Essays in empirical finance

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-Wirtschaftsmathematiker

Sebastian Opitz

aus Schwerin

Hamburg, 2017

Prüfungskommission:

Vorsitzender: Prof. Dr. Timo Busch
Erstgutachter: Prof. Dr. Alexander Szimayer
Zweitgutachter: Prof. Dr. Knut Haase

Tag der Disputation: 02. Oktober 2017

Für meine Familie.

Danksagung

An dieser Stelle sei allen Personen gedankt, die mich auf dem Weg zu meiner Promotion unterstützt und maßgeblich zum Gelingen und Erfolg dieser Arbeit, die während meiner Tätigkeit als wissenschaftlicher Mitarbeiter an der Professur für Finanzwirtschaft der Universität Hamburg entstand, beigetragen haben.

Mein ganz besonderer Dank gilt meinem Doktorvater, Herrn Prof. Dr. Alexander Szimayer. Ich danke ihm für die Zeit, die er in die Betreuung meiner Dissertation investiert hat und für seine fachliche Unterstützung, die in vielen konstruktiven Diskussionen meine Forschung stets mit wertvollen Denkanstößen bereicherten. Nicht zuletzt möchte ich mich bei ihm dafür bedanken, auch immer ein offenes Ohr in persönlichen Angelegenheiten zu haben.

Darüber hinaus bedanke ich mich bei meinen Kollegen und Mitdoktoranden an der Professur für Finanzwirtschaft Benjamin Nyarko, Henry Seidel, Konstantin Neinstell, Rainer Volk, Michael Herbener, Markus Michaelsen, Christian Hilpert, Aidin Miri Lavasani, Chunli Cheng und Mick Schaefer. Ihr habt ein angenehmes und motivierendes Arbeitsklima geschaffen, bei dem ich mich stets wohl gefühlt habe. Insbesondere gilt mein Dank Henry Seidel für sein Engagement im gemeinsamen, erfolgreichen Projekt und Markus Michaelsen für das Teilen des Büros während der finalen Phase meiner Promotion. Ebenso danke ich Christina Braukmann für ihre Hilfe im administrativen Bereich und ich danke allen studentischen Hilfskräften für die Erledigung teils monotoner Aufgaben.

Zu guter Letzt gilt mein besonderer Dank meiner Familie, meinen Freunden und meiner Lebensgefährtin Marlen für die unermessliche Unterstützung in vielen Bereichen außerhalb der wissenschaftlichen Umgebung. Sie haben mir in schwierigen Phasen der Promotion Halt gegeben und mich immer wieder mit neuer Energie versorgt.

Contents

List of tables

List of figures

Chapter 1

Synopsis

1.1 Motivation

The recent history of the global economy has experienced a series of financial market turbulences and crises such as Black Monday in 1987, the Asian stock market crisis in 1997, the Russian currency crisis in 1998, the collapse of the technology bubble in 2000 and the 2008 global financial crisis following the collapse of the US housing bubble in 2006. Crises like these constantly present new challenges for companies and investors. A financial crisis can be characterized by an extreme downswing of financial asset prices, and thus is directly linked with a loss of the investor's wealth. Hence, it is of the utmost importance for investors to identify possible factors that contribute to the development of a financial crisis. This may include factors such as macroeconomic factors. As a consequence, investors have an incentive to develop an early warning system for future crises that helps to reduce the risks of losses.

A main goal in finance is the accurate modeling of aggregate risks in a portfolio of financial assets. In modern portfolio theory, traditional asset pricing models like the Capital Asset Pricing Model (CAPM) and the Arbitrage Pricing Theory (APT) apply linear correlation as dependence measure between different financial assets and assume multivariate normally distributed returns (see Embrechts et al., 2002). However, numerous empirical studies in the academic literature provide evidence of non-Gaussian financial data, and consequently a non-linear dependence structure. In particular, in extreme market conditions the downside risk of financial assets increases. For instance, Longin and Solnik (2001) model the tails of multivariate distributions on the international equity market employing extreme-value theory. The authors show that the assumption of multivariate normal distributed asset returns has to be rejected for the negative tail of the distribution. Poon et al. (2004) indicate that extreme value cross-sectional dependence of international stock indices is much stronger in bear markets than in bull markets. Ang and Chen (2002) use a GARCH model and observe asymmetry in the correlation, especially for extreme downside moves than for upside moves. Applying a copula approach, Hu (2006) and Okimoto (2008) investigate the asymmetric dependence across international stock markets, Patton (2006) finds evidence of asymmetric dependence between exchange rates. Garcia and Tsafack (2011) observe extreme asymmetric dependence of international equity and bond markets using a regime switching copula model.

The copula approach provides a useful tool to characterize the dependence structure of financial data returns (see for example Patton, 2004; Patton, 2009). Copulas are capable of capturing symmetry and asymmetry in the dependence of assets. Moreover, they allow for possible tail dependence describing the likelihood of extreme observations in one risk factor given extreme observations in another risk factor. In particular, the main benefit of copulas is the flexible modeling of dependence as they allow an isolated investigation of the marginals and dependence structure in the joint distribution of financial asset returns following Sklar's Theorem (see Sklar, 1959). Consequently, the application of copulas help to remedy the problem of misspecification in the marginals as well as the dependence structure. In addition, the copula framework can be extended to the conditional case in order to analyze the time-varying conditional dependence structure of financial risk factors. Thus, the influence of conditioning variables on the dependence structure of different risk factors can be investigated.

This doctoral thesis consists of three individual essays that empirically investigate the dependence structure in different financial markets applying the conditional copula framework. This dissertation focuses on the quantification of the dependence structure for different risk factors as well as the identification of possible drivers of the extreme asymmetric dependence. Hereby, the first essay examines the relationship of equities and bonds on the capital market with a focus on the flight-to-quality effect. The second essay investigates the shipping market, and in particular the ongoing crisis since 2008. The third essay analyzes the US housing market and is primarily concerned with the crisis following the burst of the housing bubble in 2006. The subsequent sections present the motivation, research questions, research approach, empirical findings, and contribution to the academic literature to each of the three essays.

1.2 What drives flight to quality?

The first essay 'What drives flight to quality?' investigates the impact of macroeconomic factors on the time-varying dependence structure of two of the main asset classes on the capital market: stocks and bonds. Due to extreme events like financial crises, the common positive relationship between these two asset returns breaks down and reverses into negative, possibly causing extensive implications for investors regarding diversification and risk management. As a result of the dramatic change in the stock-bond correlation, flight to quality is potentially triggered. Flight to quality describes an effect that is characterized by a drop in demand of assets with higher expected risks including stocks in favor of less risky assets such as bonds. The aim of the first essay is the identification of possible macroeconomic drivers of this effect.

Earlier studies, e.g. Barsky (1989) and Connolly et al. (2005), provide evidence of a time-varying, possible negative correlation between stock and bond returns. While Barsky (1989) accounts increased risks and reduced productivity growth for the reverse movement, Connolly et al. (2005) show a negative correlation between daily stock and bond returns following relatively high values of the implied volatility from equity index options. Several studies investigate the impact of macroeconomic factors on the stock-bond return relation. Macroeconomic conditions, such as the business cycle (see e.g. Ilmanen, 2003), the inflation environment (see e.g. Li, 2002; Ilmanen, 2003; Andersson et al., 2008; Yang et al., 2009), and monetary policy (see e.g. Li, 2002; Yang et al., 2009) influence the stock-bond co-movement.

In addition to the time variation in the stock-bond dependence structure, academic literature frequently addresses flight to quality (see e.g. Gulko, 2002; Baur and Lucey, 2009; Durand et al., 2010). This essay extends the copula-based approach by Durand et al. (2010) and allows for conditioning variables following Patton (2006). Therefore, the analysis examines commonly used macroeconomic factors following Chen et al. (1986), namely the growth rates of the gross domestic product, the industrial production and personal consumption expenditures, the inflation rate, the risk premium, the term structure, the Treasury bill rate as well as the unemployment rate in order to detect the drivers of flight to quality.

Analyzing quarterly data of real returns of the value-weighted index of US stocks and the 30-year bond index from 1952 to 2014, this study provides strong empirical evidence of the Treasury bill rate being the key driver of flight to quality. A drop of the Treasury bill rate by one standard deviation increases on average the risk of flight to quality by approximately 20%, highlighting the huge impact of monetary policy decisions on this effect. To some minor extent, the inflation rate and the growth rates of the gross domestic product as well as personal consumption expenditures significantly influence the flight-to-quality effect.

The first essay contributes to the academic literature in various ways. First, this study extends the existing literature on the influence of macroeconomic variables on the stock-bond relationship by applying a conditional copula approach. Secondly, it focuses on extreme asymmetric dependence, and it quantifies the extent of flight to quality. In this context, it establishes a functional relation between the macroeconomic factors and the conditional copula using the logistic function in the modeling of the tail dependence coefficient. In addition, the research findings have relevant practical implications for investors in terms of asset allocation.

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

The second essay 'Measuring crisis risk using conditional copulas: An empirical analysis of the 2008 shipping crisis' examines the 2008 shipping crisis, whose implications are still prevalent on the shipping market. With the beginning of the financial crisis in 2008, the demand for shipping services collapsed and freight rates as well as ship values declined dramatically. The massive surplus of transportation capacity steadily increased as more and more vessels entered the market which were ordered during the industry's boom prior to 2008. The high lead time in shipbuilding also contributed to the downswing as shipping companies have a relatively slow ability to respond to new market conditions.

The aim of the second essay is twofold. First, it quantifies the potential crisis risk in shipping applying a conditional copula approach. Secondly, it investigates whether the 2008 shipping crisis was caused endogenously by the shipping industry itself and, thus, could have been alleviated or even prevented, or whether it was caused exogenously due to the economic downturn during the financial crisis in 2008.

The crisis risk in shipping is characterized by the contrary co-movement of the two balance sheet risk factors, namely the strong decrease of the value of vessels on the asset side, represented by the Baltic Dry Index (BDI), and the simultaneous sharp increase of financing costs on the liability side, represented by the effective yield of the US Corporate B-rated Index (BY). The time-varying dependence structure of both balance sheet risk factors is modeled by a conditional copula approach following Patton (2006). In particular, the conditional asymmetric tail dependence is specified by the world fleet and the world economy, the main drivers of supply and demand of shipping services (see Stopford, 2009).

Analyzing monthly data of log-differences of BDI and BY from 1997 to 2014, this study provides strong empirical evidence that shipping crisis risk strongly increases in the second half of 2007, when simultaneously conditioning on supply and demand factors. This indicates a potential risk of a crisis in the shipping sector already about one year before the actual outburst of the crisis in late 2008. Moreover, the results suggest that shipping crisis risk is primarily driven endogenously by the oversupply of vessels (60%), and only to a lesser degree exogenously due to the global economic slowdown in consequence of the financial crisis (40%).

The empirical results provide two important conclusions. First, shipping companies could have prevented the excessive fleet growth that led to overcapacity and drop of freight rates by stopping or reducing the ordering of new vessels already in 2007. Secondly, ship financing banks could have also intervened by tightening or restraining shipping loans.

The second essay contributes to the academic literature in two ways. First, this study provides one of the first empirical applications of copulas in ship finance based on the approach by Patton (2006). Secondly, it quantifies the potential crisis risk in the shipping sector by analyzing the influence of supply and demand to freight rates and financing costs in shipping.

1.4 Default risk of mortgage credits for lenders

The third essay 'Default risk of mortgage credits for lenders' analyzes the dependence structure of house prices and default rates focusing on the extreme asymmetric dependence. The US housing market is characterized by a strong increase of house prices since the early 1990s. The rise of interest rates by the Fed starting in 2004 marks the beginning of the end of the housing boom and eventually resulted in the burst of the housing bubble in 2006. Credit defaults and foreclosures substantially increased, resulting in an oversupply of houses on the secondary market. The subsequent drop in house prices and raise in default rates eminently affected mortgage lenders as they were unable to finance new loans, faced massive liquidity problems, and even filed for bankruptcy. Due to the mortgage crisis also the US economy faced a significant slowdown and headed for a deep recession which has contributed to the emergence of the global financial crisis. The aim of this essay is the quantification of the conditional asymmetric tail dependence which will be interpreted as default crisis indicator.

The default crisis indicator describes a measure that displays the dramatic downswing of house prices and the concurrent rise in mortgage credit defaults. The dependence structure of house prices and default rates is modeled using a conditional copula approach following Patton (2006). In this context, this study applies housing supply factors, economic factors, interest rates, and mortgage loan-to-price ratios as conditioning variables in order to identify potential driving variables of the default crisis indicator.

Analyzing quarterly data of log-differences of the US house price index and first differences of total delinquent US residential mortgage loans from 1985 to 2015, this study provides statistical evidence of a positive relationship of the volume of 'new private housing units started' and the default crisis indicator. Accordingly, an increase in the log-difference of the volume of 'new private housing units started' boosts the default crisis risk. Moreover, the existing mortgage loan-to-price ratio as well as the home mortgage loan-to-price ratio positively influence the extreme asymmetric dependence of house prices and mortgage credit defaults.

The third essay makes two important contributions to the academic literature of housing economics. First, this study provides a useful tool to quantify default risk of mortgage credits for lenders. As a result, lenders are able to better adapt to changes in market conditions with the aim of diversifying their mortgage credit portfolio. Secondly, it identifies potential drivers of default risk of mortgage credits for lenders by analyzing the extreme asymmetric dependence of house prices and default rates using various economic and housing related variables.

References

Andersson, M., Krylova, E. and Vähämaa, S. (2008), 'Why does the correlation between stock and bond returns vary over time?', *Applied Financial Economics* 18(2), 139–151.

Ang, A. and Chen, J. (2002), 'Asymmetric correlations of equity portfolios', *Journal of Financial Economics* 63(3), 443–494.

Bae, K.-H., Karolyi, G. A. and Stulz, R. M. (2003), 'A new approach to measuring financial contagion', *Review of Financial studies* 16(3), 717–763.

Barsky, R. B. (1989), 'Why don't the prices of stocks and bonds move together?', *American Economic Review* 79(5), 1132–1145.

Baur, D. G. and Lucey, B. M. (2009), 'Flights and contagion - an empirical analysis of stock–bond correlations', *Journal of Financial Stability* 5(4), 339–352.

Chen, N.-F., Roll, R. and Ross, S. A. (1986), 'Economic forces and the stock market', *Journal of Business* 59(3), 383–403.

Connolly, R., Stivers, C. and Sun, L. (2005), 'Stock market uncertainty and the stock-bond return relation', *Journal of Financial and Quantitative Analysis* 40(1), 161–194.

Durand, R. B., Junker, M. and Szimayer, A. (2010), 'The flight-to-quality effect: a copula-based analysis', *Accounting & Finance* 50(2), 281–299.

Embrechts, P., McNeil, A. and Straumann, D. (2002), 'Correlation and dependence in risk management: properties and pitfalls', *Risk management: value at risk and beyond* pp. 176–223.

Garcia, R. and Tsafack, G. (2011), 'Dependence structure and extreme comovements in international equity and bond markets', *Journal of Banking & Finance* 35(8), 1954–1970.

Gulko, L. (2002), 'Decoupling', *The Journal of Portfolio Management* 28(3), 59–66.

Hu, L. (2006), 'Dependence patterns across financial markets: a mixed copula approach', *Applied Financial Economics* 16(10), 717–729.

Ilmanen, A. (2003), 'Stock-bond correlations', *The Journal of Fixed Income* 13(2), 55–66.

Li, L. (2002), 'Macroeconomic factors and the correlation of stock and bond returns'. Working paper, Yale University.

Longin, F. and Solnik, B. (2001), 'Extreme correlation of international equity markets', *The Journal of Finance* 56(2),649–676.

Okimoto, T. (2008), 'New evidence of asymmetric dependence structures in international equity markets', *Journal of Financial and Quantitative Analysis* 43(3), 787–815.

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.

Patton, A. J. (2009), Copula–based models for financial time series, *in* 'Handbook of financial time series', Springer, pp. 767–785.

Poon, S.-H., Rockinger, M. and Tawn, J. (2004), 'Extreme value dependence in financial markets: Diagnostics, models, and financial implications', *Review of Financial Studies* 17(2), 581–610.

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

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

Yang, J., Zhou, Y. and Wang, Z. (2009), 'The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence', *Journal of Banking & Finance* 33(4), 670–680.

Chapter 2

What drives flight to quality?

with Alexander Szimayer

Abstract

The relationship of equities and bonds is essential in financial markets. The returns of these two asset classes tend to be positively correlated, but in extreme situations this relation reverses. Large negative equity returns co-occur with large positive bond returns. This is potentially caused by investors reassessing their risk preferences and shifting their wealth to less risky asset classes, which is frequently termed flight to quality. We examine macroeconomic factors in order to identify the driving variables using a conditional copula model. We find that the Treasury bill rate is the most significant driver. Furthermore, the growth rates of the gross domestic product and personal consumption expenditures as well as the inflation rate have a significant impact on flight to quality. This insight is useful for asset allocation and risk management.

Acknowlegdements
A revised version of this Chapter will be published in *Accounting & Finance* and is available at Wiley via http://onlinelibrary.wiley.com/wol1/doi/10.1111/acfi.12315/full. We gratefully thank anonymous referees for valuable comments on earlier drafts.

2.1 Introduction

Understanding the dependence structure of financial asset classes is of main interest for asset allocation and risk management as it influences the portfolio strategy of investors. Large institutional investors like pension funds, insurance companies, and mutual funds particularly demand long-term investments such as stocks or long-term bonds in order to back long-term obligations (see e.g. Greenwood and Vayanos 2010, Greenwood and Vayanos 2014). Generally, we observe a positive dependence structure of these two assets, for example, Shiller and Beltratti (1992) as well as Campbell and Ammer (1993) find a small positive correlation between stock and bond returns. However, in extreme situations that relation breaks down, as the positive dependence reverses into negative, which possibly has extensive implications for diversification effects and hence asset allocation. In this constellation, the flight-to-quality effect potentially occurs.

Flight to quality describes an effect in which an investor sells risky assets like stocks in favor of investing in a less risky asset class like bonds supposed to be. Especially, in phases of market downturns we can observe flight to quality accompanied with an increased demand in the safe asset. In literature, flight to quality is often examined in the investigation of the stock-bond correlation (see for example Gulko, 2002; Baur and Lucey, 2009). In this context, Durand et al. (2010) employ a copula-based approach to model the asymmetric dependence between equities and bonds.

We pick up and extend the analysis by Durand et al. to allow for conditioning variables to figure out "What drives flight to quality?" using a conditional version of the authors' flight-to-quality copula. It is a copula that captures two types of dependencies, broad dependence and extreme dependence, respectively. The conditional copula approach is due to Patton (2006) who examines the time-variation in the dependence structure of exchange rates. More recently, Christoffersen et al. (2012) analyze international equity markets and Christoffersen and Langlois (2013) study the joint distributional dynamics of equity market factors using conditional copulas.

In order to specify the drivers of flight to quality, we investigate the influence of macroeconomic factors, namely the growth rates of the gross domestic product, the industrial production and personal consumption expenditures, the inflation rate, the Treasury bill rate, as well as the unemployment rate. Moreover, we study the factors risk premium and term structure following Chen et al. (1986). Based on previous research, we expect a negative relation between the extent of flight to quality and all macroeconomic factors but the term structure as well as the unemployment rate.[1]

This paper contributes to the existing literature by examining the influence of macroeconomic factors on the stock-bond dependence structure. In particular, we use a conditional

1 We present a concise literature overview in the subsequent section.

copula approach focusing on extreme asymmetric dependence to quantify flight to quality. For that purpose, we apply the logistic function to link macroeconomic factors and the extent of flight to quality by use of the tail dependence coefficient.

Analyzing quarterly data from 1952 to 2014 from the US market, we provide statistical evidence of a negative relationship between the Treasury bill rate, and with some limitations the inflation rate as well as the growth rates of the gross domestic product and personal consumption expenditures and flight to quality. However, none of the other factors significantly influence the flight-to-quality effect.

The remainder of this paper is structured as follows: The next section gives a brief overview of the related literature. Section 2.3 describes the dependence background and derives the conditional flight-to-quality copula. The methodology is provided in Section 2.4. The empirical results as well as the robustness check are presented in Section 2.5. Section 2.6 concludes our analysis.

2.2 Literature review

Equities and bonds represent two of the main asset classes where bonds are traditionally seen as safe asset and, therefore, as hedging instrument for equities (see e.g. Ciner et al., 2013). For instance, Campbell and Viceira (2001) highlight the attractiveness of long-term bonds for risk-averse long-term investors for hedging purposes. Wachter (2003) shows that the bond is the riskless asset for long-term investors with a maturity equal to their investment horizon.

Equities as well as bonds are priced by the sums of their discounted future cash flows, and thus the covariance of equity and bond returns should be positive. Nevertheless, various studies provide evidence of a time-varying, possible negative co-movement of these returns. For instance, Barsky (1989) discusses the contrary movement of stock and bond prices because of increased risk and reduced productivity growth. Li (2002) analyzes the stock-bond correlation in G7 countries from 1958 to 2001 on a daily and monthly basis finding large variations in the correlation.[2] Gulko (2002) investigates the relationship of stocks and bonds during crashes in the US financial market. Therefore, the author uses data from the S&P 500 and US Treasury bonds. He identifies a positive relationship before crashes followed by a negative relationship afterwards. Connolly et al. (2005) observe similar results testing daily stock and bond returns of US financial data from 1986 to 2000.

In addition to the time variation in the stock-bond correlation, studies such as Longin and Solnik (2001) and Ang and Chen (2002) examine the asymmetric dependence structure of

[2] In this context, Li also examines macroeconomic factors that propel this effect.

asset returns, and particularly scrutinize the assumption of normal dependence. Longin and Solnik (2001) apply an extreme-value approach to model the tails of multivariate distributions on the international equity market. The authors reject the null hypothesis of multivariate normality for the negative tail, but not for the positive tail. Ang and Chen (2002) provide similar results. Analyzing US stocks and the aggregate US market they observe asymmetry in the correlation especially for extreme downside moves than for upside moves, and thus reject the multivariate normal distribution. A useful tool to model the non-normal dependence of asset returns is the copula approach (see for example Patton, 2004). In particular, Garcia and Tsafack (2011) investigate the extreme asymmetric dependence of international equity and bond markets using a regime switching copula model.

When analyzing the relationship of equity and bond returns, the authors often addresses flight to quality. Recent literature examine flight to quality. Baur and Lucey (2009) show the existence of flight to quality analyzing time-varying correlations of daily data of MSCI stock and bond index returns from European countries and the US from 1995 to 2005. Durand et al. (2010) apply a copula model to indirectly detect the flight-to-quality effect by analyzing the relationship of equity and long-term bond returns. Therefore, the authors combine the dependence characteristics of the Frank and Gumbel copula. Using quarterly real returns of the CRSP value-weighted index of US stocks and the 30 year bond index over the period from 1952 to 2003 they find a one in seven chance of flight to quality.

As we are interested in the drivers of the opposing co-movement of equity and bond returns, we analyze the impact of macroeconomic factors. The literature on the effect of macroeconomic factors to asset returns dates back to Chen et al. (1986) who are one of the first to explain stock price movements by macroeconomic variables. They investigate the effect of macroeconomic factors to stock returns using Arbitrage Pricing Theory. Over a period from 1953 to 1983 the authors find evidence that amongst others industrial production, changes in the risk premium, twists in the yield curve, as well as expected and unexpected inflation significantly explain monthly equity returns. Flannery and Protopapadakis (2002) use a GARCH model of daily equity returns from 1980 to 1996 to analyze the influence of macroeconomic variables on stock returns. The authors examine two strands of factors, the nominal strand with the consumer price index (CPI), the producer price index (PPI) as well as monetary aggregate, and the real strand containing the balance of trade, the employment report and housing starts. In contrast to Chen et al. (1986), they cannot observe a significant relationship between industrial production and equity returns. The study by Boyd et al. (2005) also investigates the response of the stock market to unemployment announcements. They find that an increase in the unemployment rate is good news during expansions and bad news during recessions.

With regard to bond returns, the analysis of Hardouvelis (1988) examines the impact of macroeconomic announcements, by testing the reaction of monetary, inflation, cyclical, and trade deficit announcements. Fleming and Remolona (1997) also show the consequences of macroeconomic factor announcements for bond returns. The authors find evidence that e.g. news relating to employment, PPI, and CPI announcements force movements in bond returns.[3]

Ilmanen (2003), Andersson et al. (2008), and Yang et al. (2009) highlight macroeconomic factors that cause the time variation in the stock-bond correlation. Ilmanen (2003) investigates economic conditions and their behavior towards the stock-bond co-movement in the US as well as Japan and Germany. The author focuses on four key dimensions, namely the business cycle, the inflation environment, volatility conditions and monetary policy stance. Andersson et al. (2008) examine the impact of inflation, growth expectations and stock market uncertainty to explain the time-varying correlation between equity and bond returns using data from the US, UK and Germany. The authors identify the expected inflation to be positively related to the stock-bond correlation, and the implied volatility to be negatively related to the return correlation between stocks and bonds. Moreover, they find that the stock-bond correlation is unaffected by economic growth expectations. Yang et al. (2009) show different patterns in the correlation between stock and bond returns based to the business cycle. Analyzing the US, they document that the correlation is lower during recessions than those during expansions. Moreover, they detect a statistically significant positive influence with respect to the short rate and the inflation rate.

In summary, the investigation of the influence of macroeconomic variables to stock and bond prices is widespread in academic literature. We pick up commonly used factors to detect the drivers of flight to quality in the subsequent dependence analysis. These are the growth rates of the gross domestic product, the industrial production and personal consumption expenditures, the inflation rate, the risk premium, the term structure, the Treasury bill rate as well as the unemployment rate.

2.3 Dependence model

This section outlines our dependence model. We use the copula framework to model the dependence structure of multivariate distribution functions following Joe (1997) and Nelsen (2006). In particular, following Patton (2006), we extend the concept of copulas to the context of conditional distribution functions and specify the conditional flight-to-quality copula. For ease of exposition, we restrict ourselves to the bivariate case which can be extended to the generalized, n-dimensional case.

In the following, our setup is given by: 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

[3] Fleming and Remolona also provide an extended overview of previous work, see Fleming and Remolona (1997), p. 33, Table 1.

Borel σ-algebra, and $\mathbb{P}$ is the probability measure. The conditional distribution of (X, Y) given Z is denoted H, and the conditional marginal distributions of $X \mid Z$ and $Y \mid Z$ are denoted F and G, respectively. Let F, G and H be 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.*

The theorem by Sklar (1959) also holds in the case of conditional copulas (see Patton (2002)). Consequently, we can separate the conditional marginal distributions of the two variables from their dependence structure.

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*

$$H(x, y \mid z) = C(F(x \mid z), G(y \mid z) \mid z)\,, \tag{2.1}$$

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 (2.1) is a conditional bivariate distribution function with conditional marginal distributions F and G.

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

A special class of closed-form copulas represents the parametric family of conditional Archimedean copulas. It provides a flexible modeling of the dependence structure. These conditional copulas can be characterized by a one-dimensional function, the generator.

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

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

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

We construct a two-parameter copula using the conditional Frank copula and the conditional Gumbel copula as we expect two types of dependence in our study. Firstly, the common positive relationship of stock and bond returns has to be accommodated. The conditional Frank copula picks up this characteristic because of its similar behavior compared to the bivariate normal distribution with its correlation coefficient. Secondly, joint extreme events have to be captured as well. For this purpose, we apply the conditional Gumbel copula.

Definition 3 (Conditional Frank copula)**.** *The conditional Frank copula is defined by its generator* $\varphi_F(\,\cdot\,|\,z) : [0,1] \to [0,\infty]$ *given by*

$$\varphi_F(u\,|\,z) = \begin{cases} -\ln\left(\frac{\mathrm{e}^{-\theta(z)u}-1}{\mathrm{e}^{-\theta(z)}-1}\right), & \theta(z) \in \mathbb{R}\setminus\{0\}\,, \\ -\ln(u), & \theta(z) = 0\,, \end{cases}$$

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

$$\varphi_F^{-1}(t\,|\,z) = \begin{cases} -\frac{1}{\theta(z)}\ln\left(1+\mathrm{e}^{-t}\left(\mathrm{e}^{-\theta(z)}-1\right)\right), \theta(z) \in \mathbb{R}\setminus\{0\}\,, \\ \mathrm{e}^{(-t)}, \qquad\qquad\qquad\qquad\qquad \theta(z) = 0\,, \end{cases}$$

In particular, the conditional Frank copula $C_F : [0,1]\times[0,1]\times\mathcal{Z} \to [0,1], (u,v,z) \mapsto C_F(u,v\,|\,z)$ *is given by*

$$C_F(u,v\,|\,z) = -\frac{1}{\theta}\ln\left(1+\frac{(e^{-u\theta(z)}-1)(e^{-v\theta(z)}-1)}{e^{-\theta(z)}-1}\right),\ \theta(z) \in \mathbb{R}\setminus\{0\}\,,$$

and

$$C_F(u,v\,|\,z) = \Pi(u,v) = uv,\ \theta(z) = 0.$$

Next to independence for $\theta(z) = 0$, we observe positive dependence for $\theta(z) > 0$, and respectively, negative dependence for $\theta(z) < 0$, $z \in \mathcal{Z}$. The conditional Frank copula has reflection symmetry, i.e., if $(U,V) \sim C_F(\cdot,\cdot\,|\,z)$, then $(1-U,1-V) \sim C_F(\cdot,\cdot\,|\,z)$. Moreover, if $(U,V) \sim C_F(\cdot,\cdot\,|\,z)$, then $(1-U,V)$ reverses positive and negative dependence. Special cases of the conditional Frank copula are the Fréchet-Hoeffding bounds $C_F(u,v\,|\,z) = W(u,v) = \max(u+v-1,0), \theta(z) = -\infty$, as well as $C_F(u,v|\,z) = M(u,v) = \min(u,v), \theta(z) = \infty$. However, the conditional Frank copula has no tail dependence. This is a property of the conditional Gumbel copula.

Definition 4 (Conditional Gumbel copula)**.** *The conditional Gumbel copula is defined by its generator* $\varphi_G(\,\cdot\,|\,z) : [0,1] \to [0,\infty]$ *given by*

$$\varphi_G(u\,|\,z) = (-\ln(u))^{\delta(z)}\,, u \in [0,1], \delta(z) \in [1,\infty), z \in \mathcal{Z}\,,$$

where $\varphi_G^{-1}(t\,|\,z) = \exp\left(-t^{\frac{1}{\delta(z)}}\right)$ *denotes the inverse of* $\varphi_G(\,\cdot\,|\,z)$*. In particular, for* $(u,v) \in$

$[0,1]^2,\ \delta(z) \in [1,\infty)$ *the conditional Gumbel copula is*

$$C_G(u,v\,|\,z) = \exp\left[-\left((-\ln(u))^{\delta(z)} + (-\ln(v))^{\delta(z)}\right)^{\frac{1}{\delta(z)}}\right].$$

Here, special cases of the $C_G(\cdot,\cdot\,|\,z)$ are the independence copula $\Pi(\cdot,\cdot)$ for $\delta(z)=1$, and for $\delta(z)\to\infty$ we get the upper Fréchet-Hoeffding bound $M(\cdot,\cdot)$. The conditional Gumbel copula is an extreme value copula, with upper tail dependence

$$\begin{aligned}
\lambda_U(z) &= \lim_{v\uparrow 1}\frac{1-2v+C_G(u,v\,|\,z)}{1-v}\\
&= 2-\lim_{y\downarrow 0}\frac{1-\varphi_G^{-1}(2y\,|\,z)}{1-\varphi_G^{-1}(y\,|\,z)}\\
&= 2-\lim_{y\downarrow 0}\frac{1-\exp\left(-(2y)^{1/\delta(z)}\right)}{1-\exp\left(-y^{1/\delta(z)}\right)}\\
&= 2-\lim_{y\downarrow 0}\frac{2^{\frac{1}{\delta(z)}}\,y^{\frac{1}{\delta(z)}-1}\exp\left(-(2y)^{\frac{1}{\delta(z)}}\right)}{y^{\frac{1}{\delta(z)}-1}\exp\left(-y^{\frac{1}{\delta(z)}}\right)}\\
&= 2-2^{1/\delta(z)}\,, z\in\mathcal{Z}, \qquad (2.2)
\end{aligned}$$

using the generator $\varphi_G(\,\cdot\,|\,z)$ of the conditional Gumbel copula and l'Hôpital's rule. Alternatively, transforming (2.2) we obtain

$$\delta(z) = \frac{\ln(2)}{\ln(2-\lambda(z))}, z\in\mathcal{Z}\,. \qquad (2.3)$$

For $\delta(z)=1$ there exists no tail dependence, and $\delta(z)\to\infty$ implies only mass in the tails of the distribution function. The conditional Gumbel copula has not any other form of tail dependence.

We want to connect both types of dependence. Therefore, we transform the conditional Frank copula with generator $\varphi_F(\,\cdot\,|\,z)$ by the strictly increasing, conditional, convex function $f:[0,\infty]\times\mathcal{Z}\to[0,\infty]$, $x\longmapsto x^{\delta(z)}$, where $\delta(z)\geq 1, z\in\mathcal{Z}$, following Junker (2003). This function also provides the Gumbel copula generator when applied to the independence copula generator. We have

$$f(\varphi_F(u\,|\,z)\,|\,z) = (\varphi_F(u\,|\,z))^{\delta(z)} = \varphi_{tF}(u\,|\,z), z\in\mathcal{Z},$$

where $\varphi_{tF}(\,\cdot\,|\,z)$ is the generator of the conditional transformed Frank copula.

Definition 5 (Conditional transformed Frank copula)**.** *The conditional transformed Frank copula is given by the generator* $\varphi_{tF}(\,\cdot\,|\,z):[0,1]\to[0,\infty]$ *with*

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

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

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

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*

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

and

$$C_{tF}(u,v\,|\,z) = \exp\left[-\left((-\ln(u))^{\delta(z)}+(-\ln(v))^{\delta(z)}\right)^{\frac{1}{\delta(z)}}\right]\,, \textit{for } \theta(z)=0.$$

The conditional transformed Frank copula is a conditional Archimedian copula, too. It can be resetted into the two initial determined conditional copulas. Firstly, setting $\delta(z)=1$, we get $C_F(\cdot,\cdot\,|\,z)$. Secondly, for $\theta(z)\to 0$, Junker (2003) claims for the unconditional case that for a fixed $\delta(z)$ the following limit behavior holds:

$$\lim_{\theta(z)\to 0} C_{tF}(u,v\,|\,z) = C_G(u,v\,|\,z)\,.$$

Just as $C_F(\cdot,\cdot\,|\,z)$, $C_{tF}(\cdot,\cdot\,|\,z)$ tends to the independence copula $\Pi(u,v)$ for $\theta(z)\to 0$, and in case that $\delta(z)=1$, $z\in\mathcal{Z}$. Further special cases are the Fréchet-Hoeffding bounds. For $\delta(z)\to\infty$ or $\theta(z)\to\infty$ we have $C_{tF}(u,v\,|\,z)=M(u,v)$, and for $\delta(z)=1$ and $\theta(z)\to-\infty$ we get $C_{tF}(u,v\,|\,z)=W(u,v)$. The conditional transformed Frank copula has upper right tail dependence that is equal to the tail dependence of the conditional Gumbel copula with $\lambda_U(z)=2-2^{1/\delta(z)}$.

2.3.1 The conditional flight-to-quality copula

We want to measure the dependence structure in the upper left corner when large negative stock returns coincide with large positive bond returns. Thus, we need to adapt the conditional transformed Frank copula and rotate the first coordinate of $C_{tF}(\,\cdot,\cdot\,|\,z)$. Let the pair $(U^*,V^*)\sim C_{tF}(\,\cdot,\cdot\,|\,z)$, and for $U=1-U^*$, $V=V^*$, we get $(U,V)\sim C_{ftq}(\,\cdot,\cdot\,|\,z)$.

$$\begin{aligned} C_{ftq}(u,v\,|\,z) &= \mathbb{P}(U\le U, V\le V\,|\,z) \\ &= \mathbb{P}(1-U^*\le U, V^*\le V\,|\,z) \end{aligned}$$

$$
\begin{aligned}
&= \mathbb{P}(1-U \leq U^*, V^* \leq V \mid z) \\
&= \mathbb{P}(U^* \leq 1, V^* \leq V \mid z) - \mathbb{P}(U^* \leq 1-U, V^* \leq V \mid z) \\
&= v - \mathbb{P}(U^* \leq 1-U, V^* \leq V \mid z) \\
&= v - C_{tF}(1-u, v \mid z)\,,
\end{aligned}
$$

where $C_{tF}(u, v \mid z) = \mathbb{P}\left(U^* \leq u, V^* \leq v \mid z\right)$.

As a result, we get the conditional flight-to-quality copula $C_{ftq}(\,\cdot, \cdot \mid z)$ which is defined as follows:

Definition 6 (Conditional flight-to-quality copula)**.** *The conditional flight-to-quality copula* $C_{ftq} : [0,1] \times [0,1] \times \mathcal{Z} \to [0,1]$*,* $(u, v, z) \mapsto C_{ftq}(u, v \mid z)$ *is given by*

$$
C_{ftq}(u, v \mid z) = v - C_{tF}(1-u, v \mid z)
$$

for $z \in \mathcal{Z}$*, where* $C_{tF}(\,\cdot, \cdot \mid z)$ *denotes the conditional transformed Frank copula that is rotated in the first coordinate.*

In particular, replacing $\delta(z)$ by $\lambda(z)$ using Equation (2.3) we get

$$
\begin{aligned}
C_{ftq}(u, v \mid z) = v + \frac{1}{\theta(z)} \ln \Bigg[1 + (\mathrm{e}^{-\theta(z)} - 1) \exp \Bigg[- \Bigg[\left(- \ln \left(\frac{\mathrm{e}^{-(1-u)\theta(z)} - 1}{\mathrm{e}^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \\
+ \left(- \ln \left(\frac{\mathrm{e}^{-v\theta(z)} - 1}{\mathrm{e}^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \Bigg]^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \Bigg] \Bigg].
\end{aligned} \tag{2.4}
$$

The corresponding density $c_{ftq}\,(\cdot, \cdot \mid z)$ is given by

$$
c_{ftq}\,(u, v \mid z) = - \frac{\varphi''_{tF}(C_{tF}\,(1-u, v \mid z)\ \mid z)\varphi'_{tF}(1-u \mid z)\varphi'_{tF}(v \mid z)}{\left(\varphi'_{tF}(C_{tF}\,(1-u, v \mid z)\ \mid z)\right)^3}\,, \tag{2.5}
$$

where for $\theta(z) \in \mathbb{R} \setminus \{0\}$

$$
\begin{aligned}
\varphi'_{tF}(t \mid z) =& \frac{\ln(2)}{\ln(2-\lambda(z))} \frac{\theta(z)}{1-e^{t\theta(z)}} \left(- \ln \left(\frac{e^{-t\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))} - 1}\,, \\
\varphi''_{tF}(t \mid z) =& \varphi'_{tF}(t \mid z) \frac{\theta(z)}{1-e^{t\theta(z)}} \left(e^{t\theta(z)} + \frac{\frac{\ln(2)}{\ln(2-\lambda(z))} - 1}{-\ln\left(\frac{e^{-t\theta(z)}-1}{e^{-\theta(z)}-1}\right)} \right)\,,
\end{aligned}
$$

and for $\theta(z) = 0$

$$
\varphi'_{tF}(t \mid z) = \frac{\ln(2)}{\ln(2-\lambda(z))} \frac{-1}{t} \left(- \ln(t) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))} - 1}\,,
$$

$$\varphi''_{tF}(t\,|\,z) = \varphi'_{tF}(t\,|\,z)\frac{-1}{t}\left(1 + \frac{\frac{\ln(2)}{\ln(2-\lambda(z))} - 1}{-\ln(t)}\right).$$

The conditional flight-to-quality copula is a two parameter copula depending only on the parameters $\lambda(z)$ and $\theta(z)$ that fully describe the dependence structure. The coefficient $\lambda(z)$ denotes the upper left tail dependence and following Patton (2006), it will be modeled directly through the functional relationship

$$\lambda(z) = \frac{1}{1 + \exp\left(-(\lambda_{0,z} + \lambda_{1,z}{'}z)\right)}, \tag{2.6}$$

where $\lambda_{0,z}$ is the constant and $\lambda_{1,z} \in \mathbb{R}^j$ denote the parameters of the macroeconomic factor $z \in \mathcal{Z} \subseteq \mathbb{R}^j$. The parameter $\theta(z)$ represents the broad dependence. Due to the rotation of the first coordinate of $C_{tF}(\cdot,\cdot\,|\,z)$ positive and negative dependence are now reversed. Thus, a negative value of $\theta(z)$ leads to a positive dependence and vice versa.[4] As we focus on the drivers of the flight-to-quality effect, we only condition on the extreme dependence parameter $\delta(z)$ and set $\theta(z) = \theta_{0,z}$ for the main analysis.[5] For $z \in \mathcal{Z}$, we get

$$\begin{aligned} C_{ftq}\,(u, v\,|\,z) = v + \frac{1}{\theta_{0,z}} \ln \Bigg[1 + (\mathrm{e}^{-\theta_{0,z}} - 1) \exp \Bigg[- \Bigg[\left(- \ln \left(\frac{\mathrm{e}^{-(1-u)\theta_{0,z}} - 1}{\mathrm{e}^{-\theta_{0,z}} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \\ + \left(- \ln \left(\frac{\mathrm{e}^{-v\theta_{0,z}} - 1}{\mathrm{e}^{-\theta_{0,z}} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \Bigg]^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \Bigg] \Bigg]. \end{aligned} \tag{2.7}$$

In order to interpret and compare the results of the different macroeconomic factors, we then calculate the sensitivity of the tail dependence factor λ to changes in the explanatory variable by one standard deviation, given by

$$\Delta\lambda_z = \lambda\left(\bar{z} + \frac{1}{2}\sigma_z\right) - \lambda\left(\bar{z} - \frac{1}{2}\sigma_z\right), \tag{2.8}$$

where $\bar{z}$ and σ_z are the mean, and respectively, the standard deviation of macroeconomic variable $z \in \mathcal{Z}$.

In next step we present the data of our study and we derive the marginal model for the copula-based analysis.

[4] In the subsequent analysis, we quantify this type of dependence by the parameter $\theta_{ftq} = -\theta$.
[5] We investigate the general case $\theta(z)$ in the robustness check.

2.4 Marginal model

In this section, we describe our dataset and analyze its properties. The results are then used to specify the time series model for the subsequent study.

2.4.1 Data and descriptive statistics

We want to analyze the extreme asymmetric dependence between equities and bonds. Therefore, we use quarterly data of the value-weighted US stock index[6] and the 30-year US bond index provided by CRSP over the sample period from the first quarter of 1952 to the fourth quarter of 2014, altogether 252 observations.[7] In particular, we examine real returns of the value-weighted US stock index (r_E) and real returns of the 30-year US bond index (r_B) by adjusting the raw returns of both series for inflation.[8] Figure 2.1 gives the

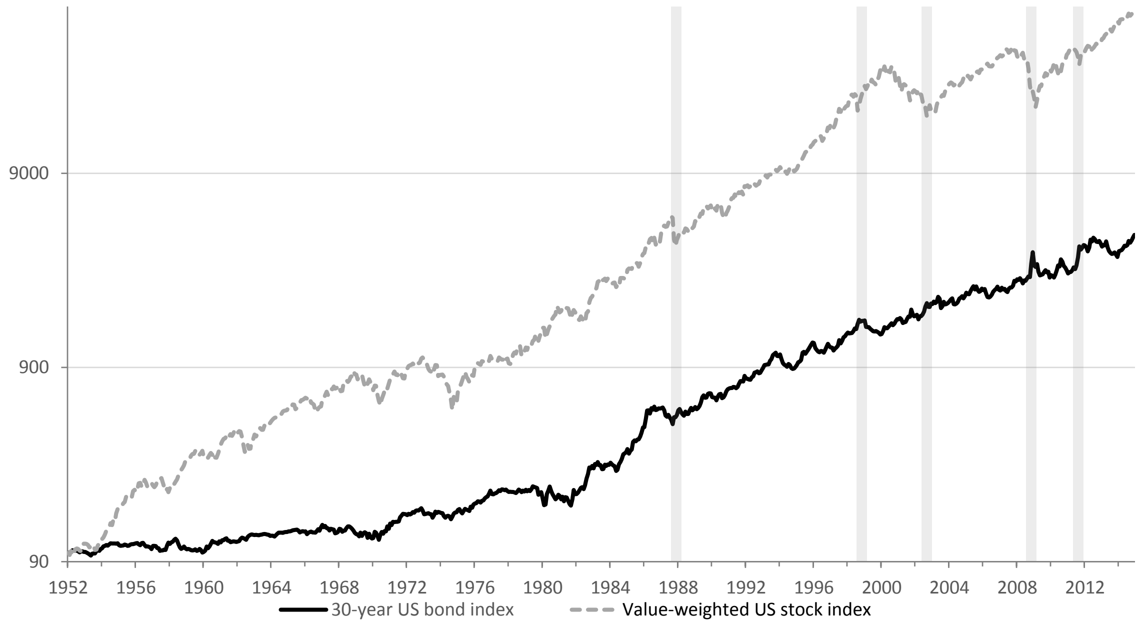


FIGURE 2.1: Development of 30-year US bond index and value-weighted US stock index

development of both indices over time. For instance, we observe a contrary performance of both indices in 1987, 2008 and 2011.

Moreover, in order to explain the flight-to-quality effect, we use macroeconomic factors given in Table 2.1. In particular, our analysis contains the 3-month Treasury bill rate (TB3), the unemployment rate (UNR), the inflation rate (INF), the growth rates of the gross domestic product (GDPR), the industrial production (INPR), and personal con-

[6] Applying the equally-weighted US stock index, we get similar results.

[7] The analysis starts from 1952 after the Federal Reserve Bank's final lifting of market controls after World War Two.

[8] We use the log-differences of the consumer price index for inflation adjustment whose data is provided by CRSP.

Table 2.1: Glossary and definitions of variables

Symbol	Variable	Definition or source
	Panel A: Basic series	
VWE	Value-weighted equities	Quarterly return on value-weighted US stock index, CRSP
B30	30-year bond	Quarterly return on 30-year bond index, CRSP
CPI	Consumer price index	Quarterly price index, CRSP
GDP	Gross domestic product	Quarterly price index, Datastream
INP	Industrial production	Quarterly price index, Datastream
PEX	Personal consumption expenditures	Quarterly price index, Datastream
UNR	Unemployment rate	Quarterly relative changes, Datastream
TB3	Treasury bill rate	End-of-period return on 3-month bills, Federal Reserve
Baa	Baa corporate bond yield	End-of-period return on bonds rated Baa and under, Federal Reserve
	Panel B: Derived series	
INF	Inflation rate	$\log(CPI(t)) - \log(CPI(t-1))$
r_E	Real return of VWE	$(1 + VWE(t))/(1 + INF(t)) - 1$
r_B	Real return of B30	$(1 + B30(t))/(1 + INF(t)) - 1$
GDPR	Growth rate of GDP	$\log(GDP(t)) - \log(GDP(t-1))$
INPR	Growth rate of INP	$\log(INP(t)) - \log(INP(t-1))$
PEXR	Growth rate of PEX	$\log(PEX(t)) - \log(PEX(t-1))$
RP	Risk premium	$Baa(t) - r(t)$
TST	Term structure	$r(t) - TB3(t-1)$

sumption expenditures (PEXR), as well as the term structure (TST), and the risk premium (RP) describing the difference of the Baa corporate bond and the long-term bond.

Table 2.2 presents the summary statistics of our data for the sample period from 1952 to 2014. Thereby, the mean, the standard deviation, the skewness as well as the kurtosis are displayed. Panel A shows the statistics for real equity and bond returns. With a value of 0.0204 against 0.0083 we observe a higher mean for equity than for bonds. Likewise, the standard deviation of the real returns of the value-weighted stock index is larger than for the real returns of the 30-year bond index. This confirms the usual assumption of better chances but also higher risks for the asset class equity compared to bonds. Moreover, the kurtosis of real bond returns is noticeably high with 9.2228. Panel B gives an overview of the four statistic measures for the macroeconomic factors. With the exception of the term structure, each factor has a positive mean. The standard deviation ranges between 0.0073 for PEXR and TB3 and 0.0652 for TST. Moreover, Table 2.3 presents the correlation matrix of the macroeconomic factors.

Table 2.2: Summary statistics of quarterly data

Panel A: Equity and bond returns					
	Symbol	Mean	SD	Skewness	Kurtosis
Value-weighted equities	r_E	0.0204	0.0836	-0.5197	3.7071
30-year bond	r_B	0.0083	0.0649	1.4251	9.2228
Panel B: Macroeconomic factors					
Inflation rate	INF	0.0088	0.0092	0.1787	6.5382
Growth rate of GDP	GDPR	0.0155	0.0100	0.0843	4.8808
Growth rate of INP	INPR	0.0072	0.0188	-0.6669	5.5497
Growth rate of PEX	PEXR	0.0161	0.0073	-0.2387	5.4318
Risk premium	RP	0.0190	0.0651	-1.2860	9.1269
Term structure	TST	-0.0028	0.0652	1.3888	9.6179
Treasury bill rate	TB3	0.0110	0.0073	0.7875	4.0228
Unemployment rate	UNR	0.0592	0.0164	0.5682	3.0233

Panel A presents summary statistics of quarterly value-weighted real equity returns and 30-year real bond returns of US financial data between the second quarter in 1952 and the fourth quarter in 2014, altogether 251 observations for each time series. Panel B presents summary statistics of macroeconomic factors we apply in our study.

Next to these time series which we call for simplicity base series, we examine two additional types of time series: first differences, and unexpected changes of the macroeconomic factor $z \in \mathcal{Z}$. The first differences time series is calculated by

$$\Delta z_t = z_t - z_{t-1}\,, \qquad \text{for } t = t_0, ..., T\,.$$

The time series of unexpected changes is understood as the residuals ε of the AR(1) model

$$z_t = c + \varphi z_{t-1} + \varepsilon_t\,, \qquad \text{for } t = t_0, ..., T\,,$$

where c is a constant, and φ is the parameter of the autoregressive model. Thus, we get

$$\varepsilon_t = z_t - (c + \varphi z_{t-1})\,.$$

These macroeconomic series serve as input series for the computation of the tail dependence coefficient $\lambda(z)$ in (2.6).

Table 2.4 presents the expected effects of macroeconomic factors on the extent of flight to quality of real returns of stocks and bonds as suggested by literature. We hypothesize the inflation rate, the growth rate of the industrial production, the risk premium as well as the Treasury bill rate to have an inverse relation to the extent of flight to quality because recent literature find a positive dependence between these variables and the time-varying stock-bond correlation (see e.g. Chen et al. (1986), Andersson et al. (2008) and Ilmanen

Table 2.3: Correlation matrix of macroeconomic variables

	INF	GDPR	INPR	PEXR	RP	TST	TB3	UNR
INF	1.0000	-	-	-	-	-	-	-
GDPR	0.3173	1.0000	-	-	-	-	-	-
INPR	-0.0876	0.6635	1.0000	-	-	-	-	-
PEXR	0.4278	0.7612	0.4172	1.0000	-	-	-	-
RP	0.4576	0.2822	0.1238	0.3098	1.0000	-	-	-
TST	-0.4684	-0.2897	-0.1257	-0.3169	-0.9981	1.0000	-	-
TB3	0.5728	0.3999	-0.0219	0.4925	0.2041	-0.2219	1.0000	-
UNR	0.0457	-0.0110	-0.0994	0.0080	-0.0628	0.1020	0.0466	1.0000

This table presents the linear correlation coefficients for macroeconomic variables from the second quarter in 1952 to the fourth quarter in 2014.

(2003)). In contrast, we expect a positive relationship of the corresponding variable for

Table 2.4: Hypotheses: Effect of macroeconomic factors on the extent of flight to quality

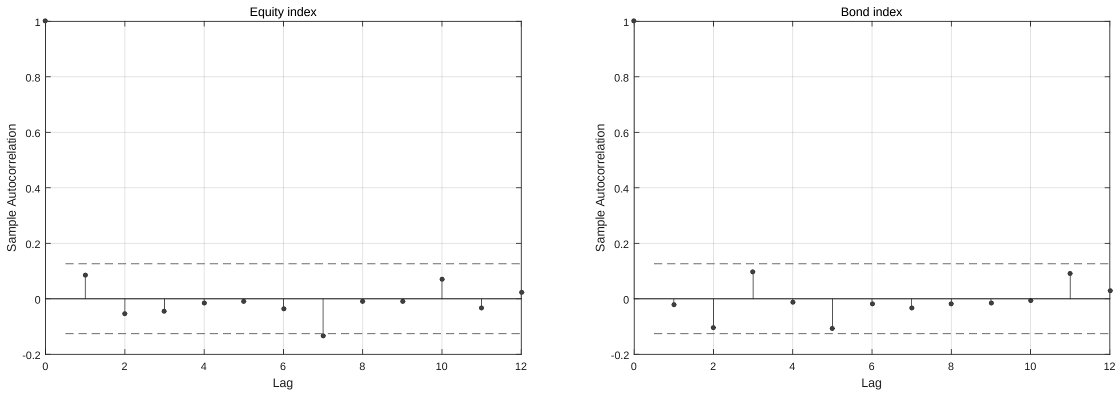
Factor	Effect	Literature
Inflation	$-$	e.g. Andersson et al. (2008), Yang et al. (2009)
Growth rate of GDP	$\pm$	e.g. Andersson et al. (2008) (*insignificant*)
Growth rate of INP	$-$	e.g. Chen et al. (1986)
Growth rate of PEX	$\pm$	e.g. Christiansen and Ranaldo (2007) (*insignificant*)
Risk premium	$-$	e.g. Chen et al. (1986)
Term structure	$+$	e.g. Chen et al. (1986)
Treasury bill rate	$-$	e.g. Ilmanen (2003), Yang et al. (2009)
Unemployment rate	$+$	e.g. Boyd et al. (2005)

This table presents the expected effect of macroeconomic factors on the extent of flight to quality. $+$ denotes the hypothesis of a positive relationship of the corresponding variable on tail dependence, while $-$ indicates a negative relationship, respectively. $\pm$ denotes that recent literature findings vary and are often insignificant.

the term structure and the unemployment rate (see e.g. Boyd et al. (2005) and Chen et al. (1986)). Moreover, we also suppose the growth rate of the gross domestic product and the growth rate of personal consumption expenditures to negatively influence tail dependence. However, previous work as in Andersson et al. (2008) and Christiansen and Ranaldo (2007) cannot provide statistical evidence with respect to these factors.

2.4.2 Time series properties

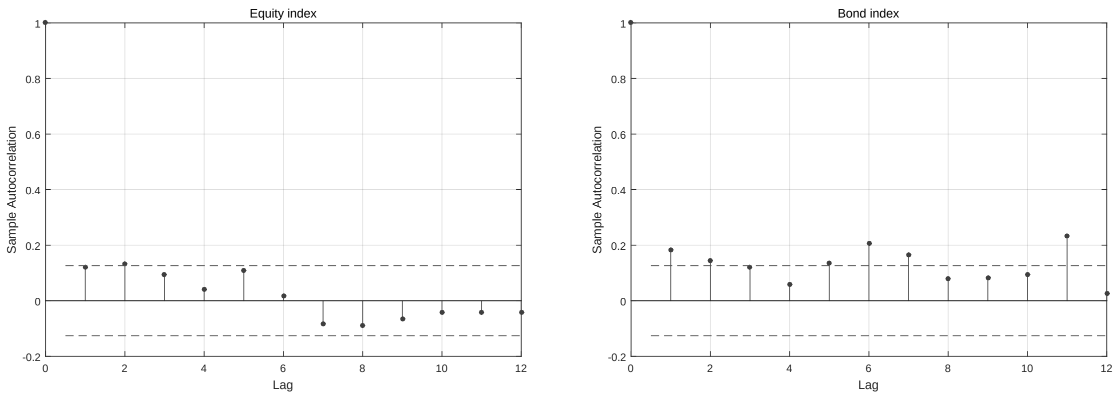
In order to derive the time series model of real equity and bond returns, we now analyze its properties. Figure 2.2 shows the sample autocorrelation with a possible maximum lag of 12 for a confidence band of 95% for the real returns of (a), the value-weighted equity index and (b), the 30-year bond index. Both time series indicate no reasonable lag structure. Only real equity returns show some autocorrelation at lag 7 with a value of -0.1348, but the extent is hardly relevant. Using the modulus of real returns Figure 2.3 presents the



(a) Value-weighted equity returns (b) 30-year bond returns

FIGURE 2.2: Sample autocorrelation function of real returns

sample autocorrelation with a possible maximum lag of 12. Here, we observe exceedances for the modulus of equity returns for lag 2 in (a). It takes values of 0.1332 for lag 2 which can be seen as negligible. In (b), we observe autocorrelation in the modulus of the bond return series for several lags including lag 1, lag 6 and lag 11 with values of 0.1926, 0.2064 and 0.2452, respectively, indicating heteroscedasticity, and thus, a change in the variance of the bond time series. We control for heteroscedasticity in finding regime-switches in the



(a) Value-weighted equity returns (b) 30-year bond returns

FIGURE 2.3: Sample autocorrelation function of modulus of real returns

squared real return series of the 30-year bond index.[9] In order to identify structural breaks in the variance of the bond return series, we follow a CUSUM approach by Yao (1988). Specifically, we use the structural break point analysis by Andreou and Ghysels (2002) applying a CUSUM test of squared returns. Table 2.5 presents the change point analysis for squared real bond returns. We use a minimal period length of 16 quarters, and take the Bayesian information criterion (BIC) as selection criterion for different model possibilities.

[9] We also applied a GARCH approach. However, the GARCH model could not sufficiently explain the autocorrelation of squared bond returns.

Table 2.5: Change point analysis for real bond returns

# Change points	0	1	2	3	4
BIC	-1.1025	-1.1111	-1.1112	-1.1128*	-1.1101
Change point 1	-	2008:4	1979:4	1980:1	1968:4
Change point 2	-	-	2008:4	1986:2	1980:1
Change point 3	-	-	-	2008:4	1986:2
Change point 4	-	-	-	-	2008:4

This table presents the change point analysis using the structural break point analysis by Andreou and Ghysels (2002) for squared real bond returns from the second quarter in 1952 to the fourth quarter in 2014. The minimal period length is set to 16 quarters. The BIC serves as the model selection criterion. The BIC-optimal specification is indicated by *.

Its lowest value is -1.1128. Thus, the favored model for bond returns has three change points with four regimes from 1952:2 to 1979:4, 1980:1 to 1986:1, 1986:2 to 2008:3, and 2008:4 to 2014:4. Earlier studies confirm the location of the first two change points (see Garcia and Perron (1996)). When specifying the sample autocorrelation of squared real bond returns for the four different regimes, the lag structure vanishes. Therefore, we take into account the structural break points for changes in the variance. Table 2.6 presents the summary statistics of bond returns for the four regimes classified by the structural break point analysis before. Noticeably, the second as well as the fourth regime have the

Table 2.6: Summary statistics of real bond returns for different regimes

	Obs.	Mean	SD	Skewness	Kurtosis
1952:2 - 2014:4	251	-0.0001	0.0649	1.4251	9.2228
1952:2 - 1979:4	111	-0.0110	0.0341	0.0023	3.3631
1980:1 - 1986:1	25	0.0217	0.1033	0.1469	2.3638
1986:2 - 2008:3	90	0.0031	0.0548	0.0213	2.3698
2008:4 - 2014:4	25	0.0154	0.1243	1.3449	4.8691

This table presents summary statistics of quarterly real bond returns between 1952 and 2014. The returns of the 30 year bond index are classified by their regime switches using structural break point analysis by Andreou and Ghysels (2002).

fewest number of observations with 25 quarters each, whereas the first period has 111 observations, and respectively the third time span contains 90 quarters.

The mean of real bond returns remarkably changes for all regimes. Thereby, the first regime has a negative mean with a value of -0.0110. The mean is highest for the second period with 0.0217. In particular, we observe a strong variation of the standard deviation over the regimes. Here, the standard deviation is the lowest in the first regime with a value of 0.0341. In the third regime, it is almost twice as high as in the first period. The standard deviation is highest in the period from 2008:4 to 2014:4, and with 0.1243 it is nearly four times higher than between the second quarter of 1952 and the fourth quarter of 1979. Altogether, this strengthens integrating structural changes in our analysis. We also check for cross-correlation between equity and bond returns. As Figure 2.4 shows, we find a significant cross-correlation at the 95%-level with a value of 0.1465 for lag 2. This

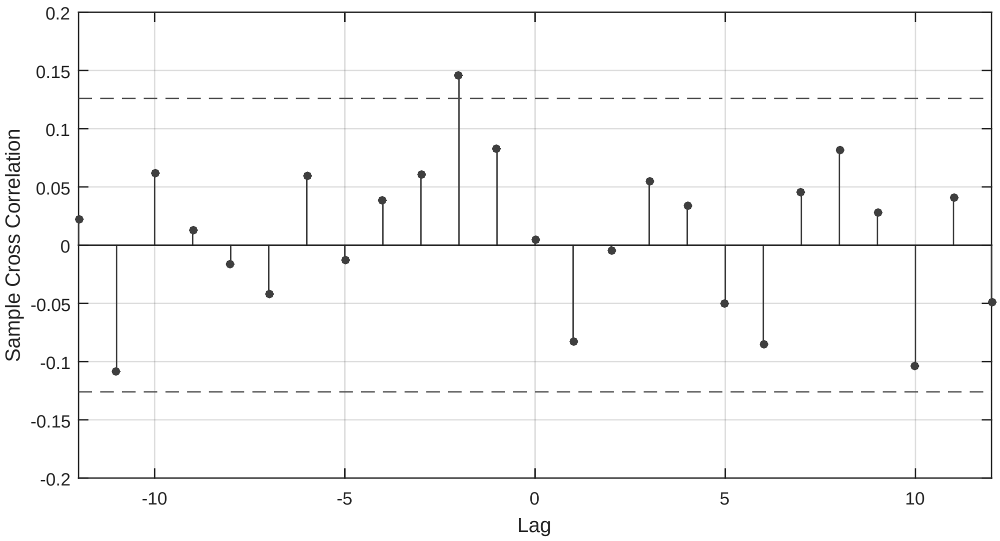
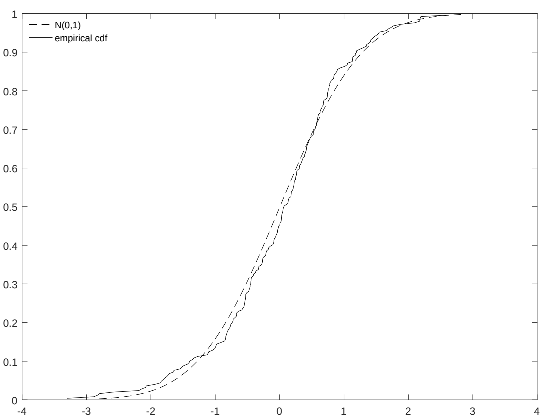


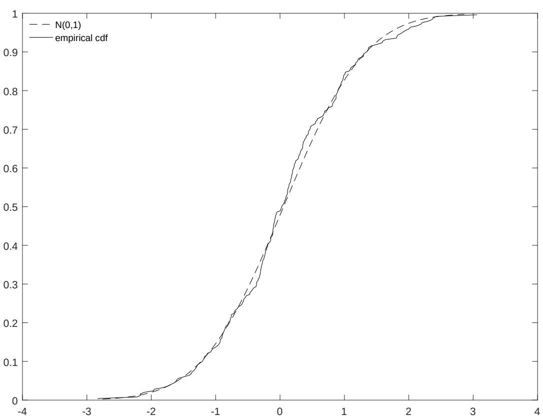
FIGURE 2.4: Sample cross-correlation of value-weighted equity returns and 30-year bond returns

indicates that past real bond returns for lag 2 explain the present movement of real equity returns.

The summary statistics of real value-weighted equity returns in Table 2.2 as well as real bond returns for different regimes in Table 2.6 recommend the application of normally distributed margins. Visually, the empirical distributions of the two real return series are a good fit compared to the normal distribution, see Figure 2.5. In particular, the results



(a) Empirical vs. theoretical distribution: VWE



(b) Empirical vs. theoretical distribution: B30

FIGURE 2.5: Marginal distribution plots: empirical vs. theoretical distribution

of the Kolmogorov-Smirnov test and the Anderson-Darling test in Table 2.7 substantiate our assumption as both tests cannot reject normally distributed margins at any usual confidence level.

Table 2.7: Distribution tests of standardized residuals

	VWE		B30	
	KS test	AD test	KS test	AD test
5%-level test statistic	0.0575	1.1466	0.0494	0.5189
5%-level critical value	0.0855	2.4930	0.0855	2.4930
p-value	0.3711	0.2887	0.5622	0.7274

This table presents the 5%-level test statistics of Kolmogorov-Smirnov test (KS) as well as Anderson-Darling test (AD). The null hypothesis is that the data is normally distributed.

2.4.3 Time series model

We have specified the dependence structure of equity and bond returns by the conditional flight-to-quality copula given in chapter 2.3.1. In order to estimate the dependence parameters in the subsequent analysis, the data need to be conditionally independent and identically distributed. Therefore, we develop an appropriate time series model by considering the properties of the univariate, as well as the bivariate real return series.

We have shown that both, the value-weighted US stock index as well as the 30 year bond index have a negligible autocorrelation structure in their real return series. Analyzing the modulus of real returns, the bond time series shows strong autocorrelation, indicating a time-varying variance structure of the series. We detect these changes in finding structural breaks using the change point analysis by Andreou and Ghysels (2002). Besides, we find significance in the cross-correlation of real equity and bond returns at lag 2. Thus, past movements of real bond returns explain the current performance of real equity returns. Moreover, we assume both margins to be normally distributed as not only the visual verification shows merely minor deviations but also distribution tests confirm our assumption.

Putting all together, we build the time series model for real equity returns r_E and real bond returns r_B, such that

$$\begin{bmatrix} r_{E,t} \\ r_{B,t} \end{bmatrix} = \begin{bmatrix} \mu_E + \kappa_{E,1} r_{B,t-2} \\ \mu_B \end{bmatrix} + \begin{bmatrix} \eta_{E,t} \\ \eta_{B,t} \end{bmatrix} , \quad \text{for } \ t = 4, ..., 252 \, ,$$

where μ_E and μ_B denote the constants for real equity returns, and respectively, real bond returns. The parameter $\kappa_{E,1}$ is the regression coefficient. The time-varying variance is expressed by the bivariate term η_t. It is given by

$$\eta_t = \begin{bmatrix} \eta_{E,t} \\ \eta_{B,t} \end{bmatrix} = \begin{bmatrix} \sigma_E \varepsilon_{E,t} \\ \sigma_{B,t} \varepsilon_{B,t} \end{bmatrix} , \quad \text{for } \ t = 4, ..., 252 \, ,$$

where $(\varepsilon_{E,t}, \varepsilon_{B,t})$ denote the error term, which is independent over time with standard normal margins[10] and conditional copula $C_{ftq}(\,\cdot, \cdot \,|\, z)$. The standard deviation of the real

[10] In the robustness analysis, we also check for t-distributed margins.

equity return series σ_E is constant. Based on our findings in section 2.4.2 the standard deviation of the real bond return series $\sigma_{B,t}$ is regime dependent with

$$\sigma_{B,t} = \begin{cases} \sigma_{B,I} & 4 \leq t < \tau_1 \\ \sigma_{B,II} & \tau_1 \leq t < \tau_2 \\ \sigma_{B,III} & \tau_2 \leq t < \tau_3 \\ \sigma_{B,IV} & \tau_3 \leq t \leq 252\,, \end{cases}$$

where $\tau_1 = 113$ (1980:1), $\tau_2 = 138$ (1986:2), and $\tau_3 = 228$ (2008:4) are the three identified regime-switching points. The model is estimated in the following dependence analysis using the maximum likelihood approach.

In addition, we also examined models with different specifications in the mean and variance equation. We allowed for constant mean and constant variance, time-varying mean and variance, as well as time-varying mean and constant variance for the bond time series. Using the BIC, the model given above is optimal and hence selected for the subsequent dependence analysis.

2.5 Empirical results

We have specified the copula model and the marginal model. This section now presents the results of the maximum-likelihood estimation. We first estimate the extent of flight to quality in the unconditional model and then compare our results with the study of Durand et al. (2010) whose dataset is more than a decade shorter. Subsequently, we identify the drivers of flight to quality by analyzing a model with multiple macroeconomic factors and single factor models, respectively. We then check for robustness.

2.5.1 Unconditional model

The dependence structure of real equity and bond returns is analyzed using constant factors of λ and θ in the conditional flight-to-quality copula in equation (2.7). The copula parameters λ_{ftq} and θ_{ftq}, as well as the parameters of the time series model are estimated using the maximum-likelihood approach. The results are presented in Table 2.8. Both parameters of the flight-to-quality copula are significant at the 1% level. First, the parameter $\theta_{ftq} = 2.7683$ confirms the assumption of a usual positive correlation between stock and bond returns. This common relationship is sustained by the empirical correlation of model residuals with a value of 0.1487, as well as the two scale-invariant measures ρ_S and τ with values of 0.1575 and 0.1104, respectively. Secondly, the tail dependence in the fourth quadrant is measured by the parameter λ_{ftq}. Its value of 0.1586 indicates an almost one-in-six chance of observing flight to quality given extreme negative equity

TABLE 2.8: ML-estimates for the unconditional model

Coeff.	Estimate	SE	z-value
	Mean equation		
μ_E	0.0208***	0.0056	3.7309
$\kappa_{E,1}$	0.1633**	0.0689	2.3686
μ_B	0.0067**	0.0029	-2.3000
	Regime dependent variances		
σ^2_E	0.0067***	0.0006	11.8591
$\sigma^2_{B,I}$	0.0012***	0.0002	7.8613
$\sigma^2_{B,II}$	0.0117***	0.0037	3.1923
$\sigma^2_{B,III}$	0.0029***	0.0005	5.6502
$\sigma^2_{B,IV}$	0.0148***	0.0031	4.7853
	Dependence parameters		
λ_{ftq}	0.1586***	0.0573	2.7674
θ_{ftq}	2.7683***	0.7763	3.5660
LL	659.2746	BIC	-5.0944
ρ 0.1487	ρ_S 0.1575		τ 0.1104

This table presents the maximum-likelihood estimates for both, the time series model and the flight-to-quality copula over the period from the first quarter of 1953 to the fourth quarter of 2014. Moreover, the standard error (SE), the z-value, as well as the model diagnostics log-likelihood (LL) and Bayesian information criterion (BIC) are given. ** and *** represent statistical significance at the 5% and 1% level, respectively.

returns. Compared to the study of Durand et al. (2010), we notice an increase in the extreme asymmetric dependence of real equity and bond returns by more than two percent. Moreover, all estimated time series parameters are highly statistical significant at the 5% level, and 1% level, respectively.

Figure 2.6 presents the contour lines of the flight-to-quality copula with its estimated parameters λ_{ftq} and θ_{ftq}, as well as the pairs of univariate equity and bond returns. The margins are scaled to standard normal. Figure 2.6 clearly shows the existence of flight to quality. Several data points are observable in the upper left corner of Figure 2.6. Altogether, there are 6 observations at the 10% level where the 10% highest bond returns co-occur with the 10% lowest equity returns. These points include 1987:4, 1998:3, 2000:4, 2002:3, 2008:4, and 2011:3, and therefore, all relevant financial crisis. These are Black Monday and its consequences in 1987, the LTCM crisis in 1998, the burst of the technology bubble starting in 2000 and causing the stock market downturn in 2002, the financial crisis in 2008 following the bankruptcy of Lehman Brothers, and the debt-ceiling crisis in summer 2011.[11]

[11] Moreover, at the 20% level five additional data points are included with 1960:1, 2001:3, 2002:2, 2008:3 and 2010:2.

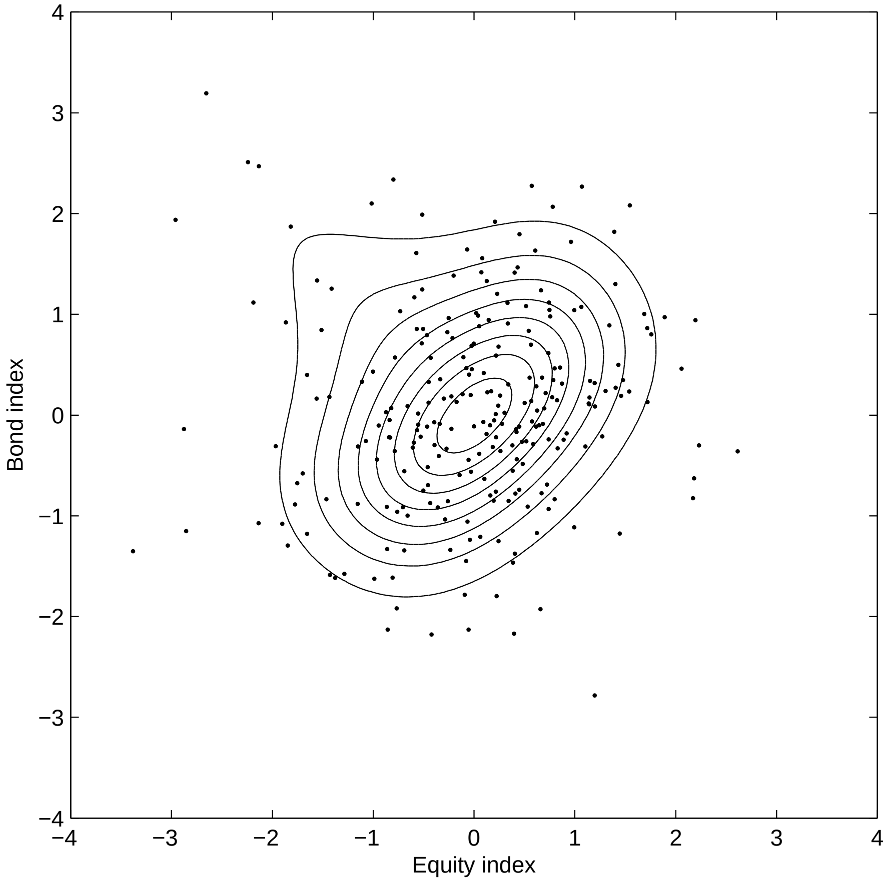


FIGURE 2.6: Scatter plot of equity and bond returns

2.5.2 Conditional model

Having documented the existence of flight to quality, we now aim at identifying the drivers of this effect based on the functional relationship of macroeconomic variables and tail dependence in Equation (2.6). In particular, we quantify the sensitivity of tail dependence to changes in the explanatory variable by one standard deviation ($\Delta\lambda_z$) given in Equation (2.8) indicating how a change of a specific macroeconomic factor affects the extent of flight to quality. The estimates for each factor and each time series are given in Table 2.9. Next to $\Delta\lambda_z$ the maximum-likelihood estimation parameters $\lambda_{0,z}$ and $\lambda_{1,z}$ and their standard errors (SE), as well as the log-likelihood (LL) for model diagnostic are displayed. Panel A presents the results for the base series. We observe that the constant parameter $\lambda_{0,z}$ is negative and highly significant at the 1% level for all factors but TB3 and UNR. With respect to the $\lambda_{1,z}$-coefficients, we detect statistical significance for four macroeconomic factors to be possible drivers of flight-to-quality, the inflation rate, the growth rates of the gross domestic product and personal consumption expenditures and the Treasury bill

TABLE 2.9: Sensitivity of tail dependence: lag 1

Factor	**Summary statistics**		**ML-Estimates**				**Sensitivity**	**Diagnostics**
z	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\Delta\lambda_z$	LL
Panel A: Base series of z								
INF	0.0088	0.0092	-1.7887***	0.4560	-33.1782**	16.8934	-0.0301	655.2067
GDPR	0.0156	0.0101	-1.0074***	0.3576	-40.2340**	19.2405	-0.0553	661.4128
INPR	0.0072	0.0187	-2.1389***	0.5303	-8.5518	21.7476	-0.0144	654.0444
PEXR	0.0161	0.0084	-1.0226***	0.3572	-35.2485**	14.8438	-0.0415	661.1686
RP	0.0012	0.0974	-2.2184***	0.5365	-1.6136	3.6795	-0.0139	653.3539
TST	0.0027	0.0654	-1.6660***	0.4286	0.3199	3.8077	0.0028	659.2859
TB3	0.0111	0.0073	0.4476	0.2790	-171.8045***	41.4361	-0.1938	672.7472
UNR	0.0594	0.0162	-1.8692*	1.1219	3.3104	17.3420	0.0071	659.2921
Panel B: First differences of z								
INF	0.0000	0.0095	-2.2375***	0.5507	-7.9517	46.5026	-0.0066	655.4577
GDPR	0.0000	0.0103	-1.6703***	0.4307	2.2728	24.7754	0.0031	659.2844
INPR	0.0000	0.0185	-1.7499***	0.4293	-21.0415	15.4201	-0.0491	659.5764
PEXR	0.0000	0.0084	-2.2440***	0.6183	37.5274	59.3678	0.0275	656.3363
RP	0.0000	0.1326	-1.9308***	0.4839	-4.0875*	2.1195	-0.0602	660.3163
TST	0.0003	0.0922	-2.3793***	0.5831	4.6546*	2.8270	0.0335	655.2037
TB3	0.0000	0.0023	-1.6751***	0.4137	-123.7333*	64.1392	-0.0379	660.2178
UNR	0.0001	0.0038	-1.6964***	0.4272	29.9101	69.8850	0.0150	659.3514
Panel C: Unexpected changes of z								
INF	0.0000	0.0082	-1.6320***	0.4287	-28.8937*	17.3303	-0.0324	660.2618
GDPR	0.0000	0.0089	-2.2049***	0.5402	-34.0269	38.6623	-0.0271	655.5094
INPR	-0.0001	0.0160	-2.2065***	0.5259	-7.5180	27.3776	-0.0108	654.7783
PEXR	0.0000	0.0073	-1.6679***	0.4248	-23.4165	26.4973	-0.0227	659.7019
RP	0.0000	0.0973	-2.2233***	0.5375	-1.9917	3.6006	-0.0171	653.2780
TST	0.0001	0.0654	-1.6669***	0.4285	0.3209	3.8081	0.0028	659.2860
TB3	0.0000	0.0023	-1.6409***	0.4053	-154.5540**	64.3368	-0.0478	661.0240
UNR	0.0000	0.0038	-1.6953***	0.4269	31.4539	70.3558	0.0156	659.3570

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for all three different types of time series over the period from the first quarter of 1953 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.20, Table 2.21 and Table 2.22 in Appendix 2.A.

rate. It is highest for TB3 at the 1% level. Consequently, the log-likelihood is the highest of all analyzed factors with 672.7472. The estimated $\lambda_{1,TB3}$ has a value of -171.8045, and the sensitivity of the tail dependence coefficient to changes in the Treasury bill rate is negative as well with a value of $\Delta\lambda_{TB3} = -0.1938$. Therefore, a drop of the Treasury bill rate by one standard deviation increases on average the risk of flight to quality by 19.38%. Accordingly, an increase in the level of TB3 reduces this risk. The inflation rate and the growth rate of the gross domestic product as well as the growth rate of personal consumption expenditures are statistically significant to a lesser degree at the 5% level. The sensitivities of tail dependence towards changes in the factors are negative as well with values of -0.0301 for INF, -0.0553 for GDPR and -0.0415 for PEXR. Nevertheless, in comparison to TB3, the value of the sensitivity is less than one third for GDPR, around one fifth for PEXR and even less than one sixth for INF. That means, although the $\lambda_{1,z}$-estimators are statistically significant, the impact of changes of INF, GDPR and

PEXR to the extent of flight to quality is considerably lower. Analyzing the remaining macroeconomic variables, we cannot observe statistical significance for $\lambda_{1,z}$. Consequently, only TB3 and INF confirm the hypotheses introduced in section 2.4.1. In contrast to the existing literature, we find statistical significant results for GDPR as well as PEXR. However, INPR, RP, TST and UNR do not provide statistical evidence to influence the co-movement of stock and bond returns, and therefore do not confirm existing research.

The estimates for first differences are given in Panel B of Table 2.9. Next to the constant parameters that are statistically significant at the 1% level we only find empirical evidence of RP, TST as well as TB3 at the 10% level to have an impact on flight to quality. For unexpected changes in Panel C, $\lambda_{1,TB3}$ is statistical significant at the 5% level. Alongside TB3, we also find statistical significance at the 10% level for $\lambda_{1,INF}$. Moreover, the other factors are not statistically significant with respect to first differences or unexpected changes. It is remarkable that $\Delta\lambda_{TB3}$ considerably reduces to less than one fifth for first differences and less than one fourth for unexpected changes when comparing both results to the one for base series. This circumstance is possibly driven by a decrease in the standard deviation of the time series.

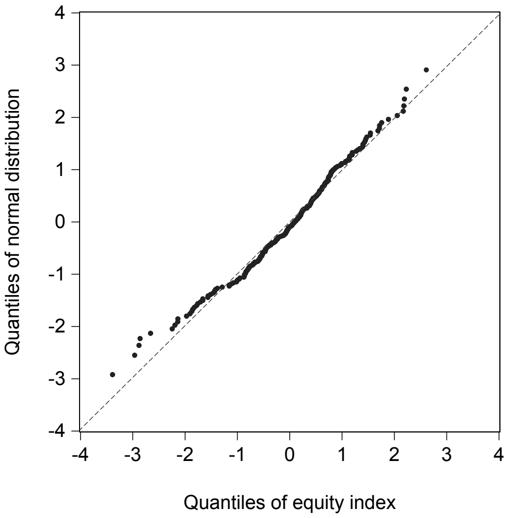
Overall, four macroeconomic factors are worth considering as possible drivers of flight to quality, namely INF, GDPR, PEXR and TB3, where, the latter appears to be most important. The TB3 factor is statistically significant for all three types of time series, and in particular, its high impact on tail dependence quantified by the sensitivity in the level time series indicates this. Furthermore, none of the remaining factors seem to influence the flight-to-quality effect.

2.5.3 Robustness

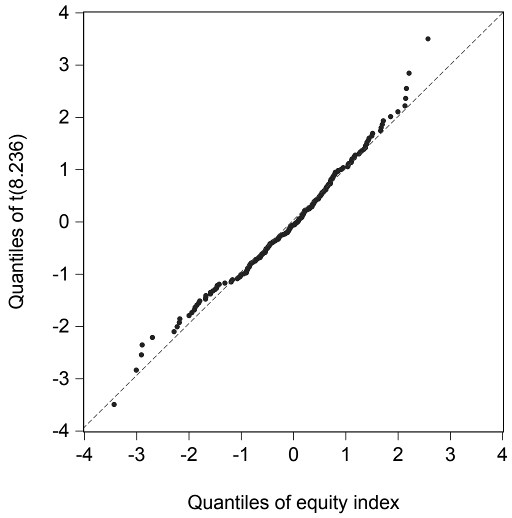
We now conduct a series of analysis, in order to check the robustness of our results. We focus on the change of the marginal distributions, use an alternative lag length for the macroeconomic variables, apply a multiple model, estimate subsamples and we extend the conditional flight-to-quality copula in Equation (2.4) such that the broad dependence parameter θ also depends on changes in macroeconomic data.

2.5.3.1 Alternative marginal distribution

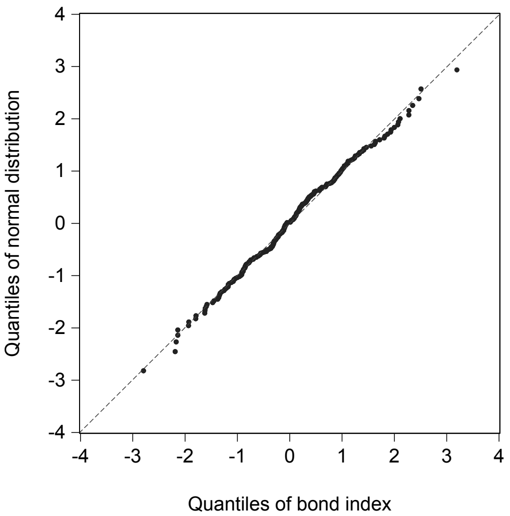
Initially, we assumed the margins to be normally distributed. Now, we investigate whether our results given in section 2.4.3 are robust with respect to this assumption. As an alternative to the rather light tailed normal distribution we use the t-distribution for both margins, see e.g. Embrechts et al. (2002). Figure 2.7 shows the QQ-plot of the empirical quantiles of real equity residuals from the first quarter of 1953 to the fourth quarter of 2014 plotted against (a) the normal distribution, and (b) the t-distribution,



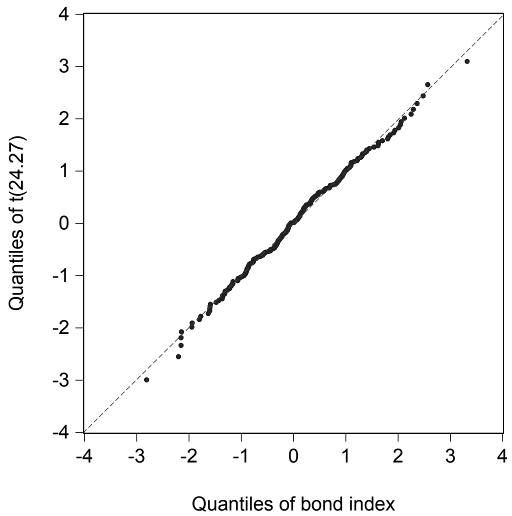
(a) QQ-plot of real equity residual quantiles versus standard normal quantiles



(b) QQ-plot of real equity residual quantiles versus Student's t quantiles



(c) QQ-plot of real bond residual quantiles versus standard normal quantiles



(d) QQ-plot of real bond residual quantiles versus Student's t quantiles

Figure 2.7: QQ-plot of real residuals

both fitted using maximum likelihood. In particular, we observe that the t-distribution fits the loss tail somewhat better than the normal distribution. Comparing the QQ-plot of the empirical quantiles of real bond residuals plotted against (c) the normal distribution and (d) the t-distribution, Figure 2.7 shows that the t-distribution does not fit the tails better than normal distribution. As well as before maximum likelihood approach is used to fit the distributions. In both cases, the corresponding parameter, that is the degree of freedom of the t-distribution, cannot be estimated accurately. We conduct a likelihood ratio test for testing the null model of normal distribution against the alternative model of t-distribution. The deviance statistics, twice the log-likelihood ratio, takes the value $d = 3.0608$. Thus, the null hypothesis of normal distribution cannot be rejected at any usual confidence level against the alternative t-distribution.

TABLE 2.10: Sensitivity of tail dependence: t-distributed margins

Factor	**Summary statistics**		**ML-Estimates**				**Sensitivity**	**Diagnostics**
z	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\Delta\lambda_z$	LL
Panel A: Base series of z								
INF	0.0088	0.0092	-1.2674***	0.3746	-26.9492*	14.0750	-0.0369	662.1873
GDPR	0.0156	0.0101	-1.0015***	0.3542	-38.6636**	19.5358	-0.0543	662.8991
INPR	0.0072	0.0187	-1.6043***	0.4264	-9.3774	14.5113	-0.0234	660.9926
PEXR	0.0161	0.0084	-1.0149***	0.3546	-33.9519**	15.0339	-0.0407	662.6436
RP	0.0012	0.0974	-1.6143***	0.4312	-0.7325	2.5958	-0.0099	660.8549
TST	-0.0027	0.0654	-1.6270***	0.4360	0.1137	3.7116	0.0010	660.8133
TB3	0.0111	0.0073	0.4048	0.2840	-166.0502***	42.4480	-0.1896	674.1742
UNR	0.0594	0.0162	-1.7890***	1.1049	2.6731	16.8752	0.0059	660.8213
Panel B: First differences of z								
INF	0.0000	0.0095	-1.7135***	0.4635	-23.6722	25.4724	-0.0292	661.1402
GDPR	0.0000	0.0103	-1.6297***	0.4380	3.7763	25.8101	0.0054	660.8254
INPR	0.0000	0.0185	-1.6675***	0.4339	-16.6888	15.0082	-0.0412	661.0388
PEXR	0.0000	0.0084	-1.5982***	0.4466	35.1491	38.9879	0.0415	661.2838
RP	0.0000	0.1326	-1.8756***	0.4867	-3.8461*	2.0694	-0.0590	661.7300
TST	0.0003	0.0922	-1.6774***	0.4749	1.3284	2.2586	0.0163	655.5123
TB3	0.0000	0.0023	-1.6303***	0.4234	-117.8586	63.8525	-0.0372	661.6998
UNR	0.0001	0.0038	-1.6495***	0.4357	21.6232	74.5223	0.0112	660.8496
Panel C: Unexpected changes of z								
INF	0.0000	0.0082	-1.5945***	0.4374	-27.4017	17.7489	-0.0315	661.1402
GDPR	0.0000	0.0089	-1.6227***	0.4453	-28.4126	27.6328	-0.0347	660.8254
INPR	-0.0001	0.0160	-1.6773***	0.4306	-16.2923	15.6998	-0.0347	661.0388
PEXR	0.0000	0.0073	-1.6310***	0.4329	-21.5308	26.8493	-0.0214	661.2838
RP	0.0000	0.0973	-1.6157***	0.4309	-0.9213	2.5852	-0.0124	660.8750
TST	0.0001	0.0654	-1.6273***	0.4356	0.1142	3.7121	0.0010	655.5123
TB3	0.0000	0.0023	-1.5988***	0.4152	-149.0357**	63.8132	-0.0474	661.6998
UNR	0.0000	0.0038	-1.6487***	0.4353	22.8946	74.9016	0.0002	660.8496

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for all three different types of time series over the period from the first quarter of 1953 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 30-year bond index with t-distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.23, Table 2.24 and Table 2.25 in Appendix 2.A.

Table 2.10 presents the results of the conditional model for the adjusted marginal distributions. In comparison to the initial analysis in Table 2.9, we observe a small increase in the log-likelihood for each macroeconomic factor but TST for unexpected changes. However, there is no substantial change in the estimation results. The constant parameter $\lambda_{0,z}$ is highly significant at the 1% level for all macroeconomic factors. Only $\lambda_{0,TB3}$ is insignificant for the base series of macroeconomic factors. As before, the inflation rate, the growth rates of the gross domestic product as well as the personal consumption expenditures and the Treasury bill rate are the potential drivers of flight to quality, with TB3 having the biggest impact on tail dependence. It provides statistical significance at the 1% level and its sensitivity is the highest in absolute terms with -0.1896 emphasizing the negative relationship of TB3 and flight to quality. In addition, GDPR as well as PEXR are statistical significant at the 5% level, INF at the 10% level. Nevertheless, these three variables have a comparatively minor impact on tail dependence. In contrast to the main analysis, only RP remains statistically significant at the 10% level for first differences. For unexpected changes, only TB3 provides statistical evidence being a driver of flight to quality.

Taken together, the use of t-distributed margins for real value-weighted equity returns and real returns from the 30-year bond index does not improve the estimation results of the initial analysis. Therefore, normal distributed margins are an appropriate choice for both real return series as already shown by the application of Kolmogorov-Smirnov test and Anderson-Darling test in Section 2.4.2. Moreover, we see that the results are robust.

2.5.3.2 Alternative lag length

In order to find drivers of the flight-to-quality effect, we use a lag of 1 for macroeconomic variables in equation (2.6). However, because of possibly delayed publications of these factors we also take a lag length of 2 into account.

The estimates are given in Table 2.11. Compared to the results in the main analysis the log-likelihood increases for most of the macroeconomic variables in each of the three different time series. For base time series and alongside TB3, the $\lambda_{1,z}$'s of INF as well as PEXR are now statistically significant at the 1% level, $\lambda_{1,GDPR}$ remains statistically significant at the 5% level, and $\lambda_{1,RP}$ now is significant at the 10% level. Analyzing first differences the estimates in Panel B are more inconsistent compared to the main analysis. Here, $\lambda_{1,INF}$ as well as $\lambda_{1,TST}$ are significant at the 1% level, $\lambda_{1,RP}$ is significant at the 5% level, and $\lambda_{1,PEXR}$ is significant at the 10% level. However, TB3 does not provide statistical evidence to have an impact on flight to quality. In addition, we observe PEXR and TB3 to have a strong impact on flight to quality at the 1% significance level for time series of unexpected changes. Furthermore, RP is statistically significant at the 10% level and INF is not statistically significant anymore. In absolute values the sensitivities to tail dependence to changes of the explanatory variable by one standard deviation increase for almost each variable, in particular when the macroeconomic variable significantly influences the flight-to-quality effect. The impact is still the highest for the Treasury bill rate with $\Delta\lambda_{TB3} = -0.2102$.

We conclude that the use of a lag length of 2 gives similar results to the main analysis. Partially, the results get even better as the statistical significance increases for example for PEXR in all three types of time series, even though TB3 for first differences and INF for unexpected changes become insignificant. As a consequence, our model choice with a lag of 1 is suitable. Particularly, we see that our results are robust.

TABLE 2.11: Sensitivity of tail dependence: lag 2

Factor	**Summary statistics**		**ML-Estimates**				**Sensitivity**	**Diagnostics**
z	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\Delta\lambda_z$	LL
Panel A: Base series of z								
INF	0.0088	0.0092	-0.8734**	0.3643	-74.5771***	27.6776	-0.1005	661.8143
GDPR	0.0156	0.0101	-0.8451**	0.4121	-67.5233**	29.8508	-0.0775	662.7651
INPR	0.0072	0.0187	-1.6658***	0.4308	-2.9970	14.0435	-0.0074	659.2995
PEXR	0.0161	0.0084	-0.0583	0.3233	-96.9045***	22.2892	-0.1123	666.7520
RP	0.0012	0.0974	-2.1183***	0.5588	6.7044*	3.6114	0.0634	660.0954
TST	-0.0027	0.0654	-2.1129***	0.5964	-9.2410	6.5358	-0.0597	659.6108
TB3	0.0111	0.0073	0.6588**	0.3349	-206.6112***	51.5686	-0.2102	674.4382
UNR	0.0594	0.0162	-1.7400	1.1059	1.1964	17.2462	0.0026	659.2817
Panel B: First differences of z								
INF	0.0000	0.0095	-2.4666***	0.6391	51.3617***	19.7655	0.0355	654.9866
GDPR	0.0000	0.0103	-1.6426***	0.4282	21.8013	26.0081	0.0306	659.8739
INPR	0.0000	0.0185	-1.6575***	0.4326	2.2915	16.2608	0.0057	659.2907
PEXR	0.0000	0.0084	-1.6958***	0.4457	-58.4044*	34.9143	-0.0646	660.3458
RP	0.0000	0.1326	-1.8888***	0.5046	4.7860**	2.3338	0.0728	660.9520
TST	0.0003	0.0922	-2.2858***	0.5355	-4.7218***	1.7270	-0.0366	655.5849
TB3	0.0000	0.0023	-2.2090***	0.5382	-38.1011	224.6679	-0.0078	654.0977
UNR	0.0001	0.0038	-1.6771***	0.4280	15.9189	62.6647	0.0081	659.3088
Panel C: Unexpected changes of z								
INF	0.0000	0.0082	-1.6021***	0.4219	-18.8260	31.7059	-0.0215	659.3433
GDPR	0.0000	0.0089	-1.7164***	0.4477	-24.3134	32.0372	-0.0279	659.5893
INPR	-0.0001	0.0160	-1.6715***	0.4324	-0.4671	17.9165	-0.0010	659.2804
PEXR	0.0000	0.0073	-1.8854***	0.4201	-155.2790***	29.3113	-0.1312	665.9420
RP	0.0000	0.0973	-2.1293***	0.5608	7.2112*	3.7359	0.0672	660.2737
TST	0.0001	0.0654	-2.0862***	0.5833	-9.2429	6.5390	-0.0597	659.6161
TB3	0.0000	0.0023	-1.7730***	0.4042	-314.5934***	59.5274	-0.0891	662.8496
UNR	0.0000	0.0038	-1.6753***	0.4278	15.7145	63.2760	0.0079	659.3083

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for all three different types of time series with a time lag of 2 periods over the period from the first quarter of 1953 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.26, Table 2.27 and Table 2.28 in Appendix 2.A.

2.5.3.3 Multi-factor model

We have estimated the sensitivity of tail dependence using one macroeconomic variable in equation (2.6). Now, we check the impact of multiple factors to our analysis. Table 2.12 presents the results for the multi-factor estimations using all macroeconomic variables for each of the three types of time series over the period from the first quarter of 1953 to the fourth quarter of 2014. Analyzing base series, we detect TB3 to be highly significant at the 1% level with a value of -200.7137. Moreover, GDPR is significant at the 10% level. The estimation outcomes for first differences show significance at the 1% level for TST. INF and RP are significant at the 5% level. For unexpected changes of macroeconomic factors TB3 shows the highest statistical significance at the 1% level. GDPR is significant at the 5% level, and INF, TST as well as UNR provide statistical evidence to be possible drivers of flight to quality at the 10% significance level. For all three types of time series

TABLE 2.12: ML-estimates for multiple macroeconomic factors: lag 1

	Macroeconomic time series					
	Base series of z		First differences of z		Unexpected changes of z	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE
λ_0	0.2365	1.3555	-2.7598***	0.8402	-1.8808***	0.4920
$\lambda_{1,INF}$	-27.3769	35.1747	-174.2413**	79.6819	-98.7190*	51.4157
$\lambda_{1,GDPR}$	-107.9193*	55.2598	-3.6763	47.0848	-128.9051**	57.6644
$\lambda_{1,INPR}$	33.8873	22.5483	0.8133	33.4274	36.5346	30.5110
$\lambda_{1,PEXR}$	79.7707	54.7294	-2.2819	67.0583	-11.9506	43.4032
$\lambda_{1,RP}$	4.5532	4.9258	-18.7578**	8.0407	-7.2853	8.7748
$\lambda_{1,TST}$	-2.5138	6.5112	-42.5179***	11.8674	-25.7373*	15.2528
$\lambda_{1,TB3}$	-200.7137***	75.1103	-30.5896	279.0629	-492.7575***	139.4867
$\lambda_{1,UNR}$	11.7388	17.0640	-100.8719	113.1169	-251.5480*	128.8719
θ	-3.3366***	0.7368	-2.1260***	0.5806	-2.9597***	0.6787
LL	680.6108		666.3476		669.6946	

This table reports the maximum-likelihood estimates for Equation (2.6) of multiple macroeconomic factors for all three different types of time series over the period from the first quarter of 1953 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.29 in Appendix 2.A.

the broad dependence parameter θ_0 provides statistical significance at the 1% level.

Overall, TB3 as well as GDPR are noteworthy to be possible drivers of flight to quality and therefore the results of our main analysis are robust. However, the application of a multi-factor model makes an adequate interpretation of the estimation results difficult and it increases the standard error for almost each estimate because all factors interact and are not independent.

2.5.3.4 Subsample

We now split our dataset in half and form two disjoint subsamples. The first subsample covers the period from the first quarter of 1953 to the second quarter of 1983, and consequently the second subsample starts in the first quarter of 1984 and finishes with the fourth quarter of 2014.[12] For the first subsample the estimates are given in Table 2.13. We only observe statistical significance at the 10% level for the base series of TST. None of the other factors significantly influences the extreme asymmetric dependence of stock and bond returns for each of the three types of time series. In particular, the estimation results show increased standard errors. Table 2.14 presents the maximum-likelihood results for the second subsample from the first quarter of 1984 to the fourth quarter of 2014 using all three types of time series for macroeconomic factors. For base series, the Treasury bill rate is highly significant at the 1% level. With a value of -0.1993, the sensitivity of tail dependence is highest for TB3, too. Moreover, we observe a significant influence of the unemployment rate at the 10% level. Its $\Delta\lambda_{UNR} = 0.1072$ also shows a strong impact on

[12] While splitting the dataset, we do not change the time series model.

TABLE 2.13: Sensitivity of tail dependence: subsample from 1953 - 1983

Factor	**Summary statistics**		**ML-Estimates**				**Sensitivity**	**Diagnostics**
z	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\Delta\lambda_z$	LL
			Panel A: Base series of z					
INF	0.0109	0.0099	-1.0506	$1.1305 \cdot 10^{0}$	-156.5946	$2.8000 \cdot 10^{2}$	-0.0933	362.4368
GDPR	0.0184	0.0116	-3.1629	$4.3820 \cdot 10^{0}$	-61.3264	$4.2478 \cdot 10^{2}$	-0.0097	361.4294
INPR	0.0078	0.0229	-6.6724	$6.8766 \cdot 10^{1}$	-55.9834	$1.4294 \cdot 10^{3}$	-0.0011	361.4086
PEXR	0.0188	0.0087	-0.4649	$0.8185 \cdot 10^{0}$	-115.1647	$1.0700 \cdot 10^{2}$	-0.0648	362.4552
RP	0.0201	0.0841	-20.7122	$1.8188 \cdot 10^{5}$	-100.2311	$1.2509 \cdot 10^{6}$	0.0000	357.4682
TST	-0.0137	0.0497	-181.3438*	$1.0716 \cdot 10^{2}$	1147.6830*	$6.7626 \cdot 10^{2}$	0.0000	364.7356
TB3	0.0127	0.0076	0.2440	$1.2269 \cdot 10^{0}$	-227.2838	$1.9585 \cdot 10^{2}$	-0.1153	363.1669
UNR	0.0568	0.0168	-18.2254	$1.7989 \cdot 10^{7}$	-7.1711	$2.3100 \cdot 10^{8}$	0.0000	361.4049
			Panel B: First differences of z					
INF	0.0002	0.0071	-20.6687	$7.7434 \cdot 10^{1}$	-1075.6350	$4.1168 \cdot 10^{3}$	0.0000	361.9465
GDPR	0.0002	0.0131	-19.2861	$1.5739 \cdot 10^{7}$	-6.3236	$1.8347 \cdot 10^{7}$	0.0000	361.4049
INPR	0.0003	0.0249	-16.3494	$1.8887 \cdot 10^{6}$	-9.6746	$2.2203 \cdot 10^{7}$	0.0000	361.4049
PEXR	0.0001	0.0096	-54.5027	$3.7108 \cdot 10^{2}$	-2581.6790	$1.7916 \cdot 10^{4}$	0.0000	367.2406
RP	0.0001	0.1146	-6.4837	$5.8989 \cdot 10^{1}$	-18.4308	$3.8156 \cdot 10^{2}$	-0.0038	358.3637
TST	-0.0003	0.0716	-24.0323	$7.7094 \cdot 10^{5}$	89.6642	$2.0297 \cdot 10^{7}$	0.0000	367.8692
TB3	0.0001	0.0030	-7.4684	$1.4165 \cdot 10^{2}$	-974.1818	$4.5414 \cdot 10^{4}$	-0.0020	359.4523
UNR	0.0006	0.0044	-19.3393	$2.1671 \cdot 10^{7}$	30.6347	$3.2090 \cdot 10^{7}$	0.0000	361.4049
			Panel C: Unexpected changes of z					
INF	0.0000	0.0065	-4.0797	$4.1518 \cdot 10^{0}$	-256.4570	$3.3593 \cdot 10^{2}$	-0.0303	361.8270
GDPR	0.0000	0.0108	-4.3005	$7.3445 \cdot 10^{0}$	-97.4921	$3.7185 \cdot 10^{2}$	-0.0145	361.4586
INPR	0.0000	0.0211	-20.6356	$3.1004 \cdot 10^{7}$	2.5324	$5.3350 \cdot 10^{7}$	0.0000	361.4049
PEXR	0.0000	0.0081	-6.2298	$5.0363 \cdot 10^{0}$	-360.9790	$3.1866 \cdot 10^{2}$	-0.0079	363.5833
RP	0.0000	0.0833	-20.1924	$1.0637 \cdot 10^{1}$	-71.5225	$3.6128 \cdot 10^{1}$	0.0000	364.8810
TST	0.0000	0.0492	-8.2610	$8.7429 \cdot 10^{1}$	42.8577	$5.2038 \cdot 10^{2}$	0.0007	361.6524
TB3	0.0000	0.0029	-9.0675	$3.8833 \cdot 10^{2}$	-986.9599	$1.1381 \cdot 10^{5}$	-0.0005	357.4362
UNR	0.0000	0.0044	-19.3477	$5.5613 \cdot 10^{6}$	25.8645	$7.5757 \cdot 10^{7}$	0.0000	361.4049

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for all three different types of time series over the period from the first quarter of 1953 to the second quarter of 1983 using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.30, Table 2.31 and Table 2.32 in Appendix 2.A.

tail dependence. None of the remaining factors is statistically significant. With respect to first differences in Panel B, only PEXR is significantly different of 0 with a value of 83.6327 at the 10% level and a sensitivity to tail dependence of 0.1249. Furthermore, Panel C presents no significant factors for unexpected changes.

Overall, it is difficult to estimate extreme dependence for subsamples due to the small sample sizes which is reflected in higher standard errors compared to the main analysis. However, for the first subsample TST and for the second period TB3 and with some limitations PEXR as well as UNR provide statistical significance. Thus, our results of the main analysis are robust.

Table 2.14: Sensitivity of tail dependence: subsample from 1984 - 2014

Factor	Summary statistics		ML-Estimates				Sensitivity	Diagnostics
z	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\Delta\lambda_z$	LL
Panel A: Base series of z								
INF	0.0068	0.0080	-0.9814**	0.4949	0.7509	27.4592	0.0012	300.3643
GDPR	0.0124	0.0069	-0.7716*	0.4674	-17.3450	24.7072	-0.0237	300.5834
INPR	0.0058	0.0121	-0.9630**	0.4665	-5.3872	17.6532	-0.0128	300.4059
PEXR	0.0131	0.0067	2.6838	33.9538	2.6838	33.9538	0.0010	300.3687
RP	0.0098	0.0773	-1.0191**	0.4728	3.0505	4.8841	0.0466	300.8746
TST	0.0085	0.0771	-0.9598**	0.4702	-2.7822	4.9275	-0.0425	300.8008
TB3	0.0094	0.0066	0.5262	0.3226	-144.3465***	50.7933	-0.1993	307.8509
UNR	0.0618	0.0148	-3.4064*	1.4936	37.9665*	20.4456	0.1072	301.5080
Panel B: First differences of z								
INF	-0.0002	0.0116	-0.9763**	0.4777	-0.2139	22.9434	-0.0005	300.3638
GDPR	-0.0002	0.0068	-0.9367**	0.4771	51.2511	41.0570	0.0701	301.1228
INPR	-0.0001	0.0089	-1.0122**	0.4683	-15.1217	41.4939	-0.0263	300.4439
PEXR	-0.0001	0.0071	-0.8241	0.5079	83.6327*	42.9702	0.1249	303.4730
RP	-0.0011	0.1101	-0.9244**	0.4568	3.0183	2.5169	0.0674	300.9132
TST	0.0011	0.1095	-0.9231**	0.4567	-3.0446	2.5459	-0.0677	300.9144
TB3	-0.0002	0.0013	-0.9728**	0.4657	17.7263	310.0891	0.0046	300.3678
UNR	-0.0002	0.0029	-1.0039**	0.4592	43.5411	78.9689	0.0247	300.4996
Panel C: Unexpected changes of z								
INF	0.0000	0.0079	-0.9766**	0.4638	0.8066	27.4194	0.0013	300.3644
GDPR	0.0000	0.0059	-0.9652**	0.4722	8.6578	43.9238	0.0102	300.3906
INPR	0.0000	0.0083	-1.0174**	0.4619	-15.7082	33.9091	-0.0255	300.4607
PEXR	0.0000	0.0060	-0.8797*	0.4795	42.7211	54.3036	0.0532	301.0657
RP	0.0000	0.1067	-1.0142**	0.4743	1.9330	3.4175	0.0403	300.6281
TST	0.0000	0.0766	-0.9827**	0.4684	-2.7629	4.9466	-0.0419	300.7984
TB3	0.0000	0.0012	-0.9739**	0.4587	-48.8560	286.7315	-0.0117	300.3990
UNR	0.0000	0.0029	-1.0222**	0.4640	53.7780	75.8943	0.0306	300.6002

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for all three different types of time series over the period from the first quarter of 1984 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.33, Table 2.34 and Table 2.35 in Appendix 2.A.

2.5.3.5 Alternative copula model

In the following, we investigate two additional copula models. First, we also consider the broad dependence parameter to be dependent of the macroeconomic variables. In the main analysis, we assume the broad dependence parameter θ to be constant as we are particularly interested in the drivers of flight to quality. The conditional broad dependence parameter is specified using the functional relationship

$$\theta(z) = \theta_{0,z} + \langle \theta_{1,z}, z \rangle \ ,$$

where $\theta_{0,z}$ is the constant and $\theta_{1,z} \in \mathbb{R}^j$, $z \in \mathcal{Z} \subseteq \mathbb{R}^j$, denote the coefficients of the conditioning macroeconomic factors. The maximum likelihood estimation results for the extended conditional flight-to-quality copula are presented in Table 2.15. As for the base series in Panel A, we observe that TB3 is the only factor with a significant $\lambda_{1,z}$-parameter.

TABLE 2.15: Sensitivity of tail dependence: full conditioning model

Factor	Summary statistics		ML-Estimates: λ				ML-Estimates: θ				Sensitivity	Diagnostics
z	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\theta_{0,z}$	SE	$\theta_{1,z}$	SE	$\Delta\lambda_z$	LL
Panel A: Base series of z												
INF	0.0088	0.0092	-1.3260***	0.4136	-26.7823	20.3446	-2.7205**	1.1656	-13.8887	69.8577	-0.0353	662.6271
GDPR	0.0156	0.0101	-1.2815*	0.6899	-32.5109	42.9181	-1.5926	1.5736	-79.9994	90.7251	-0.0402	662.6271
INPR	0.0072	0.0187	-1.6889***	0.4931	1.7457	28.1995	-2.7094***	0.8191	-29.7769	37.8889	0.0043	659.8649
PEXR	0.0161	0.0084	-1.3608	0.8517	-25.7998	47.0297	-1.1934	1.7785	-99.5229	101.5965	-0.0267	662.8449
RP	0.0012	0.0974	-1.6916***	0.4318	-2.2489	3.3543	-2.7298***	0.7661	5.7731	8.2589	-0.0287	659.8259
TST	-0.0027	0.0654	-1.6660***	0.4292	0.6067	6.2763	-2.7729***	0.7765	-1.6343	12.2538	0.0053	659.3129
TB3	0.0111	0.0073	0.3088	0.3875	-169.0403***	46.4406	-2.2815	1.7013	-76.2228	109.3423	-0.1786	673.1056
UNR	0.0594	0.0162	-3.5411**	1.4773	28.7404	19.3989	0.6645	2.4235	-55.9319	40.4520	0.0556	660.0509
Panel B: First differences of z												
INF	0.0000	0.0095	-1.7464***	0.4501	-42.1800**	19.0380	-2.8559***	0.7785	80.2772	58.2050	-0.0510	660.7444
GDPR	0.0000	0.0103	-1.6734***	0.4333	10.7700	38.1199	-2.8155***	0.7673	-39.9851	64.4849	0.0148	659.5948
INPR	0.0000	0.0185	-1.6597***	0.4310	19.2751	13.1698	-3.0687***	0.7825	-72.0663**	32.4853	0.0478	661.3817
PEXR	0.0000	0.0084	-1.5980***	0.4482	45.7190	45.0581	-2.9469***	0.8155	-52.1473	69.2206	0.0540	659.9845
RP	0.0000	0.1326	-2.0547***	0.4820	-5.7400***	2.2058	-2.5709***	0.7017	14.0734**	7.0087	-0.0773	663.1246
TST	0.0003	0.0922	-1.7919***	0.4413	5.1167***	1.8752	-2.8405***	0.7654	-11.1850	7.4868	0.0580	660.5099
TB3	0.0000	0.0023	-1.6421***	0.4148	-38.2137	254.8116	-2.9178***	0.8023	-208.5839	372.9352	-0.0119	660.3765
UNR	0.0001	0.0038	-1.7111***	0.4257	48.5972	114.2626	-2.7793***	0.7973	-45.1696	213.4711	0.0241	659.3786
Panel C: Unexpected changes of z												
INF	0.0000	0.0082	-1.6146***	0.4261	-30.6774	20.5569	-2.8720***	0.8130	17.8087	78.0989	-0.0348	660.3098
GDPR	0.0000	0.0089	-1.7249***	0.4423	-20.0026	48.6635	-2.8454***	0.7744	-75.8165	89.8985	-0.0228	660.8886
INPR	-0.0001	0.0160	-1.6158***	0.4306	19.2954	23.3700	-3.0934***	0.8159	-65.5809*	35.3001	0.0427	660.7869
PEXR	0.0000	0.0073	-1.7106***	0.4421	-12.7950	61.4170	-2.8422***	0.7909	-87.4967	101.7947	-0.0121	660.6533
RP	0.0000	0.0973	-1.7206***	0.4353	-3.0710	2.8515	-2.6905***	0.7631	9.1301	8.3025	-0.0385	660.2630
TST	0.0001	0.0654	-1.6678***	0.4301	0.6109	6.2692	-2.7682***	0.7774	-1.6480	12.2367	0.0053	659.3133
TB3	0.0000	0.0023	-1.6438***	0.4108	-110.2644	187.8619	-2.9250***	0.8029	-195.3531	443.5300	-0.0340	661.2631
UNR	0.0000	0.0038	-1.7268***	0.4241	66.8543	112.1839	-2.7656***	0.7990	-87.3814	238.0642	0.0324	659.4488

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for all three different types of time series when conditioning on both dependence parameters as given by Equation (2.4) using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.36, Table 2.37 and Table 2.38 in Appendix 2.A.

More precisely, it is significant at the 1% level with a value of -169.0403. In particular, we cannot find a significant influence of changes in the macroeconomic data to the broad dependence parameter θ leaving the initial conditional flight-to-quality copula to be sufficient. With regard to first differences in Panel B, RP as well as TST are significant at the 1% level. Moreover, $\lambda_{1,INF}$ is statistically significant at the 5% level. For unexpected changes, each macroeconomic variable is insignificant to be a possible driver of flight to quality. For both types of time series INPR significantly influences broad dependence (at the 5% level for first differences and at the 10% level for unexpected changes). Moreover RP is significant at the 5% level for first differences. Accordingly, the conditional broad dependence parameter $\theta(z)$ is predominantly quantified by the constant parameter $\theta_{0,z}$. When comparing the constant and the conditional copula setup using the Bayesian information criterion, there is no unambiguous BIC-optimal specification. However, for TB3 the constant broad dependence setup fits better for each time series. Consequently, the constant broad dependence parameter in the initial dependence model is a suitable choice.

Second, we examine a conditional version of the symmetrized Joe-Clayton copula following Patton (2006). It is specified by

$$\begin{aligned} C_{SJC}(u, v \,|\, \lambda^+(z), \lambda^-(z)) = 0.5 \Big(& C_{JC}(u, v \,|\, \lambda^+(z), \lambda^-(z)) \\ & + C_{JC}(1-u, 1-v \,|\, \lambda^-(z), \lambda^+(z)) + u + v - 1 \Big) \end{aligned} \tag{2.9}$$

where

$$\begin{aligned} C_{JC}(u, v \,|\, \lambda^+(z), \lambda^-(z)) = 1 - \Bigg(1 - \Bigg(& \Big[1 - (1-u)^{\kappa(z)} \Big]^{-\gamma(z)} \\ & + \Big[1 - (1-v)^{\kappa(z)} \Big]^{-\gamma(z)} - 1 \Bigg)^{-1/\gamma(z)} \Bigg)^{1/\kappa(z)} \end{aligned}$$

denotes the Joe-Clayton copula with

$$\kappa(z) = \frac{1}{\log_2(2 - \lambda^+(z))} \text{ and } \gamma(z) = -\frac{1}{\log_2(\lambda^-(z))},$$

for $\lambda^+(z), \lambda^-(z) \in (0,1)$. It allows for conditional upper tail dependence $\lambda^+(z)$ as well as conditional lower tail dependence $\lambda^-(z)$ which are specified similar to $\lambda(z)$ in Equation (2.6). The findings in Table 2.16 illustrate that only the first differences time series of RP significantly influences the upper tail at the 1% level. However, we do not find statistical evidence of lower tail dependence in $\lambda^-_{\cdot,z}$. Applying BIC, the conditional version of the symmetrized Joe-Clayton copula provides the worst model fit compared to all other model specifications, and consequently is inappropriate for this analysis.

Moreover, we investigate multiple factors for the two additional copula models for base series. Table 2.17 gives the results. With respect to the extended flight-to-quality copula, we find INF (1% level) and TB3 (10% level) for the conditional extreme asymmetric

TABLE 2.16: Sensitivity of tail dependence: symmetrized Joe-Clayton copula

Factor	**Summary statistics**		**ML-Estimates: λ^+**				**Sensitivity**	**ML-Estimates: λ^-**				**Sensitivity**	**Diagnostics**
z	$\bar{z}$	σ_z	$\lambda^+_{0,z}$	SE	$\lambda^+_{1,z}$	SE	$\Delta\lambda^+_z$	λ^-0,z	SE	λ^-1,z	SE	$\Delta\lambda^-_z$	LL
Panel A: Base series of z													
INF	0.0088	0.0092	-4.1268	3.1949	0.8570	219.2004	0.0001	-5.3079	12.9284	0.9422	705.1702	0.0000	645.1237
GDPR	0.0156	0.0101	-4.1753	3.9177	0.8501	254.2342	0.0001	-5.3045	14.3976	0.9191	745.0578	0.0000	645.1330
INPR	0.0072	0.0187	-4.1579*	2.3239	0.9765	107.0141	0.0003	-5.2978	7.2313	0.9804	422.8127	0.0000	645.1404
PEXR	0.0161	0.0084	-4.3301	4.6053	0.7799	263.7311	0.0001	-5.3053	14.3270	0.8773	737.2999	0.0000	645.1516
RP	0.0012	0.0974	-4.6012	3.5133	-6.8417	36.7912	-0.0066	-14.8863	195482.2000	-6.9650	721035.8000	0.0000	644.6831
TST	-0.0027	0.0654	-4.2698*	2.4782	1.2182	29.6637	0.0011	-5.3013	8.7154	0.1502	86.9697	0.0000	645.1692
TB3	0.0111	0.0073	-3.9207	3.5008	0.8350	267.8674	0.0001	-5.3113	15.6644	0.9539	901.0888	0.0000	645.0768
UNR	0.0594	0.0162	-4.1517	8.1018	0.9647	130.7719	0.0003	-5.3402	29.3745	0.7759	449.9267	0.0000	645.1432
Panel B: First differences of z													
INF	0.0000	0.0095	-4.1019*	2.3345	0.8911	198.7848	0.0001	-5.2921	7.3696	0.9945	743.1530	0.0000	645.1222
GDPR	0.0000	0.0103	-4.1507*	2.3075	1.0134	186.9569	0.0002	-5.2946	7.4842	0.9774	727.7007	0.0000	645.1450
INPR	0.0000	0.0185	-4.4691*	2.6078	0.6838	185.4965	0.0001	-5.2933	7.7058	0.6764	425.0510	0.0001	645.1597
PEXR	0.0000	0.0084	-3.7359**	1.8731	1.0222	220.2887	0.0002	-5.2869	8.0247	0.9945	797.4930	0.0000	645.0261
RP	0.0000	0.1326	-5.8208**	2.3500	-16.6826***	5.0522	-0.0079	-15.4040	169432.6000	6.5135	466064.6000	0.0000	646.9743
TST	0.0003	0.0922	-4.5955*	2.7319	8.6150	13.1564	0.0081	-16.0483	1019.5040	-35.7027	1922.2180	0.0000	646.6360
TB3	0.0000	0.0023	-3.7936**	1.9030	0.9943	1162.6460	0.0000	-5.2942	9.2642	0.9995	1863.8360	0.0000	645.0595
UNR	0.0001	0.0038	-3.8025**	1.9386	1.0027	467.8549	0.0001	-5.2956	9.2489	0.9948	1888.0050	0.0001	645.0633
Panel A: Unexpected changes of z													
INF	0.0000	0.0082	-4.1415*	2.3961	0.8580	235.1243	0.0001	-5.2872	9.9436	0.9730	807.5865	0.0000	645.1269
GDPR	0.0000	0.0089	-3.9597*	2.1296	0.9454	212.7477	0.0002	-5.2929	7.3939	0.9724	890.1426	0.0001	645.1004
INPR	-0.0001	0.0160	-4.4906	2.8077	0.4569	157.6833	0.0001	-5.2865	9.1729	0.2760	475.1410	0.0001	645.1632
PEXR	0.0000	0.0073	-4.0841*	2.2102	0.9702	287.9220	0.0001	-5.2943	7.8883	0.9797	951.5740	0.0000	645.1233
RP	0.0000	0.0973	-4.6082	3.3977	-6.2922	35.9676	-0.0061	-5.2996	7.8421	-0.1128	74.5890	-0.0001	645.2197
TST	0.0001	0.0654	-4.2897*	2.3856	1.2401	30.6145	0.0011	-5.2933	7.6073	0.0651	91.2345	0.0000	645.1748
TB3	0.0000	0.0023	-3.9744*	2.0894	0.9833	1135.0350	0.0000	-5.2912	9.2266	0.9958	1956.2530	0.0000	645.1153
UNR	0.0000	0.0038	-4.1193*	2.2967	1.0077	565.8672	0.0001	-5.2968	9.7532	0.9821	1794.5140	0.0000	645.1423

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for all three different types of time series using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins for the symmetrized Joe-Clayton copula. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.39, Table 2.40 and Table 2.41 in Appendix 2.A.

TABLE 2.17: Alternative conditional copula model: multiple estimation

Full FTQ copula			SJC copula		
Coeff.	Estimate	SE	Coeff.	Estimate	SE
λ_0	-3.8303*	2.2029	λ_0^+	0.5223	7.7726
$\lambda_{1,INF}$	153.5560***	59.1117	$\lambda_{1,INF}^+$	-65.1926	274.1299
$\lambda_{1,GDPR}$	88.3205	85.1658	$\lambda_{1,GDPR}^+$	-300.9730	307.7856
$\lambda_{1,INPR}$	-36.5215	32.7574	$\lambda_{1,INPR}^+$	158.0910	162.1173
$\lambda_{1,PEXR}$	-92.0256	85.9596	$\lambda_{1,PEXR}^+$	59.0262	98.8439
$\lambda_{1,RP}$	7.9218	10.0904	$\lambda_{1,RP}^+$	-5.8951	32.0702
$\lambda_{1,TST}$	14.2589	13.4107	$\lambda_{1,TST}^+$	-15.6825	47.0404
$\lambda_{1,TB3}$	-225.0929*	121.4915	$\lambda_{1,TB3}^+$	-443.8574	536.6402
$\lambda_{1,UNR}$	34.4174	27.2954	$\lambda_{1,UNR}^+$	26.3701	114.4251
θ_0	3.7770	2.6982	λ_0^-	-267.9176	64421.3400
$\theta_{1,INF}$	-138.5232	116.1185	$\lambda_{1,INF}^-$	28.5911	3154641.0000
$\theta_{1,GDPR}$	-361.9959**	145.9954	$\lambda_{1,GDPR}^-$	-4.1986	5197096.0000
$\theta_{1,INPR}$	122.8053**	59.1686	$\lambda_{1,INPR}^-$	0.1007	1853904.0000
$\theta_{1,PEXR}$	196.0876	139.5745	$\lambda_{1,PEXR}^-$	16.0594	4345022.0000
$\theta_{1,RP}$	-1.5225	21.9043	$\lambda_{1,RP}^-$	209.7440	676008.3000
$\theta_{1,TST}$	-19.8827	35.5558	$\lambda_{1,TST}^-$	-131.6231	1183649.0000
$\theta_{1,TB3}$	-95.5991	128.6734	$\lambda_{1,TB3}^-$	15.3263	3506774.0000
$\theta_{1,UNR}$	-29.5883	46.2103	$\lambda_{1,UNR}^-$	-42.5363	1080021.0000
LL	677.9518			667.9363	

This table reports the maximum-likelihood estimates using base series of multiple factors for alternative conditional copula models over the period from the first quarter of 1953 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.42 in Appendix 2.A.

dependence coefficient $\lambda_{\cdot,z}$ to be possible drivers of flight to quality. For the conditional broad dependence parameter, GDPR as well as INPR are significant at the 5% level. Analyzing the symmetrized Joe-Clayton copula, we cannot find upper or lower tail dependence reinforcing the poor performance of this copula model to our data.

2.5.3.6 10-year US bond index as dependent variable

We now replace the 30-year bond index as dependent variable and instead investigate the CRSP 10-year US bond index. Therefore, we had to reinvestigate the time series properties in order to specify the mean and variance dynamics. Due to a sample autocorrelation of the 10-year bond index return at lag 5 the estimation period reduces by one quarter and now covers the period from the second quarter in 1953 to the fourth quarter in 2014.

The results in Table 2.18 are similar compared to the estimates of the main analysis. Each of the four factors from the main analysis that significantly influences flight to quality is now significant at the 1% level. Moreover, we observe a slight increase in the sensitivity of tail dependence to changes in the macroeconomic variable where TB3 remains the factor with the highest impact on flight to quality.

TABLE 2.18: Sensitivity of tail dependence: 10-year bond index

Factor	**Summary statistics**		**ML-Estimates**				**Sensitivity**	**Diagnostics**
z	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\Delta\lambda_z$	LL
Panel A: Base series of z								
INF	0.0089	0.0092	-1.3285***	0.3814	-31.8474***	12.2698	-0.0406	738.7691
GDPR	0.0155	0.0100	-0.9938***	0.3455	-48.2761***	16.9941	-0.0615	739.5011
INPR	0.0069	0.0184	-1.8366***	0.4413	-6.4298	16.1199	-0.0135	736.7721
PEXR	0.0160	0.0083	-1.0927***	0.3635	-38.5950***	14.3355	-0.0415	738.8872
RP	0.0009	0.0981	-1.8403***	0.4419	-0.2089	3.3611	-0.0024	736.7544
TERM	-0.0027	0.0657	-1.8499***	0.4480	-0.7014	4.7567	-0.0054	736.7711
TB3	0.0111	0.0074	0.6720***	0.2414	-181.9784***	38.0330	-0.2179	754.3164
UNR	0.0597	0.0160	-1.9260	1.2592	1.3890	20.3028	0.0026	736.7535

This table reports the maximum-likelihood estimates for Equation (2.6) using one macroeconomic factor. The estimation results are given for base time series over the period from the second quarter of 1953 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 10-year bond index with normally distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the macroeconomic variable by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.43 in Appendix 2.A.

Altogether, the use of real returns of the 10-year bond index shows the robustness of our estimation results. In particular, we notice somewhat better results when applying the 10-year bond index.

2.5.3.7 10-year Treasury rate as macroeconomic variable

In addition to the 3-month Treasury bill rate, we now investigate the 10-year Treasury rate for each of the three types of time series and the two lag lengths 1 and 2. Due to missing data, the analysis for the 10-year Treasury rate covers the period from the first quarter in 1954 to the fourth quarter in 2014. The estimation results are given in Table 2.19. We observe statistical significance at the 1% level of the TB10 to be a possible driver of flight to quality for base series and for both lags. Moreover, the sensitivity of the tail dependence coefficient to changes in the 10-year Treasury rate is negative in each case. Consequently, a rise in the TB10 reduces on average the risk of flight to quality. In absolute values, it is highest for base series with $\Delta\lambda_{TB10} = -0.0913$. However, compared to the 3-month Treasury rate, $\Delta\lambda_{TB10}$ is less than half of $\Delta\lambda_{TB3}$.

Taken as a whole, the results of the TB10 are similar but less pronounced compared to the TB3. Particularly, given the high correlation of 90% of both factors we find that short-term monetary policy actions are the main driver of flight to quality.

2.6 Conclusion

This study explores the impact of macroeconomic factors on the time variation of the flight-to-quality effect among the stock and bond market. Flight to quality describes rare events

Table 2.19: Sensitivity of tail dependence: 10-year Treasury rate

Series	**Summary statistics**		**ML-Estimates**				**Sensitivity**	**Diagnostics**
	$\bar{z}$	σ_z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\Delta\lambda_z$	LL
base	0.0186	0.0047	1.9672***	0.5598	-81.4281***	18.4225	-0.0913	659.7624
1diff	0.0000	0.0037	-2.2094***	0.5386	-19.6690	101.2308	-0.0065	639.3551
unexp	0.0001	0.0037	-2.2032***	0.5378	-22.5082	100.3225	-0.0074	639.3797

This table reports the maximum-likelihood estimates for Equation (2.6) using the 10-year Treasury rate as macroeconomic factor. The estimation results are given for all three different types of time series over the period from the first quarter of 1954 to the fourth quarter of 2014 using real value-weighted equity returns and real returns from the 30-year bond index with normally distributed margins. In particular, this table presents the sensitivity of tail dependence to changes of the 10-year Treasury rate by one standard deviation in Equation (2.8). Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 2.44 in Appendix 2.A.

like financial crisis when investors leave assets with higher expected risks including stocks and demand for less risky assets including bonds. In such a situation, the common positive relationship between stock and bond returns breaks down, and the correlation of these two asset classes reverses into negative. This results in possibly extensive implications for asset allocation and risk management. The sole use of broad dependence and negligence of extreme asymmetric dependence can become ineffective for diversification because of underestimation and mispricing of risk.

We pick up this problem to figure out "What drives flight to quality?". Therefore, we derive a conditional copula, based on the approach of Durand et al. (2010). The conditional flight-to-quality copula is a joint copula function representing the two states of dependence structure. It combines the characteristics of the Frank copula which analyzes the usual positive relationship and the Gumbel copula that reflects the tails of the distribution. In order to establish a functional relation between the macroeconomic variables and the copula, we directly model the tail dependence coefficient using the logistic function.

Using CRSP data of quarterly real returns of the value-weighted index of US stocks and the 30-year bond index from 1952 to 2014, we find that maximum-likelihood estimation provides strong empirical evidence of the Treasury bill rate being the key driver of flight to quality. Especially, we observe a negative relation between the Treasury bill rate and tail dependence. Quantifying the sensitivity to tail dependence, a decrease of the Treasury bill rate by one standard deviation increases on average the flight-to-quality risk indicator by approximately 20%, highlighting the huge impact of monetary policy decisions on financial assets, and consequently the relationship of stocks and bonds. With some limitations, the inflation rate and the growth rates of the gross domestic product as well as personal consumption expenditures significantly influence the coincidence of large negative equity returns and large positive bond returns. We perform a series robustness checks that mostly confirm our results. However, the use of a multi-factor model, the investigation of subsamples as well as the addition of a conditional broad dependence parameter cannot consistently provide statistical evidence for the inflation rate, the growth rate of the gross domestic product and the growth rate of personal consumption expenditures to be possible drivers of flight to quality. The remaining factors do not significantly influence the flight-to-quality effect.

Taken as a whole, the results of our analysis show that the Treasury bill rate may be used to predict the prospective movement of flight to quality. Therefore, the Treasury bill rate is useful for improving strategic asset allocation decisions as well as pricing and reporting risks more precisely. For base series of macroeconomic factors in the main analysis it is noteworthy that our findings are consistent with the results of the existing literature presented in Table 2.4 with respect to the Treasury bill rate as well as the inflation rate. In contrast to Andersson et al. (2008) and Christiansen and Ranaldo (2007), we provide statistical significance for both the growth rate of the gross domestic product and the growth rate of personal consumption expenditures to influence flight to quality. These contrary findings are possibly due to the authors' investigation on linear correlation of stocks and bonds whereas we focus on extreme asymmetric dependence. For the remaining macroeconomic variables we cannot confirm the results of the existing literature as our estimation outcomes are insignificant.

Further research opportunities in this area could be the analysis of other asset classes, especially the use of gold as save asset. Additionally, other independent variables like liquidity and commodities but also behavioral factors can be included in this analysis. Furthermore, the investigation of the multi-asset case might be an interesting extension which we leave for future research.

2.A Model estimates

TABLE 2.20: ML-estimates for one-factor model: lag 1

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0195***	0.0052	0.0196***	0.0055	0.0196***	0.0052	0.0193***	0.0055	0.0202***	0.0051	0.0194***	0.0056	0.0194***	0.0052	0.0195***	0.0055
$\kappa_{E,1}$	0.1532**	0.0674	0.1414**	0.0709	0.1635**	0.0676	0.1463**	0.0711	0.1618**	0.0664	0.1634**	0.0690	0.1052	0.0741	0.1621**	0.0699
μ_B	0.0012	0.0029	0.0019	0.0029	0.0011	0.0029	0.0018	0.0029	0.0012	0.0029	0.0016	0.0029	0.0033	0.0029	0.0017	0.0029
	Regime dependent variances															
σ^2_E	0.0063***	0.0005	0.0067***	0.0006	0.0063***	0.0005	0.0067***	0.0006	0.0062***	0.0005	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0109***	0.0034	0.0114***	0.0036	0.0110***	0.0034	0.0115***	0.0035	0.0109***	0.0033	0.0117***	0.0036	0.0106***	0.0033	0.0117***	0.0037
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0077***	0.0025	0.0153***	0.0030	0.0076***	0.0028	0.0153***	0.0030	0.0073	0.0056	0.0149***	0.0031	0.0169***	0.0028	0.0148***	0.0031
	Dependence parameters															
$\lambda_{0,z}$	-1.7887***	0.4560	-1.0074***	0.3576	-2.1389***	0.5303	-1.0226***	0.3572	-2.2184***	0.5365	-1.6660***	0.4286	0.4476	0.2790	-1.8692*	1.1219
$\lambda_{1,z}$	-33.1782**	16.8934	-40.2340**	19.2405	-8.5518	21.7476	-35.2485**	14.8438	-1.6136	3.6795	0.3199	3.8077	-171.8045***	41.4361	3.3104	17.3420
$\theta_{0,z}$	-2.2931***	0.6526	-3.0409***	0.8072	-2.2818***	0.6967	-3.0342***	0.8115	-2.1653***	0.6458	-2.7716***	0.7767	-3.5426***	0.7659	-2.7552***	0.7779
LL	655.2067		661.4128		654.0444		661.1686		653.3539		659.2859		672.7472		659.2921	
BIC	-5.0394		-5.0894		-5.0300		-5.0875		-5.0244		-5.0723		-5.1808		-5.0723	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.21: ML-estimates for one-factor model of first differences: lag 1

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0195***	0.0053	0.0195***	0.0055	0.0189***	0.0054	0.0204***	0.0051	0.0196***	0.0054	0.0192***	0.0052	0.0192***	0.0055	0.0195***	0.0055
$\kappa_{E,1}$	0.1690**	0.0699	0.1631**	0.0690	0.1649**	0.0694	0.1502**	0.0666	0.1784**	0.06996	0.1804***	0.0672	0.1614**	0.0690	0.1592**	0.0694
μ_B	0.0010	0.0029	0.0016	0.0029	0.0012	0.0029	0.0014	0.0029	0.0018	0.0029	0.0010	0.0029	0.0016	0.0029	0.0017	0.0029
	Regime dependent variances															
σ^2_E	0.0063***	0.0005	0.0067***	0.0006	0.0067***	0.0006	0.0061***	0.0005	0.0067***	0.0006	0.0063***	0.0005	0.0067***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0110***	0.0035	0.0117***	0.0037	0.0114***	0.0036	0.0104***	0.0031	0.0111***	0.0033	0.0108***	0.0033	0.0113***	0.0035	0.0116***	0.0036
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0084**	0.0037	0.0149***	0.0031	0.0152***	0.0031	0.0091	0.0096	0.0152***	0.0032	0.0085**	0.0034	0.0151***	0.0031	0.0150***	0.0032
	Dependence parameters															
$\lambda_{0,z}$	-2.2375***	0.5507	-1.6703***	0.4307	-1.7499***	0.4293	-2.2440***	0.6183	-1.9308***	0.4839	-2.3793***	0.5831	-1.6751***	0.4137	-1.6964***	0.4272
$\lambda_{1,z}$	-7.9517	46.5026	2.2728	24.7754	-21.0415	15.4201	37.5274	59.3678	-4.0875*	2.1195	4.6546*	2.8270	-123.7333*	64.1392	29.9101	69.8850
$\theta_{0,z}$	-2.1933***	0.6530	-2.7628***	0.7761	-2.7546***	0.7617	-2.1150***	0.6544	-2.6670***	0.7207	-2.1979***	0.6309	-2.8778***	0.7926	-2.8001***	0.7998
LL	655.4577		659.2844		659.5764		656.3363		660.3136		655.2037		660.2178		659.3514	
BIC	-5.0414		-5.0723		-5.0746		-5.0485		-5.0806		-5.0394		-5.0798		-5.0728	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.22: ML-estimates for one-factor model of unexpected changes: lag 1

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0192***	0.0055	0.0197***	0.0051	0.0195***	0.0052	0.0194***	0.0055	0.0202***	0.0051	0.0194***	0.0056	0.0192***	0.0055	0.0196***	0.0055
$\kappa_{E,1}$	0.1578**	0.0683	0.1612**	0.0670	0.1665**	0.0674	0.1612**	0.0688	0.1627**	0.0666	0.1634**	0.0690	0.1577**	0.0685	0.1587**	0.0696
μ_B	0.0018	0.0029	0.0009	0.0029	0.0010	0.0029	0.0016	0.0029	0.0013	0.0029	0.0016	0.0029	0.0017	0.0029	0.0017	0.0029
	Regime dependent variances															
σ^2_E	0.0067***	0.0006	0.0063***	0.0005	0.0063***	0.0005	0.0067***	0.0006	0.0062***	0.0005	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0114***	0.0036	0.0109***	0.0034	0.0110***	0.0034	0.0116***	0.0036	0.0108***	0.0033	0.0117***	0.0036	0.0112***	0.0035	0.0116***	0.0036
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0154***	0.0031	0.0081***	0.0029	0.0080**	0.0033	0.0151***	0.0031	0.0073	0.0056	0.0149***	0.0031	0.0152***	0.0031	0.0150***	0.0032
	Dependence parameters															
$\lambda_{0,z}$	-1.6320***	0.4287	-2.2049***	0.5402	-2.2065***	0.5259	-1.6679***	0.4248	-2.2233***	0.5375	-1.6669***	0.4285	-1.6409***	0.4053	-1.6953***	0.4269
$\lambda_{1,z}$	-28.8937*	17.3303	-34.0269	38.6623	-7.5180	27.3776	-23.4165	26.4973	-1.9917	3.6006	0.3209	3.8081	-154.5540**	64.3368	31.4539	70.3558
$\theta_{0,z}$	-2.8116***	0.7717	-2.2966***	0.6622	-2.2506***	0.6795	-2.8337***	0.7860	-2.1666***	0.6451	-2.7716***	0.7767	-2.9527***	0.8002	-2.7969***	0.8001
LL	660.2618		655.5094		654.7783		659.7019		653.2780		659.2860		661.0240		659.3570	
BIC	-5.0801		-5.0418		-5.0359		-5.0756		-5.0238		-5.0723		-5.0863		-5.0728	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.23: ML-estimates for one-factor model: t-distributed margins

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0215***	0.0055	0.0220***	0.0054	0.0218***	0.0054	0.0217***	0.0055	0.0218***	0.0055	0.0218***	0.0055	0.0216***	0.0051	0.0219***	0.0054
$\kappa_{E,1}$	0.1333**	0.0665	0.1255*	0.0675	0.1404**	0.0668	0.1310*	0.0677	0.1458**	0.0664	0.1457**	0.0663	0.0944	0.0701	0.1448**	0.0671
μ_B	0.0020	0.0029	0.0019	0.0029	0.0017	0.0029	0.0018	0.0029	0.0017	0.0029	0.0016	0.0029	0.0032	0.0028	0.0017	0.0029
	Regime dependent variances															
σ^2_E	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0066***	0.0007	0.0067***	0.0008
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0117***	0.0042	0.0116***	0.0041	0.0118***	0.0042	0.0117***	0.0041	0.0118***	0.0042	0.0119***	0.0042	0.0107***	0.0039	0.0119***	0.0043
$\sigma^2_{B,III}$	0.0030***	0.0007	0.0030***	0.0007	0.0030***	0.0006	0.0030***	0.0007	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0007	0.0030***	0.0006
$\sigma^2_{B,IV}$	0.0143***	0.0038	0.0143***	0.0038	0.0142***	0.0039	0.0143***	0.0038	0.0140***	0.0038	0.0139***	0.0038	0.0160***	0.0034	0.0138***	0.0038
	Dependence parameters															
$\lambda_{0,z}$	-1.2674***	0.3746	-1.0015***	0.3542	-1.6043***	0.4264	-1.0149***	0.3546	-1.6143***	0.4312	-1.6270***	0.4360	0.4048	0.2840	-1.7890***	1.1049
$\lambda_{1,z}$	-26.9492*	14.0750	-38.6636**	19.5358	-9.3774	14.5113	-33.9519**	15.0339	-0.7325	2.5958	0.1137	3.7116	-166.0502***	42.4480	2.6731	16.8751
$\theta_{0,z}$	-2.8914***	0.7912	-2.9907***	0.8053	-2.7925***	0.8012	-2.9820***	0.8101	-2.7569***	0.7810	-2.7418***	0.7794	-3.5069***	0.7651	-2.7306***	0.7799
ν_E	6.4532	7.8037	6.3358	7.9422	10.5993	7.8012	6.2696	8.0706	10.6259	7.8278	10.5423	7.7148	11.3437	8.2848	5.7344	7.7483
ν_B	28.9590	77.5372	17.2845	71.8486	15.7578	79.1495	25.6505	61.4572	16.5669	73.9136	17.0025	71.7502	22.4994	49.1195	27.6727	70.0341
LL	662.1873		662.8991		660.9926		662.6436		660.8549		660.8133		674.1742		660.8213	
BIC	-5.0512		-5.0570		-5.0416		-5.0549		-5.0405		-5.0401		-5.1479		-5.0402	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.24: ML-estimates for one-factor model of first differences: t-distributed margins

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0217***	0.0055	0.0218***	0.0054	0.0213***	0.0054	0.0220***	0.0056	0.0218***	0.0054	0.0210***	0.0052	0.0216***	0.0054	0.0219***	0.0054
$\kappa_{E,1}$	0.1485**	0.0660	0.1452**	0.0668	0.1479**	0.0668	0.1379**	0.0687	0.1609**	0.0673	0.1955**	0.0661	0.1444**	0.0663	0.1429**	0.0671
μ_B	0.0017	0.0029	0.0017	0.0029	0.0013	0.0029	0.0019	0.0029	0.0018	0.0029	0.0023	0.0028	0.0017	0.0029	0.0017	0.0029
	Regime dependent variances															
σ^2_E	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0066***	0.0008	0.0066***	0.0009	0.0067***	0.0008	0.0067***	0.0008
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0116***	0.0042	0.0119***	0.0042	0.0117***	0.0042	0.0120***	0.0045	0.0112***	0.0038	0.0093***	0.0025	0.0115***	0.0041	0.0118***	0.0042
$\sigma^2_{B,III}$	0.0030***	0.0007	0.0030***	0.0006	0.0030***	0.0007	0.0030***	0.0007	0.0030***	0.0007	0.0028***	0.0005	0.0030***	0.0006	0.0030***	0.0006
$\sigma^2_{B,IV}$	0.0146***	0.0038	0.0139***	0.0038	0.0141***	0.0039	0.0136***	0.0040	0.0144***	0.0039	0.0070	0.0259	0.0142***	0.0038	0.0140***	0.0038
	Dependence parameters															
$\lambda_{0,z}$	-1.7135***	0.4635	-1.6297***	0.4380	-1.6675***	0.4339	-1.5982***	0.4466	-1.8756***	0.4867	-1.7251***	0.4749	-1.6303***	0.4234	-1.6495***	0.4357
$\lambda_{1,z}$	-23.6722	25.4723	3.7763	25.8101	-16.6888	15.0082	35.1491	38.9891	-3.8461*	2.0694	2.9570	2.2586	-117.8586	63.8532	21.6232	74.5194
$\theta_{0,z}$	-2.6630***	0.7576	-2.7312***	0.7790	-2.7590***	0.7787	-2.7617***	0.7774	-2.6286***	0.7218	-2.4590***	0.7389	-2.8490***	0.8007	-2.7594***	0.8064
ν_E	10.7126	7.8724	10.5049	7.9925	10.7868	8.0820	10.2197	7.5385	10.9207	8.2307	8.1346	5.0669	10.6932	7.9664	10.6266	7.8181
ν_B	32.2916	98.0758	12.0550	73.2053	14.0417	64.0229	29.8734	81.8611	6.7700	44.2078	31.6102	44.6653	29.5134	79.5422	11.2371	82.0675
LL	661.1402		660.8254		661.0388		661.2838		661.7300		655.5123		661.6998		660.8496	
BIC	-5.0428		-5.0402		-5.0419		-5.0439		-5.0475		-4.9974		-5.0473		-5.0404	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.25: ML-estimates for one-factor model of unexpected changes: t-distributed margins

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0216***	0.0055	0.0218***	0.0055	0.0216***	0.0054	0.0218***	0.0055	0.0217***	0.0055	0.0218***	0.0055	0.0215***	0.0054	0.0219***	0.0054
$\kappa_{E,1}$	0.1409**	0.0657	0.1412**	0.0657	0.1423**	0.0666	0.1444**	0.0661	0.1462**	0.0666	0.1457**	0.0663	0.1414**	0.0658	0.1426**	0.0674
μ_B	0.0019	0.0029	0.0016	0.0029	0.0015	0.0029	0.0016	0.0029	0.0017	0.0029	0.0016	0.0029	0.0018	0.0029	0.0017	0.0029
Regime dependent variances																
σ^2_E	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0116***	0.0042	0.0117***	0.0042	0.0118***	0.0042	0.0118***	0.0041	0.0118***	0.0042	0.0119***	0.0042	0.0114***	0.0040	0.0118***	0.0042
$\sigma^2_{B,III}$	0.0030***	0.0007	0.0030***	0.0007	0.0030***	0.0006	0.0030***	0.0007	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006
$\sigma^2_{B,IV}$	0.0145***	0.0038	0.0140***	0.0038	0.0143***	0.0039	0.0141***	0.0038	0.0140***	0.0038	0.0139***	0.0038	0.0143***	0.0038	0.0140***	0.0038
Dependence parameters																
$\lambda_{0,z}$	-1.5945***	0.4374	-1.6227***	0.4453	-1.6773***	0.4306	-1.6310***	0.4329	-1.6157***	0.4309	-1.6273***	0.4356	-1.5988***	0.4152	-1.6487***	0.4353
$\lambda_{1,z}$	-27.4017	17.7489	-28.4126	27.6327	-16.2923	15.6997	-21.5307	26.8493	-0.9213	2.5852	0.1142	3.7121	-149.0357**	63.8124	22.8946	74.9015
$\theta_{0,z}$	-2.7849***	0.7774	-2.8614***	0.7890	-2.8049***	0.7920	-2.7943***	0.7841	-2.7585***	0.7808	-2.7418***	0.7794	-2.9216***	0.8078	-2.7571***	0.8061
ν_E	10.6472	7.9052	10.6835	8.1530	10.6950	7.9351	10.7005	8.1316	10.6461	7.8560	10.5423	7.7149	10.7142	7.9780	10.6389	7.8232
ν_B	9.4608	88.5545	13.7802	64.8081	27.9674	72.1065	26.6040	64.9948	11.6852	74.9023	12.3019	71.7986	29.1679	77.7523	11.2851	81.7802
LL	661.7393		661.5173		661.0970		661.1836		660.8750		660.8133		662.5044		660.8533	
BIC	-5.0476		-5.0458		-5.0424		-5.0431		-5.0406		-5.0401		-5.0538		-5.0405	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.26: ML-estimates for one-factor model: lag 2

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0189***	0.0054	0.0201***	0.0054	0.0195***	0.0055	0.0206***	0.0054	0.0199***	0.0054	0.0196***	0.0055	0.0205***	0.0052	0.0195***	0.0055
$\kappa_{E,1}$	0.1192	0.0822	0.1289*	0.0753	0.1617**	0.0691	0.1203	0.0786	0.1851***	0.0706	0.1913***	0.0715	0.1142	0.0752	0.1631**	0.0697
μ_B	0.0019	0.0029	0.0020	0.0029	0.0017	0.0029	0.0027	0.0029	0.0013	0.0029	0.0013	0.0029	0.0035	0.0028	0.0016	0.0029
	Regime dependent variances															
σ^2_E	0.0067***	0.0006	0.0066***	0.0006	0.0067***	0.0006	0.0066***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0116***	0.0035	0.0116***	0.0036	0.0117***	0.0037	0.0112***	0.0036	0.0113***	0.0035	0.0113***	0.0035	0.0105***	0.0033	0.0117***	0.0037
$\sigma^2_{B,III}$	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0137***	0.0032	0.0149***	0.0030	0.0149***	0.0031	0.0145***	0.0027	0.0150***	0.0031	0.0150***	0.0032	0.0166***	0.0028	0.0148***	0.0031
	Dependence parameters															
$\lambda_{0,z}$	-0.8734**	0.3643	-0.8451**	0.4121	-1.6658***	0.4308	-0.0583	0.3233	-2.1183***	0.5588	-2.1129***	0.5964	0.6588**	0.3349	-1.7400	1.1059
$\lambda_{1,z}$	-74.5771***	27.6776	-67.5233**	29.8508	-2.9970	14.0435	-96.9045***	22.2892	6.7044*	3.6114	-9.2410	6.5358	-206.6112***	51.5686	1.1964	17.2462
$\theta_{0,z}$	-2.9788***	0.7316	-2.7998***	0.7186	-2.7739***	0.7795	-3.2413***	0.7388	-2.5663***	0.7153	-2.5688***	0.7161	-3.4204***	0.7006	-2.7627***	0.7765
LL	661.8143		662.7651		659.2995		666.7520		660.0954		659.6108		674.4382		659.2817	
BIC	-5.0927		-5.1003		-5.0724		-5.1325		-5.0788		-5.0749		-5.1948		-5.0722	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.27: ML-estimates for one-factor model of first differences: lag 2

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0202***	0.0053	0.0194***	0.0055	0.0194***	0.0056	0.0202***	0.0055	0.0203***	0.0057	0.0202***	0.0054	0.0203***	0.0051	0.0195***	0.0055
$\kappa_{E,1}$	0.1679**	0.0679	0.1747**	0.0680	0.1647**	0.0690	0.1318*	0.0742	0.1842***	0.0675	0.1669**	0.0674	0.1586**	0.0667	0.1617**	0.0690
μ_B	0.0011	0.0029	0.0017	0.0029	0.0016	0.0030	0.0018	0.0029	0.0016	0.0029	0.0010	0.0029	0.0011	0.0029	0.0017	0.0029
	Regime dependent variances															
σ^2_E	0.0063***	0.0005	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0063***	0.0005	0.0062***	0.0005	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0108***	0.0035	0.0116***	0.0036	0.0117***	0.0037	0.0119***	0.0039	0.0121***	0.0037	0.0111***	0.0034	0.0109***	0.0034	0.0117***	0.0037
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0079**	0.0031	0.0150***	0.0030	0.0149***	0.0031	0.0144***	0.0031	0.0148***	0.0031	0.0082**	0.0036	0.0076	0.0058	0.0149***	0.0031
	Dependence parameters															
$\lambda_{0,z}$	-2.4666***	0.6391	-1.6426***	0.4282	-1.6575***	0.4326	-1.6958***	0.4457	-1.8888***	0.5046	-2.2858***	0.5355	-2.2090***	0.5382	-1.6771***	0.4280
$\lambda_{1,z}$	51.3617***	19.7655	21.7895	26.0081	2.2915	16.2608	-58.4044*	34.9143	4.7860**	2.3338	-4.7218***	1.7270	-38.1011	224.6679	15.9189	62.6647
$\theta_{0,z}$	-2.1234***	0.6238	-2.8350***	0.7810	-2.7732***	0.7811	-2.7871***	0.7649	-2.7189***	0.7261	-2.3060***	0.6333	-2.1905***	0.6525	-2.7879***	0.7876
LL	654.9866		659.8739		659.2907		660.3458		660.9520		655.5849		654.0977		659.3088	
BIC	-5.0376		-5.0770		-5.0723		-5.0808		-5.0857		-5.0424		-5.0304		-5.0725	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.28: ML-estimates for one-factor model of unexpected changes: lag 2

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0193***	0.0055	0.0196***	0.0055	0.0195***	0.0056	0.0216***	0.0052	0.0200***	0.0054	0.0196***	0.0055	0.0195***	0.0054	0.0195***	0.0055
$\kappa_{E,1}$	0.1508*	0.0855	0.1512**	0.0709	0.1632**	0.0689	0.1232	0.0757	0.1859***	0.0703	0.1913***	0.0715	0.1738***	0.0658	0.1617**	0.0691
μ_B	0.0017	0.0029	0.0017	0.0029	0.0016	0.0029	0.0026	0.0028	0.0014	0.0029	0.0013	0.0029	0.0013	0.0029	0.0017	0.0029
	Regime dependent variances															
σ^2_E	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0066***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0068***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0013***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0117***	0.0036	0.0117***	0.0037	0.0117***	0.0037	0.0114***	0.0038	0.0114***	0.0035	0.0113***	0.0035	0.0119***	0.0040	0.0117***	0.0037
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0146***	0.0032	0.0148***	0.0031	0.0149***	0.0031	0.0139***	0.0027	0.0150***	0.0031	0.0150***	0.0032	0.0147***	0.0031	0.0149***	0.0031
	Dependence parameters															
$\lambda_{0,z}$	-1.6021***	0.4219	-1.7164***	0.4477	-1.6715***	0.4324	-1.8854***	0.4201	-2.1293***	0.5608	-2.0862***	0.5833	-1.7730***	0.4042	-1.6753***	0.4278
$\lambda_{1,z}$	-18.8260	31.7059	-24.3134	32.0372	-0.4671	17.9165	-155.2790***	29.3113	7.2112*	3.7359	-9.2429	6.5390	-314.5934***	59.5274	15.7145	63.2760
$\theta_{0,z}$	-2.8378***	0.7910	-2.7418***	0.7683	-2.7684***	0.7776	-2.8874***	0.6788	-2.5707***	0.7120	-2.5698***	0.7162	-2.8472***	0.7271	-2.7845***	0.7868
LL	659.3433		659.5893		659.2804		665.9420		660.2737		659.6161		662.8496		659.3083	
BIC	-5.0727		-5.0747		-5.0722		-5.1260		-5.0802		-5.0749		-5.1010		-5.0725	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.29: ML-estimates for multi-factor model with lag 1

	Macroeconomic time series					
	Base series		First differences		Unexpected changes	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE
			Mean equation			
μ_E	0.0200***	0.0047	0.0193***	0.0053	0.0207***	0.0053
$\kappa_{E,1}$	0.1282*	0.0730	0.0912	0.0557	0.1329*	0.0683
μ_B	0.0032	0.0027	0.0014	0.0028	0.0021	0.0028
			Regime dependent variances			
σ_E	0.0068***	0.0006	0.0067***	0.0006	0.0069***	0.0006
$\sigma_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma_{B,II}$	0.0105***	0.0033	0.0110***	0.0037	0.0103***	0.0032
$\sigma_{B,III}$	0.0030***	0.0005	0.0030***	0.0006	0.0029***	0.0005
$\sigma_{B,IV}$	0.0156***	0.0025	0.0155***	0.0046	0.0142***	0.0036
			Dependence parameters			
λ_0	0.2365	1.3555	-2.7598***	0.8402	-1.8808***	0.4920
$\lambda_{1,INF}$	-27.3769	35.1747	-174.2413**	79.6819	-98.7190*	51.4157
$\lambda_{1,GDPR}$	-107.9193*	55.2598	-3.6763	47.0848	-128.9051**	57.6644
$\lambda_{1,INPR}$	33.8873	22.5483	0.8133	33.4274	36.5346	30.5110
$\lambda_{1,PEXR}$	79.7707	54.7294	-2.2819	67.0583	-11.9506	43.4032
$\lambda_{1,RP}$	4.5532	4.9258	-18.7578**	8.0407	-7.2853	8.7748
$\lambda_{1,TST}$	-2.5138	6.5112	-42.5179***	11.8674	-25.7373*	15.2528
$\lambda_{1,TB3}$	-200.7137***	75.1103	-30.5896	279.0629	-492.7575***	139.4867
$\lambda_{1,UNR}$	11.7388	17.0640	-100.8719	113.1169	-251.5480*	128.8719
θ_0	-3.3366***	0.7368	-2.1260***	0.5806	-2.9597***	0.6787
LL	680.6108		666.3476		669.6946	
BIC	-5.0886		-4.9736		-5.0006	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.30: ML-estimates for one-factor model: sub-period from 1953:1 to 1983:2

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0188**	0.0087	0.0189**	0.0091	0.0185**	0.0087	0.0203**	0.0090	0.0242**	0.0085	0.0217**	0.0093	0.0192**	0.0085	0.0185**	0.0086
$\kappa_{E,1}$	0.2656*	0.1608	0.3121**	0.1484	0.3163**	0.1595	0.3025**	0.1511	0.3620*	0.2089	0.1674	0.1676	0.2977**	0.1441	0.3165**	0.1483
μ_B	-0.0013	0.0034	-0.0030	0.0035	-0.0032	0.0035	-0.0015	0.0035	-0.0026	0.0035	-0.0022	0.0036	-0.0009	0.0035	-0.0033	0.0034
Regime dependent volatilities																
σ^2_E	0.0068***	0.0009	0.0068***	0.0009	0.0068***	0.0009	0.0069***	0.0008	0.0062***	0.0007	0.0073***	0.0010	0.0068***	0.0008	0.0068***	0.0009
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0113**	0.0054	0.0114**	0.0055	0.0113**	0.0054	0.0112**	0.0050	0.0113***	0.0089	0.0082***	0.0027	0.0113**	0.0052	0.0113**	0.0054
Dependence parameters																
$\lambda_{0,z}$	$-1.0506 \cdot 10^{0}$	$1.1305 \cdot 10^{0}$	$-3.1629 \cdot 10^{0}$	$4.3820 \cdot 10^{0}$	$-6.6724 \cdot 10^{0}$	$6.8766 \cdot 10^{1}$	$-0.4649 \cdot 10^{0}$	$0.8185 \cdot 10^{0}$	$-2.0712 \cdot 10^{1}$	$1.8188 \cdot 10^{5}$	$-1.8134^{*} \cdot 10^{2}$	$1.0716 \cdot 10^{2}$	$0.2440 \cdot 10^{0}$	$1.2269 \cdot 10^{0}$	$-1.8225 \cdot 10^{1}$	$1.7989 \cdot 10^{7}$
$\lambda_{1,z}$	$-1.5659 \cdot 10^{2}$	$2.8000 \cdot 10^{2}$	$-6.1326 \cdot 10^{1}$	$4.2478 \cdot 10^{2}$	$-5.5983 \cdot 10^{1}$	$1.4294 \cdot 10^{3}$	$-1.1516 \cdot 10^{2}$	$1.0700 \cdot 10^{2}$	$-1.0023^{*} \cdot 10^{2}$	$1.2509 \cdot 10^{6}$	$1.1477^{*} \cdot 10^{3}$	$6.7626 \cdot 10^{2}$	$-2.2728 \cdot 10^{2}$	$1.9585 \cdot 10^{2}$	$-7.1711 \cdot 10^{0}$	$2.3100 \cdot 10^{8}$
$\theta_{0,z}$	-2.9517***	1.0776	-2.4916**	1.0968	-2.3456**	1.0426	-3.2296***	1.2019	-1.6627**	0.7658	-2.5694***	0.7340	-3.2797***	0.9973	-2.3231**	0.9993
LL	362.4368		361.4294		361.4086		362.4552		357.4682		364.7356		363.1669		361.4049	
BIC	-5.5872		-5.5707		-5.5703		-5.5875		-5.5057		-5.6249		-5.5992		-5.5703	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.31: ML-estimates for one-factor model of first differences: sub-period from 1953:1 to 1983:2

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0175**	0.0087	0.0185**	0.0089	0.0185**	0.0090	0.0172*	0.0094	0.0202**	0.0099	0.0176**	0.0088	0.0200**	0.0096	0.0185**	0.0084
$\kappa_{E,1}$	0.3476**	0.1508	0.3165**	0.1498	0.3165**	0.1568	0.4747**	0.2139	0.2393	0.2148	0.4741**	0.2069	0.3759*	0.2064	0.3165**	0.1481
μ_B	-0.0036	0.0035	-0.0033	0.0034	-0.0033	0.0036	-0.0036	0.0035	-0.0026	0.0036	-0.0036	0.0036	-0.0032	0.0036	-0.0033	0.0034
Regime dependent volatilities																
σ^2_E	0.0069***	0.0009	0.0068***	0.0008	0.0068***	0.0010	0.0066***	0.0009	0.0071***	0.0010	0.0065***	0.0008	0.0068***	0.0009	0.0068***	0.0009
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0108***	0.0050	0.0113**	0.0054	0.0113**	0.0054	0.0253**	0.2089	0.0085**	0.0043	0.0253	0.2036	0.0098	0.0062	0.0113**	0.0054
Dependence parameters																
$\lambda_{0,z}$	$-2.0669 \cdot 10^{1}$	$7.7434 \cdot 10^{1}$	$-1.9286 \cdot 10^{1}$	$1.5739 \cdot 10^{7}$	$-1.6349 \cdot 10^{1}$	$1.8887 \cdot 10^{6}$	$-5.4503 \cdot 10^{1}$	$3.7108 \cdot 10^{2}$	$-6.4837 \cdot 10^{0}$	$5.8989 \cdot 10^{1}$	$-2.4032 \cdot 10^{1}$	$7.7094 \cdot 10^{5}$	$-7.4684 \cdot 10^{0}$	$1.4165 \cdot 10^{2}$	$-1.9339 \cdot 10^{1}$	$2.1671 \cdot 10^{7}$
$\lambda_{1,z}$	$-1.0756 \cdot 10^{3}$	$4.1168 \cdot 10^{3}$	$-6.3236 \cdot 10^{0}$	$1.8347 \cdot 10^{7}$	$-9.6746 \cdot 10^{0}$	$2.2203 \cdot 10^{7}$	$-2.5817 \cdot 10^{3}$	$1.7916 \cdot 10^{4}$	$-1.8431 \cdot 10^{1}$	$3.8156 \cdot 10^{2}$	$8.9664 \cdot 10^{1}$	$2.0297 \cdot 10^{7}$	$-9.7418 \cdot 10^{2}$	$4.5414 \cdot 10^{4}$	$3.0635 \cdot 10^{1}$	$3.2090 \cdot 10^{7}$
$\theta_{0,z}$	-2.3797***	0.7243	-2.3232***	0.8846	-2.3232*	1.3344	-2.2458***	0.7409	-2.5783**	1.1373	-2.2033***	0.7678	-2.4539**	1.0558	-2.3232**	0.9421
LL	361.9465		361.4049		361.4049		367.2406		358.3637		367.8692		359.4523		361.4049	
BIC	-5.5792		-5.5703		-5.5703		-5.6659		-5.5204		-5.6762		-5.5383		-5.5703	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.32: ML-estimates for one-factor model of unexpected changes: sub-period from 1953:1 to 1983:2

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0224***	0.0075	0.0205***	0.0080	0.0113	0.0081	0.0211***	0.0082	0.0217**	0.0093	0.0216**	0.0093	0.0178**	0.0088	0.0185**	0.0087
$\kappa_{E,1}$	0.3776***	0.1294	0.3266**	0.1561	0.3516**	0.1419	0.2849*	0.1475	0.1715	0.1678	0.1668	0.1674	0.4606**	0.2148	0.3164**	0.1472
μ_B	-0.0005	0.0033	-0.0024	0.0033	-0.0062*	0.0037	-0.0020	0.0034	-0.0022	0.0036	-0.0022	0.0036	-0.0038	0.0033	-0.0033	0.0034
Regime dependent volatilities																
σ^2_E	0.0069***	0.0008	0.0069***	0.0008	0.0067***	0.0008	0.0069***	0.0008	0.0073***	0.0010	0.0073***	0.0010	0.0067***	0.0008	0.0068***	0.0008
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0011***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0117**	0.0058	0.0113**	0.0054	0.0112**	0.0051	0.0093***	0.0034	0.0081***	0.0026	0.0082***	0.0027	0.0120	0.0104	0.0113**	0.0054
Dependence parameters																
$\lambda_{0,z}$	-4.4277 $\cdot 10^0$	3.3214 $\cdot 10^0$	-1.5141 $\cdot 10^1$	4.3432 $\cdot 10^1$	-1.4155** $\cdot 10^1$	6.3619 $\cdot 10^0$	-6.0169 $\cdot 10^0$	4.8673 $\cdot 10^0$	-2.0192* $\cdot 10^1$	1.0637 $\cdot 10^1$	-1.6110 $\cdot 10^2$	9.9916 $\cdot 10^1$	-1.0964 $\cdot 10^1$	3.5975 $\cdot 10^2$	-1.8758 $\cdot 10^1$	4.6340 $\cdot 10^6$
$\lambda_{1,z}$	-5.0645 $\cdot 10^2$	4.1659 $\cdot 10^2$	-6.6754 $\cdot 10^2$	2.0601 $\cdot 10^3$	-2.6695** $\cdot 10^2$	1.1847 $\cdot 10^2$	-3.8675 $\cdot 10^2$	3.4403 $\cdot 10^2$	-7.1523** $\cdot 10^1$	3.6128 $\cdot 10^1$	1.0006 $\cdot 10^3$	6.1876 $\cdot 10^2$	-1.7159 $\cdot 10^3$	9.3241 $\cdot 10^4$	1.7756 $\cdot 10^3$	3.6000 $\cdot 10^8$
$\theta_{0,z}$	-2.6241	0.7922	-2.3933	0.7459	-2.6192	0.7462	-2.7133	0.7763	-2.5752	0.7347	-2.5663	0.7335	-1.9961	0.8394	-2.3233	0.7371
LL	362.9848		361.9786		364.6634		363.9309		364.8810		364.4788		358.6426		361.4049	
BIC	-5.5962		-5.5797		-5.6237		-5.6117		-5.6273		-5.6207		-5.5250		-5.5703	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.33: ML-estimates for one-factor model: sub-period from 1984:1 to 2014:4

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0211***	0.0079	0.0208***	0.0078	0.0211***	0.0079	0.0211***	0.0078	0.0212***	0.0078	0.0212***	0.0079	0.0201***	0.0072	0.0220***	0.0076
$\kappa_{E,1}$	0.0888	0.0810	0.0789	0.0849	0.0823	0.0877	0.0903	0.0856	0.0925	0.0827	0.0906	0.0823	0.0385	0.0889	0.0690	0.0937
μ_B	0.0117**	0.0056	0.0116**	0.0056	0.0115**	0.0056	0.0118**	0.0056	0.0112**	0.0056	0.0114**	0.0057	0.0118**	0.0054	0.0123**	0.0055
	Regime dependent volatilities															
σ^2_E	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0009	0.0067***	0.0009	0.0067***	0.0009	0.0066***	0.0009
$\sigma^2_{B,II}$	0.0135*	0.0073	0.0131*	0.0069	0.0135*	0.0072	0.0136*	0.0074	0.0132*	0.0080	0.0133*	0.0081	0.0111*	0.0058	0.0152*	0.0087
$\sigma^2_{B,III}$	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005
$\sigma^2_{B,IV}$	0.0144***	0.0029	0.0146***	0.0028	0.0146***	0.0030	0.0144***	0.0029	0.0142***	0.0028	0.0143***	0.0029	0.0160***	0.0027	0.0141***	0.0026
	Dependence parameters															
$\lambda_{0,z}$	-0.9814**	0.4949	-0.7716*	0.4674	-0.9630**	0.4665	-1.0073	0.6515	-0.9838**	0.4792	-0.9598**	0.4702	0.5262	0.3226	-3.4064**	1.4936
$\lambda_{1,z}$	0.7509	27.4592	-17.3450	24.7072	-5.3872	17.6532	2.6838	33.9538	1.9670	3.4368	-2.7822	4.9275	-144.3465***	50.7933	37.9665*	20.4456
$\theta_{0,z}$	-2.5949*	1.3253	-2.6656**	1.3190	-2.6042**	1.3252	-2.5910*	1.3365	-2.5551*	1.3542	-2.6162*	1.3645	-3.3922***	1.3039	-2.2637*	1.2728
LL	300.3643		300.5834		300.4059		300.3687		300.6411		300.8008		307.8509		301.5080	
BIC	-4.4559		-4.4594		-4.4565		-4.4559		-4.4603		-4.4629		-4.5766		-4.4743	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.34: ML-estimates for one-factor model of first differences: sub-period from 1984:1 to 2014:4

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0211***	0.0079	0.0212***	0.0077	0.0213***	0.0078	0.0207***	0.0079	0.0211***	0.0078	0.0214***	0.0078	0.0212***	0.0079	0.0211***	0.0077
$\kappa_{E,1}$	0.0887	0.0868	0.0924	0.0843	0.0787	0.0848	0.1034	0.0852	0.08822	0.0920	0.0496	0.1061	0.0902	0.0814	0.0781	0.0894
μ_B	0.0118**	0.0057	0.0119**	0.0056	0.0115**	0.0055	0.0128**	0.0057	0.0117**	0.0057	0.0112**	0.0057	0.0118**	0.0058	0.0115**	0.0056
Regime dependent volatilities																
σ^2_E	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0009	0.0067***	0.0008	0.0067***	0.0009	0.0067***	0.0008	0.0067***	0.0008
$\sigma^2_{B,II}$	0.0135*	0.0073	0.0134*	0.0077	0.0134*	0.0076	0.0142	0.0091	0.0135*	0.0076	0.0137*	0.0081	0.0136*	0.0073	0.0131*	0.0070
$\sigma^2_{B,III}$	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0029***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005
$\sigma^2_{B,IV}$	0.0144***	0.0029	0.0145***	0.0031	0.0146***	0.0030	0.0138***	0.0032	0.0144***	0.0029	0.0138***	0.0027	0.0144***	0.0030	0.0147***	0.0029
Dependence parameters																
$\lambda_{0,z}$	-0.9763**	0.4777	-0.9367**	0.4771	-1.0122**	0.4683	-0.8241	0.5079	-0.9744*	0.5118	-0.9231**	0.4567	-0.9728**	0.4657	-1.0039**	0.4592
$\lambda_{1,z}$	-0.2139	22.9434	51.2511	41.0570	-15.1217	41.4939	83.6327*	42.9702	0.0311	2.3764	-3.0446	2.5459	17.7263	310.0891	43.5411	78.9689
$\theta_{0,z}$	-2.5948*	1.3488	-2.6795**	1.3517	-2.4950*	1.3055	-3.0306**	1.3459	-2.5986*	1.3967	-2.7315*	1.3979	-2.5932*	1.3284	-2.6408**	1.3147
LL	300.3638		301.1228		300.4439		303.4730		300.3638		300.9144		300.3678		300.4996	
BIC	-4.4558		-4.4681		-4.4571		-4.5060		-4.4558		-4.4647		-4.4559		-4.4580	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.35: ML-estimates for one-factor model of unexpected changes: sub-period from 1984:1 to 2014:4

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0211***	0.0079	0.0211***	0.0078	0.0211***	0.0078	0.0210***	0.0081	0.0212***	0.0078	0.0212***	0.0079	0.0206***	0.0079	0.0212***	0.0077
$\kappa_{E,1}$	0.0885	0.0817	0.0894	0.0821	0.0778	0.0876	0.1089	0.0816	0.0916	0.0817	0.0905	0.0823	0.0766	0.0815	0.0753	0.0912
μ_B	0.0117**	0.0057	0.0118**	0.0056	0.0114**	0.0055	0.0121**	0.0057	0.0113**	0.0056	0.0114**	0.0057	0.0116**	0.0058	0.0115**	0.0056
Regime dependent volatilities																
σ^2_E	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0008	0.0067***	0.0009	0.0067***	0.0009	0.0067***	0.0009	0.0067***	0.0008	0.0067***	0.0008
$\sigma^2_{B,II}$	0.0135*	0.0073	0.0136*	0.0073	0.0134*	0.0073	0.0144	0.0088	0.0133*	0.0080	0.0133*	0.0081	0.0132*	0.0070	0.0131*	0.0070
$\sigma^2_{B,III}$	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005	0.0028***	0.0005
$\sigma^2_{B,IV}$	0.0144***	0.0029	0.0144***	0.0029	0.0147***	0.0030	0.0142***	0.0032	0.0143***	0.0028	0.0143***	0.0029	0.0146***	0.0029	0.0147***	0.0029
Dependence parameters																
$\lambda_{0,z}$	-0.9748**	0.4732	-0.9685**	0.4869	-1.0186**	0.4616	-0.8075*	0.4568	-1.0142**	0.4747	-0.9518**	0.4716	-0.9891**	0.4641	-1.0045**	0.4593
$\lambda_{1,z}$	0.3765	26.2909	2.5386	41.2076	-11.9121	26.2810	45.4830	53.9445	1.9330	3.4175	-2.7871	4.9230	-110.4720	249.3391	51.5545	76.7495
$\theta_{0,z}$	-2.5972*	1.3325	-2.5949*	1.3276	-2.5653**	1.3079	-2.7081*	1.3892	-2.5602*	1.3577	-2.6166*	1.3647	-2.6542**	1.3141	-2.6453**	1.3121
LL	300.3639		300.3663		300.4451		301.1450		300.6281		300.8013		300.5762		300.5737	
BIC	-4.4558		-4.4559		-4.4572		-4.4684		-4.4601		-4.4629		-4.4593		-4.4592	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.36: ML-estimates for one-factor model: full conditioning model

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0190***	0.0056	0.0198***	0.0055	0.0192***	0.0055	0.0197***	0.0055	0.0178***	0.0058	0.0195***	0.0056	0.0195***	0.0052	0.0188***	0.0055
$\kappa_{E,1}$	0.1498**	0.0704	0.1374*	0.0752	0.1601**	0.0725	0.1408*	0.0762	0.1571**	0.0689	0.1608**	0.0710	0.1055	0.0740	0.1635**	0.0659
μ_B	0.0020	0.0029	0.0020	0.0030	0.0020	0.0030	0.0020	0.0029	0.0014	0.0029	0.0016	0.0029	0.0033	0.0028	0.0013	0.0029
Regime dependent variances																
σ^2_E	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0066***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0115***	0.0036	0.0113***	0.0035	0.0115***	0.0036	0.0111***	0.0034	0.0118***	0.0037	0.0117***	0.0037	0.0107***	0.0033	0.0121***	0.0038
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0151***	0.0031	0.0151***	0.0031	0.0149***	0.0040	0.0151***	0.0033	0.0147***	0.0030	0.0148***	0.0031	0.0166***	0.0028	0.0151***	0.0032
Dependence parameters																
$\lambda_{0,z}$	-1.3260***	0.4136	-1.2815*	0.6899	-1.6889***	0.4931	-1.3608	0.8517	-1.6916***	0.4318	-1.6660***	0.4292	0.3088	0.3875	-3.5411**	1.4773
$\lambda_{1,z}$	-26.7823	20.3446	-32.5109	42.9181	1.7457	28.1995	-25.7998	47.0297	-2.2489	3.3543	0.6067	6.2763	-169.0403***	46.4406	28.4704	19.3989
$\theta_{0,z}$	-2.7205**	1.1656	-1.5926	1.5736	-2.7094***	0.8191	-1.1934	1.7785	-2.7298***	0.7661	-2.7729***	0.7765	-2.2815	1.7013	0.6645	2.4235
$\theta_{1,z}$	-13.8887	69.8577	-79.9994	90.7251	-29.7769	37.8889	-99.5229	101.5965	5.7731	8.2589	-1.6343	12.2538	-76.2228	109.3423	-55.9319	40.4520
LL	660.7259		662.6271		659.8649		662.8449		659.8259		659.3129		673.1056		660.0509	
BIC	-5.0617		-5.0770		-5.0547		-5.0787		-5.0544		-5.0503		-5.1615		-5.0562	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.37: ML-estimates for one-factor model of first differences: full conditioning model

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0198***	0.0057	0.0193***	0.0055	0.0190***	0.0055	0.0196***	0.0056	0.0160***	0.0054	0.0196***	0.0056	0.0194***	0.0056	0.0195***	0.0056
$\kappa_{E,1}$	0.1367*	0.0758	0.1618**	0.0697	0.1628**	0.0695	0.1567**	0.0705	0.1269	0.0840	0.1270	0.0845	0.1591**	0.0685	0.1585**	0.0688
μ_B	0.0015	0.0029	0.0016	0.0029	0.0017	0.0029	0.0020	0.0029	0.0011	0.0029	0.0014	0.0029	0.0018	0.0029	0.0017	0.0029
Regime dependent variances																
σ^2_E	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0065***	0.0005	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0113***	0.0036	0.0118***	0.0037	0.0114***	0.0035	0.0117***	0.0039	0.0111***	0.0033	0.0116***	0.0035	0.0114***	0.0036	0.0117***	0.0036
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0030***	0.0006	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0157***	0.0029	0.0150***	0.0032	0.0149***	0.0034	0.0147***	0.0035	0.0138***	0.0024	0.0145***	0.0027	0.0150***	0.0033	0.0150***	0.0033
Dependence parameters																
$\lambda_{0,z}$	-1.7464***	0.4501	-1.6734***	0.4333	-1.6597***	0.4310	-1.5980***	0.4482	-2.0547***	0.4820	-1.7919***	0.4413	-1.6421***	0.4148	-1.7111***	0.4257
$\lambda_{1,z}$	-42.1800**	19.0380	10.7700	38.1199	19.2751	13.1698	45.7190	45.0581	-5.7400***	2.2058	5.1167***	1.8752	-38.2137	254.8116	48.5972	114.2626
$\theta_{0,z}$	-2.8559***	0.7785	-2.8155***	0.7673	-3.0687***	0.7825	-2.9469***	0.8155	-2.5709***	0.7017	-2.8405***	0.7654	-2.9178***	0.8023	-2.7793***	0.7973
$\theta_{1,z}$	80.2772	58.2050	-39.9851	64.4849	-72.0663**	32.4853	-52.1473	69.2206	14.0734**	7.0087	-11.1850	7.4868	-208.5839	372.9352	-45.1696	213.4711
LL	660.7444		659.5948		661.3817		659.9845		663.1246		660.5099		660.3765		659.3786	
BIC	-5.0618		-5.0525		-5.0669		-5.0557		-5.0810		-5.0599		-5.0588		-5.0508	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.38: ML-estimates for one-factor model of unexpected changes: full conditioning model

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean equation																
μ_E	0.0192***	0.0056	0.0194***	0.0055	0.0191***	0.0055	0.0196***	0.0055	0.0169***	0.0057	0.0195***	0.0056	0.0194***	0.0055	0.0195***	0.0056
$\kappa_{E,1}$	0.1541**	0.0711	0.1518**	0.0709	0.1640**	0.0725	0.1576**	0.0705	0.1424*	0.0728	0.1608**	0.0711	0.1532**	0.0689	0.1572**	0.0684
μ_B	0.0018	0.0029	0.0016	0.0029	0.0022	0.0029	0.0017	0.0029	0.0012	0.0029	0.0016	0.0029	0.0018	0.0029	0.0017	0.0029
Regime dependent variances																
σ^2_E	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006	0.0066***	0.0005	0.0067***	0.0006	0.0067***	0.0006	0.0067***	0.0006
$\sigma^2_{B,I}$	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002	0.0012***	0.0002
$\sigma^2_{B,II}$	0.0114***	0.0037	0.0116***	0.0036	0.0114***	0.0035	0.0114***	0.0035	0.0119***	0.0037	0.0117***	0.0037	0.0112***	0.0035	0.0117***	0.0037
$\sigma^2_{B,III}$	0.0029***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma^2_{B,IV}$	0.0154***	0.0031	0.0151***	0.0032	0.0148***	0.0037	0.0152***	0.0036	0.0144***	0.0028	0.0148***	0.0031	0.0151***	0.0032	0.0151***	0.0033
Dependence parameters																
$\lambda_{0,z}$	-1.6146***	0.4261	-1.7249***	0.4423	-1.6158***	0.4306	-1.7106***	0.4421	-1.7206***	0.4353	-1.6678***	0.4301	-1.6438***	0.4108	-1.7268***	0.4241
$\lambda_{1,z}$	-30.6774	20.5569	-20.0026	48.6635	19.2954	23.3700	-12.7950	61.4170	-3.0710	2.8515	0.6109	6.2692	-110.2644	187.8619	66.8543	112.1839
$\theta_{0,z}$	-2.8720***	0.8130	-2.8454***	0.7744	-3.0934***	0.8159	-2.8422***	0.7909	-2.6905***	0.7631	-2.7682***	0.7774	-2.9250***	0.8029	-2.7656***	0.7990
$\theta_{1,z}$	17.8087	78.0989	-75.8165	89.8985	-65.5809*	35.3001	-87.4967	101.7947	9.1301	8.3025	-1.6480	12.2367	-195.3531	443.5300	-87.3814	238.0642
LL	660.3098		660.8886		660.7869		660.6533		660.2630		659.3133		661.2631		659.4488	
BIC	-5.0583		-5.0630		-5.0621		-5.0611		-5.0579		-5.0503		-5.0660		-5.0514	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.39: ML-estimates for one-factor model: symmetrized Joe-Calyton copula

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0207***	0.0059	0.0206***	0.0059	0.0206***	0.0061	0.0205***	0.0058	0.0206***	0.0064	0.0204***	0.0060	0.0206***	0.0061	0.0205***	0.0061
$\kappa_{E,1}$	0.1656*	0.0855	0.1665*	0.0873	0.1671*	0.0864	0.1686*	0.0871	0.1693*	0.0889	0.1699**	0.0854	0.1644*	0.0871	0.1671*	0.0875
μ_B	0.0018	0.0031	0.0018	0.0033	0.0017	0.0031	0.0017	0.0032	0.0016	0.0033	0.0017	0.0032	0.0019	0.0031	0.0018	0.0033
	Regime dependent volatilities															
σ^2_E	0.0068***	0.0006	0.0068***	0.0006	0.0068***	0.0006	0.0068***	0.0006	0.0069***	0.0007	0.0069***	0.0006	0.0068***	0.0006	0.0068***	0.0006
$\sigma^2_{B,I}$	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002
$\sigma^2_{B,II}$	0.0120***	0.0042	0.0120***	0.0041	0.0120***	0.0040	0.0120***	0.0040	0.0121***	0.0042	0.0120***	0.0042	0.0121***	0.0044	0.0121***	0.0041
$\sigma^2_{B,III}$	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006
$\sigma^2_{B,IV}$	0.0129***	0.0038	0.0130***	0.0039	0.0130***	0.0048	0.0132***	0.0044	0.0133***	0.0042	0.0134***	0.0039	0.0126***	0.0039	0.0129***	0.0035
	Dependence parameters															
$\lambda^+_{0,z}$	-4.1268	3.1949	-4.1753	3.9177	-4.1579*	2.3239	-4.3301	4.6053	-4.6012	3.5133	-4.2698*	2.4782	-3.9207	3.5008	-4.1517	8.1018
$\lambda^+_{1,z}$	0.8570	219.2004	0.8501	254.2342	0.9765	107.0141	0.7799	263.7311	-6.8417	36.7912	1.2182	29.6637	0.8350	267.8674	0.9647	130.7719
$\lambda^-_{1,z}$	-5.3079	12.9284	-5.3045	14.3976	-5.2978	7.2313	-5.3053	14.3270	-14.8863	$> 10^5$	-5.3013	8.7154	-5.3113	15.6644	-5.3402	29.3745
$\lambda^-_{1,z}$	0.9422	705.1702	0.9191	745.0578	0.9804	422.8127	0.8773	737.2999	-6.9650	$> 10^5$	0.1502	86.9697	0.9539	901.0888	0.7759	449.9267
LL	645.1237		645.1330		645.1404		645.1516		644.6831		645.1692		645.0768		645.1432	
BIC	-4.9358		-4.9359		-4.9360		-4.9361		-4.9323		-4.9362		-4.9355		-4.9360	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.40: ML-estimates for one-factor model of first differences: symmetrized Joe-Calyton copula

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0207***	0.0059	0.0206***	0.0058	0.0206***	0.0059	0.0206***	0.0061	0.0225***	0.0061	0.0204***	0.0059	0.0206***	0.0063	0.0206***	0.0060
$\kappa_{E,1}$	0.1653*	0.0878	0.1665*	0.0851	0.1686**	0.0846	0.1633*	0.0844	0.1181	0.0897	0.1414	0.0916	0.1639*	0.0853	0.1640*	0.0865
μ_B	0.0018	0.0031	0.0018	0.0031	0.0017	0.0031	0.0020	0.0032	0.0021	0.0033	0.0016	0.0031	0.0019	0.0031	0.0019	0.0033
	Regime dependent volatilities															
σ^2_E	0.0068***	0.0006	0.0068***	0.0006	0.0068***	0.0006	0.0068***	0.0006	0.0070***	0.0006	0.0069***	0.0006	0.0068***	0.0006	0.0068***	0.0006
$\sigma^2_{B,I}$	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002
$\sigma^2_{B,II}$	0.0120***	0.0041	0.0120***	0.0040	0.0119***	0.0040	0.0122***	0.0042	0.0101***	0.0029	0.0120***	0.0039	0.0121***	0.0042	0.0121***	0.0040
$\sigma^2_{B,III}$	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006
$\sigma^2_{B,IV}$	0.0129***	0.0049	0.0130***	0.0035	0.0134***	0.0046	0.0122***	0.0034	0.0133***	0.0034	0.0132***	0.0035	0.0124***	0.0037	0.0124***	0.0038
	Dependence parameters															
$\lambda^+_{0,z}$	-4.1019*	2.3345	-4.1507*	2.3075	-4.4691*	2.6078	-3.7359**	1.8731	-5.8208**	2.3500	-4.5955*	2.7319	-3.7936**	1.9030	-3.8025**	1.9386
$\lambda^+_{1,z}$	0.8911	198.7848	1.0134	186.9569	0.6838	185.4965	1.0222	220.2887	-16.6826***	5.0522	8.6150	13.1564	0.9943	1162.6460	1.0027	467.8549
$\lambda^-_{1,z}$	-5.2921	7.3696	-5.2946	7.4842	-5.2933	7.7058	-5.2869	8.0247	-15.4040	$> 10^5$	-16.0483	1019.5040	-5.2942	9.2642	-5.2956	9.2489
$\lambda^-_{1,z}$	0.9945	743.1530	0.9774	727.7007	0.6764	425.0510	0.9945	797.4930	6.5135	$> 10^5$	-35.7027	1922.2180	0.9995	1863.8360	0.9948	1888.0050
LL	645.1222		645.1450		645.1597		645.0261		646.9743		646.6360		645.0595		645.0633	
BIC	-4.9358		-4.9360		-4.9361		-4.9350		-4.9508		-4.9480		-4.9353		-4.9353	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.41: ML-estimates for one-factor model of unexpected changes: symmetrized Joe-Calyton copula

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0206***	0.0060	0.0206***	0.0059	0.0204***	0.0061	0.0207***	0.0061	0.0204***	0.0059	0.0204***	0.0060	0.0206***	0.0060	0.0206***	0.0060
$\kappa_{E,1}$	0.1661*	0.0861	0.1655**	0.0844	0.1705**	0.0850	0.1649*	0.0843	0.1709**	0.0863	0.1701**	0.0858	0.1655*	0.0853	0.1658*	0.0858
μ_B	0.0018	0.0034	0.0019	0.0031	0.0016	0.0033	0.0018	0.0032	0.0017	0.0032	0.0017	0.0031	0.0018	0.0033	0.0018	0.0034
	Regime dependent volatilities															
σ^2_E	0.0068***	0.0006	0.0068***	0.0006	0.0069***	0.0006	0.0068***	0.0006	0.0069***	0.0006	0.0069***	0.0006	0.0068***	0.0006	0.0068***	0.0006
$\sigma^2_{B,I}$	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002
$\sigma^2_{B,II}$	0.0120***	0.0042	0.0121***	0.0040	0.0120***	0.0040	0.0120***	0.0040	0.0120***	0.0043	0.0120***	0.0042	0.0121***	0.0044	0.0120***	0.0041
$\sigma^2_{B,III}$	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006	0.0030***	0.0006
$\sigma^2_{B,IV}$	0.0129***	0.0043	0.0126***	0.0034	0.0133***	0.0049	0.0128***	0.0044	0.0134***	0.0041	0.0135***	0.0040	0.0127***	0.0038	0.0129***	0.0044
	Dependence parameters															
$\lambda^+_{0,z}$	-4.1415*	2.3961	-3.9597*	2.1296	-4.4906	2.8077	-4.0841*	2.2102	-4.6082	3.3977	-4.2897*	2.3856	-3.9744*	2.0894	-4.1193*	2.2967
$\lambda^+_{1,z}$	0.8580	235.1243	0.9454	212.7477	0.4569	157.6833	0.9702	287.9220	-6.2922	35.9676	1.2401	30.6145	0.9833	1135.0350	1.0077	565.8672
$\lambda^-_{1,z}$	-5.2872	9.9436	-5.2929	7.3939	-5.2865	9.1729	-5.2943	7.8883	-5.2996	7.8421	-5.2933	7.6073	-5.2912	9.2266	-5.2968	9.7532
$\lambda^-_{1,z}$	0.9730	807.5865	0.9724	890.1426	0.2760	475.1410	0.9797	951.5740	-0.1128	74.5890	0.0651	91.2345	0.9958	1956.2530	0.9821	1794.5140
LL	645.1269		645.1004		645.1632		645.1233		645.2197		645.1748		645.1153		645.1423	
BIC	-4.9359		-4.9356		-4.9362		-4.9358		-4.9366		-4.9362		-4.9358		-4.9360	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.42: ML-estimates for alternative conditional copula model: multiple estimation

	Full FTQ copula			SJC copula		
	Coeff.	Estimate	SE	Coeff.	Estimate	SE
			Mean equation			
	μ_E	0.0197***	0.0051	μ_E	0.0180***	0.0063
	$\kappa_{E,1}$	0.1250	0.0883	$\kappa_{E,1}$	0.1804	0.1023
	μ_B	0.0022	0.0028	μ_B	0.0014	0.0033
			Regime dependent variances			
	σ_E	0.0068***	0.0006	σ_E	0.0070***	0.0007
	$\sigma_{B,I}$	0.0012***	0.0002	$\sigma_{B,I}$	0.0012***	0.0002
	$\sigma_{B,II}$	0.0114***	0.0035	$\sigma_{B,II}$	0.0111***	0.0041
	$\sigma_{B,III}$	0.0030***	0.0005	$\sigma_{B,III}$	0.0031***	0.0006
	$\sigma_{B,IV}$	0.0167***	0.0035	$\sigma_{B,IV}$	0.0371***	0.0385
			Dependence parameters			
	λ_0	-3.8303*	2.2029	λ_0^+	0.5223	7.7726
	$\lambda_{1,INF}$	153.5560***	59.1117	$\lambda_{1,INF}^+$	-65.1926	274.1299
	$\lambda_{1,GDPR}$	88.3205	85.1658	$\lambda_{1,GDPR}^+$	-300.9730	307.7856
	$\lambda_{1,INPR}$	-36.5215	32.7574	$\lambda_{1,INPR}^+$	158.0910	162.1173
	$\lambda_{1,PEXR}$	-92.0256	85.9596	$\lambda_{1,PEXR}^+$	59.0262	98.8439
	$\lambda_{1,RP}$	7.9218	10.0904	$\lambda_{1,RP}^+$	-5.8951	32.0702
	$\lambda_{1,TST}$	14.2589	13.4107	$\lambda_{1,TST}^+$	-15.6825	47.0404
	$\lambda_{1,TB3}$	-225.0929*	121.4915	$\lambda_{1,TB3}^+$	-443.8574	536.6402
	$\lambda_{1,UNR}$	34.4174	27.2954	$\lambda_{1,UNR}^+$	26.3701	114.4251
	θ_0	3.7770	2.6982	λ_0^-	-267.9176	64421.3400
	$\theta_{1,INF}$	-138.5232	116.1185	$\lambda_{1,INF}^-$	28.5911	3154641.0000
	$\theta_{1,GDPR}$	-361.9959**	145.9954	$\lambda_{1,GDPR}^-$	-4.1986	5197096.0000
	$\theta_{1,INPR}$	122.8053**	59.1686	$\lambda_{1,INPR}^-$	0.1007	1853904.0000
	$\theta_{1,PEXR}$	196.0876	139.5745	$\lambda_{1,PEXR}^-$	16.0594	4345022.0000
	$\theta_{1,RP}$	-1.5225	21.9043	$\lambda_{1,RP}^-$	209.7440	676008.3000
	$\theta_{1,TST}$	-19.8827	35.5558	$\lambda_{1,TST}^-$	-131.6231	1183649.0000
	$\theta_{1,TB3}$	-95.5991	128.6734	$\lambda_{1,TB3}^-$	15.3263	3506774.0000
	$\theta_{1,UNR}$	-29.5883	46.2103	$\lambda_{1,UNR}^-$	-42.5363	1080021.0000
LL		682.5454			664.4337	
BIC		-4.9264			-4.7803	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 2.43: ML-estimates for one-factor model: 10-year US bond index

	Macroeconomic factor z															
	INF		GDPR		INPR		PEXR		RP		TST		TB3		UNR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean equation															
μ_E	0.0095	0.0071	0.0106	0.0072	0.0096	0.0071	0.0101	0.0072	0.0094	0.0070	0.0094	0.0070	0.0118*	0.0068	0.0095	0.0070
$\kappa_{E,1}$	0.2481**	0.1100	0.2400**	0.1080	0.2694**	0.1084	0.2432**	0.1108	0.2714**	0.1072	0.2757**	0.1071	0.1659*	0.0963	0.2728**	0.1075
$\kappa_{E,2}$	0.2357*	0.1321	0.2135	0.1329	0.2409*	0.1323	0.2259*	0.1338	0.2435*	0.1329	0.2430*	0.1333	0.1636	0.1271	0.2432*	0.1342
μ_B	0.0260***	0.0026	0.0260***	0.0026	0.0258***	0.0026	0.0260***	0.0026	0.0258***	0.0026	0.0258***	0.0026	0.0274***	0.0025	0.0258***	0.0026
$\kappa_{B,1}$	-0.1874***	0.0607	-0.1928***	0.0609	-0.1875***	0.0611	-0.1904******	0.0608	-0.1864***	0.0612	-0.1864***	0.0612	-0.1559***	0.0561	-0.1863***	0.0610
$\kappa_{B,1}$	-0.0552*	0.0284	-0.0540*	0.0280	-0.0582**	0.0280	-0.0560**	0.0283	-0.0589**	0.0288	-0.0592**	0.0288	-0.0491*	0.0264	-0.0589**	0.0279
	Regime dependent volatilities															
σ^2_E	0.0066***	0.0006	0.0066***	0.0006	0.0066***	0.0006	0.0066***	0.0006	0.0066***	0.0006	0.0066***	0.0006	0.0067***	0.0006	0.0066***	0.0006
$\sigma^2_{B,I}$	0.0010***	0.0001	0.0010***	0.0001	0.0010***	0.0001	0.0010***	0.0001	0.0010***	0.0001	0.0010***	0.0001	0.0010***	0.0001	0.0010***	0.0001
$\sigma^2_{B,II}$	0.0056***	0.0019	0.0056***	0.0018	0.0057***	0.0019	0.0056***	0.0018	0.0057***	0.0019	0.0057***	0.0019	0.0050***	0.0016	0.0057***	0.0019
$\sigma^2_{B,III}$	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0013***	0.0002	0.0014***	0.0002	0.0013***	0.0002
	Dependence parameters															
$\lambda_{0,z}$	-1.3285***	0.3814	-0.9938***	0.3455	-1.8366***	0.4413	-1.0927***	0.3635	-1.8403***	0.4419	-1.8499***	0.4480	0.6720***	0.2414	-1.9260	1.2592
$\lambda_{1,z}$	-31.8474***	12.2698	-48.2761***	16.9941	-6.4298	16.1199	-38.5950***	14.3355	-0.2089	3.3611	-0.7014	4.7567	-181.9784***	38.0330	1.3890	20.3028
$\theta_{0,z}$	-1.8406**	0.7361	-1.9767***	0.7389	-1.6259**	0.6962	-1.8926***	0.7328	-1.6063**	0.6886	-1.6159**	0.6893	-3.0029***	0.8019	-1.6030**	0.6921
LL	738.7691		739.5011		736.7721		738.8872		736.7544		736.7711		754.3164		736.7535	
BIC	-5.6920		-5.6979		-5.6758		-5.6929		-5.6757		-5.6758		-5.8179		-5.6756	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.44: ML-estimates for 10-year Treasury rate series

	Macroeconomic time series					
	Base series		First differences		Unexpected changes	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE
			Mean equation			
μ_E	0.0190***	0.0051	0.0207***	0.0052	0.0207***	0.0052
$\kappa_{E,1}$	0.1008	0.0718	0.1559**	0.0680	0.1555**	0.0680
μ_B	0.0038	0.0029	0.0010	0.0030	0.0010	0.0030
			Regime dependent variances			
σ_E	0.0068***	0.0006	0.0062***	0.0005	0.0062***	0.0005
$\sigma_{B,I}$	0.0013***	0.0002	0.0012***	0.0002	0.0012******	0.0002
$\sigma_{B,II}$	0.0105***	0.0033	0.0110***	0.0034	0.0110***	0.0034
$\sigma_{B,III}$	0.0030***	0.0005	0.0029***	0.0005	0.0029***	0.0005
$\sigma_{B,IV}$	0.0168***	0.0031	0.0078	0.0062	0.0078	0.0063
			Dependence parameters			
λ_0	1.9672***	0.5598	-2.2094***	0.5386	-2.2032***	0.5378
$\lambda_{1,TB10}$	-81.4281***	18.4225	-19.6690	101.2308	-22.5082	100.3225
θ_0	-3.8902***	0.7490	-2.1877***	0.6697	-2.1919***	0.6706
LL	659.7624		639.3551		639.3797	
BIC	-5.1601		-4.9928		-4.9930	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

References

Andersson, M., Krylova, E. and Vähämaa, S. (2008), 'Why does the correlation between stock and bond returns vary over time?', *Applied Financial Economics* 18(2), 139–151.

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

Ang, A. and Chen, J. (2002), 'Asymmetric correlations of equity portfolios', *Journal of Financial Economics* 63(3), 443–494.

Baur, D. G. and Lucey, B. M. (2009), 'Flights and contagion - an empirical analysis of stock–bond correlations', *Journal of Financial Stability* 5(4), 339–352.

Boyd, J. H., Hu, J. and Jagannathan, R. (2005), 'The stock market's reaction to unemployment news: Why bad news is usually good for stocks', *The Journal of Finance* 60(2), 649–672.

Campbell, J. Y. and Ammer, J. (1993), 'What moves the stock and bond markets? a variance decomposition for long-term asset returns', *The Journal of Finance* 48(1), 3–37.

Campbell, J. Y. and Viceira, L. M. (2001), 'Who should buy long-term bonds?', *American Economic Review* 91(1), pp. 99–127.

Chen, N.-F., Roll, R. and Ross, S. A. (1986), 'Economic forces and the stock market', *Journal of Business* 59(3), 383–403.

Christiansen, C. and Ranaldo, A. (2007), 'Realized bond-stock correlation: Macroeconomic announcement effects', *Journal of Futures Markets* 27(5), 439–469.

Christoffersen, P., Errunza, V., Jacobs, K. and Langlois, H. (2012), 'Is the potential for international diversification disappearing? a dynamic copula approach', *Review of Financial Studies* 25(12), 3711–3751.

Christoffersen, P. and Langlois, H. (2013), 'The joint dynamics of equity market factors', *Journal of Financial and Quantitative Analysis* 48(5), 1371–1404.

Ciner, C., Gurdgiev, C. and Lucey, B. M. (2013), 'Hedges and safe havens: An examination of stocks, bonds, gold, oil and exchange rates', *International Review of Financial Analysis* 29, 202–211.

Connolly, R., Stivers, C. and Sun, L. (2005), 'Stock market uncertainty and the stock-bond return relation', *Journal of Financial and Quantitative Analysis* 40(1), 161–194.

Durand, R. B., Junker, M. and Szimayer, A. (2010), 'The flight-to-quality effect: a copula-based analysis', *Accounting & Finance* 50(2), 281–299.

Embrechts, P., McNeil, A. and Straumann, D. (2002), 'Correlation and dependence in risk management: properties and pitfalls', *Risk management: value at risk and beyond* pp. 176–223.

Flannery, M. J. and Protopapadakis, A. A. (2002), 'Macroeconomic factors do influence aggregate stock returns', *Review of Financial Studies* 15(3), 751–782.

Fleming, M. and Remolona, E. (1997), 'What moves the bond market?', *Economic Policy Review* 3(4), 31–50.

Garcia, R. and Perron, P. (1996), 'An analysis of the real interest rate under regime shifts', *Review of Economics and Statistics* 78(1), 111–125.

Garcia, R. and Tsafack, G. (2011), 'Dependence structure and extreme comovements in international equity and bond markets', *Journal of Banking & Finance* 35(8), 1954–1970.

Greenwood, R. and Vayanos, D. (2010), 'Price pressure in the government bond market', *American Economic Review* 100(2), 585–590.

Greenwood, R. and Vayanos, D. (2014), 'Bond supply and excess bond returns', *Review of Financial Studies* 27(3), 663–713.

Gulko, L. (2002), 'Decoupling', *The Journal of Portfolio Management* 28(3), 59–66.

Hardouvelis, G. A. (1988), 'Economic news, exchange rates and interest rates', *Journal of International Money and Finance* 7(1), 23–35.

Ilmanen, A. (2003), 'Stock-bond correlations', *The Journal of Fixed Income* 13(2), 55–66.

Joe, H. (1997), *Multivariate Models and Dependence Concepts*, Chapman & Hall, London.

Junker, M. (2003), Modelling, estimating and validating multidimensional distribution functions-with applications to risk management, PhD thesis, University of Kaiserslautern.

Li, L. (2002), 'Macroeconomic factors and the correlation of stock and bond returns'. Working paper, Yale University.

Longin, F. and Solnik, B. (2001), 'Extreme correlation of international equity markets', *The Journal of Finance* 46(2), 649–676.

Nelsen, R. B. (2006), *An Introduction to Copulas*, Springer.

Patton, A. J. (2002), Applications of copula theory in financial econometrics, PhD 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.

Shiller, R. J. and Beltratti, A. E. (1992), 'Stock prices and bond yields: Can their comovements be explained in terms of present value models?', *Journal of Monetary Economics* 30(1), 25–46.

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

Wachter, J. A. (2003), 'Risk aversion and allocation to long-term bonds', *Journal of Economic Theory* 112(2), 325–333.

Yang, J., Zhou, Y. and Wang, Z. (2009), 'The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence', *Journal of Banking & Finance* 33(4), 670–680.

Yao, Y.-C. (1988), 'Estimating the number of change-points via schwarz'criterion', *Statistics & Probability Letters* 6(3), 181–189.

Chapter 3

Measuring crisis risk using conditional copulas: An empirical analysis of the 2008 shipping crisis[1]

with Henry Seidel

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.

[1] A revised version of this Chapter is published in *Journal of Applied Econometrics*, 2018, 33(2), 281–298, and is available at Wiley via http://onlinelibrary.wiley.com/wol1/doi/10.1002/jae.2609/full. We gratefully thank anonymous referees for valuable comments on earlier drafts. We also thank the participants of the Spring 2015 Conference of the Multinational Finance Society for helpful comments.

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 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 a certain rating class, specific vessel values are less easy to observe[2]. Instead, one may look on freight rates, which not only show a strong correlation to vessel values but also a higher liquidity and transparency (see Tsolakis et al., 2003; Adland and Koekebakker, 2007; Albertijn et al., 2011). Therefore, 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

[2] 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.

analyze whether a sharp increase of supply or a sharp decrease of demand increases the 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.

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

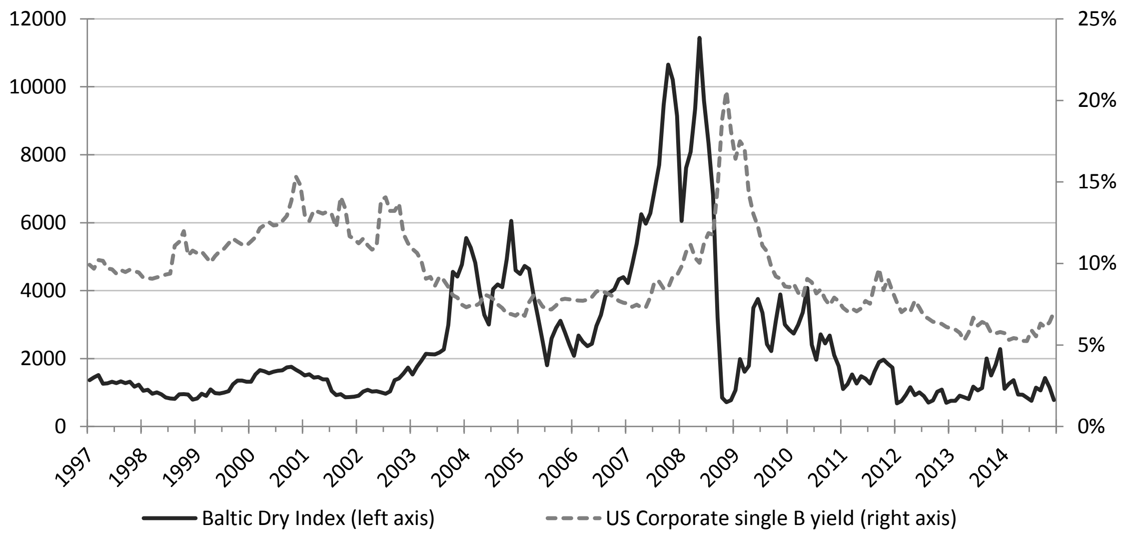


Figure 3.1: Development of freight rates and financing costs

The main driver for global seaborne transportation is the global economy. It determines the demand for commodities and goods and by this 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 bonds' 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. But vessel supply reaction is slow due to the time-to-build delay of typically 18 to 36 months (see Kalouptsidi, 2014). However, 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 led vessel prices 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).

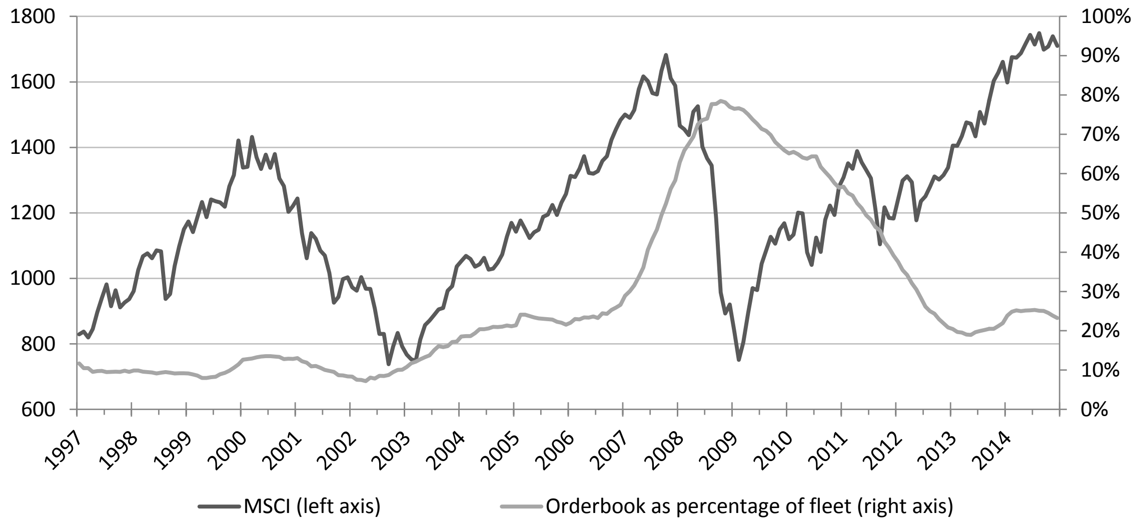


Figure 3.2: Development of demand and supply of maritime transportation services

Most shipping companies have a quite limited access to the capital market. New vessels are therefore mainly financed through bank loans, which usually cover 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 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 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[3] of 69% on average compared to a mean leverage 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 them 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 and mostly rated BB or B. Of those bonds 13 had defaulted within the observation period which exceeds by far the theoretical default probability of BB- and

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

B-rated bonds (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 huge 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 also directly determined by freight rates as the price of a vessel can be regarded as the present value of its future 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 embedded 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 seems plausible to use freight rates for capturing ship price risks in shipping companies' balance sheets.

A further critical aspect in this context is the 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, so 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 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). Freight rates determine a vessel's profitability, and thus also its value (see Tsolakis et al., 2003; Adland and Koekebakker, 2007). For this reason, we employ the Baltic Dry Index (BDI) as a proxy for asset side risk. The BDI is a composite index of four dry bulk timecharter 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 costs 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 US 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.[4] 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.

[4] 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	Effective yield of BofA Merrill Lynch US 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-fleet-ratio	$\text{O}(t)/\text{F}(t)$
Δ^3_{OFR}	Three-month differences of OFR	$\text{OFR}(t) - \text{OFR}(t-3)$
Δ^3_{MSCI}	Three-month log-differences of MSCI	$\log(\text{MSCI}(t)) - \log(\text{MSCI}(t-3))$

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.

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

where $\beta_{BDI,0}$ and $\beta_{BY,0}$ denote the constants, B_i is the coefficient matrix of the i-th VAR lag, $i = 1, ..., p$, $\varepsilon_{BDI,t}$ 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

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

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

To identify the model specification for the given dataset, 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.[5] 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 absolute value of the two residual time series of the VAR(4) model using a minimal period length of 24 months. The obtained change points are given in Table 3.3. For either of the two

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 absolute value 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 *.

risk factors, BDI and BY, we obtain a BIC optimal specification with one change 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 model given by the mean equation (3.1) with a VAR(4) and the variance equation (3.3) is scrutinized based on the standardized residuals of the quasi maximum likelihood estimation. For the ensuing conditional dependence analysis it is crucial that the error

[5] In Appendix 3.B in Table 3.18, we also provide results for 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.

terms are independent. This is analyzed by the Breusch-Godfrey LM test for serial correlation. For both standardized residual series, BDI and BY, and lag orders ranging from 1 to 12 months, we cannot find significant serial correlation at any usual confidence level, see Table 3.4. To see whether the heteroscedasticity in the marginal data is appropriately

TABLE 3.4: Breusch-Godfrey LM test for serial correlation

	BDI		BY	
Lag order i	$R^2(T-i)$	p-value	$R^2(T-i)$	p-value
1	0.0645	0.7996	0.0271	0.8694
2	0.4713	0.7900	0.0825	0.9596
3	0.4727	0.9249	0.1340	0.9875
4	0.5403	0.9695	0.2068	0.9950
5	1.6688	0.8928	2.2865	0.8082
6	3.3032	0.7699	2.3635	0.8834
7	3.3648	0.8493	3.0104	0.8840
8	6.6595	0.5738	3.0357	0.9321
9	7.4875	0.5865	3.5561	0.9381
10	8.4073	0.5891	3.5588	0.9651
11	8.4467	0.6728	3.6870	0.9782
12	8.4472	0.7493	3.7198	0.9880

This table presents the Breusch-Godfrey LM statistics for serial correlation of Breusch-Godfrey test for different lag orders using standardized residuals of the quasi maximum likelihood estimation of Equations (3.1) and (3.3), see Breusch (1978) and Godfrey (1978).

modeled by the volatility regimes given in (3.3), the ARCH LM test is employed for lag orders ranging from 1 to 12 months. The standardized residuals of the BDI show signs

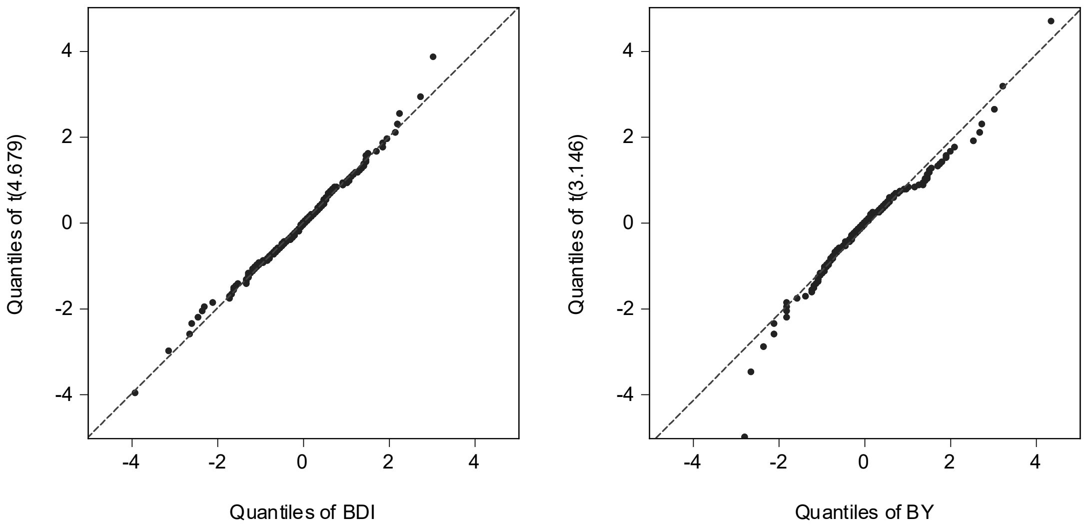
TABLE 3.5: ARCH LM test of standardized residuals of risk factors

	Main model specification				Extended variance model specification			
	BDI		BY		BDI		BY	
Lag order i	ARCH LM	p-value	ARCH LM	p-value	ARCH LM	p-value	ARCH LM	p-value
1	5.9306*	0.0149	0.3847	0.5351	0.9220	0.3370	0.3924	0.5311
2	6.9913*	0.0303	0.6281	0.7305	1.7852	0.4096	0.6408	0.7259
3	6.9544	0.0734	1.1513	0.7647	2.3939	0.4948	1.1643	0.7616
4	7.1949	0.1259	2.2390	0.6919	2.5572	0.6344	2.2483	0.6902
5	7.4227	0.1911	4.0576	0.5412	2.6958	0.7468	4.0491	0.5424
6	7.4247	0.2833	7.0485	0.3164	4.0925	0.6642	7.0373	0.3174
7	12.2969	0.0912	7.8556	0.3455	6.3306	0.5017	7.8627	0.3449
8	12.4179	0.1335	7.9180	0.4415	6.4965	0.5918	7.9258	0.4407
9	12.7378	0.1748	9.9391	0.3554	7.5075	0.5844	9.9141	0.3575
10	12.8098	0.2345	9.9230	0.4473	8.9979	0.5323	9.8980	0.4495
11	13.1314	0.2848	10.2933	0.5042	9.7058	0.5570	10.2686	0.5064
12	13.5586	0.3298	10.8217	0.5443	9.9227	0.6227	10.7967	0.5464

This table presents the ARCH LM statistics of ARCH test (see Engle, 1982) for different lag orders using standardized residuals of the quasi maximum likelihood estimation of Equations (3.1) and (3.3). The null hypothesis is no ARCH up to the selected lag. * indicates the rejection of H_0 at the 5% level.

of heteroscedasticity for lag order 1 and lag order 2 at the 5%-level, whereas the standardized residuals of the BY exhibit no significant heteroscedasticity for all lag orders at any usual confidence level, see Table 3.5. The remaining heteroscedasticity in the BDI series can be adequately captured by taking the 2 change point specification, with change points 09/2003 and 09/2008, given in Table 3.3, and extending the definition of $\sigma_{BDI,t}$ in (3.3) appropriately. For the extended setup, the ARCH LM test cannot detect any significant heteroscedasticity for all lag orders at any usual confidence level, see Table 3.5. Further, we have checked the impact of this effect on the main analysis presented later in Section 3.4 and found that the results are barely affected, see Table 3.17. Since the extension to the two change point setup can be considered ad-hoc and has little impact on the main analysis, we opt for keeping the preferred formulation following Andreou and Ghysels (2002).

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. Accordingly, we investigated the fit of the assumed t-distribution to the standardized residuals of the quasi maximum likelihood estimation for BDI and BY visually by QQ-plots as well as the plots for empirical vs. theoretical distribution, see Figure 3.3 and Figure 3.4.

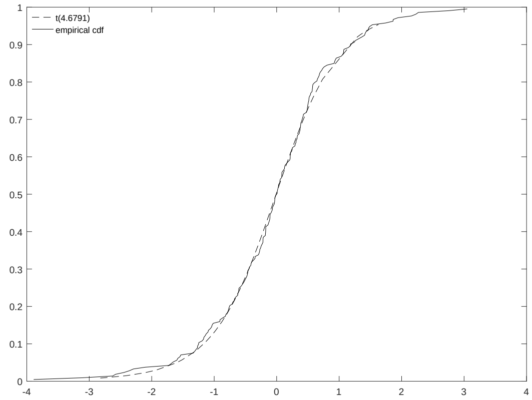


(a) QQ-plot of BDI residual quantiles versus Student's t quantiles

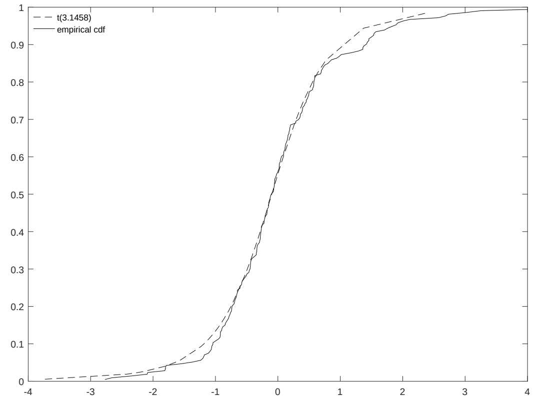
(b) QQ-plot of BY residual quantiles versus Student's t quantiles

FIGURE 3.3: QQ-plots of standardized residuals

The positive first impression is confirmed by the results of the Kolmogorov-Smirnov test and the Anderson-Darling test. The results in Table 3.6 show that both tests cannot reject the t-distribution at any usual confidence level. Accordingly, the t-distribution appears to be a suitable choice for the conditional marginal distributions.



(a) Empirical vs. theoretical distribution: BDI



(b) Empirical vs. theoretical distribution: BY

Figure 3.4: Marginal distribution plots: empirical vs. theoretical distribution

Table 3.6: Distribution tests of standardized residuals

	BDI		BY	
	KS test	AD test	KS test	AD test
5%-level test statistic	0.0394	0.2614	0.0561	0.8369
5%-level critical value	0.0925	2.4931	0.0925	2.4931
p-value	0.8831	0.9640	0.4997	0.4550

This table presents the test statistics of Kolmogorov-Smirnov test (KS) as well as Anderson-Darling test (AD). The null hypothesis is that the data is t-distributed.

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.

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

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). This copula caters for broad dependence governed by the conditional parameter $\theta(Z)$ taking values in $\mathbb{R}$, where a positive (negative) value corresponds to broad negative (positive) dependence, and for conditional upper left tail dependence $\lambda(Z)$ taking values in $[0,1]$ that specifically captures the shipping crisis (sharply decreasing BDI and sharply increasing BY). It is defined by

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

and is illustrated by the contour plots of the unconditional density (with standard normal margins) in Figure 3.5. Following Patton (2006), we model the conditional upper left tail dependence $\lambda(z)$ directly through the logistic function with

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

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

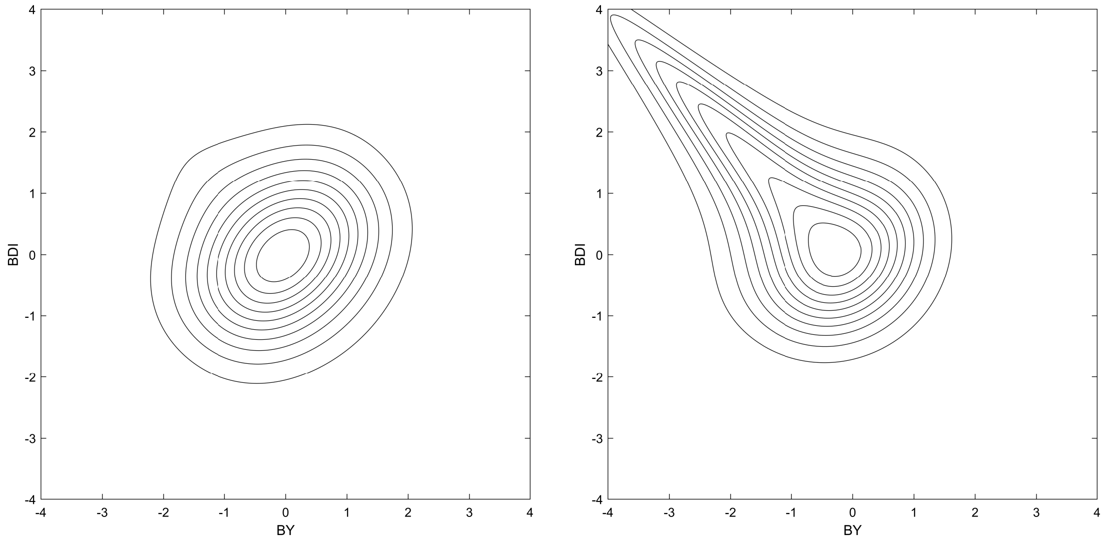
Next to the conditional extreme dependence parameter $\lambda(z)$, the relationship of BDI and BY is characterized by the conditional broad dependence parameter $\theta(z)$ in $C_{mtF}(\cdot,\cdot|z)$. Our focus is placed on the asymmetric dependence, so we set $\theta(z) = \theta$ for the main analysis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

[6] See Appendix 3.A for details.

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

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



(a) $\lambda = 0.06$, $\theta = 1.3$ (b) $\lambda = 0.26$, $\theta = 1.3$

FIGURE 3.5: Contour plots of mtF-Copula with standard normal margins

3.4 Empirical results

We have specified the marginal model in Equation (3.1) and Equation (3.3), 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 estimation results and afterwards check for robustness. We apply a one-step maximum-likelihood approach using the explicit form of the copula density given in Equation (A.9) in Appendix 3.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. 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 3.7.

The unconditional shipping crisis risk is obtained by Model (1). Using Equation (3.7) the estimate of $\kappa_{\lambda,0}$ of -2.8618 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-month changes 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 at the 10% level, 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-month MSCI returns $\kappa_{\lambda,MSCI}$ 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) yields to 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 0.0040, 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 broad dependence parameter θ is not significant in any of the setups. The complete model estimates can be found in Table 3.13 Appendix 3.B.

The resulting time-dependent realizations of the tail dependence coefficients λ for each model setup are plotted in Figure 3.6. Figure 3.6(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 3.6(b)), shipping crisis risk increases sharply between the middle of 2007 and 2009 but remains below 10% in the remaining sample period. Considering 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 3.6(c) shows the tail dependence coefficient when using only the lagged demand side changes (MSCI) as conditional parameter (Model (3)). There is only a short amplitude in the first quarter of 2009 which is too late to be a warning signal. Finally, the tail dependence coefficient in Model (4), which includes both supply and demand side factors as conditions for the extreme dependence of BDI and bond yields, is plotted in Figure 3.6(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 3.6(b) it is way more distinct.

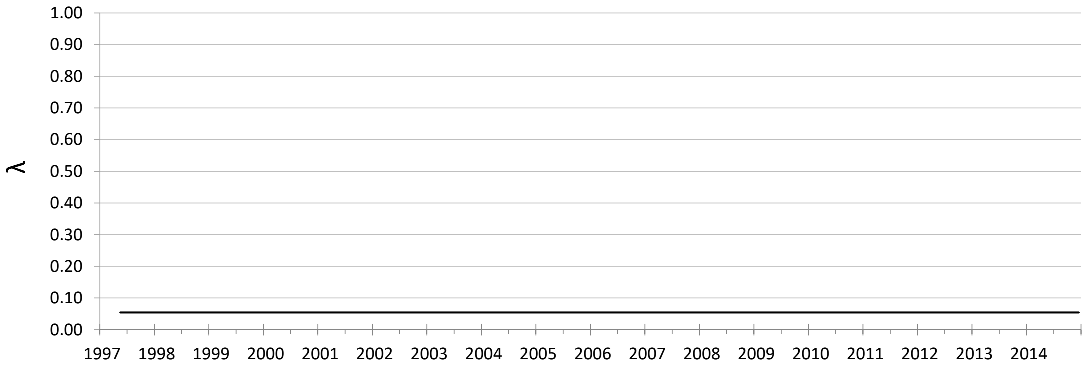
Overall, Figure 3.6 depicts that especially observing supply side developments helps to estimate the conditional crisis risk in the shipping market. While changes of the MSCI World

Table 3.7: Maximum-likelihood coefficient estimates

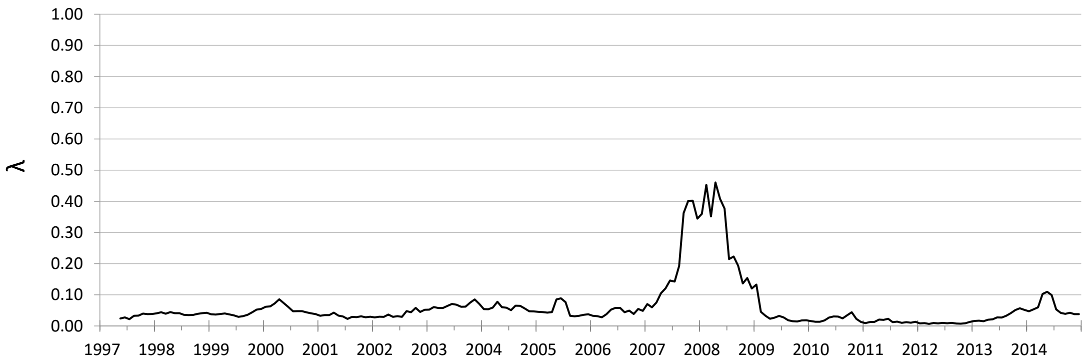
Model	(1)	(2)	(3)	(4)
Conditioning factors	none	$\Delta^3_{OFR,t-3}$	$\Delta^3_{MSCI,t-3}$	$\Delta^3_{OFR,t-3}$ & $\Delta^3_{MSCI,t-3}$
Panel A: Parameter estimates				
$\kappa_{\lambda,0}$	-2.8618**	-3.1200*	-2.9762**	-16.1937**
	[1.2813]	[1.8899]	[1.4633]	[6.8477]
$\kappa_{\lambda,OFR}$		0.9207		4.7857***
		[0.6693]		[1.7621]
$\kappa_{\lambda,MSCI}$			-0.4474	-3.2838***
			[0.7272]	[1.2399]
θ	0.1067	-0.0041	0.0660	0.3685
	[0.6501]	[0.6608]	[0.6299]	[0.4712]
Panel B: Regression diagnostics				
LL	392.2926	394.5423	392.6298	398.5649
AIC	-3.4556	-3.4674	-3.4493	-3.4959
BIC	-3.0439	-3.0399	-3.0218	-3.0526
Panel C: Hypotheses testing (one-sided)				
H_0-hypothesis		(2)	(3)	(4)
$\kappa_{\lambda,OFR} \leq 0$	t-statistic	1.3756		2.7150
	p-value	0.0845		0.0033
$\kappa_{\lambda,MSCI} \geq 0$	t-statistic		-0.6152	-2.6483
	p-value		0.2692	0.0040
$\kappa_{\lambda,OFR} \leq 0 \ \vee$ $\kappa_{\lambda,MSCI} \geq 0$	p-value			0.0040[1]

This table presents the maximum-likelihood estimates of the dependence parameters over the sample period from 05/1997 to 12/2014. LL is the log-likelihood and AIC (Akaike information criteria) as well as BIC (Bayesian information criteria) are the information criteria for model selection. *, **, 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 3.B

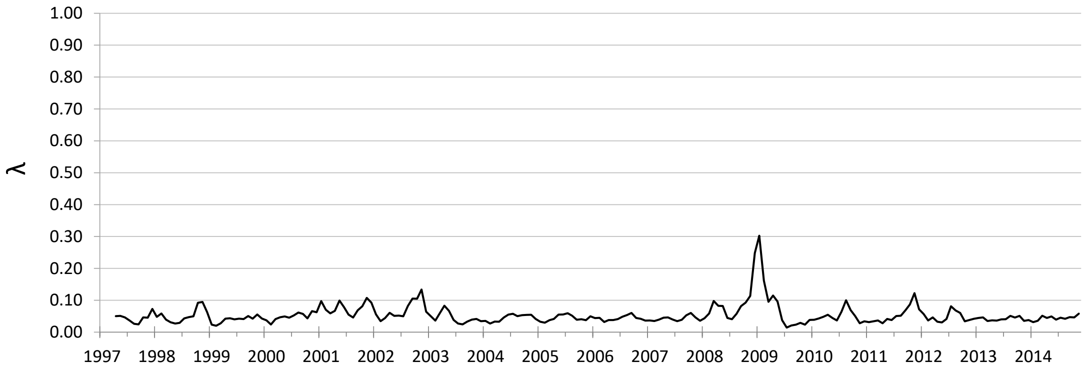
[1] By some calculation it can be shown that a conservative upper bound for the joint p-value can be obtained as the maximum of the individual p-values.



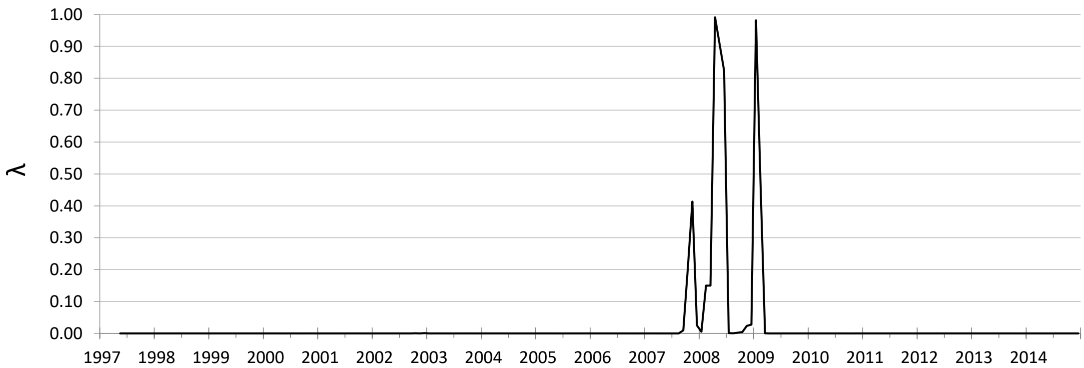
(a) Model (1): unconditional



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



(c) Model (3): MSCI



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

Figure 3.6: Tail dependence coefficients for different model setups

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 therefore carry out an extended robustness analysis and, in particular, test the out-of-sample performance of our approach.

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 investigate alternative conditional copula models and also different lag structures as well as window widths of the conditioning factors. 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 achieves also 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 3.8. 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 3.8: Estimation results: out-of-sample analysis

Estimation period	# obs.	$\kappa_{\lambda,0}$	$\kappa_{\lambda,OFR}$	$\kappa_{\lambda,MSCI}$
05/1997-06/2006	110	-7.5291**	1.9466$^{\bullet}$	-4.8072***
		[3.3577]	[1.4772]	[1.2987]

This table presents the maximum-likelihood estimates of the dependence parameters over the sample period from 05/1997 to 06/2006. $^{\bullet}$, **, and *** denote statistical significance at the 20%, 5%, and 1% level, respectively. Figures in [ ] are standard errors. The complete model estimates can be found in Table 3.14 in Appendix 3.B.

---

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 3.8) 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 3.14 in Appendix 3.B.

Figure 3.7 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.

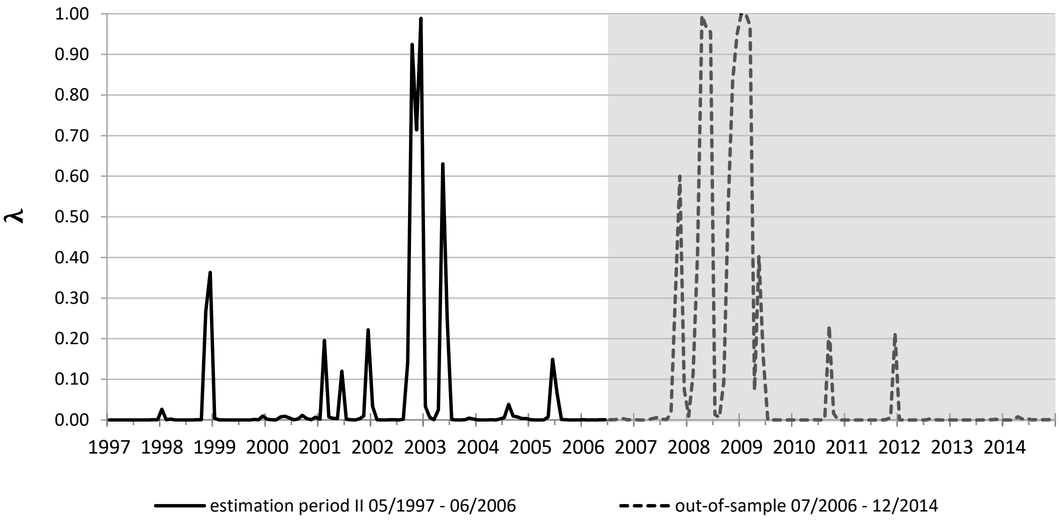


Figure 3.7: Out-of-sample estimation of shipping crisis risk

3.4.2.2 Alternative copula models

In the main analysis, we apply the conditional mirrored transformed Frank copula that we suppose to be suitable for the dependence structure focused on in this paper. In the following we investigate the robustness of our results regarding the conditional copula model. We investigate the nested sub-models, which are the conditional mirrored Frank copula (by setting $\lambda(Z) = 0$) and the conditional mirrored Gumbel copula (by setting $\theta(Z) = 0$). Further, we also investigate the conditional mirrored Clayton and t-copula. We expect that our results also hold for Gumbel and Clayton, as both allow for asymmetric tail dependence. However, this does not apply to the two other cases. The Frank copula does not allow for tail dependence and the t-copula is symmetric though allowing for tail dependence.

First, the dependence structure for conditional mirrored transformed Frank copula C_{mtF} is broadened by also allowing the parameter θ to depend also on the conditional variables Z. That is, in addition to Equation (3.7), we have

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

Then the conditional mirrored Frank copula is obtained by setting $\lambda(Z) = 0$ and the conditional mirrored Gumbel copula is obtained by setting $\theta(Z) = 0$ in Equations (3.7) and (3.9), respectively.

The conditional mirrored Clayton copula[8] can be parameterized by its conditional tail dependence parameter $\lambda(Z)$, which is modelled as given in Equation (3.7). The conditional mirrored t-copula has two parameters, the conditional degrees of freedom $\eta(Z)$ taking values $\mathbb{R}^+$ and conditional correlation $\rho(Z)$ taking values in $[-1, 1]$.

$$\eta(z) = \exp\left(\kappa_{\eta,0} + \kappa_{\eta,OFR} \cdot \Delta^3_{OFR} + \kappa_{\eta,MSCI} \cdot \Delta^3_{MSCI}\right) , \tag{3.10}$$

$$\rho(z) = \frac{1 - \exp\left(-\left(\kappa_{\rho,0} + \kappa_{\rho,OFR} \cdot \Delta^3_{OFR} + \kappa_{\rho,MSCI} \cdot \Delta^3_{MSCI}\right)\right)}{1 + \exp\left(-\left(\kappa_{\rho,0} + \kappa_{\rho,OFR} \cdot \Delta^3_{OFR} + \kappa_{\rho,MSCI} \cdot \Delta^3_{MSCI}\right)\right)} , \tag{3.11}$$

where Equation (3.10) is similar to Equation (3.7) and Equation (3.11) is similar to Equation (19) of Patton (2006) in a related setup.

Table 3.9 presents the maximum-likelihood estimates. The estimates of the dependence parameters for the extended conditional mirrored transformed Frank model, Full conditioning mtF-copula in Table 3.9, are in line with those of the main model, Model (4) in Table 3.7. 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. The log-likelihood of the extended specification rises by 1.8932 to 400.4581. Conducting a likelihood ratio test produces a test statistics of 3.7864 that is below the 10%-level critical value of 4.61 and is not supporting the conditional broad dependence in Equation (3.9). This finding is confirmed by AIC and BIC.

Next, the results for the Frank and the Gumbel specification are discussed, which both nest into the full model. The Frank specification cannot incorporate tail dependence, and hence the log-likelihood drops by 5.703 compared to the full model. The likelihood ratio statistics takes the value of 11.4060 rejecting the conditional Frank as null against the full model as alternative, what is confirmed by AIC and BIC. In fact, the conditional Frank cannot capture a relevant characteristic of the data which is asymmetric extremal dependence, the upper left tail dependence. In contrast, the conditional mirrored Gumbel copula is picking up that very characteristic. But it is not that flexible in the center of the distribution. The likelihood ratio statistics of testing the Gumbel specification as null against the full model as alternative takes the value of 8.6870 with a corresponding p-value of 0.0338 giving not an overly clear picture. The Gumbel specification is producing fairly significant parameter estimates, which are smaller but in line with the conclusion of the main analysis.

Finally, the non-nested model formulations are discussed. The mirrored conditional Clay-

[8] The conditional mirrored Clayton copula $C_{mC}(u, v \,|\, z)$ is obtained from the Clayton $C_C(u, v \,|\, z)$ copula by $C_{mC}(u, v \,|\, z) = v - C_C(1 - u, v \,|\, z)$, for $(u, v, z) \in [0, 1] \times [0, 1] \times \mathcal{Z}$, where the Clayton copula is given in Nelsen (2006), chap. 4.3.

ton copula caters for upper left tail dependence. The parameter estimates are highly significant and in line with the results of the main analysis. Using AIC to assess the model fit, we find that the full model is slightly better. However, this order reverses when considering BIC instead. The mirrored conditional t-copula is not performing well, with almost all parameter estimates being not significant and the worst AIC and BIC compared to all other specifications. As expected, the symmetry of this model is not fitting the characteristics of the data explaining the poor performance.

Overall, the key results presented in the main analysis are confirmed and are therefore robust. The Clayton specification fits the data well and is close to the transformed Frank specification. This also holds for the Gumbel specification but to a lesser extent. The conditional mirrored Frank copula and the mirrored conditional t-copula both perform poorly.

3.4.2.3 Alternative lag lengths and window widths of conditioning factors

Estimating extreme dependence parameters reliably 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. In our main analysis we use a window width of three months and a lag of three months. In the following we vary the window width between one, two, three, and six months as well as the lag between one, two, and three months. The corresponding maximum-likelihood estimates of the conditioning parameters $\kappa_{\lambda,OFR}$ and $\kappa_{\lambda,MSCI}$ are given in Table 3.10.

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

3.4.2.4 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 US corporates. But shipping is a very special

TABLE 3.9: Estimation results: alternative copula models

Parameter		$\kappa_{\cdot,0}$		$\kappa_{\cdot,OFR}$		$\kappa_{\cdot,MSCI}$
			Full conditioning mtF-copula			
λ		-15.7552**		4.5410**		-3.2278**
		[7.9825]		[2.0424]		[1.4192]
θ		0.3002		1.0590**		0.0281
		[0.4855]		[0.4956]		[0.5631]
	LL	400.4581	AIC	-3.4949	BIC	-3.0199
			Mirrored Frank copula			
θ		0.3591		1.2164***		-0.1509
		[0.4625]		[0.4547]		[0.4838]
	LL	394.7551	AIC	-3.4694	BIC	-3.0419
			Mirrored Gumbel copula			
λ		-5.6118**		1.7834**		-1.1721**
		[2.4392]		[0.8009]		[0.5162]
	LL	396.1146	AIC	-3.4822	BIC	-3.0547
			Mirrored Clayton copula			
λ		-13.9782**		4.1204***		-3.0530***
		[5.9705]		[1.5343]		[1.1416]
	LL	397.4176	AIC	-3.4945	BIC	-3.0670
			Mirrored t-copula			
η		4.6009		-1.4992		-0.8129
		[5.1201]		[1.7405]		[2.0516]
ρ		0.1049		0.4360**		-0.0760
		[0.1751]		[0.2075]		[0.1806]
	LL	396.9447	AIC	-3.4617	BIC	-2.9868

This table presents the maximum-likelihood estimates for alternative copula models over the sample period from 05/1997 to 12/2014. λ, θ, η and ρ denote the copula dependence parameters. $\kappa_{\cdot,0}$, $\kappa_{\cdot,OFR}$ and $\kappa_{\cdot,MSCI}$, $\cdot \in \{\lambda, \theta\, \eta, \rho\}$, denote the estimates for the intercept and the conditioning factors $\Delta^3 OFR_{t-3}$ and $\Delta^3 MSCI_{t-3}$. LL is the log-likelihood and AIC (Akaike information criteria) as well as BIC (Bayesian information criteria) are the information criteria for model selection. *, **, 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 3.15 and Table 3.16 in Appendix 3.B.

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 US Corporate Shipping Index that is also published by BofA Merrill Lynch. The effective yield of this index compared to the US Corporate B Index yield is shown in Figure 3.8. 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

Table 3.10: Estimation results: alternative lag lengths and window widths

Lag i	Estimate	Window width j 1	2	3	6
1	$\kappa_{\lambda,0}$	-7.6609*	-4.4574•	-3.3676•	-3.8986•
	$\kappa_{\lambda,OFR}$	0.3657	0.8702	0.6427	1.1207
	$\kappa_{\lambda,MSCI}$	-2.4792**	-0.9252	-0.6172	-0.5882
	LL	395.7748	394.1147	394.5174	395.1484
2	$\kappa_{\lambda,0}$	-9.1914•	-3.4344*	-3.9250•	-4.6768•
	$\kappa_{\lambda,OFR}$	2.8500*	1.0990*	1.3046•	1.6037•
	$\kappa_{\lambda,MSCI}$	-1.4798	-0.6601•	-0.6378•	-0.7568
	LL	397.3769	396.3303	396.6333	396.9770
3	$\kappa_{\lambda,0}$	-4.5448**	-4.7858*	-16.1937**	-3.8283
	$\kappa_{\lambda,OFR}$	0.9426**	1.4779*	4.7857***	1.2174
	$\kappa_{\lambda,MSCI}$	-1.6159***	-1.2592**	-3.2838***	-0.6526
	LL	397.0702	397.0805	398.5649	396.9314

This table presents the maximum-likelihood estimates of the dependence parameters over the sample period from 05/1997 to 12/2014 for different lag lengths and window widths. LL denotes log-likelihood. •, *, **, and *** denote statistical significance at the 20%, 10%, 5%, and 1% level, respectively. The complete estimation results can be found in Tables 3.20 to 3.23 in Appendix 3.B.

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 3.11. The results are generally similar to those when using the broad US corporate bond yield (see Table 3.7), but the level of statistical significance of the estimates in the combined setup in model (4) is reduced.

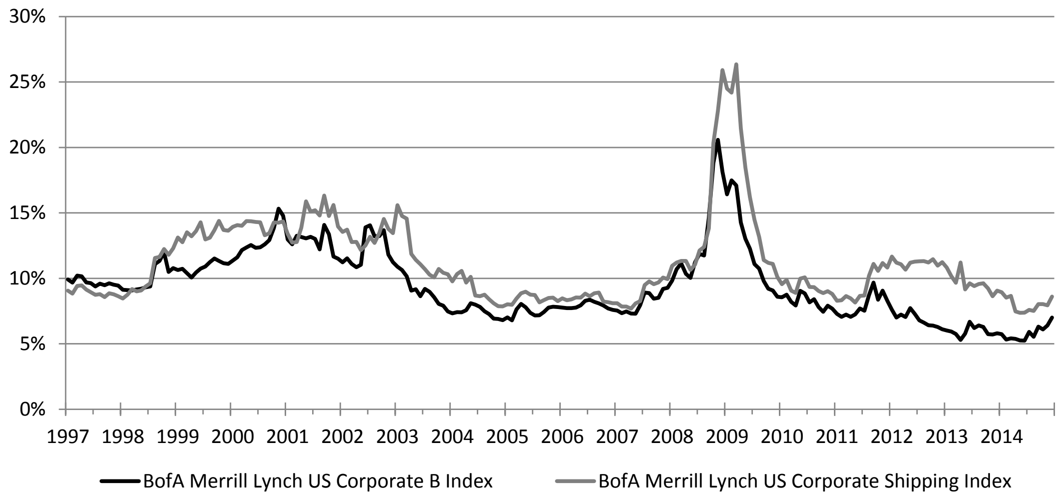


Figure 3.8: Effective yields of US corporate bond (B) index and US high-yield shipping bond index

TABLE 3.11: 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				
$\kappa_{\lambda,0}$	-2.3007**	-3.5907*	-2.2879*	-4.3187$^\bullet$
	[1.0786]	[1.9935]	[1.2113]	[3.2101]
$\kappa_{\lambda,OFR}$		1.1777$^\bullet$		1.4595$^\bullet$
		[0.7516]		[1.1317]
$\kappa_{\lambda,MSCI}$			-1.0284$^\bullet$	-1.1154$^\bullet$
			[0.6429]	[0.8640]
θ	0.2661	0.5081	-0.1634	0.4049
	[0.7346]	[0.5444]	[0.7606]	[0.5585]
Panel B: Regression diagnostics				
LL	400.8678	402.4842	404.8297	406.9892
AIC	-3.5082	-3.5140	-3.5361	-3.5471
BIC	-3.0490	-3.0390	-3.0611	-3.0562

This table presents the maximum-likelihood estimates of the dependence parameters over the sample period from 05/1997 to 12/2014. LL is the log-likelihood and AIC (Akaike information criteria) as well as BIC (Bayesian information criteria) are the information criteria for model selection. *, **, 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 3.24 in Appendix 3.B.

[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.

Taken together, the yield of a shipping bond index is theoretically appealing, but is impractical for our use due to its lagged behavior and the illiquidity of the contained bonds. Therefore, we stay with the broad index for B-rated US corporate bonds, which should theoretically also reflect the rating implied financing costs of shipping companies.

3.4.2.5 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.

[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.

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 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

$$OFR_t = \alpha + \beta\, FR_t^{Age>20y} + \eta_t^{OFR}. \tag{3.12}$$

The residuals η^{OFR} of Equation (3.12) are used as an alternative orderbook-to-fleet figure[10]. The plot of the residual orderbook-to-fleet series given in Figure 3.9 reveals a similar pattern as the original series OFR.

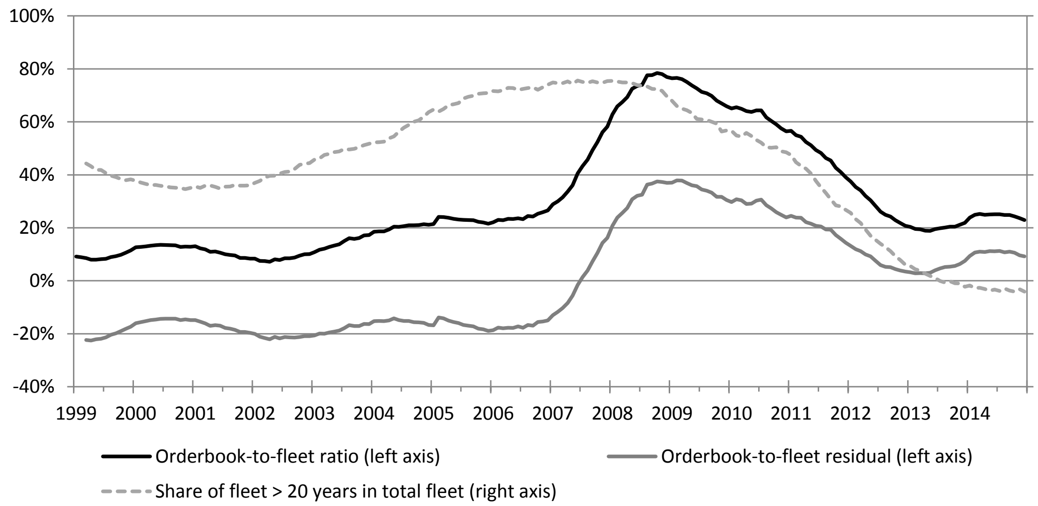


Figure 3.9: Adjustment of orderbook-to-fleet ratio

We re-estimate the model in two ways replacing OFR by η^{OFR} and MSCI by EX, respectively, where the three-month changes of EX are considered by two lags. Table 3.12 shows that the changes of the conditioning variables still yield robust and significant estimates. Adjusting the orderbook-to-fleet ratio hardly effects the estimation results compared to the initial model (see Table 3.7). 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

[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 (3.12) are $\alpha = 0.3104$ [0.0145] and $\beta = 1.4253$ [0.2423].

TABLE 3.12: Estimation results: alternative conditioning variables

Conditioning factors	$\Delta^3_{OFR,t-3}$ & $\Delta^3_{EX,t-2}$	$\Delta^3_{\eta^{OFR},t-3}$ & $\Delta^3_{MSCI,t-3}$
	Panel A: Parameter estimates	
$\kappa_{\lambda,0}$	-7.6296***	-14.5813**
	[1.9114]	[6.0838]
$\kappa_{\lambda,OFR}$	2.5850***	
	[0.5497]	
$\kappa_{\lambda,\eta^{OFR}}$		4.3905***
		[1.5985]
$\kappa_{\lambda,MSCI}$		-2.9237***
		[1.0419]
$\kappa_{\lambda,EX}$	-2.9592***	
	[0.6200]	
θ	0.1465	0.4061
	[0.4969]	[0.5284]
	Panel B: Regression diagnostics	
LL	401.5471	325.2043[1]
AIC	-3.5420	-3.2305
BIC	-3.0807	-2.7413

This table presents the maximum-likelihood estimates of the dependence parameters over the sample period from 05/1997 to 12/2014 for alternative conditioning variables. $\Delta^3_{OFR,t-3}$ and $\Delta^3_{\eta^{OFR},t-3}$ are the three months delayed three-month changes 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-month log-returns of the MSCI World index and $\Delta^3_{EX,t-2}$ is the two months delayed three month relative change of exports of maritime bulk goods. LL is the log-likelihood and AIC (Akaike information criteria) as well as BIC (Bayesian information criteria) are the information criteria for model selection. *, **, 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 3.25 in Appendix 3.B. [1] Sample period 03/1999 - 12/2014.

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.

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 that 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 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 other asset classes 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.

3.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 Patton (2006) and extend the concept of copulas to the context of conditional distribution functions.

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). Its conditional version $C_{tF}(\cdot,\cdot\,|\,Z)$ is parameterized by $(\theta(Z),\delta(Z))$ taking values in $\mathbb{R}\times[1,\infty)$ and is given by

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

and

$$C_{tF}(u,v\,|\,z) = \exp(-((-\ln(u))^{\delta(z)}+(-\ln(v))^{\delta(z)})^{\frac{1}{\delta(z)}}), \text{for } \theta(z)=0, \tag{A.2}$$

for $(u,v,z)\in[0,1]\times[0,1]\times\mathcal{Z}$.

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 $C_F(\cdot,\cdot|Z)$ for $\delta(Z)=1$, and the conditional Gumbel copula $C_G(\cdot,\cdot|Z)$ for $\theta(Z)=1$, respectively. The conditional transformed Frank copula combines the properties of its parent copulas C_F and C_G.[11] Thus, the parameter $\theta(Z)$ from the conditional Frank copula describes the broad dependence of the two variables where a positive (negative) value of θ corresponds to positive (negative) dependence 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:

$$\lambda(z) = 2-2^{1/\delta(z)}\,, z\in\mathcal{Z}\,, \tag{A.3}$$

or alternatively

$$\delta(z) = \frac{\ln(2)}{\ln(2-\lambda(z))}\,. \tag{A.4}$$

Following Patton (2006), we model the conditional tail dependence directly through the

[11] For more details on the Frank and Gumbel copula see Nelsen (2006), chap. 4.3.

logistic function with

$$\lambda(z) = \frac{1}{1 + \exp\left(-(\kappa_{\lambda,0} + \kappa_\lambda{}' z)\right)}\,, \tag{A.5}$$

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 $\lambda = 1$.

A shipping crisis can be associated with sharply decreasing freight rates and sharply increasing financing costs. To capture this tail dependence, we rotate the first coordinate of $C_{tF}(\cdot,\cdot\,|\,z)$. As a consequence, the broad dependence reverses as a positive value of θ leads to negative dependence and vice versa. Let the pair $[U^*, V^*]' \sim C_{tF}(\cdot,\cdot\,|\,z), z \in \mathcal{Z}$, then for $U = 1 - U^*$, $V = V^*$, we define the conditional mirrored transformed Frank copula $C_{mtF}(\cdot,\cdot\,|\,z)$ by

$$\begin{aligned} C_{mtF}(u, v\,|\,z) &= \mathbb{P}(U \leq u, V \leq v\,|\,z) = \mathbb{P}(1 - U^* \leq u, V^* \leq v\,|\,z) \\ &= v - C_{tF}(1 - u, v\,|\,z)\,, \end{aligned} \tag{A.6}$$

for $(u, v, z) \in [0,1] \times [0,1] \times \mathcal{Z}$. Replacing $\delta(z)$ by $\lambda(z)$ using Equation (A.4) we obtain for $\theta(z) \in \mathbb{R} \setminus \{0\}$

$$\begin{aligned} C_{mtF}\,(u, v\,|\,z) = v + \frac{1}{\theta(z)} \ln \Bigg[1 + (e^{-\theta(z)} - 1) \exp \Bigg[- \Bigg[\left(- \ln \left(\frac{e^{-(1-u)\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \\ + \left(- \ln \left(\frac{e^{-v\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \Bigg]^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \Bigg] \Bigg]\,, \end{aligned} \tag{A.7}$$

and for $\theta(z) = 0$

$$C_{mtF}(u, v\,|\,z) = v - \exp \left(- \left((- \ln (1 - u))^{\frac{\ln(2)}{\ln(2-\lambda(z))}} + (- \ln (v))^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \right)^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \right). \tag{A.8}$$

The corresponding density $c_{mtF}\,(\cdot,\cdot\,|\,z)$ is given by

$$c_{mtF}\,(u, v\,|\,z) = - \frac{\varphi''_{tF}(C_{tF}\,(1-u, v\,|\,z)\;|\,z) \varphi'_{tF}(1-u\,|\,z) \varphi'_{tF}(v\,|\,z)}{\left(\varphi'_{tF}(C_{tF}\,(1-u, v\,|\,z)\;|\,z)\right)^3}\,, \tag{A.9}$$

where for $\theta(z) \in \mathbb{R} \setminus \{0\}$

$$\varphi'_{tF}(t\,|\,z) = \frac{\ln(2)}{\ln(2-\lambda(z))} \frac{\theta(z)}{1 - e^{t\theta(z)}} \left(- \ln \left(\frac{e^{-t\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))} - 1}\,,$$

$$\varphi''_{tF}(t\,|\,z) = \varphi'_{tF}(t\,|\,z)\frac{\theta(z)}{1-e^{t\theta(z)}}\left(e^{t\theta(z)} + \frac{\frac{\ln(2)}{\ln(2-\lambda(z))}-1}{-\ln\left(\frac{e^{-t\theta(z)}-1}{e^{-\theta(z)}-1}\right)}\right) ,$$

and for $\theta(z) = 0$

$$\varphi'_{tF}(t\,|\,z) = \frac{\ln(2)}{\ln(2-\lambda(z))}\frac{-1}{t}\left(-\ln(t)\right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}-1} ,$$

$$\varphi''_{tF}(t\,|\,z) = \varphi'_{tF}(t\,|\,z)\frac{-1}{t}\left(1 + \frac{\frac{\ln(2)}{\ln(2-\lambda(z))}-1}{-\ln(t)}\right) .$$

3.B Model estimates

Table 3.13: 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	0.0140	0.0095
	$\beta_{BDI1,1}$	-0.2603	0.1815	-0.2468	0.1818	-0.2567	0.1816	-0.2680	0.1771
	$\beta_{BDI1,2}$	-0.0472	0.1909	-0.0657	0.1911	-0.0538	0.1912	-0.1105	0.1843
	$\beta_{BDI1,3}$	0.0150	0.1694	0.0305	0.1658	0.0128	0.1695	0.0173	0.1647
	$\beta_{BDI1,4}$	-0.1182	0.1927	-0.0662	0.1899	-0.1233	0.1948	-0.0322	0.1909
	$\beta_{BDI2,1}$	0.0928	0.0688	0.0910	0.0688	0.0922	0.0687	0.1059	0.0649
	$\beta_{BDI2,2}$	-0.0611	0.0732	-0.0560	0.0724	-0.0613	0.0734	-0.0631	0.0692
	$\beta_{BDI2,3}$	-0.0110	0.0645	-0.0046	0.0649	-0.0046	0.0652	0.0279	0.0625
	$\beta_{BDI2,4}$	-0.0911	0.0573	-0.0815	0.0568	-0.0932	0.0604	-0.0845	0.0583
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	0.1508**	0.0650
	$\beta_{BY1,2}$	-0.0529	0.0509	-0.0538	0.0518	-0.0580	0.0513	-0.0952*	0.0532
	$\beta_{BY1,3}$	0.0120	0.0596	0.0242	0.0607	0.0157	0.0604	0.0210	0.0635
	$\beta_{BY1,4}$	0.0974*	0.0579	0.1050*	0.0581	0.0973*	0.0586	0.1311**	0.0623
	$\beta_{BY2,1}$	0.0107	0.0186	0.0130	0.0187	0.0114	0.0185	0.0117	0.0197
	$\beta_{BY2,2}$	-0.0348*	0.0197	-0.0324*	0.0196	-0.0346*	0.0197	-0.0342*	0.0204
	$\beta_{BY2,3}$	0.0295	0.0212	0.0309	0.0211	0.0299	0.0214	0.0349	0.0243
	$\beta_{BY2,4}$	-0.0166	0.0187	-0.0165	0.0188	-0.0203	0.0196	-0.0200	0.0211
		Regime dependent variances							
BDI	$\sigma^2_{BDI,I}$	0.0165***	0.0048	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	0.0844***	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	0.0113*	0.0069
		Degrees of freedom of marginal distributions							
BDI	ν_{BDI}	4.3477**	1.8686	4.3636**	1.7719	4.3096**	1.8224	4.0140**	1.6326
BY	ν_{BY}	3.1559***	1.0154	3.2169***	1.0677	3.1928***	1.0265	3.0227***	0.9934
		Dependence parameters							
	$\kappa_{\lambda,0}$	-2.8618**	1.2813	-3.1200*	1.8899	-2.9762**	1.4633	-16.1937**	6.8477
	$\kappa_{\lambda,OFR}$			0.9207	0.6693			4.7857***	1.7621
	$\kappa_{\lambda,MSCI}$					-0.4474	0.7272	-3.2838***	1.2399
	θ	0.1067	0.6501	-0.0041	0.6608	0.0660	0.6299	0.3685	0.4712
LL		392.2926		394.5423		392.6298		398.5649	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

TABLE 3.14: 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	$\beta_{BDI,0}$	0.0009	0.0112	-0.0004	0.0110	0.0038	0.0097
	$\beta_{BDI1,1}$	-0.3351	0.2084	-0.3296	0.2149	-0.3699	0.2047
	$\beta_{BDI1,2}$	0.1466	0.1895	0.0886	0.1887	0.1103	0.1811
	$\beta_{BDI1,3}$	-0.5256***	0.1879	-0.5065**	0.2156	-0.4926**	0.2022
	$\beta_{BDI1,4}$	-0.0615	0.2229	0.0008	0.1692	0.0603	0.1653
	$\beta_{BDI2,1}$	0.1906**	0.0908	0.1653**	0.0833	0.1918**	0.0771
	$\beta_{BDI2,2}$	-0.0023	0.0883	-0.0386	0.0899	-0.0289	0.0827
	$\beta_{BDI2,3}$	0.0003	0.0877	-0.0050	0.0834	0.0292	0.0795
	$\beta_{BDI2,4}$	0.0606	0.0760	0.0421	0.0744	0.0351	0.0700
BY	$\beta_{BY,0}$	-0.0037	0.0042	-0.0028	0.0040	-0.0034	0.0037
	$\beta_{BY1,1}$	0.1015	0.0837	0.1338	0.0918	0.1707**	0.0824
	$\beta_{BY1,2}$	0.0438	0.0699	-0.0240	0.0661	-0.0312	0.0623
	$\beta_{BY1,3}$	-0.0748	0.0808	-0.0553	0.0807	-0.0493	0.0749
	$\beta_{BY1,4}$	0.1235	0.0861	0.1337*	0.0789	0.1055	0.0657
	$\beta_{BY2,1}$	0.0350	0.0357	0.0276	0.0333	0.0239	0.0308
	$\beta_{BY2,2}$	-0.0344	0.0345	-0.0314	0.0331	-0.0308	0.0317
	$\beta_{BY2,3}$	-0.0137	0.0361	-0.0101	0.0344	-0.0182	0.0317
	$\beta_{BY2,4}$	-0.0042	0.0380	-0.0048	0.0332	-0.0094	0.0308
		Regime dependent variances					
BDI	σ^2_{BDI}	0.0242	0.0343	0.0191	0.0163	0.0232	0.0302
BY	σ^2_{BY}	0.0049	0.0081	0.0031	0.0020	0.0035	0.0032
		Degrees of freedom of marginal distributions					
BDI	ν_{BDI}	2.6121**	1.3220	2.9809*	1.5804	2.6281**	1.2558
BY	ν_{BY}	2.4586**	1.0548	2.9345**	1.1704	2.6640***	0.9799
		Dependence parameters					
	$\kappa_{\lambda,0}$	-3.1193	4.1983	-7.5291**	3.3577	-8.9589	6.9048
	$\kappa_{\lambda,OFR}$	0.2725	1.2517	1.9466	1.4772	2.2400	2.6499
	$\kappa_{\lambda,MSCI}$	1.2414	1.9896	-3.8072***	1.2987	-4.3504	2.9879
	θ	0.2931	1.2212	0.3900	0.7229	0.4189	0.6907
LL		252.0577		271.0555		293.2115	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

Table 3.15: ML-estimates for alternative copula model I

	Model	Full mtF-copula		Mirrored Frank copula		Mirrored Gumbel copula	
	Parameter	Estimate	SE	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))					
BDI	$\beta_{BDI,0}$	0.0150	0.0095	0.0138	0.0096	0.0139	0.0095
	$\beta_{BDI1,1}$	-0.2497	0.1817	-0.2246	0.1810	-0.2293	0.1787
	$\beta_{BDI1,2}$	-0.1212	0.1810	-0.0496	0.1913	-0.1086	0.1867
	$\beta_{BDI1,3}$	-0.0207	0.1660	-0.0445	0.1667	0.0229	0.1636
	$\beta_{BDI1,4}$	0.0343	0.1874	-0.0333	0.1911	-0.0177	0.1833
	$\beta_{BDI2,1}$	0.0831	0.0639	0.0790	0.0656	0.0960	0.0661
	$\beta_{BDI2,2}$	-0.0689	0.0674	-0.0520	0.0722	-0.0548	0.0708
	$\beta_{BDI2,3}$	0.0299	0.0596	0.0039	0.0647	0.0266	0.0646
	$\beta_{BDI2,4}$	-0.0657	0.0618	-0.0584	0.0588	-0.0827	0.0587
BY	$\beta_{BY,0}$	-0.0051	0.0034	-0.0050	0.0033	-0.0047	0.0035
	$\beta_{BY1,1}$	0.1463**	0.0631	0.1525***	0.0580	0.1525**	0.0630
	$\beta_{BY1,2}$	-0.0773	0.0525	-0.0328	0.0504	-0.0893*	0.0533
	$\beta_{BY1,3}$	0.0321	0.0635	0.0365	0.0590	0.0259	0.0626
	$\beta_{BY1,4}$	0.1323**	0.0638	0.1064*	0.0561	0.1274**	0.0595
	$\beta_{BY2,1}$	0.0173	0.0186	0.0159	0.0174	0.0137	0.0186
	$\beta_{BY2,2}$	-0.0339*	0.0199	-0.0299	0.0199	-0.0314	0.0199
	$\beta_{BY2,3}$	0.0386*	0.0232	0.0338	0.0209	0.0364*	0.0220
	$\beta_{BY2,4}$	-0.0236	0.0206	-0.0209	0.0184	-0.0212	0.0204
		Regime dependent variances					
BDI	$\sigma^2_{BDI,I}$	0.0174***	0.0062	0.0164***	0.0051	0.0164***	0.0048
	$\sigma^2_{BDI,II}$	0.0877***	0.0285	0.0942***	0.0293	0.0841***	0.0245
BY	$\sigma^2_{BY,I}$	0.0028**	0.0014	0.0028**	0.0014	0.0025***	0.0009
	$\sigma^2_{BY,II}$	0.0111*	0.0067	0.0097	0.0060	0.0087**	0.0042
		Degrees of freedom of marginal distributions					
BDI	ν_{BDI}	3.8899**	1.5791	4.1946**	1.7969	4.2152**	1.6369
BY	ν_{BY}	3.0161***	0.9716	2.9507***	0.9074	3.3317***	1.1038
		Dependence parameters					
	$\kappa_{\lambda,0}$	-15.7552**	7.9825			-5.6118**	2.4392
	$\kappa_{\lambda,OFR}$	4.5410**	2.0424			1.7834**	0.8009
	$\kappa_{\lambda,MSCI}$	-3.2278**	1.4192			-1.1721**	0.5162
	$\kappa_{\theta,0}$	0.3002	0.4855	0.3591	0.4625		
	$\kappa_{\theta,OFR}$	1.0590**	0.4956	1.2164***	0.4547		
	$\kappa_{\theta,MSCI}$	0.0281	0.5631	-0.1509	0.4838		
LL		400.4581		394.7551		396.1146	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), (3.7), and (3.9) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

TABLE 3.16: ML-estimates for alternative copula model II

	Model	Mirrored Clayton copula		Mirrored t-copula	
	Parameter	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))			
BDI	$\beta_{BDI,0}$	0.0138	0.0095	0.0127	0.0098
	$\beta_{BDI1,1}$	-0.2622	0.1764	-0.2442	0.1837
	$\beta_{BDI1,2}$	-0.1023	0.1847	-0.0424	0.1824
	$\beta_{BDI1,3}$	0.0245	0.1653	0.0263	0.1629
	$\beta_{BDI1,4}$	-0.0322	0.1889	-0.0079	0.1915
	$\beta_{BDI2,1}$	0.0966	0.0651	0.1052	0.0662
	$\beta_{BDI2,2}$	-0.0609	0.0693	-0.0450	0.0730
	$\beta_{BDI2,3}$	0.0174	0.0628	0.0078	0.0666
	$\beta_{BDI2,4}$	-0.0785	0.0581	-0.0660	0.0583
BY	$\beta_{BY,0}$	-0.0050	0.0035	-0.0046	0.0032
	$\beta_{BY1,1}$	0.1515**	0.0654	0.1439**	0.0576
	$\beta_{BY1,2}$	-0.0977	0.0538	-0.0191	0.0502
	$\beta_{BY1,3}$	0.0153	0.0633	0.0392	0.0598
	$\beta_{BY1,4}$	0.1284**	0.0606	0.1113*	0.0590
	$\beta_{BY2,1}$	0.0138	0.0195	0.0227	0.0175
	$\beta_{BY2,2}$	-0.0337*	0.0202	-0.0265	0.0193
	$\beta_{BY2,3}$	0.0372	0.0233	0.0346*	0.0202
	$\beta_{BY2,4}$	-0.0223	0.0208	-0.0241	0.0183
		Regime dependent variances			
BDI	$\sigma^2_{BDI,I}$	0.0167***	0.0053	0.0170***	0.0050
	$\sigma^2_{BDI,II}$	0.0820***	0.0263	0.0884***	0.0269
BY	$\sigma^2_{BY,I}$	0.0027**	0.0012	0.0027**	0.0013
	$\sigma^2_{BY,II}$	0.0106*	0.0060	0.0088*	0.0052
		Degrees of freedom of marginal distributions			
BDI	ν_{BDI}	4.1250**	1.7254	4.5108**	2.1386
BY	ν_{BY}	3.1176***	1.0333	2.9930***	0.9170
		Dependence parameters			
	$\kappa_{\lambda,0}$	-13.9782**	5.9705		
	$\kappa_{\lambda,OFR}$	4.1204***	1.5343		
	$\kappa_{\lambda,MSCI}$	-3.0530***	1.1416		
	$\kappa_{\eta,0}$			4.6009	5.1201
	$\kappa_{\eta,OFR}$			-1.4992	1.7405
	$\kappa_{\eta,MSCI}$			-0.8129	2.0516
	$\kappa_{\rho,0}$			0.1049	0.1751
	$\kappa_{\rho,OFR}$			0.4360**	0.2075
	$\kappa_{\rho,MSCI}$			-0.0760	0.1806
LL		397.4176		396.9447	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.7), (3.10), and (3.11) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

TABLE 3.17: ML-estimates for extended variance specification

	Parameter	Estimate	SE
		Mean equation (VAR(4))	
BDI	$\beta_{BDI,0}$	0.0156*	0.0085
	$\beta_{BDI1,1}$	-0.1705	0.1585
	$\beta_{BDI1,2}$	0.0020	0.1548
	$\beta_{BDI1,3}$	-0.0046	0.1379
	$\beta_{BDI1,4}$	0.0212	0.1506
	$\beta_{BDI2,1}$	0.1142	0.0707
	$\beta_{BDI2,2}$	0.0180	0.0690
	$\beta_{BDI2,3}$	0.0254	0.0588
	$\beta_{BDI2,4}$	-0.0894	0.0619
BY	$\beta_{BY,0}$	-0.0033	0.0033
	$\beta_{BY1,1}$	0.1727***	0.0590
	$\beta_{BY1,2}$	-0.0757	0.0531
	$\beta_{BY1,3}$	0.0333	0.0594
	$\beta_{BY1,4}$	0.1294**	0.0586
	$\beta_{BY2,1}$	0.0174	0.0190
	$\beta_{BY2,2}$	-0.0193	0.0190
	$\beta_{BY2,3}$	0.0455**	0.0177
	$\beta_{BY2,4}$	-0.0228	0.0193
		Regime dependent variances	
BDI	$\sigma^2_{BDI,I}$	0.0078***	0.0020
	$\sigma^2_{BDI,II}$	0.0319***	0.0093
	$\sigma^2_{BDI,III}$	0.0088***	0.0214
BY	$\sigma^2_{BY,I}$	0.0027**	0.0012
	$\sigma^2_{BY,II}$	0.0091*	0.0048
		Degrees of freedom of marginal distributions	
BDI	ν_{BDI}	4.8914**	2.0692
BY	ν_{BY}	3.6119***	1.1692
		Dependence parameters	
	$\kappa_{\lambda,0}$	-3.9936	2.6902
	$\kappa_{\lambda,OFR}$	1.3785	0.9317
	$\kappa_{\lambda,MSCI}$	-0.7321	0.5552
	θ	-0.1171	0.5616
LL		398.8738	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

TABLE 3.18: ML-estimates for VAR(0)-model

	Parameter	Estimate	SE
		Mean equation (VAR(0))	
BDI	$\beta_{BDI,0}$	0.0098	0.0082
BY	$\beta_{BY,0}$	-0.0048	0.0033
		Regime dependent variances	
BDI	$\sigma^2_{BDI,I}$	0.0079***	0.0020
	$\sigma^2_{BDI,II}$	0.0325***	0.0114
	$\sigma^2_{BDI,III}$	0.1409***	0.0501
	$\sigma^2_{BDI,IV}$	0.0738***	0.0203
BY	$\sigma^2_{BY,I}$	0.0024***	0.0007
	$\sigma^2_{BY,II}$	0.0172	0.0110
	$\sigma^2_{BY,III}$	0.0063**	0.0027
		Degrees of freedom of marginal distributions	
BDI	ν_{BDI}	5.4388**	2.6940
BY	ν_{BY}	3.1693***	1.0497
		Dependence parameters	
	$\kappa_{\lambda,0}$	-11.5815	3.5114
	$\kappa_{\lambda,OFR}$	3.6999	1.0715
	$\kappa_{\lambda,MSCI}$	-2.4468	0.7150
	θ	0.1158	0.4783
LL		406.1437	

This table presents the maximum-likelihood model estimates specified in Equations (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

Table 3.19: ML-estimates of independent periods and test for equality of parameters

	Period	I: 5/1997-12/2007		II: 1/2008-12/2014		
	Parameter	Estimate	SE	Estimate	SE	T
			Mean equation			
BDI	$\beta_{BDI,0}$	0.0071	0.0110	0.0120	0.0323	0.1441
	$\beta_{BDI1,1}$	-0.3205	0.2335	0.2329	0.4198	1.1519
	$\beta_{BDI1,2}$	0.2974	0.2179	-1.2086***	0.3849	-3.4052^{a}
	$\beta_{BDI1,3}$	-0.2370	0.2123	1.0952***	0.3664	3.1461^{a}
	$\beta_{BDI1,4}$	-0.0738	0.2224	-0.1146	0.4574	-0.0802
	$\beta_{BDI2,1}$	0.2789***	0.0887	-0.0238	0.1363	-1.8613^{b}
	$\beta_{BDI2,2}$	0.0282	0.0971	-0.1157	0.0992	-1.0366
	$\beta_{BDI2,3}$	-0.0101	0.0887	0.0867	0.0960	0.7411
	$\beta_{BDI2,4}$	0.0726	0.0832	-0.2805***	0.0797	-3.0657^{a}
BY	$\beta_{BY,0}$	-0.0027	0.0032	-0.0024	0.0118	0.0237
	$\beta_{BY1,1}$	0.0876	0.0675	0.1540	0.1451	0.4152
	$\beta_{BY1,2}$	0.0707	0.0620	-0.1029	0.1159	-1.3213
	$\beta_{BY1,3}$	-0.0186	0.0766	0.2128	0.1532	1.3505
	$\beta_{BY1,4}$	0.1254**	0.0616	0.0278	0.1532	-0.5913
	$\beta_{BY2,1}$	0.0394	0.0269	0.0097	0.0304	-0.7307
	$\beta_{BY2,2}$	-0.0296	0.0258	-0.0223	0.0380	0.1595
	$\beta_{BY2,3}$	-0.0196	0.0256	0.0599*	0.0362	1.7934^{b}
	$\beta_{BY2,4}$	-0.0081	0.0278	-0.0232	0.0316	-0.3572
			Regime dependent variances			
BDI	σ^2_{BDI}	0.0181*	0.0095	0.0752	0.0527	1.0660
BY	σ^2_{BY}	0.0053	0.0098	0.0054***	0.0012	0.0131
			Degrees of freedom of marginal distributions			
BDI	ν_{BDI}	3.6772*	2.1314	3.2874*	1.7891	-0.1401
BY	ν_{BY}	2.3090***	0.7374	40.2654	223.4621	0.1699
			Dependence parameters			
	$\kappa_{\lambda,0}$	-14.8861*	8.9526	-2.3229	2.7699	1.3406
	$\kappa_{\lambda,OFR}$	4.1012**	1.9543	1.0605	1.0512	-1.3703
	$\kappa_{\lambda,MSCI}$	6.1837	4.0287	-0.6461	1.2359	-1.6207
	θ	0.3323	0.6627	-0.3808	1.5857	-0.4150
LL		317.9753		106.0606		

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) of independent periods and displays the test for equality of parameters. The null hypothesis is equality of corresponding regression parameters for the two independent samples. $T = \frac{\text{Estimate}_{\text{I}} - \text{Estimate}_{\text{II}}}{\sqrt{\text{SE}_{\text{I}}^2 + \text{SE}_{\text{II}}^2}}$ denotes the test statistic which we assume to be asymptotically normally distributed. ^{a} and ^{b} reject the null hypothesis at the 1% and 10% level (two-tailed). *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 3.20: 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	$\beta_{BDI,0}$	0.0148	0.0098	0.0131	0.0097	0.0124	0.0097	0.0131	0.0097
	$\beta_{BDI1,1}$	-0.2083	0.1758	-0.2345	0.1813	-0.2369	0.1805	-0.2359	0.1801
	$\beta_{BDI1,2}$	-0.0335	0.1941	-0.0469	0.1913	-0.0659	0.1914	-0.0707	0.1903
	$\beta_{BDI1,3}$	-0.0100	0.1683	-0.0071	0.1686	-0.0013	0.1685	0.0103	0.1666
	$\beta_{BDI1,4}$	-0.0677	0.1920	-0.0867	0.1939	-0.0834	0.1929	-0.0614	0.1918
	$\beta_{BDI2,1}$	0.0506	0.0700	0.0715	0.0686	0.0744	0.0690	0.0791	0.0686
	$\beta_{BDI2,2}$	-0.0809	0.0723	-0.0632	0.0719	-0.0599	0.0724	-0.0584	0.0721
	$\beta_{BDI2,3}$	-0.0159	0.0637	-0.0073	0.0639	-0.0031	0.0647	-0.0016	0.0644
	$\beta_{BDI2,4}$	-0.1003*	0.0568	-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
	$\beta_{BY1,1}$	0.1701***	0.0566	0.1552***	0.0592	0.1520**	0.0592	0.1498**	0.0598
	$\beta_{BY1,2}$	-0.0432	0.0513	-0.0433	0.0513	-0.0433	0.0517	-0.0524	0.0519
	$\beta_{BY1,3}$	0.0176	0.0602	0.0162	0.0597	0.0191	0.0601	0.0236	0.0601
	$\beta_{BY1,4}$	0.1044*	0.0578	0.1007*	0.0579	0.1021*	0.0578	0.1065*	0.0576
	$\beta_{BY2,1}$	0.0053	0.0206	0.0083	0.0183	0.0094	0.0181	0.0107	0.0182
	$\beta_{BY2,2}$	-0.0393*	0.0206	-0.0367*	0.0217	-0.0349*	0.0210	-0.0350*	0.0204
	$\beta_{BY2,3}$	0.0281	0.0212	0.0292	0.0212	0.0296	0.0212	0.0292	0.0212
	$\beta_{BY2,4}$	-0.0175	0.0184	-0.0160	0.0186	-0.0163	0.0187	-0.0189	0.0186
				Regime dependent variances					
BDI	$\sigma^2_{BDI,I}$	0.0172***	0.0052	0.0167***	0.0050	0.0166***	0.0048	0.0166***	0.0048
	$\sigma^2_{BDI,II}$	0.0904***	0.0232	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
	$\sigma^2_{BY,II}$	0.0082**	0.0039	0.0079**	0.0039	0.0081**	0.0040	0.0080**	0.0039
				Degrees of freedom of marginal distributions					
	ν_{BDI}	4.0584***	1.4404	4.1862**	1.6355	4.2600**	1.6595	4.2354***	1.6329
	ν_{BY}	3.2609***	1.0292	3.3037***	1.0704	3.2604***	1.0770	3.2739***	1.0607
				Dependence parameters					
	$\kappa_{\lambda,0}$	-7.6609*	4.3616	-4.4574	3.2350	-3.3676	2.5144	-3.8986	2.8473
	$\kappa_{\lambda,OFR}$	0.3657	1.1396	0.8702	0.9974	0.6427	0.6585	1.1207	0.8912
	$\kappa_{\lambda,MSCI}$	-2.4792**	1.0549	-0.9252	0.9276	-0.6172	0.7409	-0.5882	0.8020
	θ	0.3482	0.4849	0.1987	0.5304	0.0424	0.6763	0.0715	0.5827
LL		395.7748		394.1147		394.5174		395.1484	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

TABLE 3.21: 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	$\beta_{BDI,0}$	0.0137	0.0097	0.0119	0.0097	0.0123	0.0096	0.0120	0.0096
	$\beta_{BDI1,1}$	-0.1408	0.1859	-0.2170	0.1821	-0.2249	0.1819	-0.2345	0.1793
	$\beta_{BDI1,2}$	0.0424	0.1860	-0.0796	0.1860	-0.0821	0.1883	-0.1051	0.1854
	$\beta_{BDI1,3}$	-0.0673	0.1715	-0.0141	0.1687	-0.0123	0.1649	-0.0044	0.1671
	$\beta_{BDI1,4}$	-0.0820	0.1980	-0.0584	0.1919	-0.0441	0.1886	-0.0380	0.1897
	$\beta_{BDI2,1}$	0.1451**	0.0678	0.0894	0.0680	0.1049	0.0668	0.0963	0.0676
	$\beta_{BDI2,2}$	-0.0524	0.0761	-0.0551	0.0720	-0.0457	0.0711	-0.0454	0.0717
	$\beta_{BDI2,3}$	-0.0002	0.0680	0.0143	0.0652	0.0203	0.0660	0.0118	0.0652
	$\beta_{BDI2,4}$	-0.0645	0.0586	-0.0851	0.0570	-0.0825	0.0568	-0.0843	0.0566
BY	$\beta_{BY,0}$	-0.0040	0.0032	-0.0046	0.0034	-0.0045	0.0034	-0.0053	0.0034
	$\beta_{BY1,1}$	0.1899***	0.0535	0.1520***	0.0588	0.1562***	0.0585	0.1502**	0.0602
	$\beta_{BY1,2}$	-0.0034	0.0502	-0.0338	0.0511	-0.0434	0.0518	-0.0733	0.0518
	$\beta_{BY1,3}$	0.0225	0.0589	0.0276	0.0607	0.0319	0.0600	0.0240	0.0601
	$\beta_{BY1,4}$	0.1050*	0.0568	0.1079*	0.0581	0.1141**	0.0582	0.1153**	0.0579
	$\beta_{BY2,1}$	0.0258	0.0184	0.0139	0.0179	0.0172	0.0181	0.0133	0.0181
	$\beta_{BY2,2}$	-0.0414**	0.0206	-0.0352*	0.0203	-0.0355*	0.0205	-0.0334	0.0204
	$\beta_{BY2,3}$	0.0253	0.0204	0.0304	0.0209	0.0312	0.0208	0.0300	0.0212
	$\beta_{BY2,4}$	-0.0140	0.0174	-0.0157	0.0190	-0.0166	0.0189	-0.0192	0.0187
				Regime dependent variances					
BDI	$\sigma^2_{BDI,I}$	0.0174***	0.0057	0.0166***	0.0049	0.0163***	0.0045	0.0164***	0.0047
	$\sigma^2_{BDI,II}$	0.1177***	0.0337	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
	$\sigma^2_{BY,II}$	0.0074**	0.0033	0.0082**	0.0041	0.0080**	0.0040	0.0082**	0.0040
				Degrees of freedom of marginal distributions					
	ν_{BDI}	3.8811***	1.4124	4.2091***	1.6176	4.2811***	1.6174	4.2556***	1.6379
	ν_{BY}	3.1788***	0.9259	3.2152***	1.0039	3.2516***	1.0303	3.2699***	1.0476
				Dependence parameters					
	$\kappa_{\lambda,0}$	-9.1914	6.6705	-3.4344*	1.9695	-3.9250	2.5832	-4.6768	3.2405
	$\kappa_{\lambda,OFR}$	2.8500*	1.4683	1.0990*	0.6438	1.3046	0.9114	1.6037	1.1358
	$\kappa_{\lambda,MSCI}$	-1.4798	1.3730	-0.6601	0.5127	-0.6378	0.4901	-0.7568	0.6935
	θ	0.2647	0.4669	-0.0835	0.6188	-0.0119	0.5870	0.0363	0.5247
LL		397.3769		396.3303		396.6333		396.9770	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

TABLE 3.22: 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	$\beta_{BDI,0}$	0.0085	0.0096	0.0115	0.0097	0.0140	0.0095	0.0128	0.0097
	$\beta_{BDI1,1}$	-0.2815	0.1785	-0.2294	0.1831	-0.2680	0.1771	-0.2314	0.1820
	$\beta_{BDI1,2}$	-0.0740	0.1837	-0.1060	0.1887	-0.1105	0.1843	-0.0949	0.1879
	$\beta_{BDI1,3}$	-0.1545	0.1709	-0.0079	0.1651	0.0173	0.1647	0.0263	0.1662
	$\beta_{BDI1,4}$	-0.0793	0.1902	-0.0638	0.1919	-0.0322	0.1909	-0.0612	0.1939
	$\beta_{BDI2,1}$	0.0881	0.0675	0.0980	0.0669	0.1059	0.0649	0.0851	0.0691
	$\beta_{BDI2,2}$	-0.0670	0.0716	-0.0450	0.0717	-0.0631	0.0692	-0.0574	0.0725
	$\beta_{BDI2,3}$	0.0120	0.0637	0.0317	0.0661	0.0279	0.0625	0.0041	0.0655
	$\beta_{BDI2,4}$	-0.0807	0.0574	-0.0868	0.0595	-0.0845	0.0583	-0.0889	0.0591
BY	$\beta_{BY,0}$	-0.0050	0.0035	-0.0047	0.0034	-0.0048	0.0034	-0.0050	0.0034
	$\beta_{BY1,1}$	0.1457**	0.0632	0.1549**	0.0627	0.1508**	0.0650	0.1466**	0.0629
	$\beta_{BY1,2}$	-0.0520	0.0512	-0.0812	0.0525	-0.0952	0.0532	-0.0739	0.0524
	$\beta_{BY1,3}$	0.0223	0.0638	0.0352	0.0606	0.0210	0.0635	0.0253	0.0620
	$\beta_{BY1,4}$	0.1072*	0.0580	0.1202**	0.0599	0.1311**	0.0623	0.1118*	0.0592
	$\beta_{BY2,1}$	0.0093	0.0183	0.0150	0.0182	0.0117	0.0197	0.0121	0.0185
	$\beta_{BY2,2}$	-0.0357*	0.0194	-0.0316	0.0198	-0.0342*	0.0204	-0.0327	0.0200
	$\beta_{BY2,3}$	0.0332	0.0232	0.0363*	0.0205	0.0349	0.0243	0.0308	0.0214
	$\beta_{BY2,4}$	-0.0173	0.0189	-0.0251	0.0192	-0.0200	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
	$\sigma^2_{BDI,II}$	0.0888***	0.0291	0.0862***	0.0265	0.0844***	0.0266	0.0860***	0.0246
BY	$\sigma^2_{BY,I}$	0.0027**	0.0012	0.0025***	0.0009	0.0028**	0.0014	0.0025***	0.0010
	$\sigma^2_{BY,II}$	0.0089*	0.0050	0.0083**	0.0041	0.0113*	0.0069	0.0083**	0.0041
		Degrees of freedom of marginal distributions							
	ν_{BDI}	4.3186**	1.9220	4.3886**	1.8289	4.0140**	1.6326	4.2450***	1.6214
	ν_{BY}	3.1195***	1.0175	3.3192***	1.0684	3.0227***	0.9934	3.2874***	1.0908
		Dependence parameters							
	$\kappa_{\lambda,0}$	-4.5448**	1.9130	-4.7858*	2.5338	-16.1937**	6.8477	-3.8283	3.9130
	$\kappa_{\lambda,OFR}$	0.9426**	0.4723	1.4779*	0.7579	4.7857***	1.7621	1.2174	1.1859
	$\kappa_{\lambda,MSCI}$	-1.6159***	0.5540	-1.2592**	0.6349	-3.2838***	1.2399	-0.6526	0.8364
	θ	0.0493	0.5151	-0.0113	0.5224	0.3685	0.4712	-0.0238	0.6752
LL		397.0702		397.0805		398.5649		396.9314	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

Table 3.23: 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	0.0078	0.0099	0.0118	0.0096
	$\beta_{BDI1,1}$	-0.2491	0.1751	-0.2822	0.1740	-0.3957**	0.1698	-0.2406	0.1793
	$\beta_{BDI1,2}$	-0.0896	0.1939	-0.1271	0.1871	-0.1841	0.1841	-0.0999	0.1859
	$\beta_{BDI1,3}$	0.0493	0.1675	0.0489	0.1685	0.0819	0.1721	0.0215	0.1652
	$\beta_{BDI1,4}$	-0.0518	0.1927	-0.0094	0.1897	-0.0222	0.2007	-0.0759	0.1930
	$\beta_{BDI2,1}$	0.0692	0.0704	0.0693	0.0681	0.0831	0.0689	0.0830	0.0676
	$\beta_{BDI2,2}$	-0.0720	0.0718	-0.0906	0.0694	-0.1174*	0.0682	-0.0547	0.0710
	$\beta_{BDI2,3}$	-0.0250	0.0629	-0.0171	0.0626	-0.0240	0.0564	-0.0128	0.0636
	$\beta_{BDI2,4}$	-0.1014*	0.0583	-0.1079*	0.0576	-0.1235**	0.0587	-0.0952*	0.0562
BY	$\beta_{BY,0}$	-0.0050	0.0033	-0.0065*	0.0033	-0.0083**	0.0033	-0.0057*	0.0034
	$\beta_{BY1,1}$	0.1393**	0.0582	0.1417**	0.0573	0.1115**	0.0548	0.1416**	0.0591
	$\beta_{BY1,2}$	-0.0719	0.0516	-0.0833	0.0509	-0.0964	0.0508	-0.0749	0.0513
	$\beta_{BY1,3}$	0.0219	0.0600	0.0233	0.0592	0.0215	0.0599	0.0149	0.0596
	$\beta_{BY1,4}$	0.1164**	0.0583	0.1179**	0.0595	0.1102*	0.0609	0.1026*	0.0584
	$\beta_{BY2,1}$	0.0110	0.0178	0.0109	0.0171	0.0152	0.0175	0.0117	0.0179
	$\beta_{BY2,2}$	-0.0376*	0.0197	-0.0442**	0.0189	-0.0546***	0.0181	-0.0314	0.0197
	$\beta_{BY2,3}$	0.0258	0.0202	0.0277	0.0194	0.0248	0.0178	0.0304	0.0213
	$\beta_{BY2,4}$	-0.0291	0.0179	-0.0231	0.0189	-0.0232	0.0190	-0.0176	0.0187
				Regime dependent variances					
BDI	$\sigma^2_{BDI,I}$	0.0175***	0.0053	0.0174***	0.0050	0.0183***	0.0055	0.0171***	0.0049
	$\sigma^2_{BDI,II}$	0.0858***	0.0240	0.0851***	0.0227	0.0830***	0.0219	0.0900***	0.0227
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*	0.0046	0.0078**	0.0034
				Degrees of freedom of marginal distributions					
	ν_{BDI}	4.1763**	1.6281	4.3334***	1.6589	4.4393**	1.8391	4.0103***	1.2555
	ν_{BY}	3.2073***	1.0531	3.2411***	1.0602	3.1279***	0.9956	3.3808***	1.0439
				Dependence parameters					
	$\kappa_{\lambda,0}$	-3.0364	1.8480	-4.7768*	2.8267	-12.0204***	2.8642	-7.4945	7.7334
	$\kappa_{\lambda,OFR}$	1.0927	0.8410	1.9674	1.1984	4.8451***	1.0784	2.3876	2.2672
	$\kappa_{\lambda,MSCI}$	0.2530	1.0705	1.1399	0.9321	4.5743***	1.0541	-1.1744	1.5577
	θ	-0.1202	0.6578	0.0759	0.5389	0.1968	0.4727	0.1333	0.4882
LL		395.3921		397.9497		399.8700		398.7177	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

TABLE 3.24: 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	0.0104	0.0099	0.0125	0.0095
	$\beta_{BDI1,1}$	-0.0969	0.1781	-0.0862	0.1768	-0.0780	0.1822	-0.0484	0.1769
	$\beta_{BDI1,2}$	0.0744	0.2012	0.0685	0.2030	0.0923	0.1936	0.0669	0.1970
	$\beta_{BDI1,3}$	0.0728	0.1904	0.0956	0.1868	-0.0257	0.1960	-0.0010	0.1924
	$\beta_{BDI1,4}$	-0.2054	0.1717	-0.1821	0.1684	-0.1884	0.1775	-0.1904	0.1748
	$\beta_{BDI2,1}$	0.0927	0.0666	0.0872	0.0659	0.1005	0.0672	0.0816	0.0650
	$\beta_{BDI2,2}$	-0.0569	0.0723	-0.0554	0.0718	-0.0740	0.0740	-0.0575	0.0668
	$\beta_{BDI2,3}$	-0.0012	0.0633	0.0005	0.0634	0.0557	0.0631	0.0355	0.0601
	$\beta_{BDI2,4}$	-0.0987	0.0612	-0.0939	0.0614	-0.1439**	0.0626	-0.0699	0.0655
BY	$\beta_{SY,0}$	-0.0002	0.0033	0.0009	0.0033	-0.0003	0.0032	0.0018	0.0031
	$\beta_{SY1,1}$	0.0307	0.0595	0.0403	0.0600	0.0420	0.0569	0.0319	0.0575
	$\beta_{SY1,2}$	0.0610	0.0596	0.0677	0.0617	0.0738	0.0584	0.0714	0.0598
	$\beta_{SY1,3}$	0.0730	0.0596	0.0924	0.0595	0.0737	0.0549	0.1172**	0.0576
	$\beta_{SY1,4}$	0.0532	0.0571	0.0647	0.0563	0.0932	0.0600	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	-0.0299*	0.0163	-0.0138	0.0165
	$\beta_{SY2,3}$	0.0079	0.0174	0.0072	0.0173	0.0146	0.0161	-0.0013	0.0154
	$\beta_{SY2,4}$	-0.0112	0.0189	-0.0100	0.0187	-0.0320	0.0171	-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	0.0942***	0.0330	0.0932***	0.0285
BY	$\sigma^2_{SY,I}$	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	0.0089**	0.0040	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}	4.2687**	1.9802	4.3706**	1.9931	4.2012**	2.0567	4.1554**	1.7948
	ν_{BY}	4.3500***	1.6285	4.4382***	1.7113	4.2754***	1.5915	4.3082***	1.5977
Dependence parameters									
	$\kappa_{\lambda,0}$	-2.3007**	1.0786	-3.5907*	1.9935	-2.2879*	1.2113	-4.3187	3.2101
	$\kappa_{\lambda,OFR}$			1.1777	0.7516			1.4595	1.1317
	$\kappa_{\lambda,MSCI}$					-1.0284	0.6429	-1.1154	0.8640
	θ	0.2661	0.7346	0.5081	0.5444	-0.1634	0.7606	0.4049	0.5585
LL		400.8678		402.4842		404.8297		406.9892	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors.

Table 3.25: ML-estimates for alternative conditioning variables

Conditioning factors		$\Delta^3_{OFR,t-3}$ & $\Delta^3_{EX,t-2}$		$\Delta^3_{\eta OFR,t-3}$ & $\Delta^3_{MSCI,t-3}$	
	Parameter	Estimate	SE	Estimate	SE
		Mean equation (VAR(4))			
BDI	$\beta_{BDI,0}$	0.0086	0.0097	0.0206*	0.0114
	$\beta_{BDI1,1}$	-0.2745	0.1787	-0.2813	0.2132
	$\beta_{BDI1,2}$	-0.1302	0.1838	-0.1901	0.1999
	$\beta_{BDI1,3}$	-0.0029	0.1703	0.2524	0.1756
	$\beta_{BDI1,4}$	-0.1150	0.1920	-0.1502	0.2412
	$\beta_{BDI2,1}$	0.0997	0.0687	0.1365*	0.0703
	$\beta_{BDI2,2}$	-0.0785	0.0732	-0.0733	0.0793
	$\beta_{BDI2,3}$	0.0231	0.0656	0.0383	0.0685
	$\beta_{BDI2,4}$	-0.0967	0.0606	-0.1123*	0.0619
BY	$\beta_{BY,0}$	-0.0069**	0.0033	-0.0059	0.0041
	$\beta_{BY1,1}$	0.1398**	0.0594	0.2172***	0.0696
	$\beta_{BY1,2}$	-0.1040**	0.0506	-0.1869***	0.0646
	$\beta_{BY1,3}$	0.0152	0.0595	0.0854	0.0728
	$\beta_{BY1,4}$	0.1063*	0.0567	0.0981	0.0687
	$\beta_{BY2,1}$	0.0143	0.0183	0.0084	0.0209
	$\beta_{BY2,2}$	-0.0396**	0.0191	-0.0268	0.0218
	$\beta_{BY2,3}$	0.0363*	0.0192	0.0376	0.0236
	$\beta_{BY2,4}$	-0.0259	0.0180	-0.0198	0.0224
		Regime dependent variances			
BDI	$\sigma^2_{BDI,I}$	0.0173***	0.0060	0.0196**	0.0081
	$\sigma^2_{BDI,II}$	0.0936***	0.0303	0.0847***	0.0326
BY	$\sigma^2_{BY,I}$	0.0025***	0.0010	0.0027**	0.0012
	$\sigma^2_{BY,II}$	0.0086**	0.0041	0.0099*	0.0055
		Degrees of freedom of marginal distributions			
	ν_{BDI}	4.1605**	1.9277	3.7948**	1.6939
	ν_{BY}	3.2001***	0.9980	3.2647***	1.2207
		Dependence parameters			
	$\kappa_{\lambda,0}$	-7.6296***	1.9114	-14.5813**	6.0838
	$\kappa_{\lambda,OFR}$	2.5850***	0.5497	4.3905***	1.5985
	$\kappa_{\lambda,MSCI}$	-2.9592***	0.6200	-2.9237***	1.0419
	θ	0.1465	0.4969	0.4061	0.5284
LL		401.5471		325.2043	

This table presents the maximum-likelihood model estimates specified in Equations (3.1), (3.3), (3.6), and (3.7) over the sample period from 05/1997 to 12/2014. LL is the log-likelihood. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Figures in [ ] are standard errors. [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.

Breusch, T. S. (1978), 'Testing for autocorrelation in dynamic linear models', *Australian Economic Papers* 17(31), 334–355.

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.

Engle, R. F. (1982), 'Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation', *Econometrica: Journal of the Econometric Society* 50(4), 987–1007.

Godfrey, L. G. (1978), 'Testing against general autoregressive and moving average error models when the regressors include lagged dependent variables', *Econometrica: Journal of the Econometric Society* 46(6), 1293–1301.

Goff, S., Odell, M., Ross, A., and Stothard, M. (2014), 'Germany's banks race to get loan books shipshape', Financial Times - Jan 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', Financial Times - Dec 12, 2011.

Chapter 4

Default risk of mortgage credits for lenders

Abstract

This paper applies a conditional copula model to investigate the dependence structure of house prices and default rates by analyzing their extreme dependence in order to quantify the default risk of mortgage credits for lenders. Therefore, we use housing supply factors and economic factors as well as interest rates and mortgage loan-to-price ratios as explaining variables. Examining quarterly data from 1985 to 2015 we find that new housing units starts, the existing mortgage loan-to-price ratio as well as the home mortgage loan-to-price ratio can be used to quantify the default risk of mortgage credits for lenders.

4.1 Introduction

Since the early 1990s US house prices experienced a steep rise accompanied by an exceptional growth of subprime lending in the mortgage market which allowed borrowers with impaired credit histories and low incomes to buy properties (see Ackermann, 2008). Borrowing at a spread compared to prime borrowers and even accepting a higher mortgage than the property is worth, subprime borrowers hoped that house prices would continue to rise and that they are able to enter the prime mortgage market and refinance at prime rates (see Daglish, 2009). However, after the increase of interest rates by the Fed starting in 2004, the downward spiral of house prices began and caused the burst of the housing bubble in 2006. Accordingly, borrowers could not refinance loans and had incentives to default on their mortgages (see Mayer et al., 2009). Credit defaults and foreclosures substantially increased, resulting in an oversupply of houses on the secondary market. This continued the drop in house prices as well as the raise in default rates which also eminently affected mortgage lenders. Due to the absence of mortgage payments, they faced massive liquidity problems and were unable to finance new loans. Numerous foreclosures raised their costs for fees and taxes and they suffered losses as the home equity drastically declined. Consequently, many mortgage lenders, most of them subprime mortgage lenders, declared bankruptcy, announced significant losses or were put up for sale (see Bianco et al., 2008).

In this paper, we analyze the dramatic downswing of house prices and the concurrent rise in mortgage credit defaults with the aim to identify potential driving variables of this effect. For that reason, we apply a conditional copula approach following Patton (2006) and analyze the conditional dependence structure of the FHFA US house price index and total delinquent US residential mortgage loans. In particular, we focus on the quantification of the conditional tail dependence which we interpret as default crisis indicator.

Therefore, the paper uses different types of factors as conditioning variables. First, it examines housing supply factors, namely the supply of existing and new homes on market as well as new private housing units started. Second, it analyzes economic factors, i.e., the consumer price index for housing, the gross domestic product and the S&P 500 US stock market index. Third, it investigates the 1-year adjustable-rate mortgage, the 30-year fixed-rate mortgage and the Treasury bill rate as interest rate factors, and fourth, it scrutinizes mortgage loan-to-price ratios for existing mortgage loans, home mortgage loans and new mortgage loans.

Analyzing quarterly data from 1985 to 2015, we provide statistical evidence of a positive relationship of the volume of new private housing units started and the default crisis indicator. Moreover, we find that existing as well as home mortgage loan-to-price ratios positively influence the extreme asymmetric dependence of house prices and mortgage credit defaults. However, none of the other factors consistently influences the risk indicator.

The rest of the paper is organized as follows: The next section gives an overview of the relevant literature. Section 4.3 provides the data and presents the conditional copula model in order to characterize the dependence structure of house prices and delinquency rates. Section 4.4 discusses the empirical results and conducts a series of robustness tests. The paper concludes with a discussion and implications in Section 4.5.

4.2 Literature review

The US housing market represents an important part of the US financial system. With a volume of over US$10 trillion mortgage debt outstanding for one- to four-family residences in the first quarter of 2016[1], it significantly influences the US economy. Therefore, it is of major importance to understand the dependence structure of housing prices and delinquency rates, especially, in view of the burst of the housing bubble in 2006 and the subsequent subprime crisis. For instance, Sanders (2008) finds a strong, inverse relationship of house prices and delinquency rates in the 2005 to 2008 period while analyzing data from Arizona, California and Nevada. Likewise, Kau et al. (2011) address that the increase in defaults is accompanied with the substantial collapse in house prices.

We use the copula framework in order to allow for a flexible specification of the dependence structure of house prices and default rates including a nonlinear relationship. There is only little existing literature on the application of copulas for the mortgage market. Zimmer (2012) analyzes quarterly changes in housing prices in four US states that were particularly hit by the housing crisis. By exploring various copula specifications, Zimmer scrutinizes the use of the Gaussian copula model as in Li (2000) to quantify the risk of structured mortgage-based securities, i.e. collateralized debt obligations. Extreme events appear to be unrelated, and consequently, the Gaussian copula might be inappropriate. Ho et al. (2015) replicate and extend the study by Zimmer using an updated dataset while applying a nonparametric copula estimator. The authors find similar results. Zimmer (2015) investigates the co-movement of housing prices for four US census divisions using vine copulas. The author shows that multivariate vine copulas assembled from non Gaussian distributions more realistically capture co-movements in housing prices. Gupta and Majumdar (2015) examine different copula models and their ability in forecasting real US housing prices and the authors compare the results to linear benchmarks. They provide evidence of an outperformance of each copula model, especially the t-copula.

In our study, we apply a conditional copula model that caters for nonlinearity, and particularly asymmetric tail dependence. We investigate different determinants that possibly trigger the co-movement of house prices and delinquency rates. We concentrate on four

[1] Source: https://www.federalreserve.gov/econresdata/releases/mortoutstand/current.htm

areas of factors: housing supply factors, economic factors, interest rates as well as mortgage credits. First, with respect to housing supply, Glaeser et al. (2008) point out that the oversupply of housing during a boom is one of the primary ways in which housing bubbles may create substantial welfare losses. Conefrey and Whelan (2013) analyze the influence of months supply of new homes and months supply of existing homes to real house prices. The authors exhibit that the impact of months supply of new homes on house prices is larger than for months supply of existing homes.

Second, as for economic factors, Goodhart and Hofmann (2008) detect that shocks to GDP and the CPI have significant effects on house prices. Beltratti and Morana (2010) investigate general macroeconomic conditions and housing markets in G7 using a factor vector autoregressive model. Analyzing factors like the growth rate of real GDP, interest rates, the nominal money growth rate, real stock price and real oil price the authors display a strong impact of macroeconomic shocks in determining house price fluctuations. Adams and Füss (2010) also emphasize the significant impact of macroeconomic factors on house prices. For this purpose, they generate the variable economic activity by using the matrix consisting of real money supply, real consumption, real industrial production, real GDP as well as employment and by calculating its first principal component.

Third, in terms of interest rates, Taylor (2007) shows that low interest rates in 2003 and 2004 may be responsible for an increase in house prices accompanied by an excessive demand for mortgages due to cheaper mortgage credits. Jarocinski and Smets (2008) argue that monetary policy significantly influences residential investments. Danis and Pennington-Cross (2008) find that changes in interest rates affects prepayment, default, and delinquency. Likewise, Daglish (2009) exhibits that default probabilities are highly sensitive to changes in interest rates and house prices. Especially, subprime borrowers' credit quality is highly sensitive to interest rate fluctuations. Adams and Füss (2010) figure out a negative relationship of long-term interest rates and house prices since other fixed-income assets become more attractive relative to residential property which consequently reduces the demand of houses. Agnello and Schuknecht (2011) point out a significant influence of short-term interest rates on house prices not only in phases of booms but also in phases of busts. In contrast, Coleman et al. (2008) ascertain that mortgage interest rates were not found to have a significant relationship with house prices when other factors were taken into account. Equally, Kuttner (2012) only detects a small impact of interest rates on house prices and that the effect is too small to explain the US real estate boom. Moreover, the author suggests that the interest rate sensitivity of house prices depends on the present conditions. In an environment of strongly changing house prices, interest rate adjustments may have a larger effect than in an environment of stable house prices.

Fourth, mortgage credits do influence delinquency rates and house prices. With respect to default rates, Mian and Sufi (2009) find evidence of an increase in defaults due to an increase in credits, particularly in regions of high subprime share. Addressing the deterioration of credit underwriting, Mayer et al. (2009) argue that borrowers with the lowest credit scores and highest loan-to-value ratios were matched with the most complicated products resulting in highest default rates. Similarly, Dell'Ariccia et al. (2012) suggest that the relaxation of lending constraints is connected to an increase in the default of mortgage credits. Gimeno and Martinez-Carrascal (2010) analyze the relationship of house prices and house purchase loans in Spain. The authors confirm the existence of interdependence between both factors. Especially, they provide evidence that over-indebtedness results in a house price overvaluation, and therefore, induces the decrease of house prices. Agnello and Schuknecht (2011) show that the growth rate of real credit to the private sector strongly influences the probability of house price busts. Demyanyk and Van Hemert (2011) show the increased risk of defaults of borrowers with high loan-to-value ratio compared to borrowers whose loan-to-value ratio is low. In this context, the authors blame the deteriorated quality of loans and the relaxation of mortgage lending standards. In a recent study Favara and Imbs (2015) illustrate that exogenous expansion in mortgage credit has significant effects on house prices. Notably, they point out increasing volume and number of loans, and increasing loan to income ratios result in a rise of house prices.

Taken together, this paper contributes to the literature of housing economics. Therefore, we apply a conditional copula approach to empirically examine the time-varying extreme asymmetric dependence of house prices and delinquency rates. A main contribution of this study is the identification of potential drivers of default risk of mortgage credits for lenders when analyzing the co-movement of these two aforementioned factors using macroeconomic as well as other housing related variables. In particular, these variables are the supply of existing and new homes on market, new private housing units started, the consumer price index for housing, the gross domestic product, the S&P 500 US stock market index, the 1-year adjustable-rate mortgage, the 30-year fixed-rate mortgage, the 3-month Treasury bill rate, existing, new as well as all home mortgages.

4.3 Modeling

This section describes the data set as well as its properties in order to specify the time series model. It then presents the conditional dependence model for the subsequent empirical analysis.

4.3.1 Data description and properties

In this paper, we investigate the extreme asymmetric dependence of house prices and delinquency rates in order to quantify the possible crisis risk of strongly decreasing house prices accompanied by strongly increasing delinquency rates. Therefore, we analyze quarterly data over the sample period from the first quarter of 1985 to the second quarter of

2015, altogether 122 periods. Representing house prices, we employ the FHFA US house price index (HPI).[2] HPI is a broad measure of the movement of single-family house prices. It is a weighted, repeat-sales index which measures average price changes in repeat-sales or refinancing on the same properties in 363 US metropolises. With respect to delinquency rates, we use total delinquent MBA residential mortgage loans that include all types of loans (DLQ) serviced by mortgage companies, commercial banks, and others.[3] More precisely, we apply log-differences of HPI (LHPI) as well as the level time series DLQ in order to investigate the dependence structure of both factors. Attention should be paid to the fact that the two variables might originate from different populations. However, they both refer to all US residential transactions such that we recommend their application. Figure 4.1 shows the development of both level data series over time. We observe a steady

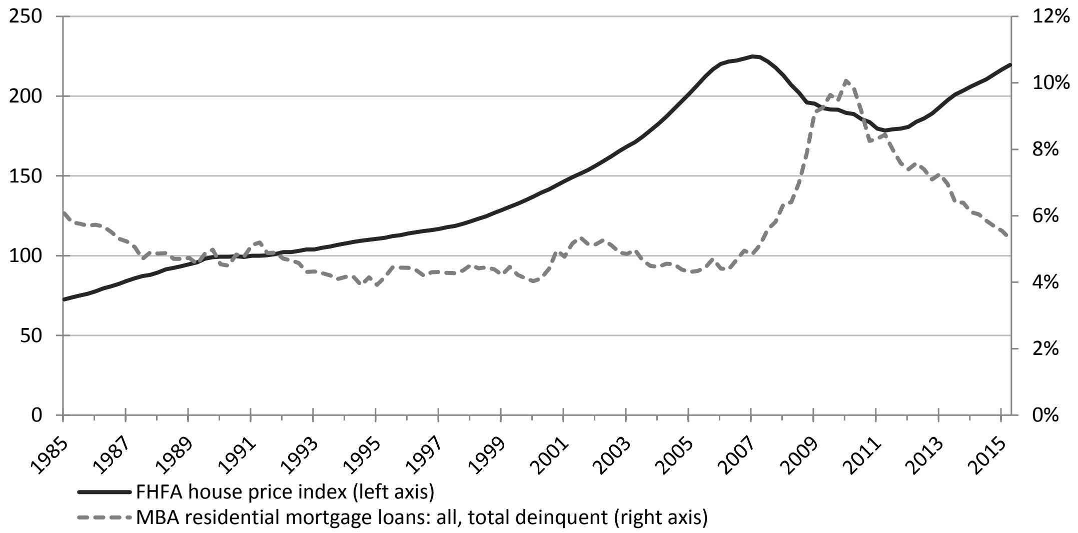


FIGURE 4.1: Development of US house price index and delinquent US residential mortgage loans

increase of house prices from 1985 to 2006, followed by a drop until 2012 and a subsequent return towards its peak. The delinquency rate ranged between 4% and 6% from 1985 to 2007 and then almost doubled within two years. Afterwards, DLQ slowly returned back to its initial range. In particular, the plot reveals the opposing movement of both time series starting in late 2006.

In order to examine a possible crisis risk of dropping house prices accompanied by increasing delinquency rates we investigate different conditioning factors that possibly influence the opposite movement of both variables. Regarding the housing supply, we investigate log-differences of the supply of existing homes on market (ESUP), the supply of new homes on market (NSUP) and the amount of new private housing units started (NHUS). With

[2] In the robustness analysis we also investigate the S&P Case-Shiller home price index (CS).

[3] Next to prime and subprime loans, DLQ also includes loans that are insured by the Federal Housing Administration and loans that are guaranteed by the Veterans Administration. See: https://www.mba.org/news-research-and-resources/research-and-economics/single-family-research/national-delinquency-survey

respect to economic factors, our study examines log-differences of the consumer price index for housing (CPI), the gross domestic product (GDP) as well as the S&P 500 US stock market index (S&P). We analyze first differences of three different types of interest rates: the 30-year fixed-rate mortgage (FRM), the 1-year adjustable-rate mortgage (ARM) which is particularly preferred by subprime mortgage borrowers due to low initial mortgage rates (see e.g. Posey and Yavas (2001), Johnson and Li (2014)), and the 3-month Treasury bill rate (TB3). In addition, we examine first differences of different mortgage loan-to-price ratios as proxy for mortgage credits. These are the loan-to-price ratios for existing home mortgages (EMOR), for home mortgages (HMOR) and for new home mortgages (NMOR). Table 4.1 gives an overview of all data. In particular, all input series of the conditioning

Table 4.1: Glossary and definitions of variables

Symbol	Variable	Source	Input time series
	Panel A: Dependent variables		
HPI	House price index	FHFA	Log-difference
DLQ	Residential mortgage loan rates: all, total delinquent	MBA	Level
	Panel B: Conditioning variables z		
ESUP	Volume of supply of existing homes on market	NAR	Log-difference
NSUP	Volume of supply of new homes on market	U.S. Census Bureau	Log-difference
NHUS	Volume of new private housing units started	U.S. Census Bureau	Log-difference
CPI	Consumer price index for housing	BLS	Log-difference
GDP	Gross domestic product	BEA	Log-difference
S&P	S&P 500 US stock market index	NYSE	Log-difference
ARM	1-year adjustable-rate mortgage	Freddie Mac	First difference
FRM	30-year fixed-rate mortgage	Freddie Mac	First difference
TB3	3-month Treasury bill rate	Federal Reserve	First difference
EMOR	Existing home mortgage loan-to-price ratio	FHFB	First difference
HMOR	All home mortgage loan-to-price ratio	FHFB	First difference
NMOR	New home mortgage loan-to-price ratio	FHFB	First difference

This table presents the dependent variables for the main analysis as well as the conditioning variables. All data can be obtained by Thomson Reuters Datastream.

variables $z \in \mathcal{Z}$ are standardized and lagged by 2 periods in order to take time until consideration into account.

4.3.2 Mean and variance dynamics

The mean dynamics of HPI and DLQ are modeled using a VAR(1) process as indicated by BIC[4], i.e.

$$\begin{bmatrix} LHPI_t \\ DLQ_t \end{bmatrix} = \begin{bmatrix} \beta_{HPI,0} \\ \beta_{DLQ,0} \end{bmatrix} + B_1 \begin{bmatrix} LHPI_{t-1} \\ DLQ_{t-1} \end{bmatrix} + \begin{bmatrix} \sigma_{HPI,t}\, \varepsilon_{HPI,t} \\ \sigma_{DLQ,t}\, \varepsilon_{DLQ,t} \end{bmatrix}, t = t_0, ..., T, \tag{4.3.1}$$

where $\beta_{HPI,0}$ and $\beta_{DLQ,0}$ denote the constants, the coefficient matrix B_1 is specified as

$$B_1 = \begin{bmatrix} \beta_{HPI,1} & \beta_{HPI,2} \\ \beta_{DLQ,1} & \beta_{DLQ,2} \end{bmatrix}, \tag{4.3.2}$$

$\sigma_{HPI,t}$ and $\sigma_{DLQ,t}$ are the corresponding time-dependent standard deviations , $\varepsilon_{HPI,t}$ and $\varepsilon_{DLQ,t}$ describe the error time series with zero mean, unit variance and conditional joint distribution $H(\cdot, \cdot|z)$, $z \in \mathcal{Z}$. The error term series is not identically distributed, but given z, $[\varepsilon_{HPI,t}, \varepsilon_{DLQ,t}]'$ form an independent time series.

In order to control for heteroscedasticity in the variance dynamics, this paper employs the structural break point analysis by Andreou and Ghysels (2002). In particular, it investigates the modulus of the residual time series of HPI and DLQ of the VAR(1) model using a minimal period length of 20 quarters. The obtained BIC-optimal change points are given in Table 4.2. We obtain two change points in 1993:3 and 2007:2 for HPI as well as one change point in 2008:1 for DLQ. Accordingly, the standard deviations of our time series model $\sigma_{HPI,t}$ and $\sigma_{DLQ,t}$ are regime dependent and given DLQ

$$\sigma_{HPI,t} = \begin{cases} \sigma_{HPI,1}\,, & 2 \leq t < \tau_1\,, \\ \sigma_{HPI,2}\,, & \tau_1 \leq t < \tau_2\,, \\ \sigma_{HPI,3}\,, & \tau_2 \leq t \leq 122 \end{cases} \quad \text{and} \quad \sigma_{DLQ,t} = \begin{cases} \sigma_{DLQ,1}\,, & 2 \leq t < \tau_3\,, \\ \sigma_{DLQ,2}\,, & \tau_3 \leq t \leq 122\,, \end{cases} \tag{4.3.3}$$

where $\tau_1 = 35$ $(1993:3)$, $\tau_2 = 90$ $(2007:2)$ and $\tau_3 = 93$ $(2008:1)$.

In order to identify the marginal distributions of HPI and DLQ, we have a look at the skewness and the kurtosis of the standardized residuals.[5] The skewness for both time series is close to 0 with -0.34 for HPI and 0.35 for DLQ. Moreover, the standardized residuals of HPI and DLQ have a kurtosis of round about 3. Therefore, we apply the normal distribution for both margins. Figure 4.2 shows the empirical and theoretical distributions of standardized residuals for HPI (a) and DLQ (b), respectively. Both plots shows minor

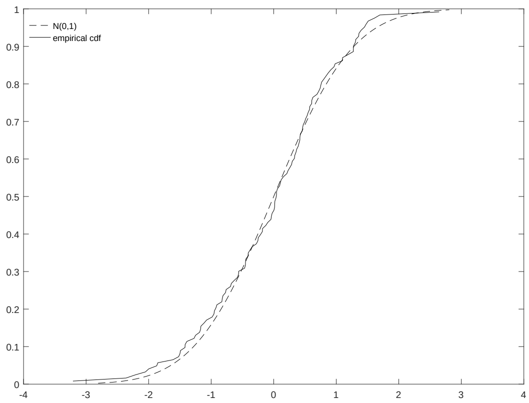
[4] We do not apply the AIC preferred VAR(6) model as it increases the number of coefficients to 24 which is difficult to estimate for an analysis with 122 observations.

[5] The standardized residuals are the least squares error terms of the VAR(1) model with time-varying volatilities.

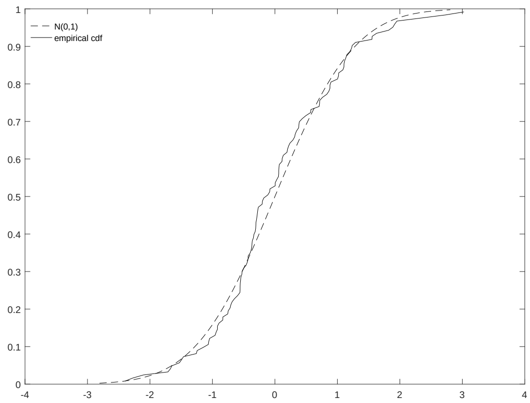
TABLE 4.2: Change point analysis for VAR(1)-residuals of HPI and DLQ

Panel A: HPI					
# Change Points	0	1	2*	3	4
BIC	-679.2666	-688.3649	-695.2530	-693.7089	-689.3810
Change Point 1	-	2007:2	1993:3	1993:3	1993:3
Change Point 2	-	-	2007:2	2003:1	2000:3
Change Point 3	-	-	-	2007:2	2005:3
Change Point 4	-	-	-	-	2010:3
Panel B: DLQ					
# Change Points	0	1*	2	3	4
BIC	-779.3380	-782.8334	-780.9573	-779.0412	-777.6401
Change Point 1	-	2008:1	1990:1	1995:2	1990:1
Change Point 2	-	-	2008:1	2000:3	1995:2
Change Point 3	-	-	-	2008:1	2000:3
Change Point 4	-	-	-	-	2008:1

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 HPI in Panel A, and DLQ in Panel B from the first quarter of 1985 to the second quarter of 2015. The minimal period length is set to 20 quarters. The BIC-optimal specification is indicated by *.



(a) Empirical vs. theoretical distribution: HPI



(b) Empirical vs. theoretical distribution: DLQ

FIGURE 4.2: Marginal distributions of standardized residuals

deviations of the empirical distribution compared to the standard normal distribution. Nevertheless, applying Kolmogorov-Smirnov test as well as Anderson-Darling test provide evidence that the null hypothesis of standard normal margins cannot be rejected at any reasonable significance level (see Table 4.3).[6]

[6] In the robustness analysis, we also apply t-distributed margins whose tails are heavier compared to the normal distribution.

TABLE 4.3: Distribution tests of standardized residuals

	HPI		DLQ	
	KS test	AD test	KS test	AD test
5%-level test statistic	0.0481	0.4313	0.0799	0.6996
5%-level critical value	0.1215	2.4938	0.1215	2.4938
p-value	0.9272	0.8169	0.3970	0.5589

This table presents the test statistics of Kolmogorov-Smirnov test as well as Anderson-Darling test. The null hypothesis is that the data is standard normal distributed.

4.3.3 Conditional copula framework

Our objective is to investigate the relationship of house prices and delinquency rates. In order to specify the dependence structure of both risk factors, we use a copula model following Joe (1997) and Nelsen (2006). In particular, we follow Patton (2006) and extend the concept of copulas to the context of conditional distribution functions. Our focus is the application of Sklar's theorem (1959), as it allows a separate treatment of the conditional marginal distributions and the dependence structure. It is given by

$$H(x, y \mid z) = C(F(x \mid z), G(y \mid z) \mid z). \tag{4.3.4}$$

where F and G denote the conditional univariate distributions of the random variables X and Y, respectively, given $z \in \mathcal{Z}$. Here, $\mathcal{Z}$ describes the domain of the conditioning random variable Z. C is a conditional copula which is a conditional distribution function on $[0,1]^2 \times \mathcal{Z}$ with uniform margins. As a consequence, we now can use any two conditional univariate margins F and G and any conditional copula C to specify the conditional joint distribution H of our two risk factors.

The dependence structure of house prices and delinquency rates is specified by the conditional mirrored transformed Frank copula $C_{mtF}(\cdot,\cdot|z)$ which is due to Junker (2003). For $\theta(z) \in \mathbb{R} \setminus \{0\}$ it is defined as

$$\begin{aligned} C_{mtF}\left(u, v \mid z\right) = v + \frac{1}{\theta(z)} \ln \Bigg[1 + (e^{-\theta(z)} - 1) \exp \Bigg[- \Bigg[\left(- \ln \left(\frac{e^{-(1-u)\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \\ + \left(- \ln \left(\frac{e^{-v\theta(z)} - 1}{e^{-\theta(z)} - 1} \right) \right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \Bigg]^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \Bigg] \Bigg]. \end{aligned} \tag{4.3.5}$$

and for $\theta(z) = 0$ we obtain

$$C_{mtF}(u, v \,|\, z) = v - \exp\left(- \left((-\ln(1-u))^{\frac{\ln(2)}{\ln(2-\lambda(z))}} + (-\ln(v))^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \right)^{\frac{\ln(2-\lambda(z))}{\ln(2)}} \right). \tag{4.3.6}$$

The corresponding density $c_{mtF}(\cdot, \cdot \,|\, z)$ is given by

$$c_{mtF}(u, v \,|\, z) = -\frac{\varphi''_{tF}(C_{tF}(1-u, v \,|\, z) \,|\, z)\varphi'_{tF}(1-u \,|\, z)\varphi'_{tF}(v \,|\, z)}{\left(\varphi'_{tF}(C_{tF}(1-u, v \,|\, z) \,|\, z)\right)^3}, \tag{4.3.7}$$

where $C_{tF}(\cdot, \cdot \,|\, z)$ denotes the transformed Frank copula, and $\varphi'_{tF}(\cdot, \cdot \,|\, z)$ as well as $\varphi''_{tF}(\cdot, \cdot \,|\, z)$ are the derivatives of the copula generator $\varphi_{tF}(\cdot, \cdot \,|\, z)$.[7] The copula C_{mtF} combines the extreme asymmetric dependence with parameter $\lambda(z)$ and the broad dependence with parameter $\theta(z)$. The conditional upper left tail dependence $\lambda(z)$ will be quantified through the logistic function Patton (2006), such that

$$\lambda(z) = \frac{1}{1 + \exp(-(\lambda_{0,z} + \lambda_{1,z} z))}, \tag{4.3.8}$$

where $\lambda_{0,z}$ is the constant, and $\lambda_{1,z}$ denote the parameters of the conditioning factors $z \in \mathcal{Z}$ given in Table 4.1. In particular, $\lambda \in (0, 1)$ describes the crisis risk where the sensitivity to a crisis is highest for λ tending to 1. Moreover, we specify the broad dependence by

$$\theta(z) = \theta_{0,z} + \theta_{1,z} z, \tag{4.3.9}$$

where $\theta_{0,z}$ and $\theta_{1,z}$ are the corresponding constant and coefficient of the conditioning variables $z \in \mathcal{Z}$, respectively. For the main analysis, we set $\theta(z) = \theta_{0,z}$ constant and investigate the conditional case in the subsequent robustness analysis in Section 4.4.2.2.

Taken as a whole, our time series model is specified by a VAR(1) model in Equation (4.3.1) with time-varying volatilities in Equation (4.3.3) and normal distributed innovations $\varepsilon_{HPI,t}$ and $\varepsilon_{DLQ,t}$. The dependence structure is specified by the conditional mirrored transformed Frank copula $C_{mtF}(\cdot, \cdot|z)$ in Equation (4.3.5). The corresponding conditional joint distribution H is given by

$$H(x, y \,|\, z) = C_{mtF}(\mathcal{N}(x \,|\, z), \mathcal{N}(y \,|\, z) \,|\, z). \tag{4.3.10}$$

[7] The transformed Frank copula, its generator and the corresponding derivatives are specified in Appendix 4.A.

4.4 Empirical results

In the following, we present the one-step estimation results for our conditioning variables in Table 4.1 using the maximum-likelihood approach. Subsequently, we check for robustness.

4.4.1 Estimation results

We now quantify the crisis risk in the mortgage market for the unconditional setup as well as for conditioning factors that possibly influence the contrary co-movement of HPI and DLQ introduced in Section 4.3.1. The maximum-likelihood estimates are presented in Table 4.4. For the unconditional case in Panel A, $\lambda_0 = -2.1378$ and is significant at

TABLE 4.4: Estimation results

Factor	**ML-Estimates**						
z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\theta_{0,z}$	SE	LL
Panel A: Unconditional model							
none	-2.1378*	1.2679	-	-	-0.8700	1.1530	1061.5536
Panel B: Housing supply							
ESUP	-1.8670*	1.0875	-0.4509	0.6420	-1.0586	1.1996	1061.8806
NSUP	-7.2171	18.8941	2.8366	10.4499	-0.0817	0.6962	1062.6552
NHUS	-10.4701	6.5708	6.5032**	3.1180	-0.2196	0.5748	1067.8875
Panel C: Economic factors							
CPI	-1.8717*	1.0994	-0.2543	0.3678	-1.1205	1.2456	1061.9667
GDP	-2.1381*	1.2691	-0.0147	0.8151	-0.8733	1.1568	1061.5541
S&P	-1.9572*	1.0594	0.7968	0.7943	-1.3754	1.1261	1062.5616
Panel D: Interest rates							
ARM	-1.8245*	1.0080	-0.2757	0.6438	-1.2123	1.2019	1061.7807
FRM	-16.9480	68.2051	-8.1432	31.6884	-0.0765	0.5578	1062.7156
TB3	-2.1712	1.3711	0.2572	0.9450	-0.8689	1.1580	1061.6363
Panel E: Mortgage credits							
EMOR	-1.4020*	0.7427	0.6486*	0.3340	-2.1260*	1.2855	1063.5884
HMOR	-1.3593*	0.7214	0.5650*	0.3147	-2.1318	1.1342	1063.4276
NMOR	-1.8573*	1.0096	0.6422	0.5520	-1.2002	1.1361	1062.2640

This table reports the maximum-likelihood estimates for Equation (4.3.8) from the first quarter of 1985 to the second quarter of 2015 for HPI and DLQ. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 4.12, Table 4.14 and Table 4.15.

the 10% level. Thus, we get a value for the constant tail dependence λ of 0.1055 using Equation (4.3.8) which indicates the existence of extreme asymmetric dependence, such that an ongoing analysis of the influencing factors to crisis risk is reasonable. Panel B provides the results for housing supply. We find empirical evidence of a positive influence of NHUS to crisis risk at the 5% significance level. As a consequence, the rise in new

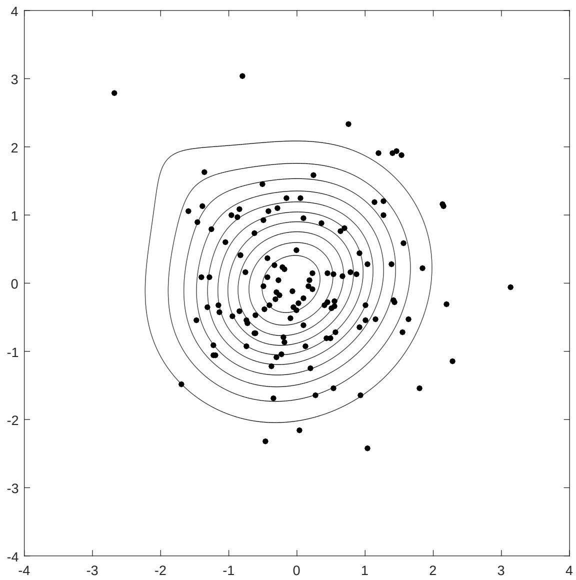


FIGURE 4.3: Contour and scatter plot with standard normal margins

housing units starts significantly increases the risk of a crisis. However, ESUP and NSUP do not significantly influence the co-movement of HPI and DLQ which is in contrast to Conefrey and Whelan (2013). By contrast to the literature, none of the economic factors in Panel C provides statistical significance to have an impact on the extreme asymmetric dependence of HPI and DLQ. Likewise, the estimates for interest rates in Panel D are not statistically significant at a reasonable significance level for neither of the three rates. In terms of mortgage loan-to-price ratios in Panel E, we find significance for EMOR as well as HMOR, both at the 10% significance level. In particular, the $\lambda_{1,\cdot}$-coefficients for EMOR and HMOR are positive with EMOR having a slightly bigger impact because of its higher value compared to HMOR. Thus, an increase in the loan-to-price ratios rises the conditional asymmetric dependence of HPI and DLQ. Moreover, we cannot observe a significant relation for the loan-to-price ratio of new home mortgages and the conditional crisis risk.

Taken together, NHUS at the 5% significance level as well as EMOR and HMOR at the 10% level are able to empirically influence the extreme asymmetric dependence of HPI and DLQ. These factors also have the highest log-likelihood, with NHUS being on top. None of the other variables seem to have an impact on crisis risk in the mortgage market. Now, we run a series of robustness checks to verify our findings.

4.4.2 Robustness

In the robustness analysis, we scrutinize the effect of standard normal errors for marginals by allowing for t-distributed margins. In addition, we apply alternative conditional copula models by also allowing the broad dependence parameter of the mirrored transformed

Frank copula to be time-dependent, and by examining the conditional symmetrized Joe-Clayton copula as well as the conditional t-copula. Moreover, we consider alternative dependent variables by analyzing the S&P Case-Shiller home price index (CS) instead of HPI and by using unexpected changes of DLQ (UDLQ).

4.4.2.1 Change of marginal distribution

We want to allow for heavier tails in the marginals than normal distribution, and thus, we analyze our model with t-distributed margins. Table 4.5 presents the results. We observe

TABLE 4.5: Estimation results: t-distributed margins of HPI and DLQ

Factor	**ML-Estimates**						
z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\theta_{0,z}$	SE	LL
			Panel A: Unconditional model				
none	-1.8439*	1.1171	-	-	-1.1893	1.2608	1062.1442
			Panel B: Housing supply				
ESUP	-1.6150	0.9927	-0.3357	0.5003	-1.3812	1.3368	1062.5754
NSUP	-13.8349	21.6837	-6.4792	9.3859	-0.1612	0.5601	1064.4419
NHUS	-9.7878	6.1259	6.1679**	2.8716	-0.2256	0.5952	1068.1251
			Panel C: Economic factors				
CPI	-1.6609*	0.9707	-0.2219	0.3366	-1.3924	1.3036	1062.6113
GDP	-1.7509*	1.0043	-0.0160	0.5625	-1.3076	1.2564	1062.3016
S&P	-1.8070*	1.0236	0.6978	0.7626	-1.4761	1.1537	1063.1584
			Panel D: Interest rates				
ARM	-1.6640*	0.9482	-0.2430	0.6070	-1.4226	1.2656	1062.3844
FRM	-14.1879	36.4693	-6.9349	17.1284	-0.0883	0.5546	1063.4239
TB3	-1.8338	1.1176	0.1499	0.6728	-1.2094	1.2549	1062.2821
			Panel E: Mortgage credits				
EMOR	-1.3490*	0.7367	0.6000*	0.3598	-2.1629*	1.3001	1064.1746
HMOR	-1.3143*	0.7191	0.5335	0.3393	-2.1740	1.3241	1064.0422
NMOR	-1.6854*	0.9652	0.5449	0.6098	-1.4011	1.2022	1062.8160

This table reports the maximum-likelihood estimates for Equation (4.3.8) from the first quarter of 1985 to the second quarter of 2015 for HPI and DLQ with t-distributed margins. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 4.12, Table 4.16 and Table 4.17.

a slight increase of the log-likelihood in comparison to the estimations in section 4.4.1 for all conditioning variables, although ν_{HPI} and ν_{DLQ} estimates exhibit a large standard error (see Appendix 4.B Table 4.16 and Table 4.17). Especially, NHUS with -6.1679 at the 5% level as well as EMOR at the 10% level remain significant variables to influence the conditional crisis probability with marginal increasing t-statistics for both. However, HMOR is not significant anymore.

Overall, the use of normal margins for the model seems to be suitable as t-distributed margins for HPI and DLQ do not significantly enhance the estimation results of the initial analysis. Moreover, we see that the results are robust.

4.4.2.2 Alternative copula models

Subsequently, we apply three additional conditional copula models. First, we extend the main model specification by the functional relationship as given by Equation (4.3.9) in order to condition on broad dependence, too. The estimates are shown in Table 4.6. With

Table 4.6: Estimation results: full conditioning mtF-Copula

Factor	**ML-Estimates**								
z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\theta_{0,z}$	SE	$\theta_{1,z}$	SE	LL
Panel A: Unconditional model									
none	-2.1378*	1.2679	-	-	-0.8700	1.1530	-	-	1061.5536
Panel B: Housing supply									
ESUP	-1.7786*	1.0181	-0.5559	0.9739	-1.3269	1.2434	0.4456	1.2084	1061.9954
NSUP	-5.7593	8.0138	2.4227	4.2543	-0.1170	0.7353	-0.7982	0.8171	1063.2727
NHUS	-1.8899*	1.1269	-0.2654	0.6407	-0.8585	1.1977	1.8722**	0.9879	1062.9220
Panel C: Economic factors									
CPI	-1.7733*	1.0252	-0.2879	0.5297	-1.3145	1.3387	0.2185	1.0804	1062.0218
GDP	-2.0455*	1.1595	0.0621	1.0582	-1.0233	1.1639	-0.2354	0.9758	1061.6187
S&P	-1.5276**	0.6634	0.9850*	0.5242	-2.6321**	1.2721	-1.4351	1.1498	1064.1224
Panel D: Interest rates									
ARM	-1.8156*	1.0036	-0.2871	0.7911	-1.2250	1.2216	0.0566	0.9128	1061.7850
FRM	-3.3358	2.3773	-1.5824	1.5567	-0.7060	0.9341	0.9126	0.9509	1062.5811
TB3	-1.8425*	1.0397	0.5205	0.9806	-1.4868	1.1794	-0.6905	1.2012	1061.8492
Panel E: Mortgage credits									
EMOR	-1.1598**	0.5716	0.6900**	0.3505	-3.1442**	1.4554	-1.1590	1.4900	1064.0556
HMOR	-1.2187*	0.6249	0.5917	0.4165	-2.6366*	1.4362	-0.5883	1.6027	1063.4962
NMOR	-1.8199*	1.0171	0.6641	0.6560	-1.2832	1.3288	-0.1583	1.1118	1062.2594

This table reports the maximum-likelihood estimates for Equation (4.3.8) and for Equation (4.3.9) from the first quarter of 1985 to the second quarter of 2015 for HPI and DLQ with both dependence parameters to be time dependent. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 4.12, Table 4.18 and Table 4.19.

respect to the broad dependence parameter $\theta(z), z \in \mathcal{Z}$, NHUS is statistically significant at the 5% level for $\theta_{1,\cdot}$ indicating a negative broad dependence of HPI and DLQ. None of the other factors provide evidence to have an effect on the broad dependence of the two risk factors regarding $\theta_{1,z}$, $z \in \mathcal{Z}$. With respect to $\theta_{0,z}$, we find statistical significance at the 5% level for S&P as well as for EMOR, and at the 10% level for HMOR. This is consistent with the results of the main analysis for constant broad dependence. Moreover, due to the addition of conditional broad dependence the extreme dependence parameter loses significance, such that NHUS as well as HMOR are not significant anymore. However, the existing mortgage loan-to-price ratio gains explanatory power and is now significant at the 5% significance level. In addition, also S&P provides evidence to have an impact on conditional extreme asymmetric dependence at the 10% level. Furthermore, the model fit reduces for each estimation in comparison to the main analysis when including the time-varying component for the broad dependence.

Second, we analyze the conditional mirrored version of the symmetrized Joe-Clayton (SJC) copula which allows for lower tail dependence λ^- as well as upper tail dependence λ^+.[8] Both tails are quantified equally to λ in the main analysis using Equation (4.3.8). The

TABLE 4.7: Estimation results: conditional mirrored symmetrized Joe-Clayton copula

Factor	**ML-Estimates**								
z	$\lambda^+_{0,z}$	SE	$\lambda^+_{1,z}$	SE	$\lambda^-_{0,z}$	SE	$\lambda^-_{1,z}$	SE	LL
Panel A: Unconditional model									
none	-2.9444	4.3466	-	-	-2.7747	3.8966	-	-	1053.3964
Panel B: Housing supply									
ESUP	-2.6853	2.1551	-0.3952	2.5665	-2.9436	3.5160	-0.0003	3.1146	1058.9190
NSUP	-4.3713	4.0215	1.7362	2.1545	-11.3721	18.0596	-5.4702	8.0104	1060.3760
NHUS	-4.2663	9.2375	-0.5922	4.6293	-4.6333**	2.2803	3.3920***	1.2084	1062.2110
Panel C: Economic factors									
CPI	-2.8895	2.4412	-0.0192	1.6379	-2.9436	3.7271	-0.0002	2.4775	1059.0140
GDP	-2.9447	2.3110	-0.0002	2.4255	-2.9446	2.9954	0.0015	3.3927	1059.0620
S&P	-3.8857	5.7013	1.5477	3.7417	-2.9435	3.1247	-0.0009	3.4426	1059.0900
Panel D: Interest rates									
ARM	-2.8143	2.2516	-0.0591	1.8956	-13.5457	11.0058	5.5898	3.9761	1060.0000
FRM	-5.6017	3.8809	3.0938	2.2022	-2.9444	3.0436	0.0000	5.0319	1061.6320
TB3	-2.9457	2.3979	0.0021	2.7549	-2.9449	3.2086	0.0005	3.8285	1059.1480
Panel E: Mortgage credits									
EMOR	-2.2131	1.7798	0.9652	0.8219	-2.9536	3.8339	-0.0084	4.1267	1059.7750
HMOR	-2.1735	1.6541	0.7390	1.0553	-2.9438	3.7870	-0.0002	3.9597	1059.5540
NMOR	-2.5840	1.8822	0.8419	1.3526	-2.9455	3.3104	-0.0010	3.2134	1058.8770

This table reports the maximum-likelihood estimates for Equation (4.3.8) and for Equation (4.3.9) from the first quarter of 1985 to the second quarter of 2015 for HPI and DLQ with both dependence parameters to be time dependent. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 4.13, Table 4.20 and Table 4.21.

results are given in Table 4.7. None of the variables but NHUS provide evidence of a significant influence on the co-movement of HPI and DLQ which is significant for λ_1^- at the 1% level. In particular, when applying the BIC as criterion for the model fit we obtain that the conditional mirrored transformed Frank copula fits the data better than the conditional mirrored SJC copula.

8 The conditional mirrored symmetrized Joe-Clayton copula is specified in Equation (A.3) in Appendix 4.A.

Third, we check the fit of our data to the conditional mirrored t-copula which belongs to the class of elliptical copulas. It is a symmetric copula that allows for tail dependence, too. The conditional mirrored t-copula consists of two parameters, the conditional degrees of freedom $\eta(z)$ and the conditional correlation $\rho(z)$.[9] The estimation results are presented in

Table 4.8: Estimation results: conditional mirrored t-copula

Factor	**ML-Estimates**									
z	$\eta_{0,z}$	SE	$\eta_{1,z}$	SE	$\rho_{0,z}$	SE	$\rho_{1,z}$	SE	$\tilde{\lambda}_z$	LL
				Panel A: Unconditional model						
none	1.4742**	0.5818	-	-	0.0584	0.2200	-	-	0.0919	1063.5643
				Panel B: Housing supply						
ESUP	8.4363***	0.5977	5.7547***	0.4551	-0.0749	0.1856	0.0543	0.2063	0.0000	1066.0954
NSUP	1.5053**	0.6178	0.3153	0.6007	0.0379	0.2390	0.0115	0.2574	0.0843	1063.5994
NHUS	2.7775*	1.4283	-2.3988***	0.8664	0.1159	0.2259	0.3069*	0.1859	0.0095	1070.1081
				Panel C: Economic factors						
CPI	1.3655**	0.5529	0.2897	0.3786	0.0544	0.2288	-0.0427	0.2148	0.1049	1064.3262
GDP	1.5938*	0.8172	0.2964	0.4994	0.0533	0.2285	0.0095	0.2639	0.0716	1064.0866
S&P	2.8251**	1.2600	1.6978***	0.5089	0.0592	0.2166	0.1432	0.2726	0.0004	1068.2061
				Panel D: Interest rates						
ARM	1.4755**	0.6090	0.0446	0.4532	0.0542	0.2239	-0.0151	0.2681	0.0914	1063.5748
FRM	5.0577	3.1148	-2.9885*	1.6485	-0.0594	0.1925	-0.0901	0.2511	0.0000	1065.6757
TB3	1.5786**	0.7385	0.1647	0.5443	0.0642	0.2239	0.0234	0.2652	0.0771	1063.6668
				Panel E: Mortgage credits						
EMOR	1.7812*	1.0518	0.2392	1.3375	0.1027	0.2166	0.3307	0.2507	0.0592	1064.5964
HMOR	2.0095	1.5060	0.4095	1.6318	0.1067	0.2141	0.3540	0.2168	0.0378	1064.9005
NMOR	2.7629	2.1216	1.0837	1.3686	0.0828	0.2100	0.1802	0.2543	0.0020	1064.5934

This table reports the maximum-likelihood estimates for Equation (4.3.8) and for Equation (4.3.9) from the first quarter of 1985 to the second quarter of 2015 for HPI and DLQ with both dependence parameters to be time dependent. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 4.13, Table 4.22 and Table 4.23.

Table 4.8. With respect to $\eta_{1,\cdot}$ we observe statistical significance at the 1% level for ESUP, NHUS, and S&P, and for FRM at the 5% level. The conditional correlation parameter is significant for NHUS at the 10% level. The dependence model fit slightly improves for ESUP, GDP, S&P, as well as FRM compared to the model from the main analysis. For each of the other factors the BIC preferred model specification remains the conditional mirrored transformed Frank copula.

In addition, we state the median of the tail dependence coefficient by applying the functional relation

$$\lambda_z = 2 \cdot t_{\eta(z)+1}\left(-\sqrt{(\eta(z)+1)} \cdot \sqrt{(1-\rho(z))}/\sqrt{(1+\rho(z))}\right) \tag{4.4.1}$$

[9] See Appendix 4.A for details.

following Demarta and McNeil (2005). For the unconditional case, $\tilde{\lambda}$ takes a value of 0.0919 which is similar to the constant λ of the initial analysis. It is highest for CPI with $\tilde{\lambda}_{CPI} = 0.1049$. However, neither the degrees of freedom parameter nor the correlation parameter is significant at any reasonable level. For each of the variables with significant η_1 or ρ_1 parameter the median is close to the lower bound of 0.

Taken as a whole, the extension of the broad dependence $\theta(z)$ to conditionality does not improve the estimation results substantially, even though we find empirical evidence for EMOR. Apart from that, we observe a decline in statistical significance for $\lambda_{1,\cdot}$ for NHUS as well as for HMOR. Though, we provide evidence of an improvement for EMOR and S&P with respect to the conditional tail dependence parameter. In addition, the application of the conditional mirrored SJC copula and t-copula, respectively, does not fit the data better compared to the main copula model specification. Consequently, the conditional mirrored transformed Frank copula in (4.3.5) as conditional copula model for our analysis is appropriate. Moreover, we show that our empirical results are robust in most cases.

4.4.2.3 Multiple factor estimation

In addition to the one factor estimation we also estimate two different multiple factor models. First, we examine four factors containing one representative from each area by choosing the factors with the highest model fit in the main analysis using the BIC as selection criterion, namely NHUS, S&P, FRM, and EMOR. Second, we use the three significant factors from the initial investigation, i.e., NHUS, EMOR, and HMOR. Table

TABLE 4.9: Estimation results: multiple model

	Representatives		Significant variables	
Coeff.	Estimate	SE	Estimate	SE
λ_0	-9.9495*	5.7245	-6.4600	5.5093
$\lambda_{1,NHUS}$	5.0829*	2.6959	4.2948$^\bullet$	2.9497
$\lambda_{1,S\&P}$	-1.0263	1.9528		
$\lambda_{1,FRM}$	3.1280*	1.7737		
$\lambda_{1,EMOR}$	1.7788*	1.0549	4.6017$^\bullet$	3.4171
$\lambda_{1,HMOR}$			-5.1506$^\bullet$	3.9604
θ_0	-0.0221	1.0549	-0.3210	0.6417
LL	1070.9555		1066.6220	
BIC	-16.8872		-16.8556	

This table reports the maximum-likelihood estimates for Equation (4.3.8) from the first quarter of 1985 to the second quarter of 2015 for CS and DLQ with t-distributed margins. Moreover, the log-likelihood (LL) is given. $^\bullet$ and * denote statistical significance at the 20% and 10% level, respectively. Detailed estimation results are provided in Table 4.13, Table 4.25 and Table 4.26.

4.9 presents the maximum-likelihood estimates. When investigating the representatives we obtain NHUS, FRM, and EMOR to be significant at the 10% level. With respect to the significant factors in the main analysis the level of statistical significance reduces to

20% for all three variables particularly due to interdependencies and a high correlation of EMOR and HMOR. In both cases we cannot observe statistical significance for the broad dependence parameter θ_0. Altogether, the estimation of both multiple model setups suggests the robustness of the main results.

4.4.2.4 Alternative time series for HPI

Alongside HPI literature often applies the S&P Case-Shiller home price index (CS) for housing related analysis (see e.g. Goetzmann et al. (2012), Bhardwaj and Sengupta (2012)). For that reason, we replace HPI as dependent variable by CS and investigate the extreme asymmetric dependence of CS and DLQ. Figure 4.4 shows the plot of HPI and CS. Both graphs have a similar development, although the one of HPI is more pro-

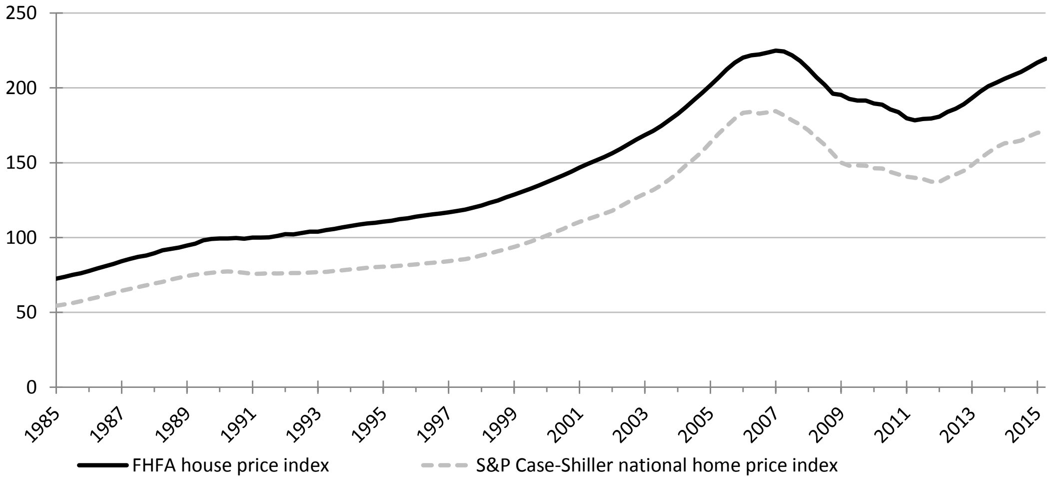


Figure 4.4: Development of US house price index and S&P Case-Shiller home price index

nounced. The use of CS requires an additional check of the mean and variance dynamics. Analog to the initial analysis, the mean dynamics follow a VAR(1) model as indicated by BIC. The structural break point analysis by Andreou and Ghysels (2002) for the modulus of the residual time series of CS provides one change point in the first quarter of 2008. Especially, we apply t-distributed margins. Table 4.10 shows the results. We observe a noticeable reduction in the log-likelihood for all conditioning variables. Moreover, none of the factors significantly influences the extreme dependence at a reasonable significance level. For the broad dependence, $\theta_{0,\cdot}$ is significant for TB3 and EMOR at the 10% significance level.

The estimates cannot support the results of the main analysis possibly due to the use of only one change point which increases the inaccuracy of the variance dynamics. Besides, the choice of lag and window width might be different for CS in comparison to HPI.

TABLE 4.10: Estimation results: S&P Case-Shiller home price index

Factor	**ML-Estimates**						**Diagnostics**
z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\theta_{0,z}$	SE	LL
Panel A: Unconditional model							
none	-2.4254	2.1117	-	-	-0.1444	1.2185	1049.4073
Panel B: Housing supply							
ESUP	-1.1251*	0.6039	-0.0516	0.3633	-1.8891	1.3055	1052.1947
NSUP	-1.2045*	0.6440	0.3376	0.3747	-2.0141	1.3027	1052.8587
NHUS	-1.1307*	0.6030	0.0100	0.3256	-1.8835	1.3625	1052.1797
Panel C: Economic factors							
CPI	-1.1593*	0.6623	0.0739	0.2818	-1.8834	1.3625	1052.2414
GDP	-1.1085*	0.5830	-0.0628	0.3332	-1.9987	1.3068	1052.2150
S&P	-1.2096*	0.6800	0.4799	0.4137	-1.7875	1.2979	1053.1717
Panel D: Interest rates							
ARM	-1.0217*	0.5763	-0.4071	0.3094	-2.1048	1.3504	1052.8650
FRM	-1.1140*	0.6089	-0.3113	0.4082	-1.9559	1.3228	1052.3630
TB3	-0.9820*	0.5213	-0.2962	0.2670	-2.3354*	1.3340	1052.6682
Panel E: Mortgage credits							
EMOR	-1.1350*	0.6219	0.4307	0.2858	-2.1621*	1.2575	1053.4472
HMOR	-1.1371*	0.6262	0.3740	0.2668	-2.0833	1.2842	1053.1627
NMOR	-1.1245*	0.6102	0.0735	0.3180	-1.9060	1.3549	1052.1908

This table reports the maximum-likelihood estimates for Equation (4.3.8) from the first quarter of 1985 to the second quarter of 2015 for CS and DLQ with t-distributed margins. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 4.12, Table 4.25 and Table 4.26.

4.4.2.5 Alternative time series for DEL

We also want to analyze whether unexpected events caused the subprime crisis. Therefore, we now investigate unexpected changes of DLQ (UDLQ) which is the residual time series of the AR(1) process of DLQ. Figure 4.5 shows the graph of UDLQ. Particularly, the rise and subsequent decrease starting in 2008 is stronger for unexpected changes of DLQ than the original time series. The time series properties remain the same. The corresponding maximum-likelihood estimates are given in Table 4.11. The log-likelihood is somewhat reduced compared to the main analysis except for NSUP and FRM. We observe that FRM is significant at the 5% level. The remaining conditioning variables are insignificant. Equally, the constant broad dependence parameter θ_0 is insignificant.

Overall, we only provide statistical evidence of a positive relationship between an increase in the fixed-rate mortgage and the conditional tail dependence. However, NHUS, EMOR and HMOR are not significant anymore. Accordingly, the use of UDLQ instead of DLQ does not improve our main results.

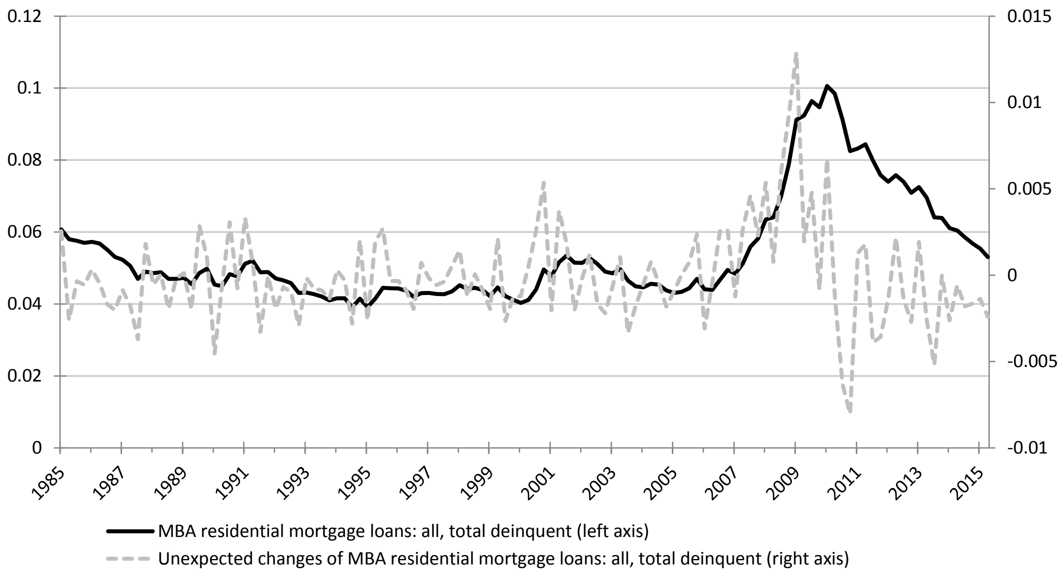


Figure 4.5: Development of delinquent US residential mortgage loans and unexpected changes of delinquent US residential mortgage loans

4.5 Conclusion

The burst of the US housing bubble in 2006 impressively showed the strong impact of the mortgage market on the US economy. Due to the mortgage crisis also the US economy faced a significant slowdown and headed for a deep recession which has contributed to the emergence of the global financial crisis. Therefore, it is of utmost importance to investigate the dependence structure of house prices and default rates in the US. We pay particular attention on sharply decreasing house prices and sharply increasing delinquency rates for the purpose of quantifying the potential default risk of mortgage credits for lenders. In this context, we apply a conditional copula approach and model the time-varying extreme asymmetric dependence of both factors using the logistic function. As possible driving variables of the co-movement, we employ housing supply factors, economic factors, interest rates as well as mortgage loan-to-price ratios.

Analyzing quarterly data from 1985 to 2015 we provide empirical evidence of a positive relationship between the volume of new private housing units started and the conditional extreme asymmetric dependence. Moreover, the loan-to-price ratios for existing home mortgages and all home mortgages significantly influence the co-movement of US house prices and default rates. Otherwise, we cannot provide evidence that economic factors do influence the co-movement of US house prices and default rates. Especially, the impact of interest rates is less than expected given the findings in most of the existing literature. Robustness checks reinforce the choice of the conditional mirrored transformed Frank copula as it provides the best data fit compared to the full model specification, the symmetrized Joe-Clayton copula, and the t-copula. Additionally, these robustness and sensitivity analyses emphasizes our estimation results.

TABLE 4.11: Estimation results: unexpected changes of DLQ

Factor	**ML-Estimates**						**Diagnostics**
z	$\lambda_{0,z}$	SE	$\lambda_{1,z}$	SE	$\theta_{0,z}$	SE	LL
Panel A: Unconditional model							
none	-2.6959	2.1818	-	-	-0.4238	1.1442	1061.0058
Panel B: Housing supply							
ESUP	-1.9171*	1.1646	-0.5669	0.6834	-0.9515	1.1819	1061.4149
NSUP	-12.6475	13.9281	-6.0259	5.9738	-0.1094	0.5633	1064.5497
NHUS	-6.2792	5.1240	3.9360	3.3760	-0.2604	0.6218	1064.1490
Panel C: Economic factors							
CPI	-2.0069*	1.1972	-0.2437	0.3945	-0.9195	1.1971	1061.2683
GDP	-2.5916	1.9978	0.0801	1.2997	-0.4756	1.1565	1061.0178
S&P	-1.8357	0.9488	0.6982	0.7638	-1.4295	1.1508	1061.8821
Panel D: Interest rates							
ARM	-1.8345*	1.0115	-0.3464	0.6646	-1.1321	1.1916	1061.2316
FRM	-6.5280*	3.4564	3.7273**	1.8666	-0.1548	0.6237	1064.9409
TB3	-2.5110	2.0188	0.4832	1.4666	-0.6172	1.1346	1061.1855
Panel E: Mortgage credits							
EMOR	-1.5217*	0.7922	0.6299	0.4273	-1.8180	1.2179	1062.7263
HMOR	-1.4525*	0.7544	0.5580	0.3789	-1.8760	1.2495	1062.6292
NMOR	-2.2058*	1.2523	0.8201	0.5779	-0.8584	1.0603	1061.7392

This table reports the maximum-likelihood estimates for Equation (4.3.8) from the first quarter of 1985 to the second quarter of 2015 for HPI and UDLQ. Moreover, the log-likelihood (LL) is given. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. Detailed estimation results are provided in Table 4.12, Table 4.27 and Table 4.28.

Overall, our findings highlight the importance in understanding the dependence structure of house prices and default rates. In this context, conditioning variables like the volume of new private housing units started, the loan-to-price ratio for existing home mortgages as well as the loan-to-price ratio for all home mortgages possibly indicate extreme asymmetric dependence of these two risk factors. This is in line with the existing literature. By contrast, neither economic factors nor interest rates consistently provide statistical evidence to have an impact on the adverse movement of house prices and default rates which might be due to the investigation of extreme asymmetric dependence in our analysis but also reflects the inconsistent findings of existing literature concerning interest rates. More importantly, we provide a useful tool to quantify the default risk of mortgage credits for lenders, such that lenders are able to better adapt to changes in market conditions in order to diversify their mortgage credit portfolio and therefore improve their risk management. In addition, in times of mortgage market downswings it conceivably advises lenders to restrain loans that borrowers might not be able to afford and to prohibit loans with high loan-to-value ratio in order to prevent the deterioration of loans.

Further research opportunities in this area could be the analysis of individual states or regions as mortgage market conditions differ more in states than the whole country. Additionally, the use of other related macroeconomic variables can be investigated.

4.A Technical appendix

Following Junker (2003) the conditional transformed Frank copula $C_{tF}(\cdot,\cdot\,|\,z)$ is given by

$$
\begin{aligned}
C_{tF}(u,v\,|\,z) = -\frac{1}{\theta(z)}\ln\Bigg[1+(e^{-\theta(z)}-1)\exp\Bigg[-\Bigg[\left(-\ln\left(\frac{e^{-u\theta(z)}-1}{e^{-\theta(z)}-1}\right)\right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}} \\
+\left(-\ln\left(\frac{e^{-v\theta(z)}-1}{e^{-\theta(z)}-1}\right)\right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}}\Bigg]^{\frac{\ln(2-\lambda(z))}{\ln(2)}}\Bigg]\Bigg], \theta(z)\in\mathbb{R}\setminus\{0\},
\end{aligned}
\tag{A.1}
$$

and for $\theta(z)=0$

$$
C_{tF}(u,v\,|\,z) = \exp\left(-\left((-\ln(u))^{\frac{\ln(2)}{\ln(2-\lambda(z))}}+(-\ln(v))^{\frac{\ln(2)}{\ln(2-\lambda(z))}}\right)^{\frac{\ln(2-\lambda(z))}{\ln(2)}}\right). \tag{A.2}
$$

The corresponding generator of the conditional transformed Frank copula is given by

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

such that for $\theta(z)\in\mathbb{R}\setminus\{0\}$ we get

$$
\begin{aligned}
\varphi'_{tF}(t\,|\,z) =& \frac{\ln(2)}{\ln(2-\lambda(z))}\frac{\theta(z)}{1-e^{t\theta(z)}}\left(-\ln\left(\frac{e^{-t\theta(z)}-1}{e^{-\theta(z)}-1}\right)\right)^{\frac{\ln(2)}{\ln(2-\lambda(z))}-1}, \\
\varphi''_{tF}(t\,|\,z) =& \varphi'_{tF}(t\,|\,z)\frac{\theta(z)}{1-e^{t\theta(z)}}\left(e^{t\theta(z)}+\frac{\frac{\ln(2)}{\ln(2-\lambda(z))}-1}{-\ln\left(\frac{e^{-t\theta(z)}-1}{e^{-\theta(z)}-1}\right)}\right),
\end{aligned}
$$

and for $\theta(z)=0$

$$
\begin{aligned}
\varphi'_{tF}(t\,|\,z) =& \frac{\ln(2)}{\ln(2-\lambda(z))}\frac{-1}{t}(-\ln(t))^{\frac{\ln(2)}{\ln(2-\lambda(z))}-1}, \\
\varphi''_{tF}(t\,|\,z) =& \varphi'_{tF}(t\,|\,z)\frac{-1}{t}\left(1+\frac{\frac{\ln(2)}{\ln(2-\lambda(z))}-1}{-\ln(t)}\right).
\end{aligned}
$$

Following Patton (2006) the conditional symmetrized Joe-Clayton copula is specified by

$$
\begin{aligned}
C_{SJC}(u,v\,|\,\lambda^+(z),\lambda^-(z)) = 0.5\Big(&C_{JC}(u,v\,|\,\lambda^+(z),\lambda^-(z)) \\
&+C_{JC}(1-u,1-v\,|\,\lambda^-(z),\lambda^+(z))+u+v-1\Big)
\end{aligned}
\tag{A.3}
$$

where

$$
C_{JC}(u,v\,|\,\lambda^+(z),\lambda^-(z)) = 1-\left(1-\left(\left[1-(1-u)^{\kappa(z)}\right]^{-\gamma(z)}\right.\right.
$$

$$+\left[1-(1-v)^{\kappa(z)}\right]^{-\gamma(z)}-1\Big)^{-1/\gamma(z)}\Bigg)^{1/\kappa(z)}$$

denotes the Joe-Clayton copula with

$$\kappa(z)=\frac{1}{\log_2(2-\lambda^+(z))} \text{ and } \gamma(z)=-\frac{1}{\log_2(\lambda^-(z))},$$

for $\lambda^+(z),\lambda^-(z)\in(0,1)$.
The conditional t-copula is given by

$$\begin{aligned}C_t(u,v\,|\,z)=\int_{-\infty}^{t^{-1}_{\eta(z)}(u)}\int_{-\infty}^{t^{-1}_{\eta(z)}(v)}&\frac{\Gamma\left(\frac{\eta(z)+2}{2}\right)}{\Gamma\left(\frac{\eta(z)}{2}\right)\eta(z)\pi\sqrt{1-\rho^2(z)}}\\&\left(1+\frac{x^2+y^2-2\rho(z)xy}{(1-\rho^2(z))\,\eta(z)}\right)^{-\frac{\eta(z)+2}{2}}\mathrm{d}y\mathrm{d}x,\end{aligned}\tag{A.4}$$

where the parameter $\eta(z)\in\mathbb{R}^+$ is specified similar to $\lambda(z)$ in Equation (4.3.8) by

$$\eta(z)=\exp\left(\eta_{0,z}+\eta_{1,z}z\right)\,,\tag{A.5}$$

and $\rho(z)\in[-1,1]$ is given similar to Equation (19) of Patton (2006) specified by

$$\rho(z)=\frac{1-\exp\left(-\left(\rho_{0,z}+\rho_{1,z}z\right)\right)}{1+\exp\left(-\left(\rho_{0,z}+\rho_{1,z}z\right)\right)}\,.\tag{A.6}$$

4.B Model estimates

TABLE 4.12: Estimation results: unconditional models I

	Model specification							
	initial & broad dep.		t-distr. margins		CS		UDLQ	
Coeff.	Est.	SE	Est.	SE	Est.	SE	Est.	SE
	Mean dynamics							
$\beta_{HPI,0}$	0.0000	0.0024	-0.0002	0.0023	-0.0014	0.0024	0.0011*	0.0006
$\beta_{HPI,1}$	0.9135***	0.0429	0.9179***	0.0428	0.9602***	0.0285	0.9173***	0.0386
$\beta_{HPI,2}$	0.0247	0.0447	0.0276	0.0439	0.0423	0.0474	0.1448	0.1318
$\beta_{DLQ,0}$	0.0036***	0.0013	0.0037***	0.0012	0.0027**	0.0011	0.0006**	0.0003
$\beta_{DLQ,1}$	-0.0839***	0.0243	-0.0843***	0.0233	-0.0453***	0.0168	-0.0688***	0.0214
$\beta_{DLQ,2}$	0.9449***	0.0233	0.9440***	0.0220	0.9522***	0.0195	0.0769	0.0975
	Variance dynamics							
$\sigma_{HPI,1}$	0.0064***	0.0010	0.0065***	0.0011	0.0041***	0.0008	0.0064***	0.0010
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0023***	0.0002	0.0119***	0.0036	0.0023***	0.0002
$\sigma_{HPI,3}$	0.0081***	0.0014	0.0080***	0.0014			0.0081***	0.0014
$\sigma_{DLQ,1}$	0.0019***	0.0001	0.0019***	0.0002	0.0019***	0.0003	0.0019***	0.0001
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0038***	0.0006	0.0037***	0.0005	0.0039***	0.0006
	Dependence parameters							
λ_0	-2.1378*	1.2679	-1.8439*	1.1171	-2.4254	2.1117	-2.6959	2.1818
θ_0	-0.8700	1.1530	-1.1893	1.2608	-0.1444	1.2185	-0.4238	1.1442
ν_{HPI}			40.1033	161.4830	3.4823***	1.3320		
ν_{DLQ}			21.2485	48.8538	7.0047	6.0841		
LL	1061.5536		1062.1442		1049.4073		1061.0058	
BIC	-16.8906		-16.8215		-16.6521		-16.8816	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.13: Estimation results: unconditional models II

	Model specification			
	SJC copula		t-copula	
Coeff.	Est.	SE	Est.	SE
Mean dynamics				
$\beta_{HPI,0}$	0.0002	0.0024	0.0000	0.0022
$\beta_{HPI,1}$	0.9172***	0.0421	0.9306***	0.0429
$\beta_{HPI,2}$	0.0175	0.0448	0.0163	0.0412
$\beta_{DLQ,0}$	0.0036***	0.0013	0.0036***	0.0012
$\beta_{DLQ,1}$	-0.0830***	0.0244	-0.0743***	0.0245
$\beta_{DLQ,2}$	0.9453***	0.0235	0.9423***	0.0220
Variance dynamics				
$\sigma_{HPI,1}$	0.0064***	0.0036	0.0065***	0.0036
$\sigma_{HPI,2}$	0.0024***	0.0010	0.0024***	0.0011
$\sigma_{HPI,3}$	0.0083***	0.0050	0.0076***	0.0042
$\sigma_{DLQ,1}$	0.0019***	0.0008	0.0019***	0.0008
$\sigma_{DLQ,2}$	0.0039***	0.0021	0.0037***	0.0018
Dependence parameters				
λ_0^+	-5.2938	9.3829		
λ_0^-	-5.2933	13.2652		
η_0			1.4742**	0.5818
ρ_0			0.0584	0.2200
LL	1060.7388		1063.5643	
BIC	-16.8773		-16.9236	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.14: ML-estimates I

	Supply side factor z						Demand side factor z					
	ESUP		NSUP		NHUS		CPI		GDP		S&P	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean dynamics												
$\beta_{HPI,0}$	-0.0002	0.0026	0.0007	0.0023	0.0003	0.0024	0.0001	0.0024	0.0000	0.0024	-0.0001	0.0023
$\beta_{HPI,1}$	0.9159***	0.0428	0.9119***	0.0428	0.9067***	0.0412	0.9142***	0.0430	0.9135***	0.0435	0.9122***	0.0417
$\beta_{HPI,2}$	0.0287	0.0492	0.0064	0.0416	0.0182	0.0468	0.0212	0.0460	0.0248	0.0463	0.0259	0.0428
$\beta_{DLQ,0}$	0.0035***	0.0013	0.0035***	0.0013	0.0042***	0.0013	0.0037***	0.0014	0.0037***	0.0013	0.0037***	0.0013
$\beta_{DLQ,1}$	-0.0845***	0.0244	-0.0778***	0.0259	-0.0973***	0.0235	-0.0825***	0.0245	-0.0840***	0.0244	-0.0856***	0.0246
$\beta_{DLQ,2}$	0.9483***	0.0236	0.9462***	0.0232	0.9378***	0.0236	0.9439***	0.0248	0.9448***	0.0234	0.9455***	0.0233
Variance dynamics												
$\sigma_{HPI,1}$	0.0064***	0.0010	-0.0063***	0.0010	0.0065***	0.0011	0.0064***	0.0010	0.0064***	0.0010	0.0064***	0.0010
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0024***	0.0002	0.0023***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0080***	0.0015	0.0081***	0.0014	0.0086***	0.0018	0.0081***	0.0014	0.0081***	0.0015	0.0078***	0.0012
$\sigma_{DLQ,1}$	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0040***	0.0006	0.0038***	0.0005	0.0039***	0.0005	0.0039***	0.0006	0.0039***	0.0006
Dependence parameters												
$\lambda_{0,z}$	-1.8670*	1.0875	-7.2171	18.8941	-10.4701	6.5708	-1.8717*	1.0994	-2.1381*	1.2691	-1.9572*	1.0594
$\lambda_{1,z}$	-0.4509	0.6420	2.8366	10.4499	6.5032**	3.1180	-0.2543	0.3678	-0.0147	0.8151	0.7968	0.7943
θ_z	-1.0586	1.1996	-0.0817	0.6962	-0.2196	0.5748	-1.1205	1.2456	-0.8733	1.1568	-1.3754	1.1261
LL	1061.8806		1062.6552		1067.8875		1061.9667		1061.5541		1062.5616	
BIC	-16.8567		-16.8693		-16.9551		-16.8580		-16.8512		-16.8678	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.15: ML-estimates II

	Interest rate z						Mortgage loan z					
	ARM		FRM		TB3		EMOR		HMOR		NMOR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean dynamics												
$\beta_{HPI,0}$	-0.0003	0.0024	0.0006	0.0024	0.0000	0.0024	0.0003	0.0022	0.0002	0.0022	-0.0003	0.0023
$\beta_{HPI,1}$	0.9168***	0.0438	0.9087***	0.0414	0.9128***	0.0432	0.9031***	0.0419	0.9059***	0.0421	0.9203***	0.0422
$\beta_{HPI,2}$	0.0280	0.0447	0.0098	0.0447	0.0240	0.0456	0.0176	0.0418	0.0192	0.0416	0.0271	0.0441
$\beta_{DLQ,0}$	0.0037***	0.0013	0.0040***	0.0012	0.0036***	0.0013	0.0036***	0.0013	0.0036***	0.0013	0.0035***	0.0013
$\beta_{DLQ,1}$	-0.0844***	0.0243	-0.0958***	0.0227	-0.0831***	0.0246	-0.0761***	0.0233	-0.0769***	0.0232	-0.0813***	0.0239
$\beta_{DLQ,2}$	0.9442***	0.0232	0.9389***	0.0215	0.9455***	0.0234	0.9442***	0.0233	0.9442***	0.0230	0.9462***	0.0230
Variance dynamics												
$\sigma_{HPI,1}$	0.0065***	0.0011	0.0068***	0.0011	0.0063***	0.0010	0.0065***	0.0010	0.0065***	0.0010	0.0065***	0.0010
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0023***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0080***	0.0014	0.0083***	0.0016	0.0080***	0.0014	0.0078***	0.0012	0.0078***	0.0012	0.0081***	0.0013
$\sigma_{DLQ,1}$	0.0019***	0.0001	0.0018***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0038***	0.0005	0.0039***	0.0006	0.0040***	0.0006	0.0039***	0.0006	0.0039***	0.0006
Dependence parameters												
$\lambda_{0,z}$	-1.8245*	1.0080	-16.9480	68.2051	-2.1712	1.3711	-1.4020*	0.7427	-1.3593*	0.7214	-1.8573*	1.0096
$\lambda_{1,z}$	-0.2757	0.6438	-8.1432	31.6884	0.2572	0.9450	0.6486*	0.3340	0.5650*	0.3147	0.6422	0.5520
θ_z	-1.2123	1.2019	-0.0765	0.5578	-0.8689	1.1580	-2.1260*	1.2855	-2.1318	1.3142	-1.2002	1.1361
LL	1061.7807		1062.7156		1061.6363		1063.5884		1063.4276		1062.2640	
BIC	-16.8550		-16.8703		-16.8526		-16.8846		-16.8820		-16.8629	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.16: ML-estimates for t-distributed margins of HPI and DLQ I

	Supply side factor z						Demand side factor z					
	ESUP		NSUP		NHUS		CPI		GDP		S&P	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean dynamics												
$\beta_{HPI,0}$	-0.0003	0.0024	-0.0018	0.0024	0.0002	0.0024	0.0000	0.0023	-0.0002	0.0023	-0.0002	0.0023
$\beta_{HPI,1}$	0.9214***	0.0426	0.9275***	0.0399	0.9116***	0.0406	0.9162***	0.0432	0.9184***	0.0429	0.9176***	0.0420
$\beta_{HPI,2}$	0.0302	0.0469	0.0571	0.0465	0.0185	0.0466	0.0227	0.0451	0.0270	0.0453	0.0265	0.0432
$\beta_{DLQ,0}$	0.0035***	0.0012	0.0031***	0.0012	0.0041***	0.0013	0.0037***	0.0012	0.0037***	0.0012	0.0036***	0.0012
$\beta_{DLQ,1}$	-0.0855***	0.0226	-0.0819***	0.0232	-0.0979***	0.0226	-0.0829***	0.0228	-0.0847***	0.0227	-0.0865***	0.0228
$\beta_{DLQ,2}$	0.9475***	0.0215	0.9549***	0.0215	0.9382***	0.0229	0.9425***	0.0223	0.9429***	0.0214	0.9453***	0.0213
Variance dynamics												
$\sigma_{HPI,1}$	0.0065***	0.0012	0.0064***	0.0011	0.0066***	0.0012	0.0064***	0.0011	0.0065***	0.0012	0.0065***	0.0011
$\sigma_{HPI,2}$	0.0023***	0.0002	0.0023***	0.0002	0.0023***	0.0002	0.0023***	0.0002	0.0023***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0080***	0.0015	0.0078***	0.0011	0.0087***	0.0018	0.0080***	0.0013	0.0080***	0.0015	0.0078***	0.0012
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0001	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0038***	0.0006	0.0040***	0.0006	0.0037***	0.0005	0.0038***	0.0006	0.0038***	0.0006	0.0038***	0.0006
Dependence parameters												
$\lambda_{0,z}$	-1.6150	0.9927	-13.8349	21.6837	-9.7878	6.1259	-1.6609*	0.9707	-1.7509*	1.0043	-1.8070*	1.0236
$\lambda_{1,z}$	-0.3357	0.5003	-6.4792	9.3859	6.1679**	2.8716	-0.2219	0.3366	-0.0160	0.5625	0.6978	0.7626
θ_z	-1.3812	1.3368	-0.1612	0.5601	-0.2256	0.5952	-1.3924	1.3036	-1.3076	1.2564	-1.4761	1.1537
ν_{HPI}	30.2490	92.5488	34.8450	123.4323	23.3643	141.8405	63.1277	383.1932	30.2450	92.7617	39.3543	159.3665
ν_{DLQ}	12.2501	18.4602	10.5944	23.2479	-12.5777	136.2593	12.2497	18.0177	12.2510	18.5671	12.2487	18.2182
LL	1062.5754		1065.5906		1068.1251		1062.6113		1062.3016		1063.1584	
BIC	-16.7892		-16.8287		-16.8802		-16.7898		-16.7847		-16.7988	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.17: ML-estimates for t-distributed margins of HPI and DLQ II

	Interest rate z						Mortgage loan z					
	ARM		FRM		TB3		EMOR		HMOR		NMOR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
							Mean dynamics					
$\beta_{HPI,0}$	-0.0003	0.0024	0.0006	0.0023	-0.0001	0.0024	0.0003	0.0022	0.0003	0.0022	-0.0003	0.0023
$\beta_{HPI,1}$	0.9183***	0.0436	0.9150***	0.0408	0.9162***	0.0430	0.9085***	0.0420	0.9084***	0.0424	0.9192***	0.0429
$\beta_{HPI,2}$	0.0296	0.0445	0.0098	0.0441	0.0262	0.0449	0.0177	0.0410	0.0174	0.0410	0.0275	0.0442
$\beta_{DLQ,0}$	0.0037***	0.0012	0.0040***	0.0011	0.0036***	0.0012	0.0036***	0.0012	0.0036***	0.0012	0.0035***	0.0012
$\beta_{DLQ,1}$	-0.0849***	0.0225	-0.0966***	0.0212	-0.0841***	0.0229	-0.0762***	0.0222	-0.0769***	0.0220	-0.0818***	0.0223
$\beta_{DLQ,2}$	0.9431***	0.0212	0.9376***	0.0200	0.9443***	0.0213	0.9429***	0.0213	0.9428***	0.0210	0.9451***	0.0210
							Variance dynamics					
$\sigma_{HPI,1}$	0.0065***	0.0011	0.0070***	0.0011	0.0064***	0.0011	0.0065***	0.0012	0.0065***	0.0011	0.0065***	0.0011
$\sigma_{HPI,2}$	0.0023***	0.0002	0.0023***	0.0002	0.0023***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0080***	0.0013	0.0084***	0.0016	0.0080***	0.0014	0.0077***	0.0012	0.0078***	0.0012	0.0080***	0.0013
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0038***	0.0006	0.0037***	0.0006	0.0038***	0.0006	0.0039***	0.0006	0.0039***	0.0006	0.0038***	0.0006
							Dependence parameters					
$\lambda_{0,z}$	-1.6640*	0.9482	-14.1879	36.4693	-1.8338	1.1176	-1.3490*	0.7367	-1.3143*	0.7191	-1.6854*	0.9652
$\lambda_{1,z}$	-0.2430	0.6070	-6.9349	17.1284	0.1499	0.6728	0.6000*	0.3598	0.5336	0.3393	0.5449	0.6098
θ_z	-1.4226	1.2656	-0.0883	0.5546	-1.2094	1.2549	-2.1629*	1.3001	-2.1740	1.3241	-1.4011	1.2022
ν_{HPI}	81.0234	650.8601	34.3620	119.4748	46.3474	210.5476	34.8463	124.2655	10.0839	255.1265	251.0495	6263.1760
ν_{DLQ}	12.2499	18.3168	12.2484	16.7512	12.2493	18.6805	12.2500	17.9970	12.2479	17.9044	12.2500	328.3180
LL	1062.3844		1063.4239		1062.2821		1064.1746		1064.0422		1062.8160	
BIC	-16.7861		-16.8031		-16.7844		-16.8154		-16.8133		-16.7932	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.18: ML-estimates for full conditioning model I

	Supply side factor z						Demand side factor z					
	ESUP		NSUP		NHUS		CPI		GDP		S&P	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
						Mean dynamics						
$\beta_{HPI,0}$	-0.0002	0.0026	0.0003	0.0024	0.0003	0.0023	0.0001	0.0024	-0.0002	0.0024	-0.0006	0.0024
$\beta_{HPI,1}$	0.9115***	0.0437	0.9185***	0.0455	0.9268***	0.0434	0.9140***	0.0431	0.9115***	0.0435	0.8947***	0.0414
$\beta_{HPI,2}$	0.0279	0.0488	0.0132	0.0442	0.0139	0.0441	0.0223	0.0469	0.0280	0.0462	0.0416	0.0465
$\beta_{DLQ,0}$	0.0036**	0.0014	0.0033**	0.0013	0.0039***	0.0013	0.0037**	0.0015	0.0037***	0.0013	0.0037***	0.0012
$\beta_{DLQ,1}$	-0.0818***	0.0248	-0.0804***	0.0252	-0.0903***	0.0245	-0.0825***	0.0257	-0.0839***	0.0244	-0.0801***	0.0242
$\beta_{DLQ,2}$	0.9461***	0.0252	0.9496***	0.0236	0.9423***	0.0230	0.9439***	0.0270	0.9446***	0.0233	0.9430***	0.0222
						Variance dynamics						
$\sigma_{HPI,1}$	0.0064***	0.0010	0.0063***	0.0010	0.0064***	0.0010	0.0064***	0.0010	0.0064***	0.0010	0.0065***	0.0010
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0024***	0.0002	0.0023***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0025***	0.0002
$\sigma_{HPI,3}$	0.0079***	0.0014	0.0081***	0.0014	0.0080***	0.0013	0.0081***	0.0015	0.0081***	0.0016	0.0078***	0.0012
$\sigma_{DLQ,1}$	0.0019***	0.0001	0.0018***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0002	0.0019***	0.0001
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0040***	0.0006	0.0040***	0.0006	0.0039***	0.0006	0.0039***	0.0006	0.0038***	0.0008
						Dependence parameters						
$\lambda_{0,z}$	-1.7786*	1.0181	-5.7593	8.0138	-1.8899*	1.1269	-1.7733*	1.0252	-2.0455*	1.1595	-1.5276**	0.6634
$\lambda_{1,z}$	-0.5559	0.9739	2.4227	4.2543	-0.2654	0.6407	-0.2879	0.5297	0.0621	1.0582	0.9850*	0.5242
$\theta_{0,z}$	-1.3269	1.2434	-0.1170	0.7353	-0.8585	1.1977	-1.3145	1.3387	-1.0233	1.1639	-2.6321**	1.2721
$\theta_{1,z}$	0.4456	1.2084	-0.7982	0.8171	1.8722**	0.9879	0.2185	1.0804	-0.2354	0.9758	-1.4351	1.1498
LL	1061.9954		1063.2727		1062.9220		1062.0218		1061.6187		1064.1224	
BIC	-16.8191		-16.8400		-16.8343		-16.8195		-16.8129		-16.8540	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.19: ML-estimates for full conditioning model II

	Interest rate z						Mortgage loan z					
	ARM		FRM		TB3		EMOR		HMOR		NMOR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
							Mean dynamics					
$\beta_{HPI,0}$	-0.0002	0.0024	-0.0001	0.0024	0.0000	0.0024	0.0004	0.0022	0.0002	0.0022	-0.0003	0.0023
$\beta_{HPI,1}$	0.9165***	0.0438	0.9225***	0.0431	0.9021***	0.0447	0.8914***	0.0424	0.9009***	0.0424	0.9194***	0.0421
$\beta_{HPI,2}$	0.0279	0.0448	0.0232	0.0464	0.0264	0.0461	0.0203	0.0420	0.0210	0.0416	0.0265	0.0453
$\beta_{DLQ,0}$	0.0037***	0.0013	0.0041***	0.0013	0.0035***	0.0013	0.0035***	0.0013	0.0036***	0.0013	0.0035***	0.0013
$\beta_{DLQ,1}$	-0.0842***	0.0243	-0.0948***	0.0242	-0.0795***	0.0246	-0.0715***	0.0219	-0.0751***	0.0226	-0.0814***	0.0241
$\beta_{DLQ,2}$	0.9442***	0.0232	0.9379***	0.0223	0.9461***	0.0235	0.9449***	0.0233	0.9440***	0.0230	0.9460***	0.0230
							Variance dynamics					
$\sigma_{HPI,1}$	0.0065***	0.0011	0.0067***	0.0009	0.0063***	0.0009	0.0066***	0.0010	0.0065***	0.0010	0.0065***	0.0010
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0023***	0.0002	0.0024***	0.0003	0.0025***	0.0003	0.0025***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0080***	0.0014	0.0083***	0.0014	0.0079***	0.0013	0.0077***	0.0012	0.0078***	0.0012	0.0080***	0.0014
$\sigma_{DLQ,1}$	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0038***	0.0005	0.0039***	0.0006	0.0039***	0.0006	0.0039***	0.0006	0.0039***	0.0006
							Dependence parameters					
$\lambda_{0,z}$	-1.8156*	1.0036	-3.3358	2.3773	-1.8425*	1.0397	-1.1598**	0.5716	-1.2187*	0.6249	-1.8199*	1.0171
$\lambda_{1,z}$	-0.2871	0.7911	-1.5824	1.5567	0.5205	0.9806	0.6900**	0.3505	0.5917	0.4165	0.6641	0.6560
$\theta_{0,z}$	-1.2250	1.2216	-0.7060	0.9341	-1.4868	1.1794	-3.1442**	1.4554	-2.6366*	1.4362	-1.2832	1.3288
$\theta_{1,z}$	0.0566	0.9128	0.9126	0.9509	-0.6905	1.2012	-1.1590	1.4900	-0.5883	1.6027	-0.1583	1.1118
LL	1061.7850		1062.5811		1061.8492		1064.0556		1063.4962		1062.2594	
BIC	-16.8156		-16.8287		-16.8267		-16.8529		-16.8437		-16.8234	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.20: ML-estimates for symmetrized Joe-Clayton copula I

	Supply side factor z						Demand side factor z					
	ESUP		NSUP		NHUS		CPI		GDP		S&P	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
	Mean dynamics											
$\beta_{HPI,0}$	0.0003	0.0027	-0.0001	0.0026	0.0001	0.0024	-0.0005	0.0024	-0.0001	0.0024	-0.0008	0.0025
$\beta_{HPI,1}$	0.9337***	0.0444	0.9282***	0.0456	0.9332***	0.0457	0.9368***	0.0436	0.9369***	0.0444	0.9391***	0.0440
$\beta_{HPI,2}$	0.0108	0.0501	0.0213	0.0488	0.0159	0.0460	0.0277	0.0449	0.0188	0.0454	0.0329	0.0493
$\beta_{DLQ,0}$	0.0032**	0.0014	0.0037**	0.0015	0.0044***	0.0013	0.0033**	0.0014	0.0036***	0.0013	0.0035**	0.0014
$\beta_{DLQ,1}$	-0.0798***	0.0253	-0.0842***	0.0274	-0.0954***	0.0251	-0.0798***	0.0256	-0.0806***	0.0246	-0.0808***	0.0247
$\beta_{DLQ,2}$	0.9520***	0.0258	0.9427***	0.0271	0.9343***	0.0226	0.9511***	0.0259	0.9456***	0.0243	0.9475***	0.0257
	Variance dynamics											
$\sigma_{HPI,1}$	0.0066***	0.0011	0.0067***	0.0011	0.0072***	0.0012	0.0066***	0.0011	0.0066***	0.0011	0.0066***	0.0011
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0025***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0081***	0.0014	0.0081***	0.0012	0.0083***	0.0016	0.0081***	0.0014	0.0080***	0.0013	0.0080***	0.0013
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0039***	0.0005	0.0041***	0.0006	0.0039***	0.0005	0.0038***	0.0006	0.0038***	0.0006	0.0038***	0.0006
	Dependence parameters											
$\lambda^+_{0,z}$	-2.6853	2.1551	-4.3713	4.0215	-4.2663	9.2375	-2.8895	2.4412	-2.9447	2.3110	-3.8857	5.7013
$\lambda^+_{1,z}$	-0.3952	2.5665	1.7362	2.1545	-0.5922	4.6293	-0.0192	1.6379	-0.0002	2.4255	1.5477	3.7417
$\lambda^-_{0,z}$	-2.9436	3.5160	-11.3721	18.0596	-4.6333**	2.2803	-2.9436	3.7271	-2.9446	2.9954	-2.9435	3.1247
$\lambda^-_{1,z}$	-0.0003	3.1146	-5.4702	8.0104	3.3920***	1.2084	-0.0002	2.4775	0.0015	3.3927	-0.0009	3.4426
LL	1058.9190		1060.3760		1062.2110		1059.0140		1059.0620		1059.0900	
BIC	-16.7687		-16.7926		-16.8226		-16.7702		-16.7710		-16.7715	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.21: ML-estimates for symmetrized Joe-Clayton copula II

	Interest rate z						Mortgage loan z					
	ARM		FRM		TB3		EMOR		HMOR		NMOR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
						Mean dynamics						
$\beta_{HPI,0}$	0.0006	0.0023	0.0002	0.0025	0.0002	0.0024	0.0005	0.0025	0.0001	0.0024	0.0004	0.0024
$\beta_{HPI,1}$	0.9318***	0.0417	0.9201***	0.0437	0.9312***	0.0439	0.9255***	0.0460	0.9283***	0.0449	0.9333***	0.0461
$\beta_{HPI,2}$	0.0060	0.0439	0.0169	0.0487	0.0149	0.0467	0.0078	0.0458	0.0166	0.0454	0.0085	0.0442
$\beta_{DLQ,0}$	0.0034**	0.0013	0.0039***	0.0014	0.0035**	0.0013	0.0034**	0.0014	0.0037***	0.0014	0.0034***	0.0013
$\beta_{DLQ,1}$	-0.0807***	0.0250	-0.0833***	0.0274	-0.0796***	0.0250	-0.0775***	0.0266	-0.0799***	0.0254	-0.0801***	0.0246
$\beta_{DLQ,2}$	0.9494***	0.0238	0.9403***	0.0250	0.9475***	0.0240	0.9475***	0.0258	0.9430***	0.0256	0.9483***	0.0232
						Variance dynamics						
$\sigma_{HPI,1}$	0.0067***	0.0012	0.0061***	0.0008	0.0066***	0.0011	0.0067***	0.0011	0.0067***	0.0011	0.0067***	0.0010
$\sigma_{HPI,2}$	0.0023***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0003	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0080***	0.0013	0.0084***	0.0013	0.0081***	0.0015	0.0081***	0.0013	0.0081***	0.0013	0.0080***	0.0013
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0020***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0039***	0.0005	0.0040***	0.0006	0.0039***	0.0006	0.0040***	0.0006	0.0040***	0.0006	0.0039***	0.0005
						Dependence parameters						
$\lambda^{+}_{0,z}$	-2.8143	2.2516	-5.6017	3.8809	-2.9457	2.3979	-2.2131	1.7798	-2.1735	1.6541	-2.5840	1.8822
$\lambda^{+}_{1,z}$	-0.0591	1.8956	3.0938	2.2022	0.0021	2.7549	0.9652	0.8219	0.7390	1.0553	0.8419	1.3526
$\lambda^{-}_{0,z}$	-13.5457	11.0058	-2.9444	3.0436	-2.9449	3.2086	-2.9536	3.8339	-2.9438	3.7870	-2.9455	3.3104
$\lambda^{-}_{1,z}$	5.5898	3.9761	0.0000	5.0319	0.0005	3.8285	-0.0084	4.1267	-0.0002	3.9597	-0.0010	3.2134
LL	1060.0000		1061.6320		1059.1480		1059.7750		1059.5540		1058.8770	
BIC	-16.7864		-16.8132		-16.7724		-16.7827		-16.7791		-16.7680	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.22: ML-estimates for t-copula I

	Supply side factor z						Demand side factor z					
	ESUP		NSUP		NHUS		CPI		GDP		S&P	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
						Mean dynamics						
$\beta_{HPI,0}$	-0.0007	0.0021	-0.0004	0.0024	0.0010	0.0017	0.0002	0.0022	0.0005	0.0024	0.0032*	0.0019
$\beta_{HPI,1}$	0.8790***	0.0390	0.9309***	0.0445	0.9021***	0.0369	0.9330***	0.0422	0.9356***	0.0438	0.9527***	0.0361
$\beta_{HPI,2}$	0.0523	0.0386	0.0266***	0.0435	0.0043	0.0311	0.0140	0.0399	0.0058	0.0446	-0.0662*	0.0323
$\beta_{DLQ,0}$	0.0051***	0.0010	0.0037***	0.0013	0.0037***	0.0009	0.0035***	0.0013	0.0037***	0.0012	0.0049***	0.0010
$\beta_{DLQ,1}$	-0.0951***	0.0195	-0.0757***	0.0271	-0.1065***	0.0202	-0.0734***	0.0245	-0.0742***	0.0239	-0.0990***	0.0180
$\beta_{DLQ,2}$	0.9186***	0.0189	0.9417***	0.0235	0.9523***	0.0163	0.9441***	0.0229	0.9402***	0.0214	0.9185***	0.0166
						Variance dynamics						
$\sigma_{HPI,1}$	0.0068***	0.0011	0.0066***	0.0011	0.0066***	0.0009	0.0065***	0.0010	0.0066***	0.0010	0.0074***	0.0011
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0024***	0.0002	0.0025***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0098***	0.0017	0.0076***	0.0012	0.0078***	0.0008	0.0078***	0.0012	0.0076***	0.0011	0.0081***	0.0010
$\sigma_{DLQ,1}$	0.0019***	0.0001	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0037***	0.0004	0.0037***	0.0004	0.0039***	0.0005	0.0038***	0.0005	0.0037***	0.0005	0.0035***	0.0004
						Dependence parameters						
$\eta_{0,z}$	8.4363***	0.5977	1.5053**	0.6178	2.7775*	1.4283	1.3655**	0.5529	1.5938*	0.8172	2.8251**	1.2600
$\eta_{1,z}$	5.7547***	0.4551	0.3153	0.6007	-2.3988***	0.8664	0.2897	0.3786	0.2964	0.4994	1.6978***	0.5089
$\rho_{0,z}$	-0.0749	0.1856	0.0379	0.2390	0.1159	0.2259	0.0544	0.2288	0.0533	0.2285	0.0592	0.2166
$\rho_{1,z}$	0.0543	0.2063	0.0115	0.2574	0.3069*	0.1859	-0.0427	0.2148	0.0095	0.2639	0.1432	0.2726
LL	1066.0954		1063.5994		1070.1081		1064.3262		1064.0866		1068.2061	
BIC	-16.8863		-16.8454		-16.9521		-16.8573		-16.8534		-16.9209	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.23: ML-estimates for t-copula II

	Interest rate z						Mortgage loan z					
	ARM		FRM		TB3		EMOR		HMOR		NMOR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
							Mean dynamics					
$\beta_{HPI,0}$	0.0001	0.0023	0.0007	0.0024	0.0001	0.0023	0.0007	0.0022	0.0008	0.0023	0.0005	0.0024
$\beta_{HPI,1}$	0.9313***	0.0433	0.8987***	0.0398	0.9326***	0.0431	0.9272***	0.0419	0.9269***	0.0416	0.9232***	0.0434
$\beta_{HPI,2}$	0.0167	0.0418	0.0156	0.0458	0.0150	0.0433	0.0023	0.0417	-0.0005	0.0434	0.0080	0.0446
$\beta_{DLQ,0}$	0.0036***	0.0012	0.0038***	0.0013	0.0037***	0.0012	0.0035***	0.0012	0.0035***	0.0012	0.0037***	0.0012
$\beta_{DLQ,1}$	-0.0742***	0.0248	-0.0885***	0.0252	-0.0756***	0.0245	-0.0717***	0.0242	-0.0716***	0.0243	-0.0799***	0.0240
$\beta_{DLQ,2}$	0.9422***	0.0222	0.9434***	0.0222	0.9414***	0.0219	0.9445***	0.0221	0.9457***	0.0220	0.9426***	0.0213
							Variance dynamics					
$\sigma_{HPI,1}$	0.0066***	0.0010	0.0057***	0.0006	0.0066***	0.0010	0.0064***	0.0010	0.0064***	0.0010	0.0063***	0.0010
$\sigma_{HPI,2}$	0.0024***	0.0003	0.0023***	0.0002	0.0024***	0.0003	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0076***	0.0012	0.0087***	0.0015	0.0076***	0.0012	0.0076***	0.0013	0.0077***	0.0014	0.0077***	0.0013
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0020***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0037***	0.0004	0.0038***	0.0005	0.0037***	0.0005	0.0037***	0.0005	0.0038***	0.0005	0.0037***	0.0005
							Dependence parameters					
$\eta_{0,z}$	1.4755**	0.6090	5.0577	3.1148	1.5786**	0.7385	1.7812*	1.0518	2.0095	1.5060	2.7629	2.1216
$\eta_{1,z}$	0.0446	0.4532	-2.9885*	1.6485	0.1647	0.5443	0.2392	1.3375	0.4095	1.6318	1.0837	1.3686
$\rho_{0,z}$	0.0542	0.2239	-0.0594	0.1925	0.0642	0.2239	0.1027	0.2166	0.1067	0.2141	0.0828	0.2100
$\rho_{1,z}$	-0.0151	0.2681	-0.0901	0.2511	0.0234	0.2652	0.3307	0.2507	0.3540	0.2168	0.1802	0.2543
LL	1063.5748		1065.6757		1063.6668		1064.5964		1064.9005		1064.5934	
BIC	-16.8450		-16.8794		-16.8465		-16.8617		-16.8667		-16.8617	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.24: Estimation results: multiple model

	Model specification			
	Representatives		Significant variables	
Coeff.	Estimate	SE	Estimate	SE
Mean dynamics				
$\beta_{HPI,0}$	0.0004	0.0023	0.0007	0.0024
$\beta_{HPI,1}$	0.9277***	0.0412	0.9006***	0.0425
$\beta_{HPI,2}$	0.0084	0.0436	0.0119	0.0460
$\beta_{DLQ,0}$	0.0043***	0.0011	0.0044***	0.0012
$\beta_{DLQ,1}$	-0.0954***	0.0205	-0.0743***	0.0244
$\beta_{DLQ,2}$	0.9354***	0.0196	0.9330***	0.0212
Variance dynamics				
$\sigma_{HPI,1}$	0.0070***	0.0012	0.0065***	0.0010
$\sigma_{HPI,2}$	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0086***	0.0017	0.0084***	0.0013
$\sigma_{DLQ,1}$	0.0018***	0.0001	0.0019***	0.0001
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0039***	0.0005
Dependence parameters				
λ_0	-9.9495*	5.7245	-6.4600	5.5093
$\lambda_{1,NHUS}$	5.0829*	2.6959	4.2948•	2.9497
$\lambda_{1,S\&P}$	-1.0263	1.9528		
$\lambda_{1,FRM}$	3.1280*	1.7737		
$\lambda_{1,EMOR}$	1.7788*	1.0549	4.6017•	3.4171
$\lambda_{1,HMOR}$			-5.1506•	3.9604
θ_0	-0.0221	1.0549	-0.3210	0.6417
LL	1070.9555		1066.6220	
BIC	-16.8872		-16.8556	

•, *, **, and *** denote statistical significance at the 20%, 10%, 5%, and 1% level, respectively.

Table 4.25: ML-estimates using S&P Case-Shiller home price index as dependent variable I

	Supply side factor z						Demand side factor z					
	ESUP		NSUP		NHUS		CPI		GDP		S&P	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Mean dynamics												
$\beta_{HPI,0}$	-0.0011	0.0023	-0.0010	0.0022	-0.0011	0.0023	-0.0012	0.0023	-0.0011	0.0023	-0.0009	0.0023
$\beta_{HPI,1}$	0.9484***	0.0294	0.9413***	0.0290	0.9478***	0.0292	0.9470***	0.0292	0.9462***	0.0292	0.9523***	0.0293
$\beta_{HPI,2}$	0.0421	0.0448	0.0424	0.0430	0.0415	0.0447	0.0437	0.0440	0.0423	0.0444	0.0341	0.0454
$\beta_{DLQ,0}$	0.0027**	0.0011	0.0027**	0.0011	0.0027**	0.0011	0.0027**	0.0012	0.0027**	0.0011	0.0029***	0.0011
$\beta_{DLQ,1}$	-0.0510***	0.0159	-0.0510***	0.0153	-0.0508***	0.0158	-0.0509***	0.0160	-0.0518***	0.0159	-0.0488***	0.0153
$\beta_{DLQ,2}$	0.9563***	0.0211	0.9557***	0.0206	0.9556***	0.0214	0.9557***	0.0218	0.9569***	0.0211	0.9513***	0.0212
Variance dynamics												
$\sigma_{HPI,1}$	0.0043***	0.0009	0.0044***	0.0010	0.0043***	0.0009	0.0043***	0.0009	0.0043***	0.0009	0.0043***	0.0009
$\sigma_{HPI,2}$	0.0125***	0.0040	0.0127***	0.0042	0.0125***	0.0039	0.0125***	0.0040	0.0126***	0.0040	0.0126***	0.0041
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0041***	0.0006	0.0040***	0.0006	0.0041***	0.0006	0.0040***	0.0006	0.0041***	0.0006	0.0041***	0.0006
Dependence parameters												
$\lambda_{0,z}$	-1.1251*	0.6039	-1.2045*	0.6440	-1.1307*	0.6030	-1.1593*	0.6623	-1.1085*	0.5830	-1.2096*	0.6800
$\lambda_{1,z}$	-0.0516	0.3633	0.3376	0.3747	0.0100	0.3256	0.0739	0.2818	-0.0628	0.3332	0.4799	0.4137
$\theta_{0,z}$	-1.8891	1.3055	-2.0141	1.3027	-1.8957	1.3248	-1.8835	1.3625	-1.9987	1.3068	-1.7875	1.2979
ν_{HPI}	3.1552***	0.9598	3.0720***	0.9321	3.1531***	0.9572	3.1354***	0.9673	3.1468***	0.9464	3.1183***	0.9433
ν_{DLQ}	9.9596	11.1273	9.5246	9.8382	9.8802	10.9020	9.6564	10.3395	10.0020	11.9440	9.7951	10.7531
LL	1052.1947		1052.8587		1052.1797		1052.2414		1052.2150		1053.1717	
BIC	-16.6584		-16.6693		-16.6582		-16.6592		-16.6588		-16.6745	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4.26: ML-estimates using S&P Case-Shiller home price index as dependent variable II

	Interest rate z						Mortgage loan z					
	ARM		FRM		TB3		EMOR		HMOR		NMOR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
							Mean dynamics					
$\beta_{HPI,0}$	-0.0013	0.0023	-0.0011	0.0023	-0.0012	0.0022	-0.0007	0.0023	-0.0008	0.0023	-0.0011	0.0023
$\beta_{HPI,1}$	0.9503***	0.0294	0.9490***	0.0288	0.9372***	0.0291	0.9428***	0.0288	0.9445***	0.0289	0.9484***	0.0292
$\beta_{HPI,2}$	0.0434	0.0440	0.0411	0.0443	0.0457	0.0433	0.0342	0.0450	0.0356	0.0451	0.0412	0.0441
$\beta_{DLQ,0}$	0.0026**	0.0011	0.0027**	0.0011	0.0026**	0.0011	0.0028**	0.0011	0.0027**	0.0011	0.0027**	0.0011
$\beta_{DLQ,1}$	-0.0520***	0.0161	-0.0527***	0.0164	-0.0511***	0.0163	-0.0478***	0.0146	-0.0477***	0.0148	-0.0507***	0.0159
$\beta_{DLQ,2}$	0.9584***	0.0209	0.9577***	0.0207	0.9594***	0.0216	0.9543***	0.0209	0.9547***	0.0210	0.9559***	0.0210
							Variance dynamics					
$\sigma_{HPI,1}$	0.0043***	0.0008	0.0043***	0.0008	0.0043***	0.0008	0.0044***	0.0010	0.0044***	0.0009	0.0043***	0.0009
$\sigma_{HPI,2}$	0.0122***	0.0036	0.0124***	0.0038	0.0123***	0.0037	0.0130***	0.0043	0.0130***	0.0043	0.0126***	0.0040
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0041***	0.0006	0.0041***	0.0006	0.0041***	0.0006	0.0041***	0.0006	0.0041***	0.0006	0.0041***	0.0006
							Dependence parameters					
$\lambda_{0,z}$	-1.0217*	0.5763	-1.1140*	0.6089	-0.9820*	0.5213	-1.1350*	0.6219	-1.1371*	0.6262	-1.1245*	0.6102
$\lambda_{1,z}$	-0.4071	0.3094	-0.3113	0.4082	-0.2962	0.2670	0.4307	0.2858	0.3740	0.2668	0.0735	0.3180
$\theta_{0,z}$	-2.1048	1.3504	-1.9559	1.3228	-2.3354*	1.3340	-2.1621*	1.2575	-2.0833	1.2842	-1.9060	1.3549
ν_{HPI}	3.2735***	1.0076	3.2092***	0.9794	3.1967***	0.9675	3.0585***	0.9105	3.0888***	0.9278	3.1494***	0.9573
ν_{DLQ}	11.8408	15.6975	9.9338	11.1969	9.8996	10.8779	11.2143	13.5011	11.3089	13.6923	10.1821	11.3961
LL	1052.8650		1052.3630		1052.6682		1053.4472		1053.1627		1052.1908	
BIC	-16.6694		-16.6612		-16.6662		-16.6790		-16.6743		-16.6584	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.27: ML-estimates using unexpected changes of DLQ as dependent variable I

	Supply side factor z						Demand side factor z					
	ESUP		NSUP		NHUS		CPI		GDP		S&P	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
						Mean dynamics						
$\beta_{HPI,0}$	0.0011*	0.0006	0.0010*	0.0006	0.0012**	0.0006	0.0010*	0.0006	0.0011*	0.0006	0.0010*	0.0006
$\beta_{HPI,1}$	0.9177***	0.0389	0.9145***	0.0360	0.8994***	0.0374	0.9185***	0.0407	0.9173***	0.0391	0.9158***	0.0380
$\beta_{HPI,2}$	0.1310	0.1286	0.1369	0.1299	0.0957	0.1298	0.1440	0.1262	0.1457	0.1319	0.1587	0.1305
$\beta_{DLQ,0}$	0.0007**	0.0003	0.0007**	0.0003	0.0008***	0.0003	0.0006**	0.0003	0.0006**	0.0003	0.0007**	0.0003
$\beta_{DLQ,1}$	-0.0710***	0.0216	-0.0715***	0.0227	-0.0863***	0.0209	-0.0680***	0.0217	-0.0685***	0.0217	-0.0696***	0.0214
$\beta_{DLQ,2}$	0.0787	0.0984	0.0642	0.1006	0.0196	0.0894	0.0743	0.0971	0.0784	0.1002	0.0821	0.0951
						Variance dynamics						
$\sigma_{HPI,1}$	0.0065***	0.0010	0.0063***	0.0010	0.0064***	0.0011	0.0064***	0.0010	0.0064***	0.0010	0.0065***	0.0010
$\sigma_{HPI,2}$	0.0023***	0.0002	0.0024***	0.0002	0.0023***	0.0002	0.0023***	0.0002	0.0023***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0081***	0.0015	0.0075***	0.0010	0.0082***	0.0014	0.0081***	0.0015	0.0081***	0.0015	0.0078***	0.0012
$\sigma_{DLQ,1}$	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0002	0.0019***	0.0002
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0042***	0.0007	0.0041***	0.0006	0.0039***	0.0006	0.0039***	0.0006	0.0038***	0.0006
						Dependence parameters						
$\lambda_{0,z}$	-1.9171*	1.1646	-12.6475	13.9281	-6.2792	5.1240	-2.0069*	1.1972	-2.5916	1.9978	-1.8357	0.9488
$\lambda_{1,z}$	-0.5669	0.6834	-6.0259	5.9738	3.9360	3.3760	-0.2437	0.3945	0.0801	1.2997	0.6982	0.7638
θ_z	-0.9515	1.1819	-0.1094	0.5633	-0.2604	0.6218	-0.9195	1.1971	-0.4756	1.1565	-1.4295	1.1508
LL	1061.4149		1064.5497		1064.1490		1061.2683		1061.0178		1061.8821	
BIC	-16.8490		-16.9004		-16.8938		-16.8466		-16.8425		-16.8566	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

TABLE 4.28: ML-estimates using unexpected changes of DLQ as dependent variable II

	Interest rate z						Mortgage loan z					
	ARM		FRM		TB3		EMOR		HMOR		NMOR	
Coeff.	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
						Mean dynamics						
$\beta_{HPI,0}$	0.0010	0.0006	0.0013**	0.0006	0.0011*	0.0006	0.0011**	0.0006	0.0011*	0.0006	0.0009	0.0006
$\beta_{HPI,1}$	0.9223***	0.0401	0.9056***	0.0373	0.9152***	0.0390	0.9088***	0.0383	0.9120***	0.0384	0.9242***	0.0380
$\beta_{HPI,2}$	0.1788	0.1246	0.0325	0.1383	0.1445	0.1294	0.1582	0.1249	0.1668	0.1235	0.1667	0.1279
$\beta_{DLQ,0}$	0.0006**	0.0003	0.0007**	0.0003	0.0006**	0.0003	0.0006*	0.0003	0.0006*	0.0003	0.0006**	0.0003
$\beta_{DLQ,1}$	-0.0694***	0.0212	-0.0643***	0.0207	-0.0676***	0.0218	-0.0637***	0.0218	-0.0643***	0.0215	-0.0679***	0.0209
$\beta_{DLQ,2}$	0.0768	0.0966	0.0094	0.1133	0.0860	0.0982	0.0649	0.0936	0.0628	0.0942	0.0632	0.0971
						Variance dynamics						
$\sigma_{HPI,1}$	0.0066***	0.0011	0.0056***	0.0007	0.0064***	0.0010	0.0065***	0.0010	0.0066***	0.0010	0.0065***	0.0010
$\sigma_{HPI,2}$	0.0023***	0.0002	0.0024***	0.0002	0.0023***	0.0002	0.0024***	0.0002	0.0024***	0.0002	0.0024***	0.0002
$\sigma_{HPI,3}$	0.0080***	0.0014	0.0086***	0.0015	0.0081***	0.0014	0.0079***	0.0013	0.0079***	0.0013	0.0081***	0.0014
$\sigma_{DLQ,1}$	0.0019***	0.0002	0.0020***	0.0002	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001	0.0019***	0.0001
$\sigma_{DLQ,2}$	0.0039***	0.0006	0.0039***	0.0006	0.0039***	0.0006	0.0039***	0.0006	0.0039***	0.0006	0.0039***	0.0006
						Dependence parameters						
$\lambda_{0,z}$	-1.8345*	1.0115	-6.5280*	3.4564	-2.5110	2.0188	-1.5217*	0.7922	-1.4525*	0.7544	-2.2058*	1.2523
$\lambda_{1,z}$	-0.3464	0.6646	3.7273**	1.8666	0.4832	1.4666	0.6299	0.4273	0.5580	0.3789	0.8201	0.5779
θ_z	-1.1321	1.1916	-0.1548	0.6237	-0.6172	1.1346	-1.8180	1.2179	-1.8760	1.2495	-0.8584	1.0603
LL	1061.2316		1064.9409		1061.1855		1062.7263		1062.6292		1061.7392	
BIC	-16.8460		-16.9068		-16.8452		-16.8705		-16.8689		-16.8543	

*, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

References

Ackermann, J. (2008), 'The subprime crisis and its consequences', *Journal of Financial Stability* 4(4), 329–337.

Adams, Z. and Füss, R. (2010), 'Macroeconomic determinants of international housing markets', *Journal of Housing Economics* 19(1), 38–50.

Agnello, L. and Schuknecht, L. (2011), 'Booms and busts in housing markets: determinants and implications', *Journal of Housing Economics* 20(3), 171–190.

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

Beltratti, A. and Morana, C. (2010), 'International house prices and macroeconomic fluctuations', *Journal of Banking & Finance* 34(3), 533–545.

Bhardwaj, G. and Sengupta, R. (2012), 'Subprime mortgage design', *Journal of Banking & Finance* 36(5), 1503–1519.

Bianco, K. M. et al. (2008), *The subprime lending crisis: Causes and effects of the mortgage meltdown*, CCH, Wolters Kluwer Law & Business.

Coleman, M., LaCour-Little, M., and Vandell, K. D. (2008), 'Subprime lending and the housing bubble: Tail wags dog?', *Journal of Housing Economics* 17(4), 272–290.

Conefrey, T. and Whelan, K. (2013), 'Supply, demand and prices in the us housing market', *UCD Centre for Economic Research Working Paper Series* .

Daglish, T. (2009), 'What motivates a subprime borrower to default?', *Journal of Banking & Finance* 33(4), 681–693.

Danis, M. A. and Pennington-Cross, A. (2008), 'The delinquency of subprime mortgages', *Journal of Economics and Business* 60(1), 67–90.

Dell'Ariccia, G., Igan, D., and Laeven, L. U. (2012), 'Credit booms and lending standards: Evidence from the subprime mortgage market', *Journal of Money, Credit and Banking* 44(2-3), 367–384.

Demarta, S. and McNeil, A. J. (2005), "The t copula and related copulas", *International Statistical Review* 73(1), 111–129.

Demyanyk, Y. and Van Hemert, O. (2011), 'Understanding the subprime mortgage crisis', *Review of Financial Studies* 24(6), 1848–1880.

Favara, G. and Imbs, J. (2015), 'Credit supply and the price of housing', *American Economic Review* 105(3), 958–992.

GIMENO, R. AND MARTINEZ-CARRASCAL, C. (2010), 'The relationship between house prices and house purchase loans: The spanish case', *Journal of Banking & Finance* 34(8), 1849–1855.

GLAESER, E. L., GYOURKO, J., AND SAIZ, A. (2008), 'Housing supply and housing bubbles', *Journal of Urban Economics* 64(2), 198–217.

GOETZMANN, W. N., PENG, L., AND YEN, J. (2012), 'The subprime crisis and house price appreciation', *The Journal of Real Estate Finance and Economics* 44(1-2), 36–66.

GOODHART, C. AND HOFMANN, B. (2008), 'House prices, money, credit, and the macroeconomy', *Oxford Review of Economic Policy* 24(1), 180–205.

GUPTA, R. AND MAJUMDAR, A. (2015), 'Forecasting us real house price returns over 1831–2013: evidence from copula models', *Applied Economics* 47(48), 5204–5213.

HO, A. T., HUYNH, K. P., AND JACHO-CHÁVEZ, D. T. (2015), 'Flexible estimation of copulas: An application to the us housing crisis', *Journal of Applied Econometrics* 31(3), 603–610.

JAROCINSKI, M. AND SMETS, F. (2008), 'House prices and the stance of monetary policy', *Federal Reserve Bank of St. Louis Review* 90, 339–366.

JOE, H. (1997), *Multivariate Models and Dependence Concepts*, Chapman & Hall/CRC Monographs on Statistics & Applied Probability, Taylor & Francis.

JOHNSON, K. W. AND LI, G. (2014), 'Are adjustable-rate mortgage borrowers borrowing constrained?', *Real Estate Economics* 42(2), 457–471.

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

KAU, J. B., KEENAN, D. C., LYUBIMOV, C., AND SLAWSON, V. C. (2011), 'Subprime mortgage default', *Journal of Urban Economics* 70(2), 75–87.

KUTTNER, K. N. (2012), 'Low interest rates and housing bubbles: still no smoking gun', In: Evanoff, D.D. (Ed.), *The Role of Central Banks in Financial Stability: How Has It Changed*, World Scientific, pp 159–185, Ch. 8.

LI, D. X. (2000), 'On default correlation: A copula function approach', *The Journal of Fixed Income* 9(4), 43–54.

MAYER, C., PENCE, K., AND SHERLUND, S. M. (2009), 'The rise in mortgage defaults', *The Journal of Economic Perspectives* 23(1), 27–50.

MIAN, A. AND SUFI, A. (2009), 'The consequences of mortgage credit expansion: Evidence from the u.s. mortgage default crisis', *The Quarterly Journal of Economics* 124(4), 1449–1496.

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

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

POSEY, L. L. AND YAVAS, A. (2001), 'Adjustable and fixed rate mortgages as a screening mechanism for default risk', *Journal of Urban Economics* 49(1), 54–79.

SANDERS, A. (2008), 'The subprime crisis and its role in the financial crisis', *Journal of Housing Economics* 17(4), 254–261.

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

TAYLOR, J. B. (2007), 'Housing and monetary policy', Working Paper 13682, National Bureau of Economic Research.

ZIMMER, D. M. (2012), 'The role of copulas in the housing crisis', *Review of Economics and Statistics* 94(2), 607–620.

ZIMMER, D. M. (2015), 'Analyzing comovements in housing prices using vine copulas', *Economic Inquiry* 53(2), 1156–1169.

Concluding remarks

This cumulative dissertation consists of three individual essays which empirically examines the dependence structure in different financial markets. The focus is on the extreme asymmetric dependence, which is modeled using a conditional copula approach.

The first essay analyzes the time-varying relationship of equity and bond returns on the capital market. The investigation focuses on flight to quality, an effect in which investors reassess their risk preferences and shift their wealth to less risky asset classes. Examining macroeconomic factors in order to identify the driving variables, the results suggest the Treasury bill rate to be a key driver of flight to quality. Furthermore, the growth rates of the gross domestic product and personal consumption expenditures as well as the inflation rate significantly influence flight to quality.

The second essay analyzes the conditional dependence structure of freight rates and ship financing costs on the shipping market. The conditional asymmetric tail dependence is specified by the main drivers of supply and demand of seaborne transportation, the world fleet and the world economy. The results suggest that the crisis risk of decreasing freight rates and rising financing costs strongly increased already about one year before the actual crisis outburst in 2008 and that the shipping crisis was predominantly driven by an oversupply of transport capacity. Consequently, market participants could have prevented or alleviated the crisis' consequences by reducing the ordering and financing of new vessels.

The third essay analyzes the dependence structure of house prices and default rates on the US residential housing market by investigating their extreme dependence. Therefore, housing supply factors and economic factors as well as interest rates and mortgage loan-to-price ratios are examined as explaining variables. The results suggest that new housing units starts, the existing mortgage loan-to-price ratio as well as the home mortgage loan-to-price ratio can be used to quantify the default risk of mortgage credits for lenders.

Zusammenfassung

Diese kumulative Dissertation setzt sich aus drei Aufsätzen zusammen, die die Abhängigkeitsstruktur an unterschiedlichen Finanzmärkten empirisch untersuchen. Der Fokus liegt dabei in der Analyse der extremen asymmetrischen Abhängigkeit, welche mittels eines bedingten Copula-Ansatzes modelliert wird.

Der erste Aufsatz untersucht die zeitveränderliche Beziehung von Aktien- und Anleiherenditen am Kapitalmarkt. Im Fokus der Untersuchung steht dabei der sogenannte 'Flight-to-quality' Effekt, bei dem Anleger ihre Risikopräferenzen neu beurteilen und ihr Vermögen aus risikobehafteten Anlagen auf vermeintlich weniger riskante Anlageklassen verlagern. Bei der Analyse von makroökonomischen Faktoren, die als mögliche Treiber des Effektes in Frage kommen, zeigen die empirischen Resultate, dass die kurzfristige Zinsrate ein Schlüsselfaktor von 'Flight to quality' ist. Darüber hinaus beeinflussen die Wachstumsraten des Bruttoinlandsprodukts und der Konsumausgaben sowie die Inflationsrate die 'Flight to quality' erheblich.

Der zweite Aufsatz untersucht die bedingte Abhängigkeitsstruktur von Frachtraten und Schiffsfinanzierungskosten am Schifffahrtsmarkt. Die bedingte extreme asymmetrische Abhängigkeit wird mithilfe der Haupttreiber von Angebot und Nachfrage des Seetransportwesen, der Weltflotte und der Weltwirtschaft, quantifiziert. Die Ergebnisse zeigen, dass das Krisenrisiko von sinkenden Frachtraten und steigenden Finanzierungskosten bereits ein Jahr vor dem tatsächlichen Ausbruch der Krise am Schiffsmarkt 2008 stark angestiegen ist. Außerdem deuten die Ergebnisse darauf hin, dass die Schifffahrtskrise überwiegend von einem Überangebot an Transportkapazitäten getragen wurde. Somit hätten die Marktteilnehmer die Auswirkungen der Krise durch eine Verringerung bei Bestellung und Finanzierung neuer Schiffe verhindern oder abmildern können.

Der dritte Aufsatz untersucht die Abhängigkeitsstruktur von Hauspreisen und Ausfallquoten am amerikanischen Wohnimmobilienmarkt, indem ihre extreme Abhängigkeit analysiert wird. Als erklärende Variablen dienen dafür Angebotsfaktoren und ökonomische Faktoren sowie Zinssätze und verschiedene Verhältnisse von Hypothekendarlehenshöhe und Hauspreisen. Die Ergebnisse zeigen, dass die Anzahl neu begonnener Hauseinheiten, das Verhältnis aus Kredithöhe und Hauspreis für bereits bestehende Häuser sowie das aggregierte Verhältnis aus Kredithöhe und Hauspreis von bestehenden und neuzubauenden Häusern verwendet werden kann, um das Kreditausfallrisiko für Kreditgeber zu quantifizieren.

Liste der Veröffentlichungen

- Eine überarbeitete Version von Kapitel 2: „What drives flight to quality“ ist zur Veröffentlichung in der Fachzeitschrift *Accounting & Finance* akzeptiert. Die Studie ist seit dem 07. Dezember 2017 online veröffentlicht und abrufbar unter:
  http://onlinelibrary.wiley.com/wol1/doi/10.1111/acfi.12315/full.
  Die Publikation der Printversion ist ausstehend.

- Eine überarbeitete Version von Kapitel 3: „Measuring crisis risk using conditional copulas: An empirical analysis of the 2008 shipping crisis“ ist in der Fachzeitschrift *Journal of Applied Econometrics*, 2018, 33(2), 281–298, veröffentlicht. Die Studie ist abrufbar unter:
  http://onlinelibrary.wiley.com/wol1/doi/10.1002/jae.2609/full.