Fachbereich Wirtschaftswissenschaft

Exogenous Variables in Dynamic Conditional Correlation Models for Financial Markets

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List of Abbreviations

ADCC	Asymmetric Dynamic Conditional Correlation
AIC	Akaike Information Criterion
ARCH	Autoregressive Conditional Heteroskedasticity
BBG	Bloomberg
BC	Bureau of the Census
BEA	Bureau of Economic Analysis
BIC	Bayesian Information Criterion
BLS	Bureau of Labor Statistics
CAPM	Capital Asset Pricing Model
CCC	Constant Conditional Correlation
CET	Central European Time
DCC	Dynamic Conditional Correlation
DCCX	Dynamic Conditional Correlation with Exogenous Variables
DOL	Department of Labor
DSTCC	Double Smooth Transition Conditional Correlation
DSTCC-CARR	Double Smooth Transition Conditional Correlation with Conditional Auto Regressive Range
ECB	European Central Bank
EMU	European Monetary Union
ES	Eurostat
FED	Federal Reserve System
FLO	Federal Labour Office
FRB	Federal Reserve Board
GARCH	Generalized Autoregressive Conditional Heteroskedasticity

GDCCX	Generalized Dynamic Conditional Correlation with Exogenous Variables
GDP	Gross Domestic Product
GMVP	Global Minimum Variance Portfolio
HCPI	Harmonized Consumer Price Index
IFO	Ifo Institute
JPM	J.P. Morgan
LL	Log-Likelihood
LM	Lagrange Multiplier
MAE	Mean Absolute Error
ML	Bank of America Merrill Lynch
MVP	Minimum Variance Portfolio
PMI	Purchase Manager Index
STCC	Smooth Transition Conditional Correlation
US	United States
VIX	Chicago Board Options Exchange Volatility Index
VSTOXX	Euro Stoxx 50 Volatility Index

1 Introduction

Correlations between time series are important in various areas. For example, modern portfolio theory is based on the concept of diversification which in turn depends on the correlation of asset returns. Specifically, as a minimum requirement, an investor needs forecasts of the covariance matrix and expected returns to calculate optimal portfolio weights. In addition, the correlation of a security to the market is a crucial input for pricing models such as the capital asset pricing model (CAPM). Similarly, basket derivatives as well as structured products are sensitive to correlation changes. Risk management is another area in which correlations are essential. Risk figures such as the value at risk cannot be computed without an estimate of the covariance matrix. Moreover, if any security is hedged with a number of other securities, the calculation of the optimal hedge ratio depends on the correlation estimate.

Since correlations are not observable, they have to be estimated. The estimate for the unconditional sample correlation is easy to compute. If there are two assets with returns r_1 and r_2, then the unconditional correlation coefficient ρ is:

$$\rho = \frac{E\left(r_1, r_2\right)}{\sqrt{E\left(r_1^2\right) E\left(r_2^2\right)}} \tag{1.1}$$

Accordingly, using this formula, it is implicitly assumed that conditional variances and conditional correlations are constant over time. However, numerous studies have shown that these linkages are in fact time-varying (Longin and Solnik, 1995; Cappiello et al., 2006b; Aslanidis et al., 2010; Berben and Jansen, 2009; Cai et al., 2009; Goetzmann et al., 2008). Even testing for a change in correlations imposes several econometric challenges. Testing for a change in correlations by splitting a sample into sub-samples might suffer from a heteroscedasticity bias caused by rising volatility during crises (Forbes and Rigobon, 2002) and is subject to a selection bias (Boyer et al., 1999). Furthermore, Billio and Pelizzon (2003) show that the choice of the window length is crucial for the analysis.[1] Addressing this issue, Boyer et al. (1999) suggest to model the data generating process taking into account conditional correlations.

[1] Corsetti et al. (2005) provide an overview of these econometric issues.

This task can be fulfilled by correlation models. Starting with the Constant Conditional Correlation model (Bollerslev, 1990) and the Dynamic Conditional Correlation model (Engle, 2002), several correlation models and extensions have been proposed in the literature. Since conditional correlation models explain the evolution of correlations over time, they can be compared to Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models that describe the dynamics of conditional variances. As such, most models are based exclusively on time series properties.

Correlation models are also different from the copula approach, another popular method to model dependencies. The copula is an intrinsically static concept that allows for a rather flexible merging of univariate marginals to a joint probability distribution and therefore allows to model rather general dependency structures. Hence, it also calls for more complex dependency measures as compared to the (linear) correlation coefficient 1.1. Moreover, empirical applications of the copula approach to more than two assets typically require severe restrictions on the functional form of the copula, limiting the potential flexibility of the approach.[2]

Yet, the influence of exogenous variables such as economic indicators on correlations has largely been ignored in the literature. Nevertheless, economic variables have the potential to simultaneously influence several time series, thereby driving conditional correlations. Moreover, using regression analysis, some studies already demonstrate that economic conditions can alter conditional correlations (Quinn and Voth, 2008; Andersson et al., 2008; Li, 2002). In addition, it is established that economic variables help explaining the conditional mean (Guidolin and Timmermann, 2008; Aït-Sahalia and Brandt, 2001) and the conditional volatility (Engle and Rangel, 2008; Engle et al., 2009; Whitelaw, 1994) of asset returns.

Several areas of empirical research might benefit from employing correlation models which allow for the influence of exogenous variables. For example, there is an ongoing debate on the existence of contagion among stock market returns and its potential triggers. Since many studies define contagion as a change in conditional correlations (King and Wadhwani, 1990; Forbes and Rigobon, 2002; Corsetti et al., 2005), correlation models with exogenous variables could be employed to identify contagion and its causes. Another line of research focuses on the benefits of international diversification

[2]For a survey on copulas see for instance Joe (1997) or Embrechts et al. (2002). Recently, dependency measurement and theoretical as well as empirical issues of the copula approach have been coherently discussed by Yener (2012).

(e.g. Solnik et al., 1996; Longin and Solnik, 1995, 2001; Goetzmann et al., 2008) and asset-allocation (e.g. Ang and Bekaert, 2002; d'Addona and Kind, 2006; Guidolin and Timmermann, 2008). In this line of research, it is interesting to see why correlations between markets change. Similarly, quite a few studies focus on the convergence in the Eurozone (Cappiello et al., 2006b; Berben and Jansen, 2005) and search for drivers that explain increasing correlations among Eurozone markets.

Against this background, this dissertation presents a thorough, in-depth analysis of conditional correlations models which incorporate exogenous variables. The strength and weaknesses of the models are discussed in order to suggest which model to use for a certain research purpose. Furthermore, the models are employed in several empirical applications.

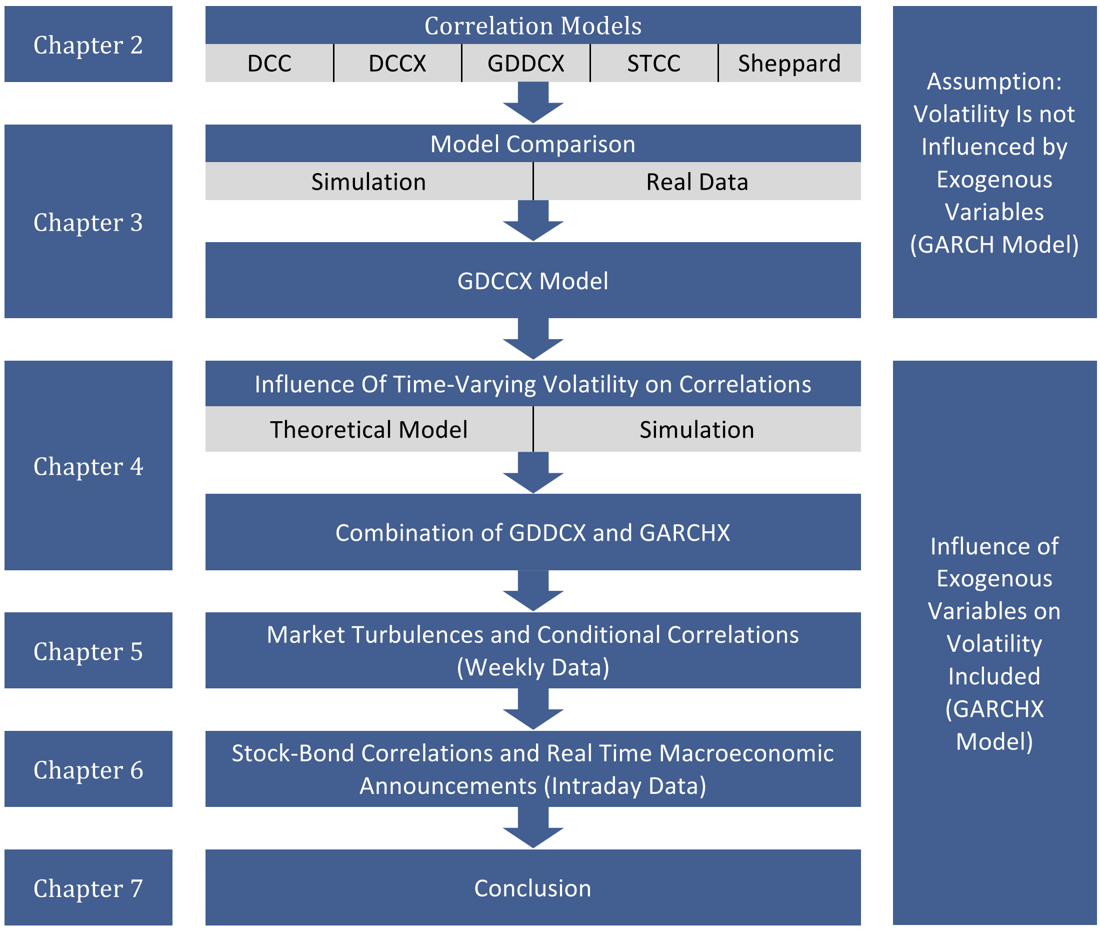


Figure 1.1: Dissertation Outline

The outline of the dissertation is illustrated in Figure 1.1. In chapter 2, the correlation models are discussed in depth. The Dynamic Conditional Correlation (DCC) Model proposed by Engle (2002) is taken as a starting point since this model is used frequently in practice and academic research. The model is based on the assumption that the conditional correlations are a weighted average of past innovations, the long term average, and recent conditional correlations. However, the effect of exogenous variables is ignored. Vargas (2008) extends the DCC model to incorporate the influence of exogenous variables and introduces the Dynamic Conditional Correlation with Exogenous Variables (DCCX) model. Yet, this model implicitly assumes that all conditional correlations within a correlation matrix are equally affected by the exogenous variable. However, this assumption becomes highly inappropriate if many assets are included. This thesis contributes to the literature of conditional correlation models by relaxing this assumption and introduces the generalized DCCX (GDDCX) model. An additional feature of this model is the possibility to separate the effect of the exogenous variable on conditional correlations from the influence on conditional variances.

Two additional approaches to exogenous variables are discussed in chapter 2. The Smooth Transition Conditional Correlation (STCC) model proposed by Silvennoinen and Teräsvirta (2005) postulates that conditional correlations vary between two regimes driven by an exogenous variable. The Sheppard (2008) model pursuits another approach: it assumes that the symmetric square root of the covariance matrix is a function of exogenous variables. A simulation study in which the finite sample properties of all estimators are investigated completes chapter 2.

Chapter 3 compares the correlation models previously presented to each other. Two different approaches are chosen. First, a simulation experiment is conducted. Conditional correlations of a known correlation structure are estimated employing all models. Subsequently, the mean absolute error is calculated to compare the models. Second, conditional correlations are estimated using real bond market data. To determine which model works best, the statistic and economic criteria proposed by Engle and Colacito (2006) are employed. The results indicate that the GDCCX model exploits the information of the exogenous variable best compared to other models in the simulation study. Additionally, it performs well according to the statistic and economic criteria. By contrast, the STCC and the Sheppard model are outperformed by all DCC models in almost all settings. The use of the GDCCX model is highly advantageous if many time series and several exogenous variables are included simultaneously in an analysis.

The more heterogeneous the respective conditional correlations respond to the exogenous variable, the more rewarding it is to use the GDCCX model. As a result, the GDCCX model is the focus of the analysis in chapters 4 to 6.

In line with previous studies (Engle and Sheppard, 2008; Berben and Jansen, 2009; Bauer, 2011), the models investigated in chapter 2 and 3 assume that conditional variance can be best explained using a GARCH model. Thus, the effect of exogenous variables on volatility is ignored. However, recent studies find that this assumption might not be appropriate (Engle et al., 2009; Çakmakli and van Dijk, 2010; Christiansen et al., 2011). In the first part of chapter 4, a theoretical model of Forbes and Rigobon (2002) is presented which shows that, given certain conditions, a change in conditional variances results in changing conditional correlations despite the dependence structure being left unchanged. This issue is further investigated in a Monte Carlo simulation. Specifically, it is simulated that conditional variances are driven by an exogenous variable but this variable has no effect on conditional correlations. Then, ignoring the effect of the exogenous variable on conditional variances, it is examined whether the models incorrectly identify that exogenous variable drives conditional correlations. A GARCH model for the variance equation and a GDDCX model to estimate conditional correlations is employed. The results indicate that in certain cases, it is incorrectly postulated that there is an effect of the exogenous variable on conditional correlations. However, in a subsequent simulation, all parameter estimates are accurate if the effect of the exogenous variable on conditional variances is modeled. For this purpose, a GARCHX model (Hwang and Satchell, 2005; Brenner et al., 1996; Engle and Patton, 2001) is employed instead of the GARCH model used previously. As a result, in chapters 5 and 6, the GARCHX model is employed in order to estimate conditional variances and model conditional correlations with the GDCCX model.

Chapter 5 and 6 focus on empirical applications. As correlations between different asset-classes are central in both portfolio management and risk management, this dissertation examines the correlations between the most important asset classes in chapter 6: stocks and bonds. However, correlations within different bond or stock sectors are equally important. Therefore, chapter 5 investigates the determinants of conditional correlations between European bond markets as well as conditional correlations between European stock markets. The sample period covers both calm and turmoil market times. It is especially interesting whether correlations are influenced by either risk aversion, market turbulences, or the business cycle. Employing a GDCCX model and estimating conditional variances with a GARCHX model, the results indicate that both the business cycle and market turbulences drive conditional correlations. However, risk aversion has almost no effect on correlations. Moreover, it is shown that investigating several exogenous variables simultaneously is advantageous.

In chapter 6, high-frequency stock-bond correlations in the Eurozone are examined. Employing intra-day data allows to investigate the effect of macroeconomic announcements in addition to exogenous variables previously used. The results show that both risk aversion and macroeconomic announcements separately drive conditional correlations and variances of bonds and stocks in the Eurozone. Conditional correlations fall as risk aversion rises even when controlling for the influence of macroeconomic announcements and the influence of these variables on volatility. Comparing the effects of Eurozone and US announcements, the most important announcements in the US are news on nonfarm payroll employments while, in Europe, the announcement of the ECB rates receives most attention.

2 Correlation Models

2.1 Introduction

As argued in the general introduction getting correct correlation estimates is important but difficult since correlations are not observable. In addition, they are time-varying. Therefore, several correlation models have been proposed in the literature, that allow to estimate the conditional covariance matrix. Examples are the Constant Conditional Correlation (CCC) model of Bollerslev (1990) or the Dynamic Conditional Correlation (DCC) model of Engle (2002).[1] Several extensions to the DCC model have been developed either to account for asymmetries in the correlation dynamics (Cappiello et al., 2006a; Audrino and Trojani, 2007) or to better capture dynamics for a large number of assets (Franses and Hafner, 2003).[2]

However, these models are based exclusively on the time series properties. The influence of economic variables such as macroeconomic indicators on correlations has largely been ignored in the literature although these variables have the potential to simultaneously influence several time series. Yet, including exogenous variables imposes additional difficulties in the estimation procedure: Additional parameters must be estimated and it must be guaranteed that the conditional covariance matrix is positive definite at any time.

Only recently some models, which were developed, include exogenous variables. Vargas (2008) extends the DCC model to allow for exogenous variables and introduces the DCCX model. However, the model restricts the exogenous variables to influence each of the conditional correlations by the same amount. This assumption becomes increasingly more conflicting with reality the greater the number of included time series. Therefore, we relax this assumption and propose a generalized DCCX (GDCCX) model which allows for a series specific impact of the economic variable on conditional correlations.

[1] Engle (2009), Bauwens et al. (2006), and Silvennoinen and Teräsvirta (2008) provide a comprehensive overview on various other correlation models.

[2] For an introduction to correlation models see Engle (2009). Model comparisons can be found in Bauer (2011), Engle and Sheppard (2008), and Engle and Colacito (2006).

Furthermore, we allow this exogenous variables to affect conditional covariances directly and not via the change in the conditional variances.

There are also some correlation models that include the effect of exogenous variables and which are not based on the DCC model. Silvennoinen and Teräsvirta (2005) introduce the Smooth Transition Conditional Correlation (STCC) model which features a transition variable that drives the correlation between two regimes. This model is already employed in recent empirical studies. Finally, Sheppard (2008) models the square root of the conditional covariance matrix as a function of one or more exogenous variables. In this model, parameters are not directly interpretable as each element of conditional covariance matrix is a function of several parameters and crossproducts of the explanatory variables. As a result, marginal effects of the exogenous variables must be calculated for a given sample point.

The STCC model as well as the DCC type models allow for any univariate GARCH model to be used to estimate the conditional variance. In addition, Engle and Sheppard (2008), Berben and Jansen (2009), and Bauer (2011) argue that the choice of the univariate GARCH model is of minor relevance. Following this argument, we assume throughout this chapter and in chapter 3, that all conditional variances follow a GARCH (1,1) process and that the exogenous variables do not influence conditional variances. We relax this assumption from chapter 4 onwards and discuss the consequences.

This chapter proceeds as follows. As the DCCX and the GDCCX models build heavily on the DCC model, we first introduce the DCC model. Thereafter, section 2.4 presents the various models with exogenous variables and develops the generalized DCCX model. We discuss the estimation of the models in section 2.5 and study the finite sample properties of all estimators in a small Monte Carlo simulation in section 2.6. Section 2.7 summarizes and concludes the chapter.

2.2 The DCC Model

In this section, we discuss the DCC model as introduced by Engle (2002) and some recent extensions.[3] The DCC model postulates the idea that conditional correlations follow a GARCH-type structure: Conditional correlations are influenced by past con-

[3]For surveys of multivariate GARCH models, see e.g. Bauwens et al. (2006), and Silvennoinen and Teräsvirta (2008).

ditional correlations, current standardized returns, and the long-term average of the conditional correlation. Hence, the model allows for correlation clustering, but correlations can also be mean reverting.

Specifically, let r_t denote an $n \times 1$ vector of N asset returns at time t which is assumed to be conditionally normal. Without loss of generality, it is furthermore assumed that

$$E\left(r_t|\mathbf{F}_{t-1}\right) = 0, \tag{2.1}$$

$$E\left(r_t r_t'|\mathbf{F}_{t-1}\right) = \mathbf{H}_t, \tag{2.2}$$

where $\mathbf{H}_t$ is an $n \times n$ matrix with time varying conditional covariances, and $\mathbf{F}_{t-1}$ denotes the information set at time $t-1$. Any covariance matrix is positive definite by definition so that $\mathbf{H}_t$ can further be decomposed as follows

$$\mathbf{H}_t = \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t. \tag{2.3}$$

$\mathbf{R}_t$ is the $n \times n$ time varying correlation matrix and $\mathbf{D}_t$ is an $n \times n$ diagonal matrix with the square root of the conditional variances on the diagonal i.e. $\mathbf{D}_t = \text{diag}\left(\sqrt{h_{1t}}, \cdots, \sqrt{h_{nt}}\right)$. To increase the flexibility, the conditional variances can be estimated by any univariate GARCH model.

The various conditional correlations models differ in the way they explain the evolution of $\mathbf{R}_t$. For example, the constant conditional correlation (CCC) model of Bollerslev (1990) assumes that $\mathbf{R}_t$ $\forall$ t is the constant sample correlation matrix. Thus, variations in the covariance between two assets can only result from changes in the assets' conditional standard deviations. This reduces the number of parameters to be estimated and alleviates the estimation process. However, the assumption of constant conditional correlations is often too restrictive in empirical applications.

Relaxing the assumption of constant conditional correlations, Engle (2002) introduces the dynamic conditional correlation (DCC) model in which the correlations evolve according to:[4]

$$\mathbf{R}_t = \mathbf{Q}_t^{*-1}\,\mathbf{Q}_t\,\mathbf{Q}_t^{*-1}. \tag{2.4}$$

[4] A similar model was proposed by Tse and Tsui (2002). For differences between the models please see Bauwens et al. (2006) and Engle (2009).

$\mathbf{Q}_t^*$ is a diagonal matrix that contains the square roots of the diagonal elements of $\mathbf{Q}_t$. Hence, the conditional correlation between time series i and j at time t is $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$, where $q_{ij,t}$ is the i,j$^{\text{th}}$ entry of $\mathbf{Q}_t$. $\mathbf{Q}_t$ is a $n \times n$ matrix and is defined as follows:

$$\mathbf{Q}_t = \overline{\mathbf{Q}}\,(1 - a - b) + a\,\epsilon_{t-1}\epsilon'_{t-1} + b\,\mathbf{Q}_{t-1}, \tag{2.5}$$

where a and b are non-negative scalar parameters and ϵ_t is a $n \times 1$ vector with standardized residuals $\left(\epsilon_t = r_{it}/\sqrt{h_{ijt}}\right)$. $\overline{\mathbf{Q}}$ is the unconditional covariance matrix of the standardized residuals. Equation 2.5 depicts $\mathbf{Q}_t$ as a weighted average of the unconditional covariance matrix, current standardized returns, and its own past realizations.

The DCC model has several attractive features. First, similar to the CCC model it allows for a two-step estimation of the volatility and the correlation equation. For this procedure, Engle and Sheppard (2001) establish the asymptotic consistency and normality of the estimated parameters. Second, by replacing $\overline{\mathbf{Q}}$ with the sample covariance matrix of the standardized residuals, the long run correlation matrix will be equal to the sample correlation matrix. Hence, only a and b have to be estimated in the second step. Third, the resulting correlation matrices are guaranteed to be positive definite as long as $\mathbf{Q}_t$ is positive definite, a suitable starting point is chosen, and $a + b < 1$.

As suggested by Cappiello et al. (2006a) the half-life of the innovations can be approximated by: $\ln(0.5)/\ln(a^2 + b^2)$. The half-life is the expected period of time it takes until the influence of any correlation innovation has decreased by half.

The DCC model is widely used in empirical research. For example, Engle and Colacito (2006) show that DCC models can be applied for asset allocation decisions between stocks and bonds, Cappiello et al. (2006b) assess the integration of European bond and stock markets, Bali and Engle (2010) augment a capital asset pricing model with estimated correlations, and Chiang et al. (2007) document contagion among stock markets in Asia. Moreover, the DCC model is applied to currencies (van Dijk et al., 2005) and non-financial time series such as macroeconomic data (Lee, 2006).[5]

The parsimonious parameterization of the DCC model comes with some limitations. For example, it is assumed that all correlations are driven by the same dynamic pattern, which is hard to justify as the number of time series grows. Thus, Franses and

[5] See Engle (2009) for further references.

Hafner (2003) generalize the DCC model by replacing the common a with series specific a_i parameters. Another restriction imposed by the DCC model is that positive and negative shocks have symmetric effects on conditional correlations. Cappiello et al. (2006a) introduce the scalar asymmetric DCC (ADCC) model that allows conditional correlations to increase more when both returns are falling then when both are rising:[6]

$$\mathbf{Q}_t = \left(\overline{\mathbf{Q}} - a^2\overline{\mathbf{Q}} - b^2\overline{\mathbf{Q}} - g^2\overline{\mathbf{N}}\right) + a^2\epsilon_{t-1}\epsilon'_{t-1} + b^2\mathbf{Q}_{t-1} + g^2 n_{t-1}n'_{t-1}, \tag{2.6}$$

where $n_t = I\left[\epsilon_t < 0\right] \circ \epsilon_t$ and $I\left[\cdot\right]$ is a $n \times 1$ dummy variable that takes on the value one if $\epsilon_t < 0$. In addition, $\overline{\mathbf{N}} = T^{-1}\sum_{t=1}^{T} n_{t-1}n'_{t-1}$, and a, b, and g are scalar parameters.

A necessary condition for $\mathbf{Q}_t$ to be positive definite is that $g^2 n_{t-1}n'_{t-1} > 0$ which is guaranteed if $g^2 > 0$ and $n_{t-1}n'_{t-1} > 0$.[7] However, this restricts the model in a way that it only allows correlations to increase more when there is a negative shock on returns but not to increase less.

2.3 Tests for Constant Conditional Correlation

Before estimating conditional correlations, it is important to test the constant-correlation hypothesis. For this purpose, Bera and Kim (2002) test the constancy of the correlation parameter in the CCC model over time. Tse (2000) tests the null of constant correlations against an extended version of the constant correlation model. Similarly, Silvennoinen and Teräsvirta (2005) propose an Lagrange multiplier (LM) test of constant correlations against a STCC model alternative.

However, in this dissertation, we focus on the Engle and Sheppard (2001) correlation test as it is easy to implement and can be applied in settings where conditional cor-

[6] Cappiello et al. (2006a) also propose a generalized version of the ADCC model in which the parameters are allowed to vary for each correlation pair. However, this comes with the cost of additional parameters that have to be estimated.

[7] Cappiello et al. (2006a) show that a sufficient condition for $\mathbf{Q}_t$ to be positive definite is that the matrix in parentheses in equation 2.6 is positive semi-definite. This is guaranteed as long as $a^2 + b^2 + \delta g^2 < 1$ where δ is the maximum eigenvalue of $\left(\overline{\mathbf{Q}}^{-1/2}\,\overline{\mathbf{N}}\,\overline{\mathbf{Q}}^{-1/2}\right)$.

relations of several time series are examined simultaneously.[8] In this test, the null hypothesis of constant conditional correlations

$$H_0 : \mathbf{R}_t = \overline{\mathbf{R}} \; \forall \; t \tag{2.7}$$

is tested against the alternative

$$H_1 : vech(\mathbf{R_t}) = vech(\overline{\mathbf{R}}) + \beta_1 \, vech(\mathbf{R}_{t-1}) + \cdots + \beta_p \, vech(\mathbf{R}_{t-p}). \tag{2.8}$$

$\overline{\mathbf{R}}$ is the sample correlation matrix, $\mathbf{R}_t$ is the time-varying correlation matrix, and $vech$ is the half-vectorization operator. Engle and Sheppard (2001) show that H_0 implies that all coefficients of the vector autoregression

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \cdots + \beta_p Y_{t-p} + u_t \tag{2.9}$$

are equal to zero. Y_t is defined as follows: $Y_t = vech^u \left(z_t z_t' - I_N \right)$ where $vech^u$ is a modified half-vectorization operator that only includes the elements above the diagonal and $z_t = \overline{\mathbf{R}}^{-\frac{1}{2}} \; \overline{\mathbf{D}}_t^{-1} \; r_t$. The latter term is a vector of returns standardized with the estimated variances and with the symmetric square root decomposition of $\overline{\mathbf{R}}$. The test statistic $\frac{\hat{\beta}\mathbf{V}'\mathbf{V}\hat{\beta}'}{\sigma^2}$ has a limiting chi-squared distribution with $p + 1$ degrees of freedom where $\mathbf{V}$ is the $T \times (p + 1)$ matrix of regressors.[9]

2.4 Conditional Correlation Models with Exogenous Variables

2.4.1 The DCCX Model

Vargas (2008) extends the scalar ADCC model of Cappiello et al. (2006a) by allowing exogenous variables to drive correlations. The ADCCX model as described in equation 2.10 results.

$$\begin{aligned} \mathbf{Q}_t = &\left(\overline{\mathbf{Q}} - a^2\overline{\mathbf{Q}} - b^2\overline{\mathbf{Q}} - g^2\overline{\mathbf{N}} - \mathbf{K}c'\overline{x}\right) + a^2\epsilon_{t-1}\epsilon_{t-1}' + b^2\mathbf{Q}_{t-1} + \\ &g^2 n_{t-1}n_{t-1}' + \mathbf{K}c'x_{t-1}. \end{aligned} \tag{2.10}$$

[8] An implementation of this test can be found, for example, in the UCSD GARCH toolbox.

[9] I.e. $\mathbf{V} = [1, Y_{t-1}, Y_{t-2}, \cdots, Y_{t-p}]$.

x_t is a $p \times 1$ vector with p exogenous variables while $\overline{x} = T^{-1} \sum_{t=1}^{T} x_t$. c is a $p \times 1$ vector with p parameters that measure the impact of the exogenous variables on $\mathbf{Q}_t$. The model implies that all correlations are equally influenced by any exogenous variable. $\mathbf{K}$ is a $n \times n$ matrix which can either be an identity matrix or a matrix of ones. In the former case the exogenous variables are restricted to drive conditional variances ($q_{ii,t}$) only, in the latter case conditional correlations are influenced as well. Note that if g is zero, the model will reduce to the DCCX model and will not account for any asymmetries in the conditional correlations.

Engle and Sheppard (2001) show that a necessary and sufficient condition for the correlation matrix to be positive definite is that $\mathbf{Q}_t$ is positive definite. Since both the DCCX and the ADCCX do not ensure that $\mathbf{Q}_t$ is positive definite, Vargas proposes to bound c between 0 and 1. However, that fails to ensure positive definiteness of $\mathbf{Q}_t$ if the exogenous variables are negative. In addition, bounding c between 0 and 1 restricts the model to only allowing conditional correlations to increase (decrease) when the exogenous variables rise (fall). As there is no general condition which guarantees that $\mathbf{Q}_t$ is positive definite, we estimate the model using constrained maximum likelihood. The parameter space is restricted so that the smallest eigenvalue for any estimated $\mathbf{Q}_t$ is positive (see section 2.5 for more details).

2.4.2 The Generalized DCCX Model

The DCCX model restricts the exogenous variables to influence all correlations in an equal way. This assumption is unrealistic if the number of time series and the number of correlations to be estimated grows. Therefore, we propose to generalize the DCCX model (GDCCX model) in which the exogenous variables can influence all correlations separately:

$$\mathbf{Q}_t = \left(\overline{\mathbf{Q}} - a\,\overline{\mathbf{Q}} - b\,\overline{\mathbf{Q}} - \sum_{i=1}^{p} \mathbf{c}_i\,\overline{x_i} \right) + a\,\epsilon_{t-1}\epsilon_{t-1}' + b\,\mathbf{Q}_{t-1} + \sum_{i=1}^{p} \mathbf{c}_i\,x_{i,t-1}, \qquad (2.11)$$

where $x_1, x_2, \ldots, x_p$ represent the exogenous variables and $\overline{x}_i = T^{-1}\sum_{t=1}^{T} x_{i,t}$. $\mathbf{c}_i$ is a $n \times n$ parameter matrix with zeros on the diagonal.[10] The zeros on the diagonal ensure that the exogenous variables influence conditional covariances directly and not via the change in the conditional variances.[11] By definition, the conditional correlation is $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$ so that the exogenous variables drive conditional covariances, $q_{ij,t}$, in the numerator but not the conditional variances, $q_{ii,t}$.

Similar to the DCCX model, the generalized version does not ensure that the resulting correlation matrix is positive definite. To make parameter estimation feasible, again, a constrained maximum likelihood estimation is employed (see section 2.5 for more details) and we use the estimated DCCX values as starting values for the generalized version. While the number of parameters to be estimated rises from $3n + 2 + p$ for the DCCX model to $3n + 2 + p\frac{n(n-1)}{2}$, it is still more parsimonious then, e.g., the STCC model or the model proposed by Sheppard.

2.4.3 The STCC Model

A number of recent papers discuss conditional correlation models that allow the conditional correlations to switch between distinct values. For example, Pelletier (2006) assumes that an unobserved first-order Markov process drives the transition between different correlation regimes. A similar approach is proposed by Silvennoinen and Teräsvirta (2005). They introduce the smooth transition conditional correlation (STCC) model in which conditional correlations change between two correlation matrices $\mathbf{R}_1$ and $\mathbf{R}_2$ according to an observed exogenous variable:

$$\mathbf{R}_t = (1 - G_t)\,\mathbf{R}_1 + G_t\mathbf{R}_2, \tag{2.12}$$

[10]For example, for three time series and two exogenous variables that would be:

$$\sum_{i=1}^{p}\mathbf{c}_i\, x_{i,t-1} = \begin{bmatrix} 0 & c_{121} & c_{131} \\ c_{121} & 0 & c_{231} \\ c_{131} & c_{231} & 0 \end{bmatrix} x_{1,t-1} + \begin{bmatrix} 0 & c_{122} & c_{132} \\ c_{122} & 0 & c_{232} \\ c_{132} & c_{232} & 0 \end{bmatrix} x_{2,t-1}$$

[11]In the empirical analysis we found that restricting the parameters on the diagonal to be zero does not alter other results. Furthermore, the model is more parsimonious.

where G_t is the transition function which is bounded between zero and one. The elements of $\mathbf{R}_1$ and $\mathbf{R}_2$ are parameters of the model. Although $\mathbf{G}_t$ can be any transition function, most authors use the logistic function:

$$G_t = \left(1 + e^{-\gamma(s_t - c)}\right)^{-1},\ \gamma > 0, \tag{2.13}$$

where s_t is the transition variable, γ determines the speed of the transition, and c is the midpoint of the transition, i.e. the value of the transition variable for which G_t takes the value 0.5. It is furthermore assumed that the conditional variances follow an univariate GARCH process. In the special case $\mathbf{R}_t = \mathbf{R}_1\ \forall\, t$, the model reduces to the CCC model. Furthermore, as long as both $\mathbf{R}_1$ and $\mathbf{R}_2$ are positive semi-definite, the resulting conditional correlation matrices are guaranteed to be positive semi-definite. However, letting γ and c vary among correlations would possibly suspend this feature so that both parameters are restricted to be constant for all conditional correlations.

Although estimation using a two-step approach is possible, asymptotic consistency and normality of this estimator has not been established. Therefore, the parameters of the STCC model are either jointly estimated (Aslanidis et al., 2010; Berben and Jansen, 2005) or estimated iteratively by concentrating the likelihood.[12] However, the number of parameters to be estimated grows quickly with the number of time series. For example, using a univariate GARCH(1,1) process to model the variance, the model has $n^2 + 2n + 2$ parameters. Thus, estimation can be difficult due to numerical problems.

Silvennoinen and Teräsvirta (2005) point out that there is no change in the resulting estimated conditional correlations for γ values greater than 100. Therefore, they restrict γ to be smaller than 100. Furthermore, as shown in equation 2.13, they restrict γ to be greater than zero. We relax the latter restriction for two reasons. First, we find that it is not necessary for the model interpretation. If γ is less than zero, a value of s_t greater than c results in a transition of the conditional correlation matrix from $\mathbf{R}_2$ to $\mathbf{R}_1$. Second, the estimation performance improves substantially. Therefore, we restrict γ to values between -100 and 100. Furthermore, we replace s_t in equation 2.13 with s_{t-1} so that all estimations are based on the same information set in order to facilitate the comparison of the models.

[12] Silvennoinen and Teräsvirta (2005) propose to divide the parameters into three sets and iteratively maximize the log likelihood over one set of parameters while leaving the other sets of parameters constant. This procedure is repeated until the estimator converges.

As the STCC model only allows one exogenous variable to drive conditional correlations, Silvennoinen and Teräsvirta (2009) recently proposed an extension of the STCC model in which they introduce a second transition variable: the Double Smooth Transition Conditional Correlation (DSTCC) GARCH model. However, the additional flexibility due to the second exogenous variable has to be weighted against the number of parameters to be estimated which is $2n^2 + n + 4$.

The STCC model is employed in some recent empirical papers to model conditional correlations. For example, Silvennoinen and Teräsvirta (2005) explain correlations of up to five single US stocks with lagged realized volatility. Other studies (Berben and Jansen, 2005; Aslanidis et al., 2010; Savva and Aslanidis, 2010) investigate comovements among equity markets in order to assess the degree of integration. These papers use time as transition variable which implies a gradual change of one correlation regime to another but restricts the correlation to move in only one direction. Aslanidis et al. (2010) employ a DSTCC model and take US stock market volatility as the second transition variable. Yang et al. (2009) document that macroeconomic variables drive the correlations between stocks and bonds.

2.4.4 The Sheppard Model

Another model which allows for the inclusion of exogenous variables is presented by Sheppard (2008). He factorizes $\mathbf{H}_t$ using the spectral decomposition. That is the factorization of a symmetric positive definite matrix $\mathbf{A}$ into $\mathbf{A} = \mathbf{V}\boldsymbol{\Lambda}\mathbf{V}'$ where $\boldsymbol{\Lambda}$ is the diagonal matrix of eigenvalues. The corresponding eigenvectors form the columns of a matrix $\mathbf{V}$. The matrix $\mathbf{A}$ can further be decomposed to:

$$\mathbf{A} = \mathbf{V}\boldsymbol{\Lambda}^{1/2}\,\boldsymbol{\Lambda}^{1/2}\mathbf{V}', \tag{2.14}$$

where $\boldsymbol{\Lambda}^{1/2}$ is the symmetric square-root of the matrix $\mathbf{A}$. Sheppard assumes that the symmetric square-root of the conditional covariance matrix is a linear function of one or more exogenous variables:

$$\mathbf{H}_{t+1} \quad = \mathbf{B}\left(\mathbf{I}_n \otimes \mathbf{x}_t\right)\left(\mathbf{I}_n \otimes \mathbf{x}_t'\right)\mathbf{B}', \tag{2.15}$$

and

$$\sqrt{\mathbf{H}_{t+1}} \quad = \quad \mathbf{B}\left(\mathbf{I}_n \otimes \mathbf{x}_t\right), \tag{2.16}$$

where $\mathbf{x}_t$ is a $p \times 1$ vector with p exogenous variables and $\mathbf{I}_n$ is a $n \times n$ identity matrix where n is the number of time series. $\mathbf{B}$ is a block symmetric $n \times np$ parameter matrix and consists of n^2 blocks so that there are in total $n(n+1)/2$ different blocks. Each block is a $1 \times p$ vector. For example, for 3 time series and 2 exogenous variables, the square-root of the conditional covariance matrix is:

$$\sqrt{\mathbf{H}_{t+1}} \quad = \quad \begin{bmatrix} b_{111}x_{1t} + b_{112}x_{2t} & b_{121}x_{1t} + b_{122}x_{2t} & b_{131}x_{1t} + b_{132}x_{2t} \\ b_{121}x_{1t} + b_{122}x_{2t} & b_{221}x_{1t} + b_{222}x_{2t} & b_{231}x_{1t} + b_{232}x_{2t} \\ b_{131}x_{1t} + b_{132}x_{2t} & b_{231}x_{1t} + b_{232}x_{2t} & b_{331}x_{1t} + b_{332}x_{2t} \end{bmatrix}$$

where b_{ijq} are the sensitivity parameters that measure the influence of each exogenous variable $q = 1, \cdots, p$ on each distinct element of $\sqrt{\mathbf{H}_{t+1}}$. In contrast, each element of $\mathbf{H}_{t+1}$ is a function of several parameters and cross-products of the explanatory variables, which can be seen by rearranging equation 2.15:

$$\mathbf{H}_{t+1} = \mathbf{B}\left(\mathbf{I}_n \otimes \mathbf{x}_t\mathbf{x}_t'\right)\mathbf{B}'. \tag{2.17}$$

As a result, the parameters b_{ijq} are not directly interpretable. However, the average partial effect of each exogenous variable on each element of the conditional covariance matrix can be calculated. This is simply the first derivative of $\mathbf{R}_t$ with respect to each exogenous variable. It is also possible to test for the influence of each exogenous variable on each element of the covariance matrix by applying a Wald test.

The model described by equation 2.17 restricts the correlations to be constant in case of only one exogenous variable. The reason is that the exogenous variable influences both conditional variances and covariances in a similar way so that the effect of the exogenous variables simply cancels out.[13] Therefore, Sheppard proposes to augment

[13] From equation 2.16 it can be derived that $h_{ij,t} = \left(\sum_{k=1}^{n} b_{ik} \otimes b_{jk}\right)\left(x_t \otimes x_t\right)$ where b_{ik} and b_{kj} are $p \times 1$ parameter blocks from $\mathbf{B}$. In case that there is only one exogenous variable x_t is a scalar and $\left(x_t \otimes x_t\right) = x_t^2$. Using $\rho_{ij} = \frac{h_{ij}}{\sqrt{h_{ii}}\sqrt{h_{jj}}}$ gives $\rho_{ij,t} = \frac{\left(\sum_{k=1}^{n} b_{ik} \otimes b_{jk}\right) x_t^2}{\sqrt{\left(\sum_{k=1}^{n} b_{ik} \otimes b_{ik}\right) x_t^2}\sqrt{\left(\sum_{k=1}^{n} b_{jk} \otimes b_{jk}\right) x_t^2}}$ where x_t^2 cancel out so that $\rho_{ijt} = \frac{\left(\sum_{k=1}^{n} b_{ik} \otimes b_{jk}\right)}{\sqrt{\left(\sum_{k=1}^{n} b_{ik} \otimes b_{ik}\right)}\sqrt{\left(\sum_{k=1}^{n} b_{jk} \otimes b_{jk}\right)}}$.

the model in equation 2.17 into a simple multivariate ARCH framework where lagged return cross-products are also included:

$$\mathbf{H}_{t+1} = \mathbf{B}\left(\mathbf{I}_n \otimes \mathbf{x}_t \mathbf{x}_t'\right)\mathbf{B}' + \mathbf{A} \circ \mathbf{RC}_t, \tag{2.18}$$

where $\mathbf{A}$ is a symmetric positive semi-definite $n \times n$ matrix with parameters and $\mathbf{RC}_t$ is a $n \times n$ matrix with lagged return cross-products: $\mathbf{RC}_t = \sum_{d=1}^{t} r_d r_d'$. Due to the influence of the lagged return cross-products the correlation is now varying even when there is only one exogenous variable. Another possibility is to include a constant so that the number of exogenous variables is always greater one. In addition, as long as a constant is included, the model guarantees that $\mathbf{H}_{t+1}$ is positive definite even though there are no constraints on the parameter space which greatly alleviates the estimation process. Therefore, we also include a constant in all estimations. However, estimation can be time consuming as the number of parameters in equation 2.18 is $\frac{(n^2+n)(p+1)}{2}$ where p is the number of exogenous variables including a constant.

2.5 Model Estimation

In line with the number of time series and exogenous variables the number of parameters to be estimated grows for the models. The model estimation is therefore very important. All models are estimated by maximum likelihood.[14] The sample log likelihood, LL, that is maximized with respect to all parameters is:[15]

$$\begin{aligned} LL &= -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + \log|\mathbf{H}_t| + r_t'\mathbf{H}_t^{-1}r_t\right); \\ &= -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log|\mathbf{D}_t| + \log|\mathbf{R}_t| + \epsilon_t'\mathbf{R}_t^{-1}\epsilon_t\right); \\ &= -\frac{1}{2}\sum_{t=1}^{T}\left(n\log(2\pi) + 2\log\sum_{i=1}^{n} h_{iit} + \log|\mathbf{R}_t| + \epsilon_t'\mathbf{R}_t^{-1}\epsilon_t\right). \end{aligned} \tag{2.19}$$

$|\mathbf{H}_t|$ denotes the determinant of the matrix $\mathbf{H}_t$. It is generally not necessary to assume that residuals are normally distributed since Bollerslev and Wooldridge (1992) show

[14] All computations are performed with Matlab. The code for the estimation of the GARCH and the DCC models was taken from the UCSD GARCH toolbox.

[15] Details can be found in Engle (2002), Engle and Sheppard (2001), or Sheppard (2008).

that maximizing 2.19 results in a consistent estimator in these cases. Thus, 2.19 has a quasi-maximum likelihood interpretation.

As proposed by Engle and Sheppard (2001) and Engle (2002), we estimate the DCC, the DCCX, and the GDCCX model in two steps in order to improve the numerical performance of the estimation routine. In the first step the variance part of 2.19 is maximized which is equivalent to estimating univariate GARCH models. In the second step the log likelihood function

$$LL_C = -\frac{1}{2}\sum_{t=1}^{T}\left(\log|\mathbf{R}_t| + \epsilon_t'\mathbf{R}_t^{-1}\epsilon_t\right) \tag{2.20}$$

is maximized conditioning on the parameters estimated in the first step, i.e. given the estimated standardized residuals. Engle and Sheppard (2001) show that this limited information estimator is consistent but not fully efficient. Therefore, we correct the standard errors to account for this loss in efficiency as suggested by Engle and Sheppard (2001) and Engle (2009).

Silvennoinen and Teräsvirta (2005) estimate the STCC model iteratively by concentrating the likelihood since the number of parameters is quite large. However, in order to increase efficiency and speed, we jointly estimate the conditional variances and correlations (Aslanidis et al., 2010).

In section 2.4 we argued that the DCCX models as well as the GDCCX model impose several linear and non-linear constraints on the parameter space. As suggested by de Goeij and Marquering (2004) and Chou and Liao (2008), we restrict the parameter space for these models so that the smallest eigenvalue of any estimated $\mathbf{R_t}$ is positive. As a result, we have an optimization problem with inequality constraints. We tested two optimization methods. First, as suggested by Greene (2008) and Hamilton (1994) it is possible to translate the constrained problem to an unconstrained one by imposing some sort of penalty function for constraints that are near or beyond the boundary. Yet, different penalty functions might lead to different solutions. Second, sequential quadratic programming methods can be applied which focus on the solution of the Karush-Kuhn-Tucker equations.[16] After running extensive simulations and tests with real data, we find that both methods yield equal estimates. However, using the penalty functions is preferable in terms of estimation speed.

[16]See Fletcher (2000) or Levy (2009) for introductions to constrained optimization.

A general drawback of estimating the models by constrained maximum likelihood is that it has to be assumed that both the true as well as the estimated parameters fall within the interior of the allowable parameter space. Otherwise asymptotic standard errors are not valid.[17] This is especially relevant for the STCC γ parameter. The parameter is restricted to values between -100 and +100. Therefore, if the γ estimate is on the boundary, similar to Silvennoinen and Teräsvirta (2005), we do not report standard errors for this parameter.

All models are estimated by quasi-maximum likelihood with robust standard errors (Bollerslev and Wooldridge, 1992). Hafner and Herwartz (2008) as well as Lucchetti (2002) argue that employing analytical derivatives instead of numerical scores is preferable for quasi-maximum likelihood estimation and inference if the number of model parameters is high. Therefore, we employ analytical derivatives for the estimation of both Sheppard's model and the STCC model.[18] We find that although the resulting parameter estimates remain unchanged, the speed of estimation improves remarkably.

2.6 A Simulation Study

In this section, we study the estimators discussed in section 2.4 in a simulation. Similar to Silvennoinen and Teräsvirta (2005) and Hafner and Herwartz (2008), we estimate parameters from samples with simulated correlated data and compare them to the true parameters for different sample sizes. For each model we create samples in which the true correlation evolves according to the pattern implied by the respective model.[19] That allows us to investigate the finite sample properties as well as the empirical performance of the estimators.

We generate 1000 samples with two normally distributed random time series for each estimator and for each sample size. We assume that the series exhibit time-varying volatility clustering and evolve according to a GARCH(1,1) model. The exogenous variable is a normally distributed random variable with unit variance. The generated conditional correlations between the two series evolve according to the correlation struc-

[17] See Hamilton (1994) for details. In addition, Schoenberg (1997) points out that in finite samples standard errors have to be corrected if the estimated parameters are in the region of the boundaries.

[18] All DCC models are estimated applying numerical derivatives since the optimization is less demanding for the optimizer due to the two-step estimation.

[19] We employ all models on the same sample in order to compare the model performance in chapter 3.

ture implied by the respective model. All correlation model parameters are randomly selected from the allowable parameter space whereas the values of the GARCH model are fix and are representative of typical financial time series. The selected GARCH parameters are as follows:

Series	ω_i	α_i	β_i
1	0.01	0.03	0.95
2	0.02	0.04	0.93

The sample sizes are 500, 1000, 2500, and 5000. To avoid any initialization effects, we simulate 1000 observations in addition to the target sample size and remove the first 1000 observations before estimating the models. For each model parameter, we calculate the 90% as well as the 95% confidence intervals. Also, we determine whether the confidence interval includes the true parameter. The empirical rejection frequency should approach the nominal level of the test as the sample size grows. Figure 2.1 reports the percentage of simulations in which the true parameter is not included in the 90% or the 95% confidence interval, respectively.

Rejection frequencies for the DCCX model are higher than the nominal level if the sample size is only 500 observations: 16.7% for the 10% and 10.1% for the 5% nominal level. However, this effect vanishes as the sample size grows. With 5000 observations the rejection frequencies are 11.4% and 6.1% and thus only slightly different from the nominal levels. Similar to the DCCX model, GDCCX rejection frequencies decline as the sample size grows. Yet, the differences between empirical rejection frequency and nominal level of the test is lower for all sample sizes. Therefore, the GDCCX model is better in case of smaller sample sizes such as 1000 observations.

The rejection frequencies for the STCC model parameters $\mathbf{R}_1$ and $\mathbf{R}_2$ are close to the nominal level for all sample sizes. By contrast, the rejection frequency for the γ parameter is declining as sample size grows but the rejection frequency is severely higher then the nominal level (14.5% and 9.9%, respectively) even if the sample size is 5000. This is not surprising as Silvennoinen and Teräsvirta (2005) show that changes in the γ parameters at the upper end of the allowable parameter space result only in minimal changes in the estimated conditional correlations which makes optimization very difficult. In addition, the γ parameter is bounded between -100 and 100. As pointed out by Schoenberg (1997), standard errors have to be corrected if the parameter

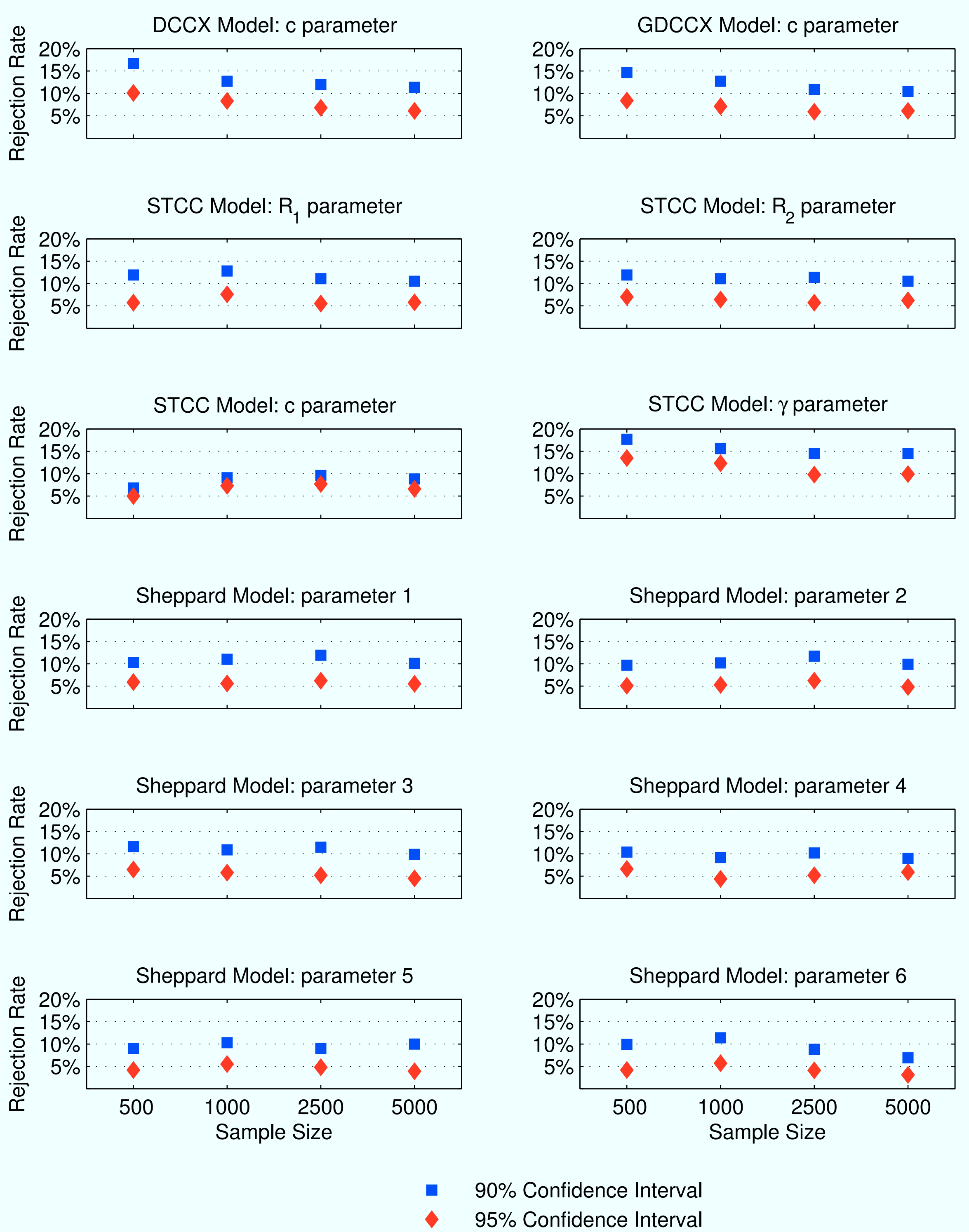


Figure 2.1: Empirical Rejection Frequencies for Different Parameters and Sample Sizes

estimate is on the boundary.[20] Rejection frequencies for the c parameter are lower but they rise as the sample size grows from 500 to 2500 observations. In addition, the rejections frequencies for the 90% confidence intervals are lower then expected. As the total number of parameters estimated is the highest for the STCC model, both the number of replications and the sample size might still be too low.

Finally, the sample size does not matter for the Sheppard model estimates. However, we find that some rejection frequencies are slightly lower or higher than the nominal level. Like the STCC model, different parameter settings for the Sheppard model might result in the same or very similar estimated conditional correlations.

We also compute the difference between the models' estimated and the true parameters. Table 2.1 reports the mean differences for all model parameters. Table 2.2 shows the standard deviations of the differences.

Table 2.1: Model Parameter Differences: Mean

Model	Parameter	Sample Size: 500	Sample Size: 1000	Sample Size: 2500	Sample Size: 5000
DCCX	c	0.000	−0.001	0.000	0.000
GDCCX	c	0.000	0.000	0.000	0.000
STCC	R_1	0.002	−0.002	−0.003	0.001
	R_2	−0.004	0.004	0.000	0.000
	γ	−22.047	−16.808	−11.735	−9.844
	c	−0.016	−0.015	0.014	−0.008
Sheppard	parameter 1	0.001	−0.003	0.000	−0.001
	parameter 2	0.004	0.001	0.000	0.000
	parameter 3	0.000	0.001	0.000	0.001
	parameter 4	−0.001	−0.001	0.000	0.000
	parameter 5	0.002	0.001	0.002	0.000
	parameter 6	−0.001	0.001	0.000	0.000

We find that the mean difference is close to zero for almost all models. The largest mean difference can be observed for the STCC model γ parameter highlighting the difficulties during the estimation of that parameter again. Yet, the differences become smaller as the sample size grows. In addition, the standard deviations of the differences decline for all parameters as the sample size is increased from 500 to 5000 observations. Notably, the smallest differences and the smallest standard deviations of the differences can be observed for the GDCCX and the DCCX model.

[20] We do not report standard errors for the γ parameter if the estimate is on the boundary.

Table 2.2: Model Parameter Differences: Standard Deviations

Model	Parameter	Sample Size: 500	Sample Size: 1000	Sample Size: 2500	Sample Size: 5000
DCCX	c	0.031	0.020	0.011	0.006
GDCCX	c	0.023	0.016	0.009	0.006
STCC	R_1	0.113	0.101	0.083	0.035
	R_2	0.120	0.098	0.078	0.055
	γ	33.869	33.454	30.381	27.485
	c	0.372	0.315	0.297	0.266
Sheppard	parameter 1	0.065	0.047	0.027	0.026
	parameter 2	0.035	0.021	0.014	0.011
	parameter 3	0.067	0.045	0.028	0.026
	parameter 4	0.062	0.038	0.036	0.015
	parameter 5	0.035	0.019	0.026	0.008
	parameter 6	0.064	0.041	0.036	0.015

These results are confirmed by our next test. We compute the mean absolute error of the conditional correlation estimates for all models and the same sample sizes as before. Table 2.3 displays the results. It turns out that mean absolute errors for all models decline as the sample size grows. In addition, the results indicate that the STCC model conditional correlation estimates are very close to the true estimates despite higher rejection frequencies as the mean absolute errors are the second lowest among the correlation models with exogenous variables. Interestingly, conditional correlations estimated by the Sheppard model are even closer to the true conditional correlations than the DCC model.

Table 2.3: Mean Absolute Error of Conditional Correlation Estimates

	Sample Size			
Model	500	1000	2500	5000
DCC	0.038	0.027	0.017	0.012
DCCX	0.049	0.033	0.021	0.015
GDCCX	0.048	0.036	0.022	0.016
STCC	0.045	0.026	0.017	0.012
Sheppard	0.023	0.016	0.010	0.007

2.7 Summary

In this chapter, we argue that it is useful to model conditional correlations. Furthermore, as conditional correlations between two time series might be influenced by exogenous variables, the effect of these variables should not be neglected by the correlation models. Therefore, we present several correlation models that incorporate the effect of one or several exogenous variables and propose the GDCCX model.

First, we explain the DCC model (Engle, 2002) that neglects the influence of exogenous variable but is the basis for two of the models. Conditional correlations are modeled similar as conditional volatilities are explained in a GARCH model: they are a weighted average of past innovations, the previous estimate and the long-term average correlation. As such, conditional correlations are a function of past time series properties, but the DCC model does not include the effect of exogenous variables. Thus, Vargas (2008) introduces the DCCX model in which conditional correlations evolve similar to the DCC model but are also driven by exogenous variables. As the model allows the exogenous variables to influence all conditional correlation in an equal way only, we propose the GDCCX model that relaxes that restriction. In addition, we modify the model to ensure that the exogenous variables influence conditional covariances directly and not via the change in the conditional variances. That also alleviates the interpretation of the coefficients and reduces the number of parameters to be estimated.

Thereafter, we explain the STCC model (Silvennoinen and Teräsvirta, 2005). It allows conditional correlations to switch between distinct values driven by only one exogenous variable. Finally, we present the Sheppard (2008) model. The symmetric square-root of the conditional covariance matrix is modeled as a function of one or more exogenous variables. Each element of the conditional covariance matrix is a function of several parameters and crossproducts of the explanatory variables. As a result, parameters are not directly interpretable but average marginal effects can be calculated.

Going forward, we discuss the model estimation. The DCC type models can be estimated using a two step estimation. As the DCCX and the GDCCX model do not guarantee that estimated conditional correlations are positive definite, we restrict the parameter space for these models so that the smallest eigenvalue of any estimated correlation matrix is positive.

In the last section, we compare the performance and the finite sample properties of all estimators in a Monte Carlo experiment. We find that the empirical rejection frequencies are close the nominal level of the the tests for all models. Moreover, the difference between the empirical rejection frequency and the nominal level diminishes as the sample size grows. Calculating the mean absolute error of the conditional correlation estimates further confirms the accuracy of the estimators.

3 Comparison of the Models

3.1 Introduction

In the previous chapter, we introduced conditional correlations models that allow exogenous variables to affect correlations and discussed the model properties. It remains yet to be established which model works best in different contexts. This is the focus of this chapter. We pursue two different approaches to comparing the models.

First, we test the models in a simulation study in which the true correlation structure is known but, as opposed to the experiment in the previous chapter, not implied by the models. In addition, the calculation of the mean absolute error allows us to generally assess the value of including exogenous variables in correlation models. Furthermore, we will establish how the models react to different correlation settings.

Our second approach is to apply the models to real data. Obviously, real correlations are not measurable and hence unknown. Comparing the models is, thus, not as straight forward as it was in the simulation study. Yet, both statistical and economic criteria can be employed. While statistical criteria such as information criteria are easy to calculate, they lack an economic basis. Therefore, several studies evaluate covariance estimates within an asset allocation framework (e.g. Fleming et al., 2001, 2003). An investor calculates optimal portfolio weights given a vector of expected returns and the estimated covariance matrix. However, using the realized portfolio return or the Sharpe ratio in order to compare models is critical as they depend on the correct specification of both expected returns and the covariance matrix.[1] Therefore, Engle and Colacito (2006) argue that correlation models can be ranked according to the variance of the mean variance optimal portfolio and develop a test statistic. We employ these criteria with datasets of daily returns as we have to assume that the conditional expected value of return is constant. We take bond returns from the Eurozone as well as from the US covering up to 20 years.

[1] Chopra and Ziemba (1993) point out that "errors in means are about ten times as important as errors in variances and covariances".

In addition to comparing the models, these datasets allows us to investigate on an interesting empirical question: Does risk aversion influence conditional correlations in different settings? Several studies demonstrate that growing risk aversion results in rising conditional correlations among international equity markets which in turn diminishes diversification benefits (Cappiello et al., 2006a; Solnik et al., 1996; Kasch-Haroutounian, 2005). Other authors analyze the conditional correlations between stock and bond returns and observe a flight-to-quality effect (Cappiello et al., 2006a; Andersson et al., 2008; Connolly et al., 2005; Kim et al., 2006; Baele et al., 2010; Aslanidis and Christiansen, 2010). Conditional correlations between bond returns have received less attention. Hunter and Simon (2005) use a bivariate conditional correlation GARCH model to show that rising risk aversion, as measured by the conditional volatility of US bond markets, results in lower conditional correlations among US, German and Japanese government bonds. Also, focusing on the volatility of European bond markets, Skintzi and Refenes (2006) as well as Christiansen (2007) find evidence of volatility spillovers from the US to European government bond markets.

Yet, the conditional correlation between different bond sectors, such as corporate bonds and government bonds, has been largely neglected in existing studies. This is remarkable as investors are currently trying to diversify supposedly risk free government bond portfolios into other sectors. An exception is the study of Brière et al. (2008). They find that during periods of financial turmoil conditional correlations between European bond sectors decrease. However, their analysis depends crucially on the correct identification of crisis periods (Boyer et al., 1999).

We examine the conditional correlation of bond sectors using two datasets: one for Europe and one for the US. We include government and corporate bonds. Corporate bonds are furthermore segmented into investment grade and high yield since returns of the higher quality bonds are mostly driven by interest rate risk whereas for high yield bonds default risk is most important. In line with prior research (Andersson et al., 2008; Connolly et al., 2005, 2007; Bali and Engle, 2010; Silvennoinen and Thorp, 2010; Kim et al., 2006), we employ the implied volatility of equity market options in order to capture the perceived risk aversion in the market.

In the next section, we compare the correlation models in a simulation study. Thereafter, we focus on testing the various correlation models with real data. Different testing criteria are explained in section 3.3.1. Section 3.3.2 describes the data and results are reported and discussed in section 3.3.3. Section 3.4 summarizes and concludes.

3.2 Comparing Models by Simulation

In this section, we compare the models discussed in section 2.4 in a Monte Carlo simulation. For ease of comparison, we follow Engle (2002) in the design of this experiment. Similar to the simulation in section 2.6, the correlation structure is known. However, in this section, the correlation structure is not implied by the respective models, but we assume that it follow the processes as illustrated in Figure 3.1.

That includes the assumptions that conditional correlation are constant (*Constant*) or that they evolve according to a sine waves with low and high frequency (*Sine* and *Fast Sine*). Moreover, we simulate that there is a single jump in correlations in the middle of the sample period (*Step*) or that there are multiple jumps with constant changes otherwise (*Ramp*).

Our study is based on 1000 observations that are simulated 200 times.[2] For each replication, we generate two normally distributed random time series that exhibit time varying variances according to a GARCH (1,1) model. The GARCH parameters are the same as in our previous simulation as displayed in section 2.6. We employ the true conditional correlations as exogenous variables. As this is a near perfect predictor, it should facilitate the estimation. We also include the DCC model in our simulation study in order to quantify the benefits of adding exogenous variables in a correlation model.

The models are assessed by comparing the estimated conditional correlations with the true conditional correlations. Therefore, we calculate the mean absolute error (MAE) as follows

$$MAE = \frac{1}{R}\frac{1}{T}\sum_{r=1}^{R}\sum_{t=1}^{T}|\hat{\rho}_{rt} - \rho_{rt}|, \quad (3.1)$$

[2]Preliminary simulation results indicated that increasing the number of simulations does not yield any additional insights.

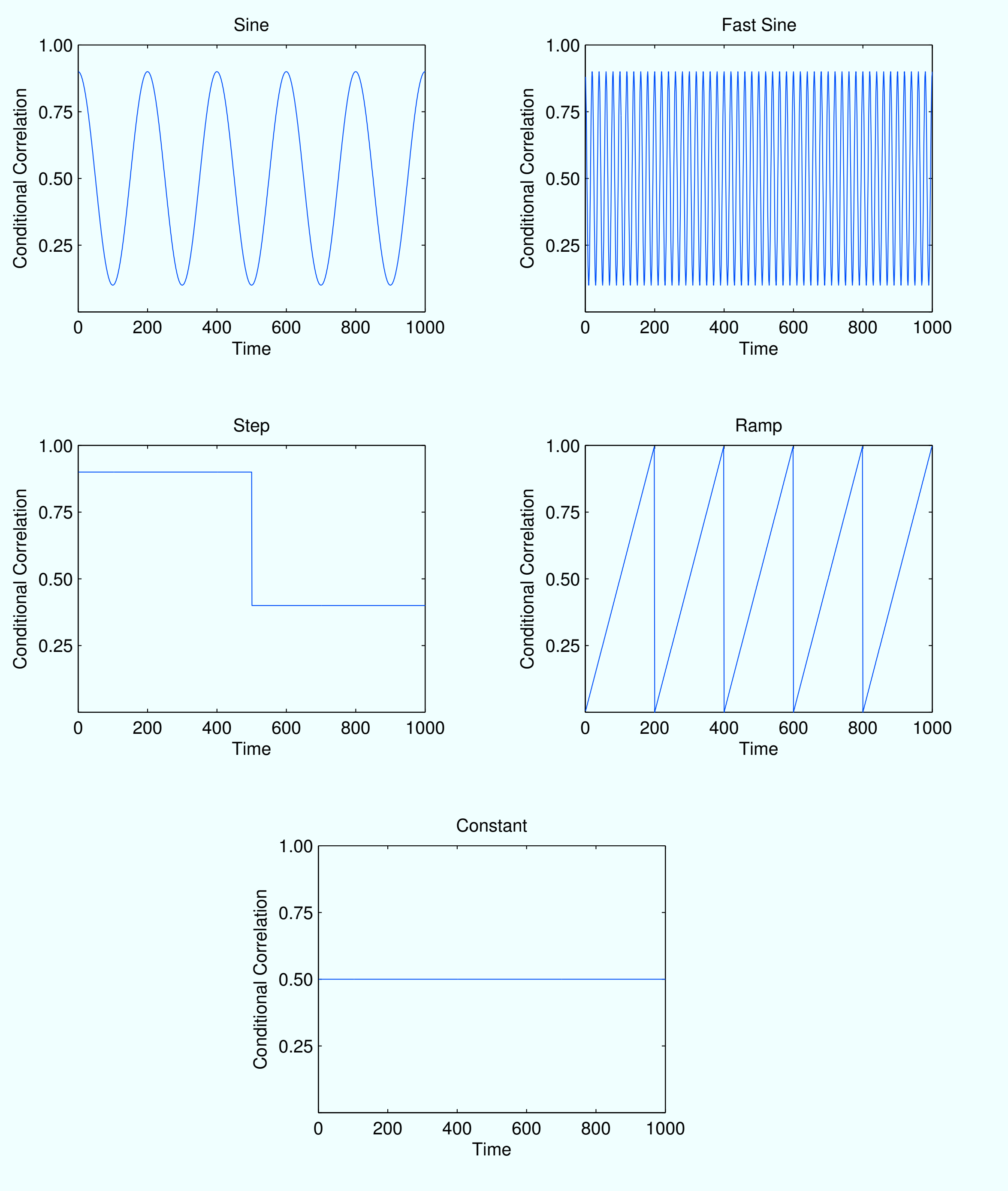


Figure 3.1: Simulated Correlation Structures

where T is the number of observations, R is the number of replications, and $\hat{\rho}_{rt}$ and ρ_{rt} are the estimated and true conditional correlations, respectively. Thus, the smaller the MAE, the better is the model in estimating conditional correlations. The computed MAE are presented in Table 3.1 with the lowest MAE for each correlation experiment in bold. Furthermore, Figure 3.2 depicts the sum of the MAE over all replications and all five experiments.

Table 3.1: Mean Absolute Error of Conditional Correlation Estimates

Model	Sine	Fast Sine	Step	Ramp	Constant
DCC Model	0.139	0.227	0.071	0.158	**0.025**
DCCX Model	0.127	0.139	0.078	0.131	0.025
GDCCX Model	**0.028**	**0.084**	**0.026**	**0.053**	0.025
STCC Model	0.044	0.090	0.030	0.057	0.023
Sheppard Model	0.166	0.173	0.201	0.200	0.028

The results are astonishing. The GDCCX model clearly uses the information of the exogenous variable best as the sum of the MAE is the lowest. Furthermore, it is the best model in all settings except for the constant correlation. Its total MAE is only a third of the total MAE of the DCC model. The STCC model performs almost as good as the GDCCX model - although a bit weaker for the Sine type correlations. The DCCX model is still better than the DCC model. However, the Sheppard model performs even worse than the DCC model that does not use the exogenous data.

We conclude that the gains for using exogenous variables can be substantial as indicated by the much lower total MAE for the GDCCX and the STCC model. Employing an exogenous variable reduces the mean absolute error by about two thirds. The reduction is greatest for the *Sine* and the *Ramp* as conditional correlations are constantly and sometimes abruptly changing but lower for the *Fast Sine* as correlations here change too quickly for any model. Interestingly, the Sheppard model performs better than the DCC model in this setting as its MAE is lower. However, in total the Sheppard model is the weakest model as it is on average even better to employ a DCC model - ignoring the exogenous data - than to use the Sheppard model. Note that this is obviously not a consequence of a too small sample size as the simulation study in chapter 2 showed that this sample proved to be sufficient to get reliable results.

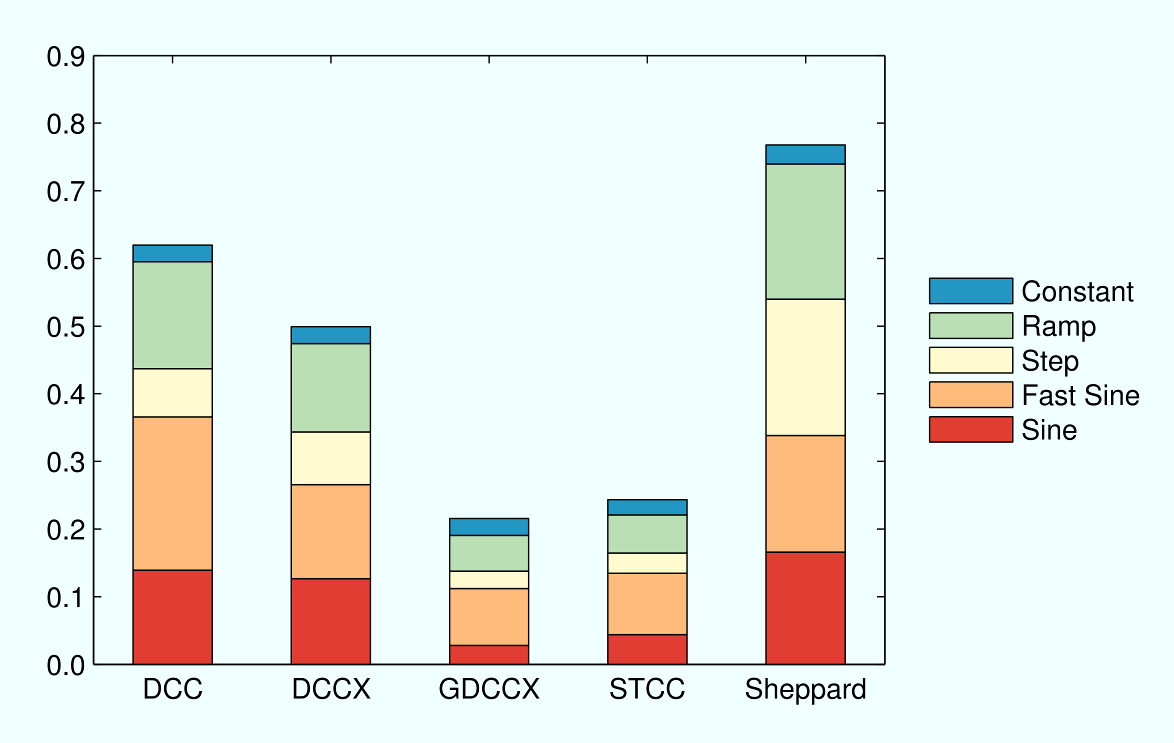


Figure 3.2: Sum of Mean Absolute Errors

3.3 Comparing Models by Employing Bond Market Data

In this section, we compare the five correlation models to each other using real data. First, we present several testing criteria. Then, we describe the bond market data used in the study. Finally, we discuss the results employing all models explained in section 2.4.

3.3.1 Testing Criteria

Conditional correlation models can be compared using statistical or economic criteria. Statistical criteria are, e.g., the Akaike or the Bayesian Information Criterion or specification tests such as the likelihood ratio test. However, testing the DCC model against the DCCX or the GDCCX model, one has to account for the two-step estimation procedure.[3] Furthermore, the DCC model and both the STCC and the model proposed

[3] See Engle and Sheppard (2001) for details on the correction.

by Sheppard are non-nested. A popular test for non-nested models is the Vuong (1989) test which can also be employed to compare the models.

Some recent papers assess the model performance in an economic application (Bauer and Missong, 2008; Engle and Colacito, 2006; Milunovich and Thorp, 2006; Thorp and Milunovich, 2007) as conditional correlation forecasts are a key input into many financial decisions. An important and widely evaluated application is the mean-variance portfolio optimization.[4] One approach is to form the global minimum variance portfolio (GMVP). Its vector of portfolio weights w_t is calculated using:

$$w_t = \frac{\mathbf{H}_t^{-1}\iota}{\iota'\mathbf{H}_t^{-1}\iota}, \tag{3.2}$$

where $\mathbf{H}_t$ is the forecasted conditional covariance matrix at time t, and ι is a vector of ones. By assuming that the returns on all assets are equal this approach avoids the specification of expected returns for all assets. Yet, this assumption is quite unrealistic especially in an asset allocation framework and seldom used in practice. Another approach is to construct a portfolio using the general mean-variance optimization so that:

$$w_t = \frac{\mathbf{H}_t^{-1}\mu_t}{\mu_t'\mathbf{H}_t^{-1}\mu_t}, \tag{3.3}$$

where μ_t is the vector of expected returns in excess of the risk free rate. As expected returns are unknown, many studies use ex-post means instead and evaluate the risk and return of the optimal portfolios. However, Engle and Colacito (2006) point out that performing a mean-variance optimization is a combined test of the correct specification of expected returns and the forecasted covariance matrix. In addition, Chopra and Ziemba (1993) argue that correctly estimated covariances are not as important as correctly estimated expected returns for the construction of the optimal portfolio.

Yet, Engle and Colacito (2006) show that if expected returns are constant, i.e. $\mu_{i,t} = \mu_i \; \forall \; t$, it will still be possible to rank covariance forecasts according to the variance of the optimal portfolio. The reason is that for every vector of expected returns a portfolio which is optimized on the true covariance will have a lower or equal variance than a

[4]The use of further economic applications and testing criteria is discussed in Patton and Sheppard (2009), Engle et al. (2008) as well as in Engle and Sheppard (2001).

portfolio which is optimized on any other covariance matrix. It is generally assumed that the true expected value of return is constant for daily or higher frequency data.

Moreover, the significance of the difference between two conditional correlation models can be tested by employing the Diebold and Mariano (1995) test statistic. First, the estimated difference between the realized covariance of the two models is computed as follows:

$$d_t = \left(w'_{t,A} r_t\right)^2 - \left(w'_{t,B} r_t\right)^2 , \tag{3.4}$$

where $w_{t,A}$ and $w_{t,B}$ are the weights for the respective optimal portfolio calculated from the forecasted covariance matrices $\mathbf{H_t^A}$ and $\mathbf{H_t^B}$ of the two models while r_t is a vector with returns. Second, d_t is regressed on a constant using a Newey-West covariance matrix to account for heteroscedasticity, autocorrelation, and nonnormality. The null hypothesis is that the mean of d_t is 0. Engle and Colacito (2006) propose a weighted version of this test and modify equation 3.4 in order to further adjust for heteroscedasticity:

$$v_t = d_t \left[2 \left(\mu' \left(\mathbf{H_t^A}\right)^{-1} \mu \right) \left(\mu' \left(\mathbf{H_t^B}\right)^{-1} \mu \right) \right]^{1/2} . \tag{3.5}$$

In a second step, v_t is regressed on a constant using a Newey-West covariance matrix, and the null hypothesis is that the mean of v_t is 0.

3.3.2 Data

3.3.2.1 Bond Return Data

We employ several bond indices in order to both conduct a comprehensive test on the correlation models and to investigate conditional correlations between these indices. An overview is presented in Table 3.2.

We construct a dataset consisting of aggregate data on government, investment grade corporate, and high yield corporate bond indices provided by Bank of America Merrill Lynch which are widely used in practice. The indices are obtained for the Euro area as well as for the United States. All six indices are based on bond prices observed in the secondary market. Index constituents are capitalization weighted except for the two

Table 3.2: Dataset: European and US Bond Sectors

Name	Abbrev.	Source	Ticker	Obs.	Start	End
			European Bonds			
Government	EURGov	ML	EG00	2854	01/04/1999	03/31/2010
Investment Grade Corporate	EURCorp	ML	ER00	2854	01/04/1999	03/31/2010
High Yield Corporate	EURHY	ML	HEC0	2854	01/04/1999	03/31/2010
Change in VSTOXX Index	VSTOXX	BBG	VSTOXX	2854	01/04/1999	03/31/2010
			US Bonds			
Government	USGov	ML	G0Q0	5101	01/03/1990	03/31/2010
Investment Grade Corporate	USCorp	ML	C0A0	5101	01/03/1990	03/31/2010
High Yield Corporate	USHY	ML	HUC0	3332	01/03/1990	03/31/2010
Change in VIX Index	VIX	BBG	VIX	5101	01/03/1990	03/31/2010

Note: The table provides an overview on the dataset. ML is the Bank of America Merrill Lynch, and BBG is Bloomberg.

high yield corporate indices which are capitalization weighted but cap issuer exposure at 3% for the Euro area and at 2% for the US.[5] Also, in order to guarantee their liquidity all bonds included in the indices must satisfy minimum size and maturity criteria.[6]

Daily data for the European indices is available from 12/31/1997. However, as pointed out by Munves (2004), prior to the introduction of the Euro in 1999 the presence of currency risk was a significant constraint for many investors, and liquidity was very low especially in the high yield market. Therefore, we exclude the time period before 1999 so that the sample period for the European indices is 04/01/1999-03/31/2010. Daily data for the US indices is available since 10/31/1986 for the government and the corporate bond index and since 12/31/1996 for the high yield index.

[5]This is common practice after the downgrade of Ford and GM from investment grade to high yield in 2005 as these two issuers would otherwise dominate the respective indices.

[6]For a complete list of index guidelines please refer to www.mlindex.ml.com.

3.3.2.2 The Exogenous Variable: Risk Aversion

Several authors document the effects of risk aversion on conditional correlations in different markets and employing different methods and sampling frequencies. For example, the effect of risk aversion on conditional correlations between stock markets is investigated by Solnik et al. (1996), Kasch-Haroutounian (2005), Cappiello et al. (2006a), and Cai et al. (2009). These studies find that increasing risk aversion results in rising conditional correlations among international equity markets. Also, stock bond correlations are affected by risk aversion as growing risk aversion triggers a flight-to-quality (Connolly et al., 2005; Cappiello et al., 2006a; Kim et al., 2006; Connolly et al., 2007; Andersson et al., 2008; Aslanidis and Christiansen, 2010, 2011; Baele et al., 2010).

As risk aversion is not measurable, these studies proxy risk aversion with the implied volatility of equity options as it incorporates all information available to market participants on future volatility. Specifically, we use the change in volatility indices as exogenous variables for the correlation models. We employ the change in the Euro Stoxx 50 Volatility Index (VSTOXX) for the Eurozone. For the US we use the change in the Chicago Board Options Exchange Volatility Index (VIX). Both are popular measures of the implied volatility of index options over the next 30 days on the Euro Stoxx 50 Index and the S&P 500 Index respectively. Data is available since 1/4/1999 for the VSTOXX and since 1/2/1990 for the VIX.

3.3.2.3 The Datasets

Combining the volatility and the bond data, we get three datasets: first, the European aggregate bond data and the VSTOXX index starting at 1/4/1999; second, the US aggregate bond indices and the VIX index which are available since 1/2/1997. We construct a third dataset which includes the US government and the investment grade corporate index only. That allows us to expand the length of the time series considerably as all series are at least available since 1/31/1990.

For all indices, we compute the continuously compounded daily returns. Furthermore, all returns are expressed in local currency. For the volatility indices, we calculate the daily differences. It is worth looking at the unconditional correlations in Tables 3.3 and 3.4. In all samples the government and investment grade corporate bond indices are on average strongly correlated while the high yield indices are unsurprisingly uncorrelated with government bonds. They also exhibit a very low correlation with the investment grade corporate bonds.

Table 3.3: European Bonds: Unconditionals Correlations

	EURGov	EURCorp	EURHY	VSTOXX
EURGov	1			
EURCorp	0.89	1		
EURHY	-0.05	0.09	1	
VSTOXX	0.26	0.19	-0.24	1

Table 3.4: US Bonds: Unconditional Correlations

	USGov	USCorp	USHY	VIX
USGov	1			
USCorp	0.91	1		
USHY	0.01	0.29	1	
VIX	0.02	0.15	-0.19	1

Moreover, it is interesting if conditional correlations are constant over time or if they are time-varying. Therefore, we employ the Engle and Sheppard (2001) test for constant conditional correlations.[7] Table 3.5 and 3.6 display results on the test for European and US bond markets, respectively. The test reveals that conditional correlations are in fact time-varying for most time series. An exception are conditional correlations between European government and high yield bonds. We cannot reject the hypothesis of constant conditional correlations for these series according to the Engle and Sheppard (2001) test.

Table 3.5: European Bonds: Engle Sheppard (2001) Test for Constant Conditional Correlations

	EURGov	EURCorp
EURCorp	659.809***	
EURHY	21.858	47.621***

Descriptive statistics on all datasets can be found in Table 3.7. The descriptive statistics show that all markets exhibit an average positive return. Interestingly, in the first dataset the more risky asset classes fared worse. The reason is that the sample period

[7]See section 2.3 for details.

Table 3.6: US Bonds: Engle Sheppard (2001) Test for Constant Conditional Correlations

	USGov	USCorp
USGov	1287.800***	
USHY	120.427***	69.688***

covers both the burst of the dotcom bubble in 2000/2001 and the financial crisis in 2008. The other US samples cover a larger time period so that the effect of these events is less pronounced. It can also be noted that all returns series are heavily left skewed and exhibit fat-tails. Moreover, they are non-normal as indicated by a Jarque–Bera test. In addition, the minima and maxima of the returns indicate the presence of outliers as the minimum of the US high yield index is a 16 standard deviation event.

Both the non-normality and the presence of outliers might severely affect the estimation since all models assume that asset returns are conditionally normal. Therefore, some authors truncate outliers (Silvennoinen and Teräsvirta, 2005) or standardize the data (Cappiello et al., 2006a). However, Engle (2002) argues that results have a quasi-maximum likelihood estimation interpretation when returns are non-normal. Furthermore, a standardization of the data would make the interpretation of the coefficients more difficult so that we do not transform the data.

Table 3.7: Descriptive Statistics

Abbreviation	Mean	Mean p.a.	Min.	Max.	Std. Dev.	Skewn.	Kurtosis
			European Bonds				
EURGov	0.02%	4.42%	−1.17%	1.10%	0.22%	−0.23	1.38***
EURCorp	0.02%	4.26%	−0.82%	0.60%	0.17%	−0.53	1.62***
EURHY	0.02%	3.62%	−5.01%	2.62%	0.45%	−1.85	17.54***
VSTOXX	0.00		−13.98	22.64	1.76	1.63	25.62***
			US Bonds				
USGov	0.03%	6.35%	−1.96%	2.07%	0.29%	−0.24	2.45***
USCorp	0.03%	7.05%	−2.31%	1.97%	0.31%	−0.37	2.69***
USHY	0.02%	6.30%	−4.60%	2.81%	0.29%	−2.22	37.00***
VIX	0.00		−17.36	16.54	1.48	0.44	19.13***

Note: The table reports descriptive statistics for the variables employed in the analysis. *** denotes series that differ from a normal distribution at 1% level as indicated by a Jarque–Bera test.

In line with Silvennoinen and Teräsvirta (2005) and Engle and Colacito (2006) we multiply the return series with a fixed factor in order to enhance the numerical performance of the estimator and to avoid rounding errors. Rounding errors can easily be encountered given that daily returns for bond indices are small in magnitude and the effects of exogenous variables on the correlations might even be smaller. We generally found that optimization is less numerically demanding when the dimensions of the return and the exogenous data are similar. Therefore, we multiply the return series with 1000. As the mean of the return series is non-zero we demean the return series.

3.3.3 Empirical Results

3.3.3.1 European Bond Sectors

Table 3.8 reports the results of running the models on the first sample with different European aggregate bond sectors indices: government, investment grade corporate, and high yield corporate bonds. The change in the VSTOXX Index is our exogenous variable.

The top panel contains the estimated parameters of the DCC and the DCCX model. For both the DCCX and the GDCCX model, the c parameter is the influence of the exogenous variable as shown in equation 2.10. It turns out that, for the DCCX model, the influence of the exogenous variable on the conditional correlations between government, investment grade corporate and high yield corporate bonds is negative but not significant.

The second panel reports the estimated parameters for the GDCCX model. The influence of the exogenous variable is indicated by the $c_1 - c_3$ parameters (see equation 2.11) and is broken down by correlation pair.

For example, the exogenous variable drives conditional correlations between European government and investment grade corporate bonds significantly downwards as the coefficient c_1 is negative (-0.0021) and significant. The exogenous variable's influence on the conditional correlation between government and high yield corporate bonds is also negative (-0.0024) but not significant as indicated by coefficient c_2. Finally, the conditional correlation between investment grade corporate and high yield corporate bonds

Table 3.8: European Bonds: Influence of Risk Aversion Changes on Conditional Correlations (Trivariate Model)

DCCX-Model				**DCC-Model**	
	a	0.0236***	(0.0048)	0.0245***	(0.0051)
	b	0.9722***	(0.0067)	0.9711***	(0.0073)
	c	-0.0038	(0.0026)		
GDCCX-Model					
	a	0.0215***	(0.0045)		
	b	0.9760***	(0.0060)		
		EURGov		EURCorp	
$c_1 - c_3$	EURCorp	-0.0021***	(0.0006)		
	EURHY	-0.0024	(0.0029)	0.0002	(0.0029)
STCC-Model					
	c	1.2609***	(0.0732)		
	γ	100			
		EURGov		EURCorp	
R_1	EURCorp	0.9224***	(0.0051)		
	EURHY	-0.0432*	(0.0240)	0.0743***	(0.0197)
		EURGov		EURCorp	
R_2	EURCorp	0.8657***	(0.0200)		
	EURHY	-0.0565	(0.0671)	0.0801	(0.0668)
Sheppard Model (Partial Effects)					
		EURGov		EURCorp	
	EURCorp	-0.0592***	[0.0066]		
	EURHY	-0.1611*	[0.0776]	-0.1566*	[0.0971]

Note: The table reports the results of estimating the conditional correlation of European government, investment grade corporate and high yield corporate bonds using the change in the VSTOXX Index as exogenous variable. The sample period is 1/5/1999-3/31/2010. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses, p-values in brackets.

is almost not affected by the exogenous variable as the coefficient c_3 is not significant and close to zero (0.0002).

In panel three, results for the STCC model are presented. The conditional correlation changes from the correlation matrix $\mathbf{R}_1$ to $\mathbf{R}_2$ as the exogenous variable exceeds c (see equation 2.12 and 2.13). The speed of the transition is measured by γ where values close to 0 indicate a very slow and values close to 100 or -100 a vary rapid transition.

For example, the conditional correlation between European government and investment grade corporate bonds is 0.9224 if the exogenous variable is less than 1.26. Once the exogenous variable exceeds this value, conditional correlations quickly (as γ is 100) fall to 0.8657.

The bottom panel reports the partial effects of an increase of the exogenous variable on the conditional correlations as estimated by the Sheppard model. Estimated parameters are omitted as they are not directly interpretable. Instead, the partial effects evaluated at the sample mean are displayed. For example, the effect of an increase in the exogenous variable is that conditional correlations between government and investment grade corporate bonds decrease as the partial effect is negative.

Considering the conditional correlation between the government and the investment grade corporate bonds, the picture is quite clear: The GDCCX, the STCC, and the Sheppard model all reveal that there is a significant flight-to-quality effect. The conditional correlation between government and corporate bonds drops significantly when risk aversion, as measured by the change in the VSTOXX index, rises. Figure 3.3 depicts the conditional correlation between government and investment grade corporate bonds as estimated by the different models.

While correlations estimated by the DCCX and the GDCCX model are close to those estimated by the DCC model, the correlations estimated by the STCC and the Sheppard model exhibit a different pattern. Notably, the greatest differences between conditional correlations estimated by the DCC and the GDCCX model are after 9/11 and in the wake of the Lehman collapse in September and October 2008. In addition, all estimated conditional correlations share a common feature: they drop considerably during the financial crisis. However, the estimates of the actual level of conditional correlations during the crisis vary widely among the models: the DCC type models find that conditional correlations fall to about 0.6. Correlations estimated by the STCC model are not lower than 0.86 and the minimum of the conditional correlations estimated by the Sheppard model is as low as 0.2.

We now turn to the correlation between government and high yield corporate as well as between high yield corporate and investment garde corporate bonds as shown in Table 3.8. We find that the picture is more ambiguous. The coefficients of the GDCCX model indicate that there is no significant influence of the exogenous variable on the correlations while the Sheppard model suggests a drop in correlations - but only at the

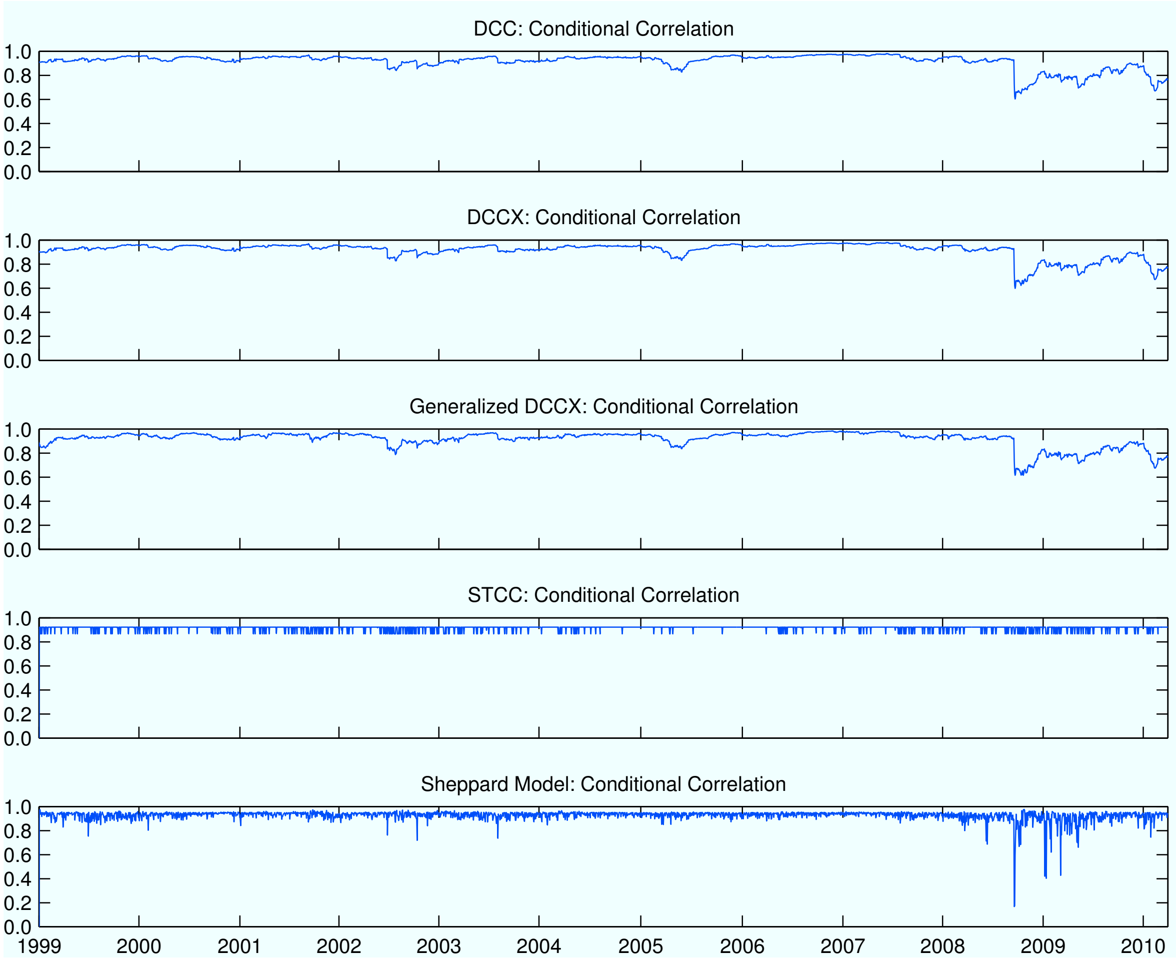


Figure 3.3: European Government and Investment Grade Corporate Bond Conditional Correlations

10% level of significance. The STCC model shows that there is only one correlation regime close to the respective unconditional correlations. Finally, the c parameter for the DCCX model is insignificant.

This result is not surprising given that the model depends on the assumption of a common effect of the exogenous variable on all conditional correlations, which clearly seems not to be true in this sample. That illustrates an important result: By assuming that there is a common effect of the exogenous variable on all conditional correlations, the DCCX model misses the influence of the risk aversion on the government/investment grade corporate bond correlation. This is an clear argument in favor of the generalized version of the DCCX model.

In order to further analyze the impact of the common parameters on the model results, we repeat the analysis but only with two indices, i.e. we drop the investment grade corporate index. The parameter estimations are reported in Table 3.9. In addition, Figure 3.4 plots the estimated conditional correlations.

A comparison between Figures 3.3 and 3.4 shows that conditional correlations between government and high yield corporate bonds are much lower than between government and investment grade corporate bonds. Specifically, the correlation between government and investment grade corporate bond is around 0.8 to 1 during non-crisis periods while it is around 0 between high yield corporate and government bonds. This is not surprising as credit risk is more important for high yield corporate bonds than for investment grade corporate bonds. More astonishing is that the conditional correlations between government and high yield corporate bonds barely change during the financial crisis.

Comparing parameter estimates for the conditional correlations between the trivariate estimation in Table 3.8 and the bivariate estimation in 3.9, the largest changes can be observed for the DCCX and the STCC model. This is not surprising since both restrict some parameters to be equal for all conditional correlations in the trivariate case. The STCC model assumes that there is a common place and speed of the transition (i.e. a common c and γ) and the DCCX model restricts the c parameter to be equal for all correlations.

The parameter for the DCCX and the GDCCX model are both negative but still insignificant at the 5% level. By contrast, the Sheppard model finds that risk aversion significantly drives conditional correlations between government and high yield corporate bonds. However, the STCC model indicates that a change in the VSTOXX index greater than 6.69 results in rising correlations which seems to be counterintuitive at a first view.

To understand the difference in the sign of the effect, it is important to notice the differences in the models. The DCCX models and the Sheppard model are built on the assumption that the exogenous variable has a constant effect on the conditional correlations while the STCC model distinguishes two correlation regimes. However, the second correlation regime might be observed only once, e.g. there is a correlation "outlier". This happens if the location of transition between the two regimes is close to the maximum or minimum of the exogenous variable and the speed of the transition is very high. Values of 6.69 for c and 95.53 for γ might reflect correlation outliers after

Table 3.9: European Government and High Yield Corporate Bonds: Influence of Risk Aversion Changes on Conditional Correlations (Bivariate Model)

DCCX-Model			**DCC-Model**	
a	0.0000	(0.0087)	0.0059*	(0.0033)
b	0.5600***	(0.1644)	0.9858***	(0.0080)
c	-0.0105*	(0.0057)		
GDCCX-Model				
a	0.0058	(0.0035)		
b	0.9775***	(0.0139)		
c_1	EuroGov			
EURHY	-0.0061*	(0.0036)		
STCC-Model				
c	6.6920***	(0.0777)		
γ	95.5272	(307.6408)		
R_1	EuroGov			
EURHY	-0.0468	(0.0431)		
R_2	EuroGov			
EURHY	0.7039***	(0.0868)		
Sheppard Model (Partial Effects)				
	EuroGov			
EuroHY	-0.1784***	[0.0002]		

Note: The table reports the results of estimating the conditional correlation of European government and high yield corporate bonds using the change in the VSTOXX Index as exogenous variable. The sample period is 1/5/1999-3/31/2010.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses, p-values in brackets.

large changes in the VSTOXX index. Correlation outliers are also visible in Figure 3.4. In this case no general conclusion regarding the influence of the transition variable on the correlation can be drawn from the results of the STCC model.

Overall, we see that the influence of risk aversion on conditional correlations between government and high yield corporate bonds is weak and particularly not as strong as the effect of risk aversion on government and investment grade corporate bonds.

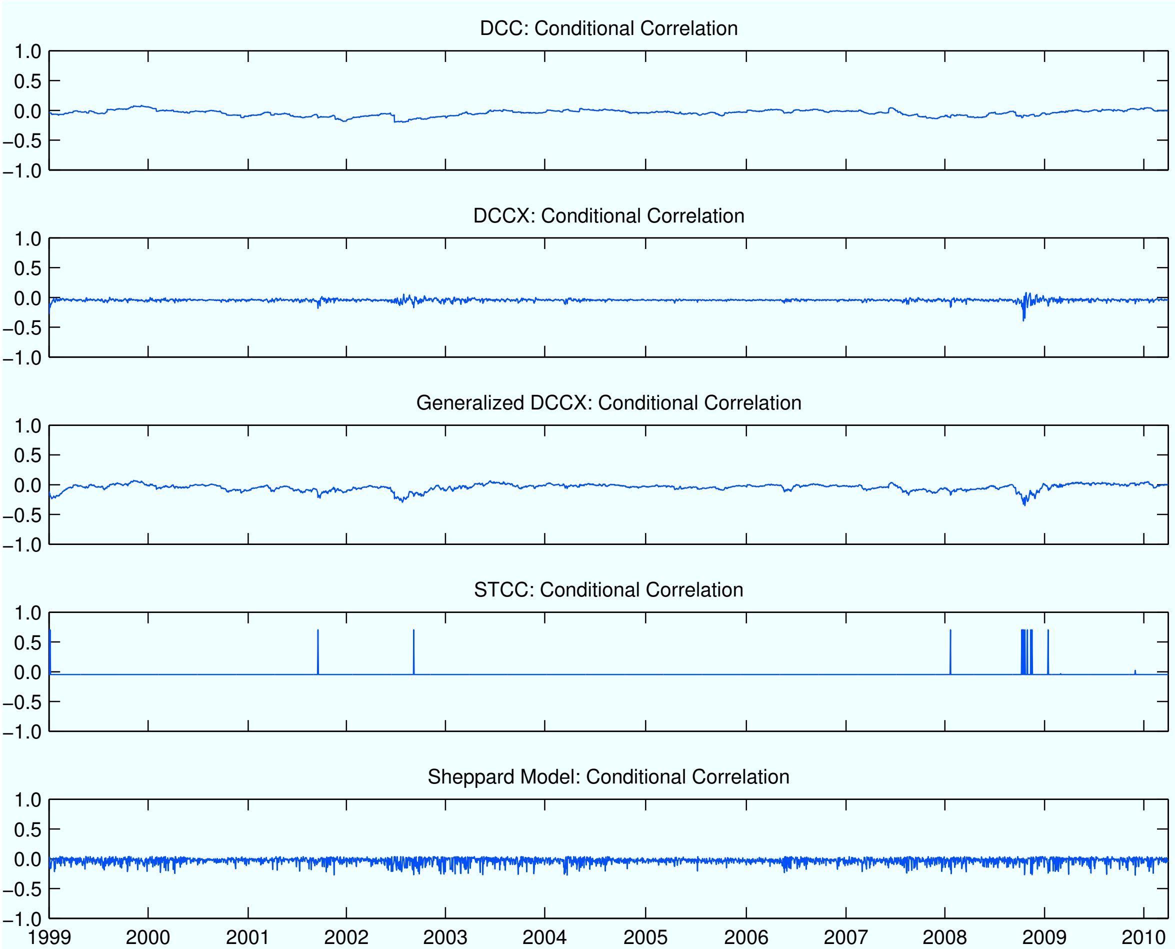


Figure 3.4: European Government and High Yield Corporate Bond Conditional Correlations

3.3.3.2 US Bond Sectors

We repeat the analysis on a sample with US bond sectors. Results are reported in Table 3.10. Similar to our previous analysis, we include government bonds, investment grade corporate, and high yield corporate bonds. We take the change in the VIX index as exogenous variable and find that the flight-to-quality effect is even stronger than in the Eurozone.

All models show that conditional correlations decrease if risk aversion, as measured by the VIX index, rises. Specifically, the estimated c parameter of the DCCX model is negative and significant indicating a negative effect of the exogenous variable on the conditional correlations.

Table 3.10: US Bonds: Influence of Risk Aversion Changes on Conditional Correlations (Trivariate Model)

DCCX-Model				**DCC-Model**	
	a	0.0737***	(0.0158)	0.0791***	(0.0158)
	b	0.9214***	(0.0182)	0.9155***	(0.0183)
	c	-0.0112***	(0.0029)		
GDCCX-Model					
	a	0.0731***	(0.0143)		
	b	0.9219***	(0.0163)		
		USGov		USCorp	
$c_1 - c_3$	USCorp	-0.0014***	(0.0003)		
	USHY	-0.0102**	(0.0044)	-0.0094**	(0.0039)
STCC-Model					
	c	1.0050***	(0.0138)		
	γ	100			
		USGov		USCorp	
R_1	USCorp	0.9592***	(0.0041)		
	USHY	0.2086***	(0.0261)	0.3376***	(0.0232)
		USGov		USCorp	
R_2	USCorp	0.8099***	(0.0664)		
	USHY	0.0871*	(0.0480)	0.2976***	(0.0387)
Sheppard Model (Partial Effects)					
		USGov		USCorp	
	USCorp	-0.0877***	[0.0187]		
	USHY	-0.1342***	[0.0000]	-0.1149***	[0.0000]

Note: The table reports the results of estimating the conditional correlation of US government, investment grade corporate and high yield corporate bonds using the change in the VIX Index as exogenous variable. The sample period is 1/2/1997-3/31/2010.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses, p-values in brackets.

The GDCCX model further differentiates the effect of the exogenous variable on each conditional correlation. For example a rise of the VIX index influences the conditional correlation between government and investment grade corporate bonds to a lesser extent than the conditional correlation between government and high yield corporate bonds (see Table 3.10). This is confirmed by the Sheppard model but not by the STCC model as there the largest influence of risk aversion is the government/investment grade corporate bond correlation. Specifically, conditional correlation between government

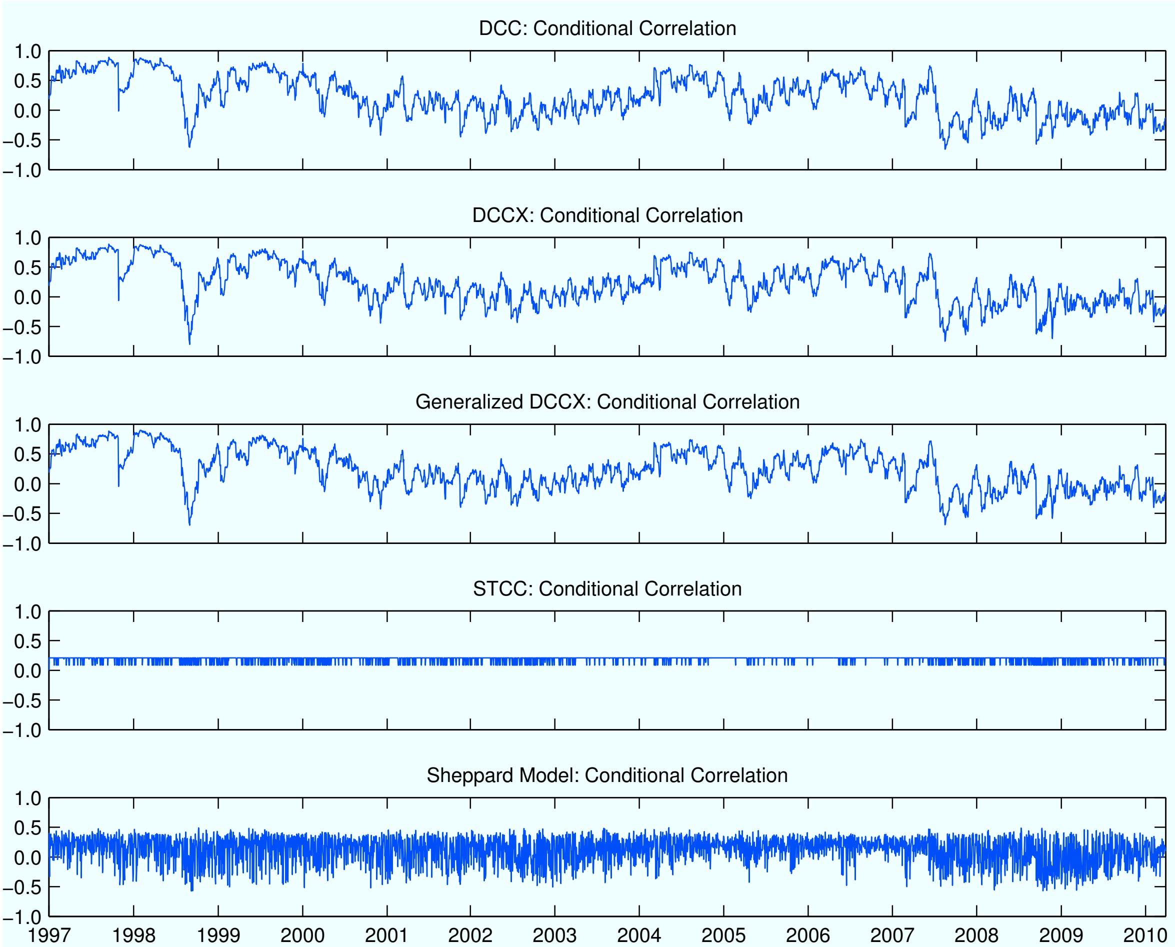


Figure 3.5: US Government and High Yield Corporate Bond Conditional Correlations

and investment grade corporate bonds decrease quickly ($\gamma = 100$) from 0.96 to 0.81 if the VIX increases more than 1.005 points while the correlation between government and high yield corporate bonds falls from 0.2086 to 0.0871.

Figure 3.5 stresses the differences between the models. While the estimated conditional correlations of the DCC type models are somewhat similar, conditional correlations as estimated by the STCC model jump frequently between two regimes, and the Shepard model conditional correlations largely fluctuate. Notably, the DCC correlations are not as smooth as in the Eurozone as the estimated half life of the innovations is about 4.4 days in the US while it is 12.4 days in the Eurozone. As suggested by Cappiello et al. (2006a) the half-life is approximated by: $\ln(0.5) / \ln(a^2 + b^2)$. The half-life is the expected period of time it takes until the influence of any correlation innovation has decreased by half.

Table 3.11: US Government and Investment Grade Corporate Bonds: Influence of Risk Aversion Changes on Conditional Correlations (Bivariate Model)

DCCX-Model			**DCC-Model**	
a	0.0622***	(0.0111)	0.0748***	(0.0158)
b	0.9356***	(0.0118)	0.9220***	(0.0169)
c	-0.0358***	(0.0019)		

GDCCX-Model

a	0.0670***	(0.0152)
b	0.9297***	(0.0161)
c_1	USGov	
USCorp	-0.0017***	(0.0004)

STCC-Model

c	1.0095***	(0.1140)
γ	100	
R_1	USGov	
USCorp	0.9467***	(0.0033)
R_2	USGov	
USCorp	0.8281***	(0.0501)

Sheppard Model (Partial Effects)

	USGov	
USCorp	-0.0280***	[0.0057]

Note: The table reports the results of estimating the conditional correlation of US government and investment grade corporate bonds using the change in the VIX Index as exogenous variable. The sample period is 1/3/1990-3/31/2010.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses, p-values in brackets.

In order to test the robustness of the results we ran the analysis with a longer sample covering more than 20 years of daily observations from 1/1990 to 3/2010. However, this is a bivariate model as this sample only includes the government and the investment grade corporate bonds. Results are presented in Table 3.11.

They largely confirm the results of the previous analysis. Other than in the European sample, the estimated c parameter for the STCC model is almost identical to the one previously estimated. Thus, the common c parameter for all correlations imposes no

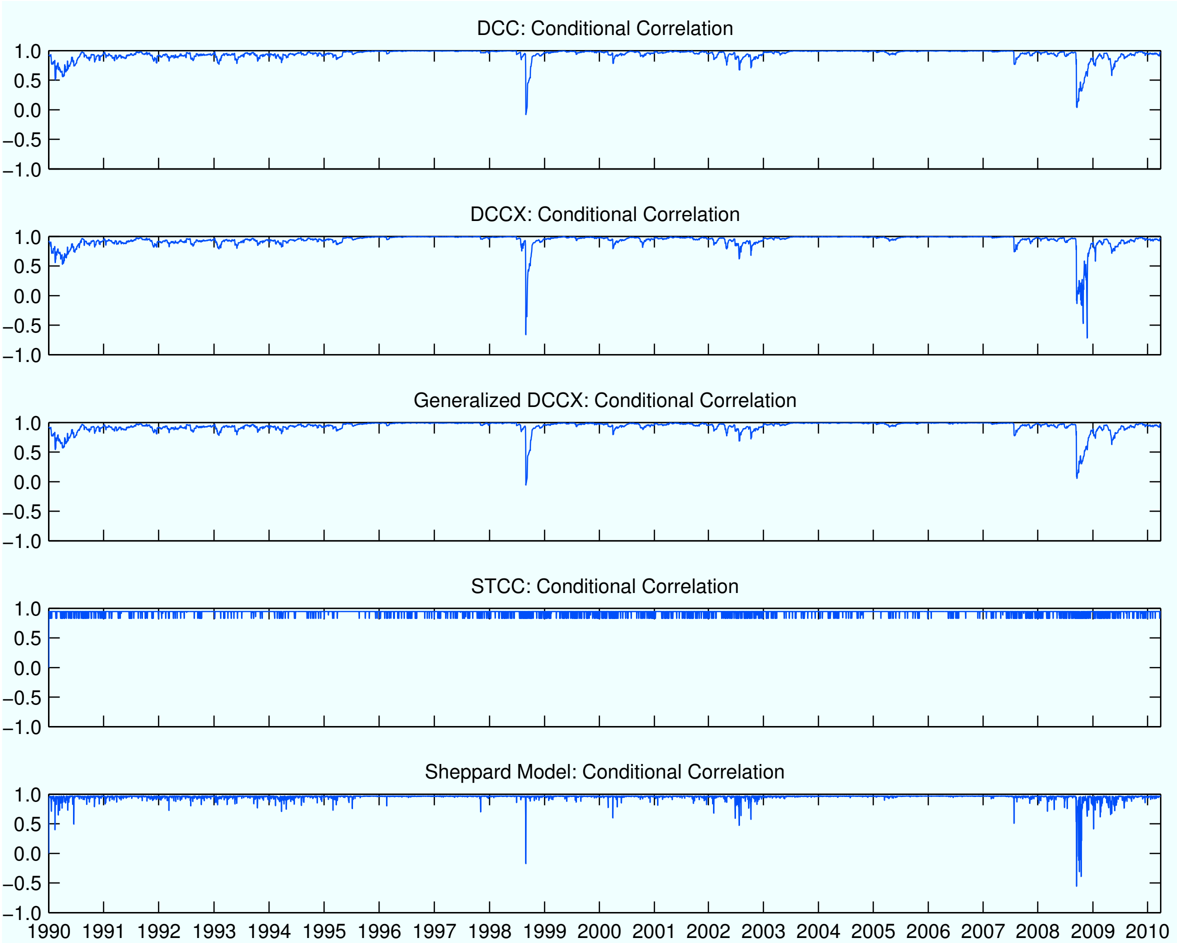


Figure 3.6: US Government and Investment Grade Corporate Bond Conditional Correlations

additional restriction. Figure 3.6 also shows that both during the subprime crisis as well as during the burst of the dot-com bubble conditional correlations were lower.

3.3.3.3 Comparison by Statistical and Econometric Criteria

After estimating the coefficients of the models, we compare the models using the selection criteria proposed in section 3.3.1. Table 3.12 reports several statistical criteria.

Looking at the AIC and the BIC, the GDCCX model performs best in the US samples. For the European samples, the DCC model is best according to the BIC while the AIC favors the GDCCX and the STCC. Generally, according to the statistical criteria, the performance of the DCC-type models is somewhat similar. By contrast, the

Table 3.12: Statistical Criteria

	DCC Model	DCCX Model	GDCCX Model	STCC Model	Sheppard Model
European Government, Investment Grade, and High Yield Corporate Bonds					
LL	−15649.778	−15648.053	**-15629.604**	−15883.451	−16671.083
AIC	10.975	10.974	**10.963**	11.143	11.695
BIC	10.988	10.999	**10.992**	11.178	11.733
Param.	11	12	14	17	18
European Government and High Yield Corporate Bonds					
LL	−13289.321	−13294.328	−13287.360	**-13282.907**	−13976.980
AIC	9.318	9.323	9.318	**9.315**	9.801
BIC	**9.335**	9.341	9.337	9.336	9.820
Param.	8	9	9	10	9
US Government, Investment Grade, and High Yield Corporate Bonds					
LL	−17890.388	−17871.776	**-17782.521**	−19059.471	−19346.052
AIC	10.745	10.735	**10.682**	11.451	11.623
BIC	10.765	10.757	**10.708**	11.482	11.656
Param.	11	12	14	17	18
US Government and Investment Grade Corporate Bonds					
LL	−18501.106	−18411.540	**-18406.544**	−19835.020	−19942.682
AIC	7.257	7.222	**7.220**	7.781	7.823
BIC	7.267	7.234	**7.232**	7.794	7.834
Param.	8	9	9	9	10

Note: The table reports the log-likelihood values (LL), the values of the Akaike (AIC) and Bayesian information criteria (BIC), and the number of parameters (Param.) we have to estimate.

STCC model performs worse in all samples except in the sample which only includes European government and high yield corporate bonds. Moreover, the Sheppard model always ranks last. Although the DCC model does not consider the influence of exogenous variables, it outperforms the STCC and the Sheppard model if BIC is chosen as criterion.

The economic criteria reveal the differences between the DCC type models on the one hand and the STCC and the Sheppard model on the other hand. Table 3.13 presents the volatility of portfolios formed with the estimated covariance matrix of the respective models. The lowest standard deviation is normalized to 100. As described in section 3.3.1, results are reported for both the global minimum variance portfolio (GMVP) and for the mean variance optimal portfolio which is calculated using realized mean-returns (MVP).

Table 3.13: Economic Criteria: Comparison of Volatilities

	DCC Model	DCCX Model	GDCCX Model	STCC Model	Sheppard Model
European Government, Investment Grade, and High Yield Corporate Bonds					
GMVP	100.215	100.415	**100.000**	105.483	107.773
MVP	**100.000**	100.234	100.426	113.401	110.137
European Government and High Yield Corporate Bonds					
GMVP	100.449	100.793	100.634	**100.000**	114.289
MVP	**100.000**	100.180	100.131	100.169	113.813
US Government, Investment Grade, and High Yield Corporate Bonds					
GMVP	102.172	101.455	**100.000**	141.329	122.845
MVP	**100.000**	101.276	100.614	137.957	148.763
US Government and Investment Grade Corporate Bonds					
GMVP	100.739	100.294	**100.000**	113.762	123.070
MVP	100.093	103.436	**100.000**	109.244	113.016

Note: The table reports the sample standard deviations of global minimum variance portfolios (GMVP) and minimum variance portfolios subject to a required return (MVP). The lowest standard deviation is normalized to 100 so that a value of 105 means that using the forecasts of the best model a 5% higher return could be required.

For the aggregate bond indices, the GDCCX, the DCCX, and the DCC perform best. The volatility of portfolios formed with the covariance matrix from the STCC or the Sheppard model is much higher. Again, the sample which only includes the European government and high yield corporate bonds is an exception as the STCC model performs well in that case. Interestingly, the DCC model usually performs better than the GDCCX model when portfolios are calculated using realized mean-returns. By contrast, the opposite is true for the global minimum variance portfolios. However, differences between the DCC type models are only modest.

Next, the models are tested by using the Diebold–Mariano approach. This allows to compare two models with another. The Diebold–Mariano approach yields similar results as our previous test. That can be inferred from Tables 3.14 and 3.15. In these Tables, a significant positive number means the model of the row is better than the model of the column. If the coefficient is not significant, the test is inconclusive. For example, the GDDCX model outperforms the STCC model as the test statistic (-2.288)

Table 3.14: Economic Criteria: Unweighted Diebold-Mariano-Test Statistics for a Global Minimum Variance Portfolio

	DCC Model	DCCX Model	GDCCX Model	STCC Model
European Government, Investment Grade, and High Yield Corporate Bonds				
DCCX Model	-0.520			
GDCCX	0.520	1.076		
STCC Model	-2.309**	-2.130**	-2.288**	
Sheppard Model	-2.518**	-2.483**	-2.563**	-0.719
European Government and High Yield Corporate Bonds				
DCCX Model	-1.773*			
GDCCX	-0.637	0.598		
STCC Model	0.716	1.331	0.785	
Sheppard Model	-5.033***	-4.842***	-4.896***	-5.107***
US Government, Investment Grade, and High Yield Corporate Bonds				
DCCX Model	1.473			
GDCCX	1.631	1.254		
STCC Model	-2.117**	-2.143**	-2.256**	
Sheppard Model	-2.761***	-2.809***	-3.177***	1.315
US Government and Investment Grade Corporate Bonds				
DCCX Model	2.175**			
GDCCX	1.662*	0.919		
STCC Model	-3.003***	-3.105***	-3.206***	
Sheppard Model	-4.510***	-4.600***	-4.693***	-3.229***

Note: The table reports the unweighted Diebold-Mariano test statistics of equal predictive accuracy of the models for all datasets used. A significant positive number means the model of the row is better than the model of the column. The panel shows results for the global minimum variance portfolio.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

is significantly less than zero. Both the weighted and the unweighted versions of the test find that the STCC model and the Sheppard model are significantly outperformed by the DCC type models. The only exception is the conditional correlation between European government and high yield corporate bonds since the STCC model is not outperformed by the other models in this sample. The differences between the DCC, the DCCX and the GDCCX model are mostly not significant. Comparing the STCC and the Sheppard model only results in significant results in the sample with European government and high yield corporate bonds and in the sample with US government

Table 3.15: Economic Criteria: Weighted Diebold-Mariano-Test Statistics Using Expected Returns

	DCC Model	DCCX Model	Generalized DCCX	STCC Model
European Government, Investment Grade, and High Yield Corporate Bonds				
DCCX Model	-2.016**			
GDCCX	-0.033	0.286		
STCC Model	-4.384***	-4.352***	-4.352***	
Sheppard Model	-5.171***	-5.119***	-5.011***	-1.557
European Government and High Yield Corporate Bonds				
DCCX Model	-1.089			
GDCCX	0.797	1.140		
STCC Model	-1.212	-0.056	-1.017	
Sheppard Model	-6.264***	-6.129***	-6.340***	-6.123***
US Government, Investment Grade, and High Yield Corporate Bonds				
DCCX Model	0.432			
GDCCX	0.165	-0.360		
STCC Model	-4.063***	-3.945***	-4.211***	
Sheppard Model	-3.287***	-3.037***	-3.345***	-0.241
US Government and Investment Grade Corporate Bonds				
DCCX Model	0.324			
GDCCX	1.757*	0.000		
STCC Model	-3.149***	-2.526**	-3.148***	
Sheppard Model	-3.712***	-3.655***	-3.970***	-1.047

Note: The table reports the weighted Diebold-Mariano test statistics of equal predictive accuracy of the models for all datasets used. A significant positive number means the model of the row is better than the model of the column. Portfolios are constructed employing expected returns estimated by the sample mean of the return series for the complete sample.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and investment grade corporate bonds. In these samples, the STCC model significantly outperforms the Sheppard model.

In summary, we find that the differences within the DCC type model are not as large. However, all DCC type models outperform the STCC and the Sheppard model, respectively. The Sheppard model performs worst in all samples and with all testing criteria. The STCC model is worse than the DCC type models except for the sample with European government and high yield corporate bonds in which the test is not significant. However, as we have seen by plotting conditional correlations (see Figure 3.4), conditional correlations estimated by the STCC model are almost constant.

3.4 Summary

In this chapter, we compare the performance of conditional correlation models in different settings. First, we conduct a simulation study employing the true conditional correlation as exogenous variable. We find that GDCCX model uses the information of the exogenous variable best in all settings. The STCC model performs almost as good as the GDCCX model and the DCCX model is still better than the DCC model that does not account for the effect of exogenous variables. By contrast, the Sheppard model performs even worse than the DCC model. Interestingly, the Sheppard model performs well in a setting where correlation change very quickly. Furthermore, we demonstrate that employing models which account for a potential effect of an exogenous variable reduces the mean absolute estimation error by about two thirds. We conclude that the gains for using exogenous variables can be substantial.

We then turn to an application of the correlation models employing real data. We include bond sector data for the Eurozone and the US in our analysis. Our empirical results can be summarized as follows. First, the greater the number of time series analyzed and the more heterogeneous the respective conditional correlations respond to the exogenous variable the more rewarding it is to use the GDCCX model instead of the DCCX model. For example, in a sample with European government, corporate investment grade and corporate high yield bonds, conditional correlations between investment grade and government bonds react differently to risk aversion than conditional correlations between high yield and investment grade bond. That effect is captured by the GDCCX model since there are coefficients that measure the influence of the exogenous variable on each correlation separately. Yet, there is only one coefficient that measures the effect of the exogenous variable on all correlations in the DCCX model. As a result, this coefficient is not significant and cannot be interpreted as well. Also, the GDCCX model performs well in terms of both statistic and economic criteria. Second, the most striking result when comparing the different models is that the DCC, the DCCX and the GDCCX model outperform the Sheppard and the STCC model in most settings with respect to both statistical and economic criteria.

By the choice of our exogenous variable, we also address an empirical research question in this chapter. We investigate the influence of risk aversion on conditional correlations. We find statistical evidence for a flight-to-quality effect. When risk aversion rises, the conditional correlation between government and corporate bonds falls. That holds true both for the US and the Eurozone and can be observed for either investment grade or high yield bonds though the results are not as strong for high yield bonds in the Eurozone. The results are robust among all models we consider. As opposed to equity investments, the benefits of diversification between different bond sectors are not diminished in times of market turbulences. Our findings further indicate that the conditional correlation between investment grade and high yield corporate bonds fall in the US but not in the Eurozone.

4 Exogenous Variables in Correlation and Volatility

4.1 Introduction

In the models presented in the previous chapters, we assumed that all conditional variances are sufficiently described by a univariate GARCH (1,1) model. This approach is supported by Engle and Sheppard (2008), Berben and Jansen (2009), and Bauer (2011) who argue that the choice of the GARCH model is of minor relevance given that patterns of conditional variances produced by many univariate GARCH models are similar. Moreover, we assumed that the exogenous variables affect conditional correlations but do not affect conditional variances. This is justified since Schwert (1989) examines the stock volatility from 1857 to 1987 and does not find any macroeconomic variable that explains return volatility. Likewise, a study of Paye (2010) provides little support for volatility predictability by exogenous variables.

However, Officer (1973) demonstrates that market volatility can be related to industrial production. Recently, the modeling of volatility as a function of exogenous variables has gained additional attention. For example, Engle et al. (2009) provide evidence that economic fundamentals such as inflation and industrial production growth drive stock market volatility. Çakmakli and van Dijk (2010) demonstrate that a number of macroeconomic variables can help predicting US stock volatility between 1980 and 2005. Christiansen et al. (2011) get similar results for the foreign exchange, the commodity, and the bond market. Last, Engle and Rangel (2008) find that volatility in macroeconomic and financial factors are important determinants of increased volatility.

The influence of exogenous variables on conditional variance is important for correlation models and is the focus of this chapter. As already noted by King and Wadhwani (1990) and later by Forbes and Rigobon (2002), a change in the conditional variance of one time series can result in increasing conditional correlations. Corsetti et al. (2005) argue that this is true only under certain restrictive assumptions regarding the dependence structure and the time-series specific variance. However, provided these assumptions hold, a change in the exogenous variable can drive conditional correlations without changing the dependence structure of the time series.

We further investigate the consequences of a misspecification of the variance equation in the GDCCX model. We present the GARCHX model that is an extension of a GARCH model but allows exogenous variables to drive conditional variances. This model is employed in a simulation experiment. We simulate time series in which conditional variances are influenced by an exogenous variable according to a GARCHX model but conditional correlations are not. Then, we estimate a GDCCX model assuming that conditional variances are driven by a GARCH (1,1) process and that only conditional correlations are affected by the exogenous variable. We repeat the simulation for various different sample sizes, exogenous variables, correlation structures, and parameter constellations. We find that in some settings, the parameter estimates are biased as the model incorrectly finds an influence of the exogenous variable on the conditional correlations.

We therefore propose to replace the GARCH model in the variance equation of the GDCCX model by a GARCHX model to capture the effect of exogenous variables on conditional variances. We repeat the previous simulation experiment with this estimator and demonstrate that parameter estimates are unbiased in all settings now.

This chapter proceeds as follows. In the next section, we discuss a theoretical model that describes the interrelation between variances and correlations. In section 4.3, we introduce the GARCHX model. We investigate how the GDCCX model estimation is affected if exogenous variables drive conditional variances instead of correlations and examine how result change once the variance equation is correctly specified with a GARCHX model. Section 4.5 summarizes and concludes.

4.2 The Interrelation Between Variance and Correlation

In this section, we discuss the interaction between variance and correlation. Forbes and Rigobon (2002) argue that conditional correlations rise as conditional variances increase during periods of crisis. As a result, testing for a change in correlations suffers from heteroscedasticity bias.[1]

[1]Ronn et al. (2009), Loretan and English (2000), and Boyer et al. (1999) also document this bias employing a different statistical framework and more restrictive assumptions.

Specifically, Forbes and Rigobon (2002) assume that the rates of return r_i and r_j in two markets i and j are stochastic variables and are linked as follows:[2]

$$r_i = \beta_0 + \beta_1 \, r_j + \epsilon_i, \tag{4.1}$$

where β_1 is the constant strength of the dependence and ϵ_i are zero-mean market-specific shocks that are uncorrelated with r_j. Hence, variance of r_i and covariance of r_i and r_j can be expressed by:

$$\mathrm{Var}\,(r_i) = \beta_1^2 \, \mathrm{Var}\,(r_j) + \mathrm{Var}\,(\epsilon_i)\,, \tag{4.2}$$

$$\mathrm{Cov}\,(r_i, r_j) = \beta_1 \, \mathrm{Var}\,(r_j)\,. \tag{4.3}$$

Plugging 4.2 and 4.3 into the correlation definition yields:

$$\mathrm{Corr}\,(r_i, r_j) = \frac{\beta_1 \, \mathrm{Var}\,(r_j)}{\sqrt{\beta_1^2 \, \mathrm{Var}\,(r_j) + \mathrm{Var}\,(\epsilon_i)}\sqrt{\mathrm{Var}\,(r_j)}},$$

and can be rearranged as follows:

$$\mathrm{Corr}\,(r_i, r_j) = \left[1 + \frac{\mathrm{Var}\,(\epsilon_i)}{\beta_1^2 \, \mathrm{Var}\,(r_j)}\right]^{-\frac{1}{2}}. \tag{4.4}$$

Equation 4.4 shows that $\mathrm{Corr}\,(r_i, r_j)$ is a function of $\mathrm{Var}\,(r_j)$, $\mathrm{Var}\,(\epsilon_i)$, and β_1. Let us now assume that there are is a high and a low variance regime denoted by H and L, respectively, where

$$\mathrm{Var}\,(r_j|H) = (1 + \delta_1)\ \mathrm{Var}\,(r_j|L)\,,\ \ \delta_1 > 0, \tag{4.5}$$

and δ_1 is a measure of the proportional increase in the variance. H corresponds to a crisis caused by an exogenous shock in market j. The distinction between crisis and non-crisis periods is exogenously determined. In addition, it is assumed that

$$\mathrm{Var}\,(\epsilon_i|H) = \mathrm{Var}\,(\epsilon_i|L) = \mathrm{Var}\,(\epsilon_i)\,, \tag{4.6}$$

$$\mathrm{Corr}\,(r_j, \epsilon_i|H) = \mathrm{Corr}\,(r_j, \epsilon_i|L) = 0, \tag{4.7}$$

[2]The following illustration of the Forbes and Rigobon (2002) model is based on Corsetti et al. (2005).

i.e. the variance of the market-specific shocks in market i is constant across variance regimes and is not correlated with r_j. Thus, the exogenous shock in market j does not affect the specific shocks in market i in any way. Applying 4.5 and 4.6 to 4.4, we get:

$$\left[1 + \frac{\mathrm{Var}\left(\epsilon_i\right)}{\beta_1^2\ \left(1+\delta_1\right)\mathrm{Var}\left(r_j|L\right)}\right]^{-\frac{1}{2}} > \left[1 + \frac{\mathrm{Var}\left(\epsilon_i\right)}{\beta_1^2\ \mathrm{Var}\left(r_j|L\right)}\right]^{-\frac{1}{2}} \tag{4.8}$$

$$\mathrm{Corr}\left(r_i, r_j|H\right) > \mathrm{Corr}\left(r_i, r_j|L\right)$$

Hence, the correlation between r_i and r_j increases in the high variance regime, although the strength of the dependence β_1 remains constant during the crisis.

However, as pointed out by Corsetti et al. (2001) and Corsetti et al. (2005), the results critically depend on assumptions 4.6 and 4.7. It is easy to imagine a situation in which a shock in market j gives rise to a higher risk aversion in all markets resulting in higher variance of the market-specific shocks in market i:

$$\mathrm{Var}\left(\epsilon_i|H\right) = \left(1+\delta_2\right)\ \mathrm{Var}\left(\epsilon_i|L\right) \tag{4.9}$$

and therefore the relation between the correlation in high and low variance regimes as expressed by 4.8 becomes:

$$\left[1 + \frac{\left(1+\delta_2\right)\mathrm{Var}\left(\epsilon_i\right)}{\beta_1^2\ \left(1+\delta_1\right)\mathrm{Var}\left(r_j|L\right)}\right]^{-\frac{1}{2}} \gtreqless \left[1 + \frac{\mathrm{Var}\left(\epsilon_i\right)}{\beta_1^2\ \mathrm{Var}\left(r_j|L\right)}\right]^{-\frac{1}{2}} \tag{4.10}$$

$$\mathrm{Corr}\left(r_i, r_j|H\right) \gtreqless \mathrm{Corr}\left(r_i, r_j|L\right)$$

depending on

$$\left(1+\delta_1\right) \gtreqless \left(1+\delta_2\right).$$

Therefore, a change in the correlation between market i and market j can be caused in different ways.

In one scenario, a shock in market j results in rising correlations. The increase in variance in market j is higher than the rise in market-specific variance ($\delta_1 > \delta_2$) although the strength of the relation β_1 does not change. This is also known as interdependence in the contagion literature (Forbes and Rigobon, 2002; Corsetti et al., 2005).

In another scenario, the higher variance in market j might be completely offset by a higher market-specific variance in market i, ($\delta_1 = \delta_2$), but the strength of the relation increases i.e. $\beta_1^H > \beta_1^L$. As a result and similar to the first scenario, conditional correlations rise. We conclude that a change in the conditional correlation might be caused by either increasing variance in one market or by a stronger dependency.[3]

In addition, one can easily imagine a scenario in which $\delta_1 = \delta_2$, and the dependence structure does not change resulting in unchanged conditional correlations. Hence, a change in variance does not necessarily influence conditional correlations.

Turning to the correlation models, it is particularly interesting what happens if a change in an exogenous variable drives the variances but not the dependence structure and vice versa.

First, we assume that the dependence structure is affected by an exogenous variable, while variances are unchanged. Furthermore, we assume that there are two exogenous regimes: in the first, called A, the dependence structure is not influenced by an exogenous variable. In the second, called B, the influence of the exogenous variable on the dependence structure is captured by a factor x so that 4.1 becomes:

$$r_i = \beta_0 + \beta_1^B \, r_j + \epsilon_i, \tag{4.11}$$

where β_1^B is defined as follows:

$$\beta_1^B = (1 + x_1) \; \beta_1^A \; , \; x_1 > 0. \tag{4.12}$$

Therefore, the following holds for correlations in regime A and B:

$$\left[1 + \frac{\mathrm{Var}\,(\epsilon_i)}{(1+x_1)^2\,(\beta_1^A)^2 \;\mathrm{Var}\,(r_j)}\right]^{-\frac{1}{2}} > \left[1 + \frac{\mathrm{Var}\,(\epsilon_i)}{(\beta_1^A)^2 \;\mathrm{Var}\,(r_j)}\right]^{-\frac{1}{2}} \tag{4.13}$$

$$\mathrm{Corr}\,(r_i, r_j|B) > \mathrm{Corr}\,(r_i, r_j|A)$$

[3] Corsetti et al. (2005) employ a standard factor model in which the returns in market i and market j are driven by a common factor and show that the results hold as well.

As expected, if an exogenous variable strengthens the relation between the markets i and j, the correlation rises.

Let us now assume that the variance in market j is affected by an exogenous variable but not the dependence structure. Again, there are two regimes: there is no influence of the exogenous variable on the variance in regime C. By contrast, in regime D, exogenous variables cause the variance in market j to increase as follows:

$$\operatorname{Var}(r_j|D) = (1+x_1)\ \operatorname{Var}(r_j|C)\,,\ \ x_1 > 0. \tag{4.14}$$

Furthermore, the market-specific variance is assumed to remain constant, i.e.

$$\operatorname{Var}(\epsilon_i|C) = \operatorname{Var}(\epsilon_i|D) = \operatorname{Var}(\epsilon_i) \tag{4.15}$$

$$\operatorname{Corr}(r_j, \epsilon_i|C) = \operatorname{Corr}(r_j, \epsilon_i|D) = 0. \tag{4.16}$$

Then, for $x_1 > 0$, the respective correlations in regimes C and D are:

$$\left[1 + \frac{\operatorname{Var}(\epsilon_i)}{\beta_1^2\ (1+x_1)\operatorname{Var}(r_j|C)}\right]^{-\frac{1}{2}} > \left[1 + \frac{\operatorname{Var}(\epsilon_i)}{\beta_1^2\ \operatorname{Var}(r_j|C)}\right]^{-\frac{1}{2}} \tag{4.17}$$

$$\operatorname{Corr}(r_i, r_j|D) > \operatorname{Corr}(r_i, r_j|C)$$

As expected, if an exogenous variable affects the variance in market j but not the market-specific variance ϵ_i, the correlation between market i and j rises. Thus, a change in the exogenous variable drives the conditional correlations without changing the dependence structure of the time series. However, as shown previously, if assumptions 4.15 and 4.16 are dropped, i.e. we assume that the market-specific variance in market i is also affected by the exogenous variables, the outcome changes: conditional correlation might increase, decrease, or not change at all.

Although we do not have a general result indicating what happens if the variance is affected by an exogenous variable, there are cases in which an influence of the exogenous variable on the variance also drives correlations.

4.3 Conditional Variance and Exogenous Variables: The GARCHX Model

In this section, we present a model that captures the influence of any exogenous variable on conditional variances. Several studies argue that macroeconomic or financial variables might help in forecasting volatility while others are more sceptical.[4] As already noted by Engle (1982), any variance function can be augmented with exogenous variables. Previous studies employ both multivariate GARCH(1,1) and GARCHX models. The former studies model conditional variance as a function of its own and exogenous variables' past squared innovations (Bollerslev, 1990; Fratzscher, 2002; Kaltenhäuser, 2003; Hunter and Simon, 2005). GARCHX models as proposed by Hwang and Satchell (2005), Brenner et al. (1996) or Engle and Patton (2001) directly include the exogenous variable in the GARCH conditional variance equation such as

$$h_t = \omega + \alpha r_{t-1} + \beta h_{t-1} + \gamma X_{t-1}, \tag{4.18}$$

where r_{t-1} is a lagged demeaned time series, h_t is the conditional variance and X_{t-1} a vector with lagged exogenous variables.[5] For $\gamma = 0$ the model reduces to the traditional GARCH(1,1) model. Han (2010) establishes the asymptotic properties. Furthermore, the GARCHX model is widely used in empirical research.[6]. Depending on the formulation of Equation 4.18, different parameter restrictions are imposed to ensure that the non-negativity condition of variance is always satisfied (Hwang and Satchell, 2005) Alternatively, the model can be estimated by constrained maximum likelihood, restricting the parameter space so that the conditional volatility process is always positive (de Goeij and Marquering, 2004).

4.4 GDCCX Simulation when an Exogenous Variable Drives Conditional Variances

In this section, we study the consequences of estimating a GDCCX model when the variance equation is misspecified. Therefore, we conduct a simulation experiment.

[4] See Christiansen et al. (2011) for an overview on these papers.
[5] An alternative formulation is replacing γX_{t-1} with γX_{t-1}^2 which ensures that the term with the exogenous variable is positive.
[6] See Fleming et al. (2008) or Han (2010) for an overview.

Specifically, we simulate time series where the conditional variances but not conditional correlations are driven by an exogenous variable. We model the influence of the exogenous variables with a GARCHX model. We include four different types of exogenous variables:

1. The exogenous variable is an independent identically-distributed random time series sampled from a normal distribution.

2. The exogenous variable is similar to defined above but exhibits conditional heteroscedasticity according to a GARCH(1,1) model. Typically, financial time series behave like series from this data generating process.

3. The exogenous variable takes on a standard normal distributed value every 100th observation only. All other observations are zero. This type of series simulates macroeconomic announcements which are usually published periodically.[7] Although the simulated announcement values are standard normally distributed, the complete time series of the exogenous variable is not normally distributed due to the large number of zeros.

4. The exogenous variable is similar to the exogenous variable as described before but the value during the announcement is one. That simulates a dummy variable which indicates the release of an macroeconomic announcement.

Furthermore, we test two different parameter sets for the GARCHX model (see Equation 4.18) that describes the influence of the exogenous variable on conditional variances:

Parameter Set	Series	ω_i	α_i	β_i	γ_i
I	1	0.01	0.03	0.90	0.00010
	2	0.01	0.03	0.90	-0.00005
II	1	0.01	0.03	0.90	0.010
	2	0.01	0.03	0.90	-0.005

[7] These types of time series are included in the empirical analysis in chapter 6.

The parameter sets differ in the dimension of the γ parameter as they vary by a factor of 100. Thus, GARCHX effects are more pronounced when parameter set II is employed.[8]

In all simulated time series, the conditional variances but not conditional correlations are driven by an exogenous variable. Two different correlation structures are tested. First, we assume that the true correlation structure of the simulated time series is generated by a DCC (1,1) model. Second, we assume that the time series are uncorrelated. In addition, we examine the effect of different sample sizes. We investigate samples with 500, 1000, 2500, and 5000 observations. All simulations are repeated 200 times.

After simulating the data, we estimate a GDCCX model and estimate conditional variances using a GARCH (1,1) model. We calculate the 90% as well as the 95% confidence intervals for the c parameter that measures the influence of the exogenous variable (see section 2.4.2 and equation 2.11). Next, we check if the confidence interval includes the true parameter. That should be the case in 95% of all simulations for the 95% confidence interval, i.e. the empirical rejection frequency should be 5%. The empirical rejection frequency should approach the nominal level as the sample size grows. The true c parameter is zero since the conditional variances are not affected by the exogenous variable. Results for the different settings are presented in Figures 4.1 and 4.2.

Employing parameter set II and assuming that the true correlation structure is generated by a DCC (1,1) model results in the most exceptional results as shown in Figure 4.1(b). If we simulate that the exogenous variables are homoscedastic or heteroscedastic normally distributed random time series the rejection frequency approaches 100% as the sample size grows . That means that the estimated c parameter of the GDCCX model is significantly different from zero in all simulations. However, the true parameter is zero as conditional correlations are not influenced by the exogenous variable. In this setting, the GDCCX estimator is biased. Most probably this is caused by the univariate GARCH model not being well specified. Obviously, the large influence of exogenous variable on the conditional variances is incorrectly assigned to a change in conditional correlations.

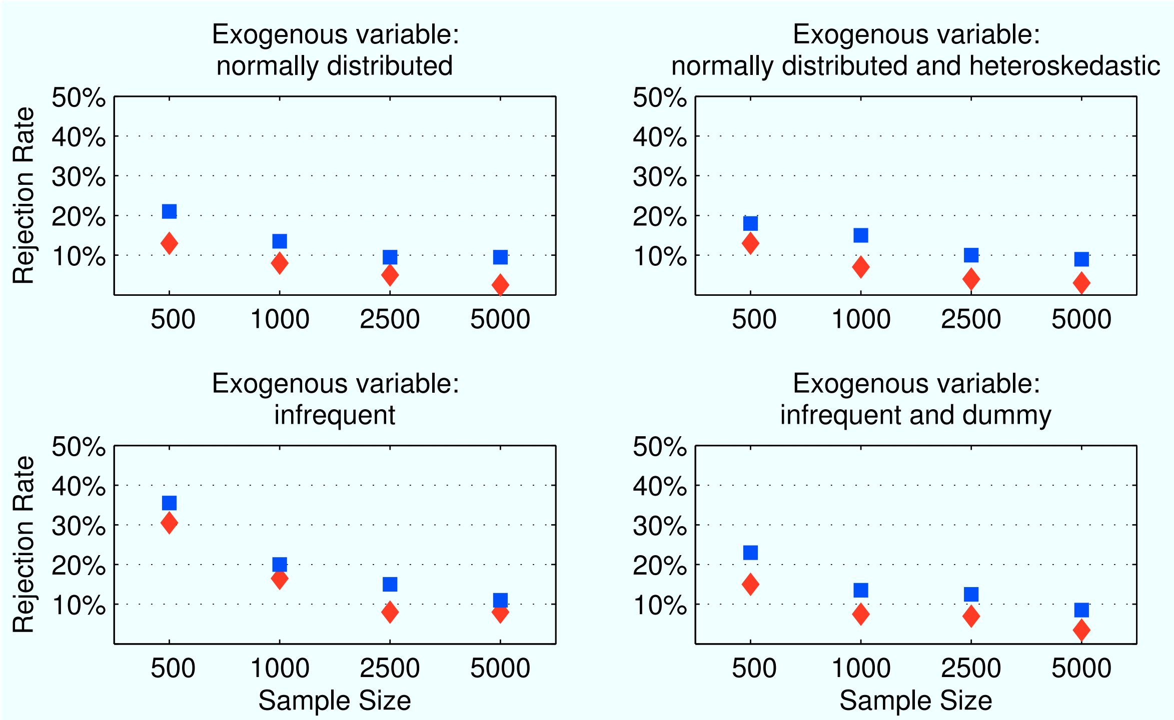
[8] We also employed parameter sets where the γ parameter is constant among series or takes on different values. However, we found that changing the parameter dimension among parameter sets is more important than changing the sign or the actual value of the parameter.

Interestingly, the results change dramatically once we change the simulation setting. For example, we employ parameter set I in Figure 4.1(a). As a result, all empirical rejection frequencies approach 5% and 10%, respectively. Therefore, the bias disappears if the simulated influence of the exogenous variable on conditional variances is not as large as in parameter set II. The same is true if the simulated time series are uncorrelated as shown in Figures 4.2(a) and 4.2(b) or if the exogenous variable is the "rare event dummy" or a dummy time series. In both cases there are further misspecifications, i.e. the exogenous variable is not normally distributed or the conditional correlations are constant and are not generated by a DCC model. As a result, the bias also disappears.

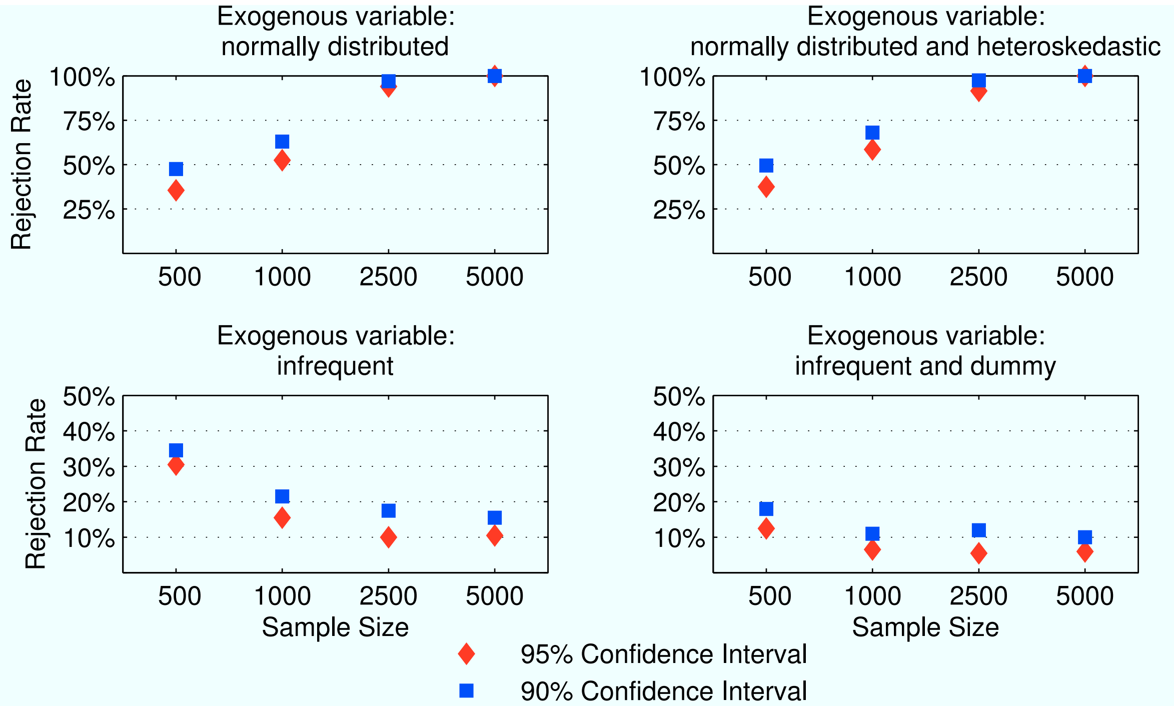
Yet, it needs a larger sample size for the empirical rejection frequencies to approach the nominal significance values in all settings that include these additional misspecifications. As expected, a sample size of 1000 already produces empirical rejection frequencies that are close to the nominal ones if the exogenous variable is normally distributed, the true correlation structure is generated by a DCC model, and the influence of the exogenous variable on conditional variances is small.

As discussed in section 2.2 and 2.4, the DCC type models allow for any univariate volatility specification to estimate conditional variances. Thus, we can employ the GARCHX model as well. In the following, we repeat the GDCCX model estimation from above but replace the GARCH model with the GARCHX model. We are especially interested if the bias which we previously found in some settings disappears. Figures 4.3 and 4.4 present the results.

We find that the bias completely disappears once we model conditional variances with a GARCHX model. That becomes clear if Figure 4.3(b) is compared to Figure 4.1(b). Comparing all other settings to the previous experiment, there are only small differences. That is, the empirical frequencies approach the nominal levels as the sample size increases. We conclude that it is useful to model conditional variances with GARCHX model to account for the influence of an exogenous variable on volatility when estimating a GDCCX model.

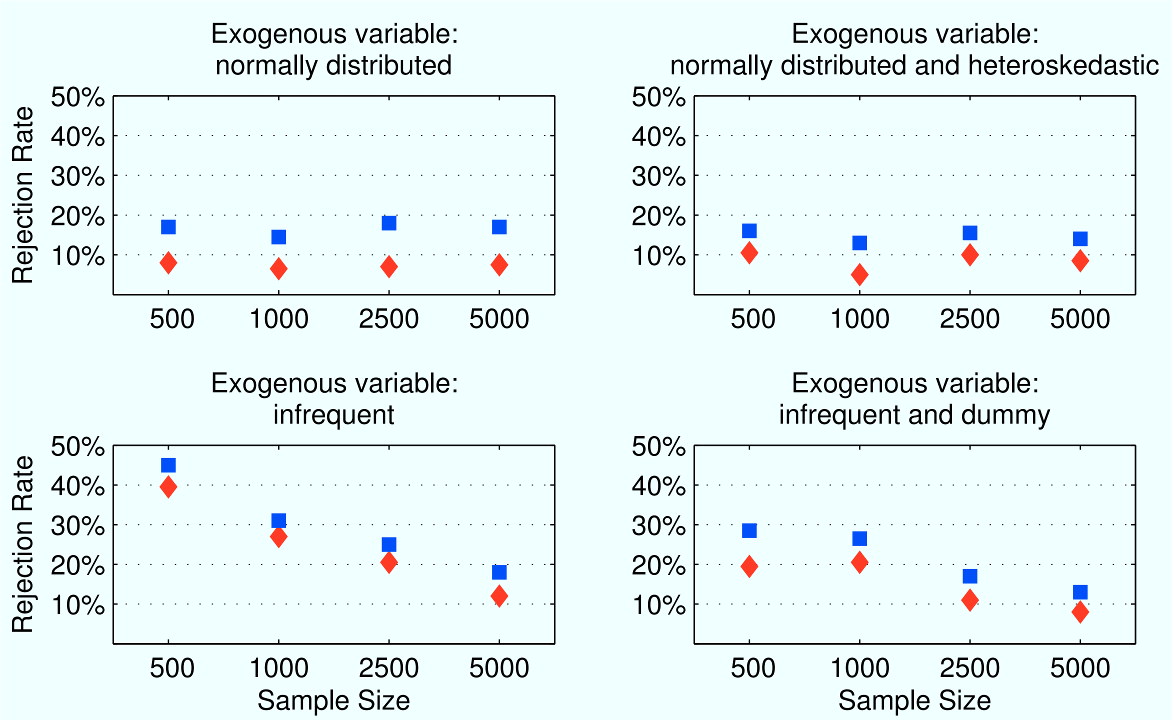


(a) True Correlation Structure: DCC; Parameter Set I

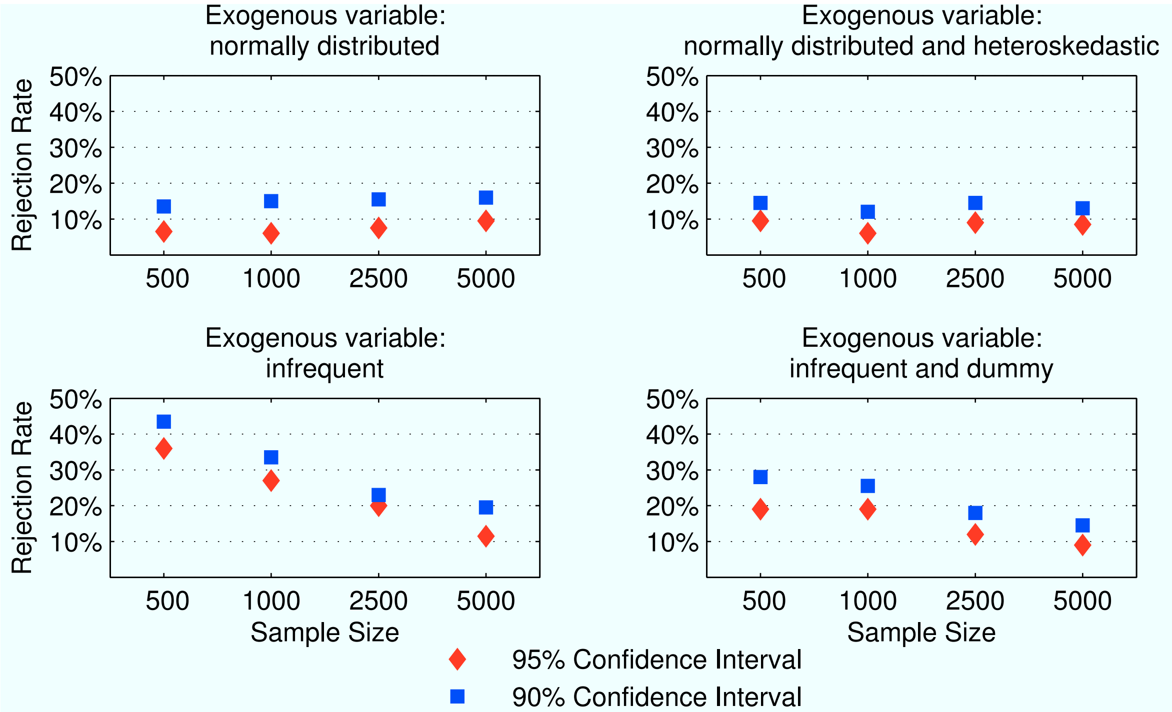


(b) True Correlation Structure: DCC; Parameter Set II

Figure 4.1: Empirical Rejection Frequencies for GDCCX/GARCH Estimations

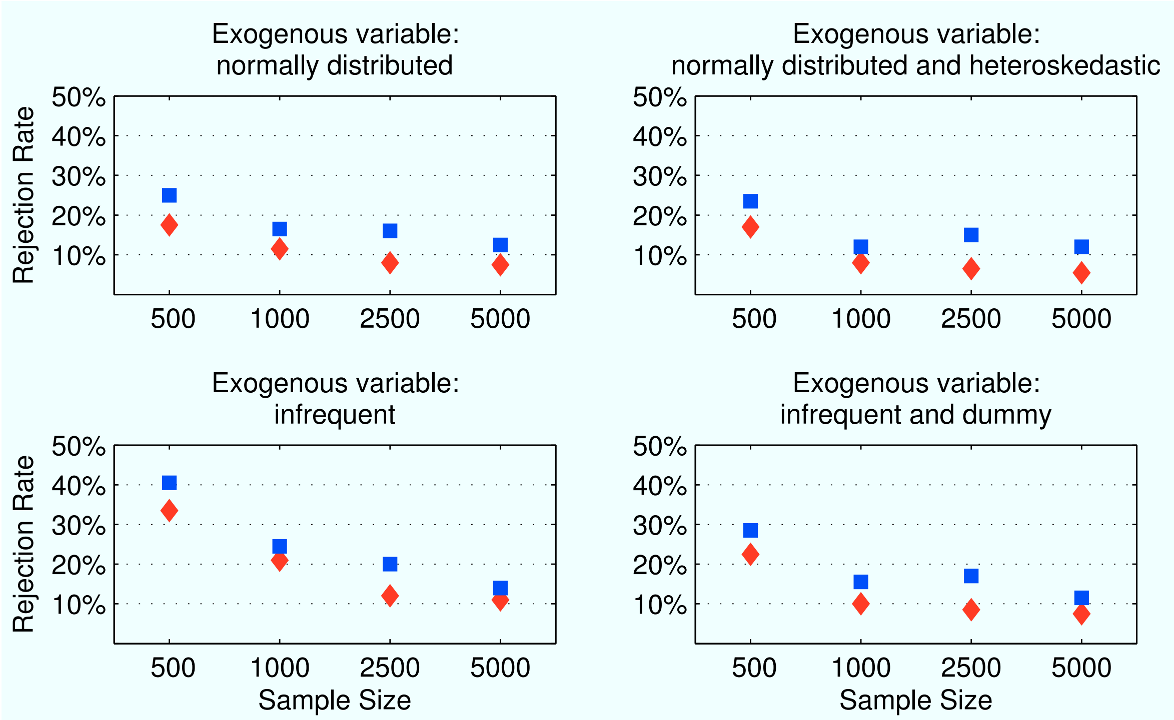


(a) True Correlation Structure: Uncorrelated; Parameter Set I

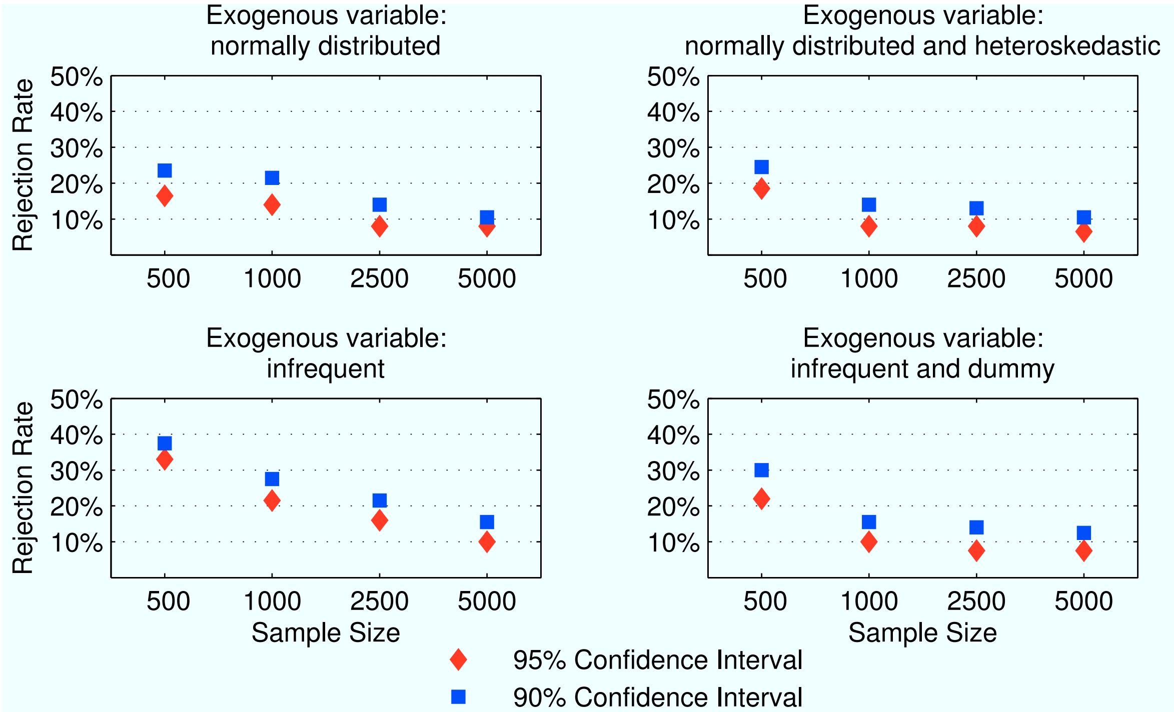


(b) True Correlation Structure: Uncorrelated; Parameter Set II

Figure 4.2: Empirical Rejection Frequencies for GDCCX/GARCH Estimations

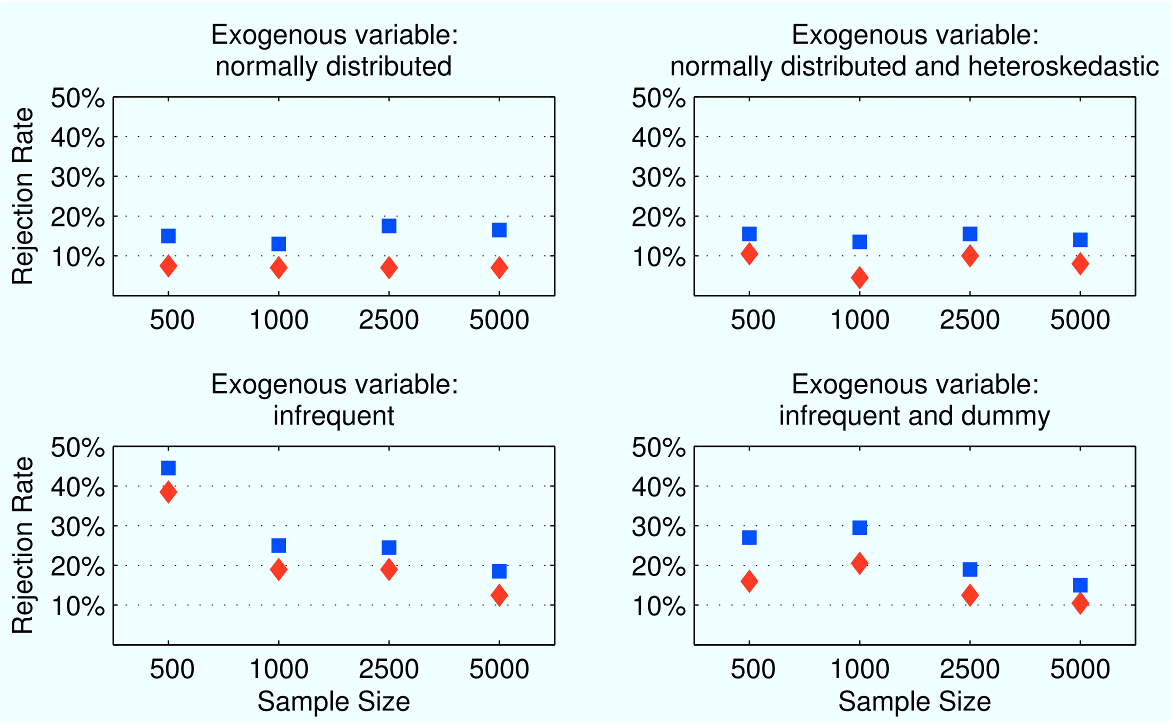


(a) True Correlation Structure: DCC; Parameter Set I

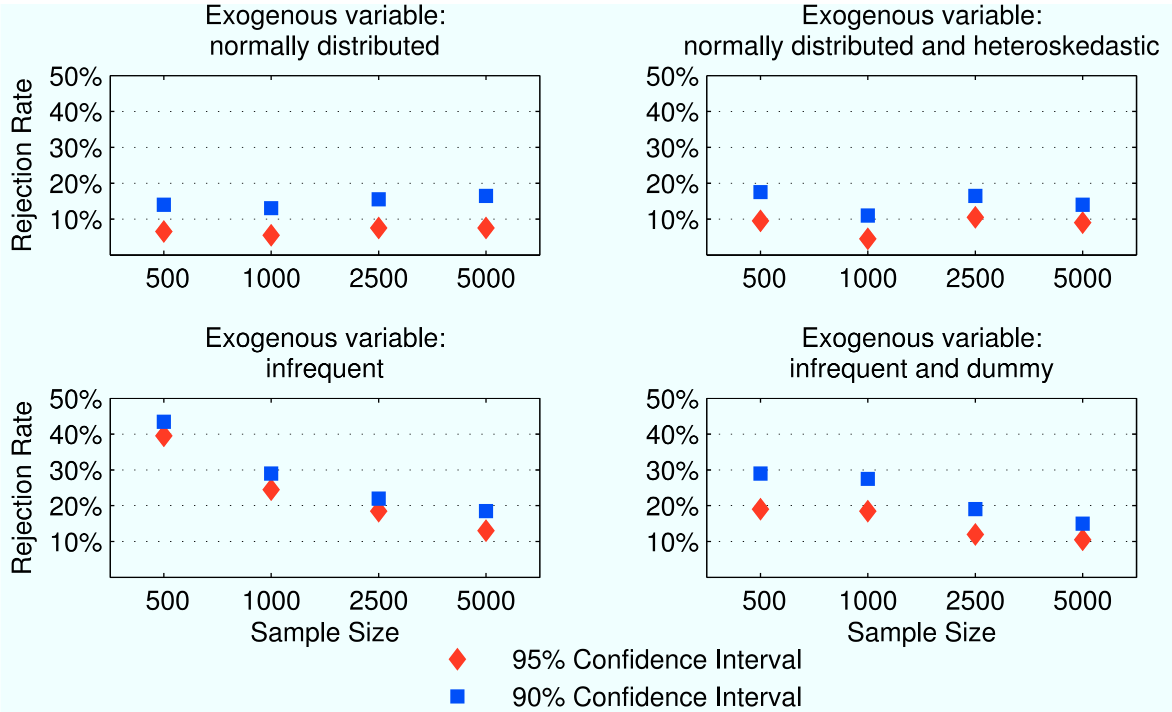


(b) True Correlation Structure: DCC; Parameter Set II

Figure 4.3: Empirical Rejection Frequencies for GDCCX/GARCHX Estimations



(a) True Correlation Structure: Uncorrelated; Parameter Set I



(b) True Correlation Structure: Uncorrelated; Parameter Set II

Figure 4.4: Empirical Rejection Frequencies for GDCCX/GARCHX Estimations

4.5 Summary

In this chapter, we investigate the consequences of a misspecification of the GDCCX model estimation. Specifically, we examine what happens if an exogenous variable influences conditional variances and the variance equation is misspecified. We argue that this question is relevant since previous research has shown that various macroeconomic as well as financial variables have an effect on conditional variances.

Therefore, we present the theoretical model of Forbes and Rigobon (2002). It is assumed that one time series is dependent on another time series as well as on time series specific shocks. It can be shown that an exogenous shock and a resulting change in conditional variance in one time series result in higher conditional correlations although the dependence structure does not change. Corsetti et al. (2005) point out that this result critically depends on the assumption that the variance of the time series specific shocks is not affected by the exogenous shocks. We demonstrate that this outcome is also true when variances are driven by an exogenous variable.

Depending on assumptions regarding the time series specific variance, the theoretical results are inconclusive. Thus, the effects of exogenous variables on conditional variances are studied in a simulation experiment. In different settings, we simulate that conditional variances but not conditional correlations are affected by an exogenous variable. We find that under certain conditions, the GDCCX estimator, which assumes that conditional variances follow a GARCH(1,1) model, is biased. These conditions include that the effect of the exogenous variable on conditional variances is very strong, the true correlation structure is generated by a DCC model, and the exogenous variable is normally distributed. Furthermore, we show that this bias is caused by the misspecification of the variance equation. If the same simulation experiment is repeated but the variance is model with a GARCHX model instead of the GARCH model, the estimator is unbiased and consistent. We conclude that it is generally reasonable to model conditional variances with a GARCHX model if conditional variances are affected by the exogenous variable.

Moreover, the GDCCX and the GARCHX model individually account for exogenous influences on the stochastic structure of financial returns. From a theoretical point of view, combining both models allows to separate the influence of exogenous variables on volatility from the impact of exogenous variables on the dependence structure of financial returns in a clear cut manner. We will consider both models in the empirical analysis in chapter 5 and chapter 6.

5 Market Turbulence and Conditional Correlations

5.1 Introduction

In the previous chapters, we lay out and discussed an econometric framework that allows us to investigate the drivers of conditional correlations. We find that the GDCCX model is particularly well suited for an empirical analysis of the determinants of conditional correlations. Moreover, we show that it is advantageous to estimate conditional variances with a GARCHX model in order to separate the effects of exogenous variables on volatility from the effects on the dependence structure.

In this chapter, we put this empirical framework into action. Specifically, we want to extend the analysis to the effects of risk aversion in general, market turbulences, as well as the business cycle on conditional correlations. Since the GDCCX model allows for the simultaneous inclusion of several exogenous variables, we are able to examine if the effect of a specific variable on correlations is dominating. By contrast, most studies employ a limited set of only one (Berben and Jansen, 2009; Yang et al., 2009) or two (Cai et al., 2009; Aslanidis et al., 2010) exogenous variables at a time.

We are especially interested in the effects of risk aversion since several authors suggest that risk aversion influences correlations. For example, Cai et al. (2009) employ a Smooth Transition Conditional Correlation (STCC) type model[1] and analyze correlations between daily international equity market returns. They find that conditional correlations are higher when risk aversion, as measured by the implied volatility of index options, is larger. Using regression analysis, Kim et al. (2006) as well as Andersson et al. (2008) demonstrate that the linkages between stocks and bonds weaken when risk aversion rises. Furthermore, Connolly et al. (2007) show that stock bond return correlations are lower and equity market correlations are higher when the VIX volatility index is above its 99% percentile. This raises the question whether there is a nonlinear impact of risk aversion on conditional correlations. For example, conditional correlations might rather be affected by extreme values of risk aversion than by risk aversion in general.

[1] Cai et al. (2009) use the Double Smooth Transition Conditional Correlation with Conditional Auto Regressive Range (DSTCC-CARR) model.

A number of studies investigate if macroeconomic fundamentals affect conditional correlations. For example, some authors find that an increase in the inflation rate results in an increase in conditional correlations between major international stock markets (Cai et al., 2009) and between bonds and stocks (Yang et al., 2009; Ilmanen, 2003; Li, 2002; Andersson et al., 2008). By contrast, the evidence on the effects of the business cycle on conditional correlations is mixed. Employing a rolling regressions approach, Erb et al. (1994) suggest that the linkage between G7 equity markets is stronger during recessions. However, King et al. (1994), Karolyi and Stulz (1996), Kizys and Pierdzioch (2006), and Andersson et al. (2008) do not find any significant effect for business-cycle fluctuations.

Turning to the linkages between international bond markets, Hunter and Simon (2005) use a bivariate conditional correlation GARCH model and find that conditional correlations between international bond returns do not increase in times of market stress. In addition, in chapter 3, we have shown that the correlation between different bond market sectors fall as risk aversion rises. However, the literature on the linkages between bond markets is scarce.

We aim to investigate the effects of risk aversion, market turbulences, and economic fundamentals in this chapter employing the empirical framework we developed in the previous chapters. Therefore, we construct a dataset that covers both bond and equity markets in the US and in the Eurozone. Thus, we can assess if there are differences in the way exogenous variables affect conditional correlations between stocks and linkages between bonds. Moreover, we can examine if the effect of exogenous variables within the Eurozone is similar to the effects on linkages between the Eurozone and the US. In addition to the large government and stock markets in Germany, France, Italy, and Spain, we also include Greece, Ireland, and Portugal in our dataset in order to document the effects of the recent European sovereign debt crisis.

To preview our results, we find that both GDP growth and market turbulences drive conditional correlations whereas risk aversion has almost no effect. The impact of market turbulences is especially pronounced in the peripheral countries. There is an important difference between bonds and stocks: While market turbulences result in a drop of conditional correlations between international bond markets, conditional correlations between stock markets rise strongly. This is a clear sign of contagion. We conclude that benefits from international diversification diminish for stock but not for bond investors in times of market turbulences. Furthermore, lower GDP growth results in higher stock return correlations and lower bond return correlations.

The outline of the chapter is as follows. In section 5.2, we describe the data we use. Section 5.3 reports and discusses the results. Section 5.4 concludes.

5.2 Data

We construct two datasets: one for bonds and one for stocks. Table 5.1 presents the details. Bond data is covered by J.P. Morgan total return government bonds indices for the United States (US) and seven European Monetary Union (EMU) countries: France, Germany, Greece, Ireland, Italy, Portugal, and Spain.

Table 5.1: Dataset

Name	Symbol	Source	Ticker	Obs.	Start	End
			Government Bonds			
US	US	JPM	USTITRLC	833	06/30/1995	09/30/2011
Germany	DE	JPM	GETITRLC	833	06/30/1995	09/30/2011
France	FR	JPM	FRTITRLC	833	06/30/1995	09/30/2011
Italy	IT	JPM	ITTITRLC	833	06/30/1995	09/30/2011
Greece	GR	JPM	GRTITRLC	702	01/09/1998	09/30/2011
Ireland	IR	JPM	IRTITRLC	833	06/30/1995	09/30/2011
Portugal	PT	JPM	PTTITRLC	833	06/30/1995	09/30/2011
Spain	ES	JPM	SPTITRLC	833	06/30/1995	09/30/2011
VDAX	VDAX	BBG	VDAX Index	833	06/30/1995	09/30/2011
VIX	VIX	BBG	VIX Index	833	06/30/1995	09/30/2011
GDP	GDP	ES	EUGNEMUQ Index	833	06/30/1995	09/30/2011
			Stocks			
US	US	FTSE	FTL3US Index	685	05/08/1998	09/30/2011
Germany	DE	FTSE	FTL3GR Index	685	05/08/1998	09/30/2011
France	FR	FTSE	FTL3FR Index	685	05/08/1998	09/30/2011
Italy	IT	FTSE	FTL3IT Index	685	05/08/1998	09/30/2011
Greece	GR	FTSE	FTL3GE Index	685	05/08/1998	09/30/2011
Ireland	IR	FTSE	FTL3IR Index	685	05/08/1998	09/30/2011
Portugal	PT	FTSE	FTL3PO Index	685	05/08/1998	09/30/2011
Spain	ES	FTSE	FTL3SP Index	685	05/08/1998	09/30/2011
VDAX	VDAX	BBG	VDAX Index	685	05/08/1998	09/30/2011
VIX	VIX	BBG	VIX Index	685	05/08/1998	09/30/2011
GDP	GDP	ES	EUGNEMUQ Index	685	05/08/1998	09/30/2011

Note: The table provides an overview on the datasets. JPM is J.P. Morgan, BBG is Bloomberg, FTSE are FTSE indices, and ES is Eurostat.

Our sample includes countries which are in the center of the current European sovereign debt crisis and countries that are considered to be safe investments. All indices are capitalization weighted, assume a reinvestment of received coupon payments or redemptions, and are based on prices observed in the secondary market. Furthermore, all bonds must satisfy certain liquidity criteria.[2]

We use FTSE All-World country indices for our stock dataset. We choose the same countries as in the bond sample. The indices are value weighted total return indices that include dividend payments. They provide a broad measure of stock market returns.[3]

For all indices, we compute the continuously compounded weekly returns from Friday to Friday. We choose to study returns at a weekly frequency in order to avoid the problems caused by non-synchronous trading (Burns et al., 1998). All returns are expressed in local currency.

We use different exogenous variables in our analysis. As described in section 3.3.2.2, the implied volatility of equity options is a popular proxy of risk aversion. We employ the VDAX volatility index as a measure of risk aversion. The index tracks the expected volatility over the next 45 days implied in index options on the German DAX stock index.[4] For analysis which include the US indices, we employ the Chicago Board Options Exchange Volatility Index (VIX) as proxy for risk aversion. The VIX is a popular measure of the implied volatility of index options on the S&P 500 Index over the next 30 days. Several authors (Connolly et al., 2005, 2007; Hunter and Simon, 2005; Cappiello et al., 2006a) point out that conditional correlations change quickly in high-stress periods. Therefore, we take the 1% percentile of the VDAX and VIX indices as a proxy for high market stress by using an appropriately defined dummy variable

Since large values of the exogenous variable result in very small values of the respective coefficient, we avoid rounding errors during optimization and calculation of standard errors by dividing the level of risk aversion by 1000. We employ quarterly Eurozone GDP growth as a proxy for the business cycle. We take quarterly growth figures from Eurostat for the Eurozone. Quarterly data is converted into weekly data by allowing the

[2]For further details on the index construction and guidelines please refer to www.morganmarkets.com.
[3]For further details on the index construction and guidelines please refer to www.ftse.com.
[4]An alternative to the VDAX volatility index is the Euro Stoxx 50 Volatility Index (VSTOXX) that tracks implied volatility of index options on the Euro Stoxx 50 Index. However, the VSTOXX index is only available since 1/4/1999. Besides, the correlation between the VSTOXX and the VDAX is very high: 0.98. Therefore, we consider both as equally representative for the Eurozone.

variable to remain constant during a quarter. This transformation of macroeconomic data has already been applied to convert monthly to daily (Cai et al., 2009) or to weekly data (Aslanidis and Christiansen, 2010).

Table 5.2: Descriptive Statistics

Symbol	Mean	Min.	Max.	Std. Dev.	Skewness	Kurtosis
			Government Bonds			
US	0.12%	−3.28%	2.57%	0.68%	−0.49	4.16***
DE	0.11%	−2.05%	1.91%	0.53%	−0.20	3.66***
FR	0.12%	−1.99%	1.89%	0.54%	−0.24	3.71***
IT	0.13%	−2.74%	4.81%	0.65%	0.06	8.11***
GR	0.02%	−15.18%	22.36%	1.75%	1.90	60.59***
IR	0.11%	−7.97%	13.16%	1.13%	1.54	35.78***
PT	0.09%	−10.95%	10.15%	1.02%	0.00	42.88***
ES	0.13%	−2.82%	4.91%	0.64%	0.02	8.27***
VDAX	22.98	10.10	64.28	9.37	1.35	4.91***
VIX	21.68	10.02	79.13	8.83	2.01	10.11***
GDP	0.43%	−2.50%	1.30%	0.58%	−2.57	12.99***
			Stocks			
US	0.02%	−20.12%	11.51%	2.75%	−0.75	8.86***
DE	−0.01%	−23.90%	15.43%	3.53%	−0.69	7.78***
FR	0.02%	−24.93%	12.58%	3.20%	−0.93	9.37***
IT	−0.07%	−24.50%	19.66%	3.38%	−0.89	10.95***
GR	−0.22%	−20.08%	18.80%	4.46%	−0.33	5.88***
IR	−0.18%	−37.10%	16.61%	4.09%	−1.50	15.25***
PT	−0.08%	−20.61%	13.09%	2.91%	−0.93	9.31***
ES	0.02%	−23.80%	13.07%	3.36%	−0.83	8.26***
VDAX	24.04	10.98	64.28	9.53	1.36	4.71***
VIX	22.43	10.02	79.13	9.31	1.89	9.23***
GDP	0.40%	−2.50%	1.20%	0.62%	−2.51	11.69***

Note: The table reports descriptive statistics for all variables.
*** denotes series that differ from a normal distribution at 1% level as indicated by a Jarque–Bera test.

All government bond indices are available at least since 12/30/1994 except for the Greece government bond index that starts at 12/31/1997.[5] The volatility index starts 1/2/1990. As Eurozone GDP growth is available since 06/30/1995 only, it determines the starting point for our bond sample. Altogether, we cover the period from 06/30/1995 to 09/30/2011. Fridays on which markets were closed are removed from the sample which gives us 833 observations. However, all analysis that include gov-

[5] Data from the US, France, and Germany are available since 12/31/1985, time series from Ireland, Italy, Spain start at 12/31/1987, while data from Portugal and Greece are only available since 12/30/1994 and 12/31/1997, respectively.

Table 5.3: European Bonds: Unconditional Correlations

	US	DE	FR	IT	GR	IR	PT	ES	VDAX	VIX	GDP
US	1										
DE	0.73	1									
FR	0.71	0.95	1								
IT	0.48	0.55	0.67	1							
GR	0.08	0.03	0.13	0.53	1						
IR	0.31	0.32	0.40	0.60	0.61	1					
PT	0.24	0.23	0.33	0.64	0.74	0.80	1				
ES	0.52	0.62	0.70	0.87	0.50	0.64	0.68	1			
VDAX	0.10	0.10	0.09	0.01	-0.02	0.05	0.03	0.04	1		
VIX	0.11	0.13	0.12	0.02	-0.03	0.05	0.04	0.05	0.86	1	
GDP	0.04	-0.03	-0.04	-0.03	-0.01	-0.02	-0.04	-0.03	-0.33	-0.44	1

Note: The table reports the unconditional correlations of our bond sample.

ernment bonds of Greece start at 12/31/1997 leaving us with a reduced sample of 702 observations.

Table 5.2 provides descriptive statistics for the bond sample. All bond markets exhibit an average positive return. With the exception of Greece, the average weekly return is about the same level in all countries. The peripheral countries in the Eurozone are riskier as measured by the range between minimum and maximum return. In addition, most time series are heavily left skewed and exhibit fat-tails. Moreover, they are non-normal as indicated by the Jarque-Bera test. We find large outliers during the last two years in the sample that can be attributed to the sovereign debt and the financial crisis.

All FTSE stock indices are available at least since 5/1/1998. That results in 685 observations from 5/8/1998 to 9/30/2011. Remarkably, average stock returns are slightly positive only for Germany, France, and Spain and even negative for all other countries. The reason for this is that our sample covers both the burst of the dot-com bubble and the recent sovereign debt crisis. As expected, the standard deviation is higher for stock than for bond index returns. Similar to the bond sample, stock returns are left skewed, exhibit fat-tails, and are non-normal.

Both the non-normality and the presence of extreme values might severely affect the estimation since the models are constructed by assuming conditionally normal asset returns. Therefore, some authors truncate extreme values (Silvennoinen and Teräsvirta, 2005) or standardize the data (Cappiello et al., 2006a; Aslanidis and Christiansen, 2010). On the other hand, we are especially interested in periods of high market stress in which the presence of extreme values is most likely. Since Engle (2002) argues that results

Table 5.4: European Stocks: Unconditional Correlations

	US	DE	FR	IT	GR	IR	PT	ES	VDAX	VIX	GDP
US	1										
DE	0.79	1									
FR	0.80	0.91	1								
IT	0.74	0.84	0.88	1							
GR	0.47	0.54	0.55	0.54	1						
IR	0.59	0.64	0.67	0.63	0.47	1					
PT	0.55	0.65	0.69	0.67	0.49	0.49	1				
ES	0.71	0.82	0.84	0.83	0.56	0.60	0.71	1			
VDAX	-0.10	-0.23	-0.20	-0.18	-0.18	-0.16	-0.16	-0.16	1		
VIX	-0.26	-0.27	-0.25	-0.25	-0.25	-0.23	-0.22	-0.23	0.86	1	
GDP	0.02	0.04	0.04	0.03	0.00	0.02	0.02	0.02	-0.39	-0.48	1

Note: The table reports the unconditional correlations of our stock sample.

have a quasi-maximum likelihood estimation interpretation if returns are non-normal, we do not truncate or standardize the data. Moreover, outliers may be accounted for by an exogenous variables, particularly by the market turbulences dummy. Similar to section 3.3.2, we multiply the return series with 1000 to avoid rounding error during estimation. Since the mean of the return series is non-zero, we demean the return series.

Table 5.3 presents the unconditional correlations of the bond sample and suggests the presence of three distinct groups: US, France, and Germany as they are considered to be the safest investments; Greece as it is the main country affected by the sovereign debt crisis during our sample period; and all other countries - namely, Ireland, Italy, Portugal, and Spain. The unconditional correlation between France and Germany is close to 1. That compares to correlations in the range of 0.24 to 0.70 between countries of the first and the third group and exceptionally low correlations between US/France/Germany and Greece (between 0.03 and 0.13). Unconditional correlations within the third group are in the range between 0.53 and 0.87 while correlations between the third group and Greece are mostly lower.

Table 5.4 provides the unconditional correlations for our stock sample. They are somewhat similar to the bond correlations with the exception of Italy and Spain which are stronger correlated with France and Germany than in our bond sample. Notably, the correlation between the volatility indices and the bond indices is negative while it is positive for stocks.

5.3 Empirical Results

5.3.1 European Bonds

At first, we estimate the conditional correlations between the bond index returns of our sample employing the DCC(1,1) model. Thus, we need conditional variances as estimated by a univariate GARCH model. In chapter 4, we have argued that it is reasonable to estimate conditional variances with a GARCHX model in order to better separate the effects of exogenous variables on volatility from the effects on the dependence structure. Parameter estimates for the univariate GARCH model and the GARCHX model are presented in Table 5.5 and 5.6, respectively.

Table 5.5: European Bonds: Univariate GARCH Models

Countries	α_0		α_1		α_2	
US	1.178*	(0.694)	0.058***	(0.019)	0.918***	(0.029)
DE	1.005*	(0.562)	0.079***	(0.026)	0.886***	(0.039)
FR	1.260*	(0.700)	0.072***	(0.026)	0.885***	(0.043)
IT	2.678**	(1.308)	0.149***	(0.040)	0.788***	(0.059)
GR	0.848	(0.620)	0.155***	(0.052)	0.842***	(0.057)
IR	1.995***	(0.769)	0.207***	(0.051)	0.783***	(0.039)
PT	0.801**	(0.373)	0.183***	(0.046)	0.817***	(0.036)
ES	1.677**	(0.783)	0.143***	(0.044)	0.820***	(0.050)

Note: The table reports the GARCH (1,1) model estimates for government bond indices in our sample.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

As almost all coefficients in Table 5.5 are significant, there are clear signs of volatility clustering in the bond return time series. By contrast, the exogenous variables we employ in our study do not influence conditional variances as the GARCHX γ coefficients depicted in Table 5.6 are not significantly different from zero with the exception of the US data.[6] Hence, conditional variances are not driven by the exogenous variables we considered. Nevertheless, we still employ the GARCHX model when estimating conditional variances in the GDCCX model in order to clearly separate the effects of the exogenous variables on the dependence structure from the effects on the volatility.

Table 5.7 presents the DCC model estimates. The sums of the DCC a and b parameters are close to one implying a high degree of persistence in the conditional correlations. Therefore, we employ the Engle and Sheppard (2001) correlation test as described in

[6]Results are unchanged if the insignificant parameters are dropped.

Table 5.6: European Bonds: Univariate GARCHX Models

Countries	Risk Aversion		Market Turbulence		GDP	
US	260.337***	(85.408)	174.351	(169.044)	−2881.405**	(1134.129)
DE	28.188	(28.375)	273.536	(201.039)	−1100.420	(693.951)
FR	30.904	(37.250)	348.669	(277.919)	−779.713	(654.704)
IT	−66.290	(62.116)	601.639	(374.589)	−1649.987	(1383.919)
GR	−4.050	(7.782)	382.021	(388.269)	−969.616	(810.326)
IR	35.903	(51.002)	923.729*	(515.484)	−1004.079	(1240.029)
PT	8.308	(67.144)	150.417	(282.964)	−545.560	(598.178)
ES	−11.833	(38.202)	463.990	(349.892)	−1246.786	(944.105)

Note: The table reports the GARCHX model estimates for government bond indices in our sample. We use three exogenous variables simultaneously. We estimate conditional correlations for each country pair separately.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

chapter 2.3. The right panel of Table 5.7 indicates that there is strong statistical evidence for time-varying correlations between almost all countries. In addition, most DCC parameter estimates are significantly different from zero.

Figure 5.1 plots the conditional correlations as calculated by the DCC model for the EMU bonds. Looking at the graphs, different periods can be identified. Conditional correlations are in the range between zero and one and rise steadily in the first period prior to the introduction of the Euro in 1999. Correlations are close to one in the second period which lasts nine years after the introduction of the Euro.

Figure 5.2 zooms into the conditional correlations of Greece. It becomes clear that Greece is an exception as the second phase starts about two years later. This may reflect the fact that Greece joined the Eurozone in 2001 two years after the introduction of the Euro due to the non compliance with the Euro deficit criteria. With the start of the financial crisis in 2008 conditional correlations decline. Particularly, there is a sudden drop at the end of 2009 which marks the beginning of the European sovereign debt crisis. Conditional correlations fall to values as low as -0.5. This is particularly interesting as the relation changed from positive to negative indicating a complete reassessment of Greek government bonds. However, since the announcement of the European Financial Stability Facility in May 2010 conditional correlations are rising once again but remain volatile.

Next, we use a GDCCX model to shed light on the economic causes of the changes in conditional correlations and model variances with a GARCHX model. That allows us to

Table 5.7: European Bonds: DCC Models

Countries		a		b		Corr-Test
DE	FR	0.099**	(0.040)	0.899***	(0.042)	378.590***
DE	IT	0.107***	(0.027)	0.892***	(0.028)	341.218***
DE	GR	0.097***	(0.031)	0.902***	(0.032)	143.117***
DE	IR	0.110***	(0.037)	0.887***	(0.038)	635.481***
DE	PT	0.107***	(0.025)	0.891***	(0.025)	430.017***
DE	ES	0.101***	(0.022)	0.898***	(0.022)	390.467***
FR	IT	0.078***	(0.017)	0.922***	(0.018)	350.700***
FR	GR	0.102***	(0.028)	0.897***	(0.029)	115.247***
FR	IR	0.111***	(0.027)	0.887***	(0.027)	561.654***
FR	PT	0.109***	(0.029)	0.889***	(0.029)	350.380***
FR	ES	0.102***	(0.032)	0.898***	(0.032)	346.704***
IT	GR	0.122***	(0.029)	0.875***	(0.030)	35.559**
IT	IR	0.070***	(0.016)	0.926***	(0.017)	196.931***
IT	PT	0.093***	(0.020)	0.905***	(0.021)	136.099***
IT	ES	0.071***	(0.016)	0.928***	(0.016)	148.201***
GR	IR	0.116***	(0.033)	0.881***	(0.034)	26.099
GR	PT	0.166***	(0.028)	0.833***	(0.028)	22.756
GR	ES	0.119**	(0.056)	0.879***	(0.057)	23.412
IR	PT	0.138***	(0.025)	0.859***	(0.025)	95.375***
IR	ES	0.117***	(0.026)	0.881***	(0.026)	202.860***
PT	ES	0.125***	(0.021)	0.872***	(0.022)	199.381***

Note: The table reports the DCC(1,1) model estimates for EMU government bond indices in our sample. Corr-Test denotes the Engle and Sheppard (2001) test for testing the null of constant correlation ($R_t = R \; \forall \; t$).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

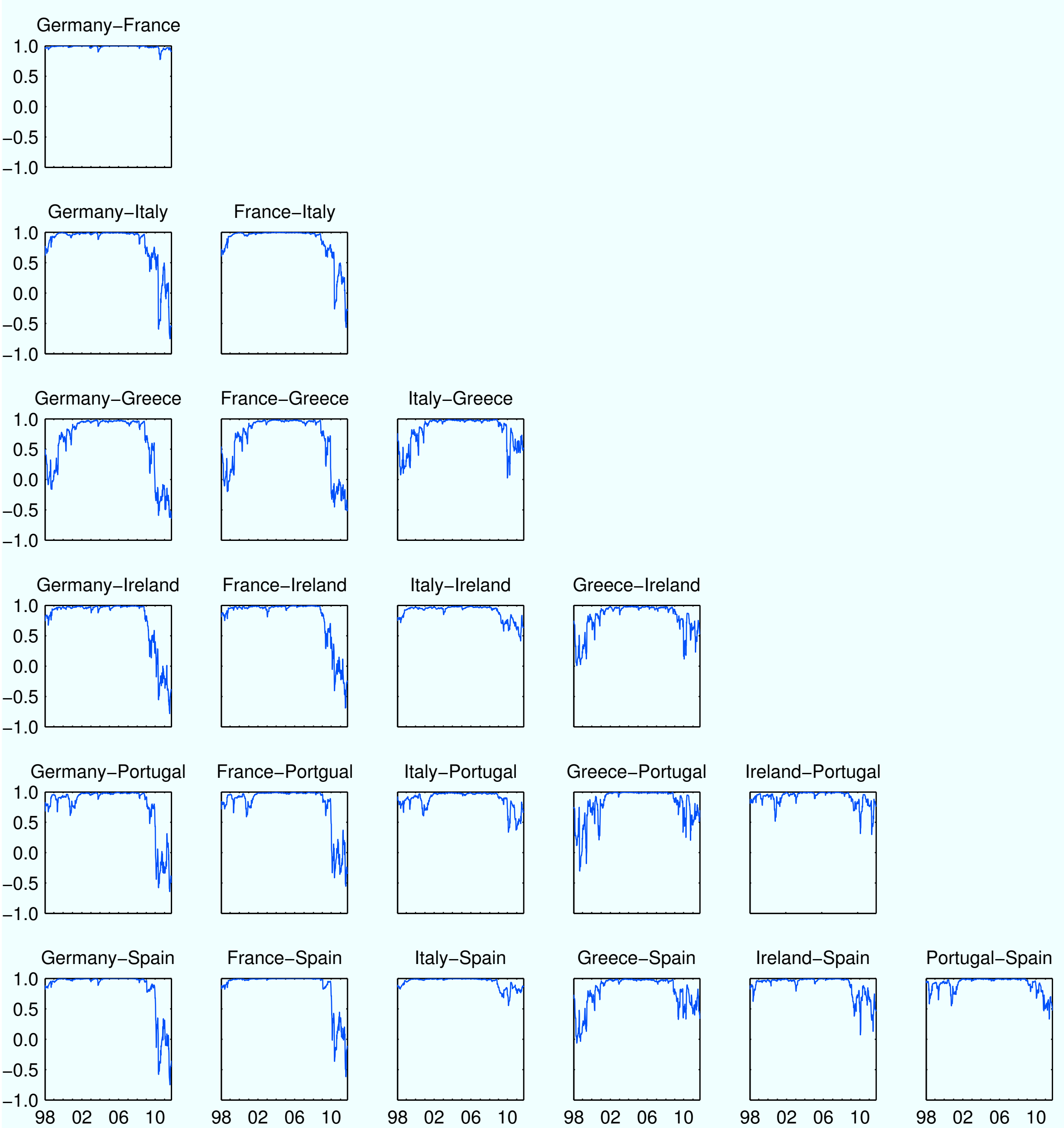


Figure 5.1: European Government Bond Conditional Correlations (DCC(1,1) Model)

better separate the effects of the variables on the dependence structure from the effects on the volatility since both models include the effects of exogenous variables. At first, we employ only one exogenous variable in the GDCCX model. Later, we simultaneously examine more variables in our two and three exogenous variables models.

Our first exogenous variable is risk aversion as measured by the VDAX volatility index. Results for the coefficient of the exogenous variable are presented in Table 5.8 in the

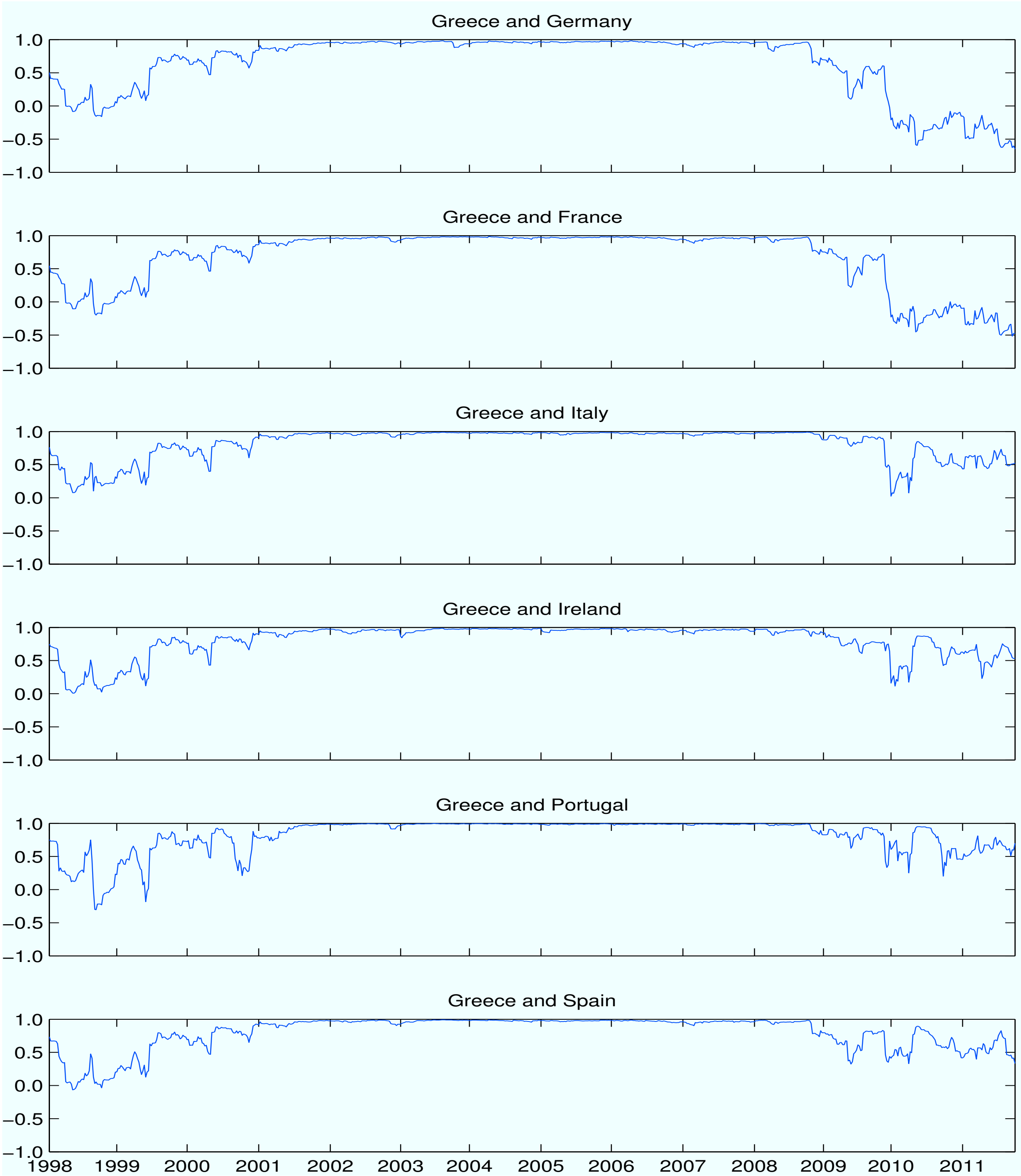


Figure 5.2: Greece Government Bond Conditional Correlations

first column. Remarkably, almost all estimated parameters are negative indicating that conditional correlations fall if risk aversion rises. However, only some coefficients for country pairs including Germany are significant. This might reflect the special status of German bonds as a "save haven".

Table 5.8: European Bonds: GDCCX Models with One Exogenous Variable

Countries		Risk Aversion		Market Turbulence		GDP	
DE	FR	−0.037***	(0.000)	−0.224**	(0.103)	0.212*	(0.112)
DE	IT	−0.043*	(0.026)	−0.373	(0.299)	0.512	(0.397)
DE	GR	−0.068	(0.064)	−1.746**	(0.803)	2.100*	(1.178)
DE	IR	−0.132	(0.081)	−0.434	(0.609)	2.279***	(0.846)
DE	PT	−0.139*	(0.084)	−0.552	(0.429)	2.515***	(0.742)
DE	ES	−0.030**	(0.014)	−0.558	(0.438)	0.293*	(0.163)
FR	IT	−0.002	(0.008)	−0.073	(0.192)	0.204	(0.221)
FR	GR	−0.046	(0.034)	−1.391**	(0.696)	2.213***	(0.857)
FR	IR	−0.088	(0.057)	−0.495	(0.474)	1.924***	(0.678)
FR	PT	−0.083	(0.057)	−0.278	(0.294)	1.775***	(0.539)
FR	ES	−0.023	(0.023)	−0.428	(0.351)	0.456**	(0.209)
IT	GR	−0.045	(0.041)	−0.532***	(0.204)	1.994***	(0.589)
IT	IR	0.035	(0.034)	−0.221	(0.267)	1.884**	(0.869)
IT	PT	−0.006	(0.016)	−0.249**	(0.105)	0.805*	(0.472)
IT	ES	−0.003	(0.008)	−0.437	(0.287)	0.156	(0.212)
GR	IR	−0.013	(0.053)	−0.554	(0.462)	2.105*	(1.116)
GR	PT	−0.036	(0.027)	−0.914***	(0.327)	0.807	(0.581)
GR	ES	−0.032	(0.042)	−1.163*	(0.614)	1.563	(0.985)
IR	PT	−0.044	(0.036)	−0.216	(0.276)	0.762*	(0.453)
IR	ES	−0.047	(0.049)	−1.060	(0.978)	1.533**	(0.633)
PT	ES	−0.034	(0.025)	−0.334	(0.227)	0.932**	(0.371)

Note: The table reports the c coefficients of the exogenous variable employing a GDCCX model for EMU government bonds. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations for each country pair separately. Risk aversion is proxied by the VDAX volatility index, market turbulence is the upper first percentile of the VDAX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

We are also interested in the evolution of correlations in times of extreme market stress. The VDAX reached its peaks in several phases of market turbulence: in the aftermath of the LTCM crisis in October 1998, in the wake of the dot-com bubble in October 2002, and in October 2008 after the collapse of Lehman Brothers. Therefore, similar to Connolly et al. (2005) we focus on the percentiles of the distribution of the volatility index. We construct a proxy for market turbulence using the first percentile of the VDAX index and employ this measure as exogenous variable. We define market turbulence m as follows: $m_t = I\left[VDAX_t > VDAX_{99}\right] \cdot VDAX_t$ where $I\left[\cdot\right]$ is an indicator function that takes on the value 1 if the argument is true and 0 otherwise.[7] The second column in Table 5.8 shows the effects of market turbulence. Conditional correlations for Greece government bond return indices significantly fall in case of market turbulence.

These results raise the question if market turbulence rather than risk aversion explains conditional correlations. Therefore, we repeat our analysis including the risk aversion measure and the proxy for market turbulence simultaneously in a two exogenous variables model.[8] As shown in Table 5.9, the results for our market turbulence proxy remain largely unchanged while the effect of risk aversion on conditional correlations diminishes. When accounting for both risk aversion and market turbulence simultaneously, risk aversion significantly explains the conditional correlations only for the linkage between France and Germany and the signs of the coefficients even changes to positive for some country pairs.

Next, as reported in third column in Table 5.10, we consider the effects of macroeconomic fundamentals on conditional correlations within the Eurozone. Using Eurozone GDP growth as a proxy for the business cycle, we find that higher GDP growth results in higher conditional correlations. The effect can be found for both correlations between the safest and the riskier countries and for correlations within riskier countries.

Employing GDP growth as the only explaining variable might be misleading as market turbulence usually coincides with lower GDP growth. Therefore, in our final analysis we employ all three exogenous variables simultaneously. Results presented in Table 5.10 confirm our previous findings. Both GDP growth and market turbulences drive conditional correlations downwards whereas risk aversion has almost no effect. Therefore, when GDP growth turns negative during a crisis, correlations decline. In addition, if there are market turbulences, conditional correlations fall even more. As expected, the impact of market turbulences is most pronounced for the peripheral countries. Furthermore, there is no general effect of risk aversion on conditional correlations since the signs of the coefficients are positive for some country pairs and are negative for other country pairs. Yet most coefficients are significantly different from zero.

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[7] Repeating all analysis with a market turbulence dummy i.e. $m_{t,alt} = I\left[VDAX_t > VDAX_{99}\right]$ leaves results qualitatively unchanged.

[8] When using both the proxy for risk aversion and for market turbulence in the two and three exogenous variables models, we remove the first percentile from the risk aversion indicator in order to better separate the effects of risk aversion and market turbulence. Employing the unchanged VDAX index does not change our results qualitatively.

Table 5.9: European Bonds: GDCCX Models with Two Exogenous Variables

Countries		Risk Aversion		Market Turbulence	
DE	FR	−0.033*	(0.019)	−0.172	(0.128)
DE	IT	−0.037	(0.029)	−0.263	(0.346)
DE	GR	−0.007	(0.045)	−1.742**	(0.809)
DE	IR	−0.130	(0.083)	−0.305	(0.502)
DE	PT	−0.122	(0.087)	−0.424	(0.512)
DE	ES	−0.020	(0.014)	−0.549	(0.506)
FR	IT	0.001	(0.010)	−0.078	(0.226)
FR	GR	−0.003	(0.023)	−1.383**	(0.705)
FR	IR	−0.080	(0.061)	−0.354	(0.435)
FR	PT	−0.071	(0.055)	−0.222	(0.301)
FR	ES	−0.001	(0.012)	−0.425	(0.358)
IT	GR	0.017	(0.019)	−0.546***	(0.202)
IT	IR	0.056	(0.038)	−0.364	(0.302)
IT	PT	0.012	(0.015)	−0.264**	(0.107)
IT	ES	0.011	(0.007)	−0.444*	(0.261)
GR	IR	0.021	(0.049)	−0.621	(0.483)
GR	PT	0.004	(0.015)	−0.916***	(0.323)
GR	ES	0.020	(0.025)	−1.191**	(0.589)
IR	PT	−0.037	(0.040)	−0.147	(0.262)
IR	ES	−0.016	(0.047)	−1.076	(1.046)
PT	ES	−0.008	(0.018)	−0.325	(0.230)

Note: The table reports the c coefficients of the exogenous variable employing a GDCCX model for EMU government bonds. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations with two exogenous variables simultaneously and for each country pair separately. Risk aversion is proxied by the VDAX volatility index, market turbulence is the upper first percentile of the VDAX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

In summary, we find that conditional correlations between bond indices fall as GDP growth declines and if there is market turbulence. From a portfolio perspective this is a very favorable result since it implies that the benefits of international diversification increase in times of market turmoils.

Table 5.10: European Bonds: GDCCX Models with Three Exogenous Variables

Countries		Risk Aversion		Market Turbulence		GDP	
DE	FR	−0.033*	(0.019)	−0.167	(0.122)	0.061	(0.083)
DE	IT	−0.037	(0.030)	−0.235	(0.333)	0.412	(0.417)
DE	GR	0.049	(0.035)	−1.585**	(0.774)	1.762*	(1.022)
DE	IR	−0.033	(0.082)	−0.187	(0.501)	2.142**	(0.888)
DE	PT	−0.072	(0.076)	−0.240	(0.515)	2.265***	(0.780)
DE	ES	−0.024*	(0.014)	−0.555	(0.539)	0.217	(0.137)
FR	IT	0.002	(0.010)	−0.058	(0.201)	0.192	(0.228)
FR	GR	0.050*	(0.027)	−1.153*	(0.630)	1.985***	(0.731)
FR	IR	−0.024	(0.048)	−0.273	(0.428)	1.790**	(0.698)
FR	PT	−0.011	(0.034)	−0.063	(0.263)	1.683***	(0.585)
FR	ES	0.003	(0.010)	−0.399	(0.349)	0.298*	(0.167)
IT	GR	0.057***	(0.016)	−0.415**	(0.176)	1.866***	(0.538)
IT	IR	0.044	(0.035)	−0.135	(0.319)	1.594**	(0.808)
IT	PT	0.025	(0.017)	−0.210**	(0.105)	0.752	(0.618)
IT	ES	0.011	(0.007)	−0.442*	(0.263)	0.016	(0.193)
GR	IR	0.042	(0.056)	−0.522	(0.531)	1.787	(1.139)
GR	PT	0.007	(0.018)	−0.910***	(0.319)	0.138	(0.479)
GR	ES	0.054**	(0.025)	−1.085**	(0.547)	1.118*	(0.655)
IR	PT	−0.018	(0.049)	−0.136	(0.274)	0.652	(0.521)
IR	ES	0.032	(0.049)	−0.846	(0.820)	1.428**	(0.601)
PT	ES	0.006	(0.018)	−0.279	(0.228)	0.640*	(0.367)

Note: The table reports the c coefficients of the exogenous variable employing a GDCCX model EMU stock indices. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations with three exogenous variables simultaneously and for each country pair separately. Risk aversion is proxied by the VDAX volatility index, market turbulence is the upper first percentile of the VDAX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

Table 5.11: European Stocks: Univariate GARCH Models

Countries	α_0		α_1		α_2	
US	36.068**	(14.971)	0.192***	(0.065)	0.773***	(0.060)
DE	109.276**	(50.962)	0.266**	(0.123)	0.671***	(0.113)
FR	24.859**	(11.738)	0.163***	(0.055)	0.831***	(0.037)
IT	44.727**	(17.642)	0.285***	(0.103)	0.715***	(0.064)
GR	17.147	(13.316)	0.064***	(0.023)	0.930***	(0.026)
IR	35.084*	(19.370)	0.129***	(0.042)	0.855***	(0.038)
PT	50.419**	(20.537)	0.233***	(0.079)	0.730***	(0.066)
ES	10.714	(6.857)	0.098***	(0.022)	0.902***	(0.026)

Note: The table reports the GARCH (1,1) model estimates for stock indices in our sample.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

5.3.2 European Stocks

We repeat the analysis with the same set of countries but now for stock indices. Similar to the bond sample, GARCH estimates as shown in Table 5.11 indicate volatility clustering. This confirms results reported by Cappiello et al. (2006a).

Turning to the results of the GARCHX model for stocks as reported in Table 5.12, we find that stock volatilities in the US, in Germany, in France, and in Italy are influenced by the exogenous variables. By contrast, we have previously shown these variables do not affect conditional bond variances. Specifically, stock volatility increase if risk aversion grows or if there are market turbulences. It is important to stress the difference between market turbulences and volatility. We define market turbulences as extremes in the VDAX index. This index is a gauge of future volatility as expected by the market whereas the estimated variance is the current volatility. In addition to risk aversion and market turbulences, also negative GDP growth results in rising volatility. Interestingly, for Greece, Ireland, Portugal, and Spain, we cannot reject the hypothesis that our set of exogenous variables does not influence conditional variances.

Table 5.13 reports the results of DCC(1,1) models on stock indices. Most parameters are significantly different from zero. Employing the Engle and Sheppard (2001) correlation test we cannot reject the hypothesis that conditional correlations are time-varying for pair-wise correlations between almost all countries included. Remarkably, the DCC model innovation parameter a is lower for stocks than for bonds. Accordingly, conditional stock correlations plotted in Figure 5.3 are smoother than conditional bond correlations (see Figure 5.1).

Table 5.12: European Stocks: Univariate GARCHX Models

Countries	Risk Aversion		Market Turbulence		GDP	
US	42.727***	(4.975)	49.489**	(24.441)	−342.353***	(110.439)
DE	43.716***	(5.324)	187.362***	(41.410)	−321.999***	(115.045)
FR	41.934***	(4.643)	120.828***	(30.574)	−332.296***	(96.468)
IT	19.768***	(6.087)	63.211**	(31.751)	−145.851*	(79.036)
GR	0.664	(0.760)	−9.683	(8.715)	8.989	(21.461)
IR	−0.663	(2.002)	1.222	(22.377)	3.365	(28.217)
PT	16.149**	(6.524)	71.128	(49.529)	−41.909	(72.162)
ES	35.413	(39.370)	123.966	(141.369)	−242.405	(341.251)

Note: The table reports the GARCHX model estimates for stock indices in our sample. We use three exogenous variables simultaneously. We estimate conditional correlations for each country pair separately.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

Table 5.13: European Stocks: DCC Models

Countries		a		b		Corr-Test
DE	FR	0.115**	(0.049)	0.851***	(0.063)	51.956***
DE	IT	0.128**	(0.061)	0.767***	(0.093)	24.739
DE	GR	0.027	(0.018)	0.957***	(0.017)	39.735***
DE	IR	0.033**	(0.014)	0.951***	(0.020)	53.485***
DE	PT	0.123***	(0.039)	0.766***	(0.085)	45.135***
DE	ES	0.052**	(0.026)	0.916***	(0.047)	24.789
FR	IT	0.084**	(0.041)	0.874***	(0.063)	18.058
FR	GR	0.025	(0.018)	0.958***	(0.015)	30.083*
FR	IR	0.032**	(0.013)	0.957***	(0.018)	38.567**
FR	PT	0.098**	(0.039)	0.832***	(0.057)	32.198*
FR	ES	0.023	(0.015)	0.955***	(0.027)	15.337
IT	GR	0.023	(0.015)	0.959***	(0.017)	42.481***
IT	IR	0.050	(0.035)	0.920***	(0.059)	30.685*
IT	PT	0.087***	(0.029)	0.837***	(0.053)	42.803***
IT	ES	0.045	(0.033)	0.917***	(0.061)	29.336
GR	IR	0.032	(0.022)	0.940***	(0.035)	34.768**
GR	PT	0.021	(0.014)	0.954***	(0.020)	34.828***
GR	ES	0.022	(0.015)	0.961***	(0.014)	42.375***
IR	PT	0.009	(0.006)	0.982***	(0.010)	41.479***
IR	ES	0.027**	(0.013)	0.954***	(0.018)	41.255***
PT	ES	0.013	(0.008)	0.978***	(0.017)	41.978***

Note: The table reports the DCC(1,1) model estimates for EMU stock indices in our sample. Corr-Test denotes the Engle Sheppard (2002) test for testing the null of constant correlation ($R_t = R \,\forall\, t$).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

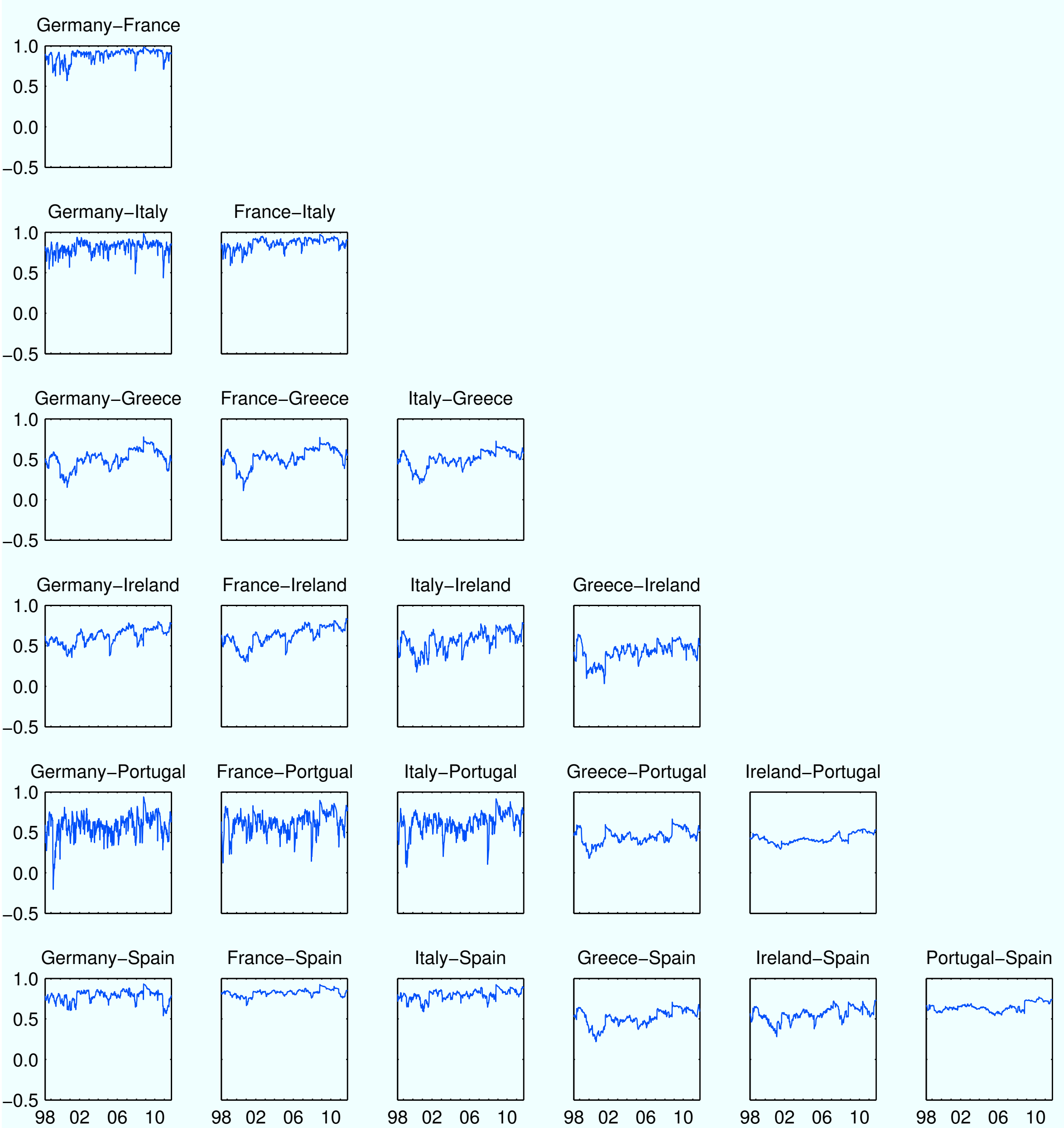

Figure 5.3: European Stocks Conditional Correlations (DCC(1,1) Model)

Figure 5.3 allows us to discuss the trends in conditional stock correlations during the last years. Berben and Jansen (2009) find that correlations rise between 1995 and 1997, and Cappiello et al. (2006b) note that correlations for large EMU countries increase in the second half of the 1990s. By contrast, we cannot observe a major trend in conditional correlations during the sample period. However, our stock sample starts 5/8/1998. At this time, the transition to a regime with higher correlations might already have been completed. In addition, the level of the conditional correlations is fluctuating

Table 5.14: European Stocks: GDCCX Models with One Exogenous Variable

Countries		Risk Aversion		Market Turbulence		GDP	
DE	FR	−0.137	(0.139)	−0.080	(0.123)	−0.640	(0.566)
DE	IT	−0.437	(0.290)	−0.995	(0.682)	0.296	(5.952)
DE	GR	−0.036	(0.171)	0.681*	(0.411)	−11.786	(7.200)
DE	IR	0.075	(0.157)	0.341	(0.388)	−3.188***	(0.812)
DE	PT	−0.627	(0.638)	−0.259	(2.351)	−9.801	(12.676)
DE	ES	0.089	(0.344)	0.536	(0.529)	−3.319	(2.493)
FR	IT	−0.178	(0.120)	−0.641**	(0.250)	0.043	(1.548)
FR	GR	−0.076	(0.155)	0.729**	(0.317)	−12.504**	(5.192)
FR	IR	0.058	(0.181)	0.074	(0.372)	−3.116***	(0.840)
FR	PT	−0.448	(0.684)	−0.195	(1.006)	−17.848	(21.393)
FR	ES	−0.388	(1.480)	1.130	(1.141)	−39.475**	(15.919)
IT	GR	−0.251*	(0.145)	0.258	(0.865)	−8.168*	(4.891)
IT	IR	−0.125	(0.376)	−0.001	(0.668)	−3.944	(2.725)
IT	PT	−0.907	(0.723)	0.322	(1.249)	−6.814	(18.298)
IT	ES	0.117	(0.522)	0.572**	(0.246)	−3.207	(4.842)
GR	IR	0.192	(0.471)	2.561***	(0.196)	−15.758***	(4.819)
GR	PT	−0.130	(0.228)	1.440***	(0.504)	−10.589***	(2.864)
GR	ES	−0.022	(0.217)	1.172***	(0.275)	−9.476**	(4.170)
IR	PT	0.127	(0.230)	1.432***	(0.302)	−5.579	(3.484)
IR	ES	0.080	(0.305)	0.674*	(0.385)	−57.065	(36.351)
PT	ES	0.120	(0.101)	3.141*	(1.677)	−59.855*	(31.401)

Note: The table reports the c coefficients of the exogenous variable employing a GDCCX model for EMU stocks. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations for each country pair separately. Risk aversion is proxied by the VDAX volatility index, market turbulence is the upper first percentile of the VDAX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

around 0.8 for the larger countries while it is lower for correlations involving Greece, Ireland, or Portugal. This finding is in line with other studies (Cappiello et al., 2006b). Overall, we conclude that the trend of convergence observed at the end of the 1990s has not continued since. Notably, all correlation estimates have another common feature: Conditional correlations jump on average about 0.17 from 10/10/2008 to 10/17/2008 as stock markets contemporaneously plunged due to the enlargening financial crisis.

Results for the GDCCX analysis which incorporates exogenous variables are presented in Table 5.14. Similar to the bond sample, conditional correlations between European stock indices are barley influenced by risk aversion as measured by the VDAX volatility index.

Employing our proxy for market turbulence as an exogenous variable reveals an important difference between bonds and stocks. Although conditional correlations between bonds indices decline in times of market turbulences, they rise for stock indices. This is a clear indication of contagion in stock markets in times of market stress. These effects can be observed for most markets and especially for the peripheral countries.

Table 5.15: European Stocks: GDCCX Models with Two Exogenous Variables

Countries		Risk Aversion		Market Turbulence	
DE	FR	−0.151	(0.137)	−0.047	(0.161)
DE	IT	−0.569	(0.370)	−0.032	(0.457)
DE	GR	−0.161	(0.183)	0.696*	(0.364)
DE	IR	0.028	(0.175)	0.325	(0.392)
DE	PT	−0.708	(0.932)	−0.409	(1.184)
DE	ES	0.000	(0.387)	0.536	(0.650)
FR	IT	0.057**	(0.026)	−0.617***	(0.132)
FR	GR	−0.202	(0.168)	0.758***	(0.246)
FR	IR	0.066	(0.217)	0.023	(0.365)
FR	PT	−0.554	(0.872)	−0.148	(0.782)
FR	ES	−1.143	(1.380)	0.710	(1.088)
IT	GR	−0.442**	(0.189)	0.681	(0.480)
IT	IR	−0.191	(0.462)	0.161	(0.624)
IT	PT	−1.202	(0.909)	0.102	(1.070)
IT	ES	−0.083	(0.384)	0.553**	(0.264)
GR	IR	−0.305	(0.332)	2.442***	(0.187)
GR	PT	−0.379	(0.236)	1.461***	(0.378)
GR	ES	−0.261	(0.193)	1.144***	(0.242)
IR	PT	−0.123	(0.210)	1.419***	(0.272)
IR	ES	−0.120	(0.316)	0.694**	(0.351)
PT	ES	−0.319	(2.334)	3.028*	(1.635)

Note: The table reports the c coefficients of the exogenous variable employing a GDCCX model. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations with two exogenous variables simultaneously and for each country pair separately. Risk aversion is proxied by the VDAX volatility index, market turbulence is the upper first percentile of the VDAX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

Turning to GDP growth as exogenous variable, we note another interesting difference between stock and bond markets as presented in the third column in Table 5.14. We find that higher GDP growth results in lower conditional correlations between stock markets. Yet, if GDP growth turns negative, conditional correlations between stock markets actually increase. These are additional indications of contagion effects between stock markets in adverse market conditions. However, in the previous section we did not find any signs of contagion for bond markets. Specifically, conditional bond return correlations fall in times of falling GDP growth while conditional stock return correlations rise.

Next, we repeat our analysis with two exogenous variables simultaneously. We use our general measure of risk aversion[9] and our proxy for market turbulence as exogenous variables. Table 5.15 presents the results. Yet, it turns out that coefficients and standard errors change only marginally. Our proxy for risk aversion does not explain conditional correlations in this specification whereas market turbulences increase correlations.

Finally, we examine all three exogenous variables together (see Table 5.16). Controlling for risk aversion as well as market turbulences, the effect of GDP growth on conditional correlations is even more pronounced than in the specification in which GDP growth is the only explaining variable (see Table 5.16). For example, all conditional stock correlations that include Greece rise when GDP growth turns negative.

By contrast, the effect of market turbulences on conditional correlations diminishes. The influence of GDP growth seems to dominate in the peripheral countries. Exceptions are the Greece-Ireland, Greece-Portugal, and Greece-Spain conditional correlations. Interestingly, all coefficients for the exogenous variable risk aversion are negative while only some are significantly different from zero.

In summary, we find that conditional stock correlations increase when there is negative GDP growth,. If there are market turbulences, conditional correlations increase even further, however, only for a limited set of countries. This diminishes any diversification benefits in portfolios of European stock indices. We also note that the effects of market turbulences on conditional correlations that we found in the one exogenous variable model mostly disappear once we take GDP growth into account. In order to avoid incorrect conclusions, we strongly suggest to examine several exogenous variables simultaneously. That is also a strong argument for choosing correlation models that allow for several exogenous variables (e.g. GDCCX, DCCX) instead of those that can only allow for one or two variables (e.g. STCC, DSTCC).

[9] Similar to our analysis with bonds, we remove the first percentile from the VDAX index when employing both the risk aversion and the market stress proxy to better separate both effects. Employing the unchanged VDAX index does not change our results qualitatively.

Table 5.16: European Stocks: GDCCX Models with Three Exogenous Variables

Countries		Risk Aversion		Market Turbulence		GDP	
DE	FR	−0.356	(0.532)	−0.217	(0.356)	−3.054	(3.559)
DE	IT	−0.873*	(0.450)	−0.218	(0.450)	−5.371	(3.501)
DE	GR	−0.326	(0.345)	0.540	(0.492)	−11.682*	(6.951)
DE	IR	−0.084	(0.287)	−0.465	(2.005)	−4.633	(5.729)
DE	PT	−1.059	(1.520)	−0.906	(1.012)	−12.711	(18.234)
DE	ES	−0.243	(0.335)	0.327	(0.482)	−4.481	(3.090)
FR	IT	−0.100	(0.100)	−1.103***	(0.426)	−3.222***	(0.640)
FR	GR	−0.531*	(0.296)	0.319	(0.238)	−13.032***	(3.983)
FR	IR	−0.522	(0.386)	−0.141	(0.328)	−6.452***	(2.398)
FR	PT	−0.017	(0.133)	−0.197	(0.404)	−4.742***	(1.283)
FR	ES	−1.916	(1.840)	−0.337	(1.220)	−43.106***	(11.211)
IT	GR	−0.709**	(0.283)	0.079	(0.628)	−10.386**	(4.648)
IT	IR	−0.401	(0.277)	−0.350	(0.626)	−6.607***	(1.939)
IT	PT	−1.807*	(1.005)	−0.395	(0.817)	−18.037	(11.019)
IT	ES	−0.342	(0.415)	0.403	(0.268)	−3.851	(3.091)
GR	IR	−0.585	(0.516)	1.899***	(0.341)	−15.387***	(5.948)
GR	PT	−0.721**	(0.316)	0.994**	(0.402)	−12.413***	(3.342)
GR	ES	−0.530**	(0.260)	0.798***	(0.255)	−9.325**	(3.673)
IR	PT	−0.217	(0.684)	0.771	(4.358)	−4.811**	(1.971)
IR	ES	−0.363	(0.411)	0.467	(0.391)	−4.167	(2.838)
PT	ES	−0.042	(0.324)	0.250	(0.477)	−4.435	(3.406)

Note: The table reports the c coefficients of the exogenous variable employing a GDCCX model EMU government bonds. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations with three exogenous variables simultaneously and for each country pair separately. Risk aversion is proxied by the VDAX volatility index, market turbulence is the upper first percentile of the VDAX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

5.3.3 US and Europe: Bonds and Stocks

Last, we extend our sample and include the US. First, we estimate time-varying correlations with a DCC(1,1) model. Results are presented in Table 5.17 for both bonds and stocks. Most parameters are significantly different from zero and shocks to correlation are typically highly persistent since the b parameter is close to one while the a parameter is close to zero. As expected, the average half-life of the innovations is much higher for bonds than for stocks. Furthermore, we employ the Engle and Sheppard (2001) correlation test for testing the null hypothesis that $\mathbf{R_t} = \mathbf{R} \; \forall \; t$. We find strong evidence against the assumption of a constant conditional coefficient for most US and

European stock and bond markets. An exception are bond conditional correlations between the US and France as well as between the US and Germany. That most likely reflects the equal perception of these government bonds as being "save havens".

Table 5.17: US and Europe: DCC Models

Countries		a		b		Corr-Test
			Government Bonds			
US	DE	0.013	(0.014)	0.963***	(0.042)	18.698
US	FR	0.018	(0.015)	0.965***	(0.034)	20.767
US	IT	0.036***	(0.011)	0.961***	(0.013)	98.233***
US	GR	0.046***	(0.012)	0.948***	(0.014)	56.930***
US	IR	0.050***	(0.010)	0.945***	(0.012)	212.865***
US	PT	0.038***	(0.014)	0.957***	(0.016)	146.163***
US	ES	0.069***	(0.012)	0.928***	(0.013)	83.482***
			Stocks			
US	DE	0.046	(0.130)	0.933***	(0.243)	31.144*
US	FR	0.017	(0.017)	0.971***	(0.042)	28.844
US	IT	0.043*	(0.023)	0.925***	(0.049)	34.052**
US	GR	0.018	(0.017)	0.961***	(0.021)	32.091*
US	IR	0.041	(0.029)	0.920***	(0.052)	43.784***
US	PT	0.044**	(0.018)	0.912***	(0.040)	40.512***
US	ES	0.027	(0.018)	0.946***	(0.070)	50.121***

Note: The table reports the DCC(1,1) model estimates for US and Eurozone government bond indices and stock indices in our sample. Correlation test denotes the Engle Sheppard (2002) test for testing the null $R_t = R \; \forall \; t$.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses. Returns have been multiplied by 1000 to improve the numerical performance of the estimation routine.

Figures 5.4 and 5.5 further illustrate the estimated conditional correlations for bond and stock markets, respectively. The level of the time-varying correlations is generally lower between the US and the EMU countries than within the EMU countries (see Figure 5.1). We determine a positive bond return linkage for most of the sample period in the range between 0.5 and 0.8. Recently, these correlations have decreased dramatically to around zero and even below zero for Italy, Greece, Ireland, Portugal, and Spain indicating a flight-to-quality during the European sovereign debt crisis. By contrast, conditional correlations between the US and Germany as well as US and France remain almost stable during that period.

Turning to the stock correlations in Figure 5.5, we find that - as expected - the level of conditional correlations is lower for Greece, Ireland, and Portugal. However, we observe

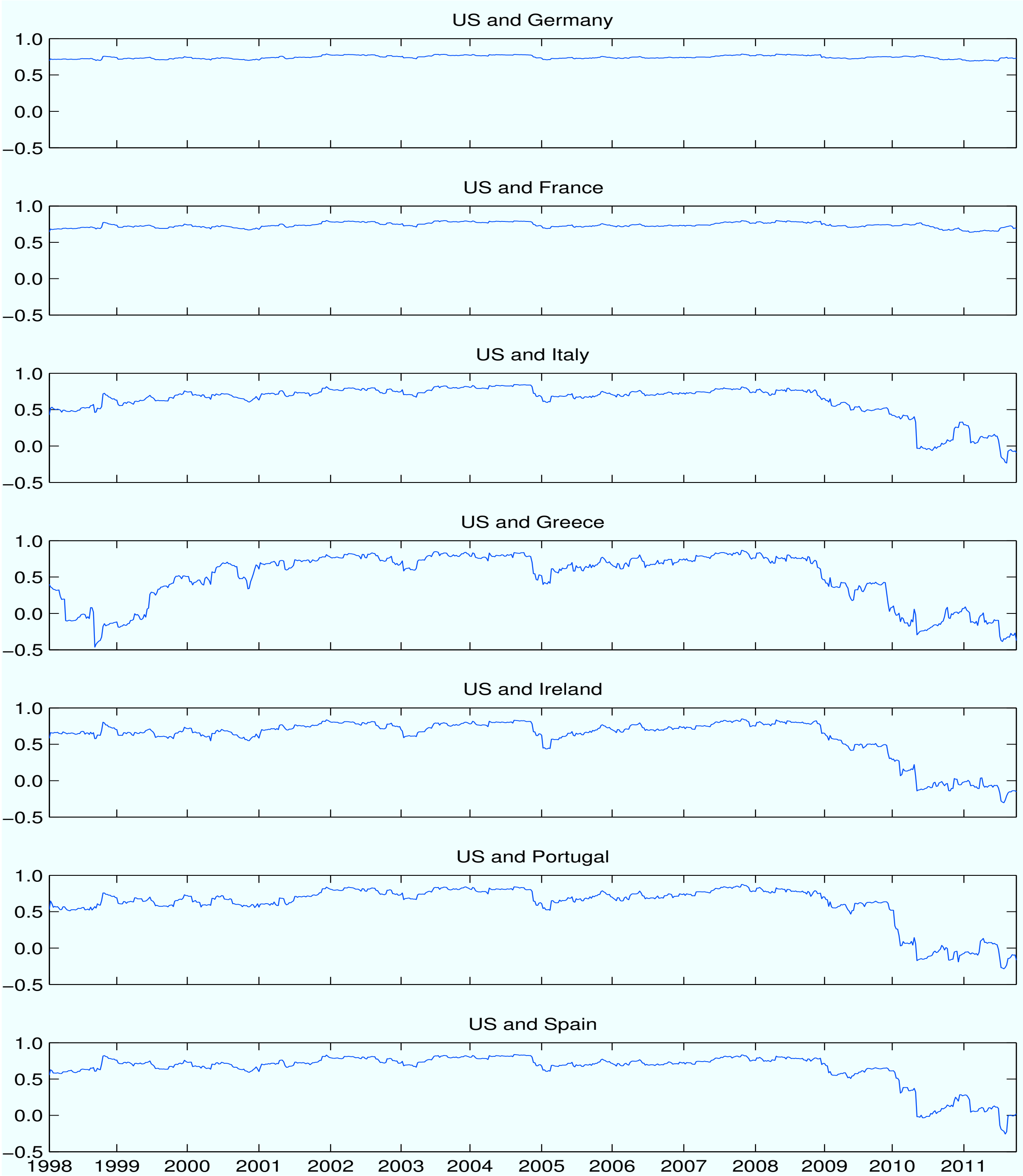

Figure 5.4: US Government Bond Conditional Correlations (DCC(1,1) Model))

some volatility in conditional correlations in the wake of the financial crisis at the end of 2008. However, the jump we find in the conditional correlations between European stock markets between 10/10/2008 and 10/17/2008 is less pronounced and limited to the correlations between the US and Greece as well as between the US and Portugal.

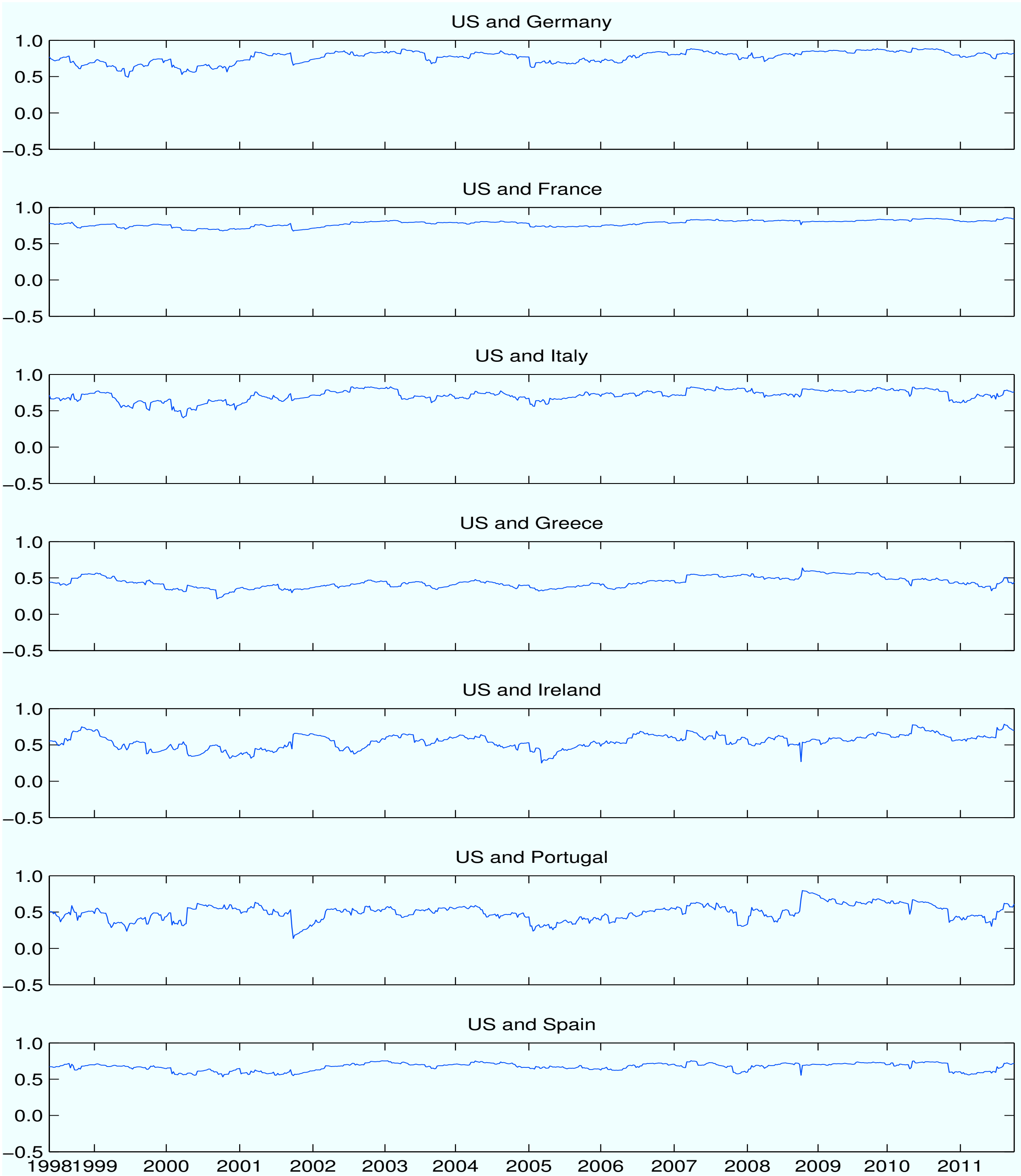

Figure 5.5: US Stocks Conditional Correlations (DCC(1,1) Model)

Comparing the stock and the bond correlations, it is remarkable that there are no trends within stock correlations as observed within bond correlations after 10/2008.

Table 5.18 reports the results of employing the GDCCX model with one exogenous variable. Since now the US are included in our sample, we measure risk aversion using the VIX index.[10] Moreover, our proxy for market turbulence is the first percentile of the VIX index and our indicator for the business cycle is European GDP growth.

Table 5.18: US and Europe: GDCCX Models with One Exogenous Variable

Countries		Risk Aversion		Market Turbulence		GDP	
				Government Bonds			
US	DE	−0.203	(0.431)	−0.411	(0.616)	0.926*	(0.486)
US	FR	−0.108	(0.145)	−0.400	(0.457)	1.512	(1.905)
US	IT	−0.210**	(0.102)	−1.043**	(0.420)	5.908***	(1.504)
US	GR	−0.456***	(0.176)	−1.129**	(0.515)	8.012***	(2.914)
US	IR	−0.318***	(0.086)	−0.980**	(0.468)	6.773***	(1.510)
US	PT	−0.293**	(0.125)	−0.752*	(0.391)	6.264***	(1.844)
US	ES	−0.266**	(0.112)	−1.078***	(0.418)	5.426***	(1.711)
				Stocks			
US	DE	0.001	(0.036)	0.017	(0.080)	−1.714*	(0.911)
US	FR	−4.848	(12.750)	−0.058	(0.143)	−2.379***	(0.296)
US	IT	−0.301***	(0.106)	−0.828**	(0.419)	0.370	(2.792)
US	GR	−0.210***	(0.053)	0.074	(0.541)	−11.372***	(3.483)
US	IR	−0.296	(0.352)	−0.243	(0.789)	−3.188***	(1.209)
US	PT	−0.530	(0.714)	−0.731	(1.159)	−23.329	(18.695)
US	ES	−0.171	(0.139)	0.027	(0.338)	−4.826***	(1.346)

Note: The table reports the c coefficients of the exogenous variable employing a GDCCX model. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations for each country pair separately. Risk aversion is proxied by the VIX volatility index, market turbulence is the upper first percentile of the VIX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

The first column of Table 5.18 shows that risk aversion significantly explains conditional correlations between bond markets in different countries. The effect is less pronounced for stock markets. However, the effects of risk aversion almost completely disappear when allowing for more than one exogenous variable (see Tables 5.19 and 5.20). Again, this is a strong argument in favor of employing conditional correlation models that allow for many exogenous variables.

Market turbulences significantly influence conditional bond correlations but not stock correlations. Specifically, if there are market turbulences, conditional correlations between the bonds fall. The effect is robust to the inclusion of other exogenous variables

[10] Reapting all analysis with the VDAX index instead of the VIX index leaves results qualitatively unchanged.

Table 5.19: US and Europe: GDCCX Models with Two Exogenous Variables

Countries		Risk Aversion		Market Turbulence	
		Government Bonds			
US	DE	0.162	(0.221)	−0.575	(0.718)
US	FR	0.094	(0.152)	−0.473	(0.508)
US	IT	0.000	(0.060)	−1.043**	(0.446)
US	GR	−0.209	(0.164)	−0.972*	(0.514)
US	IR	−0.078***	(0.021)	−1.305***	(0.212)
US	PT	−0.107	(0.102)	−0.676*	(0.389)
US	ES	0.000	(0.122)	−1.078*	(0.615)
		Stocks			
US	DE	0.013	(0.039)	0.005	(0.082)
US	FR	−4.306	(5.856)	0.763	(2.634)
US	IT	−0.050	(0.115)	−0.778*	(0.402)
US	GR	−0.332***	(0.109)	0.331	(0.359)
US	IR	0.061	(0.409)	−0.295	(0.957)
US	PT	0.072	(0.478)	−0.751	(1.371)
US	ES	0.349	(0.226)	−0.057	(0.208)

Note: The table reports the c coefficients of the exogenous variable employing a generalized DCCX model. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations with two exogenous variables simultaneously and for each country pair separately. Risk aversion is proxied by the VIX volatility index, market turbulence is the upper first percentile of the VIX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

such as risk aversion. Interestingly, most coefficients for bonds and for stocks are negative. By contrast, remember that market turbulences resulted in increasing conditional correlations between stocks in Europe. This is an indication that the European stock market are subject to contagion whereas the US is not affected.

Third, we find that the most important driver of correlations between the US and Europe are effects of the business cycle. Positive GDP growth results in increasing correlations between bonds but decreasing correlations between stocks. That is true both for bonds and for stocks and is robust to including risk aversion and market turbulence as exogenous variables.

Table 5.20: US and Europe: GDCCX Models with Three Exogenous Variables

Countries		Risk Aversion		Market Turbulence		GDP	
				Government Bonds			
US	DE	0.156	(0.162)	−0.888*	(0.502)	−4.495**	(1.757)
US	FR	0.036	(0.030)	−0.103	(0.193)	1.125	(0.842)
US	IT	0.069	(0.043)	−0.586*	(0.346)	3.929***	(1.454)
US	GR	−0.081	(0.210)	−0.736	(0.498)	4.621	(4.722)
US	IR	−0.071	(0.060)	−0.529	(0.322)	3.836*	(1.978)
US	PT	−0.016	(0.089)	−0.396	(0.346)	4.764**	(2.180)
US	ES	0.024	(0.039)	−0.717**	(0.364)	2.473*	(1.350)
				Stocks			
US	DE	−0.086	(0.059)	−0.235	(0.170)	−3.781***	(1.138)
US	FR	−5.531	(3.799)	0.051	(1.013)	−49.242**	(23.881)
US	IT	−0.145	(0.184)	−1.288**	(0.512)	−5.608	(4.450)
US	GR	−0.362***	(0.125)	0.233	(0.558)	−1.746	(2.839)
US	IR	−0.085	(0.175)	−0.414	(0.471)	−6.473***	(2.401)
US	PT	0.014	(0.426)	−0.992	(2.675)	−9.193	(8.510)
US	ES	0.328*	(0.177)	−0.408	(0.322)	−4.683***	(1.489)

Note: The table reports the c coefficients of the exogenous variable employing a generalized DCCX model. We estimate volatility with a GARCHX model. The c parameter measures the influence of the exogenous variable on the respective conditional correlations. We estimate conditional correlations with three exogenous variables simultaneously and for each country pair separately. Risk aversion is proxied by the VIX volatility index, market turbulence is the upper first percentile of the VIX index, and GDP growth is quarterly Eurozone GDP.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, robust standard errors in parentheses.

5.4 Summary

In this chapter, we employ both DCC and GDCCX models and investigate the effects of exogenous variables on bond and stock market correlations in the US and in the Eurozone between 1998 and 2011. We model volatility with a GARCHX model in order to separate the effects of the exogenous variables on volatility from the effects on the dependence structure. At first, we examine conditional correlations using the DCC model. We find no trend of further convergence among linkages between Eurozone bond and stock indices. By contrast, Eurozone bond correlations have dramatically fallen since the begin of the financial crisis.

Moreover, we show that both GDP growth and market turbulences drive conditional correlations whereas risk aversion has almost no effect. The impact of market turbulences is most pronounced for the peripheral countries. There is an important difference between bonds and stocks: When there is negative GDP growth, conditional bond correlations fall, but European stock correlations increase strongly which is a clear sign of contagion. If, in addition, there are market turbulences, this effect becomes even more pronounced, but not for all countries. In line with Hunter and Simon (2005), we conclude that international diversification benefits for stock investors but not for bond investors are diminished in times of crisis.

In addition, it is useful to examine the impact of several exogenous variables on conditional correlations simultaneously. For example, the effects of market turbulences on conditional correlations nearly disappear once we account for GDP growth. In order to avoid incorrect conclusions, we strongly suggest to examine several exogenous variables simultaneously. That is also a strong argument for choosing correlation models that allow for several exogenous variables such as the DCCX or the GDCCX model instead of those that can only allow one or two variables such as the STCC model.

6 Stock-Bond Correlations and Real Time Macroeconomic Announcements

6.1 Introduction

In this chapter, we present another application of the econometric framework, we employ in the previous chapters. Correlation dynamics between major asset clases are of special interest for asset allocation and risk management. For example, time-varying correlations might either impede or enhance the diversification benefits of a portfolio. As we examined the conditional correlations between different sectors of the same asset class in the previous chapter, in this chapter, we study correlations between different asset classes. More precisely, we investigate how risk aversion and macro announcements influence high-frequency correlations between bonds and stocks in the Eurozone.

Against this background, central questions remain unanswered. Is risk aversion determining conditional correlations or do macroeconomic announcements drive prices? Did the recent financial crisis have any (lasting) effects on stock-bond correlations? Is the direction or the size of macroeconomic announcements surprise of higher importance? Generally, do these variables change the stock-bond dependence structure or just the volatility, or both? Although there are numerous studies that investigate stock-bond correlations,[1] the literature is not yet conclusive.

Specifically, employing a high-frequency dataset, Andersen et al. (2007) and Boyd et al. (2005) find that macroeconomic announcements affect correlations. Furthermore, they show that the impact of news varies considerably during the business cycle. Christiansen and Ranaldo (2007) analyze realized correlations and highlight that the occurrence of a macroeconomic announcement but not the actual announced figure plays an important role for stock-bond correlations.

[1] An incomplete sample of relevant papers includes: Li (2002); Ilmanen (2003); Pástor and Stambaugh (2003); Boyd et al. (2005); Connolly et al. (2005); Kim et al. (2006); Andersen et al. (2007); Christiansen and Ranaldo (2007); Connolly et al. (2007); Corsi and Audrino (2007); Andersson et al. (2008); Baur and Lucey (2009); Panchenko and Wu (2009); Yang et al. (2009); Aslanidis and Christiansen (2010); Baele et al. (2010); Bansal et al. (2010) and Aslanidis and Christiansen (2011).

Using daily or lower frequency but not high-frequency data, several studies present evidence for stock and bond prices moving in the same direction during periods of higher uncertainty about long-term expected inflation (Li, 2002), high inflation expectations (Andersson et al., 2008), or high inflation rates (Yang et al., 2009). Moreover, Ilmanen (2003) suggests that the inflation level as well as the business cycle explain stock-bond correlations. By contrast, Baele et al. (2010) argue that macroeconomic factors do not drive conditional correlations. Employing quarterly data and a dynamic conditional correlation framework model, they provide evidence that rather illiquidity and flight-to-quality are important for correlations. Additionally, Bansal et al. (2010) find that correlations vary across two regimes. A high-stress regime coincides with higher risk aversion, higher trading volumes and lower stock-bond correlation. Several other studies focus on the influence of risk aversion on correlations and confirm the flight-to-quality effect (Connolly et al., 2005, 2007; Aslanidis and Christiansen, 2010, 2011; Kim et al., 2006).

We contribute to the literature across several dimensions. Using a high-frequency dataset for Eurozone stocks and bonds, we simultaneously estimate the influence of risk aversion, macroeconomic announcements, and other exogenous variables on both conditional correlations and conditional variances. We analyze conditional correlations using a GDCCX model and estimate variances with a GARCHX model as described in the previous chapters. That approach allows us to separate the effects of the exogenous variables on the dependence structure from those on the volatility. The correct specification of the variance equation is of particular importance as our sample covers the recent financial crisis, a period of extreme volatility.

We include 15 macroeconomic announcements from the US and 5 from the Eurozone and compare their influence on volatility and stock-bonds correlations. We employ real-time data, i.e. news that are available to market participants at the time of the release. Accordingly, we can analyze the information content of specific announcements and compare the importance of US to European news. For example, news that convey information regarding future cash-flows should primarily move stocks thus reducing conditional stock-bond correlations. Falling conditional correlation might also be caused by a flight-to-quality. If the announcement can be interpreted as news about the future discount rates, bond and stock prices should move in the same direction (Andersen et al., 2007).

Furthermore, most papers which analyze stock-bond correlations focus on the stock and bond correlations in the US.[2] Yet, we use a high-frequency dataset for European stocks and bonds as we want to know if the driving forces of high-frequency correlations in the Eurozone are similar to those already documented for the US.

To preview our results, we find that both risk aversion and macroeconomic announcements separately drive conditional correlations. Conditional correlations fall as risk aversion rises even when simultaneously accounting for the influence of macroeconomic announcements on conditional correlations and the influence of these variables on volatility. Interestingly, the additional effects of the financial crisis on correlations are only small. Generally, the most important news are nonfarm payrolls in the US and the European Central Bank (ECB) rate decision in Europe. For most macroeconomic announcements, the absolute value of the surprise is of higher importance for correlations than the mere occurrence of the announcement. Moreover, most macroeconomic news result in falling conditional correlations. Yet, the publication of news concerning future interest rates or inflation figures moves bond and stock prices in the same direction. We do not find any evidence that the influence of economic announcements on conditional correlations changes during the cycle. This conclusion is driven from the observation that splitting the effects of the macroeconomic variables between expansion and recession does not alter the results. Turning to the results on volatility, we present evidence that the occurrence of any macroeconomic announcement results in a higher volatility as do surprises for both stocks and bonds.

The outline of the chapter is as follows. We start by describing the data in section 6.2. We report and discuss the empirical results in section 6.3. Section 6.4 provides concluding remarks.

6.2 Data

6.2.1 Bond and Stock Returns

The data employed for this study consist of stock and bond returns as well as economic variables. As we focus on the Eurozone, we choose the Euro Stoxx 50 Future to represent the stock market. It is based on the Dow Jones Euro Stoxx 50 index which is composed

[2]Exceptions are Li (2002); Andersen et al. (2007); Connolly et al. (2007) and Andersson et al. (2008).

of 50 large blue chip companies in the Eurozone that is widely applied as benchmark index for Eurozone equities.

We use the Bund Future to calculate bond market returns. The underlying security of this future is the German 10 year treasury bond. We analyze the German bond market as it is considered to be the safest investment in the Eurozone and it is regarded as a representative of a liquid, risk-free government bond in the Eurozone. Similar to Faust et al. (2007), we prefer the Bund future over other bond market futures (such as the Bobl or the Schatz) as it is by far the most actively traded bond future in the Eurozone. Both the bond and the stock future are traded at the Eurex from 8 am to 10 pm and are highly liquid with a daily trading volume of more than 0.7 million and more than 0.9 million, respectively.

There are several advantages in using futures instead of cash indices. First, futures markets lead cash markets in terms of price discovery (Hasbrouck, 2003). Second, the contracts are actively traded, transaction costs are minimal, and no legal constraints on short selling are imposed. Third, high frequency data for futures are available from several vendors. Therefore, previous studies on correlations and volatility also focus on futures markets.[3]

Following several other studies (Andersen et al., 2007; Aslanidis and Christiansen, 2010, 2011; Andersson, 2010; Hussain, 2011), we obtain raw tick-by-tick transaction prices from Tick Data Inc.[4] The symbols are BN for the Bund future and XX for the Euro Stoxx 50 future. Both futures have four delivery months (March, June, September and December), and several contracts are traded at a time. Thus, we construct a continuous return series employing the most liquid contract. As almost all trading takes place in the contract closest to expiry, we use this contract. In practice, futures are rolled to next contract a few days prior to expiry. Similarly, we switch to the next-maturity contract as soon as the trading volume is higher in the second nearby contract, which is usually two days before maturity (McMillan and Speight, 2003).[5]

[3]For example Christiansen and Ranaldo (2007); Corsi and Audrino (2007); Andersson (2010); Bansal et al. (2010); Aslanidis and Christiansen (2010, 2011); Christiansen et al. (2011) study futures instead of cash markets.

[4]In order to verify the accuracy of the data we reconcile the data with intraday-data available on Bloomberg.

[5]Switching to the next-maturity contract earlier as done in Andersen et al. (2007) and Christiansen and Ranaldo (2007) or at a fixed date prior to expiry as in Bansal et al. (2010) or in Fleming et al. (2003) would result in more missing observations.

6.2.2 Exogenous Variables

We test several exogenous variables. Since the futures data we obtained includes details on each trade, we can calculate the trading volume in any time interval. However, Bansal et al. (2010) point out that the futures volume is heavily affected by rolling activity in the week before the expiry of the contract. In addition, there might be a time trend. Therefore, we adjust the trading volume by regressing the volume on a constant, a time trend and a dummy indicating the five trading days prior to expiry. We employ the regression residuals as our volume variable.

Bansal et al. (2010) argue that higher trading volume is associated with high-stress regimes that also feature higher volatility. Accordingly, we primarily see trading volume as a proxy for high volatility. In addition, futures trading volume is generally much lower before holidays but much higher during and after macroeconomic announcements (Balduzzi et al., 2001). Hence, we can also think of it as a proxy for liquidity.

As pointed out in section 3.3.2.2, option-implied volatility is widely regarded as a good proxy for risk aversion as it incorporates all information available to market participants on future volatility. Numerous studies on volatility and conditional correlations[6] use this measure as an estimate of market uncertainty. We obtain data on the Euro Stoxx 50 Volatility Index (VSTOXX). The index is derived from prices of the underlying Euro Stoxx 50 options and is computed daily from 9.15am to 5.30pm. We obtain intraday-data on this index from CQG Inc., which is an official Eurex data vendor.[7] The sampling interval for our VSTOXX data is two minutes. For all our analysis, we compute the log differences of the VSTOXX index.

Christiansen et al. (2011) argue that the term spread is an important variable for modeling bond and stock volatility. Therefore, we also include the daily difference between 10 year and 3 months interest rates provided by J.P. Morgan. We have neither intraday data nor a specific announcement time for this variable. Thus, we increase the frequency by allowing the variable to remain constant throughout the day.[8] Further-

[6]For example Andersson et al. (2008), Aslanidis and Christiansen (2010, 2011), Cai et al. (2009), Connolly et al. (2005, 2007), and Kim et al. (2006) analyze the VIX or the VDAX index. Bansal et al. (2010) use the VXO index.

[7]Other studies such as Le and Zurbruegg (2010), Hashimoto (2005) or Martens and Zein (2002) also employ CQG data.

[8]This transformation of data has already been applied to convert monthly to daily (Cai et al., 2009) or to weekly data (Aslanidis and Christiansen, 2010).

more, interest rates differences are lagged by one day to make sure that we keep the dataset in chronological order.

In order to measure the influence of the financial crisis in 2008 and 2009, we construct a dummy variable that is one from October 2008 to April 2009 coinciding with the financial crisis.[9]

6.2.3 Real Time Macroeconomic Announcements

We also want to investigate the effect of various macroeconomic variables on stock-bond correlations. During European trading hours macroeconomic announcements occur both in the Eurozone and in the US. Accordingly, announcements made in both regions are included.[10] Moreover, previous studies suggest that the US macroeconomic announcements are not only important for US but also for European markets (Andersen et al., 2003, 2007; Faust et al., 2007; Albuquerque and Vega, 2009; Hussain, 2011; Mittnik et al., 2011).

All announcements occur at a predefined time and are released instantaneously at a precise time. European announcements take place in the morning starting with the German unemployment rate at 9.55 am CET and ending with the ECB interest rate announcement at 1.45 pm CET (see Table 6.1). US announcements are in the afternoon starting at 2.30 pm CET.[11] All announcement data are available during our whole sample period.

Similar to Bollerslev et al. (2000) and Mittnik et al. (2011), our source for announcements and market expectations is Bloomberg. We obtain the date and time as well as the actual release and the market consensus.[12] The Bloomberg market expectation is the median forecast of a large number of economists and is widely considered as consen-

[9] As with any recession or crisis it is difficult to determine a definite starting point or. Although the collapse of Lehman Brothers was at mid September 2008, stock and bond market reacted strongest in mid October 2008 and did not rebound until April 2009.

[10] The Federal Reserve System (FED) rate decision is an exception as the release time is not included in our sample and thus not included in our analysis.

[11] Since 2007 the daylight savings time in the US starts on the second Sunday in March and ends on the first Sunday in November while in Europe it is three weeks shorter starting on the last Sunday in March and ending on the last Sunday in October. Therefore, the time difference is only 5 hours in the non-overlapping period so that announcements are one hour earlier in CET.

[12] Furthermore, in order to verify the accuracy of the release data, we reconcile Bloomberg data with data available on the website of the respective institution.

Table 6.1: Macroeconomic Announcements

Data Release	Source[a]	Number of Observations	Units	Release time (CET)
		U.S. Announcements		
Capacity utilization[e]	FRB	48	% of capacity	15:15
Construction spending	BC	47	% change mom	16:00
Consumer confidence	CB	48	Diffusion index	16:00
Consumer prices	BLS	48	% change mom	14:30
Durable good orders	BC	46	% change mom	14:30
Factory orders	BC	47	% change mom	16:00
U.S. GDP[b]	BEA	48	% change qoq	14:30
Industrial production[e]	FRB	48	% change mom	15:15
Initial claims	DOL	204	Thousands	14:30
ISM index	ISM	45	Diffusion index	16:00
New home sales	BC	47	% change mom	16:00
Nonfarm payroll employment[e]	BLS	47	Change in thousands	14:30
Producer price index	BLS	48	% change mom	14:30
Retail sales	BC	48	% change mom	14:30
Unemployment rate[e]	BLS	47	% rate	14:30
		German Announcements		
IFO index	IFO	48	Diffusion index	10:00
Unemployment	FLO	49	% rate	9:55
		Eurozone Announcements		
ECB rate decision	ECB	49	Change in pct pts	13:45
Eurozone HCPI[c]	ES	49	% change yoy	11:00
Eurozone GDP[b]	ES	48	% change qoq	11:00

Note: All frequencies are monthly except for the Initial claims which are announced weekly.
[a] Acronyms for the sources are as follows:
Bureau of Economic Analysis (BEA), Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Department of Labor (DOL), European Central Bank (ECB), Eurostat (ES), Federal Labour Office (FLO), Federal Reserve Board (FRB), Ifo Institute (IFO).
[b] Quarterly GDP figures are reported three times: advance, preliminary, and final.
[c] HCPI is the Harmonized Consumer Price Index Flash estimatate.
[d] Manufacturing PMI is the Manufacturing Purchasing Managers' Index.
[e] The following economic figures are announced at the same time: capacity utilization and industrial production; nonfarm payroll employment and the unemployment rate.

sus estimate of the market. Furthermore, we test whether the survey data is unbiased over our sample period (Flannery and Protopapadakis, 2002). For all economic market expectations except of the German unemployment rate, we cannot reject the null hypothesis that the mean of the consensus data is zero at the 5% level. Accordingly, market expectations are unbiased.

In line with Balduzzi et al. (2001), Bollerslev et al. (2000), and Andersen et al. (2003), we are especially interested in the surprise component of the announcement since, given rational markets, expectations should already be reflected in prices. The surprise is simply calculated as the median forecast minus the released value. Moreover, we standardize the surprise by its respective standard deviation in order to correct for the different units of measurement of the economic variables. It may be that the magnitude of the surprise is more important than the actual direction of the surprise when it comes to modeling correlations or volatilities. As in Christiansen et al. (2011), we also test the absolute value of the surprise. As suggested by Christiansen and Ranaldo (2007) and Andersen et al. (2003), dummy variables for each macroeconomic announcement are included to separate the influence of a mere presence of a specific announcement from any corresponding surprise. A dummy variable which becomes one if there is any macroeconomic announcement is constructed to capture the general announcement effect.[13]

Once it is established that a macroeconomic announcement influences correlations, it is still unclear how long the effect will last. Different time windows have been chosen in the previous literature. While Andersen et al. (2003) focus on the 15 minutes after the economic news, Andersen et al. (2007) consider 20 minutes for the influence of announcements on asset returns and 70 minutes on asset volatility. Our approach is different, as the persistence of any news is modeled within the DCC framework and assumed to follow a geometric lag with parameters being estimated from the data. Therefore, announcement variables take on the value of the surprise only at the time of the announcement.

6.2.4 The Dataset

The dataset covers the period from 4/30/2007 to 4/30/2011. This period includes both the tranquil period before the start of the financial crisis, the financial crisis itself and the initial recovery thereafter. Corresponding to the trading time of the VSTOXX index, the daily time interval in the sample starts at 9.15 am and ends at 5.30 pm. Similar to most studies that employ high frequency data,[14] we split trading days into 5-minute intervals. This is a compromise between microstructure biases which arise due to nonsynchronous trading and the desire to sample at a high frequency (Bollerslev

[13]Henceforth, we will label that dummy *all announcements* dummy.

[14]A sample of papers that use 5 minute data includes Andersen and Bollerslev (1998); Bollerslev et al. (2000); Andersen et al. (2001, 2003, 2007); Christiansen and Ranaldo (2007); Andersson (2010) and Aslanidis and Christiansen (2010, 2011).

et al., 2000; Andersen et al., 2001; Hansen and Lunde, 2006). As the VSTOXX sampling frequency is two minutes (i.e. we have 248 observations per day), we synchronize the data by using the last recorded VSTOXX price in any five minute interval.

Table 6.2: Descriptive Statistics

Name	Obs.	Mean	Std. Dev.	Min.	Max.	Skewn.	Kurt.
Bund Future[a]	100,625	0.00%	0.03%	-0.50%	0.35%	−0.35	11.13***
Euro Stoxx 50 Future[a]	100,624	0.00%	0.14%	-2.10%	4.84%	0.23	28.85***
Vstoxx Index[a]	100,108	0.00%	0.42%	-8.48%	10.27%	0.57	28.10***
Trading Volume Bonds	100,625	7,122	6,432	30	120,393	3.46	26.09***
Trading Volume Stocks	100,624	9,041	8,987	14	374,769	3.80	50.07***

Note: The table reports descriptive statistics for the high-frequency variables employed in the analysis. *** denotes series that differ from a normal distribution at 1% level as indicated by a Jarque–Bera test; [a]Log change of the variable.

Compared with daily or lower frequency data, high-frequency data is subject to more extreme outliers. Table 6.2 shows that, even after ignoring the overnight return, the Bund future minimum is a 16 standard deviation event whereas the maximum of the Euro Stoxx 50 future is a 34 standard deviations away from the mean. The same is true for our risk aversion measure[15] as well as for most of the other high-frequency variables. However, the estimation procedure is sensitive to extreme outliers. In addition, extreme observations of the exogenous variable might set implicit boundaries to the parameter space of the GDCCX model.[16] Therefore, we follow Silvennoinen and Teräsvirta (2005) as well as Boudt and Zhang (2010) and truncate all observations that deviate more than 10 standard deviations from the mean allowing us to keep the information contained in the outliers.[17]

Following Andersen and Bollerslev (1997), we ignore the overnight return, i.e. from the close in t-1 to the first observation in t. This period is special because it incorporates

[15]The minimum is 20 standard deviations away from the mean while the maximum 24 standard deviations outlier.

[16]An intuitive explanation is as follows: The exogenous variable influences the estimated conditional correlation with the strength of the effect measured by the parameter c. For example, the effect of an exogenous variable on conditional correlations is positive for a positive c and any observation of the exogenous variable greater than zero. Furthermore, the greater the c parameter and the observation, the greater is the effect on conditional correlations. Yet, conditional correlations are bounded between plus and minus one. Therefore, given a large outlier, the c parameter must be smaller just to make sure that the conditional correlation remain between plus and minus one for that single observation. That establishes an implicit boundary on the c parameter.

[17]I.e., all outliers are set to 10 standard deviations.

all information accumulated overnight and over-weekend and consequently has a much higher volatility.

Sometimes, there is no trading within a 5 minute interval.[18] Following Bollerslev et al. (2000) and Andersen and Bollerslev (1997), we linearly interpolate all intraday data in these cases. Calculating continuously compounded five minute returns for 1017 trading days with 99 observations per day (excluding the overnight return) gives us 100,682 observations.[19] As in section 3.3.2, we multiply the return series with 1000 and divide the exogenous variables by 100 to avoid the accumulation of rounding errors. As the mean of the time series is non-zero, we furthermore demean all time series except the dummy variables.

6.3 Empirical Results

6.3.1 The DCC Model

At first, we are interested in the conditional correlations between high-frequency returns of bonds and stocks in the Eurozone and ignore any economic explanations. We estimate a DCC(1,1)-GARCH(1,1) model (see section 2.2) as a benchmark model. Table 6.3 shows the results.

In line with previous literature, the results of the GARCH(1,1) model indicate volatility clustering. As the sums of the α_i and β_i parameters are close to one, we conclude that conditional variances are highly persistent. Turning to the correlation equation, we find clear evidence for time-varying conditional correlations. The estimated parameters of the DCC(1,1) model are highly significant and the Engle and Sheppard (2001) test[20] clearly rejects the null hypothesis of constant conditional correlations. Moreover, the innovations to the conditional correlations are highly persistent: the half-life is approximately 2 hours and 15 minutes.[21]

[18] The number of missing observations for the Bund future (0.06%) and the Eurostoxx 50 future (0.06%) is very low. Specifically, trading at the EUREX stopped shortly at 11/18/2009 and 2/4/2009 due to technical difficulties. However, on both days there were no significant market moves. Other missing occur especially if there is trading on a public holiday or just before a public holiday. The number of missing observations for the VSTOXX index is higher but still acceptable (0.24%).

[19] Furthermore, we remove the observation 3/28/2008 at 12:20 pm as there has been a mistrade affecting the Bundfuture only and reversing itself within less than two minutes.

[20] See section 2.3 for details.

[21] Please see section 2.2 for details on the calculation of the half-life of the innovations.

Table 6.3: European Bonds and Stocks: Univariate GARCH and DCC Models

	Univariate GARCH (1,1) Models					Multivariate DCC (1,1) Models		
	Bonds		Stocks			DCC Model		Corr-Test
ω_i	0.004***	(0.000)	0.024***	(0.002)	a	0.009***	(0.003)	95.722***
α_i	0.089***	(0.004)	0.108***	(0.004)	b	0.987***	(0.005)	
β_i	0.877***	(0.006)	0.886***	(0.004)				

Note: The table reports the univariate GARCH(1,1) and DCC(1,1) estimates for European bonds and stocks. Robust standard errors in parentheses. Corr-Test denotes the Engle and Sheppard (2001) test for testing the null of constant correlation ($R_t = R \; \forall \; t$).
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

The time-varying nature of the conditional correlations is highlighted by Figure 6.1. Conditional correlations fluctuate in the range between 0.31 and -0.79. Although correlations are persistent, there is no clear time trend. The highest conditional correlations are at the beginning of the sample (mid-2007) while they are lower for the rest of our sample. Interestingly, there is no distinctive change in the correlations during the recent financial crisis on the first view.

6.3.2 The GARCHX Model

We now turn to the estimation of conditional variances which allows for effects of exogenous variables. Employing a GARCHX(1,1) model and a single exogenous variable gives us a first idea which variables can help explaining volatility.[22] Results for the γ parameter are presented in Table 6.4 and 6.5 for the bond and stock market, respectively.

As expected, a rise in the VSTOXX results in higher volatility for both bonds and stocks. Notably, the effect is much stronger for stocks - possibly reflecting the overall higher stock volatility. The parameter for the financial crisis dummy is also positive and highly significant. As expected, stock and bond volatility rose during the financial crisis. Similarly, the effect is more pronounced for stocks than for bonds. In line with Christiansen et al. (2011), we find that the term spread matters for bond but not for stock volatility. The negative sign of the parameter is plausible as the term spread often becomes negative during recessions. Finally, our variable indicating the stock trading volume is significant whereas the bond volume seems to have less explanation power

[22]Please see section 4.3 for details on the GARCHX model.

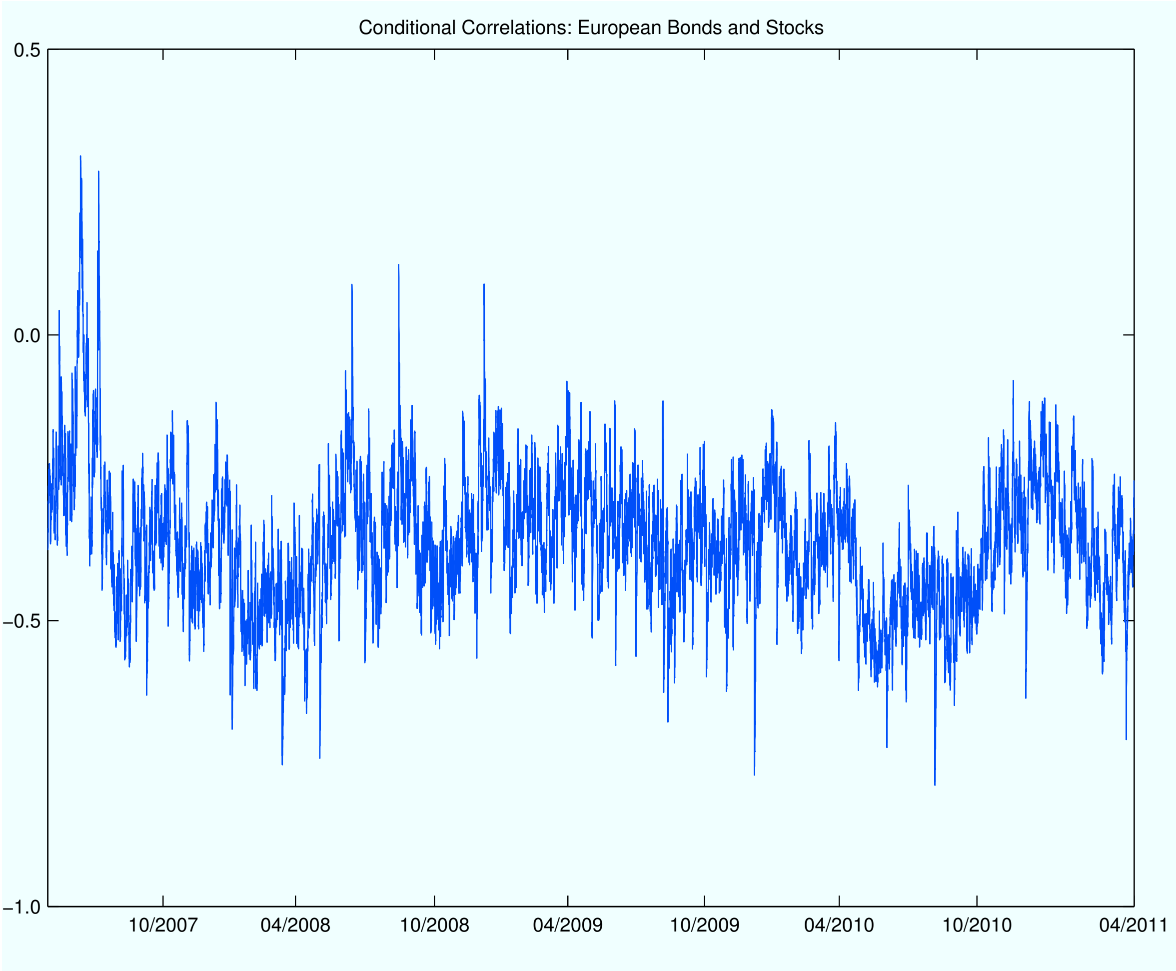

Figure 6.1: European Bonds and Stocks Conditional Correlations (DCC(1,1) Model)

when considered as the only exogenous variable.[23] Thus, lower trading volume in stocks coincides with lower volatility. This situation well describes periods before holidays or at specific times during day when volatility is low.

A glance through Tables 6.4 and 6.5 immediately indicates that volatility rises significantly during almost all economic announcements as most coefficients are positive. In addition, the coefficient for the *all announcements* dummy is positive and significant for both bonds and stocks. The effect is larger for stocks indicating that the macro news are of higher importance for stocks than for bonds. Furthermore, all models are

[23]One might argue that bond and stock trading volume should influence volatility similarly as the unconditional correlation between the level of the bond and stock trading volume is 0.44. However, the unconditional correlation between the log change of the two variables is negative (-0.37) making different effects on the respective change rates more plausible.

Table 6.4: European Bonds: GARCHX Model Separate Estimations

	High-Frequency Variables					
VSTOXX[a]	22.634**	(9.795)				
Trading Vol. Bonds[a]	0.001	(0.014)				
Trading Vol. Stocks[a]	0.366***	(0.090)				
Financial crisis	0.426***	(0.062)				
Term spread	−0.053***	(0.014)				
	Announcement Dummy[b]		**Absolute Surprise[c]**		**Surprise**	
All announcements	12.306***	(1.120)				
U.S. Announcements						
Capacity utilization[d]	3.917**	(1.633)	20.453**	(8.585)	1.596 [f]	(4.615)
Construction spending	17.680***	(4.311)	71.261***	(18.413)	5.698	(5.090)
Consumer confidence	5.554***	(1.686)	28.175***	(8.383)	−3.426 [f]	(3.140)
Consumer prices	15.425***	(2.272)	81.203***	(14.701)	0.506 [f]	(1.817)
Durable good orders	11.080***	(1.844)	55.555***	(9.833)	0.463 [f]	(0.391)
Factory orders	6.913***	(2.480)	33.795***	(12.288)	−8.873**[f]	(4.282)
U.S. GDP	9.613***	(2.482)	49.462***	(13.694)	6.779*	(3.629)
Industrial production[d]	3.917**	(1.633)	19.373**	(8.254)	5.355 [f]	(4.752)
Initial claims	14.385***	(1.479)	41.013***	(4.510)	−0.737 [f]	(0.674)
ISM index	17.886***	(4.500)	90.560***	(22.876)	3.258 [f]	(5.212)
New home sales	6.065***	(1.545)	32.086***	(8.155)	−1.890 [f]	(2.017)
Nonfarm payroll empl.[e]	59.040***	(7.959)	302.555***	(41.241)	0.943 [f]	(2.979)
Producer price index	17.828***	(3.796)	88.127***	(19.396)	2.613 [f]	(4.725)
Retail sales	22.965***	(4.367)	121.425***	(22.782)	1.828 [f]	(3.346)
Unemployment rate[e]	59.040***	(7.959)	592.980***	(200.487)	−3.896	(4.019)
German and Eurozone Announcements						
IFO index	14.527***	(4.394)	72.371***	(21.890)	7.404	(5.307)
German unemployment	−1.555*[f]	(0.808)	−7.110*[f]	(4.048)	−11.267**[f]	(5.078)
ECB rate decision	24.538***	(7.428)	198.904***	(58.413)	140.062***	(36.109)
Eurozone HCPI	2.178	(2.373)	17.697	(13.343)	9.135	(7.533)
Eurozone GDP	−1.954***[f]	(0.639)	−7.223**[f]	(3.630)	−10.140**[f]	(4.960)

Note: The table reports the γ estimates of a GARCHX(1,1) model (see Equation 4.18) for the Bund future. We run separate estimations for each γ presented. Robust standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$, [a]Log change of the variable; [b]Announcement Dummy is an indicator function that takes on the value 1 if there is an announcement and 0 otherwise; [c]Absolute value of the surprise is employed. [d, e] Economic figures are announced at the same time; [f]A GARCH (1,1) model is preferred to this estimation according to the BIC criterion.

compared to each other using the bayesian information criterion (BIC).[24] It turns out that the GARCHX model which employs the *all announcements* dummy fits the data best.

[24]Details on the bayesian information criterion are provided in in Table 6.12 in the appendix 6.A1.

Table 6.5: European Stocks: GARCHX Model Separate Estimations

	High-Frequency Variables					
VSTOXX[a]	719.603***	(98.890)				
Trading Vol. Bonds[a]	0.388	(0.334)				
Trading Vol. Stocks[a]	3.018***	(0.503)				
Financial crisis	8.732***	(1.121)				
Term spread	0.154	(0.158)				
	Announcement Dummy[b]		Absolute Surprise[c]		Surprise	
All announcements	112.019***	(10.025)				
			U.S. Announcements			
Capacity utilization[d]	52.610***	(16.835)	254.716***	(80.796)	44.895[f]	(41.199)
Construction spending	179.266***	(37.098)	844.819***	(178.269)	127.834***	(39.056)
Consumer confidence	103.867***	(32.064)	523.969***	(173.396)	−22.364[f]	(41.268)
Consumer prices	144.651***	(38.527)	786.370***	(214.720)	−23.714[f]	(24.963)
Durable good orders	167.355***	(30.400)	863.755***	(166.680)	9.290[f]	(7.977)
Factory orders	68.663***	(24.651)	308.829**	(129.336)	1.733***[f]	(0.184)
U.S. GDP	195.108***	(41.104)	1067.918***	(263.671)	57.778**	(26.845)
Industrial production[d]	52.610***	(16.835)	254.764***	(97.528)	61.587[f]	(40.242)
Initial claims	166.650***	(20.360)	494.929***	(62.955)	21.562*	(12.742)
ISM index	201.615***	(43.322)	1005.700***	(232.612)	4.157**[f]	(2.055)
New home sales	150.584***	(34.652)	737.961***	(151.454)	−21.616[f]	(52.886)
Nonfarm payroll empl.[e]	583.817***	(89.933)	2980.946***	(534.776)	11.814[f]	(44.073)
Producer price index	104.699***	(30.026)	518.100***	(155.553)	99.279***	(35.882)
Retail sales	180.913***	(45.800)	955.876***	(227.243)	−3.289**[f]	(1.518)
Unemployment rate[e]	583.817***	(89.933)	4450.223***	(745.169)	12.510[f]	(119.559)
			German and Eurozone Announcements			
IFO index	−14.949*[f]	(8.544)	−60.442[f]	(83.864)	159.977**[f]	(64.073)
German unemployment	−21.652***	(3.724)	−99.030***	(17.258)	−87.680***[f]	(26.105)
ECB rate decision	90.919***	(33.133)	786.484**	(322.700)	752.003**	(317.972)
Eurozone HCPI	−29.990***	(0.124)	−117.363***	(27.940)	−65.472*[f]	(33.603)
Eurozone GDP	−13.876[f]	(9.327)	−101.964***[f]	(22.627)	2.708***[f]	(0.287)

Note: The table reports the γ estimates of a GARCHX(1,1) model (see Equation 4.18) for the Euro Stoxx 50 future. We run separate estimations for each γ presented. Robust standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$, [a]Log change of the variable; [b]Announcement Dummy is an indicator function that takes on the value 1 if there is an announcement and 0 otherwise; [c]Absolute value of the surprise is employed. [d, e] Economic figures are announced at the same time; [f]A GARCH (1,1) model is preferred to this estimation according to the BIC criterion.

Looking at the macro indicators in detail, we see that the announcement of nonfarm payroll employment that coincides with the announcement of the unemployment rate results in the highest volatility.[25] Moreover, the two models that include this dummy

[25] Nonfarm payrolls and the unemployment rate are announced simultaneously. As both figures are drawn from different samples their economic interpretation might be divergent. However, most of the time the direction and size of the surprise are comparable.

as exogenous variable are - according to the BIC - the best among all models which use any of the single announcements. This is not surprising as Andersen et al. (2007) and Andersen and Bollerslev (1998) argue those are most important announcement for all markets.

There is a remarkable difference between the announcements in the US and the Eurozone. While the occurrence of an US announcement always results in rising conditional variances, this does not hold for all European announcements. For example, the disclosure of the IFO index results in higher volatility for bonds but lower volatility for stocks. Also, the publication of Eurozone GDP and German unemployment rate coincide with lower volatility. Calculating the BIC indicates that the GARCHX model is simply not suitable for these variables as a GARCH (1,1) model fits the data better. Thus, a specification without these exogenous variables is preferable. There might also be an economic reason why the GARCHX model does not fit the data for these European announcements. As the financial crisis started in the US and covers a large part of our sample, market participants might pay specific attention to the US announcements. Also, it might be that large parts of the volatility in this period is caused by market participants in the US who do not react to early European announcements instantly due to the time differences.[26] This would also explain why the effect of the ECB decisions, which is the latest European announcement at 1.45 pm, results in significantly higher volatility for both stocks and bonds.

As discussed in section 6.2.3, we compute the absolute value of the standardized surprise of each announcement in order to employ it as exogenous variable. Results are presented in the second column in Tables 6.4 and 6.5 and are highly significant. The second column shows that the greater the absolute surprise of each announcement, the larger the volatility. The effect is stronger for stocks than for bonds, and again an absolute surprise in nonfarm payroll employment as well as in the unemployment rate drive conditional variances the most. Similar to the estimations with the announcement dummy, we are puzzled by the negative signs of some estimations involving news from the Eurozone. Again, besides ECB rate decisions, most of the models that include the absolute surprise of news from Germany or the Eurozone do not fit the data better than a GARCH (1,1) model.

[26]This does not imply that the information is generally not taken into account by these market participants but that the exact time when the news is incorporated cannot be identified.

In column three in Tables 6.4 and 6.5, we display estimation results for GARCHX models that include the actual surprise values of the respective macroeconomic announcement. Yet, most coefficients are not significantly different from zero. Calculating the BIC indicates that both a GARCH (1,1) and models that use absolute values of the surprise fit the data better.

Again, we are interested whether the combination of several exogenous variables improves the fit to the data. We estimate several combinations of exogenous variables that include the high-frequency variables and macroeconomic announcements[27] and select the best model according to the BIC criterion. Tables 6.6 and 6.7 present the two best models for bonds and stocks, respectively. It turns out that the inclusion of the following macroeconomic announcements improves the fit of the model: nonfarm payroll employment, US GDP (stocks only), consumer prices, and initial jobless claims.

Table 6.6: European Bonds: GARCHX Model Combined Effects

	2nd Best Model Bonds		Best Model Bonds	
VSTOXX^a	19.005***	(9.518)	19.045***	(10.271)
Trading Vol. Bonds^a	0.145***	(0.055)	0.145***	(0.059)
Trading Vol. Stocks^a	0.468***	(0.073)	0.468***	(0.073)
Financial crisis	1.016***	(0.163)	1.017***	(0.169)
All Announcements	11.116***	(1.608)	11.219***	(1.588)
Term spread	−0.061***	(0.017)	−0.061***	(0.017)
Nonfarm payroll empl.^{b}	93.848***	(15.190)	93.804***	(15.042)
U.S. GDP^b	2.315	(7.411)		
Consumer prices^b	10.207***	(3.454)	10.106***	(3.398)
Initial claims^b	9.707***	(2.430)	9.792***	(2.426)
BIC	41876.685		41866.258	

Note: The table reports the γ estimates of a GARCHX(1,1) model (see Equation 4.18) for the Bund future. All parameters in each column are estimated simultaneously. Robust standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$, ^{a}Log change of the variable. ^{b} Dummy variable indicating the macroeconomic announcement.

The interpretation of the single news dummies changes as now both the individual macroeconomic news dummies and the *all announcements* dummy are included. They now explain the effects of the individual announcement on volatility in excess of the general effect of a macroeconomic announcement. The estimated coefficients are mostly similar to those already reported. An exception is the coefficient of *all announcements*

[27]That means that we use a specific to general approach in variable selection. Including all possible exogenous variables in a single estimation might result in a better fit. However, it might make numerical optimization infeasible due to the very large number of parameters that have to be estimated.

Table 6.7: European Stock: GARCHX Model Combined Effects

	Best Model Stocks		2nd Best Model Stocks	
VSTOXX[a]	467.678***	(80.563)	467.879***	(103.874)
Trading Vol. Bonds[a]	−0.377***	(0.218)	−0.384***	(0.209)
Trading Vol. Stocks[a]	5.230***	(0.497)	5.275***	(0.778)
Financial crisis	15.144***	(1.396)	15.276***	(3.351)
All Announcements	63.027***	(8.749)	66.950***	(10.858)
Term spread	0.232***	(0.094)	0.239	(0.385)
Nonfarm payroll empl.[b]	635.441***	(108.775)	634.096***	(120.251)
U.S. GDP[b]	129.108***	(51.951)		
Consumer prices[b]	77.030***	(45.604)	71.608	(46.193)
Initial claims[b]	90.207***	(21.454)	102.298***	(22.815)
BIC	306473.893		306505.300	

Note: The table reports the γ estimates of a GARCHX(1,1) model (see Equation 4.18) for the Euro Stoxx 50 future. All parameters in each column are estimated simultaneously. Robust standard errors in parentheses. $*p < 0.10$, $**p < 0.05$, $***p < 0.01$, [a]Log change of the variable. [b] Dummy variable indicating the macroeconomic announcement.

dummy for stocks. It nearly halves as we separate the most important macroeconomic announcements. The coefficients for the individual macroeconomic announcements are also smaller. However, adding the coefficient from the *all announcements* dummy roughly yields the same effects. Therefore, it is not surprising that the variable US GDP is not significant in the combined bond volatility estimation as its effect on conditional variances is not significantly different from announcements already included in the *all announcements* dummy.

Interestingly, the coefficient on the log change in the VSTOXX is smaller in the combined stock volatility estimation than in the model presented in Table 6.5 but remains significant. Most likely, the announcement of some macroeconomic variables coincides with rising risk aversion. Estimating the same specification but without any macroeconomic variables reveals that the coefficient on risk aversion rises again.

Turning to the other high-frequency variables, we find similar results as before for the bond volatility estimation. Surprisingly, in the stock volatility estimation, the coefficients for both the measure for the bund future trading volume and the term spread are now significant and change the sign.

In summary, we conclude the occurrence of any macroeconomic announcement results in a higher volatility as do surprises for both stocks and bonds in an univariate analysis. However, it does not matter if it is a negative or positive surprise. As expected, higher risk aversion results in higher volatility even when taking into account various macroeconomic announcements. Corroborating the results of the previous chapters, we also find that a multivariate analysis that includes multiple exogenous variables is preferable as the effects partly overlap.

6.3.3 The GDCCX model

We now turn to the estimation of conditional stock-bond correlations employing a GDCCX model (see section 2.4.2) with exogenous variables. Volatility is modeled with a GARCHX model as shown in Tables 6.6 and 6.7 for bonds and stocks, respectively.

At first, we are interested in the separate effects of variables on correlations. Results can be found in the left panel in Table 6.8. Similar to previous studies (Connolly et al., 2005, 2007), we see that risk aversion - as measured by the change in the VSTOXX index - is an important driver of conditional correlations. As risk aversion rises, conditional correlations between stocks and bonds fall. However, both the term spread and the dummy for the financial crisis do not significantly influence conditional correlations which contrasts with our findings on volatility. Yet, another very important driver of conditional correlations are macroeconomic announcements. The effect of the dummy that covers all announcements is negative and significant. The model that uses this dummy fits the data best according to the BIC. Lastly, we find that both higher trading volume in stocks and in bonds result in lower conditional correlations. This confirms findings of Bansal et al. (2010). They argue that higher bond and stock trading volume is associated with a high-stress regime that exhibits lower correlations between stocks and bonds. However, it might also be a result of higher trading volume coinciding with higher risk aversion or macroeconomic announcements.

Therefore, next, we estimate conditional correlations employing all previous variables simultaneously. Results are shown in right panel in Table 6.8. The effect of trading volume is now smaller but still significant. Moreover, the coefficient for the dummy on the financial crisis is now significant and positive, i.e. conditional correlations rose during the financial crisis. This is remarkable as other studies (Andersen et al., 2007; Ilmanen, 2003) demonstrate that stock bond correlations tend to rise in expansions but decrease in recessions. Yet, these studies cover different time periods. Again, there is no effect of the term spread on correlations and the coefficients of the change in

Table 6.8: European Bond and Stock Correlations in a GDCCX Model: Effect of High Frequency Variables

	Separate Estimations		Combined Estimation	
VSTOXX[a]	−64.116*	(36.201)	−65.760***	(14.184)
Trading Vol. Bonds[a]	−0.374***	(0.090)	−0.216***	(0.059)
Trading Vol. Stocks[a]	−0.374***	(0.108)	−0.273***	(0.087)
All announcements	−10.253***	(1.325)	−12.298***	(1.285)
Financial crisis	0.082	(0.104)	0.353***	(0.118)
Term spread	−0.009	(0.007)	−0.008	(0.023)

Note: The table reports the c estimates of a GDCCX model (see Equation 2.11) for European bonds and stocks. We model volatility with a GARCHX (1,1) model (see Equation 4.18 and Table 6.6 and 6.7). In the left panel, we run separate estimations for each c presented whereas in the right panel, all parameters are estimated simultaneously. Robust standard errors in parentheses.
$^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, [a]Log change of the variable

the VSTOXX index and on the dummy for the macroeconomic announcements remain negative and significant confirming our previous results.

We want to explore the effect of the specific macroeconomic announcements in more detail. Therefore, we repeat our previous estimation and consecutively add each announcement (one at a time). We employ all variables from above except the term spread as the coefficient has never been significant. Thus, a single estimation includes the respective macroeconomic announcement, VSTOXX, Trading Vol. Bonds, Trading Vol. Stocks, the *all announcements* dummy, and the Financial Crisis Dummy as exogenous variables. Table 6.9 contains the estimated c coefficients and standard errors. We analyze two different variables for each announcement: a dummy variable that takes the value 1 at the time of the announcement and 0 else as well as the absolute value of the announcement surprise.[28]

Table 6.9 highlights the importance of each single macroeconomic announcement: almost all coefficients are significant. Furthermore, we find that in almost all estimations the coefficient on risk aversion is negative and significant. We conclude that even after taking account for all kinds of macroeconomic news, risk aversion still drives conditional stock-bond correlations on a high-frequency level.

[28] Thus, we take another approach than Christiansen and Ranaldo (2007) as we do not use the actual value of the surprise as variable. A preliminary analysis including the actual value, the absolute value, and the dummy variable shows that, according to the BIC, models that employ the actual value of the macroeconomic announcements do not fit the data in almost all cases. The BIC values of this preliminary analysis are presented in Table 6.13 in appendix 6.A2.

Table 6.9: European Bond and Stock Correlations in a GDCCX Model: Macroeconomic Announcements and High-Frequency Variables

	Best Model Employs	Single Announcement		All Announcements Dummy		VSTOXX[a]	
		U.S. Announcements					
Capacity utilization[b]	Dummy	−3.317***	(0.951)	−12.126***	(1.279)	−65.809***	(18.980)
Construction spending	Dummy	−6.237**	(2.778)	−11.891***	(1.283)	−66.604**	(26.470)
Consumer confidence	Dummy	−2.517**	(1.267)	−12.214***	(1.113)	−66.013*	(37.993)
Consumer prices	Absolute Surprise	106.456***	(40.445)	−13.235***	(1.250)	−64.655**	(26.792)
Durable good orders	Absolute Surprise	−76.351***	(23.393)	−11.683***	(1.122)	−65.051**	(27.080)
Factory orders	Dummy	−4.296***	(0.771)	−12.114***	(1.718)	−66.014***	(8.805)
U.S. GDP	Absolute Surprise	−38.829***	(3.042)	−12.048***	(1.765)	−65.954***	(17.755)
Industrial production[b]	Dummy	−3.317***	(0.951)	−12.126***	(1.279)	−65.809***	(18.980)
Initial claims	Dummy	2.067***	(0.420)	−12.744***	(1.184)	−66.060	(42.157)
ISM index	Absolute Surprise	−38.163	(26.881)	−11.839***	(1.705)	−65.886	(57.273)
New home sales	Absolute Surprise	−9.894***	(3.140)	−12.209***	(1.007)	−66.475***	(18.458)
Nonfarm payroll empl.[c]	Dummy	−23.046***	(3.057)	−11.230***	(1.014)	−64.842***	(24.240)
Producer price index	Absolute Surprise	13.319***	(1.884)	−12.454***	(1.215)	−65.715***	(24.389)
Retail sales	Dummy	−5.514	(3.910)	−11.886***	(3.556)	−65.389	(74.133)
Unemployment rate[c]	Dummy	−23.046***	(3.057)	−11.230***	(1.014)	−64.842***	(24.240)
		German and Eurozone Announcements					
IFO index	Absolute Surprise	73.924***	(15.989)	−12.920***	(1.892)	−62.999***	(14.733)
German unemployment	Absolute Surprise	−6.540***	(2.424)	−12.253***	(0.965)	−65.794***	(9.858)
ECB rate decision	Absolute Surprise	169.103***	(38.264)	−13.561***	(1.382)	−68.807***	(15.811)
Eurozone HCPI	Absolute Surprise	6.340***	(2.454)	−12.315***	(1.315)	−65.494***	(15.632)
Eurozone GDP	Absolute Surprise	35.348***	(10.186)	−12.349***	(1.403)	−65.872***	(9.099)

Note: The table reports the c estimates of a GDCCX model (see Equation 2.11) for European bonds and stocks. We model volatility with a GARCHX (1,1) model (see Equation 4.18 and Table 6.6 and 6.7). Each row in the table represents a single estimation that includes the respective macroeconomic announcement, VSTOXX, Trading Vol. Bonds, Trading Vol. Stocks, the all Announcements Dummy, and Financial Crisis Dummy as exogenous variables. Best model describes if the absolute surprise or the a simple dummy is taken for of the respective announcement. Robust standard errors in parentheses.

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$, [a]Log change of the variable; [b, c] Economic figures are announced at the same time.

According to the BIC,[29] the most important announcement for conditional correlations are the nonfarm payroll and the US unemployment rate announcement that are always released at the same time. That matches our results from the volatility equation. Moreover, the ECB interest rate decision as well as the US consumer prices are almost as important as nonfarm payrolls.

The second column in Table 6.9 reports whether the best model according to the BIC either includes the dummy variable of the announcement or the absolute value of the announcement-surprise. Although Christiansen and Ranaldo (2007) show that the occurrence of an announcement by itself influences conditional correlations, we notice that the absolute surprise of an announcement sometimes drives correlations even more. That is true for all announcements in the Eurozone as well as the inflation (consumer and producer prices) and the GDP release in the US. Furthermore, for all announcements that are released at the same time,[30] we favor the model with an announcement dummy. That points towards our measure for the surprise being imprecise in case of simultaneously released announcements since the actual surprise might be a combination of the surprises of both announcements.

Interestingly, the signs of the coefficients vary among announcements. In order to calculate the total effect of a specific announcement the coefficient of the respective announcement and of the *all announcements* dummy must be added. Most releases indicating real economic shocks (i.e. GDP, unemployment, surveys of activity etc.) have a negative effect on conditional correlations in the US. However, for consumer prices in the US and in the Eurozone as well as for the ECB rate decision, we find that conditional correlations rise the more the larger the surprise. Yet, in case of no surprise, the general effect of all macroeconomic announcements dominates and conditional correlations fall as well.

This fits well theoretical models in which equity prices are determined by the present value of future cash flows.[31] Furthermore, if monetary policy is strictly anti-inflationary, market participants will assume that higher inflation makes future interest rate rises more likely and vice versa. Hence, interest rate and inflation announcements should influence the prices of bonds and stocks via the discount rate in the same way resulting

[29] Table 6.14 in appendix 6.A2 displays the BIC values for Table 6.9.

[30] The announcement of nonfarm payrolls and unemployment rate as well as the release of the industrial production and capacity utilization are the same time.

[31] An example might be the Gordon (1959) growth model.

in rising conditional correlations. By contrast, if an announcement such as GDP or the unemployment rate conveys information about future cash flows, conditional correlations between bonds and stocks should fall. Another interpretation is that these announcements trigger a flight-to-quality. Interestingly, in Eurozone the announcement of the IFO index and the GDP result in rising conditional correlations. Probably, in the Eurozone these announcements are more informative for future interest rates than for future cash flows.

Table 6.10: European Bonds and Stock Correlations in a GDCCX Model: Macroeconomic Announcements during Recession and Expansion

	Best Model	Announcement in Recession		Announcement in Expansion	
		U.S. Announcements			
Capacity utilization[a]	Dummy	−7.125	(9.396)	−21.857*	(11.719)
Construction spending	Dummy	−13.446***	(2.574)	−17.318***	(2.094)
Consumer confidence	Dummy	−6.434***	(0.653)	−15.747***	(1.811)
Consumer prices	Abs. Surpr.	68.510***	(13.766)	48.527***	(10.324)
Durable good orders	Abs. Surpr.	−68.884***	(10.145)	−211.228***	(22.215)
Factory orders	Abs. Surpr.	−58.861**	(25.070)	−121.827**	(48.871)
U.S. GDP	Dummy	2.684***	(0.736)	−26.586***	(3.546)
Industrial production[a]	Dummy	−7.125	(9.396)	−21.857*	(11.719)
Initial claims	Dummy	−1.761***	(0.573)	−16.108***	(2.731)
ISM index	Abs. Surpr.	−116.103***	(7.511)	−124.382***	(34.656)
New home sales	Abs. Surpr.	−33.415***	(9.339)	−59.784***	(11.411)
Nonfarm payroll empl.[b]	Dummy	−31.129**	(12.864)	−33.463***	(3.286)
Producer price index	Dummy	−12.599***	(1.958)	−6.855	(6.859)
Retail sales	Dummy	−24.503***	(3.846)	−12.674***	(1.745)
Unemployment rate[b]	Dummy	−31.129**	(12.864)	−33.463***	(3.286)
		German and Eurozone Announcements			
IFO index	Abs. Surpr.	73.721***	(22.421)	19.617***	(5.990)
German unemployment	Abs. Surpr.	65.188*	(37.665)	−129.100**	(50.584)
ECB rate decision	Abs. Surpr.	79.795***	(22.929)	−0.133	(0.254)
Eurozone HCPI	Dummy	−5.209	(3.664)	−14.170***	(4.700)
Eurozone GDP	Dummy	13.917***	(3.072)	−12.972*	(7.883)

Note: The table reports the c estimates of a DCCX(1,1) model (see Equation 2.11) for European bonds and stocks. We model volatility with a GARCHX(1,1) model (see Equation 4.18 and Table 6.6 and 6.7). Each row in the table represents a single estimation that includes the respective macroeconomic announcement, VSTOXX, Trading Vol. Bonds, and Trading Vol. Stocks as exogenous variables. Best model describes if the absolute surprise or the a simple dummy is taken for of the respective announcement. Robust standard errors in parentheses.
*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$, [a, b] Economic figures are announced at the same time.

Previous studies have shown that announcement effects can vary with the business cycle (Andersen et al., 2007; Boyd et al., 2005; Christiansen and Ranaldo, 2007). On average, macroeconomic announcements should not drive conditional correlations as the effects should cancel out over the full cycle. In order to further investigate the influence of the business cycle, we repeat the analysis but split the announcement variables in two parts: a recession and an expansion variable.[32] We define the beginning of the recession as the time when market participants learn that the European GDP growth turned from positive to negative and the end when GDP growth turns positive again.[33] Furthermore, we drop the *all announcements* dummy and the dummy for the financial crisis to clearly separate the effects of recession and expansion. Table 6.10 reports the results. The analysis confirms that the sign of most coefficients does not differ between periods of recession and periods of expansion. Moreover, the models that do not distinguish between contraction and expansion periods fit the data better according to the BIC.[34]

There are several possible explanations for these results. First, since our sample covers only four years, we at most cover one full cycle. This period might be too short for a valid analysis of the business cycle. Second, the shock of the financial crisis might last longer than the effects on the real economy. Therefore, we re-estimate our previous analysis but assume that the recession lasted at least until the end of our sample. However, results are qualitatively unchanged. Third, numerous definitions for the exact start and end of a recession can be applied which might also change our results. Fourth, the sample period of Andersen et al. (2007) runs from 1994 to 2002, Christiansen and Ranaldo (2007) cover the years 1988 to 2003 so that the years after the burst of the dot-com bubble are not covered. Possibly, there has been a structural break with market participants becoming more risk averse. Accordingly, announcements cause conditional stock-bond correlations to become more negative, and a flight-to-quality can be observed more often. However, a longer sample will be necessary to ultimately answer these questions.

[32] The variables that measure announcements in a recession take the value of the announcement during a recession and 0 else. The variables that measure announcements in an expansion take the value of the announcement during an expansion and 0 else.

[33] According to our definition the economy is contracting from 8/14/2008 to 11/13/2009.

[34] Table 6.15 in appendix 6.A2 displays the BIC values for Table 6.10.

6.4 Summary

In this chapter, we analyze the influence of risk aversion, macroeconomic announcements, and other variables on high-frequency correlations between bonds and stocks in the Eurozone. We find that both risk aversion and macroeconomic announcements separately drive conditional correlations and variances of bonds and stocks in the Eurozone. Conditional correlations fall as risk aversion rises even when controlling for the influence of macroeconomic announcements and the influence of these variables on volatility. Interestingly, the additional effects of the financial crisis on conditional correlations are only small. For most macroeconomic announcements, the absolute value of the surprise is of higher importance for correlations than the mere occurrence of the announcement. We get similar results when analyzing stock and bond volatility. Moreover, macroeconomic news result in falling conditional correlations. Yet, the publication of news concerning future interest rates or the release of inflation figures moves bond and stock prices in the same direction. These news convey information concerning future cash-flows or trigger a flight-to-quality. We do not find that the effect of economic announcements on conditional correlations changes during the cycle as splitting the effects of the macroeconomic variables between expansion and recession does not alter the results and offer several explanations. However, we cannot assess if this represents a structural break in the data or is caused by the particular period we cover in our dataset. Comparing the effects of Eurozone and US announcements, we find evidence that the most important announcements in the US are news on nonfarm payroll employments while in Europe the announcement of the ECB rates receives most attention.

Hence, the analysis of high-frequency data corroborates the findings of the previous chapter: A sensible approach to incorporate exogenous information in correlation models should explicitly allow for exogenous effects in both volatilities and correlations. Moreover, the advantage of multivariate exogenous variables models as compared to models allowing for just one exogenous driver has again been underlined.

Our results have also important implications for both investors as well as risk managers. We demonstrate that the stock-bond correlation falls and, hence, the diversification of a stock-bond portfolio benefits in times of rising risk aversion i.e. at the time when diversification benefits are needed most. This is an important result as it is well known that stock-stock correlations rise in times of market turbulence.

6.A Appendix

6.A1 GARCHX Modell: Bayesian Information Criterion

Table 6.11: European Bonds: GARCHX Model - Bayesian Information Criterion

	High-Frequency Variables		
VSTOXX[a]	47556.676		
Trading Vol. Bonds[a]	47600.873		
Trading Vol. Stocks[a]	47170.859		
Financial crisis	47224.536		
Term spread	47474.874		
	Announcement Dummy[b]	**Absolute Surprise[c]**	**Surprise**
All announcements	43815.434		
	U.S. Announcements		
Capacity utilization[d]	47586.567	**47585.911**	47600.680
Construction spending	**47298.972**	47379.348	47588.441
Consumer confidence	47563.415	**47560.135**	47598.967
Consumer prices	**47380.324**	47428.147	47600.793
Durable good orders	**47452.321**	47467.049	47600.804
Factory orders	**47562.629**	47563.818	47592.100
U.S. GDP	**47486.977**	47494.600	47587.426
Industrial production[d]	47586.567	**47586.027**	47598.557
Initial claims	**46781.375**	46843.125	47598.075
ISM index	47305.032	**47301.092**	47596.084
New home sales	47564.550	**47561.475**	47600.412
Nonfarm payroll empl.[e]	**45494.565**	45501.870	47598.039
Producer price index	**47277.226**	47282.450	47596.340
Retail sales	47095.341	**47080.820**	47598.023
Unemployment rate[e]	**45494.565**	45876.565	47567.510
	German and Eurozone Announcements		
IFO index	47345.566	**47342.778**	47572.583
German unemployment	47596.058	**47596.058**	47592.831
ECB rate decision	47355.989	**47342.322**	47374.050
Eurozone HCPI	47585.783	**47570.453**	47582.578
Eurozone GDP	**47592.017**	47597.998	47597.102

Note: The table reports the Bayesian Information Criterion of a GARCHX(1,1) model (see Equation 4.18) for the Bund future. Coefficients are reported in table 6.4. We run separate estimations for each model presented. The best model for each macroeconomic variable is indicated in bold.
[a]Log change of the variable; [b]Announcement Dummy is an indicator function that takes on the value 1 if there is an announcement and 0 otherwise; [c]Absolute value of the surprise is employed. [d, e] Economic figures are announced at the same time.

Table 6.12: European Stocks: GARCHX Model - Bayesian Information Criterion

	High-Frequency Variables		
VSTOXX[a]	311414.671		
Trading Vol. Bonds[a]	311688.665		
Trading Vol. Stocks[a]	311381.442		
Financial crisis	311288.786		
Term spread	311698.549		
	Announcement Dummy[b]	**Absolute Surprise[c]**	**Surprise**
All announcements			
	U.S. Announcements		
Capacity utilization[d]	**311690.523**	311691.688	311709.672
Construction spending	**311496.276**	311518.379	311669.811
Consumer confidence	311650.160	**311648.173**	311710.755
Consumer prices	**311455.901**	311484.559	311707.664
Durable good orders	**311447.518**	311454.310	311710.694
Factory orders	**311668.759**	311675.245	311711.245
U.S. GDP	**311409.067**	311443.410	311694.796
Industrial production[d]	**311690.523**	311691.971	311708.191
Initial claims	**310642.410**	310678.285	311676.504
ISM index	**311476.665**	311490.292	311711.186
New home sales	**311587.013**	311587.505	311710.381
Nonfarm payroll empl.[e]	**309956.569**	310021.888	311707.797
Producer price index	**311566.748**	311573.343	311672.805
Retail sales	311413.486	**311409.317**	311711.189
Unemployment rate[e]	**309956.569**	309992.329	311707.999
	German and Eurozone Announcements		
IFO index	311708.523	311709.538	**311703.884**
German unemployment	**311696.853**	311696.854	311704.409
ECB rate decision	311641.320	**311640.666**	311643.278
Eurozone HCPI	**311675.080**	311696.761	311709.567
Eurozone GDP	311706.417	**311704.599**	311711.247

Note: The table reports the Bayesian Information Criterion of a GARCHX(1,1) model (see Equation 4.18) for the Euro Stoxx 50 future. Coefficients are reported in table 6.5. We run separate estimations for each model presented. The best model for each macroeconomic variable is indicated in bold.
[a]Log change of the variable; [b]Announcement Dummy is an indicator function that takes on the value 1 if there is an announcement and 0 otherwise; [c]Absolute value of the surprise is employed. [d, e] Economic figures are announced at the same time.

6.A2 GDCCX Modell: Bayesian Information Criterion

Table 6.13: European Bond and Stock Correlations in a GDCCX Model with only one exogenous variable: Bayesian Information Criterion

	Announcement Dummy[b]	Absolute Surprise[c]	Surprise
	U.S. Announcements		
Capacity utilization[d]	**333680.763**	333683.468	333689.020
Construction spending	**333671.524**	333676.385	333694.296
Consumer confidence	**333690.727**	333690.782	333691.882
Consumer prices	**333691.369**	333694.860	333693.834
Durable good orders	**333661.650**	333662.912	333694.235
Factory orders	333684.659	333683.479	**333681.827**
U.S. GDP	**333677.017**	333678.793	333694.835
Industrial production[d]	**333680.763**	333684.533	333690.078
Initial claims	**333649.333**	333654.589	333693.065
ISM index	333676.002	**333674.557**	333693.595
New home sales	333692.664	**333690.041**	333694.849
Nonfarm payroll empl.[e]	**333604.076**	333609.924	333691.031
Producer price index	**333691.539**	333691.922	333694.803
Retail sales	**333671.219**	333679.409	333693.064
Unemployment rate[e]	**333604.076**	333635.860	333691.363
	German and Eurozone Announcements		
IFO index	333694.002	**333693.044**	333694.099
German unemployment	**333689.231**	333689.231	333694.844
ECB rate decision	**333692.203**	333694.807	333694.007
Eurozone HCPI	**333692.965**	333694.301	333694.825
Eurozone GDP	333694.543	**333690.837**	333691.551

Note: The table reports the Bayesian Information Criterion of a of a GDCCX model (see Equation 2.11) for European bonds and stocks. We model volatility with a GARCHX (1,1) model. We run separate estimations for each model presented where the macroeconomic variable is the only exogenous variable employed. The best model for each macroeconomic variable is in bold.
[b]Announcement Dummy is an indicator function that takes on the value 1 if there is an announcement and 0 otherwise; [c]Absolute value of the surprise is employed. [d, e] Economic figures are announced at the same time.

Table 6.14: European Bond and Stock Correlations in a GDCCX Model: Bayesian Information Criterion

	Announcement Dummy[b]	Absolute Surprise[c]
	U.S. Announcements	
Capacity utilization[d]	**333332.064**	333332.354
Construction spending	**333328.547**	333330.654
Consumer confidence	**333332.366**	333332.456
Consumer prices	333323.348	**333310.478**
Durable good orders	333317.544	**333314.779**
Factory orders	**333331.316**	333331.406
U.S. GDP	333330.208	**333328.748**
Industrial production[d]	**333332.064**	333332.431
Initial claims	**333331.841**	333332.547
ISM index	333328.541	**333326.721**
New home sales	333332.815	**333332.566**
Nonfarm payroll empl.[e]	**333285.720**	333289.240
Producer price index	333332.477	**333332.192**
Retail sales	**333329.591**	333331.390
Unemployment rate[e]	**333285.720**	333302.033
	German and Eurozone Announcements	
IFO index	333317.464	**333314.608**
German unemployment	333332.714	**333332.713**
ECB rate decision	333307.032	**333305.570**
Eurozone HCPI	333332.900	**333332.576**
Eurozone GDP	333332.698	**333331.691**

Note: The table reports the Bayesian Information Criterion of a of a GDCCX model (see Equation 2.11) for European bonds and stocks. We model volatility with a GARCHX (1,1) model. Coefficients are reported in table 6.9. We run separate estimations for each model presented. Each model includes the respective macroeconomic announcement, VSTOXX, Trading Vol. Bonds, Trading Vol. Stocks, the all Announcements Dummy, and Financial Crisis Dummy as exogenous variables. The best model for each macroeconomic variable is indicated in bold.
[b]Announcement Dummy is an indicator function that takes on the value 1 if there is an announcement and 0 otherwise; [c]Absolute value of the surprise is employed. [d, e] Economic figures are announced at the same time.

Table 6.15: European Bonds and Stock Correlations in a GDCCX Model with Macroeconomic Announcements during Recession and Expansion: Bayesian Information Criterion

	Best Model	BIC
U.S. Announcements		
Capacity utilization[a]	Dummy	333536.421
Construction spending	Dummy	333530.805
Consumer confidence	Dummy	333547.249
Consumer prices	Abs. Surpr.	333555.227
Durable good orders	Abs. Surpr.	333499.532
Factory orders	Abs. Surpr.	333541.496
U.S. GDP	Dummy	333526.463
Industrial production[a]	Dummy	333536.421
Initial claims	Dummy	333508.935
ISM index	Abs. Surpr.	333528.902
New home sales	Abs. Surpr.	333548.813
Nonfarm payroll empl.[b]	Dummy	333472.287
Producer price index	Dummy	333550.453
Retail sales	Dummy	333524.860
Unemployment rate[b]	Dummy	333472.287
German and Eurozone Announcements		
IFO index	Abs. Surpr.	333555.538
German unemployment	Abs. Surpr.	333540.661
ECB rate decision	Abs. Surpr.	333553.553
Eurozone HCPI	Dummy	333550.783
Eurozone GDP	Dummy	333550.861

Note: The table reports the Bayesian Information Criterion of a of a GDCCX model (see Equation 2.11) for European bonds and stocks. We model volatility with a GARCHX (1,1) model. Coefficients are reported in table 6.10. Each row in the table represents a single estimation that includes the respective macroeconomic announcement, VSTOXX, Trading Vol. Bonds, and Trading Vol. Stocks as exogenous variables. Best model describes if the absolute surprise or the a simple dummy is taken for of the respective announcement.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$, [a, b] Economic figures are announced at the same time.

7 Summary and Conclusion

In this dissertation, the influence of exogenous variables on conditional correlations is investigated. First, it is examined how to model the possible effects of exogenous variables. Various correlation models proposed by the previous literature are introduced: the DCC, the DCCX, the STCC, and the Sheppard model. In a next step, the DCCX model is generalized and the GDCCX model is proposed. In that model exogenous variables can drive conditional correlations in different ways. In addition, it is guaranteed that the exogenous variables affect conditional covariances but not conditional variances.

Following the investigation of the finite sample properties of all estimators, the models are compared. A simulation experiment is conducted, and estimated correlations are compared with the true conditional correlations. In order to ensure that the exogenous variable has some forecast ability, the lagged conditional correlations are employed as exogenous variable. The results show that the GDCCX model uses the information contained in the exogenous variable best as the mean absolute error is lowest for several different settings. By contrast, the Sheppard model performs even worse than a simple DCC model that does not use any exogenous data. Moreover, by accounting for the influence of exogenous variables it is possible to reduce the mean absolute error by about two thirds. This further strengthens the argument for employing exogenous variables when conditional correlations are sought to be explained.

Going forward, the models are compared to each other employing real data. As the true conditional correlations are unknown, the testing criteria developed by Engle and Colacito (2006) are used to compare the models. The DCC, the DCCX, and the GDCCX model significantly outperform the STCC and the Sheppard model. In addition, the benefits of using the GDCCX model rise as the number of time series included increases. Since real bond market data is analyzed, the interpretation of the results is meaningful. The results indicate that conditional correlation between government and corporate bonds fall as risk aversion increases, a clear sign of a flight-to-quality. This is good news from a portfolio management perspective as diversification benefits remain intact in times of crisis.

Up to this point, it is assumed that conditional variances are not influenced by the exogenous variables and can be explained with a GARCH model. However, several recent studies suggest that this assumption may not hold. Possible consequences of this misspecification of the variance equation on the estimation of conditional correlations are examined. First, a theoretical model of Forbes and Rigobon (2002) is consulted. It is demonstrated that a change in the conditional variance of one of the time series caused by an exogenous variable can result in higher conditional correlations between that time series and a second one although the dependence structure does not change. Yet, this result is based on assumptions concerning the transmission and the specific variance of the second time series. Second, a simulation study is carried out to investigate the estimation of conditional correlations if conditional variances but not correlations are driven by the exogenous variable. It is shown that the influence of the exogenous variable on the conditional correlation cannot be distinguished from the the exogenous variable driving the dependency structure in certain settings. However, once the influence of the exogenous variable on conditional variances is modeled with a GARCHX model, the effect of the exogenous variable on conditional correlations and variances is correctly specified in all settings. Going forward, conditional variances are estimated with the GARCHX model and conditional correlations with the GDCCX model.

Employing the econometric framework developed in the previous parts, several empirical research questions are addressed. First, the effects of risk aversion, market turbulence, and the business cycle on conditional correlations between weekly European bonds and between weekly European stock returns are examined. In a first step, the influence of each variable is analyzed separately. In a second step, all variables are included simultaneously. That allows investigating whether the effect of one variable is dominating and whether the effects are persistent after taking account for other exogenous variables. The results indicate that, while both GDP growth and market turbulences influence conditional correlations, the effect of risk aversion vanishes once the other variables are included in the analysis. As expected, the impact of market turbulences is most pronounced in the peripheral countries. The empirical results also show that there is an important difference between bonds and stocks. While market turbulences result in decreasing conditional correlations between international bond markets, conditional correlations between stock markets rise strongly. These are clear signs of contagion in the stock market diminishing the diversification within a stock market portfolio. Diversification is further impeded by negative GDP growth which results in higher stock return correlations. By contrast, diversification benefits remain intact in a bond portfolio since lower GDP growth coincides with decreasing bond return correlations.

In the final empirical analysis, the sample frequency is substantially increased. The dataset adopted to examine intra-day stock-bond correlations consists of 5 minute stock and bond returns. Specifically, the effects of risk aversion and macroeconomic announcements both in Europe and in the US on stock-bond correlations are investigated. Since volatility can also be influenced by exogenous variables, conditional correlations are estimated using a GDCCX model and conditional variances are modeled using a GARCHX model. Estimating the effects of the announcements on both conditional correlations and variances is particularly important since previous studies found that volatility increases considerably at the time of announcements. The results indicate that both risk aversion and macroeconomic announcements are important drivers of conditional stock-bond correlations. Conditional correlations fall as risk aversion rises. While previous studies found that the mere occurrence of an announcement matters most for correlations, the results demonstrate that the absolute value of the announcement surprise is even more important. This is also true for stock volatility. Generally, news on nonfarm payroll employments in the US and the announcement of the ECB rates drive conditional correlations most. The publication of almost all announcements results in falling conditional correlations. An exception are interest rates and inflation announcements. These news drive conditional correlations upwards. It can be concluded that these figures convey information concerning future cash-flows or that they trigger a flight-to-quality. Furthermore, the results show that the effect of the macroeconomic variables is not sensitive to the business cycle.

The results of this thesis have important implications for both academics and practitioners. It is highlighted that diversification benefits remain intact in a portfolio consisting of stocks and bonds or of different bond sectors. Moreover, a powerful econometric framework that is particularly suited for the empirical analysis of influencing factors of conditional correlations has been developed. The combination of the GDCCX and the GARCHX model allows for the simultaneous analysis of the effects of one or more exogenous variables on conditional variances and correlations. Moreover, the effects of exogenous variables on variances can be distinguished from those on the dependency structure. Therefore, this econometric framework is especially useful if a researcher is unsure whether the exogenous variables drive conditional variances, conditional correlations or both.

In the empirical analysis, the focus lies on the effects of risk aversion and macroeconomic figures on correlations between different asset classes. Assessing the correlations between different asset classes is important both for portfolio and risk management. The econometric framework can easily be applied to various research areas. For example, the CAPM postulates that the expected return of a security is a function of its correlation with the market. Remaining questions are whether price changes are caused by changes of the correlation of the security with the market and what the determinants of this correlation change are. Moreover, changes in correlations between markets in different countries are often associated with the notion of contagion. The econometric framework presented in this thesis can be employed to reveal triggers of correlation changes. Prospective studies might also investigate the ability of exogenous variables to forecast changes in correlations. This is especially interesting for applied portfolio and risk management, as exogenous variables might improve the forecasting performance of DCC models in this context. In practice, a forecasted increase in conditional correlations might induce hedging of some parts of a portfolio.

Yet, there are some interesting model extensions that remain for future research. While the GDCCX model is based on the assumption that the effect of the exogenous variable on $\mathbf{Q_t}$ is linear, that is not necessarily true. Another reasonable assumption is that the effect varies with the sign of the estimated conditional correlation. For example, it might be that the absolute value of the conditional correlations is a function of the exogenous variables. For example, the conditional correlation between two time series increases to 1 or decreases to -1, i.e. the economic connection strengthens, with larger values of an exogenous variable but decreases to 0 as a result of smaller values of the exogenous variable. If that is true, the estimated c coefficient of the GDCCX model will turn the sign depending on the conditional correlation estimated previously. Thus, the assumption that the effect of the exogenous variable is independent of the sign of previous estimated conditional correlations could be relaxed in further generalizations of the model.

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Erklärung

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