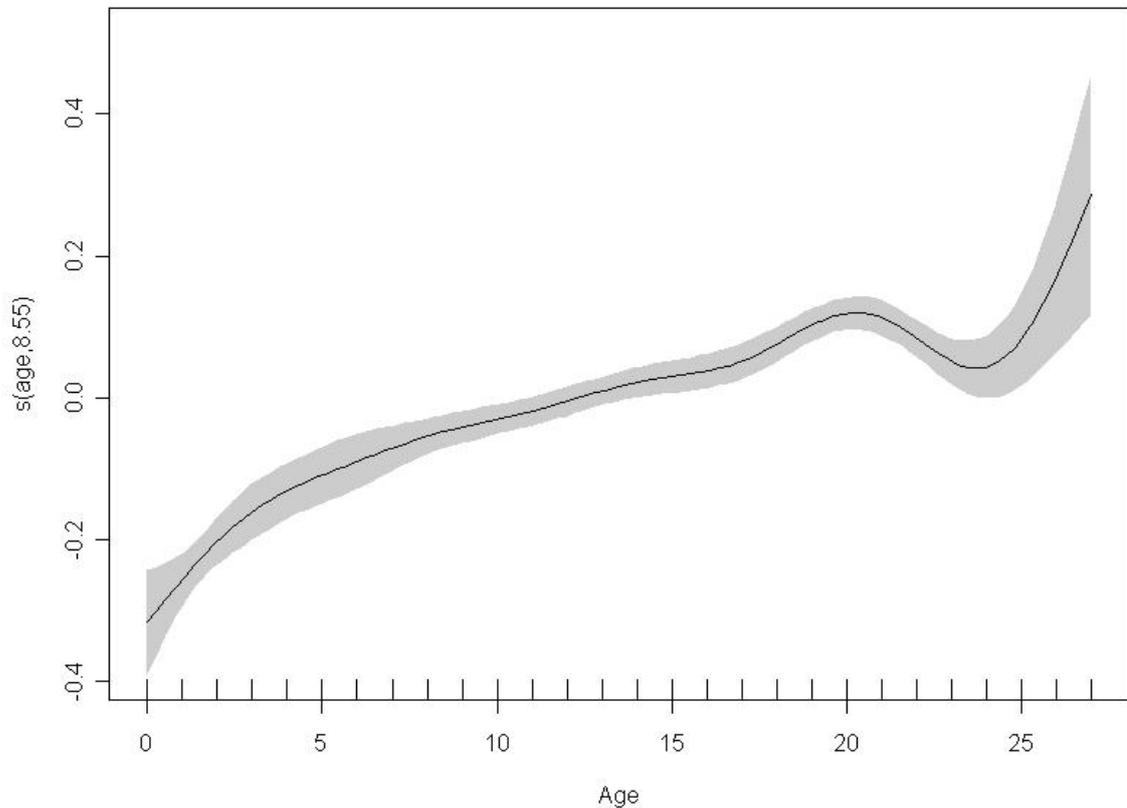


Figure 5.3: Smooth of age

Figure 5.3 shows the regression smooth of opex on age. Similarly to size we observe increasing opex due to age. As expected, vessels between 0 and 3 years of age

exhibit a considerably larger positive slope than vessels between 4 and 20 years of age. Between the age of 4 to 20 years of age the slope seems to be constant and the confidence intervals are satisfactory small. At the age of approx. 20-21 years we observe the "near-scapping-age" effect. Reaching that age the operator might decide that its not worth investing any more on maintenance since the vessel is going to be scrapped in 3 to 4 years anyway. Thus, the operator tries to make as much profit as possible during the last couple of years while reducing costs to a minimum. This drops the opex of vessels between 21 to 25 years considerably. Interestingly, we do observe another effect for old vessels. If earnings for certain vessel-types are unexpectedly high above opex the operator might find that spending some extra money on maintenance and making the vessel running another 4 to 5 years makes economic sense. Therefore, during times of very high demand for specific vessels the operator spends money on "catching-up" maintenance, and indeed our sample includes a period of very high demand for tank-vessels which lead to these observations. Due to the low number of such observations in the data sample, the confidence band of the regression at this end might be too large to draw any safe conclusions. However, it should be noted that they also exhibit a positive slope. Figure 5.4 shows the smooth function of earnings when interacted with the time charter dummy. As can be seen, there is a large and significant dependency between opex and the earnings of vessels running under time charter contract during times of low to intermediate earnings. Thus, during times of low earnings or vessels operating near break even, operators are able to save money by spending less on opex. This is interesting because this effect was, as mentioned above, suspected by Adland (2002). However, looking at times of high earnings there seems to be no significant effect of TC-earnings on opex, i.e. operators can reduce opex during times of near break even operation but do not spend more during times of unexpectedly high earnings.

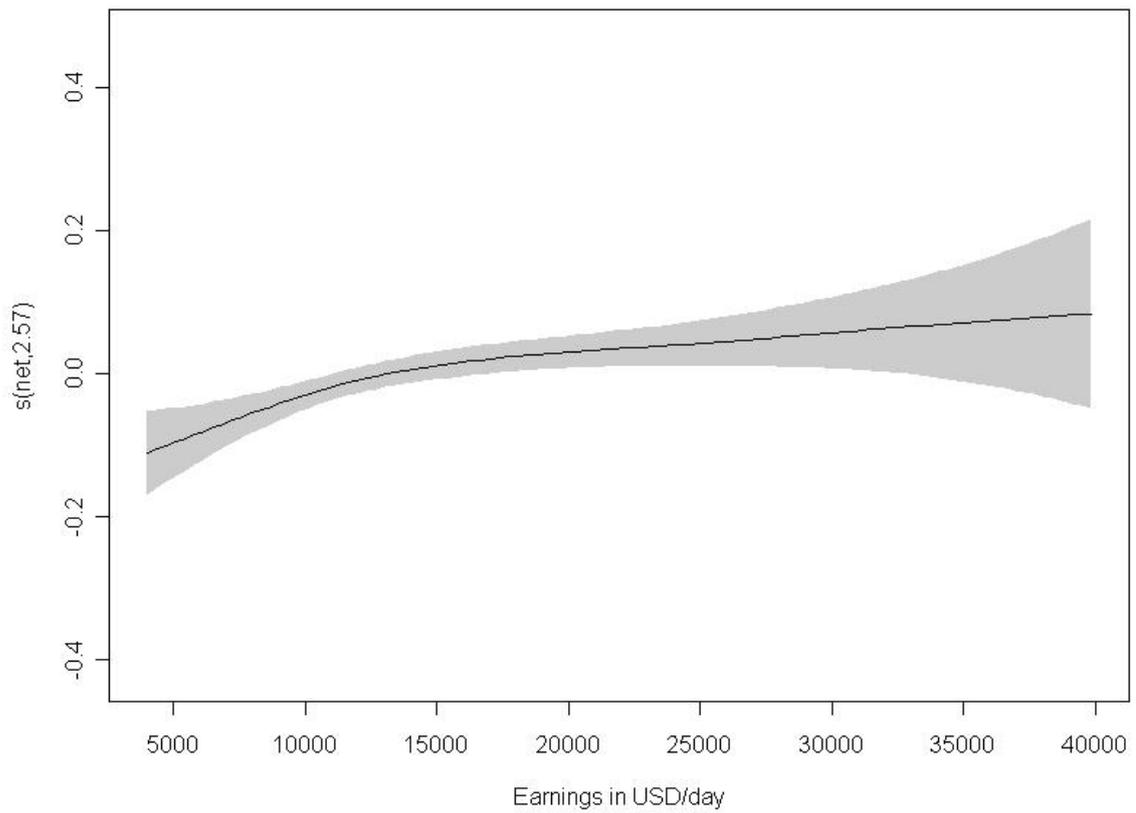


Figure 5.4: Smooth of interaction of earnings and time charter contract dummy

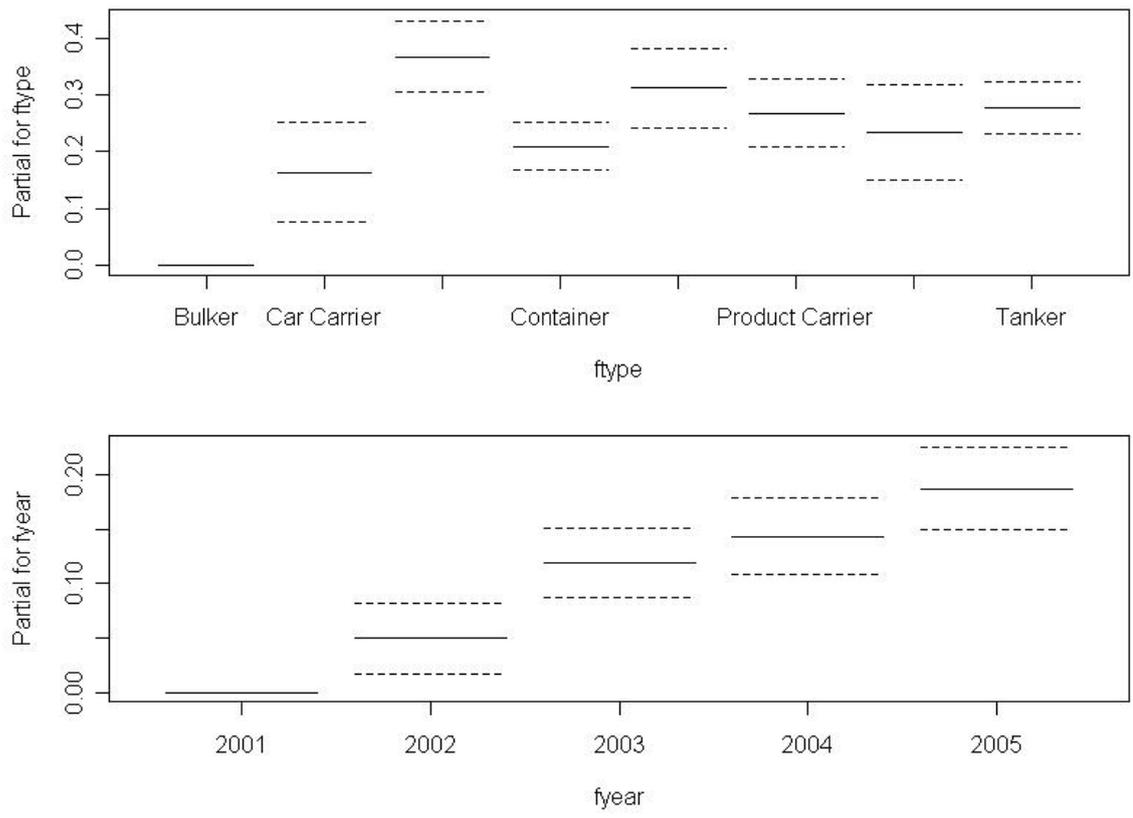


Figure 5.5: Dummy coefficients for the parametric terms

Figure 5.5 presents a graphical overview of the dummy coefficients for the parametric terms of Model 5.3. As expected it can be seen that there are large differences between the different vessel types with chemicals being the most expensive with respect to opex. The lower panel shows the development of opex over time with the biggest difference between 2002 and 2003.

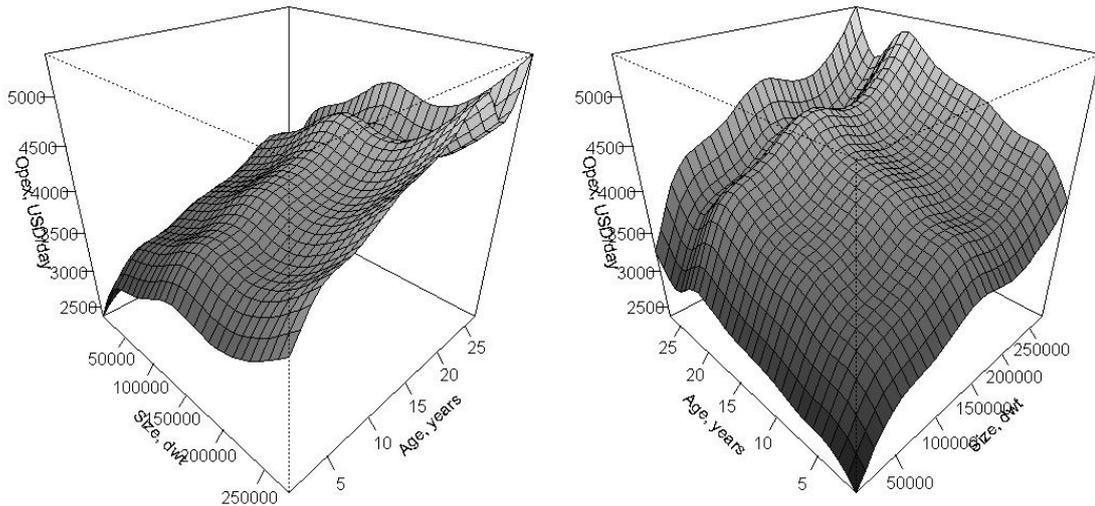


Figure 5.6: Graph of estimation grid

Figure 5.6 provides a graphical overview of an estimation grid of Model 5.3. This shows the complexity of opex just with respect to age and size holding the other factors constant. Opex for vessels of the same type with different age and size can differ by more than 200% depending on age and size with a strongly non-linear behaviour between the boundaries.

5.8 Summary and concluding remarks

The objective of this chapter is to investigate the economic determinants of opex and to construct a quantitative model which is capable of explaining the differences and

the huge variation in opex that has been observed in the recent past. To get insights into the determinants of opex we provide a detailed introduction into the practical factors of opex and the role of opex in empirical and theoretical work in shipping economics. The used GAM framework enables us to appropriately incorporate all relevant factors of opex such as type, time, age and size effects as well as effects due to the behaviour of ship operators and effects implied by regulatory infrastructure. In addition, we get as much information from the data as possible without making any strict assumption about the functional form of the relationship that exists between opex and its determinants. The results confirm the expectations on how opex depend on the factors. The explanatory power is satisfactory high, although there is still a some variation left which could not be explained. Opex do not linearly depend on age and size, i.e. assumptions like "opex increase by 1,5% per year of age" or linear or log-linear regressions to estimate size specific effects are misleading. Indeed, the dependency is of non-linear nature, i.e. opex increase with respect to age with a decreasing slope. Additionally, we observe a "near-scraping-age" effect which is explained by the behaviour of the vessels operator. Furthermore, there seem to be "standard size" effects which can reduce opex for standard-size vessels as for example approx. 170,000 dwt bulk vessels. This chapter could show that there is a dependency of opex on earnings for vessels running under TC-contract during times of low to intermediate earnings or vessels operating near break even, as suggested by Adland (2002). While making investment decisions this effect should be taken into account. In a dynamic model of specific shipping markets the "TC-earnings" effect could lead to interesting results. Specially talking about business cycles this could give new insights. Due to the short time period covered by the dataset we could not thoroughly investigate the macroeconomic reasons for the sharp increase in opex over this time span. However, there are signs that these increases are due

to excess demand for manning and increased insurance premiums as cost factors of opex. Although, in this analysis unobserved factors of opex and its effects have been approximated by last periods opex, almost 14% of the variation in opex could not be explained. For future research it would be interesting to investigate opex on a disaggregated level including vessel and operator specific effects which have not been available in our dataset. From a practical point of view the developed model allows the user to generate customized opex benchmark tables/grids which can incorporate age, size, vessel and owner specific effects up to a certain extent.

6 Summary and concluding remarks

This section summarizes the results, recapitulates the implications and shows paths for future research. As mentioned in the introduction, the evaluation of Hypotheses 1-6 has primarily been of theoretical interest while the quantitative results are important for the modelling and valuation of any cash flow driven monetary claim. The application of semi-parametric methods is of potentially large interest from an academic perspective. Moreover, the results are relevant to practical decision making which is mainly concerned with earnings (Hypotheses 1, 2, 5 and 6) and asset values (Hypotheses 3 and 4).

Hypotheses 1 and 2

Chapter 3 addressed the questions of whether there are vessel individual differences in physical time charter rates. Specifically, Hypothesis 1 stated that the quality of a vessel does affect its earnings potential, i.e. there is a two-tier Panamax dry bulk market. As a consequence it is interesting if the financial incentives are sufficient for a renewal of the fleet and additional investments in security and safety of vessels.

The quantitative model presented in Chapter 3 shows that, considering vessel and contract specific effects leads to much more precise charter rate estimates. Moreover, taking all relevant factors into account the model delivers empirical evidence for the two-tier dry bulk market hypothesis. While showing the significant effects of charter length, days forward, consumption and size, it is possible to extract quality induced

differences to charter rates through the age of the vessel. Previous research, applying parametric estimation techniques had to define quality tonnage. This was mostly done through the assumption of quality tonnage being younger than 15 years. The visual inspection of the estimated non-parametric smooth of age presented in this research supports this hypothesis. Despite this, the question of sufficiency of the given financial incentives remains open. The results do not allow for safe conclusions and this question remains for future research. As this is the first piece of research presenting empirical evidence in favour of the two-tier dry bulk market hypothesis, further research using extended datasets and alternative estimation techniques is necessary.

Hypotheses 3 and 4

Objectives of Chapter 4 were to show that the functional form of second hand chemical tanker prices are non-linear with respect to vessel individual characteristics such as size and age as well as market factors such as charter rates and newbuilding prices. Moreover, Chapter 4 aimed to show that cargo- and cargo handling diversity have larger effects on second hand prices of chemical tankers than specialisation.

Ship specific factors which have not been included in previous studies are shown to have a significant impact on prices and the explanatory power of the presented model appears to outperform linear methods of estimation. The empirical results confirm the findings in recent literature that ship valuation is a non-linear function of the main drivers such as ship size, age and market conditions. In terms of cargo- and cargo handling diversity it could be shown that with respect to the second hand price of vessels a larger set of available coating has to be preferred over having a limited number of coatings which suit more different chemicals. Capturing this effect of versatility enables us to obtain much more accurate second hand price

estimates than merely accounting for coatings through different dummy variables. The major implication is that, from an investors point of view the application of non-linear models for asset valuation allows for a more efficient capital allocation through a much more precise price estimation. This, in turn, reduces the risk of misinvestments and the risk of overestimation of recovery rates and losses in case of investment defaults.

Hypotheses 5 and 6

Previous research showed that opex function as lower boundary for physical charter rates. In addition to this it has been assumed that earnings and opex are independent. The objective of Chapter 5 was to test this assumption and to show that the employment status does affect the level of maintenance and hence operating costs. Moreover, it raised the question of whether regulatory requirements explain differences in opex, and/or if the operators economic behaviour and operating policies are a significant factor to differences in opex.

The empirical results provide evidence for the hypothesis that opex depend on the current market level. Moreover, this nexus is non-linear. Additionally, opex vary with the status of employment, i.e. time charter and spot delivery. Other factors that significantly influence opex relate to regulatory requirements and operating policies. From an investors point of view those differences are important while analysing cash flow performances and determining the probability of default of a given investment since ignoring the relation of opex to the charter market does lead to overestimation of the risks involved. This becomes clear when considering a cash flow scenario assuming worst case charter rates and, at the same time, escalating opex by any given percentage rate. Projected profits as difference between earnings and costs appear to be lower and in some cases lead to potential losses. This analy-

sis being part of any investment decision must result in suboptimal decision-making and hence suboptimal capital allocation.

Methodological issues and future research

Despite its very straightforward theory, i.e. the four shipping markets, many effects of the shipping market are difficult to quantify and require non-trivial modelling techniques capable to approximate non-linear effects. All models suggested in this thesis are capable of explaining important variables of shipping economics through their non-linear nature. Keeping the advantages, disadvantages of semi-parametric modelling in mind, GAMs seem to be a very promising way of quantitative modelling in shipping economics. Further topics which could be studied within a GAM framework are for instance the newbuilding and the scrapping market. As those markets are demand-driven and have impact onto the supply side, semi-parametric modelling of those sub-markets might lead to new insights. A fully integrated model of the shipping markets, estimated with GAMs could be used to investigate the effects of speculation and asset play.

The limitations of the research presented in this thesis are mostly concerned with methodological assumptions made and issues surrounding inference made after semi-parametric estimation (see Section 2.3). Given those methodological issues, for future research it seems worthwhile to utilize other non-linear estimation techniques from the given variety of non- and semi-parametric techniques available today. The development and application of a semi-parametric VAR framework or semi-parametric dynamic panel data estimation techniques would significantly enhance our knowledge about shipping markets as the major facilitator of economic growth and globalization.

Bibliography

- Adland, R. (2002), The time-varying risk premium in bulk shipping: New empirical evidence from the term structure of freight rates. unpublished working paper.
- Adland, R. (2003), The stochastic behaviour of spot freight rates and the risk premium in bulk shipping, PhD thesis, Massachusetts Institute of Technology.
- Adland, R. & Cullinane, K. (2006), ‘The non-linear dynamics of spot freight rates in tanker markets’, *Transportation Research Part E* **42**, 211–224.
- Adland, R., Jia, H. & Koekebakker, S. (2004), ‘The pricing of forward ship value agreements and the unbiasedness of implied forward prices in the second-hand market’, *Maritime Economics and Logistics* **6**, 109–121.
- Adland, R., Jia, H. & Strandenes, S. R. (2006), ‘Asset bubbles in shipping? an analysis of recent history in the drybulk market’, *Maritime Economics and Logistics* **8**, 223–233.
- Adland, R. & Koekebakker, S. (2007), ‘Ship valuation using cross-sectional sales data: A multivariate non-parametric approach’, *Maritime Economics and Logistics* **9**, 105–118.
- Adland, R. & Strandenes, S. (2006), ‘Market efficiency in the bulk market revisited’, *Maritime Policy and Management* **33**, 107–117.
- Baltagi, B. H. (2001), *Econometric analysis of panel data*, John Wiley & Sons, LTD.
- Beenstock, M. (1985), ‘A theory of ship prices’, *Maritime Economics and Logistics* **12**, 215–225.
- Beenstock, M. & Vergottis, A. (1989a), ‘An econometric model of the world shipping market for dry cargo, freight and shipping’, *Applied Economics* **21**, 339–356.
- Beenstock, M. & Vergottis, A. (1989b), ‘An econometric model of the world tanker market’, *Logistik and Transportation Review* **23**, 263–280.
- Beenstock, M. & Vergottis, A. (1989c), ‘An econometric model of the world market for dry cargo freight and shipping’, *Applied Economics* **21**, 339–356.
- Beenstock, M. & Vergottis, A. (1992), ‘The interdependence between the dry cargo and tanker markets’, *Logistics and Transportation Review* **29**, 3–38.

- Beenstock, M. & Vergottis, A. (1993), *Econometric Modelling of World Shipping*, Chapman & Hall, London.
- Bruno, G. S. F. (2005), Estimation and inference in dynamic unbalanced panel data models with small number of individuals, Technical report, CESPRI.
- BTCE (1994), *Structural failure of large bulk ships. Report 85*, Australian Government Publishing Service.
- Charemza, W. & Gronicki, M. (1981), ‘An econometric model of world shipping and shipbuilding’, *Maritime Policy and Management* **8**, 21–30.
- Chen, Y. & Wang, S. (2004), ‘Empirical evidence of the leverage effect on volatility in international bulk shipping market’, *Maritime Economics and Logistics* **31**, 109–124.
- Craven, P. & Wahba, G. (1979), ‘Smoothing noisy data with spline functions’, *Numerische Mathematik* **31**, 377–403.
- de Boor, C. (1978), *A Practical Guide to Splines*, Springer, New York.
- Eilers, P. & Marx, B. (1996), ‘Flexible smoothing with b-splines and penalties’, *Statistical Science* **11**, 89–121.
- Glen, D. (1997), ‘The market for second-hand ships: Further results on efficiency using cointegration analysis’, *Maritime Policy and Management* **24**, 245–260.
- Glen, D. (2006), ‘The modelling of dry bulk and tanker markets: a survey’, *Maritime Policy and Management* **33**, 431–445.
- Glen, D. & Martin, B. (1998), ‘Conditional modelling of tanker market risk using route specific freight rates’, *Maritime Policy and Management* **25**, 117–128.
- Golub, G., Heath, M. & Wahba, G. (1979), ‘Generalized cross validation as a method for choosing a good ridge parameter’, *Technometrics* **21**, 215–223.
- Goss, R. (2002), *The Handbook of Maritime Economics and Business*, LLP, London, Hong Kong, chapter The future of maritime economics, pp. 3–8.
- Green, P. & Silverman, B. (1994), *Nonparametric Regression and Generalized Linear Models*, Chapman and Hall.
- Greene, W. H. (2003), *Econometric analysis*, Prentice Hall, New Jersey.
- Gu, C. (2002), *Smoothing Spline ANOVA Models*, Springer, New York.
- Hale, C. & Vanags, A. (1992), ‘The market for second hand ships: some results on efficiency using cointegration’, *Maritime Policy and Management* **19**, 31–40.

- Hastie, T. & Tibshirani, R. (1990), *Generalized Additive Models*, Chapman & Hall, London.
- Hastie, T. & Tibshirani, R. (1993), ‘Varying-coefficient models’, *Journal of the Royal Statistical Society B* **55**, 757–796.
- Hawdon, D. (1978), ‘Tanker freight rates in the short and long run’, *Applied Economics* **10**, 203–17.
- Heisenberg, W. (1942), *Ordnung der Wirklichkeit*, Piper Verlag.
- HORSCOTCI (1992), *Ships of shame*, Australian Government Publishing Service.
- Kavussanos, M. G. (1996a), ‘Comparison of volatility in the dry-cargo ship sector - spot versus time charters, and smaller versus larger vessels’, *Journal of Transport Economics and Policy* **30**, 67–82.
- Kavussanos, M. G. (1996b), ‘Price risk modelling of different size vessels in the tanker industry’, *Logistics and Transportation Review* **32**, 161–176.
- Kavussanos, M. G. (1997), ‘The dynamics of time-varying volatilities in different size second-hand ship prices of the dry-cargo sector’, *Applied Economics* **29**, 433–443.
- Kavussanos, M. G. & Alizadeh, A. (2002a), ‘Efficient pricing of ships in the dry bulk sector of the shipping industry’, *Maritime Policy and Management* **29**, 303–330.
- Kavussanos, M. G. & Alizadeh, A. (2002b), ‘The expectation hypothesis of the term structure and premiums in dry bulk shipping freight markets’, *Journal of Transport Economics and Policy* **36**, 267–304.
- Kim, Y. & Gu, C. (2004), ‘Smoothing spline gaussian regression: more scalable computation via efficient approximation’, *Journal of the Royal Statistical Society B* **66**, 337–356.
- Koehn, S. (2008), ‘The economic determinants of vessel operating expenses: a semi-parametric approach’, *Maritime Economics and Logistics* **10**, 275–294.
- Koekebakker, S. & Adland, R. (2004), ‘Modelling forward freight rate dynamics - empirical evidence from time charter rates’, *Maritime Policy and Management* **31**, 319–335.
- Koekebakker, S., Adland, R. & Sodal, S. (2007), ‘Pricing freight rate options’, *Transportation Research Part E* **43**, 535–548.
- Koop, G. (2003), *Bayesian Econometrics*, John Wiley & Sons, London.
- Koopmans, T. C. (1939), *Tanker Freight Rates and Tankship Building*, Haarlem, Holland.

- Lancaster, P. & Salkauskas, K. (1986), *Curve and Surface Fitting: An Introduction*, Academic Press, London.
- Lyridis, D., Zacharioudakis, P., Mitrou, P. & Mylonas, A. (2004), ‘Forecasting tanker market using artificial neural networks’, *Maritime Economics and Logistics* **6**, 93–108.
- Mallows, C. (1973), ‘Some comments on C_p ’, *Technometrics* **15**, 661–675.
- Marx, B. & Eilers, P. (1998), ‘Direct generalized additive modelling with penalized likelihood’, *Computational Statistics and Data Analysis* **28**, 193–209.
- Mostafa, M. (2004), ‘Forecasting the suez canal traffic: a neural network analysis’, *Maritime Policy and Management* **31**, 139–156.
- Nelder, J. & Wedderburn, R. (1972), ‘Generalized linear models’, *Journal of the Royal Statistical Society A* **135**, 370–384.
- O’Sullivan, F., Yandall, B. & Raynor, W. (1986), ‘Automatic smoothing of regression functions in generalized linear models’, *Journal of the American Statistical Society* **81**, 96–103.
- Panayides, P. M. (2006), ‘Maritime policy, management and research: role and potential’, *Maritime Policy and Management* **33**, 95–105.
- Parker, R. & Rics, J. (1985), ‘Discussion of Silverman (1985)’, *Journal of the Royal Statistical Society B* **47**, 21–53.
- Poirier, D. J. (1995), *Intermediate Statistics and Econometrics*, MIT Press, London.
- Roberts, S. & Marlow, P. (2002), ‘Casualties in dry bulk shipping’, *Marine Policy* **26**, 437–450.
- Rowlinson, M. (1996), ‘Comment: An analysis of the quality and redistribution of dry capesize tonnage’, *Maritime Policy and Management* **23**, 407–409.
- Shimojo, T. (1979), *Economic Analysis of Shipping Freights*, Kobe University.
- Silverman, B. (1985), ‘Some aspects of the spline smoothing approach to non-parametric regression curve fitting’, *Journal of the Royal Statistical Society B* **47**, 1–21.
- Stone, M. (1977), ‘An asymptotic equivalence of choice of model by cross-validation and akaike’s criterion’, *Journal of the Royal Statistical Society B* **39**, 44–47.
- Stopford, M. (1997), *Maritime economics*, Routledge, London.
- Strandenes, S. R. (1984), Price determination in the time charter and second hand markets. Discussion paper 0584, Norwegian School of Economics and Business Administration, Bergen, Norway.

- Strandenes, S. R. (1986), *Norship: a simulation model of markets in bulk shipping*. Discussion paper 11, Norwegian School of Economics and Business Administration, Bergen, Norway.
- Strandenes, S. R. (1999), ‘Is there potential for a two-tier tanker market?’, *Maritime Policy and Management* **26**, 249–264.
- Tamvakis, M. N. (1995), ‘An investigation into the existence of a two-tier spot freight market for crude oil carriers’, *Maritime Policy and Management* **22**, 81–90.
- Tamvakis, M. N. & Thanopoulou, H. A. (2000), ‘Does quality pay? the case of the dry bulk market’, *Transportation Research Part E* **36**, 297–307.
- Timmermann, K. & McConville, J. (1996), ‘An analysis of the quality and redistribution of dry capesize tonnage’, *Maritime Policy and Management* **23**, 45–53.
- Tinbergen, J. (1959), *Selected Papers*, North Holland, Amsterdam.
- Tsolakis, S., Cridland, C. & Haralambides, H. (2003), ‘Econometric modelling of second hand ship prices’, *Maritime Economics and Logistics* **5**, 347–377.
- Veenstra, A. W. (1999), *Quantitative Analysis of Shipping Markets*, T99/3, TRAIL Thesis Series, Delft University Press, Netherlands.
- Wahba, G. (1980), Spline bases, regularization, and generalized cross validation for solving approximation problems with larger quantities of noisy data:, *in* E. Cheney, ed., ‘Approximation Theory III’, Academic Press, London.
- Wahba, G. (1983), ‘Bayesian confidence intervals for the cross validated smoothing spline’, *Journal of the Royal Statistical Society B* **45**, 133–150.
- Wahba, G. (1990), *Spline models for observational data*, SIAM, Philadelphia.
- Wood, S. (2006a), ‘Low rank scale invariant tensor product smooths for generalized additive models’, *Biometrics* **62**, 1025–1036.
- Wood, S. (2006b), *Generalized Additive Models: An Introduction with R*, Chapman & Hall, London.
- Wright, G. (2003), ‘Rational expectations in the wet bulk shipping market’, *International journal of Transport Economics* **29**, 309–318.
- Zannetos, Z. (1966), *The Theory of Oil Tankship Rates*, MIT Press, Cambridge, Mass.

List of Abbreviations

AD	Average derivative
ANN	Artificial neural network
ARCH	Auto-regressive conditional heteroscedastic
ARIMA	Auto-regressive integrated moving average
BFI	Baltic freight index
BPI	Baltic Panamax index
BTCE	Bureau of Transport and Communications Economics, Australian Government
CGT	Compensated gross tonnes
CV	Cross validation
DWT	Dead weight tonnes
EDF	Effective degrees of freedom
EGARCH	Exponential generalized auto-regressive conditional heteroscedastic
GAM	Generalized additive model
GARCH	Generalized auto-regressive conditional heteroscedastic
GCV	Generalized cross validation
HORSCOTCI	House of Representatives Standing Committee on Transport, Communications and Infrastructure, Australian Government
IACS	International Association of Classification Societies
IAME	International Association of Maritime Economists
IMO	International Maritime Organization
NB	Newbuilding

OCV	Ordinary cross validation
OPA90	Oil pollution act 1990
OPEX	Operating expenses
P-IRLS	Penalized iteratively re-weighted least squares
SH	Second-hand
TC	Time charter
TCE	Time charter equivalent
TPRS	Thin plate regression spline
UBRE	Unbiased risk estimator
VAR	Vector auto regressive
VECM	Vector error correction
VLCC	Very large crude oil carrier

Biography

Sebastian Köhn was born on 4th of August 1979 in Ludwigslust, Germany. He attended the Faculty of Mathematics at University of Hamburg from 2002 to 2004. In 2005 he received his Master of Science in Economics from University of Leicester, UK. At the same time he was invited to write his PhD thesis. In 2006 he received his Diploma in Mathematics and Economics from University of Hamburg. After working as Market Risk Analyst at the Global Shipping Research department of Commerzbank AG from 2006 to 2007, Sebastian Köhn is currently working at the Risk Controlling department of HSH Nordbank AG in Hamburg.