Essays in Financial Risk Management

Universität Hamburg

Fakultät Wirtschafts- und Sozialwissenschaften

Dissertation

zur Erlangung der Würde eines Doktors der Wirtschafts- und Sozialwissenschaften

„Dr. rer. pol.“

(gemäß der Promotionsordnung vom 24. August 2010)

vorgelegt von
Diplom-Volkswirt

Henry Seidel
aus Dresden

Hamburg, 2016

Prüfungskommission

Vorsitzender:	Prof. Dr. Alexander Bassen
Erstgutachter:	Prof. Dr. Alexander Szimayer
Zweitgutachter:	Prof. Dr. Wolfgang Drobetz
Tag der Disputation:	08. Dezember 2016

Danksagung

Diese Dissertation war für mich nur durch die Unterstützung mehrerer wichtiger Menschen möglich, wofür ich sehr dankbar bin.

Mein größter Dank gebührt meinem Doktorvater Prof. Dr. Alexander Szimayer für sein Vertrauen und seine Hilfestellung. Bei allen Fragen rund um Forschung und Lehre haben Sie sich immer für mich Zeit genommen, wobei schon mal die eine oder andere Stunde verflogen ist. Dabei vermittelten Sie mir ein Selbstverständnis von Finanzmathematik, das mich motivierte, mich auch auf unbekanntes methodisches Terrain vorzuwagen. Aber auch abseits fachlicher Fragen habe ich in Ihnen immer einen Ansprechpartner gefunden, mit dem ich auf Augenhöhe diskutieren konnte.

Mein weiterer Dank gilt meinen Kollegen und Mitdoktoranden am Lehrstuhl für Derivate Sebastian Opitz, Benjamin Nyarko, Rainer Volk, Konstantin Neinstell, Michael Herbener, Christian Hilpert und Markus Michaelsen. Ihr wart bei allen fachlichen aber auch nicht ganz so fachlichen Angelegenheiten immer zur Stelle und habt mir dazu noch das Ankommen als Neu-Hamburger sehr erleichtert. Ihr habt wesentlich dazu beigetragen, dass ich meine Doktorarbeit in einer lockeren und freundlichen Atmosphäre schreiben konnte. Ich hoffe, dass wir auch weiterhin in Kontakt bleiben und sich die entstandenen Freundschaften weiter verfestigen. Nicht unerwähnt bleiben sollen an dieser Stelle die studentischen Hilfskräfte, die mich auch bei den unliebsamen Aufgaben unterstützt haben.

Weiterhin danke ich meinen Freunden für die gemeinsame schöne Zeit, die ich den letzten Jahren mit euch teilen durfte. Ihr habt nicht unwesentlich zur spaßigen Seite meiner Promotionszeit beigetragen. Es ist schön zu wissen, dass die Kontakte trotz der Entfernung lebendig bleiben.

Meiner Familie danke ich von Herzen dafür, dass sie mir diesen Weg ermöglicht hat. Danke, dass ihr immer an mich geglaubt und mich bei diesem Vorhaben tatkräftig unterstützt habt.

Tief verbunden bin ich meiner Freundin Catharina. Danke für deine liebevolle und aufbauende Art, mit der du diese Promotion begleitet hast. Ich bin glücklich, dass wir uns auf diesem Weg kennengelernt haben und danke dir, dass du mich mit Verständnis und Geduld beim Meistern aller Herausforderungen unterstützt hast.

Zum Erfolg beigetragen haben aber auch die Eltern meiner Freundin. Euch danke ich von Herzen für das Zuhören, Mitfiebern und die kulinarische Unterstützung insbesondere in der Schlussphase meiner Promotion.

Contents

List of tables

List of figures

Chapter 1

Synopsis

1.1 Motivation

The basis of our market economy is the incentive to bear entrepreneurial risks in order to generate appropriate revenues. Financial risk management comprises '*the practice of defining the risk level a firm desires, identifying the risk level it currently has, and using derivative or other financial instruments to adjust the actual risk level to the desired risk level*' (see Chance and Brooks, 2015). Market risk is considered as a major financial risk describing a loss in value of the invested asset as a result of changed market prices or volatilities. In order to reduce or eliminate market price risk, firms regularly employ financial derivatives, which allow to hedge unexpected changes in prices to avoid cashflow uncertainty. Besides for reasons of managerial risk aversion, firms mainly hedge because it helps to reduce taxes, and most important, costs of financial distress (see Smith and Stulz, 1985). There is also strong evidence provided in literature that risk management and hedging improves the value of a firm by reducing a firm's equity sensitivity towards changes in interest rates, exchange rates or commodity prices (see Smithson and Simkins, 2005). Today, there exist markets for derivatives on a broad range of financial assets like stocks, stock indices, bonds, interest and exchanges rates or commodities. A particular problem evolves if there is no active market for derivative contracts on a firm's source of risk. Common practice in such a situation is the use of a cross hedge, which means to set up a hedge on an underlying with a price that shows a high correlation to the actual asset (Ederington, 1979).

Besides the operative risk management through financial derivatives, a firms risk policy also contains strategic measures. In 2004, the Committee of Sponsoring Organizations of the Treadway Commission (COSO) issued the *Integrated Framework*, that defines enterprise risk management as '*a process (...) designed to identify potential events that may affect the entity, and manage risk to be within the risk appetite, to provide reasonable assurance regarding the achievement of objectives*'. In this view, risk management further comprises the adjustment of the long-term strategy, which requires both firms and investors to evaluate possible adverse market developments at early stages. In classical market risk literature market data returns are usually considered to be uncorrelated, but dependent, with heavy tails and random volatility (see Embrechts et al., 2003). However, empirical investigations of the dependence structure of heavy tails of financial series rarely exist.

This doctoral thesis investigates approaches for the two aforementioned issues of operative and strategic risk management empirically using the example of the dry bulk shipping market. The shipping sector is for several reasons an interesting object of investigation. On the one hand, seaborne transportation is of vital importance for global economy. As of 2015, world seaborne shipments took around four fifths of total world merchandise trade whereas dry bulk accounts for about half of the shipped volume (see UNCTAD, 2015). On the other hand, shipping companies and investors bear substantial risks as the ongoing shipping crisis has revealed. Significant advantage of a derivative based cross hedging is demonstrated by hedging vessel resale prices using freight derivatives. For strategic risk management and investment decisions in this industry, a shipping-risk indicator is provided, which signals an increasing crisis risk with an appropriate period for consideration.

A fundamental assumption of derivative pricing, and thus, reliable hedging strategies, is the no-arbitrage paradigm. By no-arbitrage, a financial cashflow must have one single price, regardless of how it is comprised. If one and the same cashflow has different market prices at the same time, traders can gain riskless profits. For financial firms which issue financial derivatives, risk management therefore also includes to ensure that price quotations are market-conform. The last part of this thesis presents an empirical study of the German certificates market, which reveals significant violations of no-arbitrage based on parity relationships of market prices. This finding gives incentives for further improvements of banks' pricing engines and mechanisms.

1.2 Cross hedging

The first article 'Modeling and hedging vessel resale values using freight derivatives' deals with the problem of practical cross hedging strategies for resale values of vessels. Before the 2008 shipping crisis, the rising demand of transport capacity led to historical high freight rates and vessel prices, which both decreased sharply in the beginning of 2009. As a result, shipping companies not only have to cope with operative losses but particularly with more existential threats as the values of the vessels usually constitute the main part of the asset side of the balance sheet. Due to the comparatively high leverage ratios of shipping companies, these circumstances led to even more fire sales in an already distressed market.

The article provides the first empirical study of hedging the price risk in the market for second-hand dry bulk vessels. As there is no active market for contracts on future vessel values, Alizadeh and Nomikos (2012) suggest the use of forward freight agreements (FFAs) as a cross hedge for vessel prices. To follow this idea, firstly, the part of a particular vessel's price exposed to freight rate risk needs to be identified. This is done by a structural model similar to the approach of Adland and Koekebakker (2007). As independent variables the model contains both vessel specific and freight rate market factors. The hedge volume is then given by the model implied, vessel specific exposure towards FFA rates.

The hedge is implemented for 486 individual transactions of second-hand dry bulk vessels between 2005 and 2012. Using the structural model approach, an average risk reduction of 80% over a one-year hedging horizon is achieved. Compared to the classical, time series based, cross hedge as proposed by Alizadeh and Nomikos (2012), the hedge is more effective and requires on average 25% smaller hedge positions and thus, less costs of hedging. Furthermore, hedging profits are less volatile and more robust in different subperiods of the sample. However, insuring the average sample resale price of 29 million USD would require a hedge exposure in FFAs of more than 20 million USD, which rises concerns about liquidity, not only of single shipping companies, but of the FFA market as a whole.

Overall, the study provides two main contributions to academic literature. First, the hedging of vessel values using freight rate derivatives is demonstrated empirically for the first time and achieves a significant reduction of resale price risk by means of variance. Second, it is possible to increase hedging effectiveness by only hedging the non-deterministic part of a vessel's value. Especially in the ongoing shipping crisis, an active ship price risk management as demonstrated could have helped to avoid shipping insolvencies and frequent fire sales of vessels.

1.3 Conditional extreme dependence

The oversupply of transport capacity is considered a main reason for the 2008 shipping crisis. A particular problem of shipping companies is the relatively slow ability to respond to new market conditions. The market can be high at the time a vessel is ordered, but already depressed at the time of the vessel's delivery. The study 'Measuring crisis risk using conditional copulas: An empirical analysis of the 2008 shipping crisis' presents a tool for the risk management of shipping firms or investors that estimates the prevailing crisis risk in the shipping industry based on a conditional copula model. It is further investigated, to which extent the shipping crisis was caused exogenously by the collapse of the financial system or by the shipping industry itself. If the latter was the case, it could have been prevented or at least alleviated.

A 'crisis in shipping' is understood as the simultaneous, extreme, asymmetric and adverse movement of both balance sheet risk factors, in particular sharply decreasing freight rates in terms of the Baltic Dry Index (BDI), and strongly increasing financing costs measured by corporate bond yields. The dependence structure is assumed to be time-varying and explained by the supply and demand of shipping services whereas supply is proxied by the world fleet and demand by the state of the world economy (see Stopford, 2009). Following Patton (2006), the asymmetric extreme dependence is modeled using a conditional copula. The copula's tail dependence coefficient is interpreted as crisis risk.

Analyzing monthly data from 1997 to 2014, it is shown that shipping crisis risk is predominantly driven by the oversupply of vessels (60%), and only to a lower extent due to the economic downturn during the financial crisis (40%). When conditioning on both factors simultaneously, tail dependence increases strongly in the second half of 2007, and thus indicates crisis risk in the shipping sector already about one year before the actual outburst of the crisis in late 2008. Most important for practitioners, the results still hold in out-of-sample applications. Accordingly, by stopping or reducing the ordering of new vessels in 2007, shipping companies could have prevented the excessive fleet growth that led to overcapacity and slumping freight rates. Furthermore, ship financing banks could have also intervened by tightening shipping loans.

The article contributes to the literature of ship finance by providing one of the first empirical applications of copulas in shipping. Furthermore, the potential crisis risk in the shipping sector is quantified from the econometric model. The concept of conditional tail dependence is highly useful and can also be applied to further asset classes other than shipping.

1.4 Arbitrage and market efficiency

A fundamental assumption of derivative pricing models which are based on the replication of profits is no-arbitrage. Two financial securities with identical cashflows must have the same price, else, there would be opportunities for riskless profits. In the German certificates market various issuers offer comparable securities with respect to underlying, maturity or cap level. The question of interest is, if the heterogeneity of pricing models and technical conditions in different financial institutions leads to pricing inconsistencies, which allow significant arbitrage opportunities. This would be of vital concern to the risk management of certificate issuing financial institutions.

The question is investigated in the third article of this thesis, 'Arbitrage and market efficiency in the German certificates market'. For the German certificates market the prices of riskless portfolios of derivatives are compared with the price of the riskless asset. Following Stoll's 1969 famous put-call-parity, riskless portfolios consisting of a long position in a discount certificate and a long position in a put warrant are set up. The payoff at maturity of such a portfolio always equals the cap level. For this reason, the portfolios are referred to as 'boxes'. Using this parity relationship to identify arbitrage leaves the approach independent of assumed pricing models such as Black-Scholes. Because of the short-selling restriction for retail investors in this market, the analysis focuses on the underpricing of long portfolios. Once an arbitrage opportunity is identified, two different trading strategies are implemented to estimate theoretical profits. The arbitrage opportunities and profits are then analyzed by issuers, timely patterns like time of the day or day of the week, as well as maturity, volatility of the underlying asset and trading fees.

Based on almost 800 million intraday quotes of more than 1.4 million boxes, the study reveals significant arbitrage in the German certificates market. On average, every 5 of 10,000 box prices are below the arbitrage-free value. The highest price differences are found on Fridays, and in particular, in the morning and in the evening of a trading day. Market volatility is also identified as a driver for underpricings.

The study provides the first empirical analysis of arbitrage in the German certificates market as existing literature in this field is mainly focused on the U.S. option and futures markets. Despite the technical progress, the relative amount of mispricings has not been decreasing in recent years, such that there is an urgent need for further improvements of banks' pricing engines and mechanisms.

References

Adland, R. and Koekebakker, S. (2007), 'Ship valuation using cross-sectional sales data: a multivariate non-parametric approach', *Maritime Economics and Logistics* 9(2), 105–118.

Alizadeh, A. H. and Nomikos, N. K. (2012), 'Ship finance: hedging ship price risk using freight derivatives', in W. K. Talley, ed., 'The Blackwell Companion To Maritime Economics', Chapter 22, Wiley-Blackwell, West Sussex, 1st Edition.

Chance, D. M. and Brooks, R. (2015), *Introduction to derivatives and risk management*, Cengage Learning.

COSO (2004), 'Enterprise risk management - integrated framework', New York.

Ederington, L. H. (1979), 'The hedging performance of the new futures markets', *The Journal of Finance* 34(1), 157–170.

Embrechts, P., Lindskog, F., and Mcneil, A. (2003), 'Modelling dependence with copulas and applications to risk management', in S. T. Rachev, ed., 'Handbook of Heavy Tailed Distributions in Finance', Vol. 1 of *Handbooks in Finance*, Chapter 8, 329–384, North-Holland, Amsterdam.

Patton, A. J. (2006), 'Modelling asymmetric exchange rate dependence*', *International Economic Review* 47(2), 527–556.

Smith, C. W. and Stulz, R. M. (1985), 'The determinants of firms' hedging policies', *The Journal of Financial and Quantitative Analysis* 20(4), 391–405.

Smithson, C. and Simkins, B. J. (2005), 'Does risk management add value? A survey of the evidence', *Journal of Applied Corporate Finance* 17(3), 8–17.

Stoll, H. R. (1969), 'The relationship between put and call option prices', *The Journal of Finance* 24(5), 801–824.

Stopford, M. (2009), *Maritime economics*, Taylor & Francis Ltd., New York, NY, 3rd Edition.

UNCTAD (2015), *Review of maritime transport 2015*, Sales no. E.15.II.D.6, United Nations publication, New York and Geneva, available at http://unctad.org/en/PublicationsLibrary/rmt2015_en.pdf (accessed: 2016-04-16).

Chapter 2

Modeling and hedging vessel resale values using freight derivatives

Abstract

We investigate the empirical performance of hedging second-hand vessel prices in the dry bulk Panamax class using forward freight agreements. We develop and estimate a structural model incorporating the vessel's age and forward freight rates to calculate variance minimizing hedges. As reference, we also implement the best-practice approach in this context, a conventional time series based cross hedge. With both models we achieve average in-sample risk reductions of about 80% over a one-year hedging horizon. However, the hedge positions are on average 25% lower within the structural model which reduces the costs of hedging. Also the hedge profits are less volatile and risk reduction is more robust in pre- and post-crisis periods compared to the cross hedge. Our results have important implications for shipping risk management and ship financing.

Acknowledgements

We thank the participants of the 2014 workshop of the German Operations Research Society (GOR e.V.) in Regensburg for their helpful comments.

2.1 Introduction

The global financial crisis caused a major paradigm shift in shipping. Reduced demands for maritime transportation caused freight rates to drop sharply. As a consequence, ship values also decreased remarkably which distorted the balance sheet structures and creditworthiness of shipping companies. Several hundred shipping funds were forced to file bankruptcy only between the beginning of 2008 and the end of 2012. Banks responded by reducing or even stopping their activities in ship finance which worsened the situation for shipping companies even more and intensified the dynamics of distressed sales (see Müssgens, 2012).

As pointed out by Drobetz et al. (2013), a specific characteristic of shipping companies, compared to other industrial firms, is a substantial higher leverage ratio. This involves not only higher financial risks, but also balance sheet risks as the asset side of shipping companies basically consists of their vessels (see Stopford, 2009). The question is, how shipowners can effectively hedge the value of their vessels, and thus preserve the structure of their balance sheets.

Before the financial crisis, shipowners were primarily concerned about freight rate volatility rather than vessel value risk, as a survey in the Greek shipping market by Kavussanos et al. (2007) reveals. Accordingly, the topic of managing ship price risk is rarely studied in literature so far. In 2004 Clarksons introduced a derivative instrument called Forward Ship Value Agreement (FOSVA) that is intended to guarantee shipowners a specific future (second-hand) value of a generic vessel (see Adland et al., 2004). Although such a contract sounds theoretically appealing for the problem considered, there is a lack of liquidity which might be a result of potential credit risk due to high contract sizes and an over-the-counter market (see Alizadeh and Nomikos, 2009). For that reason, Alizadeh and Nomikos (2012) suggest the use of forward freight agreements (FFA) to hedge ship price risk. Freight rates are closely connected with vessel prices and show a sufficiently liquid derivative market which makes FFAs a suitable instrument for cross hedging. The authors estimate variance minimizing hedge ratios for several dry bulk vessel classes and find that FFAs are theoretically well suited for hedging second-hand values. However, their hedge strategies are not tested empirically such that real world hedge performance cannot be evaluated.

We follow the idea of Alizadeh and Nomikos (2012) and provide the first empirical study of hedging real sales prices of second-hand vessels by the use of freight derivatives. Therefore, we develop and estimate a structural model for second-hand ship values which allows to identify the risky part of vessel prices that is exposed to freight rate risk. We implement the model over a hedging horizon of one year and achieve a reasonable average risk reduction of 80%. As reference model, we also test the performance of the classical time series based cross hedge as proposed by Alizadeh and Nomikos (2012). This approach achieves an average risk reduction of 70% but requires on average 30% larger hedge positions compared to the structural model and thus higher costs of hedging. Besides, in the structural model the risk reductions are more stable with respect to shorter subperiods. Furthermore, we test both strategies by hedging the whole period between the buy and resale of a vessel. Additional robustness analyses are also provided.

The rest of the paper is structured as follows: The next section provides the literature review. Section 2.3 presents the models and the hedge setup used in this study. Data description and model estimation are provided by Section 2.4. The hedging results and robustness analyses are presented in Section 2.5. The paper concludes with a discussion and implications by Section 2.6.

2.2 Literature review

Vessel price determination is one of the main fields of research in shipping economics. As cargo ships are capital assets, their value can be viewed as the sum of expected operational incomes plus the prospective residual or resale value, respectively. In this context Beenstock (1985) explains fluctuations of vessel prices by means of structural models, whereas the price is a function of world wealth, fleet size, expected operational earnings[1], expected future second-hand prices and interest rates. Moreover, newbuilding prices are added in subsequent papers (see for example Beenstock and Vergottis, 1989). Alternatively to the portfolio theory based approaches by Beenstock and Vergottis, Strandenes (1984) suggests a simpler present value approach where second-hand prices represent the value of future freight incomes corrected for depreciation.

The second important strand of vessel value related research focuses on testing for the Efficient Market Hypothesis (EMH) to hold in this market. If the EMH as proposed by Fama (1970) holds, current vessel prices reflect all available information, such that it is not possible for investors to achieve arbitrage profits by buying and selling vessels. In order to check the validity of the EMH in the market for ships, Hale and Vanags (1992) test series of second-hand price assessments of three dry bulk size classes for cointegration using the Engle-Granger approach. Although they do not find cointegrating relationships for all pairs of vessel price series, they conclude that there are two, not further specified, exogenous factors driving the prices of vessels. Their finding is partially confirmed by Glen (1997), except that only one cointegrating vector is found. He concludes that the market might still be efficient, if the factor that drives the common trend is stochastic. However, both studies suffer from several major problems as pointed out by Alizadeh-Masoodian (2001). He clarifies that the existence of cointegration of price series is not inconsistent with market efficiency as a long run common trend does not rule out opportunities to generate excess

[1] Charter rates less operating costs.

profits in the short run. Furthermore, exploiting such opportunities is costly and risky. Following studies using several trading techniques also reveal mixed results with respect to cointegration and market efficiency (see for instance Kavussanos and Alizadeh, 2002; Adland and Koekebakker, 2004; Sodal et al., 2009).

In a more recent approach Tsolakis et al. (2003) apply cointegration methodology to estimate a structural model that describes second-hand prices of dry bulk and tanker vessels. Based on annual data from 1960 to 2001, second-hand prices are modeled as the equilibrium within a supply and demand framework where the vessel price is a function of time charter rates, newbuilding prices, the orderbook-to-fleet ratio and cost of capital. They find that the different vessel types and size classes are affected differently by the various factors, whereas newbuilding prices and time charter rates have the greatest influence. The volatilities of second-hand ship prices are analyzed by Kavussanos (1997). Fitting a GARCH model to monthly dry bulk and tanker price series between 1976 and 1995, he finds that resale prices are heteroscedastic and vary between vessel sizes, i.e. larger vessel show more volatile prices than smaller ones.

For the purpose of hedging the most obvious instrument to ensure a certain vessel price in the future would be the aforementioned FOSVA[2]. This contract is intended to guarantee shipowners a specific future (second-hand) value of a generic vessel. However, because of potential credit risk due to high contract sizes and an over-the-counter market, there is still a lack of liquidity for this relatively new product[3] (see Alizadeh and Nomikos, 2009). A second-best solution is a cross hedge that has preferably a high correlation to the risk factor, in this case vessel values. That is the case for freight rate derivatives, namely FFAs, which also show the required liquidity. Following this idea, Alizadeh and Nomikos (2012) analyze the relationship between second-hand ship prices and FFAs and find both to be cointegrated. They estimate variance minimizing hedge ratios and find a theoretical hedging effectiveness of freight derivatives of about 90%. Real world practicality and hedging performance are not demonstrated, though. Vessel price series are given by weekly estimates from the Baltic Exchange Sale & Purchase Assessments (BSPA) which relate to a standardized 5-year-old vessel, such that these results only indicate the general possibility of using FFAs for hedging ship price risks.

One shortcoming that all of these studies have in common is the use of second-hand vessel price series. These series are based on assessments and do in particular not represent traded market prices. This issue is addressed by Pruyn et al. (2011) in their review of vessel valuation literature. As the average number of sales in one month is quite low[4], one may doubt the accuracy of reported prices for 5-, 10-, 15- or 20-year-old vessels, such that

[2] See Adland et al. (2004) for description and pricing of FOSVAs.
[3] There has been no paper trade reported until mid-2013 (see Jallal, 2013).
[4] According to Syriopoulos and Roumpis (2006), there are at most five sales per month (per vessel and size class) over all ages. Only the dry bulk Handysize class shows an average of 12 sales per month.

'... it is more likely that brokers' expectations were tested rather than real market behaviour' (see Pruyn et al., 2011). Furthermore, these estimates refer to exactly defined reference vessels which introduces a further bias when applying these results to specific vessels. To overcome this problem, Adland and Koekebakker (2007) estimate a non-parametric model using realized individual sales data of Handysize vessels in the dry bulk class. In their model the resale price is determined by age, size and time charter rates at the date of sale. One important finding is that non-linearity seems to be relevant in vessel valuation, especially regarding freight rates and the vessels' ages.

Our study contributes to the existing literature by testing the classical cross hedge methodology as proposed by Alizadeh and Nomikos (2012) on real sales data of dry bulk vessels for the first time. Furthermore, we pick up the idea by Adland and Koekebakker (2007) and use individual sales data to develop and estimate a structural model for second-hand vessel prices which allows to distinguish between the deterministic and the risky part of the price. We include the age as a vessel specific factor as well as forward freight rates expressing market expectations with respect to the freight market. Non-linear effects are controlled by a cross term combining age and freight rates. We apply the model to hedge vessel values and find an average risk reduction of more than 80% which is slightly better and in particular more stable compared to the classical cross hedge. At the same time the required hedge position is on average 25% lower and thus less costly.

2.3 Methodology

In this section we introduce our structural model approach and its application for hedging vessel values. Additionally, we define the conventional cross hedge model which is the reference model in this context. We also define how we set up the hedges and introduce the measure of the theoretical hedge effectiveness to compare and evaluate the performance of both models.

2.3.1 Structural model

We follow the idea of Adland and Koekebakker (2007) and use a structural model for second-hand vessel values based on actual cross sectional sales data. The main idea is that only a part of the vessel value is exposed to freight market risk, such that the resulting hedge position in FFAs is smaller compared to hedging the total vessel value. For example, vessel prices also include the material value. Furthermore, we consider the age of the vessel as it indicates the remaining time to earn money and thereby the sensitivity towards freight rates.

We apply a multivariate structural model[5] that contains the vessel's age as a vessel individual element as well as forward freight rates to reflect the systemic risks of the freight market. In addition, we also pick up non-linearities as detected by Adland and Koekebakker (2007) by including an interaction term of age and freight rates. The value of the i-th vessel[6] V^i at its date of sale t_i is then given by

$$V_{t_i}^i = \beta_0 + \beta_{\text{Age}} \cdot \text{Age}_{t_i}^i + \beta_f \cdot f_{t_i} + \beta_{f\cdot\text{Age}} \cdot \left(f_{t_i} \cdot \text{Age}_{t_i}^i\right) + \varepsilon^i, \tag{2.1}$$

where $\text{Age}_{t_i}^i$ and f_{t_i} are the vessel's age and the price of the freight futures at t_i, respectively. By this setup, we can divide the sales price $V_{t_i}^i$ into

$$V_{t_i}^i = V_{t_i}^{i,\,\text{det}} + V_{t_i}^{i,\,\text{risk}},$$

where $V_{t_i}^{i,\,\text{det}}$ represents the deterministic part that is mainly specified by the vessel's age and given by

$$V_{t_i}^{i,\,\text{det}} = \beta_0 + \beta_{\text{Age}} \cdot \text{Age}_{t_i}^i,$$

while $V_{t_i}^{i,\,\text{risk}}$ contains the non-deterministic risk factor reflecting the state and expectations of the freight market, given by

$$V_{t_i}^{i,\,\text{risk}} = \beta_f \cdot f_{t_i} + \beta_{f\cdot\text{Age}} \cdot \left(f_{t_i} \cdot \text{Age}_{t_i}^i\right) + \varepsilon^i.$$

Only the non-deterministic part of the ship value, $V_{t_i}^{i,\,\text{risk}}$, is exposed to freight rate risk and determines the hedge volume.

2.3.2 Conventional cross hedge model

As a reference, we also apply a model based on Alizadeh and Nomikos (2012), who use the well-known regression-based cross hedge approach. Changes in the price of the risk factor ΔP_t are regressed on changes of the price of the hedge instrument ΔF_t, such that

$$\Delta P_t = \alpha + \beta \Delta F_t + \varepsilon_t\,, \qquad \varepsilon_t \overset{iid}{\sim} (0, \sigma^2).$$

In this case, the slope coefficient β can be interpreted as the variance-minimizing hedge ratio regarding the risky exposure. The regression's coefficient of determination R^2 measures the proportion of variance that can be explained through the regression and is therefore a measure for the hedge effectiveness. In the present study we follow Alizadeh and Nomikos (2012) and look on 52-week price changes of vessels of different ages and freight futures,

5 We also considered the vessel's cargo carrying capacity as well as higher powers of freight rates as explaining variables. A detailed model selection analysis is provided in Appendix A.

6 More precisely, i denotes a specific sale.

respectively. The authors analyze weekly second-hand price series provided by the Baltic Exchange referring to 5-year-old exactly specified reference vessels. In contrast, the vessels in our sample show ages of up to 30 years. Therefore, we estimate age specific hedge ratios with

$$\Delta^{52} p_t^{\text{Age}} = \alpha + \beta^{\text{Age}} \Delta^{52} f_t + \eta_t \,, \tag{2.2}$$

where $\Delta^{52} p_t^{\text{Age}} = \ln(P_t^{\text{Age}}) - \ln(P_{t-52}^{\text{Age}})$ and $\Delta^{52} f_t = \ln(F_t) - \ln(F_{t-52})$ are the 52-week log-differences of vessel prices and FFA prices, respectively. Within this setup, the error term η_t is no longer i.i.d., rather it follows a moving average process of order 51 as a result of overlapping observations. However, Alizadeh and Nomikos (2012) claim that these estimates are still consistent and unbiased.

2.3.3 Hedge setup and effectiveness

We consider the owner of vessel i, who plans to sell the respective vessel at date t_i which is the effective sales date in our sample. Furthermore, we assume that the shipowner starts the hedge l_i weeks prior to the planned sales date t_i, i.e. a hedge for vessel i is started at $t_i - l_i$. The realized vessel price $V_{t_i}^i$ is not known at inception, but is revealed to the shipowner at t_i when the hedge position is closed. With respect to the choice of a suitable hedge instrument, we rely on the results presented in Section 2.2, where freight rates have been identified as one driver of vessel prices. To reduce basis risk, we directly use FFAs as the corresponding futures contract.

In general, lower levels of (future) freight rates are associated with falling vessel prices. Because of this positive correlation, the shipowner engages in a short hedge to benefit from falling freight rates and to compensate decreasing vessel prices. The hedger's aim at a given time $t_i - l_i$ before the sale is to minimize the variance of the change of the vessel's value plus the hedge contract

$$Y^i := \left(V_{t_i}^i - \widehat{V}_{t_i - l_i}^i \left(Age_{t_i}^i \right) \right) + \sum_{j=1}^{l_i} h_{t_i - j}^i \left(f_{t_i - j + 1}\left(\tau_{ij}\right) - f_{t_i - j}\left(\tau_{ij}\right) \right) \prod_{k=1}^{j-1} \left(1 + r_{t_i - k}\right), \tag{2.3}$$

where $\widehat{V}_{t_i - l_i}^i \left(\text{Age}_{t_i}^i \right)$ is the model dependent estimated value of an Age^i-year-old vessel in $t_i - l_i$, $h_{t_i - j}^i$ is the number of hedge contracts in $t_i - j$, f denotes the freight futures contract with contract period τ_{ij}, l_i is the length of the hedging period in weeks and $r_{t_i - k}$ is the interest rate in $t_i - k$ for the return on the margin account. The value of the vessel at the start of the hedge is $\widehat{V}_{t_i - l_i}^i$ and is estimated by applying the respective model, the structural or the cross hedge model, using the age at the date of sale, $\text{Age}_{t_i}^i$. By this setup, we hedge the value of an Age^i-year-old vessel in $t_i - l_i$ and do not further have to take into account the aging-related loss of value. More precisely, within the structural model (SM), we apply the estimates of Equation (2.1) to estimate the theoretical vessel prices $\widehat{V}^{i,\text{SM}}_{t_i-l_i}\left(f_{t_i-l_i}, \text{Age}^i_{t_i}\right)$. With respect to the cross hedge (CH) model introduced in Section 2.3.2, the respective value $\widehat{V}^{i,\text{CH}}_{t_i-l_i}(\text{Age}^i_{t_i})$ is obtained through linear interpolation between the reported estimates for second-hand ship prices of the adjacent age classes, here referred to as Age^L and Age^U which is

$$\widehat{V}^{i,\text{CH}}_{t_i-l_i}\left(\text{Age}^i_{t_i}\right) = p^{\text{Age}^L}_{t_i-l_i} + \frac{\text{Age}^i_{t_i} - \text{Age}^L}{\text{Age}^U - \text{Age}^L}\left(p^{\text{Age}^U}_{t_i-l_i} - p^{\text{Age}^L}_{t_i-l_i}\right), \tag{2.4}$$

$$\text{with } \text{Age}^L < \text{Age}^i_{t_i} < \text{Age}^U$$
$$\text{and } \left(\text{Age}^L, \text{Age}^U\right) \in \{0, 5, 10, 15, 20, 30\} \text{ years.}$$

The hedge volume in the structural model is determined by the overall exposure in freight futures (see Equation (2.1)) given by

$$h^{i,\text{SM}}_{t_i-l_i} = -\left(\beta_f + \beta_{f\cdot\text{Age}} \cdot \text{Age}^i_{t_i}\right), \tag{2.5}$$

and therefore depends on the price of the risk factor f_t in $t_i - l_i$. In the cross hedge model we obtain the respective hedge ratios $\beta^i_{t_i-l_i}$ analogous to the vessel values in Equation (2.4) by a linear interpolation between the hedge ratios of the respective age classes which is

$$\beta^i_{t_i-l_i} = \beta^{\text{Age}^L}_{t_i-l_i} + \frac{\text{Age}^i_{t_i} - \text{Age}^L}{\text{Age}^U - \text{Age}^L}\left(\beta^{\text{Age}^U}_{t_i-l_i} - \beta^{\text{Age}^L}_{t_i-l_i}\right),$$

$$\text{with } \text{Age}^L < \text{Age}^i_{t_i} < \text{Age}^U$$
$$\text{and } \left(\text{Age}^L, \text{Age}^U\right) \in \{0, 5, 10, 15, 20, 30\} \text{ years.}$$

The amount of hedge contracts is then determined by the hedged proportion of the vessel's value divided by the price of the hedge instrument, given by

$$h^{i,\text{CH}}_{t_i-l_i} = -\beta^i_{t_i-l_i} \cdot \frac{\widehat{V}^{i,\text{CH}}_{t_i-l_i}\left(\text{Age}^i_{t_i}\right)}{f_{t_i-l_i}}. \tag{2.6}$$

In order to compare and evaluate the hedge results, we need a measure of the theoretical potential of risk reduction of the two models, whereas this study understands vessel price risk as the variance of vessel prices. Within the structural model as given in Equation (2.1) we assume the regression residuals ε^i and observed freight rates f_{t_i} to be independent. Then the maximum achievable reduction of variance is estimated by

$$\frac{\left(\overline{h}^{\text{SM}}\right)^2 \sigma^2_f}{\left(\overline{h}^{\text{SM}}\right)^2 \sigma^2_f + \sigma^2_\varepsilon}\ , \tag{2.7}$$

where $\overline{h}^{\text{SM}}$ represents the arithmetic average of the hedge ratios $h_{t_i}^{i,\text{SM}}$ (see Equation (2.5)) and σ_f^2 and σ_ε^2 are the variances of the freight futures (at the date of sale) and the error term ε^i, respectively (see Equation (2.1)). In the case of the regression based cross hedge, we follow Ederington (1979) and interpret the regressions' R^2s as the measures of hedge effectiveness as they indicate the proportion of total variance that can be explained by the respective models.

2.4 Data and model estimation

In this section we present and analyze the data, in particular we control for heteroscedasticity. Additionally, we estimate the models introduced before and quantify the respective hedge potentials.

2.4.1 Data

Robust model estimates require extensive data, in our case a large fleet and a correspondingly high activity in the second-hand market. In the present study we analyze the Panamax class ($60 - 99{,}999$ dwt[7]) of the dry bulk sector. Vessels of this class mainly carry coal, grain, iron ore and, to a lesser extent, minor bulks as steel products, cement and fertilizers. Despite of their size, these vessels still show a high flexibility with respect to shipping routes and the possibility to land in most ports. As of 2012, Panamax vessels account for about 38% of the carrying capacity of the world's dry bulk fleet (see Clarkson Research Services, 2013), such that this class can be seen as important to world merchandise trade and world economy.

Table 2.1: Overview of sales in sample period 2005 - 2012

Year	# Sales	∅ Age in years	∅ Size in dwt	∅ Price in USD m.	∅ FFA in USD/day	∅ FFA in USD m./year
2005	57	9.95	71,599	33.44	16,258	5.93
2006	94	12.31	72,060	25.62	15,609	5.70
2007	78	11.12	73,134	46.59	30,780	11.23
2008	31	12.13	73,104	52.68	32,909	12.01
2009	78	12.51	72,394	22.15	14,958	5.46
2010	57	13.98	74,347	24.73	17,641	6.44
2011	42	13.48	72,042	19.57	12,980	4.74
2012	49	14.38	72,771	11.66	10,178	3.71
2005 - 2012	486	12.37	72,637	29.04	18,583	6.78

Individual sales data is provided by Clarksons Shipping Intelligence Network (SIN). Data is available since January 1995 including name and size of the vessel as well as the year and

[7] deadweight tonnage

TABLE 2.2: Descriptive statistics of vessel value and FFA price series

	FFA	Newbuilt	Second-hand vessels with age				Scrap
	4TC+2Cal	0 y	5y	10y	15y	20y	30y
Level (USD m.)							
Mean	6.94	37.86	42.37	34.19	25.70	17.51	5.27
SD	3.54	8.52	19.99	17.88	14.97	11.30	1.30
Maximum	19.93	55.00	92.00	77.50	62.00	48.00	8.51
Minimum	2.86	25.75	18.00	13.00	8.00	6.00	2.58
52-week log-differences (%)							
Mean	5.88	-4.25	-6.32	-7.23	-8.84	-7.27	4.07
SD	49.83	22.10	51.45	57.33	64.03	71.52	40.26
Correlation w.r.t. +2Cal FFA							
Level	1.00	0.86	0.96	0.96	0.96	0.94	0.52
Log-differences	1.00	0.82	0.94	0.94	0.93	0.90	0.71

Descriptive statistics for level data and 52-week log-differences for Panamax ship values and 4TC+2Cal FFA prices. The level series include 394 weeks (06/17/2005 to 12/28/2012) which leaves 342 observations of 52-week log-differences. The age of scrapped vessels is assumed to be 30 years.

place of construction, price and further details like equipment, speed or fuel consumption. After removing incomplete data points and en bloc sales[8], there remain 765 sales by the end of 2012. According to the availability of FFA data, we only consider sales between January 2005 and December 2012 which leaves 486 observations. An overview of the annual distribution of vessel sales within the sample period is provided by Table 2.1. In each year there is a representative number of sales whereas we observe the fewest transactions at the peek of the shipping boom in 2008 when the prices where the highest. While the average age of the transacted vessels increases from about 10 years to more than 14 years, there is almost no variation in the size. Average vessel prices as well as future freight rates decrease as result of the shipping crisis.

For the conventional cross hedge we use series of weekly Panamax ship value assessments provided by Clarksons SIN. These series include prices of newbuilt (75-77,000 dwt), 5-year- (76,000 dwt), 10-year- (75,000 dwt), 15-year- (73,000 dwt) and 20-year-old (69,000 dwt) second-hand vessels as well as scrap values[9]. The slight differences in the size are neglected. As pointed out in Section 2.2, these values are assessments and not based on actual transactions.

Weekly data of freight rate derivatives is taken from Baltic Exchange which publishes FFA assessments since 2005. For the purpose of hedging we work with calendar FFA contracts.

8 En bloc sales contain collectively sold vessels such that it is difficult to attribute a value to each individual vessel in the sale.

9 As scrap values are only published monthly, we assume these prices to be valid for each week in the respective month.

These contracts refer to a whole calendar year available for the following year (+1Cal) up to the fifth nearest year (+5Cal) with monthly settlement. Freight rates are originally quoted in US-Dollar per day. By multiplying with the according number of days per year, we annualize these rates obtaining contract values in million US-Dollar per year. Baltic Forward Freight contracts are tradable on individual routes or route indices. For the class of Panamax vessels, the highest trading activity can be observed for contracts on the time charter average of the Baltic Panamax Index BPI 4TC (see Alizadeh and Nomikos, 2009), which is an equally weighted average of the trip-charter rates in four Baltic Exchange Panamax routes[10]. Within our analysis we follow Alizadeh and Nomikos (2012) and use the end-of-week prices of the second-nearest calender FFA, the 4TC+2Cal contract. This reduces rollover events within this study or makes it even redundant to rollover contracts when the hedging periods are short. For discounting cashflows and interest payments on the margin account we use the appropriate USD LIBOR rates from Thomson Reuters Datastream. Descriptive statistics for vessel values and FFA rates are given in Table 2.2. With the exception of the scrap value, all second-hand as well as the newbuilding price series show negative average changes over the sample period. In contrast, freight rates increase on average. Furthermore, the high positive correlations between FFAs and vessel values support the idea of using freight derivatives to hedge ship values.

The historical development of second-hand values and FFAs for the observation period from January 2005 to December 2012 is given in Figure 2.1. Obviously, freight rates exhibit a fairly

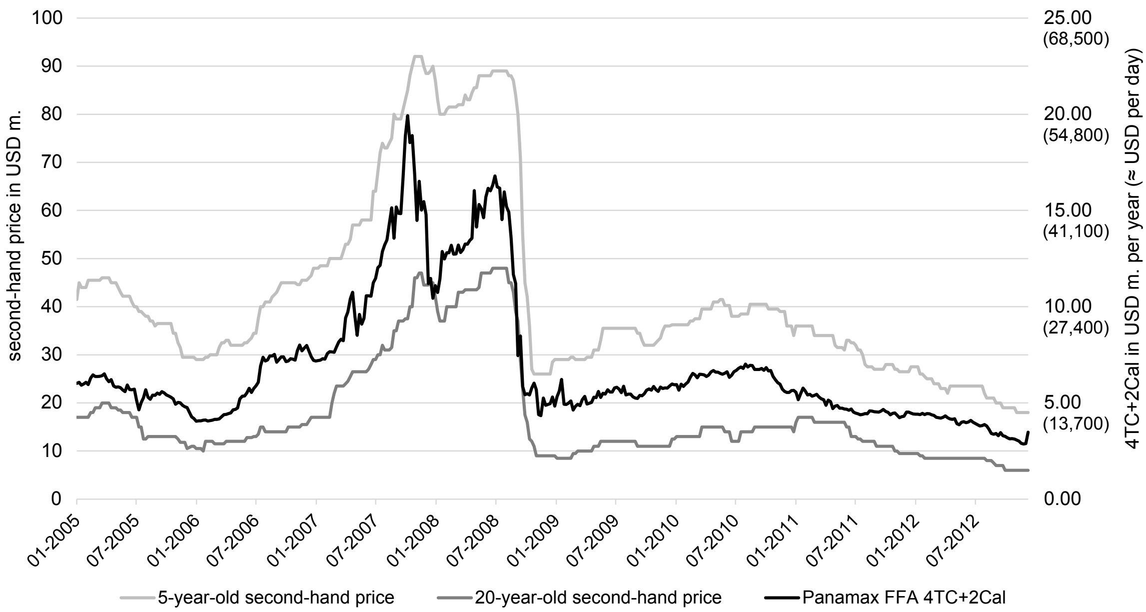


Figure 2.1: Second-hand prices and 4TC+2Cal FFA in the Panamax dry bulk sector

10 The Baltic Panamax Index (BPI) contains the routes P1A_03 (Skaw-Gibraltar transatlantic round voyage), P2A_03 (Skaw-Gibraltar trip to Taiwan-Japan), P3A_03 (Japan-South Korea transpacific round voyage) and P4_03 (Japan-South Korea trip to Skaw Passero). The respective reference vessel is at most 12 years old with a size of 74,000 dwt.

heterogeneous pattern over time with an extreme increase prior to the recent financial crisis that ended in a big drop in the beginning of 2009. Because of the different volatility regimes, we analyze the FFA log-return series for heteroscedasticity with respect to the expected level log-returns and volatility. If such breaks exist, one cannot assume a good hedging performance by models that are based on the whole sample, and might consider several subperiods instead. To identify possible change-points, we follow Andreou and Ghysels (2002) and run a least squares type test which is based on cumulative sums of OLS residuals of the weekly FFA 4TC+2Cal log-differences from 01/21/2005 to 12/28/2012. In particular, the absolute log-returns are modeled as a generic process X_t of the form

$$X_t = \mu_k + \varepsilon_t, \qquad t_{k-1} \leq t \leq t_k, \qquad 1 \leq k \leq r,$$

where $t_0 = 0$ and $t_{r+1} = T = 414$. Breakpoints and mean values are given by $k = 1, ..., r$ and μ_k, respectively. The objective equation is then given by

$$Q_r(t) = \min_{\substack{\mu_k, t_k, \\ k=1,...,r, \\ |t_{k+1}-t_k| \geq \vartheta}} \sum_{k=1}^{r+1} \sum_{t=t_{k-1}+1}^{t_k} (X_t - \mu_k)^2,$$

where ϑ is the minimal allowed regime length. The results of the test are given in Table 2.3. Bayes' information criterion indicates at most two structural breaks, and thus, three regimes, in particular 01/21/2005 - 04/13/2007 (I), 04/14/2007 - 02/13/2009 (II) and 02/14/2009 - 12/28/2012 (III). The corresponding average weekly returns and standard deviations are given in the lower part of the table. While the freight rate volatility increases up to almost 10% during the financial crisis, it is only around 3% before and thereafter. The negative mean returns of freight rates during the crisis also indicate the possible advantage of short hedging strategies.

2.4.2 Structural model estimation

For the three identified subperiods as well as for the whole sample, regression results based on Equation (2.1) are given in Table 2.4. Due to the obvious similarity of model parameters in period I and II, we subsequently run a Chow test[11], which confirms that the difference of the model parameters in the first two subperiods is not significant. Thus, even in the presence of extreme movements of freight rates and vessel prices in 2007 and 2008, the structural relationship of vessel prices and freight rates remains unchanged. However, the second structural break on 02/20/2009 is confirmed by the Chow test. According to this finding, we re-estimate the structural model (Equation (2.1)) treating the first two subperiods as one, which is then 01/21/2005 - 02/13/2009 denoted as I*, while the initial third subperiod

[11] The Chow test basically checks whether the sums of squared residuals of two individual (sub-)sample regressions add up to the residual sum of squares of the aggregate sample regression (see Chow, 1960).

TABLE 2.3: Results of CUSUM test for change-points

Change-points	Indicated dates of structural breaks				BIC
0					-1.303
1	06/19/2009				-1.317
2*	04/20/2007	02/20/2009			-1.346
3	04/20/2007	05/02/2008	05/01/2009		-1.345
4	04/20/2007	05/02/2008	05/01/2009	05/27/2011	-1.343

Weekly FFA returns (in %) in each period for 2-change-points-setup (*)

	I+II+III	I	II	III
Period	01/21/2005 - 12/28/2012	01/21/2005 - 04/13/2007	04/14/2007 - 02/13/2009	02/14/2009 - 12/28/2012
Mean	-0.06	0.47	-0.27	-0.28
SD	5.39	3.35	9.84	2.70

Upper part: CUSUM test results for weekly 4TC+2Cal FFA log-differences from 01/21/2005-12/28/2012 with a minimum period length of 52 weeks. Shown are the structural breaks identified by the test for each allowed number of change-points. The BIC-optimal specification is indicated by *.
Lower part: weekly return in each regime of the BIC-optimal specification.

remains as before 02/14/2009 - 12/28/2012, now denoted as II*. The results of the second regression are given in Table 2.5. For the whole sample the estimate of the age coefficient β_{Age} of -0.488 indicates that the value of a new ship, with age equal to zero, is reduced by nearly 0.5 million USD per one year of age, while the estimate of the FFA coefficient β_f of 5.461 implies that the value of a new ship contains about five and a half years of freight rate income. With respect to the two subperiods I* and II*, the coefficients change considerably in the second period which contains the ongoing crisis in the shipping market with smaller and less volatile freight rates. Not only is the constant β_0 in period II* close to zero, but especially the age of the vessel is less important, whereas the price of the +2Cal FFA explains most of the value.

The maximum theoretical risk reduction for the structural model is given in the lower part of Table 2.5. Given the average hedge exposure, the variance might at most be reduced by about 75%. Especially in the post-crisis period II* it becomes evident that the less volatile shipping market and the increased influence of forward freight prices on second-hand values (see Table 2.5) enhances the possibility of hedging. The coefficients of the second regression in Table 2.5 are used for hedging in this study. The results also show the non-linear relationship between age, freight rates and second-hand prices which is controlled by the interaction term $f_{t_i} \cdot \text{Age}^i_{t_i}$. As illustrated in Figure 2.2, the prices of newer vessels show a much higher sensitivity towards FFA prices than older ones. For the value of the average ship in our sample, sold at an age of 12.37 years and observing a freight futures price of 6.78 million USD per year (18,583 USD per day), the value declines more than 1.5 million USD per one year of age and increases by about 3.5 million USD per each million USD of additional annual freight income.

TABLE 2.4: Descriptive statistics and regression results for sample periods

Period	I + II + III Whole sample 01/21/2005 - 12/28/2012	I Pre-boom 01/21/2005 - 04/13/2007	II Boom and crisis 04/14/2007 - 02/13/2009	III Post-crisis 02/14/2009 - 12/28/2012
Observations	486	180	88	218
Mean $V_{t_i}^i$	29.04	29.81	49.60	20.11
Mean $\text{Age}_{t_i}^i$	12.37	11.43	11.76	13.39
Mean f_{t_i}	8.19	7.54	16.62	5.32
β_0	11.095***	18.048***	23.785***	-0.629
	[7.930]	[7.412]	[2.869]	[-0.316]
β_{Age}	-0.488***	-0.972***	-0.788	-0.203*
	[-5.075]	[-5.454]	[-1.486]	[-1.663]
β_f	5.461***	4.895***	4.436***	6.982***
	[28.179]	[12.524]	[6.314]	[18.811]
$\beta_{f\cdot\text{Age}}$	-0.158***	-0.099***	-0.132***	-0.184***
	[-11.544]	[-3.493]	[-2.880]	[-8.140]
S.E. of Reg.	6.232	3.305	12.089	2.691
Adj. R^2	0.875	0.925	0.708	0.940

Chow test[1)] on identity of model parameters

$\beta_{\text{I}} = \beta_{\text{II}}$	1.206	2.406
$\beta_{\text{I}} = \beta_{\text{III}}$	44.731***	2.395
$\beta_{\text{II}} = \beta_{\text{III}}$	5.497***	2.402

Linear regression coefficients for different sample periods. Vessel prices and freight forward rates (scaled to one year) are expressed in USD m., and age in years. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are t-statistics. [1)] Chow test checks for identity of model parameters, whereas $\beta_{\{\cdot\}} = (\beta_{0,\{\cdot\}}, \beta_{\text{Age},\{\cdot\}}, \beta_{f,\{\cdot\}}, \beta_{f\cdot\text{Age},\{\cdot\}})$ and $\{\cdot\} \in \{\text{I, II, III}\}$.

Additional robustness of the estimated model is given in Figure 2.3, where we plot the estimated second-hand prices of the structural model (whole sample) against the quoted Clarksons prices for 5-, 10-, 15- and 20-year-old vessels which are used in the cross hedge approach introduced above. Obviously, the structural model covers the experts' estimates quite well, even without regarding the vessel's carrying capacity. It is also interesting to note that the structural model picks up the sharp decline of ship values in 2008 earlier than the assessments by Clarksons probably because the FFA market shows a higher immediacy than the expert's assessments. Newbuilding and scrap prices are not regarded here as these prices are not actual second-hand prices and also strongly driven by factors other than freight rates (see Section 2.3.2).

2.4.3 Cross hedge model estimation

The most common hedging approach in practice is the classical time series based cross hedge as outlined in Section 2.3.2. The estimated slope coefficients β^{Age} and the regressions' R^2s

TABLE 2.5: Descriptive statistics and structural model regression results - corrected sample periods

Period		$\mathrm{I}^* + \mathrm{II}^*$ Whole sample 01/21/2005 - 12/28/2012	I^* Pre-boom and crisis 01/21/2005 - 02/13/2009	II^* Post-crisis 02/14/2009 - 12/28/2012
Observations		486	268	218
Mean $V_{t_i}^i$		29.04	36.31	20.11
Mean $\mathrm{Age}_{t_i}^i$		12.37	11.54	13.39
Mean f_{t_i}		8.19	8.08	5.32
β_0		11.095***	18.740***	-0.629
		[7.930]	[8.371]	[-0.316]
β_{Age}		-0.488***	-0.741***	-0.203*
		[-5.075]	[-4.574]	[-1.663]
β_f		5.461***	4.814***	6.982***
		[28.179]	[18.162]	[18.811]
$\beta_{f\cdot\mathrm{Age}}$		-0.158***	-0.136***	-0.184***
		[-11.544]	[-7.147]	[-8.140]
S.E. of Reg.		6.232	7.401	2.691
Adj. R^2		0.875	0.843	0.940
Maximum potential of variance reduction by hedging (approx.)				
$h^{i,\mathrm{SM}}$	Mean	3.44	3.17	4.51
	SD	1.20	0.95	1.48
σ_ε^2		43.10	80.67	7.14
$\sigma_{f_t}^2$		12.16	14.84	1.13
Max. variance reduction (%)		76.98	64.95	76.24

Chow test[1)] on identity of model parameters

H_0	F-statistics	95% critical value
$\beta_{\mathrm{I}^*} = \beta_{\mathrm{II}^*}$	18.076***	2.391

Linear regression coefficients for different sample periods. Vessel prices and freight forward rates (scaled to one year) are expressed in USD m., and age in years. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are t-statistics. [1)] Chow test checks for identity of model parameters, whereas $\beta_{\{\cdot\}} = (\beta_{0,\{\cdot\}}, \beta_{\mathrm{Age},\{\cdot\}}, \beta_{f,\{\cdot\}}, \beta_{f\cdot\mathrm{Age},\{\cdot\}})$ and $\{\cdot\} \in \{\mathrm{I}^*, \mathrm{II}^*\}$.

of the six age classes for the whole sample as well as for the two subperiods I^* and II^* are given in Table 2.6[12]. The coefficients β^{Age} for ships between 5 and 20 years are mostly larger than one with R^2s of about 0.90 which is similar to the results found by Alizadeh and Nomikos (2012). This indicates that hedging second-hand ship prices using FFAs may result in a risk reduction (in terms of the variance) of about 90%, but the required short position in FFAs is on average actually larger than the value of the vessel itself. The coefficients for newbuilt and scrapped vessels deviate from the others and also show lower R^2s which

[12] The parameter estimates for the three initial subperiods I, II and III are given in Table 2.15 and the results of Chow's breakpoint test in Table 2.16 in Appendix B.

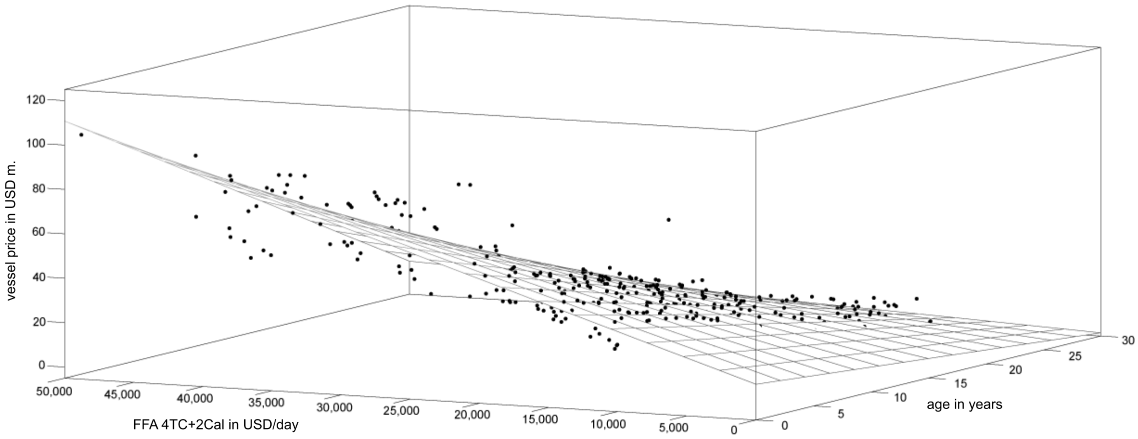


FIGURE 2.2: Fitted model vs. realized resale prices - whole sample

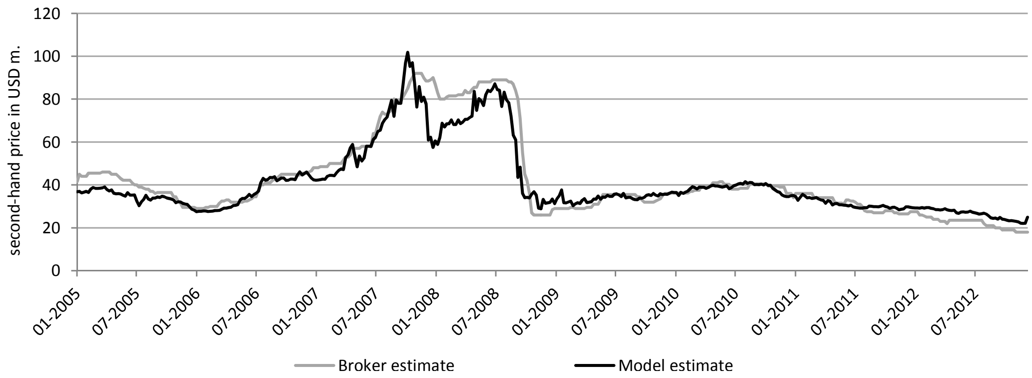
indicate a poorer explanatory power of freight rates. This appears plausible as prices of new vessels are negotiated with a large delay to their actual delivery and the scrap value only contains the material value but no further utility. Additionally, we observe that older vessels show higher hedge ratios. The lower part of Table 2.6 shows the average hedge ratios (β^{Age}) and hedge effectiveness (R^2s) of each period. The theoretical average risk reductions are about 80% for the whole sample as well as for the two subperiods. In particular, the theoretical hedge effectiveness is higher compared to the structural model.

2.5 Hedging results

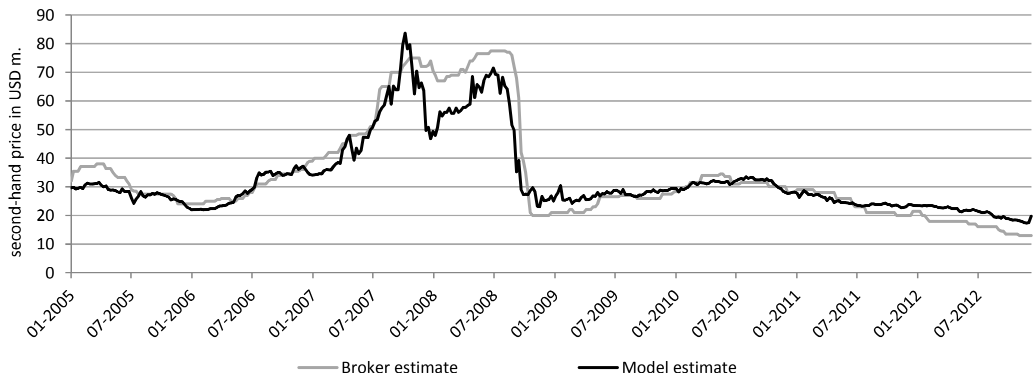
We apply the two introduced models to two different scenarios. On the one hand, we use all sales in the sample and calculate the hedge performance over a hedging period of 52 weeks. On the other hand, we take into account possible model errors, especially as the current price of the vessel is unknown at the start of the hedge. Therefore, in the second analysis we only consider those vessels that were sold repeatedly such that we have realized buy and sell prices.

2.5.1 Hedging over a fixed time horizon

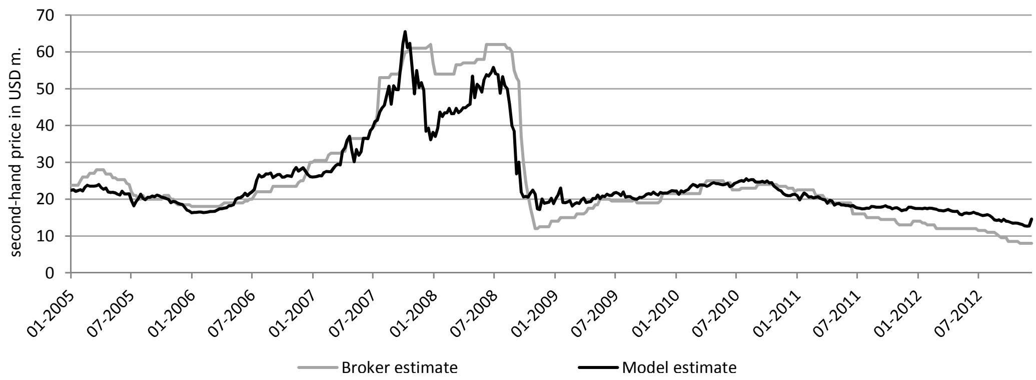
We check the hedging performance over a fixed time horizon of one year before each realized sale i, such that the hedging period is $l_i = 52$ weeks for each sale i. In such a scenario, it is possible to avoid rolling over contracts when hedging by selling open the third nearest calendar FFA which has become the second nearest calendar FFA when closing the contract one year thereafter. For example, the calendar FFA that relates to the calendar year 2008 is called *+3Cal* in 2005 but *+2Cal* in 2006. Furthermore, we assume interest rates to be deterministic which implies that futures and forward prices coincide. In particular, we



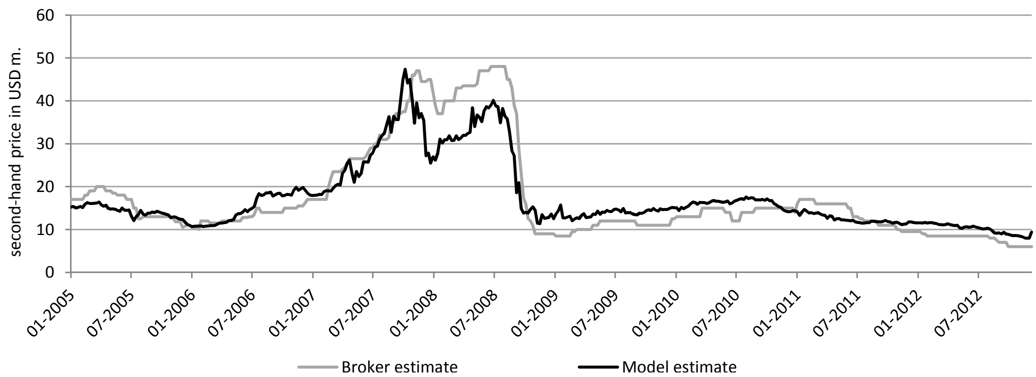
5-year-old vessel



10-year-old vessel



15-year-old vessel



20-year-old vessel

FIGURE 2.3: Vessel value comparison for different age classes

TABLE 2.6: Cross hedge model: coefficients for Panamax vessels of different ages - corrected sample periods

$$\Delta^{52} p_t^{\text{Age}} = \alpha + \beta^{\text{Age}} \Delta^{52} f_t + \eta_t\,, \qquad \text{Age} \in \{0,5,10,15,20,30\}$$

	I* + II*		I*		II*	
Period	06/16/2006 - 12/28/2012		06/16/2006 - 02/13/2009		02/14/2009 - 12/28/2012	
Observations	342		140		202	
	β^{Age}	R^2	β^{Age}	R^2	β^{Age}	R^2
0 years (new)	0.363	0.676	0.258	0.684	0.342	0.398
5 years	0.963	0.880	1.034	0.897	1.202	0.884
10 years	1.074	0.880	1.119	0.911	1.420	0.894
15 years	1.187	0.862	1.280	0.891	1.535	0.874
20 years	1.282	0.806	1.378	0.872	1.662	0.752
30 years (scrap)	0.570	0.503	0.566	0.742	1.213	0.716
Maximum potential of variance reduction by hedging (approx.)						
	β^{Age}	R^2	β^{Age}	R^2	β^{Age}	R^2
Mean	1.007	0.810	1.078	0.867	1.317	0.773

The level series include 394 weeks (17/06/2005 to 28/12/2012) which leaves 342 observations of 52-week log-differences for the whole sample. The age of scrapped vessels is assumed to be 30 years. All parameter estimates β_{Age} are significant at the 1% level.

neglect interest effects and marking-to-market due to the rather short hedging horizon. Therefore, Equation (2.3) simplifies to

$$Y^i := \left(V_{t_i}^i - \widehat{V}_{t_i-52}^i(\text{Age}_{t_i}^i)\right) + h_{t_i-52}^i \left(f_{t_i}(\tau_i) - f_{t_i-52}(\tau_i)\right),$$

such that it is ensured that the calendar year τ_i, to which a specific futures contract relates, is the same when opening and closing the hedge. In addition, the hedge contract is a *+2Cal* FFA contract when the vessel is sold which is consistent to the models considered (see Equations (2.1) and (2.2)). For reasons of generality, we assume unlimited divisibility of the annualized hedge contracts h^i. The 4TC+3Cal series is only available from 06/17/2005 restricting us to use sales from 06/15/2006[13] on, resulting into a sample of 387 sales.

The results for a hedge over a 52-week period are given in Table 2.7. Over the whole sample period (I*+II*) both models achieve almost the same good risk reduction of about 80%, whereas the structural model performs slightly better. At the same time the structural model is more effective as the required hedge position is on average 25% smaller. In period I* which includes the extreme rising and falling of freight rates, the variance reduction within the structural model is 67% and thus about 18 percentage points higher than in the cross hedge model, while the hedge exposures are on average 40% smaller compared to the cross hedge model. In period II* it is notable that the structural model leads to a similar large

[13] Recall that hedge ratios in the cross hedge approach are calculated based on 52-week log-returns.

hedge exposure as the cross hedge approach as the vessel value is almost only determined by the FFA price (see Table 2.5). However, in this period the hedge compensates almost exactly the loss in value of the vessels and reduces the variance reasonably by about 80% in both models.

TABLE 2.7: Hedging results over a one-year horizon

Model		I* + II*		I*		II*	
Hedged sales		06/15/2006 - 12/28/2012		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations[1)]		387		169		140	
		CH	SM	CH	SM	CH	SM
Hedge position	Mean	29.00	21.38	30.06	17.87	25.18	24.14
Hedge profit	Mean	-4.24	-3.58	-20.75	-13.05	2.34	2.01
	Variance	474.28	235.99	422.44	168.14	41.77	36.46
	SD	21.78	15.36	20.55	12.97	6.46	6.04
Change in values		$Y^i := \big(V^i_{t_i} - \widehat{V}^i_{t_i-52}(\mathrm{Age}^i_{t_i})\big) + h^i_{t_i-52}\big(f_{t_i}(\tau_i) - f_{t_i-52}(\tau_i)\big)$					
Unhedged ($h = 0$)	Mean	-0.52	-1.74	11.39	8.50	-2.12	-3.39
	Variance	450.96	395.40	351.40	292.28	46.04	40.40
	SD	21.24	19.88	18.75	17.10	6.79	6.36
Hedged	Mean	-4.77	-5.32	-9.37	-4.55	0.22	-1.38
	Variance	92.57	72.33	178.12	96.26	11.49	6.72
	SD	9.62	8.50	13.35	9.81	3.39	2.59
% reduction of ...	Variance	79.47	81.71	49.31	67.07	75.04	83.37
	SD	54.69	57.23	28.80	42.61	50.04	59.22

Hedge positions and profits are in USD m. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimated by the respective model. [1)] Due to the 52-week delay, the observations in the subperiods I* and II* do not sum up to the total sample observations.

Comparing these results with the estimated hedge potential of about 90% within the cross hedge model and 77% for the structural model (see Table 2.5), only the latter is able to achieve or even to exceed the predicted performance throughout the whole sample period as well as in the two subperiods. Furthermore, the large hedge exposures of the cross hedge model lead to variances of hedge profits that are actually bigger than the variances of the unhedged positions. Because of the short position, the variance of the overall position is still smaller. Another fact that stands out is that the average change of the vessel value and the average hedge profit only compensate, at least to some extent, if we consider the two subperiods individually. Over the whole sample period both the average hedge profit and the average price change are negative while the objective of reducing the risk in terms of variance is achieved. As mentioned above, compensating the change in value of expensive assets as merchant vessels requires large hedge exposures. In this analysis these are mostly higher than 20 million USD and result in an average loss of about 4 million USD which can be interpreted as the costs of hedging in this context.

2.5.2 Hedging between two resales

Estimating $V^i_{t_i-l_i}$, the time value of vessel i when starting the hedge, might distort the hedge results. Keeping in mind that the structural model shows a standard error of regression of more than 6 million USD over the whole sample period (see Table 2.5), it is possible that a gain in value over one year might actually be a loss or vice versa. Furthermore, the market for second-hand ships is quite heterogeneous not only with respect to age, but also with respect to technology, special equipment or even the specific route which effects the price of a vessel, but is not considered in any of the two models. Therefore, we want to verify the hedge strategies on those vessels, where more than one resale took place during the sample period from January 2005 to December 2012, such that we also have a real price when starting the hedge.

For this purpose, we now consider i as a pair of each two consecutive resales of one and the same vessel. The hedge is accomplished from $t_i - l_i$, the buy date of the vessel, to t_i, the day of its resale. Overall, we observe 68 pairs of specific buy prices $V^i_{t_i-l_i}$ and resale prices $V^i_{t_i}$ [14]. The average realized buy and sell prices are 32.20 and 31.18 million USD, respectively. The average time between two resales in this sample is 2.49 years and varies between 44 days and more than seven years, such that it is now necessary to rollover hedge contracts. This is done by opening a short position in the 4TC+2Cal FFA and, if applicable, rolling over hedge contracts at the end of November. For calculating the hedge results we use essentially Equation (2.3) where the estimated vessel value at the sales date $\widehat{V}^i_{t_i-l_i}$ is replaced by the observed vessel value at inception of the hedging period, the buy price $V^i_{t_i-l_i}$. This buy price is further adjusted for the deterministic aging-related loss in value implied by the respective model. The adjusted buy price in the structural model $\widehat{V}^{i,\mathrm{SM}}_{t_i-l_i}$ is then obtained as

$$\widehat{V}^{i,\mathrm{SM}}_{t_i-l_i} = V^i_{t_i-l_i} + \Big[(\beta_{\mathrm{Age}} + \beta_{f\cdot\mathrm{Age}} \cdot f_{t_i-l_i}) \cdot \Big(\mathrm{Age}^i_{t_i} - \mathrm{Age}^i_{t_i-l_i} \Big) \Big], \tag{2.8}$$

where $\mathrm{Age}^i_{t_i-l_i}$ and $\mathrm{Age}^i_{t_i}$ denote the age of vessel i at the date of acquisition and resale, respectively. In the cross hedge model, the adjustment is done similar to Equation (2.4), by linear interpolation between the quoted second-hand prices by Clarksons, such that

[14] Every two resales are analyzed independently, such that the sell price of one pair might be the buy price of another pair, in case one ship has been sold three or more times within the observed sample period.

$$\widehat{V}_{t_i-l_i}^{i,\mathrm{CH}} = V_{t_i-l_i}^{i} + \frac{p_{t_i-l_i}^{\mathrm{Age}^U} - p_{t_i-l_i}^{\mathrm{Age}^L}}{\mathrm{Age}^U - \mathrm{Age}^L}\left(\mathrm{Age}_{t_i}^{i} - \mathrm{Age}_{t_i-l_i}^{i}\right), \tag{2.9}$$

$$\text{with } \mathrm{Age}^L \le \mathrm{Age}_{t_i}^{i} < \mathrm{Age}_{t_i-l_i}^{i} \le \mathrm{Age}^U$$
$$\text{and } \left(\mathrm{Age}^L, \mathrm{Age}^U\right) \in \{0, 5, 10, 15, 20, 30\} \text{ years.}$$

As before, we assume that the buyer of the vessel knows ex ante when the vessel is sold, whereas in principle it is sufficient to know whether the ship is sold in the following year and if so, when the sale takes place. The method is analogous to Section 2.5.1. At the day of the ship's acquisition we estimate the hedge exposure until the first rollover date or the date of resale, respectively, by applying the model implied age-adjustment to the buy price (see Equation (2.8)). The same is done at each rollover date. Because of the longer hedging periods, interest rates are no longer assumed to be deterministic. Therefore, we need to take into account the interest effects on the margin account which requires an adjustment of the amount of hedge contracts by applying a tailing factor to Equations (2.5) and (2.6), respectively, and obtain

$$h_{t_i-j}^{i*} := h_{t_i-j}^{i} \cdot \frac{1}{1 + r_{t_i^s}\left(t_i^{s+1} - t_i^s\right)}, \qquad s \in \{0, ..., n_i - 1\},$$

where t_i^s denotes the dates of opening and closing futures positions. In particular, t_i^0 denotes the buy date and $t_i^{n_i}$ the sales date of the vessel. In between are the rollover dates. For tailing the hedge ratio we use the respective 12-month USD LIBOR rate. Furthermore, we consider a marking-to-market of the futures positions on a monthly basis[15] and use the one month USD LIBOR rate for the return on the margin account as stated above. Because of the long hedging period over several years, a clear assignment of resales to one of the two subperiods is hardly possible[16]. Therefore, the two subperiods are considered differently in this context by using the appropriate model to calculate the hedge dependent if the acquisition (or rollover) occurs in the first (I*) or second subperiod (II*). The results are aggregated over both subperiods.

The hedge results of this strategy are given in Table 2.8. Surprisingly, there is an average gain in value of each Age^i-year-old vessel of about 3 million USD which indicates a strategic buying and selling behavior. For the structural model the risk reduction through hedging is almost the same in both model setups with a variance reduction of almost 70%. On the other hand, the cross hedge achieves better results when using one model for the whole sample period with a risk reduction of about 43% compared to only 27% in the two-subperiod setup. In this context, it is also notable that the average hedge volume is about 40% to 58% larger within the cross hedge approach compared to the structural model. This confirms our idea

15 For practical reasons, we only consider end-of-month values of FFAs and interest rates in this analysis.
16 Most pairs of sale and resale cover both subperiods.

TABLE 2.8: Results of hedging between two resales

Model		One model ($\mathrm{I}^* + \mathrm{II}^*$)		Two models I^*, II^*	
Observations		68		68	
		CH	SM	CH	SM
Hedge position	Mean	30.01	21.45	32.81	20.82
Hedge profit	Mean	-15.72	-13.91	-16.59	-12.28
	Variance	768.60	385.89	878.46	318.67
	SD	27.72	19.64	29.64	17.85
Change in values	$Y^i := \left(V^i_{t_i} - \widehat{V}^i_{t_i - l_i}(\mathrm{Age}^i_{t_i})\right) + \sum_{j=1}^{l_i} h^i_{t_i-j}\left(f_{t_i-j+1}(\tau_{ij}) - f_{t_i-j}(\tau_{ij})\right) \prod_{k=1}^{j-1}(1 + r_{t_i-k})$				
Unhedged ($h = 0$)	Mean	3.22	3.17	3.22	3.39
	Variance	421.64	406.88	421.64	409.31
	SD	20.53	20.17	20.53	20.23
Hedged	Mean	-12.49	-10.74	-13.37	-8.90
	Variance	238.62	123.73	305.76	110.96
	SD	15.45	11.12	17.49	10.53
% reduction of...	Variance	43.41	69.59	27.48	72.89
	SD	24.77	44.85	14.84	47.93

Hedge positions and profits are in USD m. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The holding period l_i is on average 2.49 years with a standard deviation of 1.82 years.

that hedging only the risky part of vessel values reduces the hedge exposures. Furthermore, the cross hedge method does not consider prevailing market prices. In contrast, within the structural model, lower levels of freight rates result in smaller hedge positions. This also results in much smaller deviations of the hedge profit within the structural model. However, the longer hedging periods also generate much higher hedge losses compared to the one-year scenario analyzed before. The main reason lies in the pattern that FFA prices show during the observation period. While the rise of freight rates lasts about three years, the drop in 2009 is very sudden and short. Thus, most hedges accumulated big losses rather that they could benefit from the almost singular but huge profit because of decreasing freight rates. We conclude that freight rates include a large risk premium that the operator of a vessel usually earns but which is given away by the hedge. This leads to very high hedging costs as almost any upside potential is taken away. Therefore, the costs of hedging increase with the length of the hedging period. At least in the structural model we see no clear evidence that using different models in each subperiod leads to a better hedging performance than using one and the same model. In contrast, the effectiveness of the cross hedge becomes even worse when switching to a less general model setup.

2.5.3 Robustness analysis

So far, the results reveal the possibility of reducing ship price risk using freight derivatives. It is confirmed that a structural model approach outperforms a time series based cross hedge and at the same time requires a smaller hedge exposure. In this section we carry out several robustness checks whereas the sample as well as the time periods are varied. The results are compared to those in Section 2.5.1, where we carried out the hedge over a horizon of one year.

2.5.3.1 Model performance in alternative sample periods

In our analysis we applied the estimated models in the context of hedging in their respective (sub-)period. This robustness check extends this analysis not by altering the models but the sample periods they are applied to. The first case to be considered is an isolated look on the performance of the 'whole-sample-models' (I^*+II^*) in each of the two subperiods I^* and II^*. The results in Table 2.9 reveal no substantial changes in the results. We see smaller hedge positions within the cross hedge approach than in the initial setup which reduces the hedge loss when freight rates are rising and vice versa. The structural model 'loses' its good fit of regression especially in period II^* which slightly weakens the performance. In the second case, we analyze the cumulative performance of the two subperiod models over the whole period. In particular, we use the respective model in each period, but view the aggregated hedge results. The results given in Table 2.10 show a better performance of using one and the same model over the whole model period especially for the cross hedge approach. One reason might be that the bigger sample size leads to more robust coefficient estimates. However, both models still achieve reasonable risk reductions with the structural model being more effective.

TABLE 2.9: Performance of the whole-sample setup in subperiods

Model		(I^*+II^*)		(I^*+II^*)	
Hedged sales		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations		169		140	
		CH	SM	CH	SM
% reduction of ...	Variance	57.34	68.04	74.63	74.11
	SD	34.68	43.47	49.63	49.11

CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-12}$, is estimated by the respective model. The complete results are given in Table 2.17 in Appendix C.1.

TABLE 2.10: Joint performance of subperiod models over whole sample

Model		(I*+II*)		I*, II*	
Hedged sales		06/15/2006 - 02/13/2009, 02/15/2010 - 12/28/2012		06/15/2006 - 02/13/2009, 02/15/2010 - 12/28/2012	
Observations		309		309	
		CH	SM	CH	SM
% reduction of ...	Variance	59.82	76.17	51.45	72.72
	SD	36.61	51.18	30.32	47.77

CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimated by the respective model. Sales between 02/14/2009 and 02/14/2010 are excluded in both analyses. The complete results are given in Table 2.18 in Appendix C.1.

2.5.3.2 Same estimation period for both models

The structural model is estimated based on sales from 01/21/2005 to 12/28/2012. In contrast, the 4TC+3Cal FFA series, which is applied the cross hedge approach, only starts in 06/17/2005, such that the first 52-week log-difference is obtained on 06/16/2006. For this reason, we correct for the different estimation horizons by re-estimating the structural model with the first sale on 06/15/2006 which still leaves 387 sales (instead of 486 sales over the whole period). The estimated model parameters are given in Table 2.19 in Appendix C.2 and reveal no substantial changes with respect to signs or magnitude compared to the coefficients estimated before (see Table 2.5). Only the constant term is slightly smaller, such that the explanatory power of the determinants is increased. The second period (II*) is not effected by the smaller sample size at all. Accordingly, the hedge results given in Table 2.11 are almost the same as before (see Table 2.7). We conclude that the superior results of the structural model are not caused by the longer estimation horizon.

TABLE 2.11: Shorter estimation horizon for structural model: hedging results over a one-year horizon

Model		I*+II*		I*		II*	
Hedged sales		06/15/2006 - 12/28/2012		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations[1)]		387		169		140	
		CH	SM	CH	SM	CH	SM
% reduction of ...	Variance	79.47	82.21	49.31	67.76	75.04	83.37
	SD	54.69	57.82	28.80	43.22	50.04	59.22

[1)] Due to the 52-week delay, the observations in the subperiods I* and II* do not sum up to the total sample observations. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimtated by the respective model. The parameter estimates and complete hedging results are given in Table 2.19 and 2.20 in Appendix C.2.

2.5.3.3 Excluding multiple transacted vessels

In Section 2.5.2 we analyze the hedging of second-hand vessel prices with actual pairs of purchases and sales and find that there is on average a gain in the vessel value. This is not the case when analyzing value changes over a one-year horizon (see Section 2.5.1). One reason could be a strategic buying and selling behavior. Especially when the holding period of a vessel is short, speculative motives are very likely. Therefore, we check if our results hold, when excluding vessels with more than one resale from our sample[17]. The coefficient estimates of the structural model given in Table 2.21 in Appendix C.3 do not indicate significant differences. Accordingly, the hedge results given in Table 2.12 merely change.

TABLE 2.12: Sample without resales: hedging results over a one-year horizon

Model		I^*+II^*		I^*		II^*	
Hedged sales		06/15/2006 - 12/28/2012		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations[1)]		288		110		112	
		CH	SM	CH	SM	CH	SM
% reduction of ...	Variance	80.53	82.31	54.45	67.47	75.29	83.97
	SD	55.87	57.94	32.51	42.97	50.29	59.96

[1)] Due to the 52-week delay, the observations in the subperiods I^* and II^* do not sum up to the total sample observations. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimated by the respective model. The parameter estimates and complete hedging results are given in Table 2.21 and 2.22 in Appendix C.3.

2.5.3.4 Excluding vessels younger than 5 and older than 20 years

The last robustness check takes into account the way we implement the cross hedge approach of Alizadeh and Nomikos (2012). Because of the different ages of the vessels in our sample, we estimate hedge ratios and second-hand values through a linear interpolation between several quoted price series. For this purpose we also employ newbuilding prices and scrap values for 0- and 30-year-old vessels, respectively. As explained before, the two series are no second-hand prices (see Section 2.3.2). We review our study and consider only vessels between the age of 5 and 20 years. Thus, we drop the (more or less) most and least expensive vessels in the sample. Re-estimating the coefficients of the structural model (see Table 2.23 in Appendix C.4) does not uncover important changes, and also the results given in Table 2.13 do not change considerably compared to the initial setup. Though, in the cross hedge model the higher average hedge ratios for vessels between the age of 5 and 20 years (see Table 2.6) lead to increased hedge positions and thus to higher average hedge losses.

[17] There might still remain some speculative sales in the sample which cannot be identified properly.

However, the overall risk reduction in terms of the variance remains on a similar level as in the initial setup at about 80%.

TABLE 2.13: Only vessels between age of 5 and 20 years: hedging results over a one-year horizon

Model		I^*+II^*		I^*		II^*	
Hedged sales		06/15/2006 - 12/28/2012		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations[1)]		244		112		76	
		CH	SM	CH	SM	CH	SM
% reduction of ...	Variance	80.25	80.89	45.06	54.95	81.10	85.94
	SD	55.56	56.28	25.88	32.88	56.53	62.50

[1)] Due to the 52-week delay, the observations in the subperiods I^* and II^* do not sum up to the total sample observations. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimated by the respective model. The parameter estimates and complete hedging results are given in Table 2.23 and 2.24 in Appendix C.4.

2.6 Conclusion

This paper provides the first empirical study of the hedging performance of FFAs for second-hand vessel values in the dry bulk Panamax class. The financial market turmoil of the recent years caused a crisis of the shipping economy that lasts until today. The surplus of vessels and their carrying capacity not only leads to lower freight rates, but especially to historically low vessel prices. For shipowners and other parties involved in ship financing it is therefore important to have strategies for hedging against falling vessel prices. The problem is that there is no liquidly traded instrument available to directly hedge ship values. As a second-best solution Alizadeh and Nomikos (2012) suggest a classical cross hedge model using forward freight futures which show a high correlation to vessel values. We implement and adjust such a strategy to check if the theoretical high hedge efficiency is still achieved when using real transaction data. Based on cross sectional sales data, we estimate a structural model comprising the vessel's age as well as freight market information. The model allows to identify the share of the vessel value that is exposed to freight rate risk. As a reference, we also apply the conventional time series based cross hedge as proposed by Alizadeh and Nomikos (2012).

The results show a remarkable risk reduction with either approach, the structural model as well as the cross hedge model. We find a variance reduction of vessel price changes of more than 80% over a one-year hedging horizon. However, the subdivision of the vessel value into a risky and deterministic part leads to a much smaller average hedge position when using the structural model, such that the costs of hedging are reduced. Over a longer hedging period, from resale to resale, risk reduction is lower with about 70% in the structural model, but only 43% with the conventional cross hedge. Overall, the structural model outperforms the cross hedge model in every scenario and subsample considered. The reduction of variance is up to 40 percentage points higher while the required hedge position is up to 40% smaller. In order to qualify these positive results, we must be aware that models and hedges are estimated and carried out in-sample which tends to yield better performances than one might experience in an actual hedge scenario.

Additionally, we perform a comprehensive robustness analysis which especially takes into account possible disadvantages of the implementation of the cross hedge approach by Alizadeh and Nomikos (2012). The analysis confirms the findings without exception. Neither varying the estimation periods nor restructuring the sample of sales has substantial effects on the performance or the ranking of the two models.

However, given an average vessel resale value of 29 million USD, it requires an average hedge exposure within the structural model of more than 20 million USD which corresponds to more than 1000 days in the 4TC+2Cal FFA contract. Thus, a potential hedger could not only be deterred by the high hedging volumes, but also the liquidity of the FFA market is most likely insufficient. Furthermore, the high costs of hedging reveal the large risk premium included in freight rates which is given away when setting up hedges. It is therefore advisable to think about less expensive hedging possibilities. For the owner of a vessel, a high variance of vessel prices caused by an increased demand is beneficial. So it might be enough to hedge the downside risk and maintain the upside potential. This could be achieved by the use of (out-of-the-money) freight options which also cost a much lower premium. The existence of a high premium in ship values may also explain why there is no trading activity in FOSVAs. When selling such a contract, the owner of a vessel would also lose the large compensation for holding the asset.

In a practical application, the presented approach might be considered by using smaller hedge positions than those suggested by the models. The result would be a partial risk reduction while the possibility to benefit from rising shipping markets remains. Further research could be helpful to develop more detailed models that contain more variables, both vessel-specific like speed, equipment or place of construction, as well as market factors like cost of capital or commodity prices.

Appendices

A Model selection

We test several model setups incorporating vessel individual factors age and cargo carrying capacity (measured in dwt) as well as forward freight rates as a proxy of the state of the freight market and expectations of market participants. The parameter estimates for three of the regarded setups are given in Table 2.14. Unexpectedly, in setup (1) the coefficient of the vessel's capacity β_{DWT} shows a significant negative sign which is against the economic intuition that larger vessels should be more expensive than smaller ones (see Kavussanos and Visvikis, 2006). A possible explanation is that the average size of sold vessels increases in the course of the sample period while vessel prices overall decline as result of the shipping crisis. For reasons of generality, we therefore do not take the vessel's capacity into account. Furthermore, the significant estimate of β_{f^2} in setup (3) indicates a slight non-linearity in freight rates. However, with respect to a practical application for hedging, we keep things simple and neglect higher order terms of freight rates. Therefore, setup (2) is the rational choice for our analysis.

TABLE 2.14: Regression results for different structural model setups

(1) $V^i_{t_i} = \beta_0 + \beta_{\text{Age}} \cdot \text{Age}^i_{t_i} + \beta_{\text{DWT}} \cdot \text{DWT}^i + \beta_f \cdot f_{t_i} + \beta_{f\cdot\text{Age}} \cdot \left(f_{t_i} \cdot \text{Age}^i_{t_i}\right) + \varepsilon^i$

(2) $V^i_{t_i} = \beta_0 + \beta_{\text{Age}} \cdot \text{Age}^i_{t_i} + \beta_f \cdot f_{t_i} + \beta_{f\cdot\text{Age}} \cdot \left(f_{t_i} \cdot \text{Age}^i_{t_i}\right) + \varepsilon^i$

(3) $V^i_{t_i} = \beta_0 + \beta_{\text{Age}} \cdot \text{Age}^i_{t_i} + \beta_f \cdot f_{t_i} + \beta_{f^2} \cdot f^2_{t_i} + \beta_{f\cdot\text{Age}} \cdot \left(f_{t_i} \cdot \text{Age}^i_{t_i}\right) + \varepsilon^i$

Setup	(1)		(2)		(3)	
β_0	34.885^{***}	(4.754)	11.095^{***}	(1.399)	-2.316	(1.897)
β_{Age}	-0.655^{***}	(0.099)	-0.488^{***}	(0.096)	-0.512^{***}	(0.088)
β_{DWT}	-0.302^{***}	(0.058)				
β_f	5.422^{***}	(0.189)	5.461^{***}	(0.194)	8.836^{***}	(0.394)
β_{f^2}					-0.175^{***}	(0.018)
$\beta_{f\cdot\text{Age}}$	-0.151^{***}	(0.013)	-0.158^{***}	(0.014)	-0.149^{***}	(0.013)
S.E. of Reg.	6.069		6.232		5.715	
Adj. R^2	0.882		0.875		0.895	
BIC	6.498		6.540		6.377	

Linear regression coefficients for different model setups. Vessel prices (dependent variable) and annual freight forward rates (f_{t_i}) are expressed in USD m., age is in years and DWT is the capacity in 1000 dwt. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Standard errors in parentheses.

B Cross hedge model pre-estimates

TABLE 2.15: Cross hedge model: coefficients for Panamax vessels of different ages

$\Delta^{52} p_t^{\text{Age}} = \alpha + \beta^{\text{Age}} \Delta^{52} f_t + \eta_t$, Age $\in$ {0,5,10,15,20,30}								
	I + II + III		I		II		III	
Period	06/16/2006 - 12/28/2012		06/16/2006 - 04/13/2007		04/14/2007 - 02/13/2009		02/14/2009 - 12/28/2012	
Observations	342		44		96		202	
	β^{Age}	R^2	β^{Age}	R^2	β^{Age}	R^2	β^{Age}	R^2
0 years (new)	0.363	0.676	0.525	0.881	0.256	0.779	0.342	0.398
5 years	0.963	0.880	1.305	0.924	1.026	0.899	1.202	0.884
10 years	1.074	0.880	1.249	0.946	1.119	0.911	1.420	0.894
15 years	1.187	0.862	1.388	0.904	1.286	0.898	1.535	0.874
20 years	1.282	0.806	1.578	0.912	1.390	0.891	1.662	0.752
30 years (scrap)	0.570	0.503	0.138	0.094	0.578	0.774	1.213	0.716

The level series include 394 weeks (17/06/2005 to 28/12/2012) which leaves 342 observations of 52-week log-differences for the whole sample. The age of scrapped vessels is assumed to be 30 years.

TABLE 2.16: Chow's breakpoint test for regressions of second-hand price series on +2Cal FFA

$\Delta^{52} p^{\text{Age}_t} = \alpha + \beta^{\text{Age}}_{\{\cdot\}} \Delta^{52} f_t + \eta_t$, Age $\in$ {0,5,10,15,20,30} , $\{\cdot\} \in$ {I, II, III, (I + II)}			
H_0:	$\beta^{\text{Age}}_{\text{I}} = \beta^{\text{Age}}_{\text{II}}$	$\beta^{\text{Age}}_{\text{II}} = \beta^{\text{Age}}_{\text{III}}$	$\beta^{\text{Age}}_{(\text{I+II})} = \beta^{\text{Age}}_{\text{III}}$
0 years (new)	40.582	47.588	36.398
5 years	2.357	43.765	60.590
10 years	1.642	61.623	85.023
15 years	4.563	47.298	72.064
20 years	12.839	23.637	41.827
30 years (scrap)	7.767	123.831	140.393
95% critical value	3.063	3.026	3.022

F-statistics for Chow's breakpoint test according to regression results of the cross hedge approach given in Table 2.15.

Only for the 5- and 10-year-old second-hand price series the null hypothesis of non-different coefficients in the first two periods cannot be rejected. The difference of parameters for 15-year-old vessels is not significant at the 1% level. As the average age at the time of sale in the first two periods is 11.54 years and in accordance to the structural model, we decide to treat the first two subperiods as one (I*). Compared to the three-subperiods setup, the parameters of period I* are very similar as in the two individual periods I and II. We therefore expect no significant influences on the hedging results.

C Robustness results

C.1 Model performance in alternative sample periods

TABLE 2.17: Performance of the whole-sample setup in subperiods (detailed)

Model		I*+II*		I*+II*	
Hedged sales		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations		169		140	
		CH	SM	CH	SM
Hedge position	Mean	28.73	20.04	19.59	17.88
Hedge profit	Mean	-19.86	-14.64	1.80	1.49
	Variance	376.42	213.38	25.39	20.77
	SD	19.40	14.61	5.04	4.56
Change in values		$Y^i := \left(V^i_{t_i} - \widehat{V}^i_{t_i-52}(\text{Age}^i_{t_i})\right) + h^i_{t_i-52}\left(f_{t_i}(\tau_i) - f_{t_i-52}(\tau_i)\right)$			
Unhedged ($h = 0$)	Mean	11.39	10.69	-2.12	-4.95
	Variance	351.40	317.08	46.04	42.00
	SD	18.75	17.81	6.79	6.48
Hedged	Mean	-8.48	-3.95	-0.32	-3.47
	Variance	149.91	101.34	11.68	10.88
	SD	12.24	10.07	3.42	3.30
% reduction of ...	Variance	57.34	68.04	74.63	74.11
	SD	34.68	43.47	49.63	49.11

Hedge positions and profits are in USD m., CH denotes the cross hedge model, SM the structural model, and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-12}$, is estimated by the respective model.

TABLE 2.18: Joint performance of subperiod-models over whole sample (detailed)

Model		I*+II*		I*, II*	
Hedged sales		06/15/2006 - 02/13/2009, 02/15/2010 - 12/28/2012		06/15/2006 - 02/13/2009, 02/15/2010 - 12/28/2012	
Observations		309		309	
		CH	SM	CH	SM
Hedge position	Mean	24.59	19.06	27.85	20.71
Hedge profit	Mean	-10.05	-7.34	-10.29	-6.23
	Variance	333.50	190.44	381.81	164.52
	SD	18.26	13.80	19.54	12.83
Change in values		$Y^i := \left(V^i_{t_i} - \widehat{V}^i_{t_i-52}(\text{Age}^i_{t_i})\right) + h^i_{t_i-52}\left(f_{t_i}(\tau_i) - f_{t_i-52}(\tau_i)\right)$			
Unhedged ($h = 0$)	Mean	5.27	3.60	5.27	3.11
	Variance	257.81	252.76	257.81	212.77
	SD	16.06	15.90	16.06	14.59
Hedged	Mean	-4.78	-3.73	-5.02	-3.12
	Variance	103.60	60.24	125.17	58.04
	SD	10.18	7.76	11.19	7.62
% reduction of ...	Variance	59.82	76.17	51.45	72.72
	SD	36.61	51.18	30.32	47.77

Hedge positions and profits are in USD m., CH denotes the cross hedge model, SM the structural model, and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimated by the respective model. Sales between 02/14/2009 and 02/14/2010 are excluded in both analyses.

C.2 Shorter estimation horizon for the structural model

Table 2.19: Shorter estimation horizon for structural model: descriptive statistics and structural model parameters

Period	I* + II* 06/15/2006 - 12/28/2012	I* 06/15/2006 - 02/13/2009	II* 02/14/2009 - 12/28/2012
Observations	387	169	218
Mean $V_{t_i}^i$	29.04	40.56	20.11
Mean $\text{Age}_{t_i}^i$	12.81	12.07	13.39
Mean f_{t_i}	7.17	9.72	5.19
β_0	7.658***	16.829***	-0.629
	[4.694]	[4.099]	[-0.316]
β_{Age}	-0.340***	-0.598**	-0.203*
	[-3.120]	[-2.139]	[-1.663]
β_f	5.703***	4.936***	6.982***
	[26.814]	[11.984	[18.811]
$\beta_{f\cdot\text{Age}}$	-0.168***	-0.146***	-0.184***
	[-11.357]	[-5.121]	[-8.140]
S.E. of Reg.	6.553	9.052	2.691
Adj. R^2	0.879	0.806	0.940

Linear regression coefficients for different sample periods. Vessel prices and freight forward rates (scaled to one year) are expressed in USD m., and age in years. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are t-statistics.

Table 2.20: Shorter estimation horizon for structural model: hedging results over a one-year horizon (detailed)

Model		I*+II*		I*		II*	
Hedged sales		06/15/2006 - 12/28/2012		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations[1)]		387		169		140	
		CH	SM	CH	SM	CH	SM
Hedge position	Mean	29.00	22.04	30.06	17.88	25.18	24.14
Hedge profit	Mean	-4.24	-3.70	-20.75	-13.08	2.34	2.01
	Variance	474.28	252.78	422.44	171.72	41.77	36.46
	SD	21.78	15.90	20.55	13.10	6.46	6.04
Change in values		$Y^i := \left(V_{t_i}^i - \widehat{V}_{t_i-52}^i(\text{Age}_{t_i}^i)\right) + h_{t_i-52}^i\left(f_{t_i}(\tau_i) - f_{t_i-52}(\tau_i)\right)$					
Unhedged ($h=0$)	Mean	-0.52	-0.88	11.39	8.75	-2.12	-3.39
	Variance	450.96	408.70	351.40	297.22	46.04	40.40
	SD	21.24	20.22	18.75	17.24	6.79	6.36
Hedged	Mean	-4.77	-4.58	-9.37	-4.32	0.22	-1.38
	Variance	92.57	72.71	178.12	95.84	11.49	6.72
	SD	9.62	8.83	13.35	9.79	3.39	2.59
% reduction of ...	Variance	79.47	82.21	49.31	67.76	75.04	83.37
	SD	54.69	57.82	28.80	43.22	50.04	59.22

Hedge positions and profits are in USD m. [1)] Due to the 52-week delay, the observations in the subperiods I* and II* do not sum up to the total sample observations. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}_{t_i-52}^i$, is estimated by the respective model.

C.3 Excluding multiple transacted vessels

TABLE 2.21: Sample without resales: descriptive statistics and structural model parameters

Period	I* + II* 01/21/2005 - 12/28/2012	I* 01/21/2005 - 02/13/2009	II* 02/14/2009 - 12/28/2012
Observations	356	178	178
Mean $V^i_{t_i}$	28.65	36.21	21.09
Mean $\text{Age}^i_{t_i}$	11.92	11.38	12.47
Mean f_{t_i}	6.53	7.88	5.18
β_0	10.671***	20.643***	-0.627
	[6.398]	[7.069]	[-0.298]
β_{Age}	-0.500***	-0.883***	-0.206
	[-4.087]	[-4.122]	[-1.508]
β_f	5.445***	4.559***	7.006***
	[22.714]	[12.916]	[17.860]
$\beta_{f\cdot\text{Age}}$	-0.152***	-0.117***	-0.186***
	[-8.304]	[-4.350]	[-7.354]
S.E. of Reg.	6.195	7.595	2.742
Adj. R^2	0.874	0.845	0.939

Linear regression coefficients for different sample periods. Vessel prices and freight forward rates (scaled to one year) are expressed in USD m., and age in years. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are t-statistics.

TABLE 2.22: Sample without resales: hedging results over a one-year horizon (detailed)

Model		I*+II*		I*		II*	
Hedged sales		06/15/2006 - 12/28/2012		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations[1)]		288		110		112	
		CH	SM	CH	SM	CH	SM
Hedge position	Mean	29.56	22.61	30.83	18.11	25.89	25.47
Hedge profit	Mean	-2.04	-1.98	-19.13	-12.03	2.68	2.32
	Variance	470.73	232.69	506.44	170.92	43.68	39.43
	SD	21.70	15.25	22.50	13.07	6.61	6.28
Change in values		$Y^i := \left(V^i_{t_i} - \widehat{V}^i_{t_i-52}(\text{Age}^i_{t_i})\right) + h^i_{t_i-52}\left(f_{t_i}(\tau_i) - f_{t_i-52}(\tau_i)\right)$					
Unhedged ($h = 0$)	Mean	-2.48	-3.57	9.50	7.22	-2.41	-3.81
	Variance	443.88	390.92	379.46	290.03	48.28	43.39
	SD	21.07	19.77	19.48	17.03	6.95	6.59
Hedged	Mean	-4.52	-5.54	- 9.63	-4.81	0.27	-1.49
	Variance	86.43	69.16	172.84	94.34	11.93	6.95
	SD	9.30	8.32	13.15	9.71	3.45	2.64
% reduction of ...	Variance	80.53	82.31	54.45	67.47	75.29	83.97
	SD	55.87	57.94	32.51	42.97	50.29	59.96

Hedge positions and profits are in USD m. [1)] Due to the 52-week delay, the observations in the subperiods I* and II* do not sum up to the total sample observations. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimated by the respective model.

C.4 Excluding sales of vessels under 5 and over 20 years

Table 2.23: Only vessels between age of 5 and 20 years: descriptive statistics and structural model parameters

Period	I* + II* 01/21/2005 - 12/28/2012	I* 01/21/2005 - 02/13/2009	II* 02/15/2010 - 12/28/2012
Observations	310	178	132
Mean $V^i_{t_i}$	29.65	36.38	20.58
Mean $\text{Age}^i_{t_i}$	12.27	11.97	12.67
Mean f_{t_i}	6.96	8.27	5.19
β_0	12.121***	16.953***	-3.054
	[4.309]	[3.958]	[-0.835]
β_{Age}	-0.573***	-0.554*	-0.074
	[-2.752]	[-1.703]	[-0.290]
β_f	5.792***	5.324***	8.036***
	[15.622]	[10.797]	[11.593]
$\beta_{f\cdot\text{Age}}$	-0.184***	-0.179***	-0.262***
	[-6.789]	[-4.922]	[-5.374]
S.E. of Reg.	6.568	7.777	2.468
Adj. R^2	0.819	0.767	0.907

Linear regression coefficients for different sample periods. Vessel prices and freight forward rates (scaled to one year) are expressed in USD m., and age in years. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are t-statistics.

Table 2.24: Only vessels between age of 5 and 20 years: hedging results over a one-year horizon

Model		I*+II*		I*		II*	
Hedged sales		06/15/2006 - 12/28/2012		06/15/2006 - 02/13/2009		02/15/2010 - 12/28/2012	
Observations[1)]		244		112		76	
		CH	SM	CH	SM	CH	SM
Hedge position	Mean	34.83	21.85	34.07	17.33	31.32	24.49
Hedge profit	Mean	-5.83	-4.20	-26.07	-14.12	2.65	1.90
	Variance	636.19	241.43	414.08	127.61	58.32	37.20
	SD	25.22	15.54	20.35	11.30	7.64	6.10
Change in values	$Y^i := \left(V^i_{t_i} - \widehat{V}^i_{t_i-52}(\text{Age}^i_{t_i})\right) + h^i_{t_i-52}\left(f_{t_i}(\tau_i) - f_{t_i-52}(\tau_i)\right)$						
Unhedged ($h = 0$)	Mean	-1.18	-1.56	12.66	10.07	-2.65	-3.35
	Variance	529.31	413.18	282.61	205.35	53.56	42.01
	SD	25.22	20.33	16.81	14.33	7.64	6.48
Hedged	Mean	-6.67	-5.76	-13.44	-4.05	0.00	-1.44
	Variance	104.53	78.97	155.27	92.51	10.12	5.91
	SD	10.22	8.89	12.46	9.62	3.18	2.43
% reduction of ...	Variance	80.25	80.89	45.06	54.95	81.10	85.94
	SD	55.56	56.28	25.88	32.88	56.53	62.50

Hedge positions and profits are in USD m. [1)] Due to the 52-week delay, the observations in the subperiods I* and II* do not sum up to the total sample observations. CH denotes the cross hedge model, SM the structural model and SD the standard deviation. The unhedged changes of vessel values differ in both models as the value at inception of the hedge, $\widehat{V}^i_{t_i-52}$, is estimated by the respective model.

References

ADLAND, R., JIA, H., AND KOEKEBAKKER, S. (2004), 'The pricing of forward ship value agreements and the unbiasedness of implied forward prices in the second-handand market for ships', *Maritime Economics & Logistics* 6(2), 109–121.

ADLAND, R. AND KOEKEBAKKER, S. (2004), 'Market efficiency in the second-hand market for bulk-ships', *Maritime Economics & Logistics* 6(1), 1–15.

ADLAND, R. AND KOEKEBAKKER, S. (2007), 'Ship valuation using cross-sectional sales data: a multivariate non-parametric approach', *Maritime Economics and Logistics* 9(2), 105–118.

ALIZADEH, A. H. AND NOMIKOS, N. K. (2009), *Shipping derivatives and risk management*, Palgrave Macmillan, Basingstoke.

ALIZADEH, A. H. AND NOMIKOS, N. K. (2012), 'Ship finance: hedging ship price risk using freight derivatives', in W. K. TALLEY, ed., 'The Blackwell Companion To Maritime Economics', Chapter 22, Wiley-Blackwell, West Sussex, 1st Edition.

ALIZADEH-MASOODIAN, A. H. (2001), *An econometric analysis of the dry bulk shipping industry; seasonality, market efficiency and risk premia*, Ph.D. thesis, City University London.

ANDREOU, E. AND GHYSELS, E. (2002), 'Detecting multiple breaks in financial market volatility dynamics', *Journal of Applied Econometrics* 17(5), 579–600.

BEENSTOCK, M. (1985), 'A theory of ship prices', *Maritime Policy and Management* 12(3), 215–225.

BEENSTOCK, M. AND VERGOTTIS, A. (1989), 'An econometric model of the world market for dry cargo freight and shipping', *Applied Economics* 21(3), 339–356.

CHOW, G. C. (1960), 'Tests of equality between sets of coefficients in two linear regressions', *Econometrica* 28(3), 591–605.

CLARKSON RESEARCH SERVICES (2013), 'Dry bulk trade outlook February 2013', London.

DROBETZ, W., GOUNOPOULOS, D., MERIKAS, A., AND SCHRÖDER, H. (2013), 'Capital structure decisions of globally-listed shipping companies', *Transportation Research Part E: Logistics and Transportation Review* 52, 49–76, Special Issue I: Maritime Financial Management.

EDERINGTON, L. H. (1979), 'The hedging performance of the new futures markets', *The Journal of Finance* 34(1), 157–170.

FAMA, E. F. (1970), ‘Efficient capital markets: a review of theory and empirical work’, *The Journal of Finance* 25(2), 383–417.

GLEN, D. R. (1997), ‘The market for second-hand ships: further results on efficiency using cointegration analysis’, *Maritime Policy & Management* 24(3), 245–260.

HALE, C. AND VANAGS, A. (1992), ‘The market for second-hand ships: some results on efficiency using cointegration’, *Maritime Policy & Management* 19(1), 31–39.

JALLAL, C. (2013), ‘The evolution of ship value assessment’, *The Baltic* Summer 2013, 48–49.

KAVUSSANOS, M. G. (1997), ‘The dynamics of time-varying volatilities in different size second-hand ship prices of the drycargo sector’, *Applied Economics* 29(4), 433–443.

KAVUSSANOS, M. G. AND ALIZADEH, A. H. (2002), ‘Efficient pricing of ships in the dry bulk sector of the shipping industry’, *Maritime Policy & Management* 29(3), 303–330.

KAVUSSANOS, M. G. AND VISVIKIS, I. D. (2006), ‘Shipping freight derivatives: a survey of recent evidence’, *Maritime Policy & Management* 33(3), 233–255.

KAVUSSANOS, M. G., VISVIKIS, I. D., AND GOULIELMOU, M. A. (2007), ‘An investigation of the use of risk management and shipping derivatives: the case of Greece’, *Maritime Policy & Management* 34(1), 49–68.

MÜSSGENS, C. (2012), ‘Schiffsfonds droht eine Insolvenzwelle’, *Frankfurter Allgemeine Zeitung* 277, 19, 27.11.2012.

PRUYN, J. F. J., VAN DE VOORDE, E., AND MEERSMAN, H. (2011), ‘Second hand vessel value estimation in maritime economics: a review of the past 20 years and the proposal of an elementary method’, *Maritime Economics & Logistics* 13(2), 213–236.

SODAL, S., KOEKEBAKKER, S., AND ADLAND, R. (2009), ‘Value based trading of real assets in shipping under stochastic freight rates’, *Applied Economics* 41(22), 2793–2807.

STOPFORD, M. (2009), *Maritime economics*, Taylor & Francis Ltd., New York, NY, 3rd Edition.

STRANDENES, S. (1984), ‘Price determination in the time charter and second hand markets’, *Center for Applied Research, Norwegian School of Economics and Business Administration, working paper MU* 6.

SYRIOPOULOS, T. AND ROUMPIS, E. (2006), ‘Price and volume dynamics in second-hand dry bulk and tanker shipping markets’, *Maritime Policy & Management* 33(5), 497–518.

TSOLAKIS, S., CRIDLAND, C., AND HARALAMBIDES, H. (2003), ‘Econometric modelling of second-hand ship prices’, *Maritime Economics & Logistics* 5(4), 347–377.

Chapter 3

Measuring crisis risk using conditional copulas: an empirical analysis of the 2008 shipping crisis

with Sebastian Opitz

Abstract

The shipping crisis starting in 2008 was characterized by sharply decreasing freight rates and sharply increasing financing costs. We analyze the dependence structure of these two risk factors employing a conditional copula model. As conditioning factors we use the supply and demand of seaborne transportation. We find that crisis risk strongly increased already about one year before the actual crisis outburst, and that the shipping crisis was predominantly driven by an oversupply of transport capacity. Therefore, market participants could have prevented or alleviated the crisis' consequences by reducing the ordering and financing of new vessels.

Acknowledgements

We thank the participants of the Spring 2015 Conference of the Multinational Finance Society for helpful comments.

A revised version of this paper will be published in *Journal of Applied Econometrics* and is available via http://onlinelibrary.wiley.com/wol1/doi/10.1002/jae.2609/full.

3.1 Introduction

Shipping companies and banks involved in ship finance still suffer from the crisis that started in 2008. The vast number of new vessels that have been ordered during the industry's boom led to a massive surplus of transportation capacity and caused a sharp decline in freight rates and vessel values. Hundreds of shipping funds have already collapsed as they are unable to pay back interest or principal to their lenders (see Goff et al., 2014). As a consequence, ship financing banks are also deeply involved in the crisis and face immense impairment losses. European banks are especially hit as they cover about 80% of world shipping loans (see Stoltenberg, 2014). A main reason for the irrational ordering of new vessels is the delayed feedback of investment decisions because of time to build which let shipping firms neglect the investments of their competitors (see Greenwood and Hanson, 2015). Therefore, we investigate whether the shipping crisis was predominantly caused by the collapse of the financial system, and thus exogenously, or at least partially by the shipping industry itself. In the latter case it could have been prevented or at least alleviated.

The major risk factors for a shipping company's balance sheet are the value of its vessels on the asset side and its financing costs on the liability side. While the financing costs can be approximated by bond yields of an appropriate rating class, specific vessel values are less easy to observe[1]. Instead, one may look on freight rates which not only show a strong correlation to vessel values, but also a higher liquidity and transparency. We consider freight rates as the suitable instrument to capture price risks in the shipping market.

We speak of a 'crisis in shipping' when we simultaneously observe extreme asymmetric adverse movements of both balance sheet risk factors, a sharp decline of freight rates and a strong increase of financing costs. The dependence of these two factors is modeled by the main drivers of supply and demand of shipping services. Following Stopford (2009), these are the world fleet and the world economy, respectively. For the aim of our study, it is important to note that only the supply of transportation services can be controlled by market players like shipping companies through ordering new vessels or scrapping old ones. Moreover, shipping investors can decide whether to lend money for new vessels or not and at which rate. These measures could have prevented the shipping crisis.

In this paper we follow the approach of Patton (2006) and estimate the conditional asymmetric dependence of freight rates and financing costs using a conditional copula model. We capture the crisis vulnerability by interpreting the copula's tail dependence as shipping crisis risk. As conditioning factors we use the drivers of supply and demand of shipping services, the orderbook-to-fleet ratio and the world stock market index, respectively. We analyze whether a sharp increase of supply or a sharp decrease of demand leads to a rise of shipping crisis risk (c.p.). Both effects are tested individually as well as simultaneously.

We find highly significant conditional asymmetric dependence when conditioning on both supply and demand factors, a weak significance when using only the supply side factor and no significance when employing only demand shocks. Most important, we obtain strong signals for a shipping crisis already about one year before its actual outburst. The results confirm that the shipping crisis is mainly driven by overcapacity and could have been prevented to some extent.

[1] Clarksons and The Baltic Exchange publish periodic price assessments that refer to certain reference vessels. These assessments are not actual market prices and hence may not be suitable for determining the correct market value of a particular vessel.

The rest of the paper is structured as follows: In the next section we give a concise overview of the shipping crisis that started in 2008 as well as the related literature. Section 3.3 provides the data and illustrates the methodology used in our analysis. Section 3.4 discusses the empirical results and robustness analyses. The paper concludes with a discussion and implications in Section 3.5.

3.2 The shipping crisis starting in 2008

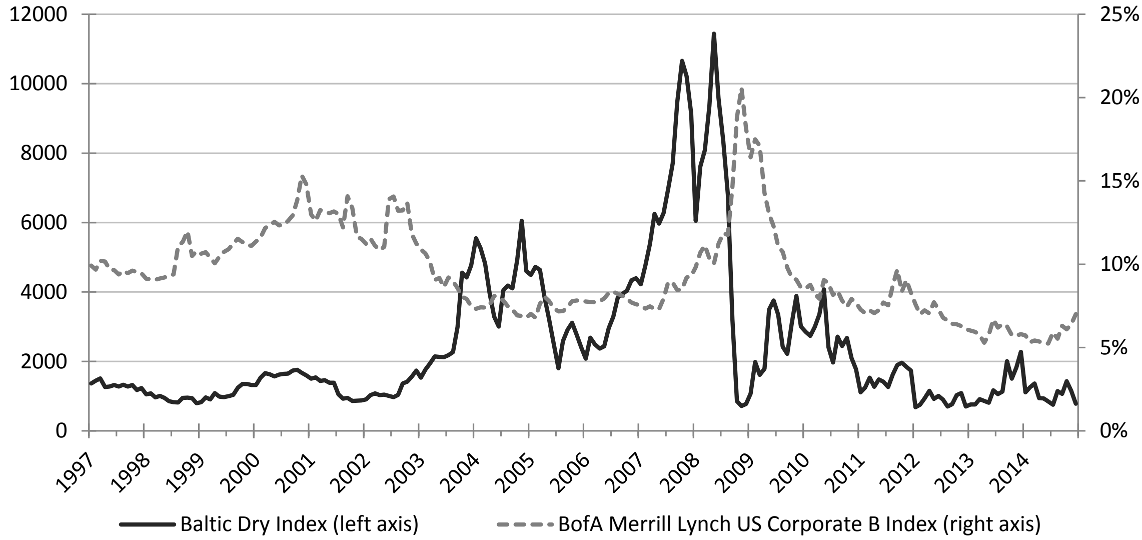


Figure 3.1: Development of freight rates and financing costs

The main driver for global seaborne transportation is the global economy. It determines the demand for commodities and goods and thus the demand for global transportation. This dependence on business cycles causes fluctuations in the demand for shipping services. Usually, a rising demand is accompanied by increasing freight rates which roughly reflect the cost of transportation and can be regarded as the main income for shipowners. The naturally strong relation between global economy and shipping has amongst others been revealed by Grammenos and Arkoulis (2002) or Drobetz et al. (2010) who find global stock market changes as a long-run systematic risk factor for expected shipping stock returns. Furthermore, Kavussanos and Tsouknidis (2014) find that stock market volatility is a main factor of global shipping bond spreads. In particular, the booming industry prior to the recent financial crisis led to an extreme increase of freight rates (see Figure 3.1) as the demand for maritime transportation services exceeded the supply. Though, the reaction of vessel supply is slow due to the time to build delay of typically 18 to 36 months (see Kalouptsidi, 2014). In order to participate in the booming market shipping companies and investors ordered more and more new vessels or bought used ones on the second-hand market which also caused vessel prices to rise sharply. The high ordering activity culminated in an orderbook-to-fleet ratio of almost 80% at the end of 2008 (see Figure 3.2).

Most shipping companies have a quite limited access to the capital market. New vessels are therefore mainly financed through bank loans usually covering about 50-80% of the market value of the vessel (see Stopford, 2009). The remaining equity part was often raised by setting up shipping funds which

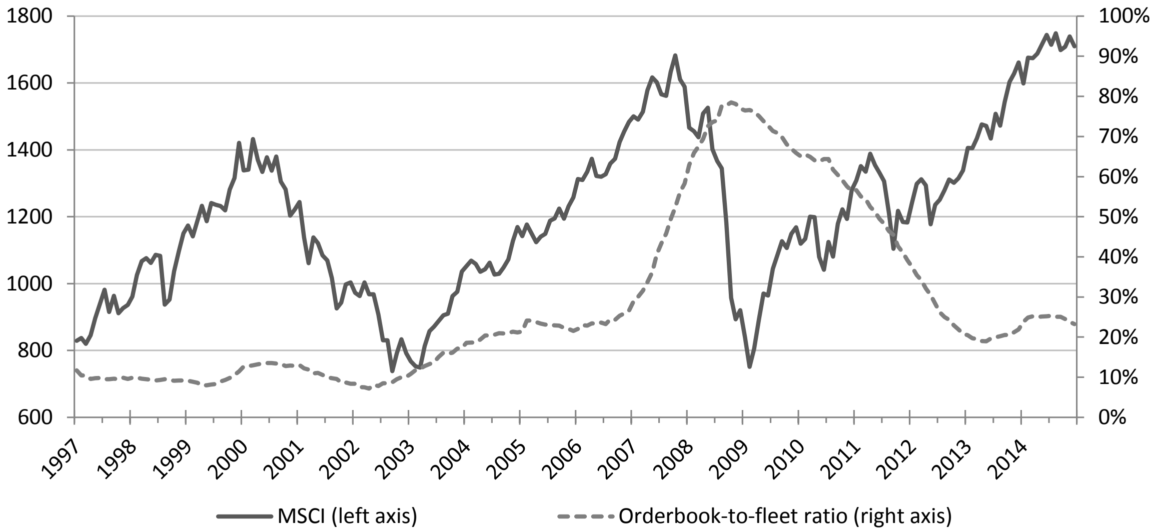


FIGURE 3.2: Development of demand and supply of maritime transportation services

became quite popular especially in Germany because of certain tax benefits. With hindsight, it appears that the easy and comparably cheap financing via shipping funds was one reason for the exorbitant ordering in the boom years as it was possible to buy vessels but bear almost no risk. Because of this financing structure, shipping companies exhibit significantly higher leverage ratios[2] of 69% on average compared to an average leverage ratio of 33% for other industrial firms (excluding financial and utility firms) as pointed out by Drobetz et al. (2013). This comparatively high share of debt makes shipping companies especially susceptible to changes in interest rates, and because of mostly speculative grade ratings, risk premiums are very high. The specific risks of shipping bonds are studied by Grammenos et al. (2008) who observe 50 high-yield shipping bonds issued between 1992 and 2004. Despite of the fact that most bonds in the sample are rated BB or B, 13 of them had defaulted within the observation period which exceeds by far the empirical default probability (see Albertijn et al., 2011). Furthermore, Kavussanos and Tsouknidis (2014) find that the average risk premium of shipping bonds is higher compared to general corporate bonds of the same rating class.

When the world economy was hit by the financial crisis, the demand for shipping services collapsed and the shipping boom found a sudden end with sharply declining freight rates and vessel values. The supply overhang of vessels became even worse as more and more vessels entered the market that had been ordered at peak prices against high lending. Unable to pay back principal or interest many shipping companies had to sell vessels at large discounts or went insolvent. The decreasing vessel values also entailed loan losses for the financing banks as shipping loans are usually collateralized by the respective vessel. Thus, with more and more defaults, banks began to cut back or even discontinue their shipping investments causing a downward spiral in vessel values (see Wright, 2011).

Freight rate volatility might therefore be regarded as the main risk factor in the shipping industry. On the one hand, freight earnings are a shipping company's primary source of income such that freight rate volatility directly affects the profitability. On the other hand, the values of vessels are directly determined by freight rates as the price of a vessel can be regarded as the present value of its future

[2] Defined as the relative share of debt to equity.

operational profits plus the discounted expected scrap value. Beenstock (1985) and Beenstock and Vergottis (1989) introduce the use of freight rates to calculate ship prices within an asset value model and embed this approach in an extensive supply and demand framework incorporating world wealth, fleet size, expected operational earnings, expected future second-hand prices and interest rates. A similar approach is shown by Tsolakis et al. (2003) who develop a structural regression model that describes second-hand prices as a function of time charter rates, newbuilding prices, the orderbook as percentage of the total fleet and the cost of capital. For bulk carriers they find that newbuilding prices, time charter rates and the cost of capital have the biggest effect on second-hand vessel prices. Significantly negative effects of the orderbook-to-fleet ratio are only detected for tankers. Adland and Koekebakker (2007) use actual second-hand sales data to estimate a non-parametric model for ship values of the dry bulk Handysize class and also find the state of freight market to be a significant factor amongst the vessel individual factors age and size. Accordingly, it is plausible to use freight rates for capturing ship price risks in shipping companies' balance sheets.

A further critical aspect in this context is irrational ordering behavior of shipping investors as a consequence of the time to build delay. As Greenwood and Hanson (2015) show in their behavioral model of shipping industry cycles, firms overinvest when the market is in a boom leading to overcapacity and low returns thereafter. Two main reasons are found. First, shipping investors overestimate the persistence of prevailing high freight rates and therefore overvalue their investments. Secondly, firms tend to neglect the investments of their competitors and order too many vessels. Moreover, Kalouptsidi (2014) finds that the presence of time to build has an increasing effect on ship prices while level and volatility of investments decline.

In general, modern financial theory implies the independence of a company's investing and financing decisions. However, the results of the above-mentioned studies suggest that cross-balance sheet interdependencies are most likely in shipping companies. Such interdependencies have been empirically proven for several industries (see Stowe et al., 1980; Jang and Ryu, 2006; Van Auken et al., 1993). They seem to occur especially when assets serve as collateral for their respective loan facilities, when the maturity of loans is matched to the maturities of the assets or when the industry faces special conditions in terms of refinancing possibilities (see Stowe et al., 1980). These conditions apply to shipping companies (see Albertijn et al., 2011). The study by Kavussanos and Tsouknidis (2014) also identifies freight earnings as a main determinant for shipping bond spreads, such that the transmission channel between asset value and financing costs most likely is bi-directional. From the perspective of risk management, regardless whether we take the perspective of a shipping company or a capital lending institution, it is therefore important not only to look at the risk factors of both sides of the balance sheet but especially at their extreme dependence and co-movement.

Extreme asymmetric dependencies cannot be described by linear dependence measures such as correlation or linear time series models such as cointegration. Alternatively, copulas can be used to capture such effects. Copulas allow to distinguish between the variables' marginal and joint distribution (see for example Patton, 2004; Chen and Fan, 2006). Junker et al. (2006) use copulas for empirically studying extreme asymmetric dependencies of interest rates. Patton (2006) extends the copula theory and allows for conditioning variables to model asymmetric exchange rate dependence. A first attempt in the literature to apply copulas in ship finance is the effort of Merikas et al. (2013) who model joint distributions of dry bulk time charter rates.

This paper contributes to the literature of ship finance by investigating the extreme dependence of the two main balance sheet risk factors, ship values/freight rates and financing costs. For that purpose, we use a conditional copula model. This is one of the first applications of copulas in ship finance. As a further important contribution we quantify the potential crisis risk in the shipping sector from the econometric model. We show that shipping crisis risk strongly increased about one year before the actual outburst of the crisis in 2008 and that the shipping crisis was mainly driven by overcapacity. Thus, market participants would have had the time and measures to prevent the intensity and persistence of the shipping crisis. We also contribute to the financial econometrics literature in general by applying conditional copulas empirically.

3.3 Modeling

In this section we describe the data set and its properties to specify our time series model. We then present the conditional dependence model for the subsequent empirical analysis.

3.3.1 Data description and properties

We investigate the extreme dependence of the two main risk factors of shipping companies' balance sheets, freight rates (assets) and financing costs (liabilities). As a proxy for asset side risk we employ the Baltic Dry Index (BDI) as it implicitly determines the values of vessels. The BDI is a composite index of four dry bulk time charter averages and represents the costs for transporting bulk goods like coal, iron ore, grains and fertilizers. The risks on the liability side are essentially changes in cost of finance. As shipping bonds are typically of non-investment grade (see Grammenos et al., 2008) we use the effective yield of the BofA Merrill Lynch U.S. Corporate B-rated Index (BY) to capture the cost of capital. For both series we use log-differences of end-of-month data over the sample period from January 1997 to December 2014, altogether 216 observations.

Moreover, we apply factors for supply and demand of maritime services that influence the co-movement of freight rates and financing costs. On the one hand, we use the orderbook-to-fleet ratio of dry bulk vessels (OFR) representing the supply of maritime services. Because of the time to build delay of new vessels, this measure has a forward looking element, where a high ratio indicates a rising supply in the near future. On the other hand, we employ the MSCI world stock market index (MSCI) as a proxy for the demand of seaborne transportation. As a worldwide equity index the MSCI reflects the expectations of future economic conditions and consequently, is connected to the demand of shipping services. Estimating extreme dependence entails the problem that only few data drive the estimation outcome. We counteract this issue by using differences over a window of three months for the conditioning variables. Moreover, we choose a lag of three months to take into account the time until consideration.[3] Table 3.1 gives an overview of the required variables for our analysis, summary statistics are shown in Table 3.2. We observe negative mean log-differences for both risk factors. Moreover, with a value of 0.2197 freight rates show a much higher volatility than corporate bond yields. In particular, the skewness of the BDI is negative with -1.4506 indicating a heavier loss tail.

[3] In the robustness analysis we also investigate different lag lengths and window widths.

TABLE 3.1: Glossary and definitions of variables

Symbol	Variable	Source/Definition
	Basic series (end-of-month)	
BDI	Baltic Dry Index	Datastream
BY	BofA Merrill Lynch U.S. Corporate B Index	Federal Reserve
O	Orderbook of dry bulk vessels (DWT)	Clarksons Shipping Intelligence
F	Fleet of dry bulk vessels (DWT)	Clarksons Shipping Intelligence
MSCI	MSCI World Price Index	Datastream
	Derived series	
LBDI	Log-difference of BDI	$\log(\text{BDI}(t)) - \log(\text{BDI}(t-1))$
LBY	Log-difference of BY	$\log(\text{BY}(t)) - \log(\text{BY}(t-1))$
OFR	Orderbook-to-fleet ratio	$\text{O}(t)/F(t)$
Δ^3_{OFR}	Three-months difference of OFR	$OFR(t) - OFR(t-3)$
Δ^3_{MSCI}	Three-months log-difference of MSCI	$\log(MSCI(t)) - \log(MSCI(t-3))$

TABLE 3.2: Summary statistics

Symbol	Mean	SD	Skewness	Kurtosis
LBDI	-0.0031	0.2197	-1.4506	10.8532
LBY	-0.0016	0.0635	0.7546	5.1946
Δ^3_{OFR}	0.0016	0.0318	0.9182	4.8221
Δ^3_{MSCI}	0.0010	0.0872	-1.1218	6.3653

This table gives the summary statistics of derived time series over the sample period from January 1997 to December 2014.

3.3.2 Mean and variance model

The mean dynamics of the monthly log-differences of BDI and BY are modeled by a vector autoregressive model of order p, i.e.

$$\begin{bmatrix} LBDI_t \\ LBY_t \end{bmatrix} = \begin{bmatrix} \beta_{BDI,0} \\ \beta_{BY,0} \end{bmatrix} + \sum_{i=1}^{p} B_i \begin{bmatrix} LBDI_{t-i} \\ LBY_{t-i} \end{bmatrix} + \begin{bmatrix} \sigma_{BDI,t}\, \varepsilon_{BDI,t} \\ \sigma_{BY,t}\, \varepsilon_{BY,t} \end{bmatrix}, \quad t = t_0, \ldots, T, \tag{3.1}$$

where $\beta_{BDI,0}$ and $\beta_{BY,0}$ denote the constants, B_i is the coefficient matrix of the i-th VAR lag, $i = 1, \ldots, p$, $\varepsilon_{BDI,t}$ and $\varepsilon_{BY,t}$ describe the error time series and $\sigma_{BDI,t}$ and $\sigma_{BY,t}$ are the corresponding time-dependent standard deviations. In particular, B_i is specified as

$$B_i = \begin{bmatrix} \beta_{BDI1,i} & \beta_{BDI2,i} \\ \beta_{BY1,i} & \beta_{BY2,i} \end{bmatrix}, \quad i = 1, \ldots, p. \tag{3.2}$$

The bivariate error term $[\varepsilon_{BDI,t}, \varepsilon_{BY,t}]$, $t = t_0, \ldots, T$, has zero mean, unit variance and conditional joint distribution $H(\cdot, \cdot|z)$, where $z \in \mathcal{Z} = \{\Delta^3_{OFR}, \Delta^3_{MSCI}\}$ is a conditioning variable describing the dynamics of H. Consequently, the innovations are not identically distributed, but, given z, $\varepsilon_{BDI,t}$ and $\varepsilon_{BY,t}$ are independent.

In order to identify the model specification for the given data set, we first determine the lag length p of the VAR model. We find that the mean dynamics follow a VAR(4) process as indicated by AIC.[4] Secondly, we control for heteroscedasticity in the variance dynamics. As a GARCH-analysis results in non-stationary variance estimates, we employ the structural break point analysis by Andreou and Ghysels (2002). In this test we employ the modulus of the two residual time series of the VAR(4) model with a minimal period length of 24 months. The obtained change points are given in Table 3.3. For either of the two risk factors, BDI and BY, we obtain a BIC optimal specification with one change

TABLE 3.3: Change point analysis for VAR(4)-residuals of BDI and BY

Panel A: BDI					
# Change Points	0	1*	2	3	4
BIC	-406.3662	-415.9446	-415.1311	-413.7200	-412.4956
Change Point 1	-	01/2008	09/2003	09/2003	09/2003
Change Point 2	-	-	09/2008	01/2008	01/2008
Change Point 3	-	-	-	01/2010	10/2010
Change Point 4	-	-	-	-	01/2012
Panel B: BY					
# Change Points	0	1*	2	3	4
BIC	-666.1948	-670.8048	-669.7191	-669.5407	-668.4873
Change Point 1	-	01/2008	11/2005	10/2000	06/2005
Change Point 2	-	-	01/2008	08/2003	06/2007
Change Point 3	-	-	-	06/2007	08/2009
Change Point 4	-	-	-	-	08/2011

This table presents the change point analysis using the structural break point test by Andreou and Ghysels (2002) for the modulus of the residual time series of BDI in Panel A, and BY in Panel B from January 1997 to December 2014. The minimal period length is set to 24 months. The BIC-optimal specification is indicated by *.

point in 01/2008. Accordingly, the standard deviations of our time series model $\sigma_{BDI,t}$ and $\sigma_{BY,t}$ are regime dependent and given by

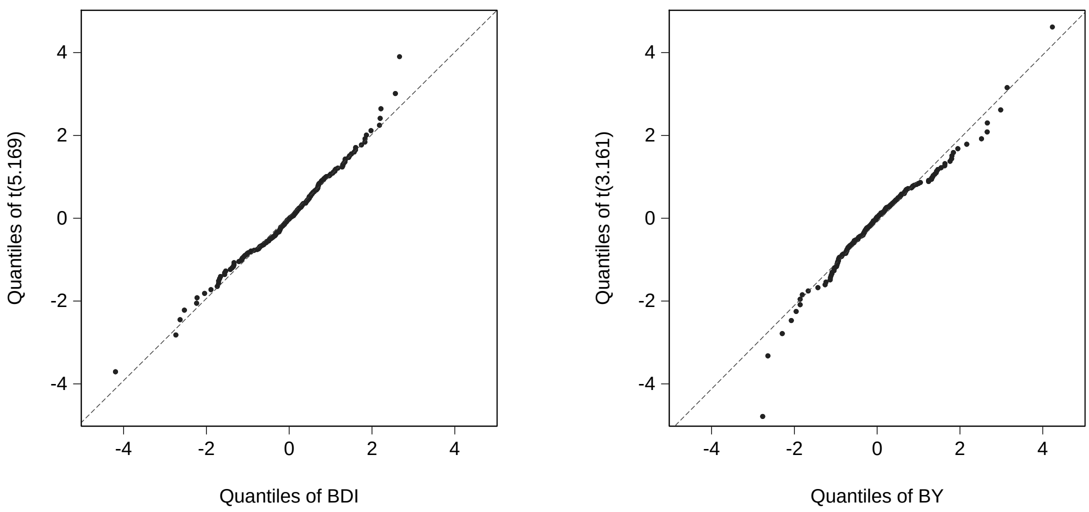
$$\sigma_{BDI,t} = \begin{cases} \sigma_{BDI,I}\,, & 5 \leq t < \tau\,, \\ \sigma_{BDI,II}\,, & \tau \leq t \leq 216 \end{cases} \quad \text{and} \quad \sigma_{BY,t} = \begin{cases} \sigma_{BY,I}\,, & 5 \leq t < \tau\,, \\ \sigma_{BY,II}\,, & \tau \leq t \leq 216\,, \end{cases} \tag{3.3}$$

where $\tau = 133$ (01/2008).

The summary statistics in Table 3.2 indicate heavier tailed distributed error terms than the rather light-tailed normal distribution. To allow for more mass in the tails we therefore assume both variables to be t-distributed. Figure 3.3 shows the QQ-plots of the empirical quantiles of the standardized residuals against the t-distribution for BDI (A) and BY (B), respectively.[5] For the errors of BDI, the t-distribution fits well at the lower tail, but shows minor deviations at the upper tail. For the errors

[4] In the robustness analysis, we also check the VAR(0) model as indicated by BIC and HQ. It is important to note that the use of a VAR(0) model results in an autocorrelation up to lag four for the residuals.

[5] The standardized residuals are the least squares error terms of the VAR(4) model with time-varying volatilities.



(a) BDI vs. Student's t

(b) BY vs. Student's t

Figure 3.3: QQ-plots of standardized residuals

of BY, the results are reversed with a good fit at the upper tail but a discrepancy at the lower tail. However, we are especially interested in modeling joint adverse movements of both risk factors, in particular a sharp decline of freight rates and a strong increase of financing costs. For this purpose, the t-distribution is a suitable choice for the conditional marginal distributions.

3.3.3 Conditional dependence model

Following Joe (1997) and Nelsen (2006), we use the copula framework to model the dependence structure of multivariate distribution functions. In this analysis, we restrict ourselves to the bivariate case as we are focusing on only two risk factors. In particular, we apply the extension of Sklar's theorem (1959) for conditional distributions as stated in Patton (2006), i.e.

$$H(x,y \,|\, z) = C(F(x \,|\, z), G(y \,|\, z) \,|\, z), \tag{3.4}$$

where F and G are the conditional univariate distributions of the random variables X and Y, respectively, given $z \in \mathcal{Z}$, where $\mathcal{Z}$ is the domain of the conditioning random variable Z. C denotes a conditional copula, which is a conditional distribution function on $[0,1] \times [0,1] \times \mathcal{Z}$ with uniform margins. Thus, any two conditional univariate margins F and G and any conditional copula C can be used to specify the conditional joint distribution H of two random variables X and Y. In our case, we apply the t-distribution for both margins, i.e. $F(x|z) = t_{\nu_{BDI}}(x)$ and $G(y|z) = t_{\nu_{BY}}(y)$, where ν_{BDI} and ν_{BY} are the respective degrees of freedom, representing the conditional univariate distributions of freight rates and financing costs, respectively.

As we are particularly interested in the asymmetric extreme dependence of freight rates and financing costs, we apply the upper left version of the tail dependence coefficient λ given by

$$\lambda = \lim_{u \uparrow 1} \mathbb{P}(Y > G^{-1}(u) | X < F^{-1}(1-u)). \tag{3.5}$$

In this setup, λ describes the likelihood of large positive observations in BY given large negative observations in BDI. Tail dependence is an important property of copulas as it is independent of the margins and solely determined by the copula itself.

To specify the dependence structure of BDI and BY, we apply the conditional mirrored transformed Frank copula $C_{mtF}(\cdot, \cdot\,|z)$[6], which is due to Junker (2003) and defined as

$$\begin{aligned} C_{mtF}\,(u,v\,|\,z) = v - \frac{1}{\theta(z)} \ln \Bigg[1 + (e^{-\theta(z)} - 1) \exp \Bigg[- \Bigg[\left(- \ln \left(\frac{e^{-u\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \\ + \left(- \ln \left(\frac{e^{-v\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \Bigg]^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \Bigg] \Bigg]. \end{aligned} \tag{3.6}$$

In our case, the conditional upper left tail dependence $\lambda(z)$ is quantified through the logistic function, such that

$$\lambda(z) = \frac{1}{1 + \exp\left(-(\kappa_{\lambda,0} + \langle \kappa_\lambda, z \rangle)\right)}\,, \tag{3.7}$$

where $\kappa_{\lambda,0}$ is the constant, and $\kappa_\lambda = (\kappa_{\lambda,OFR}, \kappa_{\lambda,MSCI})$ denotes the parameters of the conditioning factors $z = (\Delta^3_{OFR}, \Delta^3_{MSCI})^\top$. We interpret $\lambda \in [0,1]$ as shipping crisis risk where the crisis vulnerability is highest for $\lambda = 1$.

Next to the conditional extreme dependence parameter $\lambda(z)$, the relationship of BDI and BY is characterized by the conditional broad dependence parameter $\theta(z)$ in $C_{mtF}(\cdot, \cdot\,|z)$. Our focus is placed on the asymmetric dependence, so we set $\theta(z) = \theta$ for the main analysis, and explore the general case $\theta(z)$ in the subsequent robustness analysis in Section 3.4.2.

Taken together, the input data for the subsequent empirical analysis is characterized by a VAR(4) model in Equation (3.1) with time-varying volatilities in Equation (3.3). The corresponding innovations $\varepsilon_{BDI,t}$ and $\varepsilon_{BY,t}$ are t-distributed and their dependence structure is specified by the conditional mirrored transformed Frank copula $C_{mtF}(\cdot, \cdot\,|z)$ in Equation (3.6) such that the conditional joint distribution H is given by

$$H(x,y\,|\,z) = C_{mtF}\big(t_{\nu_{BDI}}(x\,|\,z), t_{\nu_{BY}}(y\,|\,z)\,|\,z\big)\,. \tag{3.8}$$

3.4 Empirical results

We have specified the marginal model in Equation (3.1), the conditional copula $C_{mtF}(\cdot,\cdot\,|z)$ in Equation (3.6) as well as the time-dependent conditional tail dependence $\lambda(z)$ in Equation (3.7). Now, we present the one-step estimation results using the maximum-likelihood approach and afterwards check for robustness.

[6] For an extensive derivation see Appendix A.

3.4.1 Estimation results

We calculate the tail dependence in three conditional model setups where the crisis risk λ is conditioned on the supply side factor OFR, the demand side factor MSCI as well as on both factors simultaneously. In addition, we also investigate the unconditional case. The maximum-likelihood estimates of the coefficients of the four different model setups are given in Table 3.4. The estimated degrees of freedom for the t-distributions of the two risk factors BDI and BY are significant in each setup and indicate non-normally distributed margins. Furthermore, the broad dependence parameter θ is not significant in any of the setups.

The unconditional shipping crisis risk is obtained by Model (1). Using Equation (3.7) the estimate of $\kappa_{\lambda,0}$ of -2.8616 can be transferred into a λ of 0.0541 or a constant crisis probability of 5.41%. In Model (2) we only condition on the delayed three-months change of the orderbook-to-fleet ratio and obtain a coefficient $\kappa_{\lambda,OFR}$ of 0.9207. Although the coefficient is not significantly different from zero, the one-sided p-value in Panel C confirms a positive relationship between the orderbook-to-fleet ratio and shipping crisis risk at the 10% significance level. In Model (3) the coefficient for the delayed three-months MSCI return $\kappa_{\lambda,MSCI}$ is negative with -0.4474, though not significant. In this case, the one-sided test also rejects that a decline of global economy causes crisis risk to rise. In contrast, the simultaneous consideration of supply and demand side changes in Model (4) results in strongly significantly positive and negative estimates for both conditioning variables OFR and MSCI, respectively. Thus, a joint increase/decrease of the orderbook-to-fleet ratio/MSCI World index significantly increases the risk of a shipping crisis. However, testing simultaneous adverse movements of both parameters in the way that $\kappa_{\lambda,OFR} > 0$ and $\kappa_{\lambda,MSCI} < 0$ is not straightforward. For our setup a conservative upper bound for the p-value can be obtained as the maximum of the individual parameter p-values which is 0.0046, the p-value of $\kappa_{\lambda,MSCI} < 0$. We interpret this as a clear indication that the probability of a shipping crisis rises remarkably if a sharp increase of the dry bulk fleet occurs during a global economic downturn. Having standardized series of our conditioning factors, we can also conclude that the share of the supply side factor influence is about 60% against a demand side factor influence of 40%. The complete model estimates can be found in Appendix B.

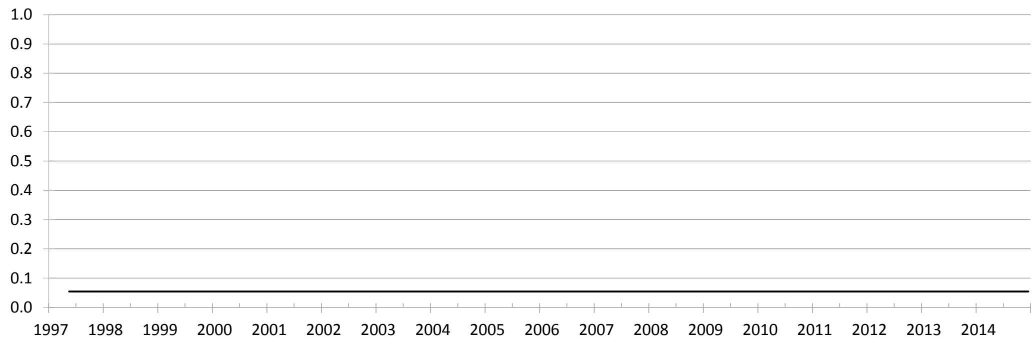
The resulting time-dependent realizations of the tail dependence coefficients λ for each model setup are plotted in Figure 3.4. Figure 3.4(A) shows the constant unconditional tail dependence of 5.41%. When including the changes on the supply side, the orderbook-to-fleet ratio (see Figure 3.4(B)), shipping crisis risk increases sharply between the middle of 2007 and 2009 but remains below 10% in the remaining sample period. With respect to the drop of the BDI that took place in late 2008 (see Figure 3.1) this approach generates a well timed warning signal. However, the indicated conditional crisis probability is at most 46% (04/2008). The third plot in Figure 3.4(C) shows the tail dependence coefficient obtained by Model (3) where only the lagged demand side changes (MSCI) are employed as conditional parameter. There is only a short amplitude in the first quarter of 2009 which is too late to be a warning signal. For Model (4) that includes both supply and demand side factors as conditions for the extreme dependence of BDI and bond yields, the tail dependence coefficient is plotted in Figure 3.4(D). While there is no crisis risk indicated before 09/2007 and after 02/2009, the coefficient fluctuates and rises up to 99% (4/2008) in between. This model setup also yields a crisis warning signal almost one year before the outbreak of the shipping crisis. Compared to the second case in Figure 3.4(B) it is much more distinct.

TABLE 3.4: Maximum-likelihood coefficient estimates

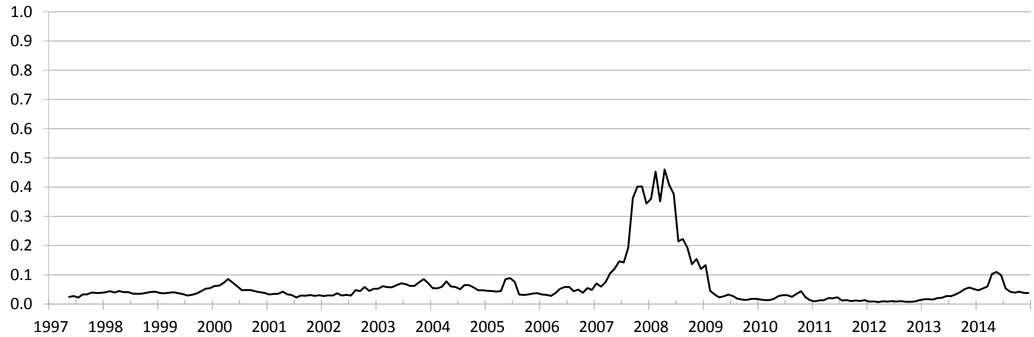
Model		(1)	(2)	(3)	(4)
Conditioning factors		none	$\Delta^3_{OFR,t-3}$	$\Delta^3_{MSCI,t-3}$	$\Delta^3_{OFR,t-3}$ & $\Delta^3_{MSCI,t-3}$
Panel A: Parameter estimates					
$\kappa_{\lambda,0}$		-2.8616**	-3.1200*	-2.9762**	-16.8814**
		[1.2813]	[1.8899]	[1.4633]	[7.1626]
$\kappa_{\lambda,OFR}$			0.9207		4.9473***
			[0.6693]		[1.8176]
$\kappa_{\lambda,MSCI}$				-0.4474	-3.4130***
				[0.7273]	[1.3099]
θ		0.1067	-0.0041	0.0660	0.3693
		[0.6501]	[0.6608]	[0.6299]	[0.4697]
Panel B: Regression diagnostics					
ν_{BDI}		4.3479**	3.6365**	3.6903**	4.0193**
		[1.8685]	[1.7719]	[1.8223]	[1.6333]
ν_{BY}		3.1559***	3.2168***	3.1928***	3.0121***
		[1.0155]	[1.0677]	[1.0265]	[0.9875]
LL		392.2926	394.5423	392.6298	398.8191
Panel C: Hypotheses testing (one-sided)					
H_0-hypothesis			(2)	(3)	(4)
$\kappa_{\lambda,OFR} \leq 0$	t-statistic		1.3756		2.7219
	p-value		0.0845		0.0032
$\kappa_{\lambda,MSCI} \geq 0$	t-statistic			-0.6152	-2.6056
	p-value			0.2692	0.0046
$\kappa_{\lambda,OFR} \leq 0 \ \vee$ $\kappa_{\lambda,MSCI} \geq 0$	p-value				0.0046[1]

$\Delta^3_{OFR,t-3}$ is the three months delayed three-months change of the orderbook-to-fleet ratio for dry bulk vessels and $\Delta^3_{MSCI,t-3}$ the three months delayed three-months log-return of the MSCI World index. ν denotes the Student-t degrees of freedom and LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors. [1] By some calculation it can be shown that a conservative upper bound for the joint p-value can be obtained as the maximum of the individual p-values.

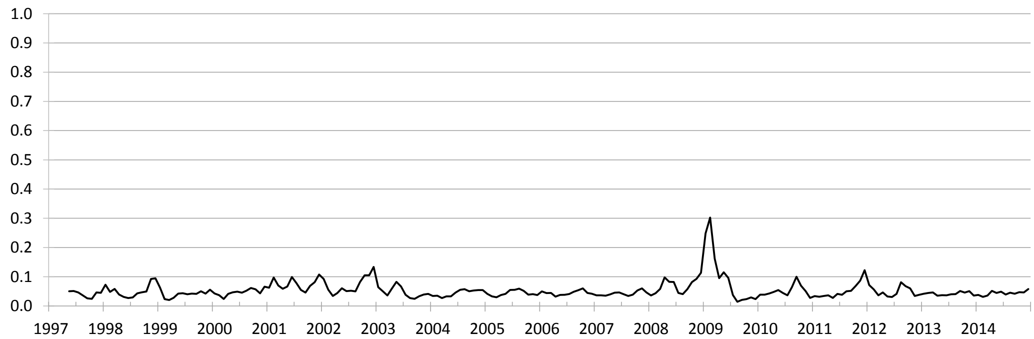
Overall, Figure 3.4 depicts that especially observing supply side developments helps to estimate the conditional crisis risk in the shipping market. While changes of the MSCI World index alone do not produce an appropriate timed amplitude of crisis risk, a simultaneous consideration of both factors yields an obvious early warning signal for a potential crisis. These results are in-sample. To be useful for shipping companies, banks and investors, the results should also hold out-of-sample. Only then it is possible for market participants to intervene by reducing neworder activities or by reducing financing neworders and thereby alleviate the enormous scale of the vessel overhang and depreciated freight rates. In the following section we carry out an extended robustness analysis and, in particular, test the out-of-sample performance of our approach.



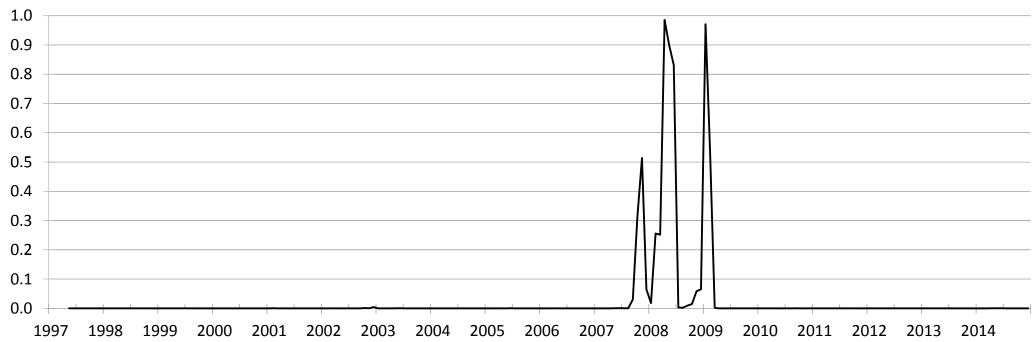
(a) Model (1): Unconditional



(b) Model (2): Orderbook-to-fleet ratio



(c) Model (3): MSCI



(d) Model (4): Orderbook-to-fleet ratio & MSCI

Figure 3.4: Tail dependence coefficients for different model setups

3.4.2 Robustness

In order to check the robustness of our analysis, we test the out-of-sample performance of the presented model. Furthermore, we test for various alternative model specifications. The dependence model is extended by a time-dependent broad dependence parameter $\theta(z), z \in \mathcal{Z}$, the marginal model is reduced to a VAR(0) model, and the lag structures and window widths of the conditioning factors are altered. In addition, we consider alternative economic variables to capture the cost of finance and the supply and demand of shipping services.

3.4.2.1 Out-of-sample performance

The empirical results show in-sample that shipping crisis risk is predominantly driven by simultaneous adverse movements of the supply and demand of shipping services. However, in practice a risk index is only useful if it also achieves reliable out-of-sample results. Therefore, we split our sample in half and re-estimate the conditional model up to 06/2006.[7] The out-of-sample shipping crisis risk is then quantified using Equation (3.7). The maximum-likelihood estimates are given in Table 3.5. Due to the reduced sample size the estimation results are less precise, and consequently, we observe a loss of statistical significance. Hence, the estimate of $\kappa_{\lambda,OFR}$ is only statistically significant at the 20% level, and $\kappa_{\lambda,MSCI}$ provides statistical evidence at the 5% level.

TABLE 3.5: Estimation results: out-of-sample analysis

Estimation period	# obs.	$\kappa_{\lambda,0}$	$\kappa_{\lambda,OFR}$	$\kappa_{\lambda,MSCI}$
05/1997-06/2006	110	-8.1254*	2.1493•	-4.1544**
		[4.6208]	[1.5026]	[1.9648]

$\kappa_{\lambda,0}$, $\kappa_{\lambda,OFR}$ and $\kappa_{\lambda,MSCI}$ denote the estimates for the intercept and the conditioning factors $\Delta^3 OFR_{t-3}$ and $\Delta^3 MSCI_{t-3}$. •, *, and ** denote statistical significance at the 20%, 10%, and 5% level, respectively. Figures in [ ] are standard errors. The complete model estimates can be found in Table 3.12 in Appendix C.

Figure 3.5 shows the in- and out-of-sample crisis parameter $\lambda(z)$. In sample, we observe an increase in $\lambda(z)$ in late 2002 that might mainly be driven by the MSCI downturn following the burst of the technology bubble. The out-of-sample graph shows three peaks between 09/2007 and 03/2009 that reach up to 100% and indicate a strong increase in shipping crisis risk about one year prior to the actual outburst of the crisis. The results demonstrate the out-of-sample applicability of our model to estimate shipping crisis risk.

3.4.2.2 Conditional broad dependence model

In the main analysis, we only condition the crisis risk parameter $\lambda(z)$ and consider the broad dependence parameter θ to be constant. Now, we also condition $\theta(z)$ on shipping supply and demand

[7] We also analyze different estimation periods, i.e. 05/1997-12/2005 and 05/1997-12/2006 with similar results. As there are no structural breaks indicated in the first half of the sample (see Table 3.3) we assume that heteroscedasticity is not an issue and employ a constant volatility in each estimation period. The model estimates can be found in Table 3.12 in Appendix C.

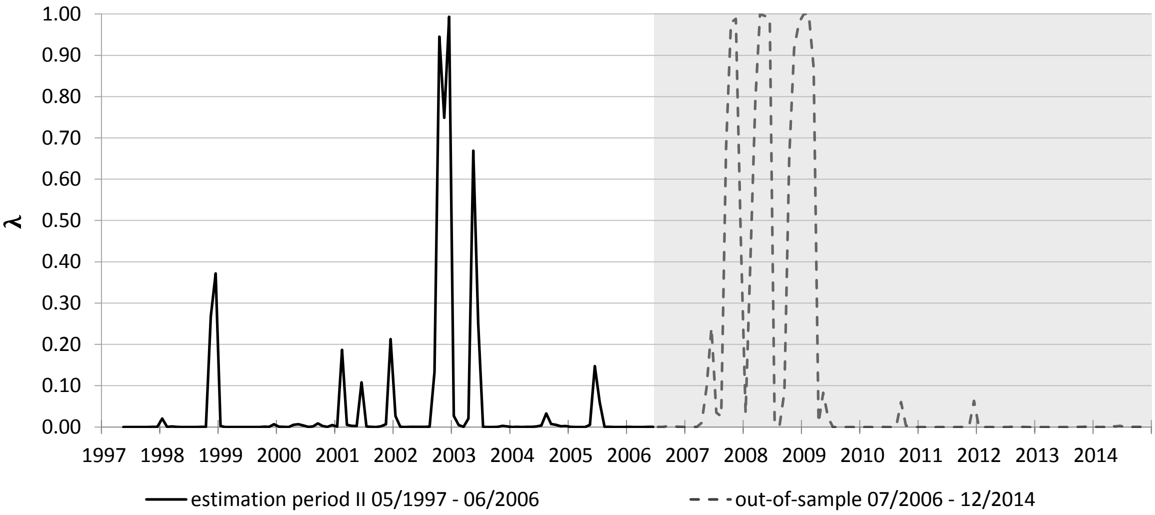


Figure 3.5: Out-of-sample estimation of shipping crisis risk

factors using the functional relationship

$$\theta(z) = \kappa_{\theta,0} + (\kappa_{\theta,OFR}, \kappa_{\theta,MSCI}) \begin{pmatrix} \Delta^3_{OFR} \\ \Delta^3_{MSCI} \end{pmatrix}, \tag{3.9}$$

where $\kappa_{\theta,0}$ is the constant, and $\kappa_{\theta,OFR}$ and $\kappa_{\theta,MSCI}$ denote the coefficients of the conditioning factors Δ^3_{OFR} and Δ^3_{MSCI}, respectively. Table 3.6 presents the maximum-likelihood estimates. In comparison to the initial dependence model the log-likelihood rises by about 1 to 399.8042. However, the significant influence of the conditioning factors Δ^3_{OFR} and Δ^3_{MSCI} on the extreme dependence parameter $\lambda(z)$ reduces to the 5% level as the standard errors increase. The ratios of influence remain almost unchanged with 59% for the OFR and 41% for the MSCI. Concerning the conditional parameter $\theta(z)$, only $\kappa_{\theta,OFR}$ is significantly different from zero at the 10% level. However, the intercept $\kappa_{\theta,0}$ as well as the sensitivity $\kappa_{\theta,MSCI}$ are not significant which is consistent with the insignificant results for the unconditional estimate of θ in Section 3.4.1. Accordingly, the addition of the conditional broad dependence parameter $\theta(z)$ does not affect the estimation results substantially. The key results presented in the main analysis are therefore considered robust.

3.4.2.3 Alternative VAR model

Initially, we apply a VAR(4) model in the mean Equation (3.1). Now, we investigate the BIC and HQ preferred VAR(0) model. The estimates of κ as well as the log-likelihood are shown in Table 3.7.

Each of the relevant parameters is only significant at the 20% level. Analogous to the VAR(4) model, the signs for $\kappa_{\lambda,OFR}$ and $\kappa_{\lambda,MSCI}$ are positive and negative, respectively. Thus, an increase of the OFR as well as a decline of the MSCI raises the tail dependence coefficient and by this the crisis risk. Likewise to the VAR(4) model, the ratio of influence is larger for the OFR than for the MSCI, in particular 65% against 35%. Because of different variance structures regarding numbers and dates

TABLE 3.6: Estimation results: full conditional model

Parameter	$\kappa_{\cdot,0}$	$\kappa_{\cdot,OFR}$	$\kappa_{\cdot,MSCI}$
λ	-14.2318**	4.1649**	-2.9236**
	[7.0416]	[1.8090]	[1.2445]
θ	0.2851	1.0092*	0.0691
	[0.4880]	[0.5208]	[0.5653]
Diagnostics	ν_{BDI}	ν_{BY}	LL
	4.0035**	3.0357***	399.8042
	[1.6158]	[0.9860]	

λ and θ denote the parameters for tail dependence and broad dependence, respectively. $\kappa_{\{\cdot\},0}$, $\kappa_{\{\cdot\},OFR}$ and $\kappa_{\{\cdot\},MSCI}$, $\{\cdot\} \in \{\lambda, \theta\}$, denote the estimates for the intercept and the conditioning factors $\Delta^3 OFR_{t-3}$ and $\Delta^3 MSCI_{t-3}$. ν denotes the Student-t degrees of freedom and LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors. The complete model estimates can be found in Table 3.13 in Appendix C.

TABLE 3.7: Estimation results: VAR(0) as mean equation

Parameter	$\kappa_{\lambda,0}$	$\kappa_{\lambda,OFR}$	$\kappa_{\lambda,MSCI}$
λ	-3.9943$^{\bullet}$	1.3787$^{\bullet}$	-0.7322$^{\bullet}$
	[2.6912]	[0.9320]	[0.5554]
Diagnostics	ν_{BDI}	ν_{BY}	LL
	4.8916**	3.6118***	398.8738
	[2.0693]	[1.1692]	

$\kappa_{\lambda,0}$, $\kappa_{\lambda,OFR}$ and $\kappa_{\lambda,MSCI}$ denote the estimates for the intercept and the conditioning factors $\Delta^3 OFR_{t-3}$ and $\Delta^3 MSCI_{t-3}$. ν denotes the Student-t degrees of freedom and LL is the log-likelihood. $^{\bullet}$, *, **, and *** denote statistical significance at the 20%, 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors. The complete model estimates can be found in Table 3.13 in Appendix C.

of structural breaks in the VAR(0) model[8], it is not possible to reasonably compare the estimates and the diagnostics with those of the initial VAR(4) setup. However, we observe autocorrelation in the VAR(0) residuals up to lag four. Our copula analysis requires conditionally independent errors, and therefore the use of the VAR(4) model in the mean equation is the appropriate choice to control for these effects.

3.4.2.4 Alternative lag lengths and window widths of conditioning factors

A reliable estimation of extreme dependence parameters is difficult since the estimates are typically driven by a few data points in the sample. In order to mitigate the misleading effect of potential outliers, we smooth the conditional variables by aggregating the conditioning factors over a window width of three months, i.e. one quarter, in our main analysis. In the following we vary the window width between 1, 2, 3, and 6 months as well as the lag between 1, 2, and 3 months. The corresponding maximum-likelihood estimates of the conditioning parameters $\kappa_{\lambda,OFR}$ and $\kappa_{\lambda,MSCI}$ are given in Table 3.8.

Table 3.8: Estimation results: alternative lag lengths and window widths

		Window width j			
Lag i	Estimate	1	2	3	6
	$\kappa_{\lambda,0}$	-6.8661$^{\bullet}$	-4.4550$^{\bullet}$	-3.3677$^{\bullet}$	-3.8987$^{\bullet}$
1	$\kappa_{\lambda,OFR}$	0.3479	0.8696	0.6427	1.1207
	$\kappa_{\lambda,MSCI}$	-2.2168*	-0.9246	-0.6172	-0.5883
	LL	395.2933	394.1147	394.5174	395.1484
	$\kappa_{\lambda,0}$	-6.7985$^{\bullet}$	-3.4345*	-3.9251$^{\bullet}$	-4.6770$^{\bullet}$
2	$\kappa_{\lambda,OFR}$	2.1731*	1.0990*	1.3047$^{\bullet}$	1.6038$^{\bullet}$
	$\kappa_{\lambda,MSCI}$	-1.0713	-0.6601$^{\bullet}$	-0.6378$^{\bullet}$	-0.7568
	LL	396.8088	396.3303	396.6333	396.9770
	$\kappa_{\lambda,0}$	-4.4223**	-4.7862*	-16.8814**	-3.8283
3	$\kappa_{\lambda,OFR}$	0.9149**	1.4781*	4.9473***	1.2173
	$\kappa_{\lambda,MSCI}$	-1.5799***	-1.2594**	-3.4130***	-0.6526
	LL	397.0611	397.0805	398.8191	396.9314

$\kappa_{\lambda,0}$, $\kappa_{\lambda,OFR}$ and $\kappa_{\lambda,MSCI}$ denote the estimates for the intercept and the conditioning factors $\Delta^j OFR_{t-i}$ and $\Delta^j MSCI_{t-i}$. LL denotes log-likelihood. $^{\bullet}$, *, **, and *** denote statistical significance at the 20%, 10%, 5%, and 1% level, respectively. The complete estimation results can be found in Tables 3.14 to 3.17 in Appendix C.

For each setup we obtain the expected signs for both parameters, where the models with a three-months lag yield the most robust estimates. With respect to the window width, we observe a similar pattern, an increasing significance up to the three-months window but no reliable estimates at the six-months window. These findings support our idea of aggregating monthly log-returns to prevent

[8] The BDI change points are 09/2003, 01/2008, and 01/2010. The BY change points are 11/2007 and 11/2009.

outliers from driving the results. However, a window width of half a year seems too restrictive as the variance in the data is nearly eliminated.

Accordingly, we conclude that a window width of three months with a lag of three months, as used in our main analysis, is a suitable and economically rational compromise. Moreover, we see that the results are robust.

3.4.2.5 Alternative time series for cost of finance

As outlined in Section 3.2 the majority of shipping bonds are rated BB or B. Therefore, we capture the cost of finance for shipping companies using the effective yield series of the BofA Merrill Lynch Bond Index for B-rated U.S. corporates. But shipping is a very special industry, and so the real cost of capital for shipping companies might differ from a broad bond index as the one chosen. In fact, a shipping specific bond index is the U.S. Corporate Shipping Index that is also published by BofA Merrill Lynch. The effective yield of this index compared to the U.S. Corporate B Index yield is shown in Figure 3.6. Although both series show a quite similar pattern, the shipping index is obviously delayed compared to the broad corporate B index. The broad bond index seems to reflect market changes faster than the shipping bond index that presumably suffers from the sparse amount of shipping bonds and their liquidity.

However, we re-estimate the main model using the effective yield of the shipping bond index in Equation (3.1). The corresponding maximum-likelihood estimates of the coefficients of the four different model setups are given in Table 3.9. The results are generally similar to those when using the broad U.S. corporate bond yield (see Table 3.4), but the level of statistical significance of the estimates in the combined setup in Model (4) is reduced.

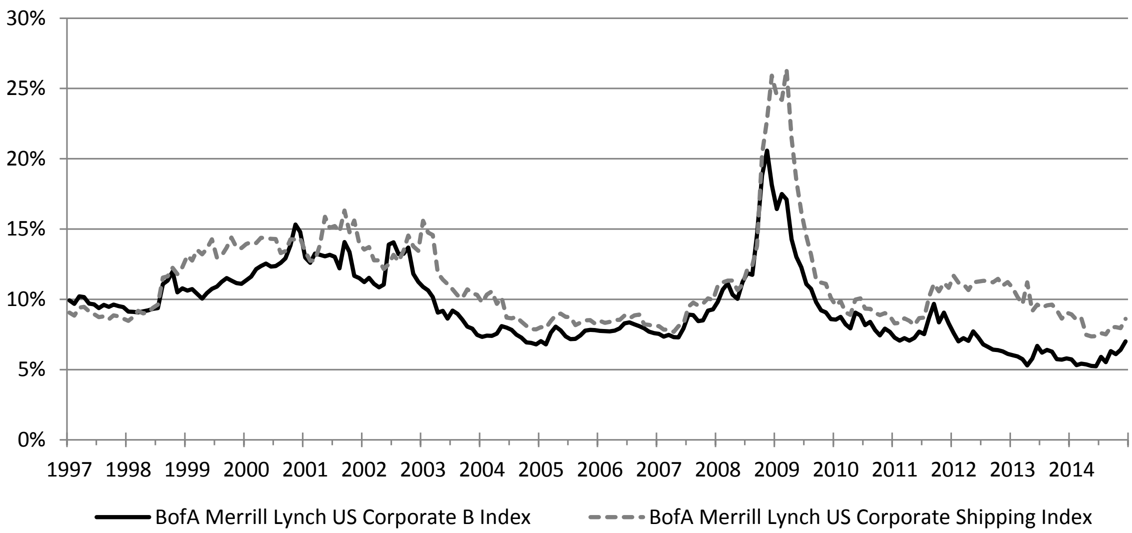


FIGURE 3.6: Effective yields of U.S. corporate bond index and U.S. high-yield shipping bond index

Taken together, the yield of a shipping bond index is only theoretically appealing, but is impractical for our use due to its lagged behavior and the illiquidity of the contained bonds. Therefore, we stay

Table 3.9: Estimation results: shipping bond index yield (SY)

Model	(1)	(2)	(3)	(4)
Conditioning factors	none	$\Delta^3_{OFR,t-3}$	$\Delta^3_{MSCI,t-3}$	$\Delta^3_{OFR,t-3}$ & $\Delta^3_{MSCI,t-3}$
		Panel A: Parameter estimates		
$\kappa_{\lambda,0}$	-2.3006**	-3.5905*	-2.3198*	-4.3187•
	[1.0785]	[1.9935]	[1.2340]	[3.2101]
$\kappa_{\lambda,OFR}$		1.1778•		1.4595•
		[0.7517]		[1.1317]
$\kappa_{\lambda,MSCI}$			-1.0594•	-1.1154•
			[0.6656]	[0.8640]
θ	0.2661	0.5081	-0.1635	0.4049
	[0.7346]	[0.5444]	[0.7525]	[0.5585]
		Panel B: Regression diagnostics		
ν_{BDI}	4.2686**	4.3708**	4.2176**	4.1554**
	[1.9801]	[1.9931]	[2.0824]	[1.7948]
ν_{SY}	4.3500***	4.4378***	4.2878***	4.3082***
	[1.6284]	[1.7111]	[1.5955]	[1.5977]
LL	400.8678	402.4842	404.8459	406.9892

$\Delta^3_{OFR,t-3}$ is the three months delayed three-months change of the orderbook-to-fleet ratio for dry bulk vessels and $\Delta^3_{MSCI,t-3}$ the three months delayed three-months log-return of the MSCI World index. ν denotes the Student-t degrees of freedom and LL is the log-likelihood. •, *, **, and *** denote statistical significance at the 20%, 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors. The complete model estimates can be found in Table 3.18 in Appendix C.

with the broad index for B-rated U.S. corporate bonds which should theoretically also reflect the rating implied financing costs of shipping companies.

3.4.2.6 Alternative conditioning variables

A similar argumentation as for the cost of finance can be thought of for the two factors representing supply and demand of seaborne transportation. The MSCI World index is only indirectly connected to the shipping market. In order to analyze a more directly related figure for the demand of bulk shipping, we employ the worldwide aggregated exports of the most important maritime bulk goods (EX)[9], iron ore, coking coal, steam coal and grain.

Furthermore, an increasing orderbook-to-fleet ratio may indicate a possible overcapacity in the future, but can also result from the age structure of the fleet. When a large share of the current fleet is

[9] Data in million tonnes from Clarksons SIN: iron ore exports from Australia, Brazil, Peru, Russia, South Africa, Ukraine and United States, coking coal exports from Australia, Canada, China, South Africa and United States, steam coal exports from Australia, Canada, China, Colombia, Indonesia, South Africa and United States and grain exports from Argentina, Australia, Canada, EU-28 and United States.

quite old, the need for replacement increases and by this the orderbook-to-fleet ratio. Therefore, we correct for the share of old vessels in the total fleet. In particular, we regress OFR on the demeaned share of vessels older than 20 years in the total fleet ($\mathrm{FR}^{Age>20y}$), such that

$$OFR_t = \alpha + \beta\, FR_t^{Age>20y} + \eta_t^{OFR}. \tag{3.10}$$

The residuals η^{OFR} of Equation (3.10) are used as an alternative orderbook-to-fleet figure[10]. The plot of the residual orderbook-to-fleet series given in Figure 3.7 reveals a similar pattern as the original series OFR.

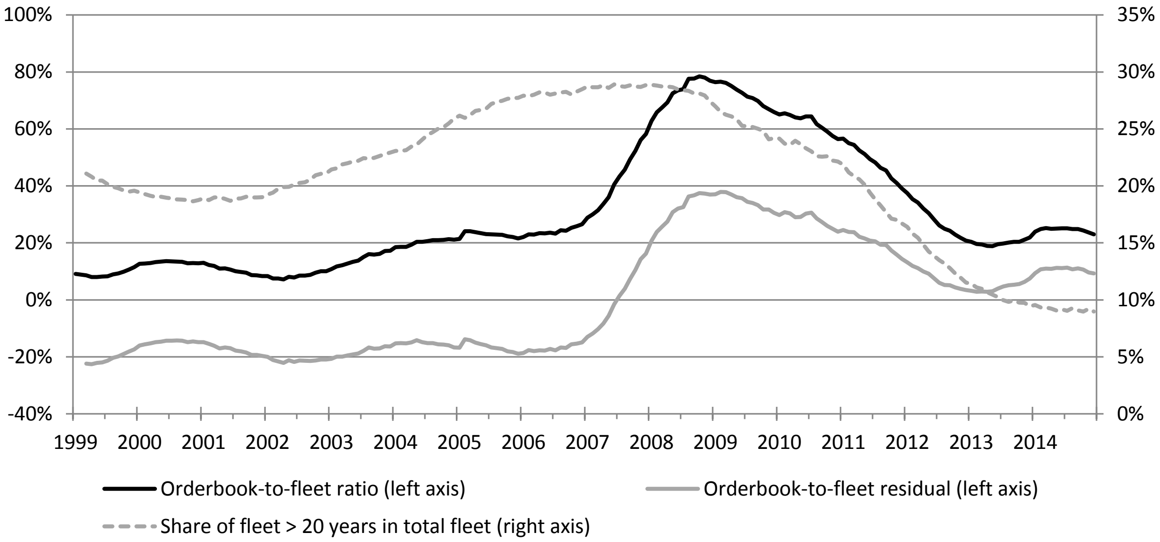


FIGURE 3.7: Adjustment of orderbook-to-fleet ratio

We re-estimate the model in two ways replacing OFR by η^{OFR} and MSCI by EX, respectively, where the three-months changes of EX are considered by two lags. Table 3.10 shows that the changes of the conditioning variables still yield robust and significant estimates. The adjustment of the orderbook-to-fleet ratio hardly effects the estimation results compared to the initial model (see Table 3.4). The signs of κ_{λ,OFR^*} and $\kappa_{\lambda,MSCI}$ are as expected and the weights of the influence on crisis risk stay at about 60% for the supply side and 40% for the demand side. Because of a shorter sample period, the log-likelihood is not comparable. However, using the exports of bulk goods instead of the world equity index changes these figures, such that the demand side has the bigger influence on crisis risk with about 54%.

We conclude that controlling for replacement orders of vessels in the orderbook-to-fleet ratio hardly effects our analysis as the results are barely changed. Furthermore, the results justify the use of the MSCI World index to control for the demand of maritime transportation. The results using the aggregated exports are similar to the main analysis. However, we prefer the MSCI as demand proxy. As a stock index reflects the expectations of future economic developments it is the appropriate forward looking demand equivalent to the orderbook-to-fleet ratio. It also shows a higher transparency with a better and more timely data availability than the aggregated export series.

[10] Data for fleet age structure is obtained from Clarksons SIN. Data is available only from 03/1999, the sample period therefore covers 190 months. The coefficients [standard errors] for Equation (3.10) are $\alpha = 0.3104$ [0.0145] and $\beta = 1.4253$ [0.2423].

TABLE 3.10: Estimation results: alternative conditioning variables

Conditioning factors	$\Delta^3_{\eta^{OFR},t-3}$ & $\Delta^3_{MSCI,t-3}$	$\Delta^3_{OFR,t-3}$ & $\Delta^3_{EX,t-2}$
	Panel A: Parameter estimates	
$\kappa_{\lambda,0}$	-14.5813** [6.0838]	-7.9315*** [1.9454]
$\kappa_{\lambda,OFR}$		2.6782*** [0.5552]
$\kappa_{\lambda,\eta^{OFR}}$	4.3905*** [1.5985]	
$\kappa_{\lambda,MSCI}$	-2.9237*** [1.0419]	
$\kappa_{\lambda,EX}$		-3.0738*** [0.6183]
θ	0.4061 [0.5284]	0.1538 [0.4939]
	Panel B: Regression diagnostics	
ν_{BDI}	3.7948** [1.6939]	3.8366** [1.9538]
ν_{BY}	3.2647*** [1.2207]	3.1954*** [0.9955]
LL	325.2043[1]	401.8757

$\Delta^3_{OFR,t-3}$ and $\Delta^3_{\eta^{OFR},t-3}$ are the three months delayed three-months change of the unadjusted and the residual orderbook-to-fleet ratio for dry bulk vessels, respectively. $\Delta^3_{MSCI,t-3}$ is the three months delayed three-months log-return of the MSCI World index and $\Delta^3_{EX,t-2}$ is the two months delayed three-months relative change of exports of maritime bulk goods. ν denotes the Student-t degrees of freedom and LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors. The complete estimation results can be found in Table 3.19 in Appendix C. [1] Sample period 03/1999 - 12/2014.

3.5 Conclusion

When the world was eventually hit by the financial crisis in late 2008, the shipping sector not only faced a significant drop in demand, but also an oversupply of vessels and transportation capacity. Consequently, freight rates and prices of vessels declined sharply and led to a wave of insolvencies of shipping companies and funds. Because of the dramatic and persistent effects of the shipping crisis, we investigate whether it could have been prevented or, to some extent, alleviated. We analyze the extreme dependence of two main balance sheet risk factors of shipping companies, freight rates and financing costs. We model their extreme co-behavior by fitting a conditional copula model which has two dependence parameters, one that captures the normal dependence and one reflecting the tail dependence. Tail dependence in our case is the probability of a sharp adverse observation in one factor (i.e., BDI down) given an extreme adverse movement in the other factor (i.e., cost of finance up). We interpret the tail dependence as shipping crisis risk which itself is explained by two factors representing the supply and demand of seaborne transportation.

The results show that shipping crisis risk has already strongly increased in the second half of 2007. A medium strong but clear signal is obtained when using only the supply side as conditioning factor, whereas the signal becomes strongest and most distinct when considering the supply and demand side developments simultaneously. We conclude that crisis risk substantially rises when a strong increase of supply hits a weakening demand. The factor estimates also indicate that positive supply side shocks might have a larger impact as the share of influence is about 60% against 40% for negative demand side shocks. In particular, a declining demand alone does not significantly increase the tail dependence coefficient. To verify our results, we perform a comprehensive robustness analysis that supports the choice of our variables and the model parametrization. Most important, we test the out-of-sample performance. The obtained signal of shipping crisis risk appears still early enough at the end of 2007 and proves the practicality of our approach.

Overall, we can conclude that already in late 2007 there have been warning signals of the possibility of a crisis in the shipping market. Furthermore, we show that the crisis in shipping is only partly driven by the drop in demand as a consequence of the financial crisis rather than the massive ordering of new ships by shipping companies themselves. Accordingly, market participants could have reduced or even stopped the ordering of new vessels about one year before the crash and thereby prevented any further fleet growth. Ship financing banks could also have intervened by tightening shipping loans.

This work is one of the first empirical applications of conditional copulas in shipping. The concept of conditional tail dependence is highly useful and can also be applied to further asset classes other than shipping. For example a closer look on the determinants of the stock-bond relationship might reveal idle diversification possibilities. Further research fields in this context could also be the dependence structures in other mortgage backed loan markets such as the real estate market.

Appendices

A Derivation of the conditional copula

We use the copula framework to model the dependence structure of multivariate distribution functions following Joe (1997) and Nelsen (2006). Especially, we follow Patton (2002) and extend the concept of copulas to the context of conditional distribution functions. In this analysis, we restrict ourselves to the bivariate case as we are focusing on only two risk factors.

Let X, Y and Z be random variables on a complete probability space $(\Omega,\mathcal{F},\mathbb{P})$, where $\Omega \equiv \mathbb{R} \times \mathbb{R} \times \mathcal{Z}$, $\mathcal{Z} \subseteq \mathbb{R}^j$, $\mathcal{F} \equiv \mathcal{B}(\mathbb{R} \times \mathbb{R} \times \mathcal{Z})$ is the Borel σ-algebra, and $\mathbb{P}$ is the probability measure. Let the conditional distribution of (X,Y) given Z be denoted H, and let the conditional marginal distributions of $X \mid Z$ and $Y \mid Z$ be denoted F and G, respectively. We assume that F, G and H are continuous.

Definition 1 (Conditional copula)**.** *The conditional copula of $(X,Y) \mid Z$, where $X \mid Z \sim F$ and $Y \mid Z \sim G$, is the conditional joint distribution function of $U \equiv F(X \mid Z)$ and $V \equiv G(Y \mid Z)$ given Z.*

Analogous to the unconditional case, Sklar's Theorem (1959) can be applied to conditional copulas.

Theorem 1 (Sklar's theorem for continuous conditional distributions)**.** *Let F be the conditional distribution of $X \mid Z$, G be the conditional distribution of $Y \mid Z$, and H be the joint conditional distribution of $(X,Y) \mid Z$. Assume that F and G are continuous in x and y. Then there exists a unique conditional copula C such that*

$$H(x,y \mid z) = C(F(x \mid z),G(y \mid z) \mid z)\,, \tag{A.1}$$

for each $(x,y) \in \bar{\mathbb{R}} \times \bar{\mathbb{R}}$, $\bar{\mathbb{R}} \equiv \mathbb{R} \cup \{\pm\infty\}$, and each $z \in \mathcal{Z}$, where $\mathcal{Z}$ is the domain of the random variable Z. Conversely, if we let F be the conditional distribution of $X \mid Z$, G be the conditional distribution of $Y \mid Z$, and C be a conditional copula, then the function H defined by Equation (A.1) *is a conditional bivariate distribution function with conditional marginal distributions F and G.*

Proof 1. *See Patton (2002), p. 58f.*

In our study, we are focusing on the conditional copula and we model the relationship of freight rates and financing costs using the class of Archimedean copulas properly extended to the conditional setup.

Definition 2 (Strict conditional Archimedean copula generator)**.** *A family of functions $(\varphi(\,\cdot \mid z))_{z\in\mathcal{Z}}$ is a strict conditional Archimedean copula generator if and only if for all $z \in \mathcal{Z}$ $\varphi(\,\cdot \mid z) : [0,1] \to [0,\infty]$ is a strict conditional Archimedean copula generator, i.e. $\varphi(\,\cdot \mid z)$ is a continuous, strictly decreasing and convex function with $\varphi(1 \mid z) = 0$ and $\varphi(0 \mid z) = \infty$, $z \in \mathcal{Z}$.*
The bivariate conditional Archimedean copula $C : [0,1] \times [0,1] \times \mathcal{Z} \to [0,1], (u,v,z) \mapsto C(u,v \mid z)$ is then

$$C(u,v \mid z) = \varphi^{-1}(\varphi(u \mid z) + \varphi(v \mid z) \mid z)\,, \tag{A.2}$$

where $\varphi^{-1}(\,\cdot \mid z) : [0,\infty] \to [0,1]$ denotes the inverse of $\varphi(\,\cdot \mid z)$.

In this case, the dependence structure between BDI and BY is modeled by a mirrored version of the conditional transformed Frank copula due to Junker (2003).

Definition 3 (Conditional transformed Frank copula)**.** *The conditional transformed Frank copula is given by the generator* $\varphi_{tF}(\,\cdot\,|\,z) : [0,1] \to [0,\infty]$ *with*

$$\varphi_{tF}(u\,|\,z) = \begin{cases} \left(-\ln\left(\frac{e^{-\theta(z)u}-1}{e^{-\theta(z)}-1}\right)\right)^{\delta(z)}, & \theta(z) \in \mathbb{R}\setminus\{0\}\,, \\ (-\ln(u))^{\delta(z)}\,, & \theta(z) = 0\,, \end{cases} \tag{A.3}$$

where the inverse $\varphi_{tF}^{-1}(\,\cdot\,|\,z) : [0,\infty] \to [0,1]$ *is given by*

$$\varphi_{tF}^{-1}(t\,|\,z) = \begin{cases} -\frac{1}{\theta(z)}\ln\left(1 + e^{-t^{1/\delta(z)}}\left(e^{-\theta(z)}-1\right)\right), & \theta(z) \in \mathbb{R}\setminus\{0\}\,, \\ \exp\left(-t^{\frac{1}{\delta(z)}}\right), & \theta(z) = 0\,, \end{cases} \tag{A.4}$$

for $(\theta,\delta) : \mathcal{Z} \to \mathbb{R}\times[1,\infty), z \mapsto (\theta(z),\delta(z))$*. In particular, the conditional transformed Frank copula* $C_{tF} : [0,1]\times[0,1]\times\mathcal{Z} \to [0,1], (u,v,z) \mapsto C_{tF}(u,v\,|\,z)$ *is given by*

$$\begin{aligned} C_{tF}(u,v\,|\,z) = -\frac{1}{\theta(z)}\ln\Bigg[1 + (e^{-\theta(z)}-1)\exp\Bigg[-\Bigg[\left(-\ln\left(\frac{e^{-u\theta(z)}-1}{e^{-\theta(z)}-1}\right)\right)^{\delta(z)} \\ + \left(-\ln\left(\frac{e^{-v\theta(z)}-1}{e^{-\theta(z)}-1}\right)\right)^{\delta(z)}\Bigg]^{\frac{1}{\delta(z)}}\Bigg]\Bigg], \textit{for } \theta(z) \in \mathbb{R}\setminus\{0\}, \end{aligned} \tag{A.5}$$

and

$$C_{tF}(u,v\,|\,z) = \exp(-((-\ln(u))^{\delta(z)} + (-\ln(v))^{\delta(z)})^{\frac{1}{\delta(z)}})\,, \textit{for } \theta(z) = 0. \tag{A.6}$$

The conditional transformed Frank copula is a conditional Archimedean copula that contains two conditional dependence parameters θ and δ coming from the nested conditional copulas, the conditional Frank copula $C_F(\cdot,\cdot\,|Z)$, and the conditional Gumbel copula $C_G(\cdot,\cdot\,|Z)$, respectively. The conditional transformed Frank copula also combines the properties of C_F and C_G.[11] Thus, parameter $\theta(z)$ from the conditional Frank copula illustrates the broad dependence of the two variables where a positive value of θ describes positive dependence and vice versa, and the conditional transformed Frank copula has upper right tail dependence quantified by the extreme dependence parameter $\delta(z)$ from the conditional Gumbel copula. The tail dependence can be calculated through the following functional relationship:

$$\lambda(z) = 2 - 2^{1/\delta(z)}\,, z \in \mathcal{Z}\,, \tag{A.7}$$

or alternatively

$$\delta(z) = \frac{\ln(2)}{\ln(2-\lambda(z))}\,. \tag{A.8}$$

[11] For a closer look at the probabilities of the Frank and Gumbel copula see Nelsen (2006), chap. 4.3.

We model the conditional tail dependence directly through the logistic function with

$$\lambda(z) = \frac{1}{1 + \exp\left(-(\kappa_{\lambda,0} + \langle \kappa_\lambda, z \rangle)\right)}\,, \tag{A.9}$$

where $\kappa_{\lambda,0}$ is the constant and $\kappa_\lambda \in \mathbb{R}^j$ denote the parameters of the conditioning factor $z \in \mathcal{Z} \subseteq \mathbb{R}^j$. Thus, $\lambda = 0$ indicates the no tail dependence, whereas we obtain pure tail dependence when the tail dependence coefficient $\lambda = 1$.

In order to model asymmetric dependencies, we rotate the first coordinate of $C_{tF}(\cdot,\cdot \mid z)$. As a consequence, the broad dependence reverses as a positive value of θ leads to negative dependence and vice versa. Let the pair $(U^*,V^*) \sim C_{tF}(\cdot,\cdot \mid z), z \in \mathcal{Z}$, then for $U = 1 - U^*$, $V = V^*$, we get

$$\begin{aligned}
\mathbb{P}(U \le u, V \le v \mid z) &= \mathbb{P}(1 - U^* \le u, V^* \le v \mid z) \\
&= \mathbb{P}(1 - u \le U^*, V^* \le v \mid z) \\
&= \mathbb{P}(U^* \le 1, V^* \le v \mid z) - \mathbb{P}(U^* \le 1-u, V^* \le v \mid z) \\
&= v - \mathbb{P}(U^* \le 1-u, V^* \le v \mid z) \\
&= v - C_{tF}(1-u, v \mid z) \\
&= C_{mtF}(u,v \mid z)\,,
\end{aligned} \tag{A.10}$$

where $C_{tF}\,(u,v \mid z) = \mathbb{P}\,(U^* \le u, V^* \le v \mid Z)$, and thus, $(U,V) \sim C_{mtF}(\cdot,\cdot \mid z)$.

The resulting conditional mirrored transformed Frank copula $C_{mtF}(\cdot,\cdot \mid z)$ is defined as follows:

Definition 4 (Conditional mirrored transformed Frank copula)**.** *The conditional mirrored transformed Frank copula* $C_{mtF} : [0,1] \times [0,1] \times \mathcal{Z} \to [0,1], (u,v,z) \mapsto C_{mtF}(u,v \mid z)$ *is given by*

$$C_{mtF}(u,v \mid z) = v - C_{tF}(1-u, v \mid z), z \in \mathcal{Z}. \tag{A.11}$$

Replacing $\delta(z)$ by $\lambda(z)$ using Equation (A.8) we obtain

$$\begin{aligned}
C_{mtF}\,(u,v \mid z) = v - \frac{1}{\theta(z)} \ln \Bigg[1 + (e^{-\theta(z)} - 1) \exp \Bigg[- \Bigg[\left(- \ln \left(\frac{e^{-u\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \\
+ \left(- \ln \left(\frac{e^{-v\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \Bigg]^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \Bigg] \Bigg].
\end{aligned} \tag{A.12}$$

B Model estimates

TABLE 3.11: ML-estimates

	Model	(1)		(2)		(3)		(4)	
Conditioning factors		unconditional		$\Delta^3_{OFR,t-3}$		$\Delta^3_{MSCI,t-3}$		$\Delta^3_{OFR,t-3}$ & $\Delta^3_{MSCI,t-3}$	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))							
BDI	$\beta_{BDI,0}$	0.0123	0.0097	0.0134	0.0097	0.0115	0.0097	0.0137	0.0096
	$\beta_{BDI1,1}$	-0.2603	0.1815	-0.2468	0.1819	-0.2567	0.1816	-0.2676	0.1780
	$\beta_{BDI1,2}$	-0.0472	0.1909	-0.0657	0.1911	-0.0538	0.1912	-0.1094	0.1853
	$\beta_{BDI1,3}$	0.0150	0.1694	0.0305	0.1657	0.0128	0.1695	0.0120	0.1651
	$\beta_{BDI1,4}$	-0.1182	0.1927	-0.0662	0.1899	-0.1233	0.1948	-0.0389	0.1921
	$\beta_{BDI2,1}$	0.0928	0.0688	0.0910	0.0688	0.0922	0.0687	0.1053	0.0649
	$\beta_{BDI2,2}$	-0.0611	0.0732	-0.0559	0.0724	-0.0613	0.0734	-0.0641	0.0695
	$\beta_{BDI2,3}$	-0.0110	0.0645	-0.0046	0.0649	-0.0046	0.0652	0.0296	0.0635
	$\beta_{BDI2,4}$	-0.0911	0.0573	-0.0815	0.0568	-0.0932	0.0604	-0.0837	0.0582
BY	$\beta_{BY,0}$	-0.0053	0.0033	-0.0050	0.0034	-0.0053	0.0034	-0.0048	0.0034
	$\beta_{BY1,1}$	0.1489**	0.0596	0.1500**	0.0595	0.1491**	0.0612	0.1503**	0.0649
	$\beta_{BY1,2}$	-0.0529	0.0509	-0.0537	0.0518	-0.0580	0.0513	-0.0950*	0.0533
	$\beta_{BY1,3}$	0.0120	0.0596	0.0242	0.0607	0.0157	0.0604	0.0220	0.0635
	$\beta_{BY1,4}$	0.0974*	0.0579	0.1050*	0.0581	0.0973*	0.0586	0.1305**	0.0622
	$\beta_{BY2,1}$	0.0107	0.0186	0.0130	0.0187	0.0114	0.0185	0.0113	0.0196
	$\beta_{BY2,2}$	-0.0348*	0.0197	-0.0324*	0.0196	-0.0346*	0.0197	-0.0345*	0.0206
	$\beta_{BY2,3}$	0.0295	0.0212	0.0309	0.0211	0.0299	0.0214	0.0340	0.0243
	$\beta_{BY2,4}$	-0.0166	0.0187	-0.0165	0.0188	-0.0203	0.0196	-0.0206	0.0211
		Regime dependent variances							
BDI	$\sigma^2_{BDI,I}$	0.0165***	0.0049	0.0165***	0.0046	0.0166***	0.0049	0.0168***	0.0056
	$\sigma^2_{BDI,II}$	0.0882***	0.0264	0.0868***	0.0249	0.0884***	0.0263	0.0845***	0.0266
BY	$\sigma^2_{BY,I}$	0.0026**	0.0011	0.0026**	0.0011	0.0026**	0.0010	0.0028**	0.0014
	$\sigma^2_{BY,II}$	0.0085*	0.0045	0.0081*	0.0042	0.0083*	0.0043	0.0114	0.0070
		Degrees of freedom of marginal distributions							
	ν_{BDI}	4.3479**	1.8685	3.6365*	1.7719	3.6903*	1.8223	4.0193**	1.6333
	ν_{BY}	3.1559***	1.0155	3.2168***	1.0677	3.1928***	1.0265	3.0121***	0.9875
		Dependence parameters							
	$\kappa_{\lambda,0}$	-2.8616**	1.2813	-3.1200*	1.8899	-2.9762**	1.4633	-16.8814**	7.1626
	$\kappa_{\lambda,OFR}$			0.9207	0.6693			4.9473***	1.8176
	$\kappa_{\lambda,MSCI}$					-0.4474	0.7273	-3.4130***	1.3099
	θ	0.1067	0.6501	-0.0041	0.6608	0.0660	0.6299	0.3693	0.4697
LL		392.2926		394.5423		392.6298		398.8191	

ν denotes the Student-t degrees of freedom. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

C Robustness results

TABLE 3.12: ML-estimates for out-of-sample analysis

	Model	05/1997-12/2005		05/1997-06/2006		05/1997-12/2006	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))					
BDI	$\beta_{BDI,0}$	-0.0012	0.0110	-0.0006	0.0109	0.0003	0.0102
	$\beta_{BDI1,1}$	-0.3241	0.2012	-0.3260	0.2193	-0.2962	0.2184
	$\beta_{BDI1,2}$	0.0728	0.1827	0.0644	0.1832	0.0946	0.1788
	$\beta_{BDI1,3}$	-0.4794**	0.2128	-0.4704**	0.2098	-0.4746**	0.2038
	$\beta_{BDI1,4}$	-0.0183	0.1704	-0.0175	0.2013	-0.0053	0.1946
	$\beta_{BDI2,1}$	0.2016**	0.0884	0.1818**	0.0850	0.2261***	0.0786
	$\beta_{BDI2,2}$	-0.0309	0.0913	-0.0343	0.0884	-0.0154	0.0839
	$\beta_{BDI2,3}$	-0.0020	0.0869	-0.0011	0.0805	0.0213	0.0795
	$\beta_{BDI2,4}$	0.0202	0.0792	0.0364	0.0737	0.0327	0.0717
BY	$\beta_{BY,0}$	-0.0041	0.0043	-0.0030	0.0040	-0.0042	0.0038
	$\beta_{BY1,1}$	0.1270	0.1003	0.1395	0.0850	0.1418*	0.0852
	$\beta_{BY1,2}$	-0.0274	0.0700	-0.0272	0.0652	-0.0305	0.0650
	$\beta_{BY1,3}$	-0.0423	0.0844	-0.0501	0.0819	-0.0468	0.0799
	$\beta_{BY1,4}$	0.1114	0.0819	0.1238	0.0822	0.1020	0.0727
	$\beta_{BY2,1}$	0.0393	0.0352	0.0351	0.0334	0.0314	0.0313
	$\beta_{BY2,2}$	-0.0341	0.0364	-0.0295	0.0333	-0.0309	0.0322
	$\beta_{BY2,3}$	-0.0172	0.0386	-0.0129	0.0340	-0.0208	0.0317
	$\beta_{BY2,4}$	-0.0059	0.0382	-0.0046	0.0334	-0.0097	0.0317
		Variances					
BDI	σ^2_{BDI}	0.0210	0.0229	0.0212	0.0234	0.0210	0.0221
BY	σ^2_{BY}	0.0036	0.0032	0.0037	0.0035	0.0033	0.0025
		Degrees of freedom of marginal distributions					
	ν_{BDI}	2.7353*	1.4016	2.6091*	1.4837	2.7410**	1.3332
	ν_{BY}	2.7327**	1.1735	2.6970**	1.0788	2.7729***	1.0436
		Dependence parameters					
	$\kappa_{\lambda,0}$	-6.7711**	3.3854	-8.1254*	4.6208	-6.7427*	3.8159
	$\kappa_{\lambda,OFR}$	1.6769	1.3393	2.1493	1.5026	1.7034	1.3688
	$\kappa_{\lambda,MSCI}$	-3.7184**	1.4804	-4.1544**	1.9648	-3.4547**	1.5859
	θ	0.3257	0.7795	0.2722	0.7322	0.2143	0.7344
LL		256.8831		272.1079		292.0951	

ν denotes the Student-t degrees of freedom. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3.13: ML-estimates for full model and VAR(0)-mean-model

	Model	Robustness 1: Full model		Robustness 2: VAR(0)-mean-model	
	Parameter	Estimate	SE	Estimate	SE
		Mean equation			
BDI	$\beta_{BDI,0}$	0.0155	0.0095	0.0098	0.0082
	$\beta_{BDI1,1}$	-0.2463	0.1804		
	$\beta_{BDI1,2}$	-0.1260	0.1815		
	$\beta_{BDI1,3}$	-0.0114	0.1644		
	$\beta_{BDI1,4}$	0.0439	0.1847		
	$\beta_{BDI2,1}$	0.0837	0.0639		
	$\beta_{BDI2,2}$	-0.0659	0.0679		
	$\beta_{BDI2,3}$	0.0276	0.0599		
	$\beta_{BDI2,4}$	-0.0650	0.0612		
BY	$\beta_{BY,0}$	-0.0050	0.0034	-0.0048	0.0033
	$\beta_{BY1,1}$	0.1487	0.0635		
	$\beta_{BY1,2}$	-0.0793	0.0529		
	$\beta_{BY1,3}$	0.0311	0.0637		
	$\beta_{BY1,4}$	0.1364	0.0638		
	$\beta_{BY2,1}$	0.0172	0.0188		
	$\beta_{BY2,2}$	-0.0333	0.0202		
	$\beta_{BY2,3}$	0.0386	0.0235		
	$\beta_{BY2,4}$	-0.0221	0.0211		
		Regime dependent variances			
BDI	$\sigma^2_{BDI,I}$	0.0170	0.0057	0.0079	0.0020
	$\sigma^2_{BDI,II}$	0.0851	0.0258	0.0325	0.0114
	$\sigma^2_{BDI,III}$			0.1409	0.0501
	$\sigma^2_{BDI,IV}$			0.0738	0.0203
BY	$\sigma^2_{BY,I}$	0.0028	0.0013	0.0024	0.0007
	$\sigma^2_{BY,II}$	0.0112	0.0066	0.0172	0.0110
	$\sigma^2_{BY,III}$			0.0063	0.0027
		Degrees of freedom of marginal distributions			
	ν_{BDI}	4.0035	1.6158	4.8916	2.0693
	ν_{BY}	3.0357	0.9860	3.6118	1.1692
		Dependence parameters			
λ	$\kappa_{\lambda,0}$	-14.2318	7.0416	-3.9943	2.6912
	$\kappa_{\lambda,OFR}$	4.1649	1.8089	1.3787	0.9320
	$\kappa_{\lambda,MSCI}$	-2.9236	1.2445	-0.7322	0.5554
θ	$\kappa_{\theta,0}$	0.2851	0.4880		
	$\kappa_{\theta,OFR}$	1.0092	0.5208		
	$\kappa_{\theta,MSCI}$	0.0691	0.5653		
	θ			-0.1171	0.5615
LL		399.8042		398.8738	

$\nu_{\{\cdot\}}$ denotes the Student-t degrees of freedom and LL the log-likelihood.

TABLE 3.14: ML-estimates with lag 1 for different window widths

	Window	1 month		2 months		3 months		6 months	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))							
BDI	$\beta_{BDI,0}$	0.0145	0.0099	0.0131	0.0097	0.0124	0.0097	0.0131	0.0097
	$\beta_{BDI1,1}$	-0.2129	0.1738	-0.2344	0.1813	-0.2369	0.1805	-0.2359	0.1801
	$\beta_{BDI1,2}$	-0.0357	0.1956	-0.0469	0.1913	-0.0659	0.1914	-0.0707	0.1903
	$\beta_{BDI1,3}$	-0.0069	0.1688	-0.0071	0.1686	-0.0013	0.1685	0.0103	0.1666
	$\beta_{BDI1,4}$	-0.0688	0.1923	-0.0867	0.1939	-0.0834	0.1929	-0.0614	0.1918
	$\beta_{BDI2,1}$	0.0517	0.0702	0.0715	0.0686	0.0744	0.0690	0.0791	0.0686
	$\beta_{BDI2,2}$	-0.0804	0.0727	-0.0632	0.0719	-0.0599	0.0724	-0.0584	0.0721
	$\beta_{BDI2,3}$	-0.0148	0.0641	-0.0073	0.0639	-0.0031	0.0647	-0.0016	0.0644
	$\beta_{BDI2,4}$	-0.0988*	0.0571	-0.0898	0.0567	-0.0881	0.0567	-0.0861	0.0571
BY	$\beta_{BY,0}$	-0.0045	0.0034	-0.0049	0.0034	-0.0048	0.0034	-0.0049	0.0034
	$\beta_{BY1,1}$	0.1718***	0.0560	0.1552***	0.0593	0.1520**	0.0592	0.1498**	0.0598
	$\beta_{BY1,2}$	-0.0420	0.0516	-0.0432	0.0513	-0.0433	0.0517	-0.0524	0.0519
	$\beta_{BY1,3}$	0.0192	0.0603	0.0162	0.0597	0.0191	0.0601	0.0236	0.0601
	$\beta_{BY1,4}$	0.1043*	0.0578	0.1007*	0.0579	0.1021*	0.0578	0.1065*	0.0576
	$\beta_{BY2,1}$	0.0051	0.0200	0.0083	0.0183	0.0094	0.0181	0.0107	0.0182
	$\beta_{BY2,2}$	-0.0396*	0.0206	-0.0367*	0.0217	-0.0349*	0.0210	-0.0350*	0.0204
	$\beta_{BY2,3}$	0.0282	0.0212	0.0292	0.0212	0.0296	0.0212	0.0292	0.0212
	$\beta_{BY2,4}$	-0.0174	0.0183	-0.0160	0.0186	-0.0163	0.0187	-0.0189	0.0186
		Regime dependent variances							
BDI	$\sigma^2_{BDI,I}$	0.0175***	0.0054	0.0167***	0.0050	0.0166***	0.0048	0.0166***	0.0048
	$\sigma^2_{BDI,II}$	0.0927***	0.0246	0.0900***	0.0258	0.0882***	0.0253	0.0881***	0.0246
BY	$\sigma^2_{BY,I}$	0.0025***	0.0009	0.0025***	0.0009	0.0025**	0.0010	0.0025***	0.0010
	$\sigma^2_{BY,II}$	0.0079**	0.0036	0.0079**	0.0039	0.0081**	0.0040	0.0080**	0.0039
		Degrees of freedom of marginal distributions							
	ν_{BDI}	4.0058***	1.4289	4.1860**	1.6352	4.2600**	1.6595	4.2353***	1.6329
	ν_{BY}	3.3235***	1.0577	3.3038***	1.0705	3.2604***	1.0771	3.2739**	1.0607
		Dependence parameters							
	$\kappa_{\lambda,0}$	-6.8661	4.3844	-4.4550	3.2334	-3.3677	2.5144	-3.8987	2.8474
	$\kappa_{\lambda,OFR}$	0.3477	0.9301	0.8696	0.9970	0.6427	0.6585	1.1207	0.8912
	$\kappa_{\lambda,MSCI}$	-2.2168*	1.1860	-0.9246	0.9267	-0.6172	0.7410	-0.5883	0.8019
	θ	0.3280	0.5001	0.1985	0.5306	0.0424	0.6763	0.0716	0.5827
LL		395.2933		394.1147		394.5174		395.1484	

$\nu_{\{\cdot\}}$ denotes the Student-t degrees of freedom and LL the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3.15: ML-estimates with lag 2 for different window widths

	Window	1 month		2 months		3 months		6 months	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))							
BDI	$\beta_{BDI,0}$	0.0139	0.0098	0.0119	0.0097	0.0123	0.0096	0.0120	0.0096
	$\beta_{BDI1,1}$	-0.1555	0.1844	-0.2170	0.1821	-0.2249	0.1819	-0.2345	0.1793
	$\beta_{BDI1,2}$	0.0246	0.1863	-0.0796	0.1860	-0.0821	0.1883	-0.1051	0.1854
	$\beta_{BDI1,3}$	-0.0618	0.1707	-0.0141	0.1687	-0.0123	0.1649	-0.0044	0.1671
	$\beta_{BDI1,4}$	-0.0654	0.1981	-0.0584	0.1919	-0.0440	0.1886	-0.0380	0.1897
	$\beta_{BDI2,1}$	0.1429*	0.0673	0.0894	0.0680	0.1049	0.0668	0.0963	0.0676
	$\beta_{BDI2,2}$	-0.0560	0.0763	-0.0551	0.0720	-0.0457	0.0711	-0.0454	0.0717
	$\beta_{BDI2,3}$	0.0029	0.0679	0.0143	0.0652	0.0203	0.0660	0.0118	0.0652
	$\beta_{BDI2,4}$	-0.0703	0.0586	-0.0851	0.0570	-0.0825	0.0568	-0.0843	0.0566
BY	$\beta_{BY,0}$	-0.0041	0.0033	-0.0046	0.0034	-0.0045	0.0034	-0.0053	0.0034
	$\beta_{BY1,1}$	0.1822***	0.0536	0.1520***	0.0588	0.1562***	0.0585	0.1502**	0.0602
	$\beta_{BY1,2}$	-0.0064	0.0504	-0.0338	0.0511	-0.0434	0.0518	-0.0733	0.0518
	$\beta_{BY1,3}$	0.0218	0.0594	0.0276	0.0607	0.0319	0.0600	0.0240	0.0601
	$\beta_{BY1,4}$	0.1074*	0.0574	0.1079*	0.0581	0.1141**	0.0582	0.1154**	0.0579
	$\beta_{BY2,1}$	0.0260	0.0183	0.0139	0.0179	0.0172	0.0181	0.0133	0.0181
	$\beta_{BY2,2}$	-0.0422**	0.0206	-0.0352*	0.0203	-0.0355*	0.0205	-0.0334	0.0204
	$\beta_{BY2,3}$	0.0259	0.0205	0.0304	0.0209	0.0312	0.0208	0.0300	0.0212
	$\beta_{BY2,4}$	-0.0139	0.0178	-0.0157	0.0190	-0.0166	0.0189	-0.0192	0.0187
		Regime dependent variances							
BDI	$\sigma^2_{BDI,I}$	0.0170***	0.0051	0.0166***	0.0049	0.0163***	0.0045	0.0164***	0.0047
	$\sigma^2_{BDI,II}$	0.1131***	0.0296	0.0913***	0.0258	0.0913***	0.0252	0.0902***	0.0256
BY	$\sigma^2_{BY,I}$	0.0025***	0.0009	0.0025***	0.0010	0.0025***	0.0009	0.0025***	0.0009
	$\sigma^2_{BY,II}$	0.0073**	0.0032	0.0082**	0.0041	0.0080**	0.0040	0.0082**	0.0040
		Degrees of freedom of marginal distributions							
	ν_{BDI}	4.0003	7.5407	4.2091***	1.6176	3.7189**	1.6174	4.2556***	1.6379
	ν_{BY}	3.2130***	0.9329	3.2152***	1.0039	3.2515***	1.0302	3.2700***	1.0476
		Dependence parameters							
	$\kappa_{\lambda,0}$	-6.7985	4.8304	-3.4345*	1.9696	-3.9251	2.5833	-4.6770	3.2405
	$\kappa_{\lambda,OFR}$	2.1731*	1.1211	1.0990*	0.6438	1.3047	0.9114	1.6038	1.1358
	$\kappa_{\lambda,MSCI}$	-1.0713	1.0779	-0.6601	0.5127	-0.6378	0.4900	-0.7568	0.6935
	θ	0.2367	0.4973	-0.0835	0.6188	-0.0119	0.5869	0.0363	0.5247
LL		396.8088		396.3303		396.6333		396.9770	

$\nu_{\{\cdot\}}$ denotes the Student-t degrees of freedom and LL the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3.16: ML-estimates with lag 3 for different window widths

	Window	1 month		2 months		3 months		6 months	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
				Mean equation (VAR(4))					
BDI	$\beta_{BDI,0}$	0.0086	0.0096	0.0115	0.0097	0.0137	0.0096	0.0128	0.0097
	$\beta_{BDI1,1}$	-0.2804	0.1786	-0.2294	0.1831	-0.2676	0.1780	-0.2314	0.1820
	$\beta_{BDI1,2}$	-0.0756	0.1840	-0.1060	0.1887	-0.1094	0.1853	-0.0949	0.1879
	$\beta_{BDI1,3}$	-0.1524	0.1711	-0.0078	0.1651	0.0120	0.1651	0.0264	0.1662
	$\beta_{BDI1,4}$	-0.0760	0.1903	-0.0638	0.1919	-0.0389	0.1921	-0.0613	0.1939
	$\beta_{BDI2,1}$	0.0874	0.0675	0.0980	0.0670	0.1053	0.0649	0.0851	0.0691
	$\beta_{BDI2,2}$	-0.0670	0.0715	-0.0450	0.0717	-0.0641	0.0695	-0.0574	0.0725
	$\beta_{BDI2,3}$	0.0118	0.0637	0.0317	0.0661	0.0296	0.0635	0.0041	0.0655
	$\beta_{BDI2,4}$	-0.0810	0.0573	-0.0868	0.0595	-0.0837	0.0582	-0.0889	0.0591
BY	$\beta_{BY,0}$	-0.0051	0.0035	-0.0047	0.0034	-0.0048	0.0034	-0.0050	0.0034
	$\beta_{BY1,1}$	0.1447***	0.0633	0.1549***	0.0627	0.1503***	0.0649	0.1466***	0.0629
	$\beta_{BY1,2}$	-0.0521	0.0513	-0.0812	0.0525	-0.0950	0.0533	-0.0739	0.0524
	$\beta_{BY1,3}$	0.0215	0.0637	0.0352	0.0606	0.0220	0.0635	0.0253	0.0620
	$\beta_{BY1,4}$	0.1074*	0.0582	0.1202**	0.0599	0.1305**	0.0622	0.1118*	0.0592
	$\beta_{BY2,1}$	0.0094	0.0183	0.0150	0.0182	0.0113	0.0196	0.0121	0.0185
	$\beta_{BY2,2}$	-0.0358*	0.0194	-0.0315	0.0198	-0.0345*	0.0206	-0.0327	0.0200
	$\beta_{BY2,3}$	0.0335	0.0232	0.0363*	0.0205	0.0340	0.0243	0.0308	0.0214
	$\beta_{BY2,4}$	-0.0173	0.0189	-0.0251	0.0192	-0.0206	0.0211	-0.0229	0.0188
				Regime dependent variances					
BDI	$\sigma^2_{BDI,I}$	0.0159***	0.0048	0.0162***	0.0046	0.0168***	0.0056	0.0166***	0.0047
	$\sigma^2_{BDI,II}$	0.0884***	0.0290	0.0862***	0.0265	0.0845***	0.0266	0.0860***	0.0246
BY	$\sigma^2_{BY,I}$	0.0026**	0.0011	0.0025***	0.0009	0.0028**	0.0014	0.0025***	0.0010
	$\sigma^2_{BY,II}$	0.0088	0.0049	0.0083**	0.0041	0.0114	0.0070	0.0083**	0.0041
				Degrees of freedom of marginal distributions					
	ν_{BDI}	4.3184**	1.9207	4.3908**	1.8299	4.0193**	1.6333	4.2450***	1.6214
	ν_{BY}	3.1376***	1.0248	3.3189***	1.0683	3.0121***	0.9875	3.2874***	1.0908
				Dependence parameters					
	$\kappa_{\lambda,0}$	-4.4223**	1.8681	-4.7862*	2.5349	-16.8814**	7.1626	-3.8283	3.9129
	$\kappa_{\lambda,OFR}$	0.9149**	0.4604	1.4781*	0.7582	4.9473***	1.8176	1.2173	1.1859
	$\kappa_{\lambda,MSCI}$	-1.5799***	0.5428	-1.2594**	0.6354	-3.4130***	1.3099	-0.6526	0.8364
	θ	0.0333	0.5198	-0.0113	0.5224	0.3693	0.4697	-0.0238	0.6752
LL		397.0611		397.0805		398.8191		396.9314	

$\nu_{\{\cdot\}}$ denotes the Student-t degrees of freedom and LL the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3.17: ML-estimates with lag 6 for different window widths

	Window	1 month		2 months		3 months		6 months	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
				Mean equation (VAR(4))					
BDI	$\beta_{BDI,0}$	0.0138	0.0098	0.0127	0.0097	0.0079	0.0099	0.0133	0.0097
	$\beta_{BDI1,1}$	-0.2491	0.1750	-0.2821	0.1740	-0.3955**	0.1695	-0.2315	0.1778
	$\beta_{BDI1,2}$	-0.0896	0.1939	-0.1270	0.1871	-0.1832	0.1856	-0.1070	0.1855
	$\beta_{BDI1,3}$	0.0493	0.1675	0.0488	0.1685	0.0836	0.1719	0.0221	0.1668
	$\beta_{BDI1,4}$	-0.0518	0.1927	-0.0094	0.1897	-0.0226	0.2006	-0.0466	0.1918
	$\beta_{BDI2,1}$	0.0692	0.0704	0.0693	0.0681	0.0821	0.0689	0.0872	0.0676
	$\beta_{BDI2,2}$	-0.0720	0.0718	-0.0906	0.0694	-0.1173*	0.0686	-0.0601	0.0711
	$\beta_{BDI2,3}$	-0.0249	0.0629	-0.0171	0.0626	-0.0239	0.0572	-0.0068	0.0649
	$\beta_{BDI2,4}$	-0.1014*	0.0583	-0.1079*	0.0576	-0.1235**	0.0587	-0.1005*	0.0567
BY	$\beta_{BY,0}$	-0.0050	0.0033	-0.0065	0.0033	-0.0083	0.0033	-0.0055	0.0034
	$\beta_{BY1,1}$	0.1393**	0.0582	0.1417**	0.0573	0.1115**	0.0548	0.1542***	0.0584
	$\beta_{BY1,2}$	-0.0719	0.0516	-0.0833	0.0509	-0.0960	0.0511	-0.0898	0.0516
	$\beta_{BY1,3}$	0.0220	0.0600	0.0233	0.0592	0.0216	0.0599	0.0159	0.0599
	$\beta_{BY1,4}$	0.1164**	0.0583	0.1179**	0.0595	0.1099*	0.0609	0.1171**	0.0591
	$\beta_{BY2,1}$	0.0110	0.0178	0.0109	0.0171	0.0150	0.0175	0.0117	0.0181
	$\beta_{BY2,2}$	-0.0376*	0.0197	-0.0442**	0.0189	-0.0545***	0.0183	-0.0332*	0.0194
	$\beta_{BY2,3}$	0.0258	0.0202	0.0277	0.0194	0.0249	0.0179	0.0304	0.0216
	$\beta_{BY2,4}$	-0.0291	0.0179	-0.0231	0.0189	-0.0232	0.0191	-0.0186	0.0194
				Regime dependent variances					
BDI	$\sigma^2_{BDI,I}$	0.0175***	0.0053	0.0174***	0.0050	0.0183***	0.0054	0.0167***	0.0046
	$\sigma^2_{BDI,II}$	0.0858***	0.0240	0.0851***	0.0227	0.0828***	0.0217	0.0887***	0.0226
BY	$\sigma^2_{BY,I}$	0.0026**	0.0010	0.0026**	0.0010	0.0026**	0.0011	0.0024***	0.0008
	$\sigma^2_{BY,II}$	0.0082*	0.0043	0.0080**	0.0040	0.0088*	0.0045	0.0081**	0.0037
				Degrees of freedom of marginal distributions					
	ν_{BDI}	3.8240**	1.6275	4.3328***	1.6586	4.4340**	1.8176	3.7811***	1.4417
	ν_{BY}	3.2072***	1.0529	3.2411***	1.0602	3.1367***	1.0012	3.4109***	1.0945
				Dependence parameters					
	$\kappa_{\lambda,0}$	-3.0376	1.8478	-4.7744*	2.8246	-11.6163***	2.8048	-8.5466	5.5977
	$\kappa_{\lambda,OFR}$	1.0933	0.8409	1.9664	1.1975	4.6906***	1.0561	3.2331	2.0146
	$\kappa_{\lambda,MSCI}$	0.2552	1.0704	1.1397	0.9321	4.4238***	1.0106	0.7202	1.3292
	θ	-0.1200	0.6576	0.0758	0.5390	0.1915	0.4731	0.1991	0.4746
LL		395.3921		397.9497		399.5967		398.6595	

$\nu_{\{\cdot\}}$ denotes the Student-t degrees of freedom and LL the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3.18: ML-estimates using shipping bond yield as risk factor for cost of capital

Model		(1)		(2)		(3)		(4)	
Conditioning factors		unconditional		$\Delta^3_{OFR,t-3}$		$\Delta^3_{MSCI,t-3}$		$\Delta^3_{OFR,t-3}$ & $\Delta^3_{MSCI,t-3}$	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
				Mean equation (VAR(4))					
BDI	$\beta_{BDI,0}$	0.0127	0.0098	0.0140	0.0097	0.0103	0.0099	0.0125	0.0095
	$\beta_{BDI1,1}$	-0.0969	0.1781	-0.0862	0.1768	-0.0783	0.1822	-0.0484	0.1769
	$\beta_{BDI1,2}$	0.0744	0.2012	0.0685	0.2030	0.0928	0.1935	0.0669	0.1970
	$\beta_{BDI1,3}$	0.0728	0.1904	0.0956	0.1868	-0.0307	0.1953	-0.0010	0.1924
	$\beta_{BDI1,4}$	-0.2054	0.1717	-0.1821	0.1684	-0.1841	0.1769	-0.1904	0.1748
	$\beta_{BDI2,1}$	0.0927	0.0666	0.0872	0.0659	0.1014	0.0671	0.0816	0.0650
	$\beta_{BDI2,2}$	-0.0569	0.0723	-0.0554	0.0718	-0.0748	0.0741	-0.0575	0.0668
	$\beta_{BDI2,3}$	-0.0012	0.0633	0.0005	0.0634	0.0593	0.0628	0.0355	0.0601
	$\beta_{BDI2,4}$	-0.0987	0.0612	-0.0939	0.0614	-0.1473**	0.0621	-0.0699	0.0655
SY	$\beta_{SY,0}$	-0.0002	0.0033	0.0009	0.0033	-0.0003	0.0032	0.0018	0.0031
	$\beta_{SY1,1}$	0.0307	0.0594	0.0403	0.0600	0.0417	0.0569	0.0319	0.0575
	$\beta_{SY1,2}$	0.0610	0.0596	0.0677	0.0617	0.0745	0.0583	0.0714	0.0598
	$\beta_{SY1,3}$	0.0730	0.0596	0.0925	0.0595	0.0723	0.0548	0.1172**	0.0576
	$\beta_{SY1,4}$	0.0532	0.0571	0.0647	0.0563	0.0951	0.0599	0.0811	0.0547
	$\beta_{SY2,1}$	0.0242	0.0172	0.0212	0.0171	0.0257	0.0164	0.0214	0.0163
	$\beta_{SY2,2}$	-0.0240	0.0175	-0.0223	0.0177	-0.0302*	0.0163	-0.0138	0.0165
	$\beta_{SY2,3}$	0.0079	0.0174	0.0072	0.0173	0.0153	0.0161	-0.0013	0.0154
	$\beta_{SY2,4}$	-0.0112	0.0189	-0.0100	0.0187	-0.0327*	0.0170	-0.0170	0.0181
				Regime dependent variances					
BDI	$\sigma^2_{BDI,I}$	0.0167***	0.0052	0.0165***	0.0049	0.0174***	0.0058	0.0165***	0.0052
	$\sigma^2_{BDI,II}$	0.0901***	0.0293	0.0862***	0.0255	0.0943***	0.0331	0.0932***	0.0285
SY	$\sigma^2_{SY,I}$	0.0021***	0.0007	0.0021***	0.0007	0.0022***	0.0007	0.0021***	0.0007
	$\sigma^2_{SY,II}$	0.0084**	0.0041	0.0082**	0.0040	0.0093**	0.0047	0.0085**	0.0042
	$\sigma^2_{SY,III}$	0.0018***	0.0005	0.0019***	0.0005	0.0018***	0.0005	0.0017***	0.0005
	$\sigma^2_{SY,IV}$	0.0122*	0.0074	0.0112*	0.0063	0.0088**	0.0039	0.0129**	0.0063
	$\sigma^2_{SY,V}$	0.0031***	0.0009	0.0031***	0.0009	0.0030***	0.0009	0.0033***	0.0010
				Degrees of freedom of marginal distributions					
	ν_{BDI}	4.2686**	1.9801	4.3708**	1.9931	4.2176**	2.0824	4.1554**	1.7948
	ν_{SY}	4.3500***	1.6284	4.4378***	1.7111	4.2878***	1.5955	4.3082***	1.5977
				Dependence parameters					
	$\kappa_{\lambda,0}$	-2.3006**	1.0785	-3.5905*	1.9935	-2.3198*	1.2340	-4.3187	3.2101
	$\kappa_{\lambda,OFR}$			1.1776	0.7517			1.4595	1.1317
	$\kappa_{\lambda,MSCI}$					-1.0594	0.6656	-1.1154	0.8640
	θ	0.2661	0.7346	0.5081	0.5444	-0.1635	0.7525	0.4049	0.5585
LL		400.8678		402.4842		404.8459		406.9892	

$\nu_{\{\cdot\}}$ denotes the Student-t degrees of freedom and LL the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3.19: ML-estimates for alternative conditioning variables

Conditioning factors		$\Delta^3_{\eta^{OFR},t-3}$ & $\Delta^3_{MSCI,t-3}$		$\Delta^3_{OFR,t-3}$ & $\Delta^3_{EX,t-2}$	
	Parameter	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))			
BDI	$\beta_{BDI,0}$	0.0206*	0.0114	0.0085	0.0097
	$\beta_{BDI1,1}$	-0.2813	0.2132	-0.2755	0.1786
	$\beta_{BDI1,2}$	-0.1901	0.1999	-0.1302	0.1844
	$\beta_{BDI1,3}$	0.2524	0.1756	-0.0034	0.1706
	$\beta_{BDI1,4}$	-0.1502	0.2412	-0.1165	0.1922
	$\beta_{BDI2,1}$	0.1365*	0.0703	0.1006	0.0687
	$\beta_{BDI2,2}$	-0.0733	0.0793	-0.0780	0.0734
	$\beta_{BDI2,3}$	0.0383	0.0684	0.0233	0.0658
	$\beta_{BDI2,4}$	-0.1123*	0.0619	-0.0959	0.0606
BY	$\beta_{BY,0}$	-0.0059	0.0041	-0.0069**	0.0033
	$\beta_{BY1,1}$	0.2172***	0.0696	0.1404**	0.0593
	$\beta_{BY1,2}$	-0.1869***	0.0646	-0.1060**	0.0509
	$\beta_{BY1,3}$	0.0854	0.0728	0.0157	0.0592
	$\beta_{BY1,4}$	0.0981	0.0687	0.1053*	0.0566
	$\beta_{BY2,1}$	0.0084	0.0209	0.0143	0.0183
	$\beta_{BY2,2}$	-0.0268	0.0218	-0.0395**	0.0192
	$\beta_{BY2,3}$	0.0376	0.0236	0.0364*	0.0193
	$\beta_{BY2,4}$	-0.0198	0.0224	-0.0260	0.0180
		Regime dependent variances			
BDI	$\sigma^2_{BDI,I}$	0.0196**	0.0081	0.0173***	0.0060
	$\sigma^2_{BDI,II}$	0.0847***	0.0326	0.0940***	0.0305
BY	$\sigma^2_{BY,I}$	0.0027***	0.0012	0.0025***	0.0010
	$\sigma^2_{BY,II}$	0.0099*	0.0055	0.0086**	0.0041
		Degrees of freedom of marginal distributions			
	ν_{BDI}	3.7948**	1.6939	3.8366**	1.9538
	ν_{BY}	3.2647***	1.2207	3.1954***	0.9955
		Dependence parameters			
	$\kappa_{\lambda,0}$	-14.5813**	6.0838	-7.9315***	1.9454
	$\kappa_{\lambda,\eta^{OFR}}$	4.3905***	1.5985		
	$\kappa_{\lambda,MSCI}$	-2.9237***	1.0419		
	$\kappa_{\lambda,OFR}$			2.6782***	0.5552
	$\kappa_{\lambda,EX}$			-3.0738***	0.6183
	θ	0.4061	0.5284	0.1538	0.4939
LL		325.2043[1]		401.8757	

$\nu_{\{\cdot\}}$ denotes the Student-t degrees of freedom and LL the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. [1] Sample period 03/1999 - 12/2014.

References

Adland, R. and Koekebakker, S. (2007), 'Ship valuation using cross-sectional sales data: a multivariate non-parametric approach', *Maritime Economics and Logistics* 9(2), 105–118.

Albertijn, S., Bessler, W., and Drobetz, W. (2011), 'Financing shipping companies and shipping operations: a risk-management perspective', *Journal of Applied Corporate Finance* 23(4), 70–82.

Andreou, E. and Ghysels, E. (2002), 'Detecting multiple breaks in financial market volatility dynamics', *Journal of Applied Econometrics* 17(5), 579–600.

Beenstock, M. (1985), 'A theory of ship prices', *Maritime Policy and Management* 12(3), 215–225.

Beenstock, M. and Vergottis, A. (1989), 'An econometric model of the world market for dry cargo freight and shipping', *Applied Economics* 21(3), 339–356.

Chen, X. and Fan, Y. (2006), 'Estimation and model selection of semiparametric copula-based multivariate dynamic models under copula misspecification', *Journal of econometrics* 135(1), 125–154.

Drobetz, W., Gounopoulos, D., Merikas, A., and Schröder, H. (2013), 'Capital structure decisions of globally-listed shipping companies', *Transportation Research Part E: Logistics and Transportation Review* 52, 49–76, Special Issue I: Maritime Financial Management.

Drobetz, W., Schilling, D., and Tegtmeier, L. (2010), 'Common risk factors in the returns of shipping stocks', *Maritime Policy & Management* 37(2), 93–120.

Goff, S., Odell, M., Ross, A., and Stothard, M. (2014), 'Germany's banks race to get loan books shipshape', Financial Times - January 14, 2014.

Grammenos, C. and Arkoulis, A. (2002), 'Macroeconomic factors and international shipping stock returns', *International Journal of Maritime Economics* 4(1), 81–99.

Grammenos, C. T., Nomikos, N. K., and Papapostolou, N. C. (2008), 'Estimating the probability of default for shipping high yield bond issues', *Transportation Research Part E: Logistics and Transportation Review* 44(6), 1123–1138.

Greenwood, R. and Hanson, S. G. (2015), 'Waves in ship prices and investment', *The Quarterly Journal of Economics* 130(1), 55–109.

Jang, S. S. and Ryu, K. (2006), 'Cross-balance sheet interdependencies of restaurant firms: a canonical correlation analysis', *International Journal of Hospitality Management* 25(1), 159–166.

Joe, H. (1997), *Multivariate models and dependence concepts*, Chapman & Hall/CRC Monographs on Statistics & Applied Probability, Taylor & Francis.

Junker, M. (2003), *Modelling, estimating and validating multidimensional distribution function - with applications to risk management*, Ph.D. thesis, University of Kaiserslautern.

JUNKER, M., SZIMAYER, A., AND WAGNER, N. (2006), 'Nonlinear term structure dependence: copula functions, empirics, and risk implications', *Journal of Banking & Finance* 30(4), 1171–1199.

KALOUPTSIDI, M. (2014), 'Time to build and fluctuations in bulk shipping', *The American Economic Review* 104(2), 564–608.

KAVUSSANOS, M. G. AND TSOUKNIDIS, D. A. (2014), 'The determinants of credit spreads changes in global shipping bonds', *Transportation Research Part E: Logistics and Transportation Review* 70, 55–75.

MERIKAS, A., MERIKA, A., AND PENIKAS, H. (2013), 'Dry bulk time charter rates joint return distribution modeling: copula-approach', *Procedia Computer Science* 17, 1125–1133.

NELSEN, R. B. (2006), *An introduction to copulas*, Springer Series in Statistics, Springer, New York, 2nd Edition.

PATTON, A. J. (2002), *Applications of copula theory in financial econometrics*, Ph.D. thesis, University of California, San Diego.

PATTON, A. J. (2004), 'On the out-of-sample importance of skewness and asymmetric dependence for asset allocation', *Journal of Financial Econometrics* 2(1), 130–168.

PATTON, A. J. (2006), 'Modelling asymmetric exchange rate dependence*', *International Economic Review* 47(2), 527–556.

SKLAR, A. (1959), 'Fonctions de répartition à n dimensions et leurs marges', *Publications de l'Institut Statistique de l'Université de Paris*, 229–231.

STOLTENBERG, K. (2014), 'Schiffsfinanzierung in der Krise: Was ist neu, was hat sich überlebt?', Presentation at the 3. Hamburger Schifffahrtsdialog (3rd Hamburg shipping dialogue), April 17, 2014.

STOPFORD, M. (2009), *Maritime economics*, Taylor & Francis Ltd., New York, NY, 3rd Edition.

STOWE, J. D., WATSON, C. J., AND ROBERTSON, T. D. (1980), 'Relationships between the two sides of the balance sheet: a canonical correlation analysis', *The Journal of Finance* 35(4), 973–980.

TSOLAKIS, S., CRIDLAND, C., AND HARALAMBIDES, H. (2003), 'Econometric modelling of second-hand ship prices', *Maritime Economics & Logistics* 5(4), 347–377.

VAN AUKEN, H. E., DORAN, B. M., AND KIL-JHIN, Y. (1993), 'A financial comparison between Korean an U.S. firms: a cross balance sheet canonical correlation analysis', *Journal of Small Business Management* 31(3), 73–83.

WRIGHT, R. (2011), 'Wave of shipping insolvencies looms for shipping industry', Financial Times - December 12, 2011.

Chapter 4

Arbitrage and market efficiency in the German certificates market

with Alexander Szimayer

Abstract

We investigate arbitrage in the German market for retail structured financial products between October 2006 and April 2015. Based on the put-call parity, we compare the risk-adjusted intraday prices of more than 1.4 million portfolios consisting of discount certificates and put warrants with the price of the risk-free asset. As there is no short-selling in this market, we only regard underpriced portfolios. Risk-free profits are quantified by two different arbitrage trading strategies, a static buy-and-hold strategy and a dynamic one. Our results show frequent arbitrage opportunities, which indicate slightly inconsistent bank pricing engines. We find market volatility to be a main driver of the occurrence and degree of arbitrage. Further factors are the day of the week, the time of the day and the issuer of the financial product. Our results indicate that the market for structured financial products in Germany is not efficient in general, but arbitrage diminishes when the costs of trading increase.

4.1 Introduction

The market for structured financial products is still one of the most important markets for retail investors in Germany. After the recent financial crisis, the outstanding notional decreased from about 139 billion Euro in September 2007 to about 69 billion Euro in March 2015 (see German Derivatives Association, 2015). The share of investment and leverage products is quite constant with about 97% and 3%, respectively. Different from other markets, the issuing financial institutions also act as market makers[1]. In this function, they are obliged to quote prices regularly, which requires pricing models that instantly reflect new market information. Especially in turbulent markets, the high volatility of the underlyings' prices requires more frequent adjustments of models and quoted market prices. We analyze whether the heterogeneity of pricing models of various issuers leads to violations of no-arbitrage in the market for structured financial products in Germany and thus to market inefficiency. In particular, we test for parity conditions of portfolios of structured products and implement trading strategies to evaluate possible risk-free profits. As there is no short-selling for retail investors in this market, we only investigate the case of long positions of portfolios that are priced below the arbitrage-free value. Our results indicate slightly inconsistent bank pricing engines resulting in frequent arbitrage opportunities.

The no-arbitrage paradigm describes a pricing relationship between two perfect financial substitutes. A financial cashflow must have one single price, no matter how it is established. We apply parity relationships based on no-arbitrage in order to analyze market efficiency in the German certificates market. In comparison to analyzing arbitrage with pricing models like Black-Scholes, parity relationships offer the advantage of detecting mispricings by simply analyzing the consistency of quoted market prices. Thus, uncertainty regarding models or parameters is avoided. We follow the usual understanding of market efficiency in this context as the absence of arbitrage opportunities (see for example Capelle-Blancard and Chaudhury, 2001).

In this article we focus on a popular subgroup of investment products, the class of discount certificates, which show a market volume of 4.4 billion Euro as of March 2015 (see German Derivatives Association, 2015). The investor of a discount certificate buys the underlying security at a discount to the prevailing market price. In compensation for the discount, the upward participation is limited by a cap level, and there are no dividend payments. The payoff of a discount certificate can be replicated by a long position in the underlying and a short position in a call option. According to the put-call parity, by adding the respective long position in a put option, this portfolio replicates the risk-free investment. We refer to such risk-free portfolios, consisting of discount certificates and put warrants, as *boxes*.

[1] Issuers of structured financial products follow a voluntary undertaking, which requires them to *"ensure that trading is possible in principle for their own structured products"* (see German Derivatives Association, 2013).

Overall, we establish more than 1.4 million boxes within the given data. By analyzing intraday prices, we identify arbitrage quotes and quantify the possible risk-free profits of two arbitrage trading strategies, a static one and a dynamic one.

To the best of our knowledge, this is the first empirical study on arbitrage in the German certificates market as prevailing literature in this field is mainly focused on U.S. option and futures markets. We analyze patterns in the occurrence of arbitrage in general as well as in the degree of mispricing. In particular, we test if a higher market volatility leads to more frequent mispricings. Furthermore, we assume that the relative frequency of arbitrage decreases in the course of the sample period due to the general technical progress in pricing models as well as in trading systems. With respect to the remaining time to maturity, we investigate the presence of the life cycle hypothesis as shown by Wilkens et al. (2003). This effect describes a surcharge on market prices charged by issuers when initiating a structured financial product. Therefore, we expect fewer arbitrage opportunities when the remaining time to maturity is high. Finally, we have a look on the performance of the issuing financial institutions.

The remainder of this paper is structured as follows: In the next section we provide the literature on parity relationship based arbitrage. Section 4.3 presents the no-arbitrage condition and the method applied in this study. Data is briefly described in Section 4.4. In Section 4.5 we present our empirical findings and provide robustness checks. The final Section 4.6 concludes the main results and provides implications.

4.2 Literature review

Evaluating market efficiency and arbitrage is one of the largest fields in empirical finance literature. We focus on literature analyzing market efficiency based on parity relationships between financial instruments. The main advantage of such methods is that they do not depend on explicit valuation models such as Black-Scholes, and hence, cannot suffer from misspecifications. Preferred tests in this field regularly employ no-arbitrage price bounds, box spreads[2] or the put-call parity.

After the first years of trading U.S. index options, Evnine and Rudd (1985) find that options on the S&P 100 frequently violate no-arbitrage conditions and the put-call parity. As they use intraday prices, they assume that problems with the real-time pricing of options lead to arbitrage opportunities. One of the first studies employing the box spread strategy is Chance (1987). He finds significant violations of arbitrage-free box spread prices and the put-call parity for options on the S&P 100 index in the first four months of 1984. However, market

[2] A box spread is a portfolio of a bull spread and a corresponding bear spread, which, under no-arbitrage, has a constant payoff consistent to the difference in exercise prices.

efficiency may still not be rejected as he uses closing prices which might not be tradable. In a similar study Ronn and Ronn (1989) analyze the box spread strategy using intraday prices of several trading days over an eight-year period from 1977 to 1984 and find small arbitrage profits only at low transaction costs. Hemler and Miller (1997) find increased box spread arbitrage profits in the aftermath of the 1987 market crash, which indicates pricing problems in highly volatile markets.

Because of the possibility of early exercise, Kamara and Miller (1995) move away from American options and use European options on the S&P 500 index. They analyze the put-call parity condition on two different samples. On the one hand, they use daily closing prices from the Chicago Board Options Exchange (CBOE) from May 1986 to May 1989, where they find much less frequent and smaller arbitrage violations than previous studies. On the other hand, results are verified against possible non-synchronicity of option prices by a sample of intraday prices. They find that mostly intraday arbitrage results in a loss as soon as the execution is delayed, and that remaining positive profits bear a substantial risk of immediacy. Also Ackert and Tian (2001) study theoretical pricing relationships implied by no-arbitrage conditions for S&P 500 index options. The results for their sample period from February 1992 to January 1994 are in line with those of the earlier studies. Frequent arbitrage possibilities are found, but diminish if considering market frictions like short-selling constraints, transaction costs or bid-ask spreads. The study of Bharadwaj and Wiggins (2001) confirms this finding for long term index options on the S&P 500.

All the above mentioned studies focus on the highly liquid U.S. options market. Similar results, i.e. no real arbitrage, have also been found for other markets, see for example Fung et al. (2004) and Fung and Mok (2001) for the Asian market (Hang Seng Index), Berg et al. (1996) for Norway (OBX stock index), Capelle-Blancard and Chaudhury (2001) for France (CAC 40 index) or Brunetti and Torricelli (2005) for Italy (MIB index).

Literature regarding the German market also addresses behavioral aspects with respect to investors' product choice and the pricing of structured financial products. The efficiency of the market for German index options is analyzed by Mittnik and Rieken (2000) who exploit put-call parity violations between February 1992 and September 1995 and obtain positive profits mainly for short hedge strategies. Thus, because of the short-selling restriction in Germany and transaction costs, market efficiency cannot be rejected. Furthermore, they find that market efficiency improves towards the end of the sample period. Stoimenov and Wilkens (2005) analyze the pricing of equity-linked structured products between August 2001 and October 2002. They find evidence for the life-cycle hypothesis for most products which means that products are priced above their fair value at issuance but the surcharge decreases towards maturity. In a recent study Entrop et al. (2015) address the characteristic of the certificates market that there are usually certain issuers offering comparable products with respect to underlying, maturity and cap level. The authors analyze the pricing and investors' product choice of 72,200 discount certificates between 2004 and 2008. They find that prices are quoted on average 0.88% above the fair value, whereas the overpricing decreases as the products mature. The issuer credit risk accounts for about 85% of the surcharge, but does not influence investors' product choice resulting in significant performance losses.

This paper contributes to the small group of literature on markets for structured financial products in Europe, especially in Germany. In particular, we analyze market efficiency based on parity relationships. For this purpose, we screen about 794 million prices of more than 1.4 million boxes consisting of discount certificates and put warrants on euro-denominated underlyings for violations of the put-call parity. Because of the short-selling restriction for these product classes, we only consider long investments in the box portfolio and therefore, focus on underpriced boxes. Furthermore, we quantify possible gains of arbitrage trading and investigate patterns in the occurrence of arbitrage. We find significant violations of the put-call parity, which cumulate especially in periods of high market volatility. There are on average more mispricings on Fridays as well as at the beginning and the end of a trading day. With respect to the issuers of the products, there are noticeable differences in the pricing performance between the various combinations of issuers. In general, there is a lower chance of an arbitrage opportunity for boxes with one and the same issuer for both products.

4.3 Methodology

We attempt to find arbitrage by violations of price parity relationships. For this reason, we develop the no-arbitrage condition in this section and explain the concept of a box. Furthermore, we describe the method and the underlying assumptions for our empirical analysis.

4.3.1 No-arbitrage

Discount certificates are tradable covered call positions, and as such they belong to the class of structured financial products. The buyer of a discount certificate purchases a certain underlying at a price less than the current market price. At maturity, the certificate promises to deliver the underlying stock or the cash equivalent if the price of the underlying is below a previously fixed cap level. If the price is equal to or above the cap level, this specific amount is paid in cash. Thus, the discount at the purchase of the certificate is exchanged against a limited upside potential in comparison to a direct investment in the underlying. Besides, discount certificates do not provide any dividend claims. Legally, these papers are classified as bearer bonds, and as such they are exposed to the risk of issuer default including a total loss of the invested capital. For the moment, we assume a default-free world, but regard the adjustment to issuer default risk in the following Section 4.3.2. The payoff further depends on the cover ratio $\frac{1}{\delta^{\mathcal{D}}}$ of the security which expresses the portion of the underlying the certificate relates to. Let $\mathcal{D}$ be a discount certificate with maturity T and payoff $\Phi_T^{\mathcal{D}}$ and S_T the ex-dividend price of the underlying in T, then

$$\Phi_T^{\mathcal{D}} = \left(\frac{1}{\delta^{\mathcal{D}}} S_T\right) \mathbf{1}_{(S_T < X)} + \left(\frac{1}{\delta^{\mathcal{D}}} X\right) \mathbf{1}_{(S_T \geq X)}, \tag{4.1}$$

where X denotes the cap of the certificate. The payoff $\Phi_T^{\mathcal{D}}$ can be replicated by a portfolio containing a long position in the underlying[3] and a short position in a call option with strike and maturity according to the discount certificate. Let $\frac{1}{\delta^{\mathcal{C}}}$ be the call's cover ratio and $\delta^{\mathcal{D}} = 1$, then the replication portfolio is

$$\begin{aligned} \mathcal{R} &= S_t - \delta^{\mathcal{C}} C_t(T) \\ &= \frac{1}{\delta^{\mathcal{D}}} \min\{S_\tau, X\} \end{aligned} \tag{4.2}$$

with payoff at maturity T

$$\begin{aligned} \Phi_T^{\mathcal{R}} &= S_T - \delta^{\mathcal{C}} \left(\frac{1}{\delta^{\mathcal{C}}} \max\{S_T - X, 0\}\right) \\ &= \min\{S_T, X\} \\ &= S_T \, \mathbf{1}_{(S_T < X)} + X \, \mathbf{1}_{(S_T \geq X)} \\ &= \Phi_T^{\mathcal{D}}. \end{aligned} \tag{4.3}$$

In a next step we consider the well known put-call parity (see Stoll, 1969). Because of no-arbitrage it is

$$S_t - C_t(T) + P_t(T) = e^{-r_f(T-t)} X, \tag{4.4}$$

where $C_t(T)$ and $P_t(T)$ are the prices of a European call option $\mathcal{C}$ and a European put option $\mathcal{P}$ written on the same underlying with equal strike price X and maturity T. The (continuously compounded) risk-free rate is denoted by r_f[4]. In practice, the option's repayment at maturity T is fixed several days before the actual maturity at a reference date τ, $\tau \leq T$ such that the payoff at maturity T is given by

$$\Phi_T^{\mathcal{C}} = \frac{1}{\delta^{\mathcal{C}}} \max\{S_\tau - X, 0\} \qquad \text{and} \qquad \Phi_T^{\mathcal{P}} = \frac{1}{\delta^{\mathcal{P}}} \max\{X - S_\tau, 0\}. \tag{4.5}$$

[3] For the purpose of valuation, the non-dividend paying underlying is usually replaced by a zero-strike call option.

[4] We use the appropriate annualized rate for the period from t to T but neglect the index to keep the notation clear. Exactly written, we have $r_{t,T}$.

By inserting Equation (4.5) in Equation (4.3) we obtain the fair value of the discount certificate at any time t before τ, given by

$$D_t(T) = \frac{1}{\delta^{\mathcal{D}}}\left(S_t - C_t(T)\right), \qquad t \leq \tau \leq T. \tag{4.6}$$

Now, we can substitute $(S_t - C_t(T))$ in Equation (4.4) by the price of the discount certificate $D_t(T)$ and define boxes $\mathcal{B}$ as a portfolio of discount certificates and put warrants, which is

$$\mathcal{B} = \delta^{\mathcal{D}}\mathcal{D} + \delta^{\mathcal{P}}\mathcal{P}, \tag{4.7}$$

where both derivatives are written on the same underlying with equal strike price X, equal maturities $T^{\mathcal{D}} = T^{\mathcal{P}}$ and equal reference dates $\tau^{\mathcal{D}} = \tau^{\mathcal{P}}$. Adjusting the positions with the respective multiples $\delta^{\mathcal{D}}$ and $\delta^{\mathcal{P}}$ ensures that one box is written on one unit of the underlying. The payoff of such a portfolio at maturity T is given by

$$\begin{aligned} \Phi_T^{\mathcal{B}} &= \delta^{\mathcal{D}} D_T(T) + \delta^{\mathcal{P}} P_T(T) \\ &= \delta^{\mathcal{D}} \frac{1}{\delta^{\mathcal{D}}} \min\{S_\tau, X\} + \delta^{P} \frac{1}{\delta^{\mathcal{P}}} \max\{X - S_\tau, 0\} \\ &= X, \end{aligned} \tag{4.8}$$

which is shown in Figure 4.1. Accordingly, the arbitrage-free price of a box at any given time t, $t \leq \tau$, is

$$B_t(T) = e^{-r_f(T-t)}X. \tag{4.9}$$

We see that dividends can be neglected without loss of generality. For the valuation of discount certificates and put warrants, future dividend payments of the underlying are essential to calculate fair market prices. However, by construction, the box' payoff at maturity is always given by the strike price or cap level X.

4.3.2 Default risk adjustment

A major assumption of no-arbitrage is a risk-free world. In contrast, the certificates and warrants considered here are regularly traded on OTC markets and are therefore exposed to issuer default risk. Especially in the aftermath of the recent financial crisis, the market became aware that the default of financial institutions is not only theoretically possible, and that these risks have to be considered in the pricing of financial instruments. Since the enactment of the regulation framework Basel III, banks are obliged to calculate a credit value adjustment (CVA) of their derivative positions to correct for the counterparty default risk. We approximate this risk surcharge following Hull and White (1995), and adjust the prices with the credit spreads of the respective issuer and time to maturity. In our setup,

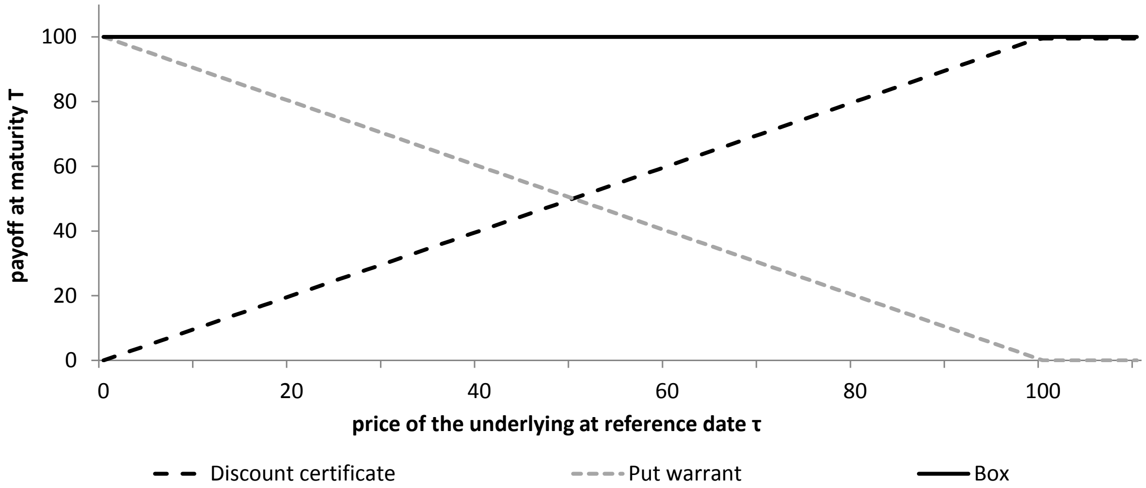


FIGURE 4.1: Box payoff with strike price X = 100

the arbitrage trader implements this adjustment by buying credit default swaps (CDS) as default insurance with a notional equal to the prevailing market prices $D_t(T)$ and $P_t(T)$ as the actual payoff is unknown. For this purpose we assume a liquid CDS market where insurance can be bought and sold on any given notional amount at negligible costs. Let $s^{\mathcal{D}}$ and $s^{\mathcal{P}}$[5] be the credit spreads of the issuers of the discount certificate $\mathcal{D}$ and put warrant $\mathcal{P}$. Assume further that the issuers' credit spreads and the prices of the underlyings are independent, then the risk-adjusted prices are given by

$$D_t^{\mathrm{df}}(T) = D_t(T)e^{s^{\mathcal{D}}(T-t)} \qquad \text{and} \qquad P_t^{\mathrm{df}}(T) = P_t(T)e^{s^{\mathcal{P}}(T-t)}, \tag{4.10}$$

such that the default-free market price of a box is

$$B_t^{\mathrm{df}}(T) = \delta^{\mathcal{D}} D_t^{\mathrm{df}}(T) + \delta^{\mathcal{P}} P_t^{\mathrm{df}}(T). \tag{4.11}$$

4.3.3 Methodology and assumptions

We combine each discount certificate and put warrant to a box given that they are written on the same underlying with equal maturity and equal cap or strike price, respectively. Furthermore, we assign all available quotes of the two products to the respective query times and calculate the default-free market prices of the box using Equation (4.11). Credit risk does not only apply to the issuers of financial products, but also to the arbitrage trader which we assume to be an institutional investor like a hedge fund or a bank. Therefore, the lending rate is assumed to be above the risk-free rate r_f, and the cost of refinancing of the

[5] We use the maturity matching credit spreads but neglect the index to keep the notation clear. Exactly written, we have $s^{\mathcal{D}_{t,T}}$ and $s^{\mathcal{P}_{t,T}}$.

arbitrage investor r_A is given by

$$r_A := r_f + s^{\mathcal{A}}, \tag{4.12}$$

where $s^{\mathcal{A}}$ is the arbitrage trader's own risk premium. With respect to Equation (4.11), an arbitrage opportunity is given every time we observe a risk-adjusted box price below the risk-adjusted present value of the strike price, which yields the arbitrage condition

$$B_t^{\text{df}}(T) < e^{-r_A(T-t)}X. \tag{4.13}$$

A box price satisfying Equation (4.13) is referred to as *arbitrage quote*.

As outlined in Section 4.3.1, the put-call parity explicitly regards European-style options, while most put warrants in our sample are American-style. In contrast to European options, American options allow the holder to exercise the option at any time $t \leq \tau$. The right of exercising the option before maturity enhances the value of the option. Especially for put options, it can be rational to exercise early if the price of the underlying is close to 0 such that the payoff of the put is maximum. Therefore, the value of an American-style put option is at least the value of the European-style put option,

$$P_t^{\text{American}}(T) \geq P_t^{\text{European}}(T). \tag{4.14}$$

For this reason, we treat American-style options as Europeans, which leads at most to a slight increase of the left hand side of Equation (4.4) and thus, to a more conservative arbitrage condition.

Furthermore, we have to make various assumptions in order to implement the outlined method. The main principle behind each assumption is to achieve a conservative arbitrage condition.

(A.1) All products, especially all discount certificates, are assumed to be cash settled. This is not only because of the lack of information about this feature, but also for technical reasons. As soon as there is a physical delivery, there is an additional stock price risk between the reference date τ and the delivery at maturity T that the investor may have to hedge. In our analysis, we also have a special look on index boxes, which are inevitably cash settled.

(A.2) As the data set contains only the reference date τ, we assume the maturity of all products to be seven calendar days after this settlement date, which is the market standard for the products considered. For the sake of plausibility, we do not regard maturities of less than one day.

(A.3) The day count conventions for interest rates are not known and may even differ between issuers. Common day count conventions are actual/360, actual/365 or actual/actual. For a conservative approach we assume the day count convention to be actual/360, which is always greater than the other two. This has two favorable effects with respect to the arbitrage condition in Equation (4.13). The left side is *compounded* with the issuers' credit spreads and increases with a longer time to maturity while the right side holds the discounted strike price and decreases with time to maturity. Thus, with a larger day count method it is less likely to obtain an arbitrage box price.

(A.4) Contracts are not divisible and there is no short-selling. As short-selling is not possible for retail investors in Germany, we will only invest in long positions of the box portfolio and only investigate boxes priced below the arbitrage-free market price. Lending and investing is possible without restrictions, especially liquidity issues are not considered. For each product, issuer default protection is bought in the form of CDS positions on corporate bonds of the respective issuer. Once entered, each CDS position is held to maturity even if the position is closed before. In particular, there is no reselling of CDS on a secondary market, although we are aware of waiving potential profits from reselling the credit insurance.

(A.5) We treat American-style warrants as European ones assuming no additional costs for early exercise. Because of the possibility of early exercise, we allow maturities for American-style put warrants up to 15 days after the maturity of the discount certificate. However, we do not consider any early exercising before the settlement date of the discount certificate. As a consequence, the maturity of the box is determined by the discount certificate.

(A.6) There is a unique interest rate for borrowing and lending, which equals the yield for German bank bonds. By assuming a higher rate for lending, opportunity costs increase, such that possible excess returns decrease, which is in line with our aim of a conservative approach.

4.3.4 Arbitrage strategies

Having identified all underpriced box quotes, we evaluate the profits of two different trading strategies. For this purpose, we also regard trading fees payable for each individual trade, i.e. buying a box involves buying the appropriate positions in the discount certificate and in the put warrant, thus two trades[6]. The two strategies considered are a static buy-and-hold strategy and a dynamic one.

Within the buy-and-hold strategy, the box is bought whenever Equation (4.13) applies, i.e. if the risk-adjusted ask price of the box portfolio plus trading fees g is below the arbitrage-

[6] We assume equal trading fees for both products.

free price. At maturity T the holder receives the strike price X times the number of boxes bought $n^{\mathcal{B}}$ [7]. The net return is

$$\rho_t,T = \frac{n^{\mathcal{B}}X}{\left(n^{\mathcal{B}}B_t^{\text{ask, df}} + 2g\right)e^{r_A(T-t)}} - 1, \tag{4.15}$$

where $B_t^{\text{ask, df}}$ is the default-free ask-price of one box and r_A is the respective bank lending rate for the time to maturity. The absolute profit at maturity T is given by

$$\omega_t,T = n^{\mathcal{B}}X - \left(n^{\mathcal{B}}B_t^{\text{ask, df}} + 2g\right)e^{r_A(T-t)}. \tag{4.16}$$

Besides holding until maturity, the arbitrage trader may sell the position as soon as the underpricing is gone, and in particular if net profits are positive. Therefore, the rational for buying the box is the same as in Equation (4.15), but we now constantly check whether there are positive profits when selling the box prior to maturity at time $t+k$ including fees for two additional trades. The investor sells the box as soon as the net return of the box sold in $t+k$ and compounded to maturity T,

$$\rho_{t+k,T} = \left(\frac{n^{\mathcal{D}}D_{t+k}^{\text{bid}} + n^{\mathcal{P}}P_{t+k}^{\text{bid}}}{\left(n^{\mathcal{B}}B_{t+k}^{\text{ask, df}} + 2g\right)e^{r_A k} + 2g}\right)e^{r_A(T-(t+k))} - 1\,, \qquad (t+k) \leq \tau < T, \tag{4.17}$$

is positive and in particular if $\rho_{t+k,T} > \rho_T$. The compounding from $t+k$ to maturity T is necessary to make a decent trading decision in the sense that the advantage of selling the portfolio compared to further holding can be evaluated. Note that a credit risk adjustment of the bid prices is not necessary. The corresponding absolute profit is

$$\omega_{t+k,T} = \left(n^{\mathcal{D}}D_{t+k}^{\text{bid}} + n^{\mathcal{P}}P_{t+k}^{\text{bid}} - \left(n^{\mathcal{B}}B_{t+k}^{\text{ask, df}} + 2g\right)e^{r_A k} - 2g\right)e^{r_A(T-(t+k))}\,, \qquad (t+k) \leq \tau. \tag{4.18}$$

4.4 Data

We use daily data of German discount certificates and put warrants between October 31, 2006 and April 2, 2015 on euro-denominated underlyings. Prices are from EUWAX (Stuttgart, Germany) and Deutsche Börse Zertifikate (Frankfurt, Germany)[8]. The initial data comprises 559,519 discount certificates and 445,242 put warrants of which 389,847 (87.6%) are American-style and 55,395 (12.4%) are European-style. We observe market prices on four points of time on each trading day, in particular at 9:50 AM, 1:20 PM,

[7] Depending on the cover ratios of both instruments, the number of boxes must not necessarily be an integer, only puts and discount certificates are indivisible.

[8] We thank Certox GmbH for providing the data.

4:20 PM and 7:50 PM, resulting in about 544 million data sets for discount certificates and 331 million data sets for put warrants.[9] Each data set contains the bid and ask price as well as the exact timestamp of the quote. A quote represents the issuers offer to buy or sell a financial product at the given price. Therefore, we generally assume all quoted prices to be valid at the time of the query regardless of the actual timestamp.

Overall, there are 34 different issuers, but with quite heterogeneous shares in the whole sample. While some issuers, such as the Bayerische Landesbank, Credit Suisse or Morgan Stanley, are only represented by a few products, others provide up to 20% of one of the two products classes. A full list of all issuers and the number of products in the sample can be found in Table 4.14 in Appendix A.

Furthermore, we use issuer specific CDS quotations for maturities of one to five years for credit risk adjustments obtained from Thomson Reuters Datastream. For maturities in between, we use linear interpolation. When there is no CDS available for a specific issuer we follow Entrop et al. (2015) and estimate the spread as the difference between the redemption yield of the iBoxx Europe Financial bond index and the risk-free rate. In this case, the risk-free rate is given by the Euro area yield curve of AAA rated government bonds (YC.AAA.SR) published by the European Central Bank. In most cases, the iBoxx approximation results in much higher spreads compared to the given CDS quotations of the other issuers such that it can be regarded as a conservative assumption. For maturities of less than one year, the respective one year spread is employed.

The arbitrage trader in our setup is assumed to be an institutional investor like a bank or a hedge fund and therefore entails a slight credit risk (see Section 4.3.3). Thus, we cannot employ the risk-free rate to reflect the cost of finance. In contrast, we use the rate for German bank bonds, which is published daily by Deutsche Bundesbank (series BBK01.WT1032) and regularly ranks above the risk-free rate. These rates are published for intervals of maturities, in particular from 1 to 2 years, 2 to 3 years, and so on. In order to obtain the cost of capital for a particular trading day, we assign each interval the respective mid-maturities (1.5 years, 2.5 years, and so on) and interpolate between these rates. For maturities of less than 1.5 years we use the "1 to 2 years"-rate.

4.5 Empirical results

The first part of this section presents the *dirty* results of arbitrage quotes. As some of the hits are obviously caused by faulty quotations, we correct for implausible quotes to obtain more reliable results within the later analysis. The actual results are based on the *cleaned* data and start in Section 4.5.2.

[9] There are mostly four quotes per day and products, but also days with fewer or no quote.

4.5.1 Primary results and data cleaning

We combine each discount certificate and put warrant to a box if they are written on the same underlying with equal maturity and equal cap or strike price, respectively. Therefore, most products participate in more than one combination. Overall we identify 1,413,656 boxes in our data with more than 794 million pairs of quotes[10]. There are 457,473 (81.8%) discount certificates and 354,292 (74.9%) put warrants involved in boxes. An overview of all boxes by issuers and underlying is provided in Table 4.15 in Appendix A.

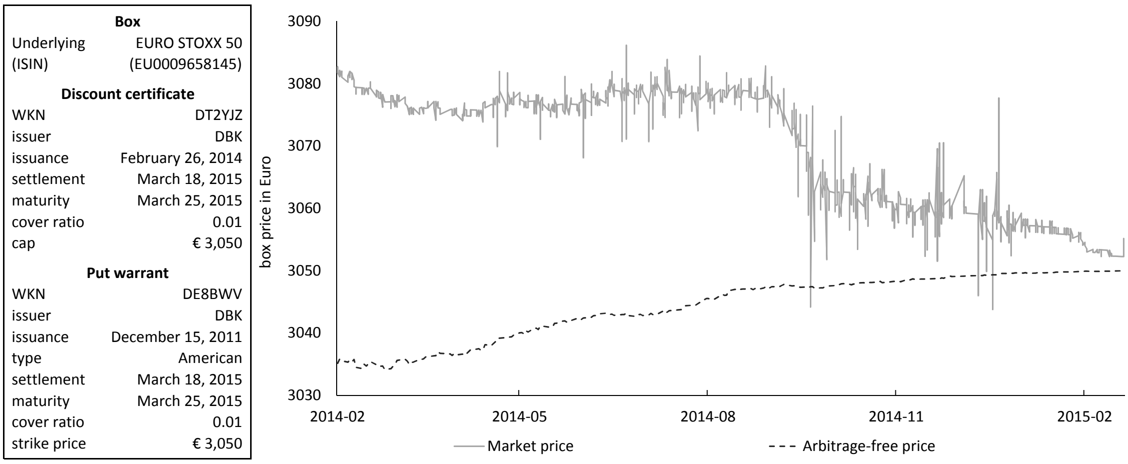


FIGURE 4.2: Price development of a sample box with arbitrage quotes

Within the found combinations of discount certificates and put warrants, we identify 910,773 (0.12%) box quotes allowing for arbitrage in 166,614 (12%) different boxes. Figure 4.2 shows the price development of a typical arbitrage box with three arbitrage opportunities. The distribution of arbitrage quotes per box in Table 4.1 indicates that some boxes are much more often priced below their arbitrage-free price. Mostly there have been increases of capital, share splits/re-splits or share buybacks of the underlying company. Such measures lead, inter alia, to adjustments of the cover ratio of the respective derivative instruments, but our data only covers the most recent cover ratio as of February 2015. To correct for such data issues, we choose the 95% quantile of the number of arbitrage quotes per box (at most 15 hits) and exclude boxes with implausbile high numbers of mispricings from our further analysis. This sample reduction of 7,896 boxes decreases the number of arbitrage quotes to 418,490.

A further criterion for cleaning the resulting data set is the difference to the fair value. As shown in Table 4.2, the majority of the arbitrage quotes are at most about 1% below the respective fair value. In contrast, some boxes are priced up to 99% below their arbitrage-

[10] Including multiple participations of the same product in different boxes. We only count the quotes during the duration of the boxes, i.e. only when there are quotes for both products.

TABLE 4.1: Arbitrage opportunities per box

# Arbitrage opportunities	# Boxes		
	Absolute	Relative	Cumulative
1	78,732	47.25%	47.25%
2	30,648	18.39%	65.65%
3	15,554	9.34%	74.98%
4	9,551	5.73%	80.72%
5	6,135	3.68%	84.40%
6	4,054	2.43%	86.83%
7	3,084	1.85%	88.68%
8	2,371	1.42%	90.11%
9	1,834	1.10%	91.21%
10	1,612	0.97%	92.17%
11 - 20	7,815	4.69%	96.86%
21 - 30	2,355	1.41%	98.28%
31 - 40	865	0.52%	98.80%
41 - 50	420	0.25%	99.05%
51 - 100	648	0.39%	99.44%
100 and more	936	0.56%	100.00%
Total	166,614	100.00%	
Quantiles			
8 (90.0%)	150,129		90.11%
15 (95.0%)*	158,718		95.26%
24 (97.5%)	162,671		97.63%
48 (99.0%)	164,956		99.00%

* indicates the chosen quantile for data cleaning.

free price. A main reason for this problem are most likely errors in the reported prices[11], which can either be due to the issuers, the exchange or the data gathering process. We treat such quotes as misquotes and correct the sample by regarding only quotes with a difference between the market price of a box and its corresponding fair value of at most 9.0934% reflecting the 99% quantile of all relative box price differences. This measure leads to a further small sample reduction of 4,185 arbitrage quotes and 2,263 boxes resulting in a final arbitrage sample 414,305 arbitrage opportunities in 156,455 boxes.

4.5.2 Arbitrage analysis

We mainly focus on two characteristics of arbitrage. On the one hand, we analyze the relative proportion of arbitrage quotes n_t^{arb} compared to all observed box quotes n_t in a

[11] For example, one quote is 0.01 Euro while the ones before and thereafter are around 10 Euro.

TABLE 4.2: Relative underpricing of boxes (with at most 15 arbitrage quotes)

Distance to fair value	# Quotes		
	Absolute	Relative	Cumulative
[0.00% - 0.01%)	30,372	7.26%	7.26%
[0.01% - 0.02%)	25,655	6.13%	13.39%
[0.02% - 0.03%)	21,549	5.15%	18.54%
[0.03% - 0.04%)	18,966	4.53%	23.07%
[0.04% - 0.05%)	16,998	4.06%	27.13%
[0.05% - 0.06%)	15,407	3.68%	30.81%
[0.06% - 0.07%)	14,289	3.41%	34.23%
[0.07% - 0.08%)	12,967	3.10%	37.33%
[0.08% - 0.09%)	11,968	2.86%	40.19%
[0.09% - 0.10%)	11,400	2.72%	42.91%
[0.10% - 0.20%)	79,133	18.91%	61.82%
[0.20% - 0.30%)	45,603	10.90%	72.72%
[0.30% - 0.40%)	29,184	6.97%	79.69%
[0.40% - 0.50%)	19,569	4.68%	84.37%
[0.50% - 0.60%)	13,515	3.23%	87.59%
[0.60% - 0.70%)	8,968	2.14%	89.74%
[0.70% - 0.80%)	6,692	1.60%	91.34%
[0.80% - 0.90%)	5,247	1.25%	92.59%
[0.90% - 1.00%)	3,873	0.93%	93.52%
[1.00% - 2.00%)	15,054	3.60%	97.11%
[2.00% - 3.00%)	4,365	1.04%	98.16%
[3.00% - 4.00%)	1,541	0.37%	98.52%
[4.00% - 5.00%)	660	0.16%	98.68%
[5.00% - 6.00%)	448	0.11%	98.79%
[6.00% - 7.00%)	311	0.07%	98.86%
[7.00% - 8.00%)	303	0.07%	98.94%
[8.00% - 9.00%)	245	0.06%	98.99%
[9.00% - 10.00%)	163	0.04%	99.03%
[10.00% and more)	4,045	0.97%	100.00%
	418,490	100.00%	

Quantile	# Quotes	Max. distance to fair value
90.00%	376,641	0.7152%
95.00%	397,565	1.2295%
97.50%	408,027	2.2631%
99.00%*	414,305	9.0934%
99.50%	416,397	62.0953%

* indicates the chosen quantile for data cleaning.

specific period of time t, which we denote as

$$p_t = \frac{n_t^{\text{arb}}}{n_t}. \tag{4.19}$$

On the other hand, we calculate the average relative difference to the fair value d_t for each time period t, given by

$$d_t = \frac{1}{n_t^{\text{arb}}} \sum_{t_i \in t} d_i \qquad \text{with} \qquad d_i = 1 - \frac{B_{t_i}^{\text{df}}(T_i)}{e^{-r_A(T_i - t_i)} X_i}, \tag{4.20}$$

where $i, i = 1, \ldots, 414{,}305$, denotes the identified arbitrage quotes. We analyze various patterns of arbitrage over time, by the remaining time to maturity, and by the issuers of the products.

4.5.2.1 Time patterns of arbitrage

The occurrence of arbitrage is assumed to be equally distributed over time. In order to check this hypothesis, we analyze the arbitrage patterns per weekday and daytime of the query. The distribution of arbitrage by weekdays is presented in Table 4.3. While the absolute number of all box quotes is similar for each day of the week with about 157 million, the number of arbitrage opportunities varies. Especially on Fridays, there are comparatively few arbitrage quotes with 0.04% of all Friday quotes, but the average proportion of arbitrage quotes is still not significantly different from the other weekdays (see Table 4.18 in Appendix B). With respect to the difference to the fair value, the average mispricing is 0.1 percentage points larger on Fridays compared to the other four weekdays. The ANOVA test in the lower part of Table 4.3 confirms this finding as the low p-values of about 0 indicate significant differences to all other mean differences. A possible explanation may be the weekend effect of stock returns as found by Jaffe and Westerfield (1985). The effect describes empirically observable, abnormally high stock returns on Fridays[12]. In general, higher returns imply a higher market volatility, which hampers an appropriate pricing of structured financial products. A further explanation for a higher market volatility on Fridays is also provided by Berument and Kiymaz (2001). They argue that traders may take weekend expectations into account, knowing that they are unable to respond on the weekend. Thus, overall trading activity is higher on Fridays. Furthermore, many futures contracts, such as the DAX index futures, mature on Fridays resulting in additional trading activity by large institutional investors.

Besides the differences between weekdays, we analyze arbitrage opportunities by the time of the day the quote is obtained. The results in Table 4.4 show that the number of overall

[12] The effect also describes abnormally low returns on Mondays, which is not the case in our sample.

Table 4.3: Market inefficiency by weekday

Weekday	Box quotes	Arbitrage quotes		Price difference	
		Absolute	Mean proportion	Mean	SD
Monday	157,914,682	87,780	0.0007	0.0029	0.0056
Tuesday	159,257,609	79,809	0.0008	0.0028	0.0055
Wednesday	158,756,120	84,876	0.0007	0.0027	0.0053
Thursday	157,964,356	97,272	0.0007	0.0028	0.0055
Friday	153,493,756	64,568	0.0008	0.0040	0.0077
All quotes	787,386,523[1]	414,305	0.0007	0.0030	0.0059

Differences in mean price differences

	Monday	Tuesday	Wednesday	Thursday
Tuesday	0.0001			
	[0.2518]			
Wednesday	0.0002	0.0001		
	[0.0000]	[0.0000]		
Thursday	0.0001	0.0000	-0.0001	
	[0.0024]	[1.0000]	[0.0012]	
Friday	-0.0011	-0.0011	-0.0013	-0.0012
	[0.0000]	[0.0000]	[0.0000]	[0.0000]

[1] The difference in total box quotes is due to the exclusion of boxes as explained in Section 4.5.1. Figures in [ ] are Bonferroni-adjusted p-values, which are capped at 1.0.

box quotes is almost equally distributed over the day while the proportion of boxes priced below their fair value is not. In the morning and in the afternoon there are on average more arbitrage opportunities whereas the largest mispricings occur in the morning and the evening. These findings can be explained by the course of a typical trading day. In the morning, new information from the previous evening, the morning or the past weekend is being processed in the market. Trade volume, price volatility and by that the absolute number of mispricings increase. The same applies in the afternoon at the 4:30 pm inquiry when the U.S. stock exchanges start trading. The fewest number of arbitrage quotes is found at the last time of inquiry (7:50 pm) when the main exchanges in Germany and Europe are already closed [13]. Afterwards, it is only possible to trade stocks over-the-counter with higher bid-ask spreads leading to fewer underpricings. The still higher average mispricing might be caused by the less liquid market and less frequent quotations by the issuers after the closing of floor trading[14]. This finding raises doubts regarding our assumption that each quote represents the current price regardless of the time it was published (see Section 4.4).

[13] Floor trading in Frankfurt ends at 5:30 pm CET.

[14] The average time difference of quotes of the put warrant and the discount certificate is highest at the last quote inquiry of the day. In particular, the average quote time differences are: morning 20.0 minutes, noon 30.0 minutes, afternoon 36.7 minutes and evening 60.1 minutes.

TABLE 4.4: Market inefficiency by query time

Query time	Box quotes	Arbitrage quotes		Price difference	
		Absolute	Mean proportion	Mean	SD
Morning (09:50 am)	196,858,565	110,261	0.0009	0.0035	0.0072
Noon (1:20 pm)	197,017,001	74,130	0.0006	0.0030	0.0066
Afternoon (4:20 pm)	198,401,153	175,687	0.0008	0.0024	0.0039
Evening (7:50 pm)	195,109,804	54,227	0.0006	0.0036	0.0071
All quotes	787,386,523[1]	414,305	0.0007	0.0030	0.0059

Differences in mean price differences

	Morning	Noon	Afternoon
Noon	0.0005	-	-
	[0.0000]		
Afternoon	0.0011	0.0006	-
	[0.0000]	[0.0000]	
Evening	-0.0001	-0.0005	-0.0011
	[0.1639]	[0.0000]	[0.0000]

[1] The difference in total box quotes is due to the exclusion of boxes as explained in Section 4.5.1. Figures in [ ] are Bonferroni-adjusted p-values.

Overall, we see significant heterogeneity in the occurrence of arbitrage box prices. For both day of the week and time of the day, there is also a slight, non-significant negative relation between the number of arbitrage quotes and the average price difference to the fair value. Taken together, a preferable time for arbitrage trading is Friday in the afternoon and evening when the chance to observe mispriced boxes and the average mispricings are highest.

4.5.2.2 Arbitrage by day

As shown by Hemler and Miller (1997) there is a higher chance of arbitrage quotes when the stock market is more volatile and stock prices fluctuate more. In such situations issuers may have problems to adjust the prices of their derivative contracts in time, which reveals extraordinarily more arbitrage opportunities for traders. Figure 4.3 shows the relative share of daily arbitrage boxes to all combinations of discounters and puts examined on the respective trading day. Moreover, the development of overall box quotes per day is given[15]. We see that the average underpricing was higher during the 2007 sub-prime crisis and the financial turmoil after the Lehmann collapse in September 2008. On the most turbulent days, about one in every 50 box prices was priced below the fair value. However, we cannot draw general conclusions as with fewer observations the relative weight of outliers increases. A second

[15] Recall that there are at most four quotes per product and day, and that one and the same product is likely to be part of several boxes. The number of box quotes must not necessarily reflect the market volume of trades.

accumulation of arbitrage quotes can be identified after the 'Black Monday' on August 18, 2011 when the market was shocked by the first downgrade of the United States sovereign debt in history. Finally, the 'Flash Crash' of 10-year U.S. Treasury yields on October 15, 2014 also led to a share of arbitrage quotes of more than 2%. For a detailed analysis of the influence of volatility on arbitrage, we have a closer look at index boxes in the following section.

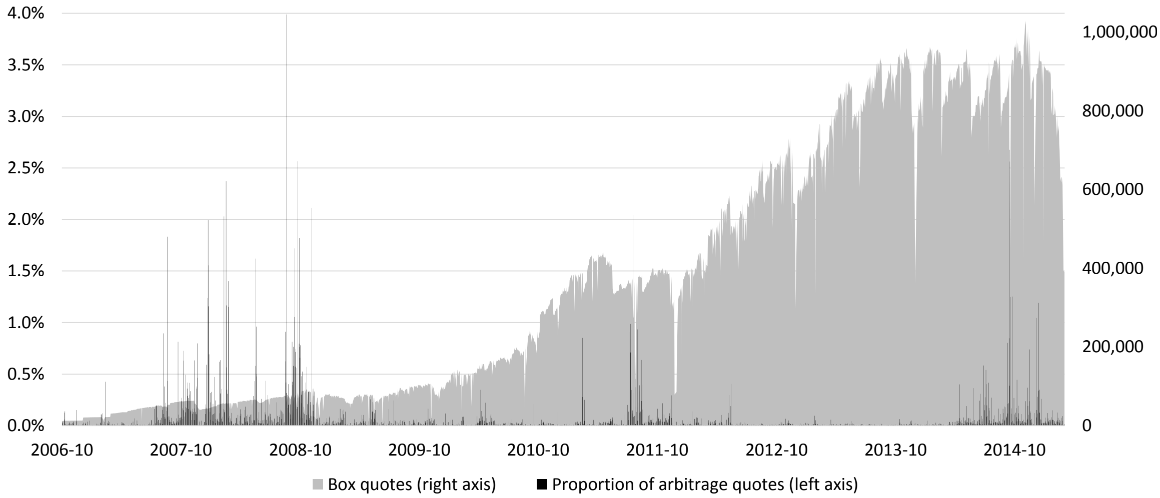


FIGURE 4.3: Relative share of arbitrage quotes per day

4.5.2.3 Arbitrage quotes by time to maturity

The pricing of structured financial products is said to be subject to a lifetime surcharge as shown by Wilkens et al. (2003), Stoimenov and Wilkens (2005) or Entrop et al. (2015). The essence of this life cycle hypothesis is that there is an additional surcharge on the theoretical price besides the risk premium. This premium is highest at the issuance of a product and decreases towards maturity. As there is no short-selling, certificates can only be sold back by investors if they have been purchased before such that issuers gain extra profits when buying back certificates because of the reduced lifetime premium. Therefore, we expect a negative influence of the remaining time to maturity on both the average price difference to the arbitrage-free box price as well as the proportion of arbitrage quotes. However, our sample is quite inhomogeneous and shows a high data density for maturities of less than one year, but much fewer observations for longer maturities. For this reason, we aggregate the observations into (non-equidistant) maturity buckets (see Table 4.20 in Appendix B). Mean price differences and standard deviations are then obtained as Nadaraya-Watson regression estimates based on bucket means and standard deviations using an Epanechnikov kernel and a bandwith of 2.5 (see for example Härdle et al., 2004). In this case, the proportion of arbitrage is obtained as equally weighted moving average of order three as $\tilde{p}_t = \frac{1}{3}(p_{t-1} + p_t + p_{t+1})$.

The plots of both characteristics are presented in Figure 4.4 and lead to contradictory conclusions. On the one hand, the proportion of arbitrage quotes decreases with increasing time to maturity, which can be interpreted as a support of the life cycle hypothesis. In addition, more than 99% of all arbitrage quotes occur with a remaining time to maturity of less than one year while the overall sample of all considered box quotes shows a 99% quantile of 742 days. On the other hand, the degree of underpricing, if it is the case, increases slightly up to 0.6% for maturities of at most one year. For longer maturities we observe increasing price differences, which is contrary to the life cycle hypothesis. The reason might be a less liquid trading with less frequent price quotations. Taken together, we cannot confirm the existence of a life cycle pricing in the German certificates market based on the given sample.

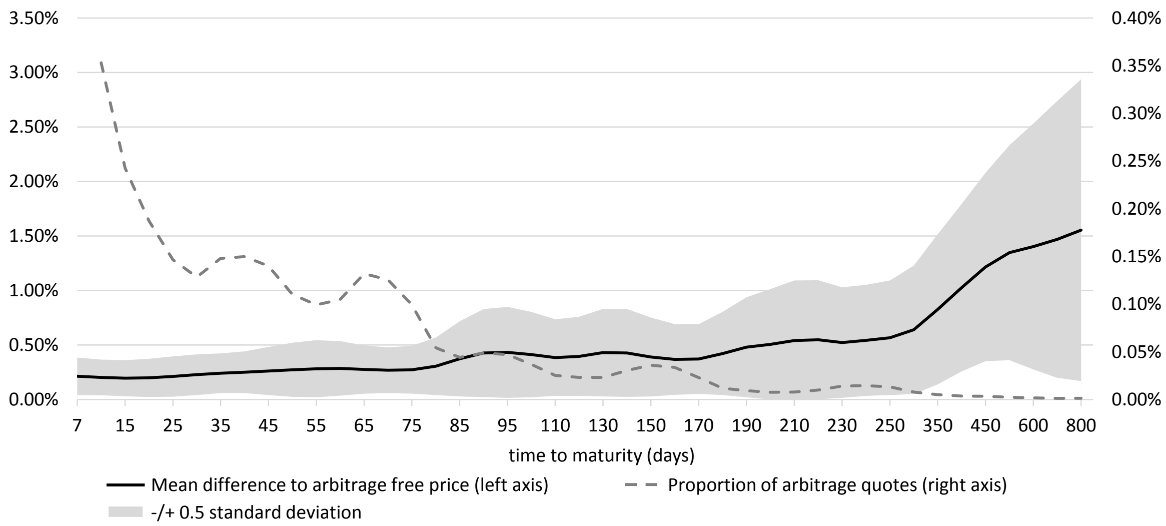


FIGURE 4.4: Mean price difference and proportion of arbitrage quotes by time to maturity

4.5.2.4 Arbitrage by underlying and volatility

More than 30% of all boxes are written on indices (see Table 4.15), most of them on the German lead index DAX 30 (about 25% of all boxes) or the EURO STOXX 50 index (about 5% of all boxes). As a physical settlement is not possible, certificates written on indices are always cash settled. Therefore, there is no price risk in the period between the settlement date and maturity, which is one of our assumptions[16]. We have a closer look at these boxes and compare them to the boxes written on single stocks. Table 4.5 provides an overview of all arbitrage opportunities of index boxes compared to boxes written on single stocks. About

[16] The interest rate risk for such a brief span may be neglected.

one in every 1000 index boxes is priced below its fair value. Thus, the ratio of arbitrage boxes in all regarded quotes is about 60% higher for index underlyings than for single stock underlyings. Especially boxes written on the DAX show a smaller average price difference to the fair value and a smaller standard deviation than boxes written on other indices or single stocks. The worst pricing is observed for boxes written on indices other than DAX or EURO STOXX 50.

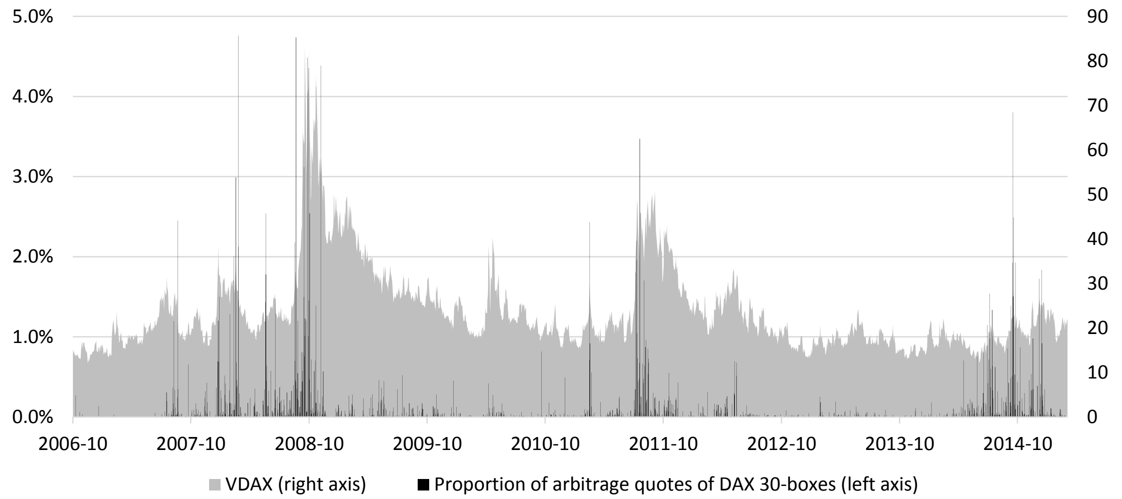
TABLE 4.5: Arbitrage by underlying: indices vs. stocks

Underlying	Box quotes	Arbitrage quotes		Price difference	
		Absolute	Mean proportion	Mean	SD
Indices	206,449,113	161,173	0.0010	0.0023	0.0041
DAX 30	149,480,500	123,355	0.0010	0.0021	0.0034
EURO STOXX 50	53,616,677	35,574	0.0010	0.0030	0.0054
Other	3,351,936	2,244	0.0052	0.0043	0.0091
Single stocks	580,937,410	253,132	0.0006	0.0034	0.0068
All quotes	787,386,523[1]	414,305	0.0007	0.0030	0.0059

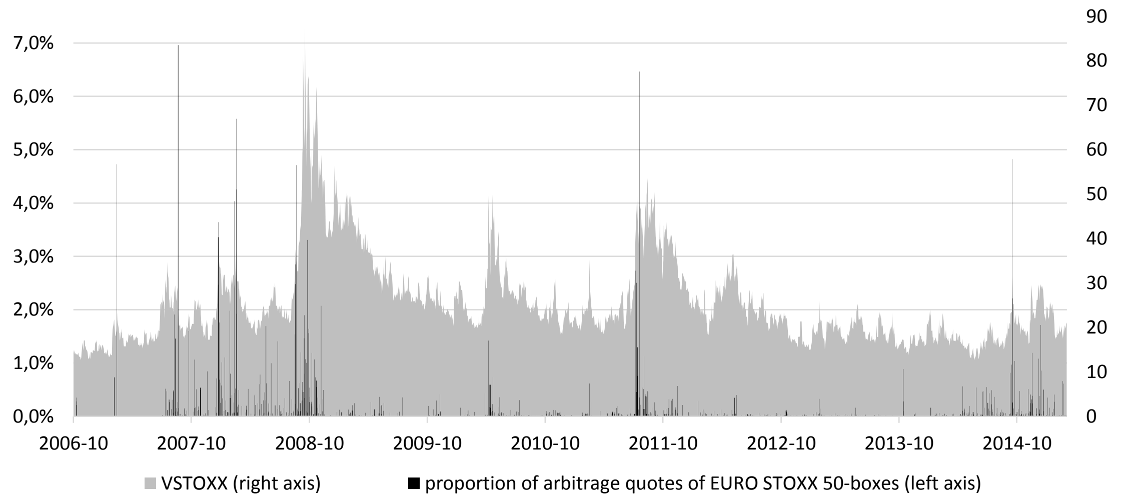
[1] The difference in total box quotes is due to the exclusion of boxes as explained in Section 4.5.1.

In order to make a decent statement of the influence of the underlying's volatility on arbitrage, we further analyze boxes written on the DAX 30 index and the EURO STOXX 50 index with respect to their volatility indices VDAX and VSTOXX, respectively. Figure 4.5 shows the proportions of arbitrage quotes compared to the developments of the two volatility indices. Evidently, accumulations of arbitrage quotes occur in times when the volatility indices are above normal levels. We test the influence of the demeaned volatility indices on the proportion of arbitrage quotes by estimating linear regression models. Quotes are accumulated on a monthly basis to obtain more distinct signals. Furthermore, we include a time trend variable as technical progress may also explain part of the pricing performance.

The estimation results are given in Table 4.6. On the one hand, for both indices the influence of volatility on the proportion of arbitrage is significantly positive with 0.0105% per one point increase of the VDAX and 0.0077% per one point increase of the VSTOXX, respectively. On the other hand, the trend variable t is not significantly different from zero in neither of the two regressions. Thus, technical progress does not lead to lower ratios of mispricings in the German certificates market. For an arbitrage trader these results have two implications. The number of arbitrage opportunities is not necessarily decreasing because of more precise pricing models and computer trading, and chances for risk-free profits are best in volatile markets.



(A) DAX 30 vs. VDAX



(B) EURO STOXX 50 vs. VSTOXX

FIGURE 4.5: Proportion of arbitrage quotes compared to the volatility of the underlying

4.5.2.5 Arbitrage by issuers

We analyze the arbitrage quotes by the respective issuers involved. To draw plausible conclusions we only focus on issuers that participate in at least 1000 boxes[17]. Due to the setup of this parity based study, we cannot see which part of the box, put warrant or discount certificate, is causing the underpricing of the box. However, the comparison of issuer combinations shows if certain issuers tend to *produce* comparatively more arbitrage box quotes than others. As a crosscheck, we also analyze those boxes where one issuer provides

[17] See Table 4.15 in Appendix A. The issuers considered are Barclays Bank, BHF-Bank, BNP Paribas, Commerzbank, Citibank, Deutsche Bank, DZ Bank, Goldman Sachs, Interactive Brokers, Landesbank Berlin, LBBW, Lang & Schwarz, Merrill Lynch, Macquarie, Morgan Stanley, Royal Bank of Scotland, Raiffeisen Centrobank, Société Générale, HSBC Trinkaus & Burkhardt, UBS, UniCredit Bank, Bankhaus Vontobel, WGZ BANK AG, and WestLB.

Table 4.6: Regression results of DAX and EURO STOXX 50 arbitrage

	DAX 30			EURO STOXX 50		
	$p_t^{\mathrm{DAX}} = \beta_0 + \beta_1 \mathrm{VDAX}_t + \beta_2 t + \varepsilon_t$			$p_t^{\mathrm{Stoxx}} = \beta_0 + \beta_1 \mathrm{VSTOXX}_t + \beta_2 t + \varepsilon_t$		
	Estimate	S.E.	t-Statistic	Estimate	S.E.	t-Statistic
β_0	0.0735**	0.0348	2.1101	0.1346***	0.0350	3.8409
β_1	0.0105***	0.0019	5.5026	0.0077***	0.0019	4.0797
β_2	0.0005	0.0006	0.7870	-0.0008	0.0006	-1.2862
n		101			101	
R^2		0.2394			0.1853	
F-stat.		15.4264			11.1456	

p_t^{DAX} and p_t^{Stoxx} (in %) are calculated according to Equation (4.19). VDAX and VSTOXX are demeaned series. The sample comprises 101 months from 11/2006 to 03/2015.

both parts of the box. If the underpricings of box portfolios are caused by inconsistent pricing methods or models, single issuer boxes should show a superior performance.

The proportion of arbitrage quotes by pairs of issuers is given in Table 4.7. The overall arbitrage proportion is given in the lower right corner and is 0.05%, which equals about one in every 2000 box quotes. Though, some of the issuers exhibit far higher ratios of arbitrage quotes. For the put issuers, we see the highest ratios of underpriced boxes for LBW, which is not quite conclusive as there are only 40 box participations with puts. High ratios are also found for boxes with INT or LSW as put issuers with average proportions of arbitrage quotes of 0.17% and 0.12%. For these issuers there are no actual credit spreads available such that the iBoxx Financial spread is applied. Even if this approximation results in general in a quite conservative risk surcharge, it may still be too low for some of the smaller issuers. Among the issuers with fully available credit spread information, CBK reveals an above average arbitrage proportion of 0.09% of all box quotes it participates in. Even the boxes where CBK issues both the put warrant and the discount certificate, are underpriced at 0.13% on average. The CDS of CBK seems to not fully reflect the default risk as considered by the market.

On the side of the discount certificate, the highest proportions of arbitrage prices are found among the issuers with the fewest products within the sample (BHF, LBW, ML, WLB). Besides these four banks, CBK again shows a high tendency to box prices below the fair value (0.09% or about 1 in every 1100 box quotes). The combination with CBK as issuer of the put warrant and BNP as issuer of the discount certificate shows the highest arbitrage proportion amongst those issuers where CDS information are available. The other way round (put warrant by BNP and discount certificate by CBK) reveals no extraordinary arbitrage.

The lowest ratios of arbitrage prices on the discount certificate side are found for INT, LBB, VON and GS (at most 0.02%) and thus among those issuers without available CDS data. On the put warrant side RCB, RBS and DZB exhibit the lowest proportions of arbitrage prices with 0.01%, 0.02% and 0.03%, respectively. Overall, mainly those issuers with comparatively small numbers of price data show the smallest ratios of underpricings.

The average differences of the risk-adjusted box prices to the arbitrage-free prices by pairs of issuers are presented in Table 4.8. The sample average is given in the lower right corner and is 0.30%. The highest average mispricing[18] is found for boxes with ML as issuer of the put warrant and RBS as discount certificate issuer with 2.09%. In general, the arbitrage quotes of these issuers show a high average price difference. Even boxes, where only RBS products are involved are considerably worse with an average 1.99% distance to the arbitrage-free box price. The smallest average mispricing is found for put-discount combinations of UNC and TUB (0.03%), CBK and BNP (0.05%) or CBK and TUB (0.06%).

Up to this point, we can conclude that the big players in the certificates market show a similar (mis-)pricing behavior as the smaller ones. Furthermore, we observe that boxes by only one issuer (elements marked with a circle in Tables 4.7 and 4.8) are on average priced more accurately than those with two issuers participating. Therefore, we isolate the single issuer boxes and test if the sample proportions are the same as for two issuer boxes by applying the normal approximation of the binomial test. To avoid distortions, we do not regard issuers that participate only on the put side or only on the discount side of a box or that have no CDS spread available. The results in Table 4.9 show that on average 0.0359% of all single issuer boxes are priced below the fair value. As the proportion for boxes by two different issuers is 0.0550%, the assumption can be overall verified at high significance. However, there are no significant differences of arbitrage proportions for CIT, DBK, EB, ML, RBS and SG. For two banks, CBK and TUB, there are even significantly more underpriced boxes among the single issuer boxes compared to having a second issuer involved. Given that our CDS data adequately reflects the issuers credit risk, this finding raises concerns about the adequacy of the different models used within these two banks. The fewest arbitrage opportunities are found for single issuer boxes of GS and DZB with slightly more than one in every 10,000 box quotes. In contrast, an analysis of the mean underpricings reveals no significant differences between two- and single issuer boxes (see Table 4.21 in Appendix B).

4.5.3 Profits of arbitrage trading

After we found that there is a significant number of mispricings in our sample, we are interested in the possible profits of an arbitrage trader in this market. We follow the minimum quoting volume requirements of the two considered exchanges EUWAX (Stuttgart) and Zertifikate Börse Frankfurt, which are 3,000 Euro or 10,000 units for leverage products like

[18] Here, we only consider pairs of issuers, where there are at least 4 arbitrage boxes.

TABLE 4.7: Relative share of arbitrage quotes by issuer and product class (in %)

Issuer of discount certificate	Issuer of put warrant: BNP	CBK	CIT	DBK	DZB	GS	ML	MQ	RBS	SG	TUB	UBS	UNC	INT	LBW	LSW	RCB	VON	all
BC	0.08	0.04	0.03	0.03	0.01	0.08	-	0.10	0.01	0.02	0.03	0.08	0.11	0.09	-	0.13	0.03	0.05	0.06
BNP	0.02	0.70	0.05	0.10	0.04	0.08	0.13	0.03	0.02	0.14	0.03	0.07	0.14	0.20	-	0.15	0.01	0.05	0.05
CBK	0.06	0.13	0.09	0.09	0.06	0.12	0.16	0.04	0.04	0.17	0.07	0.11	0.19	0.48	0.51	0.16	0.01	0.07	0.09
CIT	0.05	0.14	0.06	0.07	0.05	0.06	0.01	0.10	0.01	0.12	0.05	0.09	0.10	0.24	0.81	0.10	0.01	0.06	0.07
DBK	0.05	0.10	0.06	0.05	0.04	0.06	0.09	0.04	0.01	0.11	0.05	0.06	0.07	0.27	1.12	0.13	0.02	0.05	0.06
DZB	0.03	0.05	0.01	0.03	0.02	0.03	0.04	0.05	0.02	0.07	0.01	0.03	0.02	0.09	-	0.11	0.01	0.03	0.03
GS	0.01	0.02	0.02	0.02	0.00	0.01	0.03	0.03	0.02	0.02	0.01	0.02	0.06	0.02	-	0.04	0.00	0.02	0.02
ML	0.13	0.57	0.30	0.30	0.04	0.26	0.08	0.24	0.12	0.06	0.58	0.55	0.24	0.07	-	0.18	0.05	0.10	0.15
MQ	0.05	0.13	0.08	0.20	0.09	0.14	0.03	0.03	0.15	0.20	0.12	0.08	0.08	0.03	1.08	0.14	0.04	0.04	0.08
MS	0.05	0.09	0.09	0.08	0.04	0.05	0.02	0.05	0.04	0.16	0.08	0.13	0.49	0.07	-	0.13	0.01	0.04	0.07
RBS	0.03	0.14	0.03	0.06	0.02	0.07	0.03	0.04	0.02	0.09	0.00	0.03	0.34	0.08	-	0.08	0.00	0.02	0.04
SG	0.04	0.46	0.03	0.07	0.01	0.04	0.00	0.03	0.01	0.07	0.61	0.03	0.08	0.03	-	0.09	0.00	0.02	0.04
TUB	0.02	0.15	0.03	0.04	0.01	0.04	0.03	0.04	0.01	0.06	0.06	0.02	0.07	0.08	-	0.11	0.01	0.03	0.03
UBS	0.03	0.27	0.06	0.12	0.03	0.07	0.07	0.11	0.03	0.10	0.09	0.03	0.15	0.14	0.94	0.15	0.00	0.05	0.06
UNC	0.02	0.05	0.02	0.05	0.01	0.02	-	0.33	0.01	0.04	0.04	0.04	0.02	0.06	-	0.12	0.00	0.03	0.03
BHF	0.20	0.10	0.08	0.12	0.08	0.06	-	0.10	0.14	0.30	0.08	-	-	-	-	0.29	-	0.43	0.15
INT	0.01	-	-	-	-	0.01	-	0.02	0.01	0.00	-	-	-	0.01	-	0.04	-	0.00	0.01
LBB	0.01	0.28	0.05	0.02	0.02	-	-	-	0.01	0.01	0.30	0.01	-	0.22	-	0.04	-	0.01	0.01
LBW	0.14	0.40	0.17	0.34	0.08	0.14	0.02	0.22	0.14	0.18	0.42	0.13	0.01	0.35	-	0.13	0.06	0.09	0.16
LSW	0.02	-	-	-	-	0.03	-	-	-	-	-	-	-	-	-	0.10	0.02	0.07	0.04
RCB	0.05	0.10	-	0.07	0.05	0.08	1.04	0.14	0.02	0.08	-	0.05	0.23	0.04	-	0.02	0.00	0.04	0.04
VON	0.02	0.03	0.01	0.02	0.02	0.03	0.01	0.03	0.00	0.04	0.01	0.02	0.02	0.06	-	0.08	0.00	0.02	0.02
WGZ	0.08	0.05	0.02	0.04	0.02	0.06	-	0.14	0.06	0.07	0.03	0.02	0.01	0.15	0.08	0.06	0.01	0.05	0.05
WLB	0.11	0.28	0.13	0.17	0.13	0.13	-	0.11	0.25	0.22	0.45	0.19	-	0.03	-	0.13	0.01	0.09	0.13
All	0.04	0.09	0.05	0.06	0.03	0.06	0.08	0.05	0.02	0.10	0.04	0.05	0.07	0.17	0.79	0.12	0.01	0.04	0.05

Gray shaded area contains issuers where full CDS information is available. Circles mark entries where put warrant and discount certificate are supplied by the same issuer.

TABLE 4.8: Average difference to arbitrage-free price by issuer and product class (in %)

Issuer of discount certificate	Issuer of put warrant: BNP	CBK	CIT	DBK	DZB	GS	ML	MQ	RBS	SG	TUB	UBS	UNC	INT	LBW	LSW	RCB	VON	all
BC	0.33	0.44	0.57	0.52	0.20	0.38	-	0.31	0.38	0.21	0.45	0.26	0.27	0.16	-	0.39	0.89	0.33	0.35
BNP	0.22	0.05	0.08	0.12	0.29	0.20	0.72	0.34	0.48	0.39	0.00*	0.17	0.08	0.10	-	0.52	0.41	0.27	0.22
CBK	0.29	0.23	0.24	0.26	0.25	0.25	0.55	0.38	0.52	0.35	0.26	0.20	0.20	0.18	0.74	0.55	0.29	0.28	0.25
CIT	0.30	0.19	0.21	0.21	0.22	0.22	5.81*	0.56	0.44	0.24	0.18	0.18	0.17	0.16	0.91	0.33	0.87	0.25	0.22
DBK	0.24	0.42	0.22	0.29	0.30	0.30	0.59	0.28	0.40	0.42	0.33	0.19	0.17	0.15	0.78	0.49	1.74	0.27	0.28
DZB	0.28	0.35	0.24	0.36	0.38	0.32	0.64	0.34	0.63	0.35	0.31	0.21	0.20	0.18	-	0.58	0.63	0.33	0.31
GS	0.39	0.28	0.45	0.31	0.45	0.42	0.24	0.56	0.70	0.39	0.48	0.26	0.28	0.17	-	0.87	0.36	0.41	0.38
ML	0.85	0.25	0.32	0.27	1.42	0.52	0.27	0.65	0.21	0.51	0.25	0.37	0.34	0.57	-	0.91	0.41	0.92	0.67
MQ	0.42	0.52	0.55	0.55	0.50	0.40	1.04	0.43	0.62	0.65	0.44	0.30	0.13	0.24	0.88	0.67	0.35	0.36	0.49
MS	0.48	0.83	0.70	0.43	0.54	0.67	0.12	0.45	0.26	1.04	0.39	0.39	0.27	0.26	-	0.74	0.70*	0.41	0.55
RBS	0.48	1.53	0.97	0.24	0.25	0.21	2.09	0.40	1.99	0.62	1.91*	0.18	0.24	0.11	-	0.71	0.15	0.26	0.46
SG	0.37	0.11	0.14	0.29	0.24	0.29	0.29*	0.33	0.66	0.36	0.18	0.13	0.13	0.13	-	0.52	0.48	0.24	0.30
TUB	0.27	0.06	0.12	0.09	0.56	0.17	0.15	0.26	0.31	0.31	0.08	0.31	0.03	0.13	-	0.53	0.33	0.39	0.31
UBS	0.22	0.24	0.31	0.25	0.35	0.24	0.38	0.39	0.37	0.29	0.33	0.26	0.20	0.16	1.11	0.31	0.07	0.25	0.26
UNC	0.39	0.27	0.11	0.27	0.40	0.41	-	0.32	0.15	0.35	0.12	0.30	0.28	0.37	-	0.40	0.02*	0.45	0.33
BHF	0.47	0.53	0.67	0.65	0.73	1.02	-	0.51	0.44	0.50	0.52	-	-	-	-	0.59	-	0.11	0.52
INT	0.33	-	-	-	-	0.18	-	0.38	0.05*	0.02*	-	-	-	0.19	-	0.66	-	0.14	0.38
LBB	0.17	0.09*	0.70*	0.16*	0.06	-	-	-	0.02*	0.28	0.14*	0.23	-	0.09	-	0.74	-	0.16	0.21
LBW	0.28	0.44	0.52	0.40	0.46	0.33	0.27*	0.33	0.50	0.42	0.51	0.23	0.20*	0.25	-	0.50	0.58	0.32	0.36
LSW	0.75	-	-	-	-	0.13*	-	-	-	-	-	-	-	-	-	0.54	0.02*	0.11	0.37
RCB	0.19	0.84	-	0.71	0.05	0.31	0.66	0.54	1.49	0.15	-	0.15	0.43	0.09	-	0.59	0.51	0.20	0.32
VON	0.27	0.20	0.53	0.37	0.54	0.26	1.61*	0.32	0.26	0.39	0.34	0.25	0.25	0.21	-	0.48	0.61	0.47	0.35
WGZ	0.38	0.67	0.57	0.53	0.77	0.30	-	0.35	0.92	0.43	0.81	0.16	0.12	0.18	6.95*	0.50	0.22*	0.34	0.45
WLB	0.43	0.57	0.44	0.48	0.38	0.39	-	0.43	0.56	0.53	0.55	0.66	-	0.20	-	0.34	0.13*	0.38	0.45
All	0.32	0.32	0.28	0.29	0.32	0.28	0.64	0.40	0.63	0.38	0.32	0.21	0.21	0.17	0.99	0.53	0.73	0.32	0.30

Gray shaded area contains issuers where full CDS information is available. Circles mark entries where put warrant and discount certificate are supplied by the same issuer. * denotes pairs of issuers, where we identified at most 3 arbitrage prices.

Table 4.9: Proportion of arbitrage quotes by issuers and box participation (only issuers with available CDS spreads)

Issuer	One-sided participations		Single issuer boxes		$H_0: p_2 = p_1$	
	# Box quotes	thereof arbitrage	# Box quotes	thereof arbitrage	Z-Score $\left(\frac{\hat{p}_2-\hat{p}_1}{\hat{\sigma}(\hat{p}_2-\hat{p}_1)}\right)$	p-value
BNP	163,809,926	0.0445%	28,919,173	0.0234%	2.8048	0.0025***
CBK	114,652,852	0.0875%	5,643,211	0.1220%	-3.6551	0.0001***
CIT	68,343,350	0.0639%	6,464,000	0.0619%	0.1663	0.4340
DBK	104,370,704	0.0608%	9,986,460	0.0525%	0.8598	0.1949
DZB	107,889,369	0.0325%	10,635,684	0.0161%	1.7497	0.0401*
EB	356,125	0.2207%	116,944	0.0829%	0.8938	0.1857
GS	77,964,421	0.0422%	7,065,119	0.0123%	2.7169	0.0033***
ML	4,561,288	0.1490%	10,266	0.0779%	1.5190	0.0644
MQ	24,534,335	0.0713%	2,762,441	0.0331%	1.9463	0.0258*
RBS	26,048,529	0.0367%	1,028,791	0.0241%	0.6474	0.2587
SG	26,433,308	0.0716%	1,298,658	0.0699%	0.0872	0.4652
TUB	46,475,723	0.0287%	122,527	0.0530%	-1.6554	0.0489*
UBS	129,184,523	0.0606%	9,972,595	0.0340%	3.0731	0.0011***
UNC	46,056,439	0.0508%	5,938,185	0.0202%	2.1537	0.0156**
All	470,340,446	0.0550%	89,964,054	0.0359%	4.2548	0.0000***

This table only regards box participations between the issuers listed here. *One-sided participations* contain only boxes where a particular issuer provides either the put warrant or the discount certificate. *Single issuer boxes* are boxes where a particular issuer provides both put warrant and discount certificate. *, **, and *** denote (two-sided) statistical significance at the 10%, 5%, and 1% level, respectively.

warrants, and 10,000 Euro or 10,000 units for investment products like discount certificates (see EUWAX, 2015; Börse Frankfurt, 2015). In practice, most issuers guarantee a much higher volume per trade of 100,000 units and more such that our results only reflect the minimum possible arbitrage gains.

Furthermore, we presume a signalling effect in the moment we buy an underpriced product. A rational issuer might immediately realize the mistake and correct the quoted price. For this reason, we do not regard directly consecutive arbitrage quotes. This applies to about 10% of the 414,305 arbitrage quotes resulting in 373,419 quotes remaining. As soon as there is at least one arbitrage-free quote between two arbitrage quotes, we count these as two different arbitrage prices.

As a further consequence of the volume restriction, we cannot trade boxes where the put or the discount certificate are also part of another box at the exact same date and time. This applies to more than half of the products that participate in the identified arbitrage boxes. As the profit at maturity is known ex ante, we only trade the box with the highest prospective profit in such a situation. This leads to a final sample of 162,186 trades, which are analyzed in this setup. However, we cannot fully exclude that the volume restriction is violated when selling the box[19].

Trading fees are varied from 0 to 6 Euro per trade reflecting the different types of investors. While 6 Euro is a common fee for retail investors or semi-professional traders when trading via discount brokers, the costs of an individual trade might be significantly lower for institutional investors like banks or hedge funds. In the base scenario trading fees are neglected.

We implement the arbitrage trading strategy in two ways as described in Section 4.3.4, on the one hand in a static way as buy-and-hold strategy, and on the other hand in a dynamic way.

4.5.3.1 Static arbitrage strategy

Once an arbitrage quote occurs, we determine the required units of put warrants and discount certificates per box and buy the maximum number of boxes under the volume restrictions mentioned above. Non-divisibility of contracts is taken into account, and there are no investing restrictions. In this scenario the future profit is known as soon as the underpricing is observed as the payoff at maturity is certain and equals the cap level. Profits and returns are calculated according to Equations (4.15) and (4.16). The results of such a strategy for different trading fees is presented in Table 4.10. Unsurprisingly, the number of profitable boxes decreases with higher trading fees. At the same time, the average return per box increases as only those boxes remain profitable, which show a comparatively high difference to the arbitrage-free price. The sum of all profits over the sample period of about 8 years is at least about 3.5 million Euro. Recalling that we only analyze four quotes per day, the overall possible arbitrage profits might be even larger. The average time to maturity is also increasing with higher trading fees. This is in line with our finding in Section 4.5.2.3 that mispricings slightly increase with a longer time to maturity.

Even if the overall arbitrage profits could be higher if we considered market prices more frequently than four times per day, the required capital would also increase. Thus, because of regulatory restrictions and usual investing limits for traders, a buy-and-hold strategy as presented here is not very advisable to be implemented.

4.5.3.2 Dynamic arbitrage strategy

In a more realistic, dynamic implementation of an arbitrage trading strategy profitable positions are closed to set free liquidity for new trades. The results given in Table 4.11 show

[19] This applies to at most 4.7% of all box resales with at most 6 boxes containing the same put warrant or discount certificate at the same query time. Therefore, this issue, if relevant at all, is neglected.

TABLE 4.10: Static arbitrage strategy: mean profits at different trading fees

Fee	Traded boxes	Mean portfolio (m.)	Profit per box		Sum of profits (m.)	Return		Days to mat.	
			Mean	SD		Mean	SD	Mean	SD
0	157,820	36.57	31.12	62.44	4.91	0.0029	0.0057	72.42	81.63
1	137,177	32.93	33.66	65.78	4.62	0.0031	0.0061	75.01	83.29
2	122,379	29.96	35.61	68.59	4.36	0.0033	0.0063	76.42	84.25
3	110,514	27.49	37.32	71.18	4.13	0.0034	0.0065	77.54	85.12
4	100,646	25.49	38.88	73.63	3.91	0.0036	0.0068	78.78	86.01
5	92,258	23.72	40.32	75.96	3.72	0.0037	0.0070	79.90	87.07
6	84,727	22.11	41.81	78.32	3.54	0.0038	0.0072	80.96	87.96

Because of indivisibility of contracts, there are boxes with slightly negative profits that are not included in the analysis. Fees, portfolio volumes and profits are in Euro. Return figures are not time-adjusted.

TABLE 4.11: Dynamic arbitrage strategy: mean profits at different trading fees

Fee	Traded boxes	Mean portfolio (m.)	Profit per box		Sum of profits (m.)	Return		Days hold	
			Mean	SD		Mean	SD	Mean	SD
0	148,465	2.52	53.90	79.50	8.00	0.0050	0.0074	3.77	17.37
1	130,199	2.38	56.82	82.80	7.40	0.0052	0.0077	4.16	18.40
2	116,444	2.26	59.03	85.75	6.87	0.0054	0.0080	4.54	19.35
3	105,358	2.17	60.93	88.47	6.42	0.0056	0.0082	4.89	20.00
4	96,062	2.10	62.62	90.96	6.02	0.0057	0.0085	5.24	20.52
5	88,053	2.04	64.30	93.41	5.66	0.0059	0.0087	5.67	21.39
6	80,974	1.99	65.93	95.90	5.34	0.0060	0.0089	6.09	22.08

Fees, portfolio volumes and profits are in Euro. Return figures are not time-adjusted.

that the invested capital decreases remarkably while at the same time the average return per box as well as the overall profits increase despite of a smaller absolute number of trades. A main reason is that bid prices at which boxes are sold are regularly at least slightly above the arbitrage-free price. Secondly, there is an immense reduction of the average holding period from about 80 days in the buy-and-hold strategy to about 5 days in the dynamic strategy resulting in fewer costs of capital. The advantage of a shorter credit risk insurance period is not even considered here, as CDS are not resold on a secondary market (see assumption (A.4) in Section 4.3.3).

In Figure 4.6 we compare the quarterly profits of both strategies for a transaction fee of 6 Euro per trade. When there are more underpriced boxes as a result of a higher market volatility (see Figure 4.3), arbitrage profits are also higher. However, within the dynamic strategy profits can usually be realized within hours or days while a trader following a buy-and-hold strategy has to wait until maturity such that profits are postponed to following periods depending on the remaining time to maturity.

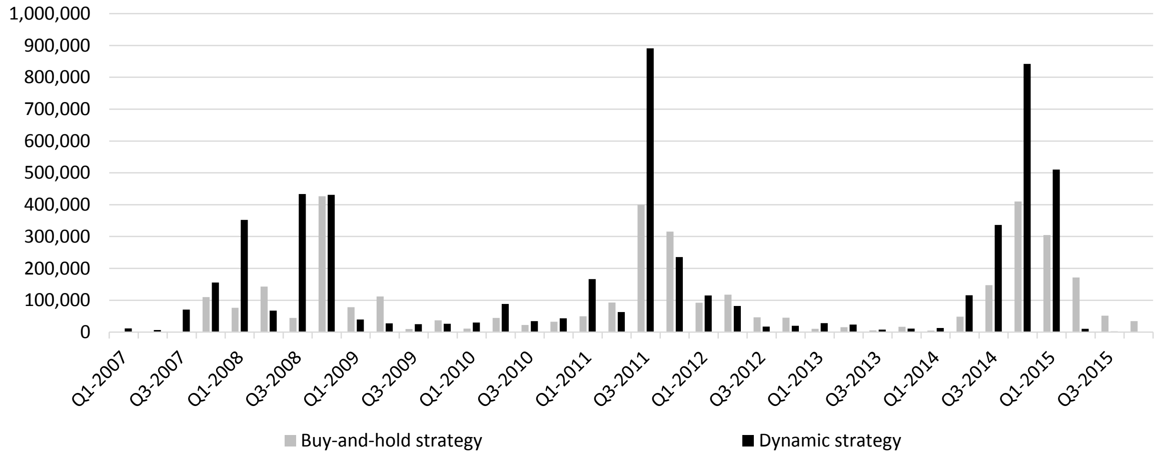


FIGURE 4.6: Profits in Euro per quarter (close of trade) by arbitrage strategy (fee = 6 Euro)

4.5.4 Robustness analysis

Before we draw further remarks of our results, we check the robustness of the most crucial assumptions. We analyze the time between the timestamps of the quotes of put warrants and discount certificates as we assume all quoted prices to be valid at the time of the query regardless of the actual timestamp (see Section 4.4). Furthermore, we recalculate profits in two ways. By neglecting issuers without actual CDS information, we control for the iBoxx approximation of default risk, and we check possible liquidity or trading restrictions by trading boxes only if they show an underpricing of 1% or more.

4.5.4.1 Time between quotes of discounter and put

An important requirement of the two considered exchanges in our study, EUWAX and Zertifikate Börse Frankfurt, is the obligation for issuers of structured financial products to submit quotes for their products between 9:00 am and 7:55 pm. Even in times without any trading activity, prices have to be renewed every 30 to 240 minutes (see Börse Frankfurt, 2014). Therefore, when the last available quotes of put warrants and discount certificates are gathered at the four fixed points of time on each trading day, the actual timestamps of the quote may be older. In particular, the timestamps of the two products are likely to differ by several minutes to some hours. However, a crucial assumption of our study is that the last available quote is always valid and tradable.

Figure 4.7 shows the number of arbitrage boxes (cleaned sample according to Section 4.5.1) by the difference in timestamps of the involved products. The majority of arbitrage quotes occurs at acceptable differences of quote timestamps such that we can assume that the identified arbitrage opportunities are actually tradable. Additionally, the plot of the average relative difference of the arbitrage box price and the arbitrage-free price in Figure 4.7

indicates no relevant dependence on the time difference in timestamps of put warrant and discount certificate.[20]

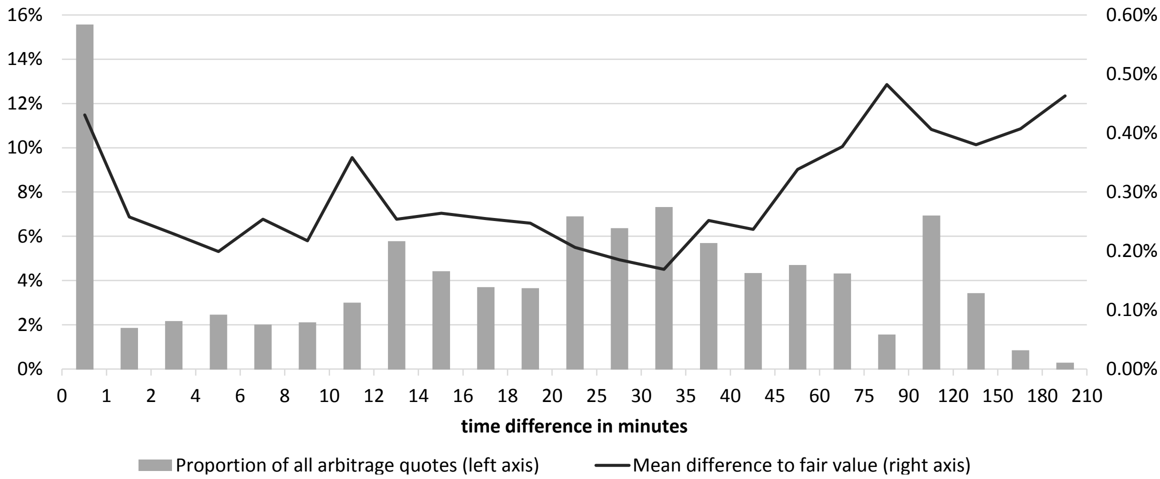


Figure 4.7: Difference between timestamps of put warrant and discount certificate per arbitrage quote (in minutes)

4.5.4.2 Only issuers with full CDS information

In order to account for issuer default risk, we adjust the market prices of put warrants and discount certificates using the approximation by Hull and White (1995) as described in Equation (4.10). For issuers with no available CDS spread, we use the difference between the yield of the iBoxx Europe Financial bond index and the risk-free rate. In our main results we did not see obvious differences for those issuers. However, if the approximation is far too conservative, we see less and smaller arbitrage opportunities such that the results could be biased. In contrast, if the actual credit risk is not fully covered by the iBoxx spread, there would be more arbitrage boxes with higher price differences. Due to our conservative setup of the study, the latter are removed by the sample cleaning as described in Section 4.5.1.

We recalculate the arbitrage profits for both strategies, but leave out all issuers with no actual CDS information to see if there are major differences to the profits presented in Section 4.5.3. For trading fees of 0 and 6 Euro the results are given in Table 4.12. The number of traded boxes decreases by about 20% in all four scenarios. All other relevant figures remain more or less unchanged. Therefore, we conclude that there are no major distortions by using the iBoxx spread, except that some arbitrage opportunities might be unidentified because of a too expensive risk insurance.

[20] The median time difference is 22.1 minutes. A linear regression of price differences on quote time differences (in minutes) results in a significant positive coefficient of 0.0007, which indicates an increase of underpricing of 0.0428 percentage points per 60 minutes differences of timestamps.

TABLE 4.12: Arbitrage profits: only issuers with full CDS information

Fee	Traded boxes	Mean portfolio (m.)	Profit per box		Sum of profits (m.)	Return		Days hold	
			Mean	SD		Mean	SD	Mean	SD
Static arbitrage strategy									
0	123,501	29.64	30.73	58.53	3.80	0.0028	0.0054	75.32	83.26
6	67,286	17.91	40.31	72.44	2.71	0.0037	0.0066	82.83	88.39
Dynamic arbitrage strategy									
0	116,934	1.96	53.28	75.14	6.23	0.0049	0.0070	3.73	18.30
6	64,166	1.59	63.79	89.81	4.09	0.0058	0.0083	6.20	23.19

Fees, portfolio volumes, and profits are in Euro. Return figures are not time-adjusted.

4.5.4.3 Only trade for noteworthy profits

As shown in Table 4.2, about 95% of all arbitrage quotes show a difference to the respective arbitrage-free box price of at most 1%. More than 40% of those prices are even only 0.10% or less below the fair value. The arbitrage profit of such boxes is usually low. A trader under liquidity restrictions may therefore only invest if the expected profit is noteworthy. Furthermore, small box price differences might be due to minor data or methodological issues.

We recalculate the arbitrage profit neglecting all arbitrage quotes which are less than 1% below the arbitrage-free box price. By this measure only about 5% of the trades regarded in the main analysis remain. The results for trading fees of 0 and 6 Euro are given in Table 4.13. As most of these boxes' profits compensate the trading fees, the number of profitable trades is similar or even the same in all four presented scenarios. Furthermore, the volume per trade is quite homogeneous such that the average capital invested over the sample period is proportionally reduced by more than 90%. In contrast to the main analysis (see Tables 4.10 and 4.11), we clearly observe that higher trading fees lead to longer holding periods within the dynamic strategy, and the average invested capital increases. At the same time, the average profit per traded box is about five to seven times as high in case of the buy-and-hold arbitrage strategy (228/216 Euro vs. 31/41 Euro). The difference in mean profits between the '0 Euro' and the '6 Euro' scenario is about 12 Euro, and therefore can almost completely be explained by the trading fees. The dynamic strategy achieves on average a profit of 263 to 280 Euro per traded box, which is more than five times higher compared to the main analysis. Most important, the overall sum of all profits decreases by 54% to 65% in the static strategy and by 65% to 75% in the dynamic arbitrage strategy, which is far less compared to the reduction of the trading volume. In other words, about 5% of all trades account for 25% to 46% of the overall profits, depending on order fees and arbitrage strategy.

Table 4.13: Arbitrage profits: only underpricings of 1% and more

Fee	Traded boxes	Mean portfolio (m.)	Profit per box		Sum of profits (m.)	Return		Days hold	
			Mean	SD		Mean	SD	Mean	SD
Static arbitrage strategy									
0	7,549	2.91	228.90	172.17	1.73	0.0212	0.0158	121.31	122.41
6	7,549	2.91	216.80	172.15	1.64	0.0201	0.0157	121.31	122.41
Dynamic arbitrage strategy									
0	7,274	0.14	280.70	199.85	2.04	0.0263	0.0187	4.84	30.27
6	7,263	0.18	263.08	198.80	1.91	0.0246	0.0185	6.65	32.04

Fees, portfolio volumes, and profits are in Euro. Return figures are not time-adjusted.

4.5.5 Discussion

For the sample period from October 2006 to April 2015 we analyze more than 794 million prices of more than 1.4 million box portfolios, each consisting of a discount certificate and a matching put warrant. After correcting for data issues, we identify 414,305 quotes where the risk-adjusted market price of the portfolio is below the arbitrage-free price. Thus, about 0.05%, or one in every 2,000, observed quotes gives the opportunity for risk-free profits. With an average underpricing of 0.30% these boxes allow for a profit of at least 5.34 million Euro by following a dynamic arbitrage strategy and assuming transaction fees of 6 Euro per trade. At this point we revisit our main assumptions and discuss the main research question, whether or not these findings actually indicate market inefficiency.

Since we have no detailed information, we assume all contracts to be cash settled rather than having a physical delivery of the underlying. As outlined in Section 4.3.3, a physical delivery always entails the price risk of the delivered underlying during the period between settlement and the actual delivery. We control for this issue by analyzing the performance of boxes written on indices, which are inevitably cash settled and do not find any generally different characteristics compared to boxes written on single stocks.

Furthermore, we control for possible issuer default risk by following the approach of Hull and White (1995) and adjust the market prices with the CDS spreads of the relevant issuer. The primary aim of this measure is to establish the risk-free world for our study rather than purchasing an actual risk insurance in an economic sense. Therefore, we do not consider it to be an issue that CDS contracts may not be tradable in a tailored way. Our results show fewer arbitrage opportunities for single issuer boxes. Assuming that the pricing model is consistent within one and the same financial institution, this can be interpreted as a proof for the applicability of the credit risk adjustment by Hull and White. For a practical implementation we recommend one of the two following workarounds. On the one hand, the more risk-averse arbitrage trader may be holding CDS of a relevant issuer with a nominal that covers the average invested capital in products of this issuer. On the other hand, a dynamic arbitrage strategy only requires short holding periods of several days such that an arbitrage trader may knowingly take the risks and not buy any default insurance at all.

A further issue is the opportunity of reporting mistrades. At both considered exchanges, Börse Frankfurt and EUWAX, '*a transaction can be subsequently cancelled (...) if the transaction came about as a result of a technical failure or was based on an order that was obviously placed at a price that was not the market standard at the time the transaction was concluded, or at a market maker quote that was not in line with the market*' (EUWAX, 2015). This option entails a significant risk for arbitrage traders who buy a portfolio consisting of two different financial products. If the mispriced part of the box is reported and approved as a mistrade, the trader is left with the full price risk in the remaining contract. Both exchanges publish lists of mistrades of which neither contained a trade from our study.

In general, for every assumption we choose the more conservative alternative in order to reduce the chance that a box price is below the fair value. This applies for example for the day count convention, the use for a single rate for borrowing and lending, or treating American-type options as European ones. Additionally, the available data set contains only four queries per day. It is therefore most certain that we only identify the tip of the iceberg, and there are more quotes allowing for risk-free profits. The overall profits could also be higher as most issuers allow multiple trading volumes instead of the minimum trading restrictions we implemented.

Consequently, we cannot confirm the efficient market hypothesis in the German certificates market in general. When taking into account the actual costs for running an arbitrage trading desk, we conclude that arbitrage opportunities exist especially at low transaction costs. At higher fees per trade, there are periods where the average arbitrage profits may not fully cover the costs for trading systems or license fees.

4.6 Conclusion

This article provides the first empirical investigation of arbitrage in the German certificates market. The vast majority of literature on this issue focuses on U.S. option and futures markets and hardly finds significant arbitrage. Arbitrage is found when markets are highly volatile or when transaction costs are low. We apply the model independent put-call parity to investigate market efficiency in the German certificates market. For this purpose, we build risk-free portfolios of put warrants and discount certificates that we refer to as boxes. Our method is straightforward. Whenever the risk-adjusted price of such a box is below the discounted cap or strike price, there is the chance of a risk-free profit and thus arbitrage. If found, we analyze the characteristics of the arbitrage boxes like the time of appearance, the remaining time to maturity and the issuers of the products involved.

We identify four major determinants of arbitrage. The time of the day, the day of the week, the volatility of the underlying asset and the issuing financial institution. We observe the highest differences between market and arbitrage-free box prices in the morning and in the evening with about 0.35%. Regarding the day of the week, the effect is stronger on Fridays with an average mispricing of 0.40% compared to about 0.28% from Monday to Thursday. Furthermore, we confirm the finding of Hemler and Miller (1997) and find a significant positive relationship between the volatility of the stock indices DAX 30 and EURO STOXX 50 and the proportion of arbitrage. In contrast, we find no proof for the validity of the life-cycle hypotheses by Entrop et al. (2015). With respect to the issuers of arbitrage boxes, we see that almost all issuers perform significantly better if they provide both parts of a box, the put warrant and the discount certificate, which indicates that at least within one and the same financial institution pricing models are consistent.

Based on four queries per day, and depending on strategy and trading fees, the maximum achievable arbitrage profit is between 3.5 and 8.0 million Euro over the whole sample period of more than 8 years. However, profits are not equally distributed over time, but rather occur cumulatively in periods with a high market volatility. Thus, in less volatile markets, arbitrage profits are lower and may not cover the fix costs for an arbitrage trading desk. Taken together, we cannot confirm market efficiency in the market for structured financial products in Germany in general, but arbitrage diminishes when considering higher costs for trading or technical equipment and license fees.

Appendices

A Issuers and underlyings

TABLE 4.14: List of issuers and number of products in sample

Issuer	Symbol	Puts	Discount certificates
	Full CDS information		
Bayerische Landesbank	BAY	-	2
Barclays Bank PLC	BC	-	7,775
BNP Paribas	BNP	70,869	62,525
Commerzbank	CBK	37,173	96,358
Citibank	CIT	39,119	49,216
Credit Suisse	CSF	-	2
Deutsche Bank	DBK	45,045	54,434
DZ Bank	DZB	28,528	63,835
Erste Bank	EB	671	326
Goldman Sachs	GS	53,397	30,717
JP Morgan	JPM	12	6
Merrill Lynch	ML	213	4,089
Macquarie	MQ	9,355	18,026
Morgan Stanley	MS	6	4,157
Nomura	NOM	1	-
Rabobank	RB	-	1
Royal Bank of Scotland	RBS	6,044	26,917
Societe Generale	SG	6,219	12,164
HSBC Trinkaus & Burkhardt	TUB	7,462	28,597
UBS	UBS	48,006	32,422
UniCredit Bank	UNC	20,624	23,921
	Partial / no CDS information		
BHF-Bank	BHF	-	842
DekaBank	DKB	-	5
Leonteq Securities AG	EFG	-	121
Interactive Brokers	INT	15,999	449
Landesbank Berlin	LBB	-	795
Landesbank Hessen-Thüringen (Helaba)	LBH	-	22
LBBW	LBW	19	2,056
Lang & Schwarz	LSW	3,496	35
Österreichische Volksbanken AG	OEV	-	7
Raiffeisen Centrobank AG	RCB	1,168	1,025
Bankhaus Vontobel	VON	51,816	36,861
WGZ BANK AG	WGZ	-	977
WestLB	WLB	-	834
Sum		445,242	559,519

TABLE 4.15: Box participations and box quotes per issuer

Issuer	Puts		Discount certificates		Put & Discount certificate	
	Box partici-pations	Box quotes	Box partici-pations	Box quotes	Box partici-pations	Box quotes
Complete CDS information						
BAY	-	-	2	176	-	-
BC	-	-	18,746	8,936,356	-	-
BNP	276,294	188,803,704	139,133	70,405,208	41,532	28,919,173
CBK	74,415	37,116,046	192,815	113,921,778	8,945	5,643,211
CIT	72,624	33,711,666	129,691	65,545,779	13,153	6,464,000
CSF	-	-	7	983	-	-
DBK	103,617	60,620,388	146,706	84,707,751	15,919	9,986,460
DZB	105,587	59,486,025	167,459	95,366,332	17,852	10,635,684
EB	868	473,785	272	121,899	222	116,944
GS	145,610	46,692,990	106,115	58,056,003	19,453	7,065,119
JPM	-	-	2	1,601	-	-
ML	1,106	813,997	11,246	6,066,327	25	10,266
MQ	40,814	19,161,356	33,830	17,083,756	5,847	2,762,441
MS	11	1,107	12,230	8,446,657	4	424
NOM	-	-	-	-	-	-
RB	-	-	6	3,908	-	-
RBS	14,139	11,620,289	41,431	25,662,841	1,134	1,028,791
SG	34,483	17,885,385	30,339	17,658,071	2,132	1,298,658
TUB	15,377	13,015,507	76,092	47,442,934	84	122,527
UBS	189,158	124,447,001	89,252	47,149,495	14,761	9,972,595
UNC	42,028	22,678,389	82,950	46,268,898	10,174	5,938,185
Partial / no CDS information						
BHF	-	-	2,104	1,685,408	-	-
DKB	-	-	9	2,421	-	-
EFG	-	-	730	562,283	-	-
INT	79,226	14,308,230	1,920	653,308	194	71,482
LBB	-	-	2,503	1,146,441	-	-
LBH	-	-	86	16,346	-	-
LBW	40	42,530	6,325	3,324,501	-	-
LSW	22,861	14,819,838	100	79,989	12	11,208
OEV	-	-	7	3,916	-	-
RCB	6,848	6,005,128	2,098	1,510,127	310	334,843
VON	188,550	123,098,727	112,483	68,659,144	19,231	13,853,943
WGZ	-	-	4,548	3,157,707	-	-
WLB	-	-	2,419	1,153,744	-	-
Sum	1,413,656	794,802,088	1,413,656	794,802,088	170,984	104,235,954

TABLE 4.16: Number of boxes per underlying

Underlying	Boxes	Underlying	Boxes
DAX (Performance-Index)	359,748	Südzucker	2,426
EURO STOXX 50	71,875	GEA Group Aktiengesellschaft	2,403
Daimler AG	40,139	Wacker Chemie	2,318
BASF SE	38,525	Banco Bilbao	2,302
Deutsche Bank	37,430	Hugo Boss AG	2,218
E.ON	35,584	Repsol YPF	2,181
BMW	35,381	DIALOG SEMICOND. LS-,10	2,082
Volkswagen Vz	34,086	FUCHS PETROL.AG VZO O.N.	1,986
Siemens	33,761	Qiagen	1,968
Bayer AG	33,628	RHEINMETALL AG	1,904
Deutsche Telekom	30,736	Aareal Bank	1,901
Commerzbank	28,077	United Internet	1,872
Lufthansa	27,872	NORDEX AG	1,816
ThyssenKrupp	27,481	Aurubis	1,751
RWE	27,109	MTU AERO ENGINES NA	1,748
Allianz	26,495	Freenet AG	1,726
Deutsche Post	25,412	Saint GOBAIN	1,708
adidas AG Namens-Aktien	23,594	Credit Agricole	1,704
SAP	22,731	ProSiebenSat.1	1,673
Infineon	22,637	SGL Carbon	1,645
K+S AG	21,457	Software AG	1,645
Münchener Rück	19,924	Renault	1,607
Linde	18,903	SolarWorld	1,533
HeidelbergCement	17,667	ENI	1,531
Metro	16,470	Fraport	1,526
Deutsche Börse AG	16,092	MDAX (Performance)	1,501
Continental	15,939	ALSTOM ORD	1,498
Lanxess	13,718	ELRINGKLINGER AG NA O.N.	1,443
Henkel Vz.	13,010	Osram Licht	1,421
Beiersdorf	12,812	Celesio	1,418
Fresenius M.C.	12,657	Hamburger Hafen und Logistik AG	1,363
Merck KGaA	12,423	SYMRISE AG INH. O.N.	1,320
Fresenius	9,582	CAC 40	1,294
Nokia	7,494	Hochtief	1,282
AXA	7,157	TecDAX (Performance)	1,151
Salzgitter	6,842	Schneider Electric	1,123
TUI	6,023	Wincor Nixdorf AG	1,067
STADA Arzneimittel	5,868	Siemens/Osram Basket	1,010
Airbus Group (EADS)	5,803	Aegon Namen	873
Société Générale	5,798	Peugeot	859
Orange	5,387	Talanx	831
Total Fina Elf	5,309	Volkswagen St	813
BNP Paribas	5,248	Vossloh	808
ArcelorMittal S.A.	5,011	Air Liquide	794
Aixtron AG	4,489	DUERR AG O.N.	794
SANOFI-AVENTIS	4,473	VINCI S.A. EO 10	754
ING	4,212	ELECTRICITE DE FRANCE EDF	724
Leoni	4,138	Drägerwerk	679
LVMH	4,101	Enel	676
Klöckner & Co SE	4,005	ALCATEL-Lucent	653
Hannover Rück	3,919	Sky Deutschland AG	648
MAN ST	3,818	Evonik Industries AG	640
Philips	3,817	ATX	579
TELEFONICA EO 1	3,652	Gerresheimer AG	567
L'Oréal	3,046	UniCredit	562
Bilfinger+Berger	3,030	GAGFAH S.A. NOM. EO 1,25	538
GDF SUEZ	2,937	Hugo Boss Vz.	535
Unilever	2,897	Veolia Environment	533
DMG MORI SEIKI	2,678	RHOEN-KLINIKUM O.N.	514
Porsche Automobil Holding SE	2,610	Michelin	512
Carrefour	2,555	BAUER AG	507
Danone	2,552	KUKA	505
Banco Santander	2,519	OMV	493
Vivendi Universal	2,497	Erste Bank	483

TABLE 4.16: Number of boxes per underlying (continued)

Underlying	Boxes	Underlying	Boxes
CARL ZEISS MEDITEC	481	Baywa NA.	83
DEUTZ AG O.N.	475	Arcandor AG	75
Deutsche Postbank	453	DBIX INDIA KURSINDEX EUR	67
Heidelberger Druckmaschinen	452	Suess Micro Tec	69
Q-Cells	422	KON. DSM NV NAM. EO 1,50	66
ASML Holding N.V.	406	PRAKTIKER BAU-U.H.HLDG ON	66
Assic. Generali	401	Unibail Eo 5	65
Iberdrola S.A. Acciones Port. EO -,75	399	OESTERREICH. POST AG	61
Morphosys	396	Kabel Deutschland Holding	58
GERRY WEBER INTERNAT.O.N.	379	PORSCHE AG VORZ AKT	55
Hypo Real Estate Holding	358	MEDION AG NPV	53
DRILLISCH AG O.N.	341	FTSE MIB	52
voestalpine	339	LPKF	52
MLP	325	ACCOR	50
MAN SE	300	Conergy	50
WIRECARD AG	294	Suez	50
Ahold	278	RHI	48
Demag Cranes AG	240	WIENER ST.VERSICHER. INH.	46
CECE (EUR, Composite Eastern	231	Ageas	45
European)		AIR BERLIN PLC EO -,25	45
RDX (Russian Depository Receipt	228	Cancom IT Systeme	45
Index)		Deutsche Annington Immobilien SE	45
Brenntag AG	227	CRH	44
Lafarge	221	FAZ	44
Telefónica Deutschland Holding AG	220	Borussia Dortmund	43
SMA Solar Technology	215	Kontron	43
DEUTSCHE WOHNEN AG INH	207	Pfeiffer Vacuum	42
PERNOD-RICARD FF 20	200	STE AIR FRANCE S.A. FF 54	42
VALLOUREC INH. EO 4	200	Strabag SE	42
Fielmann	189	FTSE 100	38
Zalando	186	Douglas Holding	38
Tognum AG	177	Rational	38
Altana	176	SAF Holland AG	37
Deutsche EuroShop	176	INTERCELL AG INH.	36
TELECOM ITALIA	160	QS Communications (QSC)	35
HEINEKEN NV EUR 2.5	153	S-BOX Dresdner Middle East	34
ANDRITZ AG	151	Kursindex	
Telekom Austria Ag	150	FIAT ORD. EO 5	33
IVG Immobilien	149	BCA INTESA LI 1000	32
Essilor Intl Eo -.35	148	COMDIRECT BANK AG	31
Pinault Print.-Red.	145	Gigaset	31
Puma	145	MSCI THE WORLD INDEX	30
Axel Springer	144	ZUMTOBEL AG INH. A	30
INDITEX	143	BWIN INTERACTIVE ENTMT AG	29
INTERBREW S.A. PARTS S.	137	Roth und Rau AG	29
Wienerberger	136	ADVA AG OPT.NETW.O.N.	27
RAIFFEISEN INTL BK-HO.INH	132	Mayr-Melnhof	27
Krones	129	RTL Group	24
Cap Gemini S.A.	120	SAGEM S.A. EO 1	24
JUNGHEINRICH AG O.N.VZO	119	Gemalto N.V.	22
Norma Group AG	116	Legrand S.A. Actions au Port. EO 4	20
Verbund	110	STMicroelectronics	20
Kion Group	106	centrotherm photovoltaics AG	19
Rocket Internet	104	TOMTOM NV AMSTERDAM	19
Singulus	104	SOLON AG F.SOLARTECH.AG	18
DAXGLOBAL BRIC KURSINDEX	103	UNIQA VERSICHERUNGEN	18
IBEX 35	103	Manz Automation AG	17
SCHOELLER-BLECKMANN OILF.	98	BOUYGUES SA EO 1	16
ArcelorMittal-Basket	97	PATRIZIA IMMOBILIEN NA ON	15
Epcos	95	Suez Environnement	15
Evotec	93	Bechtle	14
Lagardere	88	GAMESA CORP TECNOLOGICA	14
SIXT AG ORD	88	RTX EUR	13
AKZO NOBEL	83	ASML Holding N.V.	13

TABLE 4.16: Number of boxes per underlying (continued)

Underlying	Boxes	Underlying	Boxes
EVN AG	13	GRAMMER AG O.N.	3
Phoenix Solar AG	13	IMMOEAST AG INH.	3
FLUGHAFEN WIEN AG	12	MPC MUENCHMEYER	3
Immofinanz Immob. Anlagen	12	S+T SYST.INTEG.TECH.	3
Jenoptik	12	SEMPERIT AG HLDG	3
GSW Immobilien AG	11	Solarworld AG	3
Pfleiderer	11	TELE ATLAS N.V. EO-,10	3
DEPFA BANK plc	10	ACS,ACT.CO.SER.INH.EO-,50	2
TAG TEGERNSEE IMMOB.	10	KPN	2
SMARTRAC N.V. INH. EO-,50	8	MEDIGENE AG	2
LEG Immobilien AG	7	PALFINGER AG	2
VIVACON AG O.N.	7	SCHERING A G	2
Immobilien ATX	6	CECE Real Estate	1
BWT AG	6	CTX (EUR, Czech Traded Index)	1
Randstad Holdings	6	HTX (EUR, Hungarian Traded Index)	1
AT & S	5	A-TEC INDUSTRIES AG INH.	1
Fondiaria-Sai SpA	5	AEX Amsterdam	1
SOLAR MILLENNIUM AG	5	ARCELOR MITTAL A EO 0,01	1
ABN Amro	4	CA IMMOBILIEN ANLAGEN AG	1
AWD	4	Inhaber-Aktien o.N.	
BOEHLER-UDDEHOLM	4	CONWERT IMMOBILIEN INVEST	1
COLON.REAL ESTATE AG	4	H+R WASAG AG	1
EM.SPORT MEDIA AG	4	HCI CAPITAL NA O.N.	1
Fugro	4	POLYTEC HLDG AG INH. EO 1	1
GrenkeLeasing	4	Schwarz Pharma	1
ERSOL SOLAR ENERGY AG	3	Total S.A. Basket	1

B Results statistics

Table 4.17: Development of arbitrage opportunities per year

Year	Box quotes	Arbitrage quotes		Price difference	
		Absolute	Relative	Mean	SD
2006	546,844	105	0.0002	0.0031	0.0071
2007	10,424,029	10,569	0.0010	0.0038	0.0069
2008	15,511,382	40,641	0.0026	0.0065	0.0095
2009	19,879,307	6,139	0.0003	0.0039	0.0090
2010	44,033,100	9,287	0.0002	0.0056	0.0108
2011	93,079,381	68,000	0.0007	0.0038	0.0058
2012	132,511,987	21,478	0.0002	0.0026	0.0068
2013	200,645,587	15,524	0.0001	0.0015	0.0056
2014	219,537,432	188,227	0.0009	0.0019	0.0037
2015	51,217,474	54,335	0.0011	0.0030	0.0052
2006-2015	787,386,523	414,305	0.0005	0.0030	0.0059

2006 and 2015 are not fully contained in the sample as the observation period starts on October 31, 2006 and ends on April 2, 2015.

Table 4.18: Market inefficiency by weekday - analysis of proportion of arbitrage

Weekday	Box quotes	Arbitrage quotes		Price difference	
		Absolute	Mean proportion	Mean	SD
Monday	157,914,682	87,780	0.0007	0.0029	0.0056
Tuesday	159,257,609	79,809	0.0008	0.0028	0.0055
Wednesday	158,756,120	84,876	0.0007	0.0027	0.0053
Thursday	157,964,356	97,272	0.0007	0.0028	0.0055
Friday	153,493,756	64,568	0.0008	0.0040	0.0077
All quotes	787,386,523[1]	414,305	0.0007	0.0030	0.0059

Differences in mean arbitrage proportions

	Monday	Tuesday	Wednesday	Thursday
Tuesday	0.0000			
	[1.0000]			
Wednesday	0.0001	0.0001		
	[1.0000]	[1.0000]		
Thursday	0.0000	0.0000	-0.0001	
	[1.0000]	[1.0000]	[1.0000]	
Friday	0.0000	0.0000	-0.0001	0.0000
	[1.0000]	[1.0000]	[1.0000]	[1.0000]

[1] The difference in total box quotes is due to the exclusion of boxes as explained in Section 4.5.1. Figures in [ ] are Bonferroni-adjusted p-values.

TABLE 4.19: Market inefficiency by query time - analysis of proportion of arbitrage

Query time	Box quotes	Arbitrage quotes		Price difference	
		Absolute	Mean proportion	Mean	SD
Morning (09:50 am)	196,858,565	110,261	0.0009	0.0035	0.0072
Noon (1:20 pm)	197,017,001	74,130	0.0006	0.0030	0.0066
Afternoon (4:20 pm)	198,401,153	175,687	0.0008	0.0024	0.0039
Evening (7:50 pm)	195,109,804	54,227	0.0006	0.0036	0.0071
All quotes	787,386,523[1]	414,305	0.0007	0.0030	0.0059

Differences in mean arbitrage proportions

	Morning	Noon	Afternoon
Noon	0.0003		
	[0.0342]		
Afternoon	0.0001	-0.0002	
	[1.0000]	[0.4759]	
Evening	0.0003	0.0000	0.0002
	[0.0204]	[1.0000]	[0.3287]

[1] The difference in total box quotes is due to the exclusion of boxes as explained in Section 4.5.1. Figures in [ ] are Bonferroni-adjusted p-values.

TABLE 4.20: Market inefficiency by time to maturity at moment of arbitrage

Time to maturity (days)	Box quotes	Arbitrage quotes				Price difference	
		Absolute	Relative	Cumu-lative	Mean proportion	Mean	SD
(0 - 7]	144,835	6,112	1.48%	1.48%	0.0422	0.0082	0.0085
(7 - 10]	8,954,436	46,481	11.22%	12.69%	0.0052	0.0024	0.0041
(10 - 15]	11,591,358	33,468	8.08%	20.77%	0.0029	0.0019	0.0029
(15 - 20]	11,107,223	27,925	6.74%	27.51%	0.0025	0.0019	0.0028
(20 - 25]	16,254,197	30,515	7.37%	34,88%	0.0019	0.0019	0.0035
(25 - 30]	13,035,509	16,063	3.88%	38.76%	0.0012	0.0021	0.0045
(30 - 35]	11,217,395	14,411	3.48%	42.23%	0.0013	0.0023	0.0035
(35 - 40]	13,241,799	17,686	4.27%	46.50%	0.0013	0.0024	0.0033
(40 - 45]	15,474,384	28,154	6.80%	53.30%	0.0018	0.0026	0.0037
(45 - 50]	11,654,540	15,620	3.77%	57.07%	0.0013	0.0025	0.0038
(50 - 55]	10,582,812	10,994	2.65%	59.72%	0.0010	0.0028	0.0057
(55 - 60]	14,648,182	13,644	3.29%	63.01%	0.0009	0.0028	0.0057
(60 - 65]	12,093,626	12,188	2.94%	65.96%	0.0010	0.0030	0.0050
(65 - 70]	9,945,325	12,014	2.90%	68.86%	0.0012	0.0028	0.0048
(70 - 75]	12,000,820	20,951	5.06%	73.91%	0.0017	0.0026	0.0032
(75 - 80]	14,018,762	11,338	2.74%	76.65%	0.0008	0.0022	0.0037
(80 - 85]	9,454,349	4,067	0.98%	77.63%	0.0004	0.0033	0.0060
(85 - 90]	9,157,577	3,593	0.87%	78.50%	0.0004	0.0031	0.0051
(90 - 95]	13,793,141	6,956	1.68%	80.18%	0.0005	0.0048	0.0095
(95 - 100]	11,855,355	6,701	1.62%	81.80%	0.0006	0.0057	0.0110
(100 - 110]	21,031,180	7,208	1.74%	83.53%	0.0003	0.0032	0.0060
(110 - 120]	22,188,210	4,359	1.05%	84.59%	0.0002	0.0033	0.0067
(120 - 130]	21,303,727	4,733	1.14%	85.73%	0.0002	0.0042	0.0065
(130 - 140]	19,206,682	5,336	1.29%	87.02%	0.0003	0.0041	0.0074
(140 - 150]	21,043,255	4,143	1.00%	88.02%	0.0002	0.0052	0.0117
(150 - 160]	16,669,091	7,347	1.77%	89.79%	0.0004	0.0039	0.0064
(160 - 170]	20,741,879	9,165	2.21%	92.00%	0.0004	0.0029	0.0050
(170 - 180]	14,783,249	1,913	0.46%	92.46%	0.0001	0.0029	0.0045
(180 - 190]	17,942,007	2,153	0.52%	92.98%	0.0001	0.0055	0.0105
(190 - 200]	18,627,430	1,979	0.48%	93.46%	0.0001	0.0036	0.0055
(200 - 210]	16,572,865	871	0.21%	93.67%	0.0001	0.0066	0.0146
(210 - 220]	18,595,028	1,341	0.32%	94.00%	0.0001	0.0043	0.0082
(220 - 230]	14,861,567	1,655	0.40%	94.40%	0.0001	0.0058	0.0126
(230 - 240]	17,649,795	2,079	0.50%	94.90%	0.0001	0.0069	0.0121
(240 - 250]	14,265,802	2,782	0.67%	95.57%	0.0002	0.0031	0.0061
(250 - 300]	71,637,628	8,945	2.16%	97.73%	0.0001	0.0053	0.0102
(300 - 350]	62,817,593	5,189	1.25%	98.98%	0.0001	0.0084	0.0144
(350 - 400]	40,891,530	1,070	0.26%	99.24%	0.0000	0.0050	0.0109
(400 - 450]	30,817,936	1,303	0.31%	99.55%	0.0000	0.0099	0.0160
(450 - 500]	22,957,890	905	0.22%	99.77%	0.0000	0.0162	0.0188
(500 - 600]	28,286,380	643	0.16%	99.93%	0.0000	0.0117	0.0171
(600 - 700]	15,069,454	163	0.04%	99.97%	0.0000	0.0145	0.0228
(700 - 800]	5,796,893	107	0.03%	99.99%	0.0000	0.0133	0.0257
(800 - 1100]	4,257,461	35	0.01%	100.00%	0.0000	0.0178	0.0311

TABLE 4.21: Price difference by issuers and box participation (only issuers with available CDS spreads)

Issuer	One-sided participation			Single issuer boxes			$H_0 : d_2 = d_1$	
	Arbitrage quotes	Mean	SD	Arbitrage quotes	Mean	SD	Z-Score	p-value
BNP	72,876	0.0029	0.0057	6,758	0.0022	0.0045	0.9697	0.1661
CBK	100,345	0.0026	0.0049	6,883	0.0023	0.0040	0.5308	0.2978
CIT	43,696	0.0023	0.0038	4,003	0.0021	0.0031	0.2323	0.4081
DBK	63,506	0.0028	0.0052	5,241	0.0029	0.0057	-0.1779	0.4294
DZB	35,083	0.0029	0.0059	1,708	0.0038	0.0065	-0.6254	0.2659
EB	786	0.0061	0.0094	97	0.0089	0.0111	-0.3262	0.3721
GS	32,885	0.0029	0.0051	871	0.0042	0.0067	-0.7446	0.2282
ML	6,797	0.0061	0.0111	8	0.0027	0.0034	0.1224	0.4513
MQ	17,484	0.0046	0.0069	913	0.0043	0.0062	0.1251	0.4502
RBS	9,562	0.0046	0.0095	248	0.0199	0.0234	-3.3868	0.0004***
SG	18,930	0.0035	0.0063	908	0.0036	0.0063	-0.0631	0.4748
TUB	13,357	0.0028	0.0054	65	0.0008	0.0011	0.3110	0.3779
UBS	78,263	0.0021	0.0034	3,388	0.0026	0.0045	-0.5793	0.2812
UNC	23,412	0.0024	0.0039	1,200	0.0028	0.0041	-0.2661	0.3951
All	258,491	0.0028	0.0053	32,291	0.0028	0.0054	0.0277	0.4889

This table only regards box participations between the issuers listed here. *One-sided participations* contain only boxes where a particular issuer provides either the put warrant or the discount certificate. *Single issuer boxes* are boxes where a particular issuer provides both put warrant and discount certificate. *** denotes (two-sided) statistical significance at the 1% level.

TABLE 4.22: Dynamic arbitrage strategy: boxes held until maturity

Fee	Traded boxes		Profit per box		Average holding days
	Absolute	% of all	Mean	SD	
0	12,502	8.4	22.19	52.09	27.11
1	11,861	9.1	23.50	54.07	28.06
2	11,262	9.6	25.01	56.45	29.28
3	10,913	10.3	26.20	60.02	29.71
4	10,569	11.0	27.29	61.47	29.97
5	10,330	11.7	28.18	62.77	30.52
6	10,166	12.5	28.83	63.34	30.64

References

Ackert, L. F. and Tian, Y. S. (2001), 'Efficiency in index options markets and trading in stock baskets', *Journal of Banking & Finance* 25(9), 1607–1634.

Berg, E., Brevik, T., and Saettem, F. (1996), 'An examination of the Oslo stock exchange options market', *Applied Financial Economics* 6(2), 103–113.

Berument, H. and Kiymaz, H. (2001), 'The day of the week effect on stock market volatility', *Journal of Economics and Finance* 25(2), 181–193.

Bharadwaj, A. and Wiggins, J. B. (2001), 'Box spread and put-call parity tests for the S&P 500 index LEAPS market', *The Journal of Derivatives* 8(4), 62–71.

Börse Frankfurt (2014), 'Teilnahmebedingungen für das Qualitätssegment Börse Frankfurt Zertifikate Premium', Frankfurt am Main.

Börse Frankfurt (2015), 'Zertifikatebörse: Handelsteilnehmer - Emittenten', http://www.zertifikate.boerse-frankfurt.de/de/ueber-uns/zertifikateboerse/handelsteilnehmer, accessed: 2015-11-13.

Brunetti, M. and Torricelli, C. (2005), 'Put-call parity and cross-markets efficiency in the index options markets: evidence from the Italian market', *International Review of Financial Analysis* 14(5), 508–532.

Capelle-Blancard, G. and Chaudhury, M. (2001), 'Efficiency tests of the French index (CAC 40) options market', in 'EFMA 2002 London Meetings', McGill Finance Research Centre (MRFC) Working Paper.

Chance, D. M. (1987), 'Parity tests of index options', *Advances in Futures and Options Research* 2, 47–64.

Entrop, O., Fischer, G., McKenzie, M. D., Wilkens, M., and Winkler, C. (2015), 'How does pricing affect investors' product choice? - Evidence from the market for discount certificates (April 30, 2015)', Available at SSRN: http://ssrn.com/abstract=2417775.

EUWAX (2015), 'EUWAX: Segments & Initiatives - Trading', https://www.boerse-stuttgart.de/en/stock-exchange/segments-and-initiatives/euwax/trading, accessed: 2015-11-13.

Evnine, J. and Rudd, A. (1985), 'Index options: the early evidence', *The Journal of Finance* 40(3), 743–756.

Fung, J. K. W. and Mok, H. M. K. (2001), 'Index options-futures arbitrage: a comparative study with bid/ask and transaction data', *Financial Review* 36(1), 71–94.

FUNG, J. K. W., MOK, H. M. K., AND WONG, K. C. K. (2004), 'Pricing efficiency in a thin market with competitive market makers: box spread strategies in the Hang Seng index options market', *Financial Review* 39(3), 435–454.

GERMAN DERIVATIVES ASSOCIATION (2013), 'Fairness Code', Frankfurt am Main.

GERMAN DERIVATIVES ASSOCIATION (2015), 'Marktvolumen von strukturierten Wertpapieren (issues 01/2007 to 03/2015)', Frankfurt am Main.

HÄRDLE, W. K., MÜLLER, M., SPERLICH, S., AND WERWATZ, A. (2004), *Nonparametric and semiparametric models*, Springer Series in Statistics, Springer Berlin Heidelberg.

HEMLER, M. L. AND MILLER, T. W. (1997), 'Box spread arbitrage profits following the 1987 market crash: real or illusory?', *Journal of Financial and Quantitative Analysis* 32(1), 71–90.

HULL, J. AND WHITE, A. (1995), 'The impact of default risk on the prices of options and other derivative securities', *Journal of Banking & Finance* 19(2), 299–322.

JAFFE, J. AND WESTERFIELD, R. (1985), 'The week-end effect in common stock returns: the international evidence', *The Journal of Finance* 40(2), 433–454.

KAMARA, A. AND MILLER, T. W. (1995), 'Daily and intradaily tests of European put-call parity', *The Journal of Financial and Quantitative Analysis* 30(4), 519–539.

MITTNIK, S. AND RIEKEN, S. (2000), 'Put-call parity and the informational efficiency of the German DAX-index options market', *International Review of Financial Analysis* 9(3), 259–279.

RONN, A. G. AND RONN, E. I. (1989), 'The box spread arbitrage conditions: theory, tests, and investment strategies', *Review of Financial Studies* 2(1), 91–108.

STOIMENOV, P. A. AND WILKENS, S. (2005), 'Are structured products fairly priced? An analysis of the German market for equity-linked instruments', *Journal of Banking & Finance* 29(12), 2971–2993.

STOLL, H. R. (1969), 'The relationship between put and call option prices', *The Journal of Finance* 24(5), 801–824.

WILKENS, S., ERNER, C., AND RÖDER, K. (2003), 'The pricing of structured products in Germany', *The Journal of Derivatives* 11(1), 55–69.

Concluding remarks

Risks are an inevitable part of every entrepreneurial activity. The financial crisis of 2007/08 revealed the stringent necessity of an effective management of these risks. While most industries recovered quite well in the post-crisis years, the international merchant shipping branch still suffers from the crisis' consequences. The irrational ordering of new vessels in the boom years prior to the crisis led to enormous transport overcapacities, which will not be utilized by demand for years. The results are lower freight incomes, historically low vessel prices, and in consequence insolvencies of shipping companies and funds as well as loan losses of the financing banks and investors.

The tasks for all parties involved are on the one hand to find strategies for operative risk management, and on the other hand instruments for a strategic risk allocation. For the shipping branch, both issues lack an adequate interest in academic literature, especially with respect to a practical application. The empirical results of this doctoral thesis demonstrate various approaches of quantitative risk management to identify and reduce financial risks in the shipping sector.

Usually, price risks can be hedged using the respective derivative instrument. However, this is not possible for the resale value of vessels as there are no corresponding derivative contracts available. As a second-best solution, this thesis presents a so called cross hedge strategy employing freight derivatives. With such a strategy, financial losses during the crisis could have been reduced, at least to some extent. Furthermore, we introduce a measure for the crisis vulnerability in the shipping sector. As this measure indicates an increasing crisis risk with a suitable period of time before the actual outburst, it could have been useful to adjust the business strategy in time. Both approaches can also be applied to further asset classes like the real estate market.

For the issuers of financial derivatives, risk management also includes to ensure market conform pricing methods. In this context, it is especially important to avoid the underpricing of financial instruments. For the German certificates market, this thesis reveals numerous underpricings which allow professional traders risk-free profits. This result indicates the urgent need for further improvements of banks' pricing models and mechanisms.

Zusammenfassung

Risiken sind ein Teil jeder unternehmerischen Aktivität. Durch ein aktives Risikomanagement sollen diese Risiken gesteuert und begrenzt werden. Nicht zuletzt durch die zurückliegende Finanzkrise der Jahre 2007/08 wurde einmal mehr die hohe Relevanz dieser Aufgabe deutlich. Während sich nach der Krise der Großteil der Realwirtschaft innerhalb weniger Jahre wieder erholte, leidet insbesondere die internationale Schiffsbranche bis heute an den Folgen. Das massenhafte Bestellen neuer Schiffe vor der Krise führte in den Folgejahren zu einem derartigen Wachstum der Transportkapazität, dass die Nachfrage diese auf viele Jahre nicht auszulasten vermag. Die Folgen sind sinkende Einnahmen aus Frachtraten, historisch niedrige Schiffspreise und in der Konsequenz zahlreiche Insolvenzen von Reedereien und Schiffsfonds sowie Kapitalverluste bei den geldgebenden Banken und Investoren.

Aus Sicht der beteiligten Unternehmen stellen sich daher die Fragen nach wirksamen operativen Methoden der Risikoabsicherung einerseits und Instrumenten zur strategischen Risikoallokation andererseits. Beide Themen wurden für den Sektor der Handelsschifffahrt in der Literatur bisher nur unzureichend berücksichtigt, insbesondere in Hinblick auf die praktische Anwendbarkeit. Die empirischen Ergebnisse dieser Doktorarbeit zeigen am Beispiel der Schifffahrtsbranche verschiedene Möglichkeiten des quantitativen Risikomanagements auf, um finanzielle Risiken aufzudecken und zu reduzieren.

Lassen sich die meisten Preisrisiken üblicherweise mittels entsprechender derivativer Finanzprodukte absichern, ist dies für Wiederverkaufspreise von Schiffen nicht ohne Weiteres möglich, da entsprechende Kontrakte nicht gehandelt werden. Diese Arbeit untersucht eine sogenannte Cross-Hedge Strategie mittels Frachtderivaten als mögliche Alternative, wodurch zumindest ein Teil der Kapitalverluste in der Krise hätte vermieden werden können. Weiterhin wird ein Maß für die Krisenanfälligkeit des Schiffssektors hergeleitet, welches das steigende Risiko schon frühzeitig anzeigt. Solch ein Maß könnte in Zukunft helfen, die Geschäftsstrategie rechtzeitig vor Ausbruch einer Krise anzupassen. Beide Ansätze lassen sich auch auf ähnlich kapitalintensive Wirtschaftszweige beziehungsweise Assetklassen übertragen, wie zum Beispiel den Immobiliensektor.

Auf der Seite der Emittenten derivativer Finanzinstrumente umfasst Risikomanagement insbesondere auch das Sicherstellen marktgerechter Bewertungsmethoden. In diesem Zusammenhang gilt es insbesondere zu vermeiden, Finanzprodukte zu günstig am Markt zu offerieren. Für den deutschen Zertifikatemarkt zeigt diese Arbeit zahlreiche solcher Fälle auf, die es professionellen Anlegern ermöglichen würden, risikolose Erträge zu realisieren. Für die betroffenen Institute deutet dies dringend notwendige Weiterentwicklungen der eingesetzten Bewertungsmodelle und Algorithmen an.