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Flights and CAViaR - Financial Market Stability and the Stock-Bond Return Relation

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Abstract
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FLIGHTS AND CAViaR – FINANCIAL MARKET STABILITY AND THE STOCK-BOND RETURN RELATION

PURPOSE OF THE STUDY

This paper investigates the intranational dynamic relationship between daily stock and government bond returns of selected countries between January 1, 1999 and December 31, 2010 to assess financial market stability in different countries and market conditions. The underlying hypothesis of this paper is that the financial markets of the world's most advanced economies exhibit financial market stability even under extreme market conditions and potentially systemic events. The econometric framework employed to assess whether a country exhibits financial market stability or not includes modeling the time-varying conditional intranational stock-bond correlations, testing for the intranational flights between stocks and bonds, and modeling the conditional autoregressive value at risk (CAViaR) of equally weighted intranational stock-bond portfolios. These methodologies represent one of the most prominent and current tools in the field of financial econometrics and are commonly used by researchers and practitioners all around the world. Importantly, they all have the potential to provide valuable information for investors, policy makers and regulatory authorities about the cross-sectional dimension of systemic risk for assessing financial market stability under extreme market conditions and potentially systemic events.

DATA

The data employed in this paper consists of daily observations of national local currency denominated stock and government bond market total return indices of Australia, Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the United Kingdom (UK), and the United States (US) from January 1, 1999 to December 31, 2010 (3131 observations). The stock market indices are Datastream-constructed value-weighted total market indices representing the total return on a well-diversified national equity portfolio covering a minimum of 75% - 80% of the total market capitalization of each market. The bond market indices are Datastream-constructed 10-year constant maturity total return indices consisting only of the most liquid government bonds following the European Federation of Financial Analysts Societies (EFFAS) methodology.

RESULTS

The empirical results show that the world's most advanced economies, except Italy and Spain, exhibit financial market stability under extreme market conditions and potentially systemic events as assessed by their intranational stock-bond return relations. In the financially stable countries under extreme market conditions and potentially systemic events, the conditional intranational stock-bond correlations tend to stay below or close to zero, the intranational flights between stocks and bonds tend to rather reduce than aggravate the propagation of shocks, and the CAViaR of equally weighted intranational stock-bond portfolios resemble each other to a high degree without showing hardly any excessive divergent spillover effects. In Italy and Spain, the reverse applies. Overall, these results in favor of prevailing financial market stability even under extreme market conditions and potentially systemic events are relatively well in line with the rare empirical literature on financial market stability with the emphasis on cross-asset linkages in developed markets.

KEYWORDS

Stocks, government bonds, financial market stability, conditional correlation, MGARCH, CCC, DCC, ADCC, flights, contagion, market risk, VaR, CAViaR

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PAOT JA CAViaR – RAHOITUSMARKKINOIDEN VAKAUS JA OSAKKEIDEN JA VALTION VELKAKIRJOJEN VÄLINEN TUOTTOSUHDE

TUTKIELMAN TAVOITTEET

Tämä tutkielma tarkastelee valikoitujen maiden sisäistä osakkeiden ja valtion velkakirjojen välistä päivätuottojen dynamiikkaa aikavälillä 1.1.1999 - 31.12.2010 arvioidakseen rahoitusmarkkinoiden vakautta eri maissa ja markkinaolosuhteissa. Tämän tutkielman hypoteesina on, että maailman kehittyneimpien talouksien rahoitusmarkkinat ovat vakaat myös erityismarkkinaolosuhteissa ja potentiaalisesti systeemisten tapahtumien aikana. Ekonometrinen viitekehys maiden sisäisten rahoitusmarkkinoiden vakauden arviointiin sisältää ehdollisen ajassa muuttuvan osakkeiden ja valtion velkakirjojen välisen korrelaation mallintamisen, maan sisäisten osakkeiden ja valtion velkakirjojen välisten pakojen tutkimisen, ja maan sisäisten tasapainotettujen osakkeista ja velkakirjoista koostuvan portfolioiden CAViaR mallintamisen. Nämä metodologiat edustavat parhaimpia ja nykyaikaisimpia työkaluja rahoitusekonometrian osa-alueella ja niitä käyttävät niin tutkijat kuin alan ammattilaiset ympäri maailmaa. Lisäksi ne tarjoavat arvokasta informaatiota sijoittajille, lainsäätäjille ja markkinaviranomaisille systeemisestä riskistä rahoitusmarkkinoiden vakauden arvioimiseksi erityismarkkinaolosuhteissa ja potentiaalisesti systeemisten tapahtumien aikana.

LÄHDEAINEISTO

Tutkielman lähdeaineisto koostuu päivittäisistä havainnoista paikallisessa valuutoissa mitatuista Australian, Belgian, Kanadan, Ranskan, Saksan, Italian, Japanin, Alankomaiden, Espanjan, Ruotsin, Sveitsin, Iso-Britannian ja Yhdysvaltojen osake- ja valtion velkakirjakokonaistuottoindekseistä ajalta 1.1.1999 - 31.12.2010. Osakeindeksit ovat Datastreamin hallinnoimia arvopainotettuja kokonaistuottoindeksejä, jotka kattavat vähintään 75% - 80% maan kokonaisosakemarkkina-arvosta. Valtion velkakirja indeksit ovat Datastreamin hallinnoimia 10-vuotisia vakiomaturiteettisia kokonaistuottoindeksejä, jotka koostuvat vain kaikista likvideimmistä valtion velkakirjoista European Federation of Financial Analysts Societies (EFFAS) metodologian mukaisesti.

TULOKSET

Tutkielman tulokset osoittavat, että maailman kehittyneimmät taloudet, lukuun ottamatta Italiaa ja Espanjaa, ilmentävät rahoitusmarkkinoiden vakautta erityismarkkinaolosuhteissa ja potentiaalisesti systeemisten tapahtumien aikana maiden sisäisillä osakkeiden ja valtion velkakirjojen tuottosuhteilla arvioituna. Rahoitusmarkkinoiltaan vakaissa maissa erityismarkkinaolosuhteissa ja potentiaalisesti systeemisten tapahtumien aikana ehdolliset maiden sisäiset osakkeiden ja valtion velkakirjojen väliset korrelaatiot pysyvät negatiivisina tai lähellä nollaa, paot osakkeiden ja valtion velkakirjojen välillä ennemminkin vähentävät kuin pahentavat markkinashokkien haitallisia vaikutuksia, ja maiden sisäisten tasapainotettujen osakkeista ja velkakirjoista koostuvien portfolioiden CAViaR muistuttavat pitkälti toisiaan eivätkä juuri näytä liiallisia poikkeavia leviämisefektejä. Italian ja Espanjan kohdalla tulokset ovat vastakkaiset. Ylipäätään nämä rahoitusmarkkinoiden vakautta korostavat tulokset ovat suhteellisen hyvin linjassa harvinaisen eri varallisuusluokkien välisiä linkkejä painottavan rahoitusmarkkinoiden vakautta kehittyneillä markkinoilla tutkivan empiirisen kirjallisuuden kanssa.

AVAINSANAT

Osakkeet, valtion velkakirjat, rahoitusmarkkinoiden vakaus, ehdollinen korrelaatio, MGARCH, CCC, DCC, ADCC, paot, tartunta, markkinariski, VaR, CAViaR

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Abbreviations

ADCC	Asymmetric DCC model (Cappiello et al., 2006)
ADF	Augmented Dickey-Fuller test (Dickey and Fuller, 1979)
AG-DCC	Asymmetric Generalized DCC model (Cappiello et al., 2006)
AIC	Akaike information criterion (Akaike, 1974)
APARCH	Asymmetric Power ARCH model (Ding et al., 1993)
ARCH	Autoregressive Conditional Heteroskedasticity model (Engle, 1982)
$ARCH_{LM}(k)$	Lagrange Multiplier (LM) test for ARCH in residuals (Engle, 1982)
BGARCH	Bivariate GARCH
BIS	The Bank for International Settlements
CAViaR	Conditional Autoregressive Value at Risk (Engle and Manganelli, 2004)
χ^2_s	Chi-square distribution of s degrees of freedom
DCC	Dynamic Conditional Correlation (Engle and Sheppard, 2001; Engle, 2002)
DS	Datastream
EFFAS	European Federation of Financial Analysts Societies
EGARCH	Exponential GARCH model (Nelson, 1991)
ES	Expected Shortfall
ES_{DCC}	A test for the null of constant correlation (Engle and Sheppard, 2001)
EVT	Extreme value theory (see e.g. Danielsson and de Vries, 2000)
FFL	Flight-from-liquidity
FFQ	Flight-from-quality

Freddie Mac	The Federal Home Loan Mortgage Corporation
FTL	Flight-to-liquidity (also known and interchangeably referred as contagion)
FTQ	Flight-to-quality
GARCH	Generalized ARCH model (Bollerslev, 1986)
GJR-GARCH	Threshold GARCH model (Glosten et al., 1993)
HL_{DCC}	Half-life of the DCC model estimates (Engle and Sheppard, 2001)
i.i.d.	Independently and identically distributed
IM_S	A test for the null of constant correlation (Bera and Kim, 2002)
IMF	International Monetary Fund
Logl	Log-likelihood
MGARCH	Multivariate GARCH
ML	Maximum likelihood
Q(k)	Ljung-Box Q-statistics of order k residual serial correlation
$Q^2(k)$	Ljung-Box Q-statistics of order k squared residual serial correlation
$Q_{PORT}(12)$	Ljung-Box Q-statistics of order k multivariate residual serial correlation
QML	Quasi-maximum likelihood (Bollerslev and Wooldridge, 1992)
RQ	Regression quantile objective function (Engle and Manganelli, 2004)
SD	Standard deviation
SIC	Schwarz information criterion (Schwarz, 1978)
VaR	Value at Risk
VAR	Vector autoregression

1. Introduction

'I want out. I don't want to know anything about whether a particular investment is risky or not, I just want to disengage' – Alan Greenspan (Oct 7, 1998)

1.1 Background

On February 27, 2007, Freddie Mac announced that it will no longer buy the most risky subprime mortgages and mortgage related securities.[1] Soon it was time for a traditional boom-and-bust cycle to come to its second phase. The preceding boom was characterized by global run-ups in asset prices, lax lending standards, weaknesses in the credit risk transfer, and overly optimistic assessment of structured securities (Weber, 2008). For some commentators, the following bust marks an end of an era. Shortly after the early signs of the crisis had emerged in 2007, uncertainty started to spread and lead to a dramatic re-pricing of risk. What followed was a chain of events associated with abrupt shifts in market sentiment and coordinated sell-offs arising from a self-reinforcing uncertainty driven micro-level imitation between investors. At the time, no asset class was safe as levered investors were forced to quickly unwind their positions 'across-the board' to meet margin calls and shocks spread like waves throughout the financial system.

On April 27, 2010, fears centered into Europe when Standard & Poor's cut Greece's credit rating from investment grade to speculative grade (BB+), lowered Portugal's investment grade rating by two notches (from A+ to A-), and placed a negative outlook on both countries.[2] The rating agency cited weak 'macroeconomic structures' and 'amplified fiscal risks' as its primary concerns. The problems had emerged largely because of the eroded competitiveness, lack of fiscal consolidation, and sharp rises in sovereign debt levels as a result of the precedent global financial crisis (Deutsche Bundesbank, 2010). Along with the subsequent sovereign downgradings, severe money market tensions emerged and many euro-area countries began to face increasingly widening government bond yield spreads and credit default swap (CDS) premium differentials compared to traditionally more stable countries, such as Germany, Switzerland, and the United States (see Appendices 10-11). As a result of the nascent crisis of confidence, the euro-area government bond auctions no longer received strong demand which again triggered a sharp increase in the risk premiums on the bonds in other euro-area countries as well (International Monetary Fund, 2010).

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[1] Source: Federal Reserve Bank of St. Louis, The Financial Crisis: A Timeline of Events and Policy Actions, available at http://timeline.stlouisfed.org/

[2] Source: British Broadcasting Corporation, 27.04.2010, Greek bonds rated 'junk' by Standard & Poor's, available at http://www.bbc.co.uk/.

These recent crisis episodes have shown that what happens inside a major financial system can hurt others even across the world as financial integration and innovation have strengthened international asset linkages and created new, even unexpected contagion channels. Consequently, even traditionally calm and uncorrelated markets may experience sudden bursts of correlated volatility. During the crises, the central banks and policy makers across the world have taken extreme measures to stabilize the markets in form of sustained fiscal stimulus, relatively complexly structured bail-out packages, and stabilization systems. By looking at the scope of these stabilization measures, it seems that the policy makers try to avoid defaults and the consequent domino effects at any costs. These stabilization measures together with the related transfer of financial risks from the private to public sector have raised further concerns about the outlook for growth and increased inflation risk. As the global financial system is in a highly fragile state and prospects of a global contagion are extraordinarily high, an excellent opportunity to re-examine financial market stability arises.

1.2 Framework

This paper investigates the intranational dynamic relationship between daily stock and government bond (henceforth referred as bonds) returns of selected countries between January 1, 1999 and December 31, 2010 to assess financial market stability in different countries and market conditions. The underlying hypothesis of this paper is that the financial markets of the world's most advanced economies exhibit financial market stability even under extreme market conditions and potentially systemic events.[3] The econometric framework employed to assess whether a country exhibits financial market stability or not includes modeling the time-varying conditional[4] intranational stock-bond correlations, testing for the intranational flights between stocks and bonds, and modeling the conditional autoregressive value at risk (CAViaR) of equally weighted intranational stock-bond portfolios. These methodologies represent one of the most prominent and current tools in the field of financial econometrics and are commonly used by researchers and practitioners all around the world. Importantly, they all have the potential to provide valuable information for investors, policy makers and regulatory authorities about the cross-sectional dimension of systemic risk for assessing financial market stability under extreme market conditions and potentially systemic events.

[3] It is important to note that the assessment of financial market stability is conducted without any a priori definition of 'extreme market conditions' or 'potentially systemic events' to ensure as flexible interpretation of the results as possible. For a list of potentially systemic events during the sample period see Bunda et al. (2009).

[4] The difference between terms 'conditional' and 'unconditional' is that the former implies explicit dependence on a past sequence of observations, whereas the latter is related to long-term behavior of a time series, and does not assume explicit knowledge of the past.

In this paper, the framework for assessing financial market stability comprises of three parts. First, modeling the time-varying conditional intranational stock-bond correlations provides information about the levels and changes in the time-varying conditional intranational stock-bond correlations. This information is particularly important for assessing financial market stability because stock-bond correlations are at the core of investors' asset allocation decisions as they largely determine the amount of stock-bond portfolio diversification (Markowitz, 1952; Dopfel, 2003).[5] Given the time-varying nature of stock-bond correlations, the amount of stock-bond portfolio diversification with a given asset allocation is constantly changing and investors need accurate estimates of the covariance matrix of stock and bond returns for the optimal selection of portfolios (Engle and Colacito, 2006).[6] In the light of the partial erosion of international diversification benefits among the stock markets as reported for example by King and Wadhwani (1990), Bekaert and Harvey (1997), Goetzmann et al. (2005), Driessen and Laeven (2007), and Chollete et al. (2011), this paper considers the resiliency of the intranational stock-bond diversification benefits, or more precisely, the safe haven property of bonds as an important feature for financial market stability. This is because, under financial market stability, markets should remain robust even in all market conditions and investors should be able to add an asset to their portfolios that specifically reduces or limits economic losses at all times (Allen and Wood, 2006; Baur and Lucey, 2010). Borrowing from Baur and Lucey (2010), bonds qualify as a safe haven if they are uncorrelated or negatively correlated with stocks under extreme market conditions or potentially systemic events. The negative correlation implies losses reducing effects for investors since the safe haven asset increases in value as the other asset or portfolio decreases in value. Note that the definition of a safe haven does not require the correlation to be positive

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[5] However, even negative correlation is neither necessary nor sufficient condition for diversification but requires two assets in a portfolio to have a bivariate normal distribution or an investor to have a quadratic utility function (Brumelle, 1974).

[6] Assuming a generic dynamic covariance matrix, $\Omega_{t+1|t}$, between portfolio assets, an investor who constructs a portfolio of N risky assets by minimizing the portfolio variance subject to a certain portfolio return, μ_p, chooses a vector of portfolio weights, W_t, by solving the following quadratic programming problem (Andersen et al., 2006).

$$\min \; W_t'\Omega_{t+1|t}W_t \quad \text{subject to} \quad W_t' M_{t+1|t} = \mu_p$$

where the resulting portfolio weights for the risky assets satisfy

$$W_t^* = \frac{\Omega_{t+1|t}^{-1} M_{t+1|t}}{M_{t+1|t}'\Omega_{t+1|t}^{-1} M_{t+1|t}} \mu_p$$

with the optimal portfolio weight for the risk-free asset given by

$$w_{f,t}^* = 1 - \sum_{i=1}^{N} w_{i,t}^*$$

or negative on average, but relies on the bonds' property of reducing losses under extreme market conditions and potentially systemic events.[7]

Second, testing for the intranational flights between stocks and bonds provides information about the extreme changes in the time-varying conditional intranational stock-bond correlations. This information is particularly important for assessing financial market stability because extreme cross-asset linkages are at the heart of systemic risk (see e.g. Hartmann et al., 2004; Baur and Schulze, 2009). This paper distinguishes between four types of intranational cross-asset flights between stocks and bonds, namely flight-to-liquidity (FTL), flight-to-quality (FTQ), flight-from-liquidity (FFL), and flight-from-quality (FFQ). They are defined in accordance with the literature (see e.g. Forbes and Rigobon, 2002; Baur and Lucey 2006) without any explicit definitions for shocks as follows. The flight-to-liquidity from stocks and bonds (to alternative assets) is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds (from alternative assets) is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. In the context of financial market stability, special attention is paid to flight-to-liquidity and flight-to-quality effects. The former has the potential to increase the propagation of shocks and contribute negatively to the resiliency of stock-bond diversification benefits, thus weakening financial market stability. The latter has the potential to limit the propagation of shocks and contribute positively to the resiliency of stock-bond diversification benefits, thus improving financial market stability (see e.g. Gulko, 2002; Hartmann et al., 2004; Baur and Lucey, 2009).

Third, modeling the conditional autoregressive value at risk (CAViaR) of equally weighted intranational stock-bond portfolios provides economically interpretable information about the levels and changes in the market risks of equally weighted intranational stock-bond portfolios.

[7] According to Baur and Lucey (2010), an asset that is uncorrelated or negatively correlated with another asset on average is called a hedge asset and an asset that is mildly positively correlated with another asset on average is called a diversifier asset. Contrary to a safe haven asset, a hedge assets and a diversifier asset lack the specific property of reducing losses in extreme market conditions.

In the context of financial market stability, a low and stable market risk level without excessive divergent spillover effect(s) implies that a country exhibits financial market stability, whereas a high and unstable market risk level with excessive divergent spillover effects implies the reverse.

1.3 Contribution

To my best knowledge, this paper is one of the few papers in its class to investigate the time-varying differences in intranational propagation mechanisms across asset classes for assessing financial market stability in developed markets. Its main contribution to the literature is employing a new econometric framework on a current data set for assessing whether a country exhibits financial market stability or not. This study is mostly inspired by Baur and Lucey (2009, 2010), Cappiello et al. (2006), and Engle and Manganelli (2004).

1.4 Key Findings

The empirical results show that the world's most advanced economies, except Italy and Spain, exhibit financial market stability under extreme market conditions and potentially systemic events as assessed by their intranational stock-bond return relations. In the financially stable countries under extreme market conditions and potentially systemic events, the conditional intranational stock-bond correlations tend to stay below or close to zero, the intranational flights between stocks and bonds tend to rather reduce than aggravate the propagation of shocks, and the CAViaR of equally weighted intranational stock-bond portfolios resemble each other to a high degree without showing hardly any excessive divergent spillover effects. In Italy and Spain, the reverse applies. Overall, these results in favor of prevailing financial market stability even under extreme market conditions and potentially systemic events are relatively well in line with the rare empirical literature on financial market stability with the emphasis on cross-asset linkages in developed markets.

1.5 Structure

The remainder of this paper is organized as follows. Section 2 provides an overview of the selected literature on the concepts of this paper. Section 3 presents the data. Section 4 introduces the econometric framework together with the parameter estimates and diagnostics. Section 5 presents the empirical results. Section 6 offers conclusions, addresses the limitations of this study and outlines the area of future research. Section 7 contains appendices, including the EViews code written by the Author for this thesis. Finally, Section 8 lists the references.

2. Theoretical Background

This section provides an overview of the selected literature on the concepts of this paper, including financial market stability, stock-bond return relation, flights and the CAViaR.

2.1 Financial Market Stability

Financial market stability is a relatively young and hot topic among academics and practitioners due to the increased global market linkages, emergence of new contagion channels and recent adverse macroeconomic developments, among other reasons. However, as far as I know, academic studies on assessing financial market stability are still rare at least if the closely related literature on a colorful range of contagion and feedback effects is excluded. Most of the material related to financial market stability comes in the form of financial stability reviews published by central banks, who act as gatekeepers of financial market stability by mitigating systemic risk arising from both long-term financial imbalances representing time dimension of systemic risk and short-term contagion and feedback effects representing cross-sectional dimension of systemic risk (Deutsche Bundesbank, 2010).

There is currently no universally accepted definition of financial market stability mostly due to the changing structure of the financial system and the disagreement on whether financial market stability relates to a system as a whole in a broad sense or to an individual institution or a market in a narrow sense. However, a few prominent definitions have been suggested. First, financial market stability can be defined as the financial market's ability to perform its key macroeconomic functions well also in stress situations and during periods of structural adjustment (Deutsche Bundesbank, 2010). These key macroeconomic functions include efficient allocation of capital, reliable assessment and tackling of risks, and secure settlement of payments and securities transactions (Weber, 2008). Second, financial market stability can be defined by first defining its converse, financial market instability, and then considering financial market stability as a state of affairs in which episodes of instability are unlikely to occur (Allen and Wood, 2006). Third, financial market stability can be defined as a property of a system rather than a state of affairs. Accordingly, a financially stable system is one that dampens rather than amplifies shocks. Fourth, as a critique to these relatively technical and rigorous definitions, Poloz (2006) advises to think financial market stability as the man in the street sees it. According to him, the man in the street is likely to see financial market stability as being closely linked to price stability. Actually, there is a link between financial market stability and price stability, or more precisely, at least some degree of asset price stability is required for financial markets to qualify as stable (Allen and Wood, 2006). Based on the common sense, frequent asset price bubbles and periods of high volatility cannot be a sign of financial market stability. However, it is unclear whether asset price stability is always beneficial to economic welfare and whether asset price movements should happen gradually rather than suddenly because neither the process of economic growth nor the justification for gradual price adjustment is well understood (Allen and Wood, 2006). What is known is that it would be definitely costly and difficult to regulate asset prices. To summarize, financial market stability means resiliency to shocks (Das, 2003).

The assessment of financial market stability is discussed in Goodhart (2006). He argues that instead of developing rigorous analytical models, the central banks should pay more attention to the assessment of 'probability, virulence and speed of occurrence of potential shocks'. Moreover, stress tests, commonly used to assess stability of financial institutions, should relate to the system as a whole rather than to individual institutions. One of the few studies explicitly testing for financial market stability is Baur and Schulze (2009). They define financial market stability as the constant propagation of systematic (rather than idiosyncratic) shocks on a financial market in normal and extreme market conditions and develop a quantile regression model to test for it. Using daily log returns on twenty US-dollar denominated national stock indices and seven regional stock indices covering the time period from April, 1997 to July, 2007, they find that the propagation of systematic shocks increases significantly in the emerging markets in extreme market conditions compared to the propagation in normal market conditions. However, in the developed markets, the propagation of systematic shocks is rather stable. Consequently, only the developed markets meet the conditions for financial market stability.

The measures available for mitigating systemic risk are presented in Allen and Wood (2006). They distinguish between two main categories of measures, preventive and remedial. The preventive measures are related to enhancement of laws, official agencies, market conventions, official information provisions and physical infrastructure. In practice, these measures include e.g. placing legislation initiatives, creating transparency on risks, working with regulatory authorities, and securing payments and settlement processes. The remedial measures include liquidity and solvency support for those in need. Sometimes the support might involve restoring the confidence in the financial markets. Clearly, both types of measures are needed for coherent financial market architecture together with an efficient and accurate assessment of financial market stability.

2.2 Stock-Bond Return Relation

The return relation between one of the most fundamental asset classes, stocks and bonds, has intrigued academic researchers for decades because it is at the core of many financial applications such as asset pricing, portfolio management, and risk management (see e.g. Markowitz, 1952; Sharpe, 1964; Ross, 1976; Dowd, 1998). The recent economically meaningful econometric advances in multivariate modeling of the stock-bond return relation include time-variability, conditional heteroskedasticity, asymmetry, and cross-asymmetry in the conditional covariances and correlations between stock and bond returns (see e.g. Kroner and Ng, 1998; Scruggs and Glabadanidis, 2003; de Goeij and Marquering, 2004; Cappiello et al., 2006).[8] Despite the econometric advances in modeling the stock-bond return relation, no universal consensus has been reached on how stocks and bonds move together over time and what determines the time variation. Especially, the stock-bond return relation in extreme market conditions remains relatively unexplored.

To understand the level and changes in the stock-bond return relation, it is important to look at the underlying economics first. Let subscript 1 denote stocks and subscript 2 denote bonds throughout this study. Assuming that prices of stocks and bonds are determined by the present value of their anticipated future payments, the equations for prices of stocks and bonds can be expressed as follows (modifying from Ilmanen, 2003).

$$P_{1,t} = E_t\left[\sum_{t=1}^{\infty}\left(\frac{1+G_t}{1+Y_t+ERP_t}\right)^t * D_t\right] \tag{1}$$

$$P_{2,t} = E_t\left[\sum_{t=1}^{T}\frac{C_t}{(1+Y_t)^t}+\frac{FV}{(1+Y_T)^T}\right] \tag{2}$$

where G_t is the expected growth rate of infinite and uncertain stream of capital gains and dividends paid to shareholders D_t, Y_t is the government bond yield consisting of expected future short-term rate (real interest rate and the expected inflation) and the required bond term premium, ERP_t is the required equity risk premium, and C_t and FV are fixed streams of certain cash flows, coupons and face value, respectively.

[8] However, the explanations for conditional asymmetry and cross-asymmetry in the conditional covariances and correlation between stock and bond returns are still in development compared to the well-developed explanations for conditional asymmetry in the conditional variances of stock and bond returns, including the leverage effect (Black, 1976; Bekaert and Wu, 2000), the volatility feedback effect (Campbell and Hentschel, 1992; Bekaert and Wu, 2000), and the herding effect (Veronesi, 1999). For a discussion on asymmetric correlations, see Ang and Chen (2002).

Deriving from (1) and (2), the changes in the prices of stocks and bonds reflect the changing forecasts of their future payments. The variances of the components in (1) and (2) and the covariances between them constitute the variances of stock and bond returns and the covariance between them. Therefore, the changes in the variances of stock and bond returns and the covariance between them reflect the changing variances of the components in (1) and (2) and the covariances between them. The information that causes prices of stocks and bonds, the variances of stock and bond returns, and the covariance between them to change is interchangeably called 'news' or 'shock'.[9] More specifically, stocks are affected by news in real interest rate, expected inflation, and dividend yield, whereas bonds are affected by news in real interest rate, and expected inflation. Thus, news affects stocks and bonds to a different degree and may even have a different qualitative effect on them. Generally, the magnitude and persistency of news determines the magnitude and persistency of changes in prices of stocks and bonds, variances of stock and bond returns and the covariance between them. News is typically clustered in time and their intensity is generally higher in crises (Engle, 2004). However, Veronesi (1999) finds that investors tend to 'overreact to arrival of bad news in good times and underreact to good news in bad times' meaning they react more sensitively to news in good times than in bad times.[10] The covariances between stock and bond returns may change either when stocks or bonds change or when news changes. To put it bluntly, the covariance between the news processes of stocks and bonds drives the covariance between their returns. Consequently, countries with similar economies (e.g. Germany and France) or assets of similar type (e.g. stocks) will have more highly correlated news processes than countries with dissimilar economies (e.g. Germany and Australia) or assets of different type (e.g. stocks and bonds) because the same events will affect them (Cappiello et al. 2006).

Early literature on stock-bond return relation is most concerned about the predictability of returns. Keim and Stambaugh (1986) analyze the predictability of risk premiums (excess return over short-term interest rate) of stocks, long-term corporate bonds, and long-term government bonds using monthly US data from 1928 to 1978. They find that several predetermined price related variables appear to predict returns on both stocks and bonds and provide evidence of time-varying expected returns for stocks and bonds. Shortly after them, Bollerslev et al. (1988) argue that expected returns on stocks are related to macroeconomic

[9] Theoretical model for changing asset prices is well presented in Samuelson (1965).

[10] This is because in good times investors assign higher probability to a good state to continue and arrivals of bad news makes them adjust the discount rate over expected future dividends disproportionally upwards to correspond the increased uncertainty. Similarly, in bad times investors assign higher probability to a bad state to continue and arrivals of good news makes them adjust the discount rate over expected future dividends disproportionally downwards because of the prevailing uncertainty (Veronesi, 1999).

volatility. To add, Schwert (1989) studies monthly US data from 1857 to 1987 and finds that stock market volatility varies greatly in time, increases during recessions and with financial leverage as documented earlier by Black (1976). Interestingly, he finds only weak evidence that bond market volatility increases during recessions. Additionally, he argues that interest rate volatility is correlated with stock return volatility but macroeconomic volatility cannot be used to accurately forecast future stock return volatility. Around the same time, Breen et al. (1989) study monthly post-war US data and find that one-month interest rate predicts the sign and variance of excess returns on the value weighted stock index in an economically significant way. Moreover they conclude that the excess returns are more likely to be relatively less volatile and more likely to be positive during forecasted up markets. Later, Glosten et al. (1993) conclude that short-term interest rates play an important role in future stock market variance based on monthly post-war US data.

The first theoretical model to explain the (independency) of stock-bond return relation is developed in Barsky (1989) as a response to the critique towards the rational expectations present value models assuming a low positive correlation between stock and bond returns (for critique towards the rational expectations present value models, see e.g. Shiller, 1982).[11] Based on his theoretical model, there is a tendency for equity risk premiums to increase when the short-term real interest rate falls, which might occasionally induce a low negative correlation between stock and bond returns for example in a situation when the stock market declines and productivity growth slows down. This theory is later empirically questioned by Campbell and Ammer (1993) who find a significantly positive correlation between news about equity risk premium and news about real interest rates in their sub-sample.

In an attempt to put stop to the debate on whether the stock-bond return relation can be explained in terms of rational expectations present value models, Shiller and Beltratti (1992) extend the vector autoregressive representation of the dividend ratio model of Campbell and Shiller (1988) to study relation between the stock prices and long-term bond yields using annual US and UK data ranging from 1871 to 1989 and 1918-1989, respectively. They find that the correlation between changes in real stock prices and changes in long-term interest rates is more negative than what the present value model implies. They attribute this finding

[11] In the rational expectations present value models, discount rates are based on market interest rates. Therefore, an increase in expected future discount rate should cause stock and bond prices to fall, and similarly, a decrease in expected future discount rate should cause stock and bond prices to rise.

to the common discount rate effect and note that changes in long-term interest rates could contain information about the future dividends on stocks.[12]

Adding to the earlier fundamental line of research, Campbell and Ammer (1993) examine the relation between excess stock and 10-year bond returns using monthly US data from 1952 to 1987. They break the excess stock and bond returns into several components for their vector autoregressive model on excess returns. Stock return components are decomposed into changing expectations of future real dividend, future real interest rate, and future excess stock return. Long-term nominal bond return components are decomposed into changing expectations of future inflation rate (which determine the real value of the nominal par value payment made at the maturity), future real interest rates, and future excess bond return. They report a low positive correlation between stock and bond returns ($\rho = 0.20$) and discuss three offsetting effects behind the low correlation. First, variation in real interest rates promotes a low positive correlation because the prices of both assets are negatively associated with the discount rate but the variation is relatively low. Second, strong correlation between future excess returns on stocks and bonds promotes a positive correlation.[13] Third, variation in long-run expected inflation may promote a negative correlation because expectations of increased long-run inflation commonly have uncertain effect on stock and negative bond returns. Thus, positive correlation caused by the discount rate and the expected return effects are partly offset by the long-run inflation effect.

After the limited empirical success of the fundamental line of research in trying to explain the stock-bond return relation based on fundamentals, a new empirical strand with a focus on identifying stylized facts and historical patterns based on the observed data emerged. One of the most stereotypical representatives of this empirical line of research is Ilmanen (2003) who examines the correlation between the S&P 500 stock market index and the 20-year Treasury bonds using low frequency data from 1926 to 2001. He divides the sample into subsamples representing different states of the world in an attempt to explore how business cycle, inflation environment, volatility conditions, and monetary policy stance influence on stock-bond correlation. He makes numerous interesting findings. First, during business cycle expansion periods, stocks tend to outperform bonds, whereas during business cycle contraction periods, the reverse applies. This implies that stock-bond correlations tend to be

[12] For example in October 1987 crash, the long-term interest rates fell (Shiller and Beltratti, 1992).

[13] Fama and French (1989) find that expected returns on stocks and long-term bonds are positively correlated and associated with variables related to longer-term aspects of business conditions being higher when business conditions are good and lower when they are weak.

higher during business cycle expansion periods and lower during business cycle contraction periods (Andersen et al., 2007; Yang et al., 2009). Second, high inflation level causes positive correlation, low inflation implies lower correlation, and deflation might induce negative correlation. Third, high volatility is typically bad news for stocks but good news for bonds. Fourth, during periods of monetary policy easing both stocks and bonds are likely to perform well.

Extending the previous theoretical contributions of Bekaert and Grenadier (2001), Mamaysky (2002) and Li (2002) in developing affine pricing models for stocks and bonds, d'Addona and Kind (2006) develop a three-factor affine asset pricing model to obtain endogenous correlations between monthly post-war stock and bond returns and to explain how the economic (observable) variables drive the stock-bond correlation in G7 countries. They divide the covariance between stocks and bonds into five terms: interest rate risk, inflation risk, real interest rate, inflation, and dividend yield. They find that the volatility of real interest rate tends to increase the stock-bond correlation, whereas the inflation shocks tend to reduce the stock-bond correlation (assuming that stocks provide insurance against inflation), and that the volatility of dividend yield tends to reduce the stock-bond correlation by increasing the volatility of stock returns. Overall, their results are found to resemble the empirically observed correlations to a high degree.

In the literature, many studies have reported a negative relation between stock market volatility and the stock-bond correlation (see e.g. Ilmanen, 2003; d'Addona and Kind, 2006; Andersson et al., 2008). However, studies on stock-bond return relation with a particular focus on crisis periods are rare. One of the few studies on stock-bond return relation under uncertainty is Connolly et al. (2005) who investigate the forward-looking and contemporaneous association between the US stock-bond return relation and uncertainty measures (implied volatility from equity index options and detrended stock turnover) using daily data from 1986 to 2000. More specifically, Connolly et al. (2005) examine whether variation in the relative level of stock market uncertainty and a day's change in stock market uncertainty explain the future stock-bond return relation and differences in stock-bond return relation, respectively. They find a negative relation between the stock-bond correlation and the uncertainty measures. Moreover, they find that 'bond returns tend to be high (low) relative to stock returns during days when implied volatility increases (decreases) substantially and during days when stock turnover is substantially high (low)'. These findings indicate that stock-bond diversification benefits tend to increase during times of stock market uncertainty.

Drawing from the financial market integration studies, both Kim et al. (2006) and Baur (2007) investigate the stock-bond return relation in a new light. First, Kim et al. (2006) study the influence of the inter-financial market integration in the European Monetary Union (EMU) on the dynamic relationship between daily local currency denominated stock and government bond returns from March 2, 1993 to September 19, 2003. They find a downward trend in the time-varying conditional stock-bond correlations in European countries, Japan and the US and attribute it to a prolonged flight-to-quality effect caused by increased economic uncertainty in the international financial markets, especially within the EMU. Second, Baur (2007) examines both cross-country (stock-stock and bond-bond) and cross-asset (stock-bond) linkages for eight developed countries using daily data from January, 1994 to September, 2006. He claims that the low level of stock-bond correlation depends more on cross-country influences than on stock and bond market interactions.[14]

Research on emerging markets provides interesting additional evidence on the dynamics of stock-bond return relation. One of the first studies on stock-bond return relation in emerging markets is Kelly et al. (1998) who examine the stock-bond return relation in emerging markets as a function of the country's political risk. They find that the stock-bond correlation in emerging markets is higher than in developed markets because the relatively high sovereign risk level in emerging economies makes their bond returns more 'equity like'. Later, Panchenko and Wu (2009) examine the extent to which emerging stock market integration influences the joint behavior of stock and bond returns using a semi-parametric model on data covering 18 emerging market countries and the time period from January 1995 to December 2005. Panchenko and Wu (2009) find a clear link between the integration of emerging stock markets and the stock-bond return decoupling. They attribute the link to a decline in stock market segmentation risk premia that leads to 'increased demand for stocks and reduced or unchanged demand for bonds' (de Jong and de Roon, 2005).

In a very recent state-of-art research on stock-bond return relation, Baele et al. (2010) examine whether a dynamic factor model with regime-switching features in which stock and bond returns are assumed to depend on a set of economic state variables can explain the variation of stock-bond correlation between 0.60 to -0.60 over the last forty years. Their data consists of the US daily stock and bond returns and quarterly observations of economic state variables between the fourth quarter of 1968 and the fourth quarter of 2007. The economic

[14] Baur (2007) considers that the increased cross-country interdependence of financial markets might induce investors to reallocate their portfolios between assets more frequently in order to compensate for lower cross-country (international) diversification benefits.

state variables considered include quarterly observations of interest rates, inflation, the output gap, cash flow growth, fundamental and macroeconomic uncertainty measures, liquidity proxies, and the variance premium (the difference between the square of the VIX and the conditional variance of future stock prices). They find that fundamental variables primarily fail to explain the time-variation in the stock-bond correlation, but other factors such as liquidity proxies seem to work better.

To summarize, the implicit assumption of constant (Shiller and Beltratti, 1992; Campbell and Ammer, 1993) or state-dependent (Barsky, 1989) stock-bond correlation often seen in the early literature on stock-bond return relation is now considered as inadequate (see e.g. Scruggs and Glabadanidis, 2003). Many studies on stock-bond bond return relation report a low positive stock-bond correlation over long-term but often note that the correlation may occasionally plunge below zero for extended periods of time (see e.g. Ilmanen, 2003; Baur and Lucey, 2006, 2009; Guidolin and Timmerman, 2006; Andersson et al., 2008).[15] In the literature, various different arguments have been used to explain the level and changes in the stock-bond return relation. First, a positive relation can be expected if news has similar qualitative effect on stocks and bonds. The positive relation is often attributed to the partly common discount rates of stocks and bonds (see e.g. Shiller and Beltratti, 1992; Campbell and Ammer, 1993). Second, a negative relation can be expected if news has different qualitative effect on stocks and bonds. The negative relation is often associated with times of low (or high) growth, volatile stock markets, business cycle peaks, and monetary tightening and frequently caused by flight-to-quality phenomenon (see e.g. Barsky, 1989; Ilmanen, 2003; Connolly et al., 2005, 2007; Andersson et al., 2008).[16] Flight-to-quality phenomenon refers to a situation where investors substitute away from risky assets (e.g. stocks) into less risky assets (e.g. bonds) in the presence of increasing risk. It is related to precautionary saving and involves the third derivative of the utility function (Barsky, 1989). Third, a zero relation can be expected if news has independent effect on stocks and bonds. The zero relation is often related to segmented markets (see e.g. Bekaert and Harvey, 1995; Kim et al., 2006; Panchenko and Wu, 2009). In the literature, all of these arguments are present and it is not clear whether one of them dominates the others because the joint process of stock and bond returns follows an extremely complex dynamic pattern (Guidolin and Timmerman, 2006).

[15] The stock-bond correlation is higher between an index constructed of 'bond-like' stocks only and an index of government bonds than between an index constructed of all kinds of stocks and an index of government bonds (Baker and Wurgler, 2010).

[16] A critique towards the flight-to-quality hypothesis is presented in David and Veronesi (2008), who find that movements in proxies for flight-to-quality and flight-to-liquidity do not justify the extreme (negative) covariance between stocks and bonds.

Nevertheless, empirical studies have shown that the observed levels cannot be fully justified by economic fundamentals. Still, the stock-bond return relation might differ from country to country and depend on the time horizon (see e.g. Cappiello et al., 2006; Kim et al., 2006; Baur, 2007; Kim and In, 2007; Yang et al., 2009). As Li (2002) nicely puts is: 'Today, one can randomly search the term 'stock and bond correlation' on the internet, and easily find sharply contradictory opinions among market participants. When it comes to story-telling, one man's story is just as good as others. Most of these opinions are based on causal observations and lack the support of concrete evidence.'

2.3 Flights between Stocks and Bonds

The financial market integration is found to boost economic growth via risk sharing, improve allocational efficiency, and reduce macroeconomic volatility and transaction costs (Kim et al., 2006). However, as a downside to financial market integration, increased market linkages and capital mobility may influence on how financial disturbances transmit from one market or asset to other(s) and potentially cause financial market instability (see e.g. Hartmann et al., 2004). The excessive spillovers of market- or asset-specific financial disturbances causing abrupt changes in market- or asset linkages and swings in asset prices are commonly called flights. During flights, investors transmit idiosyncratic shocks from one market or asset to others by adjusting their portfolios' exposures to shared macroeconomic risks (Kodres and Pritsker, 2002). Flights and other feedback effects represent the cross-sectional dimension of systemic risk (see e.g. de Bandt and Hartmann, 2000; Hartmann et al., 2004; Baur and Lucey, 2009; Baur and Schulze, 2010; Deutsche Bundesbank, 2010).

Economic reasoning of flights remains a challenge. The underlying causes of flights are commonly believed to go far beyond real economic linkages. In fact, the abrupt changes in asset prices often occur so rapidly that controlling for changes in fundamentals is very difficult or even impossible (de Bandt and Hartmann, 2000). As fundamentals and macroeconomic news fail to explain the observed flights adequately (see e.g. Baig and Goldfajn, 1999; Kodres and Pritsker, 2002), other explanations have been suggested in the literature. One of the most common explanations offered is herding i.e. convergence in response to sudden shifts in investor sentiment or due to cross-market hedging (see e.g. Hirshleifer and Teoh, 2003; Gonzalo and Olmo, 2005; Chiang et al., 2007). Accordingly, if many portfolios have similar correlated positions, a shock to one market or asset causing a general loss of confidence (or urgent need to deleverage) on the part of investors followed by herding behavior by others could lead to correlated order flow, and most likely, to correlated movements in returns.[17] Consequently, these changes in correlations might be interpreted as responses to supply and demand effects instead of fundamental news effects (see e.g. Engle, 2009). However, as Engle (2009) points out, according to microstructure theory even correlations that change in response to order flow can be interpreted as being based on news. Therefore, flights 'may well have basis in news, if only in news about the average investor's tolerance for risk'.

Along with the repeated financial crises and other potentially systemic events[18] together with advances in econometric methods, flights have increasingly attracted scholarly attention during the last two or three decades. The literature on flights is mainly interested in identifying transmission channels, analyzing differences in shock propagation mechanisms under different market conditions, and measuring the consequent damage to economies and investors' welfare. Basically, the general underlying assumption is that 'small-return shocks propagate differently from large-return shocks' (Bae et al., 2003). The relatively extensive literature on flights between stocks and bonds has evolved in separate strands. On one hand, flight-to-liquidity strand has typically examined either stock-stock linkages (see e.g. King and Wadhwani, 1990; Hamao et al., 1990; Lin et al., 1994; Forbes and Rigobon, 2002; Bae et al., 2003; Chandra, 2005; Chiang et al., 2007; Rodriquez, 2007; Markwat et al., 2009; Kenourgios et al., 2010) or bond-bond linkages (see e.g. Baig and Goldfajn, 1999; Skintzi and Refenes, 2006; Dungey et al., 2006; Beber et al., 2009) in a cross-country context. On the other hand, flight-to-quality strand has typically examined stock-bond linkages (see e.g. Barsky, 1989; Gulko, 2002; Connolly et al., 2005) in a cross-asset context. However, a few studies have recently combined these both strands to examine stock-bond linkages (see e.g. Hartmann et al., 2004; Baur and Lucey, 2009; Connolly et al., 2007). Overall, most of the studies are related to financial crises in emerging markets because they are found to be more prone to crisis episodes and flights than developed markets (see e.g. Das, 2003; Kenourgios, 2010). However, the literature on developed markets is growing rapidly because developed markets are not immune to crises and flights either (see e.g. Dungey et al., 2006; Baur and Lucey, 2009). Specifically, the literature on cross-country flights is more extensive than cross-asset

[17] According to Kodres and Pritsker (2002), presence of information asymmetries might still aggravate correlated movements in returns.

[18] During the last three decades, the financial crises and other potentially systematic events studied in the literature on flights include e.g. the crash of October 1987, the Exchange Rate Mechanism crisis in 1992-1993, the devaluation of Mexican peso in 1995, the Asian crisis between 1997-1998, the Russian default in 1998, the collapse of the hedge fund Long Term Capital Management (LTCM) in 1998, the South American economic crisis between 1999-2002, the September 11 terrorist attacks in 2001, the US high yield market sell-off in 2002 and in 2004, the Iceland currency crisis in 2006, and the global financial crisis starting from 2007.

flights and studies on cross-country flights between stock markets far outnumber the others. However, this paper is mostly concerned about flights between stocks and bonds and does not attempt to give comprehensive overview of the literature on cross-country stock-stock or bond-bond flights.[19]

There is currently no generally accepted definition of either contagion (in this paper interchangeably referred as flight-to-liquidity) or flight-to-quality. Most commonly, contagion is defined according to Forbes and Rigobon (2002) as a significant increase in asset or market linkages after a shock to one asset or market (or many assets or markets) compared to a benchmark period. Following a similar logic, flight-to-quality is defined as a significant decrease in asset or market linkages after a shock to one asset or market (or many assets or markets) compared to a benchmark period. According to these definitions, there are no flights between assets or markets if they show a similar degree of dependency before a shock, or 'interdependence', as Forbes and Rigobon (2002) call it. To note, these are very narrow definitions for flight-to-liquidity and flight-to-quality between assets or markets and by no means the only ones. Importantly, they require no explicit definition of a shock and are subject to selection biases regarding the lengths of the benchmark and the study period. For long, flights have even been a debatable issue because some papers have found them (see e.g. King and Wadhwani, 1990) and others not (see e.g. Forbes and Rigobon, 2002). Nowadays their existence is no longer questioned in favor of 'only interdependence'- hypothesis by Forbes and Rigobon (2002) but it seems that the existence of flights is somewhat dependent on the exact definitions given for flights and methodologies employed to test for them.

The methodologies employed to study flights include for example correlation coefficient (see e.g. King and Wadhwani, 1990; Baig and Goldfajn, 1999; Forbes and Rigobon, 2002), correlations derived from (multivariate) GARCH models (Hamao et al., 1990; Lin et al., 1994; Chandra, 2005; Chiang et al., 2007; Kenourgios et al., 2010), cointegration techniques (see e.g. Longin and Solnik, 1995), direct estimation of specific transmission channel (see e.g. Eichengreen et al., 1996; Bae et al., 2003; Markwat et al., 2009), and copulas (see e.g. Gonzalo and Olmo, 2005; Rodriquez, 2007; Kenourgios et al., 2010). Of these methods, the correlation coefficient is probably the first, most popularized and easiest way to examine flights because there is no need to distinguish between different propagation mechanisms (Forbes and Rigobon, 2002). However, it comes with a couple of major drawbacks. First, it

[19] For excellent surveys on contagion literature, see de Bandt and Hartmann (2000), Claessens et al. (2001), and Dungey et al. (2005).

does not explicitly test for flights. Second, it is conditional on market volatility i.e. heteroskedasticity can induce time variation in observed correlations which might unjustifiably often provide evidence in favor of flights due to increases in market volatility.[20] To mitigate this particular issue, Forbes and Rigobon (2002) adjust for the heteroskedasticity bias under certain conditions (no endogeneity or omitted variables) and find that flights are not as common as previously reported (see e.g. King and Wadhwani, 1990; Baig and Goldfajn, 1999). Third, the correlation coefficient might not be able to fully describe the pattern of multivariate dependence unless the observations are jointly Gaussian (Gonzalo and Olmo, 2005). Given all these (and possible other) drawbacks of the correlation coefficient, more advanced techniques have been recently employed in the literature to allow for richer dependence patterns between assets or markets.

On the methodological side, correlations derived from GARCH models have become popular recently. They are found to be especially well suited to provide information on volatility transmission mechanisms between assets or markets and flexible enough to incorporate explanatory variables in the analysis, if necessary. Moreover, they account for heteroskedasticity bias directly by estimating correlation coefficients using standardized residuals. These features make GARCH models a relatively convenient method to study flights although the estimated correlations might vary depending on the MGARCH model employed to compute them (Martens and Poon, 2001). Among the wide range of GARCH models, particularly the Dynamic Conditional Correlation (DCC) class models (see e.g. Engle and Sheppard, 2001; Engle, 2002; and Cappiello et al., 2006) have proven to be particularly suitable for estimating (extreme) correlation movements (Chandra, 2005; Chiang et al., 2007; Kenourgios et al., 2010). However, even the DCC models do not explicitly test for contagion.

In the context of dynamic cross hedging, Fleming et al. (1998) study the nature of volatility linkages in the stock, bond and money markets using daily returns on the S&P 500 stock index futures, the US Treasury bond futures, and the US Treasury bill futures from 1983 to 1995. They employ a stochastic volatility model to find that there exist strong information-driven volatility linkages across the three markets which become stronger after the 1987 stock market crash. However, they do not attempt to identify the exact information that causes the comovements or to model conditional stock-bond covariances. Instead, they argue that the stock-bond diversification benefits might be endangered because risk reduction achieved by

[20] However, heteroskedasticity cannot explain why two return series that have a positive correlation on average also experience periods of negative correlation (Connolly et al., 2005).

fleeing from stocks to bonds depends on the volatility linkages across the markets. Later, Steeley (2006) examines volatility transmission between the daily stock and bond returns in the UK between June, 1984 and June, 2004, and finds that the correlation between stock and bond market shocks has recently turned negative implying enhanced diversification benefits between stocks and bonds.

One of the first empirical contributions on flights between stocks and bonds is Gulko (2002) who analyzes flight-to-quality around stock market crises from 1987 to 2000 using the US data. He defines a crisis day as a day when the S&P 500 stock market index decreases by more than 5%. Using a simple event study method, his main finding is that the US Treasury bonds provide the much needed diversification benefits when the S&P 500 index crashes meaning that the correlation between them decreases strongly and most likely changes its sign from positive to negative. Additionally, he finds that during the crises volatilities of stock and bond returns tend to increase, stocks tend to revert slightly during the days following the crash, and stock-bond correlation tends to revert quickly, but the implied volatility tends to stay up longer implying that investors have long-memory.

Relaxing of any distributional assumptions and allowing for non-linear dependence structure, Hartmann et al. (2004) examine flights between stocks and bonds by employing a non-parametric measure of extreme dependency on weekly data from G5 countries covering the period from 1987 to 1997. Their analysis of flights consists of two steps. First, they examine joint occurrences of univariate extremes between stock and bond markets to find that stock market crashes of over 20% in a week and bond market crashes of over 8% in a week are rare. Second, they analyze stock-stock, bond-bond and stock-bond linkages and dependence patterns by measuring the expected number of crashes conditional on the event that at least one market crashes. In this setting, they define flight-to-quality as a crash in the stock markets accompanied by a boom in the government bond markets and contagion as a simultaneous crash in both markets. According to their results, markets experience a simultaneous crash in approximately one out of five to eight crashes. This probability of joint crash is even lower for bond markets than it is for stock markets. Importantly, they find that flight-to-liquidity from stocks and bonds is approximately as frequent as flight-to-quality from stocks to bonds. Overall, in line with Forbes and Rigobon (2002), they conclude that flight-to-liquidity is an overestimated phenomenon that is not really prevalent among G5-countries.

Evidence of flights between stocks and corporate bonds is provided by Gonzalo and Olmo (2005) who study flights between stocks and 2- and 30-year corporate bonds using a new flexible copula model to allow for asymmetric responses to (bad) news. They find evidence of flight-to-quality between the stocks and 2-year corporate bonds when one of them is experiencing hard times and evidence of contagion when both of them are experiencing hard times. However, they find no evidence of flight-to-quality or contagion between stocks and 30-year corporate bonds.

In a recent study, Baur and Lucey (2009) analyze flights between stocks and bonds in eight developed countries using conditional correlation and regression analyses on daily data covering the period from January, 1994 to September, 2006. Defining contagion (flight-to-quality) as a significant increase (decrease) in the correlation coefficient in a crisis period compared to a benchmark period resulting in a positive (negative) correlation level, they find that flights between stocks and bonds are common in crisis periods and often occur simultaneously across countries, providing indirect evidence of cross-country contagion.

To conclude, empirical evidence has shown that flights between stocks and bonds are relative frequent and commonly associated with crisis periods (see e.g. Barsky, 1989; Gulko, 2002; Hartmann et al., 2004; Gonzalo and Olmo, 2005; Baur and Lucey, 2009; Connolly et al., 2005, 2007). Beber et al. (2009) hypothesize that flights from stocks to bonds are likely to occur faster than flights from bonds to stocks as investors are not in a similar urgency to exit the market and may be more cautious as they move into a riskier asset. Interestingly, flight-to-liquidity from stocks and bonds is found to be almost as frequent as flight-to-quality from stocks to bonds and significantly more frequent for cross-asset stock-bond correlations than for cross-market stock-stock or bond-bond correlations, which might be partly due to different type of asset linkages (see e.g. Hartmann et al., 2004; Baur and Lucey, 2009).

2.4 CAViaR

The value at risk, often abbreviated as VaR, is a highly popularized measure of market risk, although it can be extended to measure other types of risks as well (Dowd, 1998). It is developed in the early 1990s to provide senior managers with easily understandable information about the risk of a portfolio in the face of increasing portfolio complexity, episodes of high market volatility, and several risk management disasters. Today, it is widely adopted by thousands of banks, financial institutions, non-financial corporates and regulatory authorities across the world as the standard tool of risk management. The VaR is defined as a single estimate of a maximum loss in the portfolio value due to general market movements within a specified timeframe (often one or ten days) and confidence level (often 95% or 99%).

For example, the 95% one-day VaR provides information on the amount of money (or percentage of portfolio value) that a manager is 95% certain will be worse than whatever loss occurs on the next day. To put it bluntly, the VaR is a quantile of the future distribution of portfolio returns.

Commonly, the estimation procedure of the VaR consists of three stages. First, the portfolio is market-to-marked daily. Second, the distribution of portfolio returns (or the quantile of the distribution) is estimated. Third, the VaR of the portfolio is computed. Most of the dissimilarities between different VaR methodologies are related to the second step, the estimation of the distribution of the returns. Broadly speaking, the VaR methodologies can be categorized into three, the parametric (e.g. RiskMetrics (1996) and GARCH), the non-parametric (e.g. historical simulation and the hybrid model), and the semi-parametric (e.g. extreme value theory (EVT), quasi-maximum likelihood GARCH, conditional autoregressive value at risk (CAViaR)) methods. Additionally, Monte Carlo simulations and stress testing procedures are commonly employed in the VaR calculations but they are not discussed here. Generally, the parametric methods assume that the time-variation in the risk of a portfolio is related to the forecasted time-variation in the volatility of a limited number of factors and the correlation between them, assuming that the VaR is proportional to the computed standard deviation of the portfolio. The non-parametric methods assume that the time-variation in the risk of a portfolio is related to the historical experience of this portfolio and the VaR is estimated statistically. Today, the number of existing VaR methodologies is enormous and it is still growing rapidly. Most of the methodologies are based on empirical justification rather than sound statistical theory.[21]

Despite its conceptual simplicity and wide applicability, accurate estimation of the VaR has proven to be extremely challenging econometric task and all of the methodologies suggested typically have more or less shortcomings. For example, the parametric volatility models often assume that the same distribution of the portfolio returns holds for tails as well and that the distribution of the standardized residuals, the residuals standardized by their conditional standard deviation, will be normal and i.i.d.. However, empirical evidence has shown that neither of the assumptions tends to hold for high-frequency financial return data (Engle, 2004). The non-parametric historical simulation methods are based on rolling windows and assume that any return is equally likely for a certain window period ignoring any returns

[21] For a comprehensive discussion to different VaR methodologies, refer to Dowd (1998), Engle and Manganelli (2001) and http://www.gloriamundi.org/.

outside the window and that the distribution of the portfolio returns continues to hold within the window. These assumptions seem logically inconsistent and potentially sensitive to the selection biases regarding the window length and the estimation period. The semi-parametric EVT method initially proposed by Danielsson and de Vries (2000) is a very general approach to tail estimation and it is proven to be robust only for very low probability levels. Furthermore, the EVT method does not allow the portfolio risk to vary with the conditioning information set (Engle and Manganelli, 2001). To account for the shortcomings of the three above mentioned relatively basic approaches, several more sophisticated extensions of these basic models have been developed to account for the characteristics of high-frequency financial data (see e.g. Mandelbrot, 1963) and to remedy other conventional challenges in estimating the VaR These extensions include e.g. the hybrid method of Boudoukh et al. (1998), methods employing quasi-maximum likelihood GARCH properties of Bollerslev and Wooldridge (1992), and the four-moment VaR of You and Daigler (2010). Although these methods represent major advances in estimating VaR, they are not free of shortcomings either.

Recently, Engle and Manganelli (2004) propose relatively new and flexible conditional autoregressive specifications for the estimation of the VaR by regression quantiles which they call conditional autoregressive value at risk, CAViaR. Moreover, they propose the dynamic quantile (DQ) test independently derived by Chernozhukov (1999) as an overall goodness-of-fit test for the estimated CAViaR processes. Instead of modeling the whole distribution of portfolio returns and then recovering the quantile of interest in an indirect way, the CAViaR methodology concentrates on the evolution of the quantile directly. In the estimation of the CAViaR models, unknown parameters are estimated using non-linear regression quantile techniques introduced by Koenker and Bassett (1978). White (1994) has shown that the minimization of the regression quantile (RQ) objective functions is able to deliver consistent estimates under certain assumptions. Interestingly, even under a misspecification of the quantile process, the minimization of RQ objective function can be interpreted as the minimization of the Kullback-Leibler information criterion of Kullback and Leibler (1951), which is commonly used to measure the discrepancy between the true model and the estimated model. Today, the CAViaR models can be considered as one of the most robust VaR measures of market risk available. After all, they and their heavy-tailed extensions have been found to perform extremely well with financial datasets (Engle and Manganelli, 2004).

A well-developed alternative methodology for measuring the market risk is the Expected Shortfall (ES). The ES measures the expected loss given a threshold violation (a VaR violation). It qualifies as a coherent risk measure by being convex, monotonous, subadditive, transition invariant, and positively homogenous contrary to the VaR which does not fulfill the axioms of convexity and subadditivity (Artzner et al., 1999). However, the performance of the ES is difficult to test because the observations are often relatively few.

Practically, accurate VaR estimates contribute positively to our ability to manage financial risks as they enable institutions to measure the riskiness of the assets held in the trading book and allocate their capital more efficiently. They play a major role in ensuring that the institutions still do business after a catastrophic event because the VaR is supposed to provide a guide to capital reserve allocation and risk monitoring by forecasting extreme portfolio losses that capital reserves are designed to cover. For example, The Basel Committee on Banking Supervision at the Bank for International Settlements (BIS) uses VaR objective to determine capital requirements. According to the similar logic, inaccurate VaR estimates contribute negatively to our ability to manage financial risks as they lead institutions to misjudge the riskiness of the assets held in the trading book and allocate their capital sub-optimally. Still, inaccuracy of VaR estimates could have consequences on profitability and financial stability of institutions (Engle and Manganelli, 2001).

3. Data

The data employed in this paper consists of daily observations of national local currency denominated stock and government bond market total return indices of Australia, Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the United Kingdom (UK), and the United States (US) from January 1, 1999 to December 31, 2010 (3131 observations). The stock market indices are Datastream-constructed value-weighted total market indices representing the total return on a well-diversified national equity portfolio covering a minimum of 75%-80% of the total market capitalization of each market. The bond market indices are Datastream-constructed 10-year constant maturity total return indices consisting only of the most liquid government bonds following the European Federation of Financial Analysts (EFFAS) methodology.

The data selection process consists of many stages. First, the sample countries are selected based on their perennial status as one of the world's largest, well-developed, and financially stable economies that have significant role in coordinating economic policies and ensuring financial market stability. They share a long history of monitoring developments in the world economy, assessing economic policies, and providing financial solutions for debtor countries facing payment difficulties. For example, most of the sample countries are (permanent) members of the Group of Eight (G-8), the Group of Ten (G-10), and the Paris Club.[22] Second, the sample period is selected so that it enables examining and comparing both relative volatile and tranquil periods without the need for accounting for the structural break in the conditional correlations caused by the introduction of the euro in January 1, 1999 as documented by Cappiello et al. (2006). This period is also attractive because inflation was relatively modest over the entire sample suggesting that changes in inflation expectations are unlikely to be the key factor behind the variations of the stock-bond correlations (see Appendix 12). Third, the data frequency is selected considering the need for employing high frequency data to measure return dynamics that may differ even with durations of days. For example, in my sample of thirteen countries (40616 observations) the conditional correlations change by 1% or more for around 36% of the days, and by 10% or more for around 14% of the days. Additionally, there is no need for alleviating non-synchronous trading problems of daily data (Martens and Poon, 2001) by using lower frequency data because only intranational return dynamics are examined. Fourth, long-term government bonds are selected over shorter-term because long-

[22] For more information on the groups, see http://www.imf.org/external/np/exr/facts/groups.htm.

term government bonds can be considered as closer maturity substitutes to stocks (Baur and Lucey, 2006) and monetary policy operations are more likely to have an unclear influence on short-term rather than on long-term government bonds (Urich and Wachtel, 2001). Finally, the Datastream-constructed indices are selected based on their popularity in the earlier literature on stock-bond return relation (see e.g. Cappiello et al., 2006; Connolly et al., 2007).

All series are retrieved as synchronized from Datastream and no pre-adjustments whatsoever were made to the price series before they were converted to logarithmic stock and bond returns (interchangeably referred as returns throughout the paper), $r_{1,t}$ and $r_{2,t}$, by taking the first difference of the natural log of the daily closing prices in (3) and (4).

$$r_{1,t} = \log(P_{1,t}) - \log(P_{1,t-1}) \tag{3}$$

$$r_{2,t} = \log(P_{2,t}) - \log(P_{2,t-1}) \tag{4}$$

Tables 1-2 report the basic information and the most relevant statistics of the daily local currency denominated logarithmic total stock and bond returns from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). To note, the indexed stock and bond return series are shown in Appendix 2. The largest annualized total period mean returns on stocks are reported in Canada (8.68%) and Australia (7.70%), and the smallest in Japan (-0.07%) and Italy (0.54%). The largest annualized total period standard deviations of stock returns are reported in Sweden (25.35%) and the Netherlands (21.93%). The largest annualized total period mean returns on bonds are reported in Canada (5.80%) and Australia (5.28%), and the smallest in Japan (2.65%) and Switzerland (3.53%). The largest annualized total period standard deviations of bond returns are reported in the US (7.84%) and Australia (7.51%). Interestingly, the countries with largest total period returns are the same for both stocks and bonds but the countries with largest total period standard deviations are not the same ones for both stocks and bonds.

The skewness and the kurtosis are computed to provide information about the distribution of the returns. The compared skewness and the kurtosis of the normal distribution are zero and three, respectively. The skewness of stock returns ranges from -0.63 to 0.40 and the kurtosis from 6.17 to 13.61, whereas the skewness of bond returns ranges from -0.53 to 0.21 and the kurtosis from 4.21 to 8.80. The averagely negative skewness indicates that the return distributions are skewed to the left and that the large negative return deviations dominate large positive ones. The consistently high kurtosis indicates that more of the variance is due to infrequent extreme deviations as opposed to frequent modestly-sized deviations and the returns are thus said to have 'leptokurtic conditional densities'. This simply means that they have thicker tails than the density of the normal distribution with the same mean and variance.

The Jarque-Bera test statistics of Jarque and Bera (1987) is employed to test the null of normally distributed returns. It clearly rejects the null of normally distributed returns at the 5% level for all the return series. The augmented Dickey-Fuller (ADF) test statistics of Dickey and Fuller (1979) is employed to test the null of a unit root in the returns with a constant included in the test regression and lag lengths automatically chosen based on the SIC. The ADF test clearly rejects the null of a unit root at the 5% level for all of the return series indicating that all the price series are integrated of order one. The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the demeaned returns, in the squared demeaned returns, and in the cross products of demeaned returns which are computed from the auxiliary regressions. The Ljung-Box Q-statistics rejects the null of no serial correlation up to the twelfth lag at the 5% level in the demeaned returns for most of the countries, in the squared demeaned returns for all of the countries, and in the cross products of demeaned returns for all of the countries except Germany. The serial correlation means that returns today may be correlated with past days' returns. The ARCH Lagrange multiplier (LM) test statistics of Engle (1982) is employed to test the null of no ARCH effects up to the twelfth lag in the squared demeaned returns and its reported test statistics is computed as the number of observations times the observed R^2 of an auxiliary test regression. The ARCH LM test clearly rejects the null of no ARCH effects up to the twelfth lag at the 5% level in the demeaned returns for all of the countries. The heteroskedasticity means that shocks today influence volatility for many periods in the future.

To summarize, both the stock and the bond return series display many of the well documented stylized facts of high frequency financial returns including leptokurtic conditional densities, serial correlation, and heteroskedasticity (Mandelbrot, 1963). All of these (undesired) features of high frequency financial return data pose challenges for the econometric modeling. Fortunately, there are techniques that are particularly designed to overcome those challenges (Engle, 2004).

Table 1: Stock Return Statistics

This table reports basic information and the most relevant statistics of the daily local currency denominated logarithmic total stock returns from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). The currencies of denomination include the Australian dollar (AUD), the British sterling (GBP), the Canadian dollar (CAD), the Euro (EUR), the Swedish krona (SEK), and the US dollar (USD). The mean and standard deviation are expressed as daily and annualized percentages. The annualized figures are based on an assumption of 250 trading days per year and are shown in the brackets below the daily figures. The skewness and the kurtosis are employed to provide information about the distribution of the returns. The compared skewness and the kurtosis of the normal distribution are zero and three, respectively. The Jarque-Bera test statistics of Jarque and Bera (1987) is employed to test the null of normally distributed returns. The ADF test statistics of Dickey and Fuller (1979) is employed to test the null of a unit root in the returns with a constant included in the test regression and lag lengths automatically chosen based on the Schwartz information criterion (SIC) of Schwarz (1978). The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the demeaned returns, in the squared demeaned returns, and in the cross products of demeaned returns. The ARCH LM test statistics of Engle (1982) is employed to test the null of no ARCH effects up to the twelfth lag in the squared demeaned returns. The demeaned stock and bond returns, $e_{1,t}$ and $e_{2,t}$, are computed from the regressions $r_{1,t} = \mu_1 + e_{1,t}$ and $r_{2,t} = \mu_2 + e_{2,t}$, respectively. For further information, refer to EViews 7 Manuals. All series are retrieved from Datastream. *Indicates significance at the 5% level.

Country	DS code	Currency	Mean	SD	Skewness	Kurtosis	Jarque-Bera	ADF	$Q_{e1}(12)$	$Q_{e1e1}(12)$	$Q_{e1e2}(12)$	$ARCH_{e1e1}(12)$
Australia	TOTMKAU(RI)	AUD	0.0308 %	1.0099 %	-0.55	9.98	6517.92*	-57.84*	17.52	2539.10*	86.85*	726.80*
			(7.70%)	(15.97%)								
Belgium	TOTMKBG(RI)	EUR	0.0078 %	1.2138 %	-0.09	9.04	4764.24*	-50.67*	60.93*	2483.60*	102.37*	673.89*
			(1.95%)	(19.19%)								
Canada	TOTMKCN(RI)	CAD	0.0347 %	1.1651 %	-0.63	11.88	10491.66*	-42.10*	40.79*	3246.80*	86.40*	908.30*
			(8.68%)	(18.42%)								
France	TOTMKFR(RI)	EUR	0.0175 %	1.3635 %	-0.01	7.89	3112.93*	-56.47*	39.56*	1811.60*	78.19*	576.42*
			(4.38%)	(21.56%)								
Germany	TOTMKBD(RI)	EUR	0.0123 %	1.3131 %	0.40	13.61	14774.56*	-55.25*	18.24	1002.20*	54.92	520.97*
			(3.08%)	(20.76%)								
Italy	TOTMKIT(RI)	EUR	0.0022 %	1.3105 %	-0.08	9.35	5256.51*	-25.20*	56.72*	1822.10*	143.70*	634.69*
			(0.54%)	(20.72%)								
Japan	TOTMKJP(RI)	JPY	-0.0003 %	1.3732 %	-0.29	8.80	4431.24*	-54.14*	28.40*	3122.00*	72.22*	983.98*
			(-0.07%)	(21.71%)								
Netherlands	TOTMKNL(RI)	EUR	0.0055 %	1.3868 %	-0.25	8.84	4476.60*	-55.32*	56.51*	2980.70*	90.50*	833.11*
			(1.37%)	(21.93%)								
Spain	TOTMKES(RI)	EUR	0.0116 %	1.3112 %	0.06	9.05	4780.08*	-56.86*	22.17*	1169.00*	125.73*	438.07*
			(2.90%)	(20.73%)								
Sweden	TOTMKSD(RI)	SEK	0.0307 %	1.6030 %	0.06	6.17	1311.67*	-56.19*	18.75	1355.00*	78.03*	467.10*
			(7.68%)	(25.35%)								
Switzerland	TOTMKSW(RI)	CHF	0.0090 %	1.1311 %	-0.11	9.25	5094.45*	-54.46*	49.68*	2601.90*	112.62*	744.91*
			(2.25%)	(17.88%)								
UK	TOTMKUK(RI)	GBP	0.0175 %	1.2261 %	-0.18	9.11	4881.10*	-28.38*	72.49*	2446.40*	137.04*	730.97*
			(4.38%)	(19.39%)								
US	TOTMKUS(RI)	USD	0.0091 %	1.3375 %	-0.13	10.27	6892.48*	-43.31*	34.68*	3052.50*	107.71*	866.77*
			(2.28%)	(21.15%)								

Table 2: Bond Return Statistics

This table reports basic information and the most relevant statistics of the daily local currency denominated logarithmic total bond returns from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). The currencies of denomination include the Australian dollar (AUD), the British sterling (GBP), the Canadian dollar (CAD), the Euro (EUR), the Swedish krona (SEK), and the US dollar (USD). The mean and standard deviation are expressed as daily and annualized percentages. The annualized figures are based on an assumption of 250 trading days per year and are shown in the brackets below the daily figures. The skewness and the kurtosis are employed to provide information about the distribution of the returns. The compared skewness and the kurtosis of the normal distribution are zero and three, respectively. The Jarque-Bera test statistics of Jarque and Bera (1987) is employed to test the null of normally distributed returns. The ADF test statistics of Dickey and Fuller (1979) is employed to test the null of a unit root in the returns with a constant included in the test regression and lag lengths automatically chosen based on the Schwartz information criterion (SIC) of Schwarz (1978). The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the demeaned returns, in the squared demeaned returns. and in the cross products of the demeaned returns. The ARCH LM test statistics of Engle (1982) is employed to test the null of no ARCH effects up to the twelfth lag in the squared demeaned returns. The demeaned stock and bond returns, $e_{1,t}$ and $e_{2,t}$, are computed from the regressions $r_{1,t} = \mu_1 + e_{1,t}$ and $r_{2,t} = \mu_2 + e_{2,t}$, respectively. For further information, refer to EViews 7 Manuals. All series are retrieved from Datastream. *Indicates significance at the 5% level.

Country	DS code	Currency	Mean	SD	Skewness	Kurtosis	Jarque-Bera	ADF	$Q_{e2}(12)$	$Q_{e2e2}(12)$	$Q_{e1e2}(12)$	$ARCH_{e2e2}(12)$
Australia	BMAU10Y(RI)	AUD	0.0211 %	0.4748 %	-0.17	5.24	667.44*	-43.14*	24.33*	362.17*	86.85*	197.44*
			(5.28%)	(7.51%)								
Belgium	BMBG10Y(RI)	EUR	0.0198 %	0.3280 %	0.18	7.19	2308.79*	-54.36*	15.31	139.04*	102.37*	93.90*
			(4.95%)	(5.19%)								
Canada	BMCN10Y(RI)	CAD	0.0232 %	0.3632 %	-0.15	4.21	204.22*	-41.58*	15.96	187.26*	86.40*	122.05*
			(5.80%)	(5.74%)								
France	BMFR10Y(RI)	EUR	0.0185 %	0.3404 %	-0.18	5.35	735.27*	-56.45*	13.69	374.98*	78.19*	202.55*
			(4.63%)	(5.38%)								
Germany	BMBD10Y(RI)	EUR	0.0188 %	0.3358 %	-0.18	4.34	248.46*	-53.71*	15.47	367.53*	54.92	194.76*
			(4.70%)	(5.31%)								
Italy	BMIT10Y(RI)	EUR	0.0179 %	0.3079 %	-0.12	5.65	925.09*	-52.05*	28.09*	312.19*	143.70*	235.09*
			(4.48%)	(4.87%)								
Japan	BMJP10Y(RI)	JPY	0.0106 %	0.2818 %	-0.53	8.64	4295.90*	-56.86*	22.27*	1206.50*	72.22*	455.23*
			(2.65%)	(4.46%)								
Netherlands	BMNL10Y(RI)	EUR	0.0196 %	0.3229 %	-0.19	4.21	208.67*	-53.77*	13.40	264.43*	90.50*	145.34*
			(4.90%)	(5.11%)								
Spain	BMES10Y(RI)	EUR	0.0152 %	0.3350 %	0.21	8.47	3922.35*	-51.86*	32.13*	236.61*	125.73*	146.67*
			(3.80%)	(5.30%)								
Sweden	BMSD10Y(RI)	SEK	0.0206 %	0.3256 %	-0.01	4.96	501.56*	-51.02*	41.50*	413.31*	78.03*	229.77*
			(5.15%)	(5.15%)								
Switzerland	BMSW10Y(RI)	CHF	0.0141 %	0.2953 %	0.02	8.80	4387.91*	-53.95*	26.50*	97.18*	112.62*	72.72*
			(3.53%)	(4.67%)								
UK	BMUK10Y(RI)	GBP	0.0201 %	0.3704 %	-0.03	5.16	609.10*	-53.07*	27.99*	498.24*	137.04*	275.41*
			(5.03%)	(5.86%)								
US	BMUS10Y(RI)	USD	0.0187 %	0.4961 %	-0.04	5.91	1105.26*	-42.20*	26.58*	354.63*	107.71*	192.15*
			(4.68%)	(7.84%)								

4. Econometric Framework

The econometric framework employed to assess whether a country exhibits financial market stability or not includes modeling the time-varying conditional intranational stock-bond correlations, testing for the intranational flights between stocks and bonds, and modeling the conditional autoregressive value at risk (CAViaR) of equally weighted intranational stock-bond portfolios. These methodologies represent one of the most prominent and current tools in the field of financial econometrics and are commonly used by researchers and practitioners all around the world. Importantly, they all have the potential to provide valuable information for investors, policy makers and regulatory authorities about the cross-sectional dimension of systemic risk for assessing financial market stability under extreme market conditions and potentially systemic events. The computations of conditional correlation models and flights are done using the EViews 7 software, whereas the computations of CAViaR models are done using the MATLAB R2008a software. For repeatability and transparency, the EViews codes are made available by the Author in Appendix 1 and the MATLAB codes are made available by Simone Manganelli at http://www.simonemanganelli.org/Simone/Research.html. To ensure the robustness of the estimates, at least two competitive models are employed at all stages of the analysis and relevant diagnostics are computed to evaluate model adequacy in capturing the common features of financial return data.

4.1 Modeling the Stock-Bond Return Relation

Various parametric, semi-parametric and non-parametric measures have been suggested for measuring the degree of dependency and market linkages between stocks and bonds in the financial econometrics literature. However, this paper is only concerned with the parametric models or more precisely the GARCH type of parametric models because they are very widely used in practice (Engle, 2009). Among the parametric models, multivariate GARCH (MGARCH) models are particularly suited for modeling stock-bond correlation dynamics (Skintzi and Xanthopoulos-Sisinis, 2007). Since the introduction of the first and very general MGARCH model, the VECH model of Bollerslev et al. (1988), many parameterizations for the conditional (co)variance matrix of a (discrete time) stochastic vector process have been suggested.[23] Empirical evidence has shown that many of the suggested GARCH models provide good approximation of returns evolution and are capable of capturing the serial

[23] For an excellent survey on GARCH models in finance, refer to Bollerslev et al. (1992). For an excellent survey on MGARCH models, refer to Bauwens et al. (2006). For an excellent survey on volatility and correlation forecasting, refer to Andersen et al. (2006). For an excellent glossary on GARCH terms, refer to Bollerslev (2008).

dependence and volatility clustering typical for financial return series (Engle, 2004). The most well-known problems of the MGARCH models have related to the trade-off between model flexibility and parsimony and to the difficulties in verifying the conditions for the positive definiteness of the conditional (co)variance matrix, especially during the optimization of the log-likelihood function. [24] These problems represent an important explanation for why univariate modeling of conditional volatilities of stock and bond returns has reserved significantly more attention than multivariate modeling of conditional covariances and correlations between stock and bond returns (Cappiello et al., 2006).

One of the most prominent conventional MGARCH models, the BEKK model of Engle and Kroner (1995), named after Baba, Engle, Kraft, and Kroner who wrote the preliminary version of the paper, is a popular set of restrictions to the VECH model of Bollerslev et al. (1988). The BEKK model is designed to overcome the challenges of ensuring the positive definiteness of the conditional (co)variance matrix and to reduce the number of parameters to be estimated. Specifically, the diagonal BEKK specification entails a minimum number of parameters and guarantees the positive definiteness of the (co)variance matrix easily. However, it is rarely used when the number of series is exceeds 3 or 4 because the number of parameters to be estimated becomes too large (Bauwens et al., 2006). Moreover, the exact interpretation of the estimated individual coefficients is difficult to discern (Engle and Sheppard, 2001).[25]

To mitigate the issues related to construction and estimation of the conventional MGARCH models, Bollerslev (1990) initiated the Constant Conditional Correlation (CCC) class of MGARCH models with time-varying conditional (co)variances but constant conditional correlations. The CCC class models represent a major reduction in the computational complexity of the MGARCH models by allowing for a two-stage estimation of the conditional correlation matrix, being relatively parsimonious, and imposing the positive definiteness of the conditional covariance matrix easily (as long as the univariate conditional variances are positive and the correlation matrix is of full-rank). Although the CCC class models provide a convenient tool for empirical applications, many financial studies have shown that the assumption of the constant conditional correlation matrix is often inadequate.

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[24] To clarify, parameterization of an MGARCH model should be flexible enough to allow for causality between variances, and the covariance matrixes produced by MGARCH models need to be positive definite by definition.

[25] In this paper, the diagonal BEKK model was considered for the time-varying conditional intranational stock-bond correlations. However, both the DCC and the ADCC models clearly outperformed the diagonal BEKK model in terms of the model ability to capture the time-varying volatilities. Thus, the estimation of the diagonal BEKK model is not presented here for space considerations, but the parameter estimates and diagnostics of the estimated diagonal BEKK model are available from the Author upon request.

To allow for the time-varying conditional correlation matrix, Engle (2002) proposes the Dynamic Conditional Correlation (DCC) class of MGARCH models as an extension to the CCC class models. According to Engle (2002), the DCC class models are found to be particularly well defined to analyze the correlation dynamics among stock and bond returns and often outperform other widely used models such as the rolling correlation estimator, the exponential smoother of RiskMetrics (1996) and the diagonal BEKK model of Engle and Kroner (1995). Given the flexibility of the DCC class models, they are extendable to very large portfolios consisting of hundreds of assets (Engle and Sheppard, 2001).

In this paper, tests of Bera and Kim (2002) and Engle and Sheppard (2001) for the null of constant correlations are conducted before modeling the time-varying conditional correlations. Both tests involve estimation of the Constant Conditional Correlation model of Bollerslev (1990). After the rejection of the null of constant correlations, the DCC class MGARCH models considered for the time-varying conditional stock-bond correlations include the Dynamic Conditional Correlation (DCC) model of Engle (2002), and the Asymmetric Dynamic Conditional Correlation (ADCC) model of Cappiello et al. (2006). The DCC model is an extension of the Constant Conditional Correlation model of Bollerslev (1990) to allow for a time-varying correlation matrix. Theoretical foundations of the DCC model are presented in Engle and Sheppard (2001). The ADCC model is an extension of the DCC model to allow for conditional asymmetries in correlation dynamics. The ADCC model is estimated because of the recently documented economically significant stock-bond covariance and correlation asymmetries in the financial econometrics literature (see e.g. de Goeij and Marquering, 2004; Thorp and Milunovich, 2007). Theoretical foundations of the ADCC model are presented in Cappiello et al. (2006).

The estimations of the MGARCH models are done in a bivariate setting assuming that the whitened returns, or residuals, are conditionally multivariate normal with zero expected value and covariance matrix H_t. Fortunately, the assumption of conditional normality is not required for consistency and asymptotic normality of the estimated parameters because when the returns have non-normal residuals, the estimates can be interpreted as quasi-maximum likelihood (QML) estimates given that the score of the normal log-likelihood has the martingale difference property (Bollerslev and Wooldridge, 1992; Engle and Sheppard, 2001). Andreou and Werker (2010) show that for certain type of conditional mean models, including the VAR model employed in this paper, applying QML to estimate GARCH models after modeling the conditional mean does not result in a loss of efficiency. To take into account the (possible) departures from the normality assumption, the t-statistics of the estimated CCC and the univariate GARCH parameters are computed using the Bollerslev and Wooldridge (1992) robust standard errors and the t-statistics of the estimated DCC parameters using the Engle and Sheppard (2001) modified standard errors. To ensure that the QML estimates are consistent, the Bollerslev and Wooldridge (1992) moment conditions for the standardized residuals and the standardized products of residuals are employed. Under the null of consistent QML estimates, the expectation of the mean standardized residuals, (5) - (6), is zero and the expectation of the mean standardized products of residuals, (7) - (9), is one. In this setting, these moment conditions can be specified as follows.

$$MC_1 = E_{t-1}\left(\frac{\varepsilon_{1,t}}{\sqrt{h_{11,t}}}\right) = 0 \tag{5}$$

$$MC_2 = E_{t-1}\left(\frac{\varepsilon_{2,t}}{\sqrt{h_{22,t}}}\right) = 0 \tag{6}$$

$$MC_3 = E_{t-1}\left(\frac{\varepsilon_{1,t}^2}{h_{11,t}}\right) = 1 \tag{7}$$

$$MC_4 = E_{t-1}\left(\frac{\varepsilon_{2,t}^2}{h_{22,t}}\right) = 1 \tag{8}$$

$$MC_5 = E_{t-1}\left(\frac{\varepsilon_{1,t}\varepsilon_{2,t}}{h_{12,t}}\right) = 1 \tag{9}$$

Out of these carefully selected DCC class MGARCH specifications, the best performing model based on the Schwarz information criterion (SIC) of Schwarz (1978) is selected to estimate the (time-varying) stock-bond correlations and the flights because it is well known for favoring more parsimonious models than the Akaike information criterion (AIC) of Akaike (1974). [26] As a model selection tool, the information criteria are preferred to likelihood ratio tests because they are considered to lead to the asymptotically correct model selection and likelihood ratio tests are not appropriate under the QML interpretation of the results (see e.g. EViews 7 Manuals; Cappiello et al., 2006).

[26] The EViews 7 software computes the AIC as $\frac{-2l}{T} + \frac{2k}{T}$ and the SIC as $\frac{-2l}{T} + \frac{klog(T)}{T}$, where l is the value of the likelihood function, k is the number of parameters estimated, and T is the number of observations.

4.1.1 Modeling the Conditional Means of the Stock and Bond Returns

The estimations of the MGARCH models start by fitting a bivariate vector autoregressive (VAR) filtering process to whiten the stock and bond return series. It is particularly important to account for autocorrelation and cross-correlation found in returns when modeling the conditional (co)variances because all the MGARCH models estimated here inherently assume that the residuals are conditionally multivariate normal with zero expected value and covariance matrix H_t (see e.g. Kroner and Ng, 1998; de Goeij and Marquering, 2004; Thorp and Milunovich, 2007).

Let subscript 1 denote stocks, subscript 2 denote bonds, and r_t be a 2×1 vector of logarithmic stock and bond returns, $r_t = [r_{1,t} r_{2,t}]'$, where the conditional mean equation for each return series is modeled as a stationary VAR(p) process with 2×1 parameter vector μ to capture means of the return series and 2×2 parameter matrices φ_p to capture (possible) autocorrelations and cross-correlations up to the order p. To select the lag length p, the following VAR models up to eight lags are estimated for the conditional mean and the value of p that minimizes the AIC is selected to demean and whiten the stock and bond returns.[27] However, in the case the suggested lag length is zero, the VAR(1) model is arbitrarily selected.

$$r_t = \mu + \sum_{\mathrm{p}=1}^{\mathrm{P}} \Phi_p r_{t-p} + \varepsilon_t \tag{10}$$

$$\begin{bmatrix} r_{1,t} \\ r_{2,t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \varphi_{11}^1 & \varphi_{12}^1 \\ \varphi_{21}^1 & \varphi_{22}^1 \end{bmatrix} \begin{bmatrix} r_{1,t-1} \\ r_{2,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \varphi_{11}^p & \varphi_{12}^p \\ \varphi_{21}^p & \varphi_{22}^p \end{bmatrix} \begin{bmatrix} r_{1,t-p} \\ r_{2,t-p} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{11}$$

Given the information set $\Im_{t-1}$ at time t-1, the demeaned and whitened returns (henceforth referred as residuals), $\varepsilon_{i,t}$, are assumed to be conditionally normally distributed with zero mean and (co)variance matrix H_t as follows.

$$\varepsilon_t | \Im_{t-1} \sim N(0, H_t) \tag{12}$$

where the conditional (co)variance matrix H_t consists of conditional variances $h_{ii,t}$ and conditional covariances $h_{ij,t}$.

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[27] For comparison, Kroner and Ng (1998) use a VAR of ten lags without testing for the optimal lag length, and de Goeij and Marquering (2004) use a VAR of five lags based on the AIC.

Tables 3-4 report the VAR parameter estimates and diagnostics for the stock and bond returns. Many of the parameters are significant even at relatively high lags which is common for leptokurtic financial return data (de Goeij and Marquering, 2004). After modeling the conditional mean, there is a significant reduction in the cross-correlation of the residuals compared to the cross-correlation of the demeaned returns in Tables 1-2. However, the White's test statistics of White (1980) on residuals and squared residuals indicate that heteroskedasticity is still strongly present in all series and needs to be properly addressed.

4.1.2 Testing for the Null of Constant Conditional Stock-Bond Correlations

Before the estimations of the time-varying conditional stock-bond correlations, it is important to test whether the conditional stock-bond correlations are actually time-varying as documented by earlier by Engle and Sheppard (2001), Bera and Kim (2002), Scruggs and Glabadanidis (2003), de Goeij and Marquering (2004), and Cappiello et al. (2006), among others. Additional tests are particularly important because rejection of the null of constant correlations is one of the primary motivations for studying time-varying correlations (and testing for flights) in this paper. To ensure the robustness of the test results, two of the most empirically robust tests for the null of constant correlations are conducted. They are the studentized version of the information matrix test (IM_S) of Bera and Kim (2002) and the DCC test (ES_{DCC}) of Engle and Sheppard (2001).[28] They both require estimation of the Constant Conditional Correlation (CCC) model of Bollerslev (1990), where the conditional residual (co)variance matrix, H_t, can be modeled as proportional to the product of the corresponding conditional standard deviations, $\mathrm{h}_{11,\mathrm{t}}$ and $\mathrm{h}_{22,\mathrm{t}}$, and leaving the conditional correlation, ρ_{12}, constant. The CCC model can be specified as follows.

$$\mathrm{H_t = D_t R D_t} \tag{13}$$

$$\mathrm{H_t} = \begin{bmatrix} \sqrt{\mathrm{h}_{11,\mathrm{t}}} & 0 \\ 0 & \sqrt{\mathrm{h}_{22,\mathrm{t}}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12} \\ \rho_{21} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{\mathrm{h}_{11,\mathrm{t}}} & 0 \\ 0 & \sqrt{\mathrm{h}_{22,\mathrm{t}}} \end{bmatrix} \tag{14}$$

$$\mathrm{h}_{11,\mathrm{t}} = \mathrm{m}_1 + \mathrm{a}_1 \varepsilon_{\mathrm{t}-1}^2 + \mathrm{b}_1 \mathrm{h}_{\mathrm{t}-1} \tag{15}$$

[28] A third prominent test for the null of constant conditional correlation against an ARCH in correlation alternative in a multivariate setting is proposed by Tse (2000).

$$\mathrm{h}_{22,\mathrm{t}} = \mathrm{m}_2 + \mathrm{a}_2\varepsilon_{\mathrm{t}-1}^2 + \mathrm{b}_2\mathrm{h}_{\mathrm{t}-1} \tag{16}$$

$$\mathrm{h}_{12,\mathrm{t}} = \rho_{12}(\sqrt{\mathrm{h}_{11,\mathrm{t}}\mathrm{h}_{22,\mathrm{t}}}) \tag{17}$$

$$\rho_{12} = \frac{\mathrm{h}_{12,\mathrm{t}}}{\sqrt{\mathrm{h}_{11,\mathrm{t}}}\sqrt{\mathrm{h}_{22,\mathrm{t}}}} \tag{18}$$

The studentized version of the information matrix test (IM_S) of Bera and Kim (2002) is a test for the null of constant correlation against a diffuse alternative in a bivariate setting.[29] The IM_S statistics is computed as follows.

$$IM_S = \frac{\left[\sum_{t=1}^{T}\psi_t\right]^2}{\sum_{t=1}^{T}(\psi_t - \frac{\sum_{t=1}^{T}\psi_t}{T})^2} \tag{19}$$

where $\psi_t = \hat{\xi}_{1,t}^2\hat{\xi}_{2,t}^2 - 1 - 2\hat{\rho}^2$, $\hat{\xi}_{1,t} = \frac{\hat{u}_{1,t} - \hat{\rho}\hat{u}_{2,t}}{\sqrt{1-\hat{\rho}^2}}$, $\hat{\xi}_{2,t} = \frac{\hat{u}_{2,t} - \hat{\rho}\hat{u}_{1,t}}{\sqrt{1-\hat{\rho}^2}}$, $\hat{\rho}$ is the ML estimate of the constant correlation coefficient from the bivariate CCC model, and $\hat{u}_{1,t}$ and $\hat{u}_{2,t}$ are the estimates of the bivariate CCC model residuals standardized by their inverse square root of the residual covariance matrix. Under the null of constant conditional correlation, the IM_S statistics is asymptotically distributed as χ_1^2. Theoretical foundations of the IM_S statistics are presented in Bera and Kim (2002).

The DCC test (ES_{DCC}) of Engle and Sheppard (2001) is a test for the null of constant correlation against an alternative of dynamic conditional correlation in a multivariate setting. The ES_{DCC} statistics is computed by first jointly standardizing the vector of univariate standardized CCC model residuals by the symmetric square root decomposition of the estimated CCC correlation matrix, and then artificially regressing the outer products of the jointly standardized residuals (regressand) on a matrix, X, consisting of a constant and the lagged outer products of the jointly standardized residuals (regressors). Under the null of constant conditional correlation, all of the estimated regression parameters, $\hat{\delta}$, including the constant, should be zero. The test statistics can then be computed as $\frac{\hat{\delta}X'X\hat{\delta}'}{\hat{\sigma}^2}$ which is asymptotically distributed as χ_{s+1}^2, where $\hat{\delta}$ denotes the estimated regression parameters, X is

[29] The studentized version of the information matrix test is selected because it has been reported to be more robust to non-normality than the original efficient score version of the information matrix test (Bera and Kim, 2002).

a matrix consisting of the regressors, and s denotes the number of lags employed in the test. In this thesis, the number of lags employed in the test is one. Theoretical foundations of the ES_{DCC} statistics and discussion on the difficulties in implementation of this type of test are presented in Engle and Sheppard (2001).

Table 5 reports the parameter estimates and diagnostics of the CCC-GARCH(1,1) model together with the applicable Bollerslev and Wooldridge (1992) moment conditions and the test results for the null of constant conditional correlations. In the ML estimations of the CCC-GARCH(1,1) model, the presample covariance backcasting parameter is set to 0.7, and the Marquardt algorithm of Marquardt (1963) with maximum of 500 iterations and the convergence limit of 0.0001 is employed.[30] To note, no convergence problems were encountered in the optimizations and only few runs were needed to obtain the convergence. The Bollerslev and Wooldridge (1992) moment conditions signify that the QML estimates are consistent. The Ljung-Box Q-statistics on the residuals standardized by their inverse square root of residual covariance matrix indicate that the performance of the CCC-GARCH(1,1) model of conditional second moments is satisfactory. Because the estimation is done using the EViews built-in procedures, no further details on the estimations are given here. For further information on the estimation of the CCC model refer to Bollerslev (1990), EViews 7 Manuals, and the EViews code in Appendix 1. Based on the test results of the both tests for the null of constant correlations, the CCC model is considered as an inadequate description of the conditional stock-bond correlations. This finding is well in line with the recent financial econometrics literature (see e.g. Bera and Kim, 2002; Scruggs and Glabadanidis, 2003)

4.1.3 Modeling the Time-Varying Conditional Stock-Bond Correlations

The estimations of the time-varying conditional stock-bond correlations consist of two stages because the DCC and the ADCC models are particularly designed to allow for the two-stage estimation of the conditional correlation matrix. In the two-stage estimation, univariate GARCH models are first estimated for each residual series and then, the parameters of the DCC models are estimated using the standardized residuals, the residuals standardized by their conditional standard deviation, from the first stage estimation. According to Engle and Sheppard (2001), in the two-stage estimation procedure, the likelihood function of the DCC models (L) can be decomposed into two quasi-likelihood parts, the volatility part

[30] EViews 7 default settings.

($QL_{volatility}$) and the correlation part ($QL_{correlation}$) assuming that $\varepsilon_t|\Im_{t-1}\sim N(0, H_t)$.[31] Once the first stage has been estimated, the second stage is estimated using the correctly specified likelihood, conditioning on the parameters in the first stage likelihood. For further details on efficiency and asymptotic consistency of the two-stage estimation, refer to Engle and Sheppard (2001).

4.1.3.1 First Stage: Univariate GARCH Specification Search

In the first stage, a set of carefully selected univariate GARCH models is fitted to the residual series and the univariate GARCH models with the lowest SIC are selected to standardize the residuals by their conditional standard deviations for the second stage. The purpose of the first stage specification search is to minimize the risk that univariate volatility models would lead to inconsistent correlation estimates. However, the choice of univariate volatility model is not likely to affect the correlations much because the sign of the standardized residuals is not affected by the choice of model and many GARCH models are known to produce similar type of volatility patterns (Cappiello et al., 2006).

Often, the GARCH model of Bollerslev (1986) is found to provide a sound description of the conditional variance of financial returns with sensible constraints on coefficients and using only very few parameters (Bollerslev, 1986; Engle, 2004). However, as a drawback, it assumes symmetric response of current volatility to positive and negative lagged residuals. Consequently, it fails to take into account the well-documented leverage effects i.e. the tendency of negative return shocks to generate more volatility than positive ones of the same magnitude (see e.g. Black, 1976; Nelson, 1991; Engle and Ng, 1993; Glosten et al., 1993; Bekaert and Harvey, 1997; Campbell and Hentschel, 1992; Veronesi, 1999; Bekaert and Wu, 2000). Therefore, it is particularly important to also consider the most prominent asymmetric

[31] Assuming that $\varepsilon_t|\Im_{t-1}\sim N(0, H_t)$, the log-likelihood function of the DCC models can be decomposed into two quasi-likelihood functions as follows (Engle and Sheppard, 2001).

$$L = -\frac{1}{2}\sum_{t=1}^{T}(klog(2\pi) + 2\log(|D_t|) + log(|R_t|) + u_t' R_t^{-1} u_t)$$

$$QL_{volatility} = -\frac{1}{2}\sum_{t=1}^{k}(Tlog(2\pi) + \sum_{t=1}^{T}(\log(h_{ii,t}) + \frac{\varepsilon_{i,t}^2}{h_{ii,t}}))$$

$$QL_{correlation} = -\frac{1}{2}\sum_{t=1}^{T}(log(|R_t|) + u_t' R_t^{-1} u_t)$$

extensions of the GARCH model.[32] Engle and Ng (1993) find that asymmetric GARCH models such as and the GJR-GARCH and the EGARCH models work very well in practice and often outperform the standard GARCH model, although the exponential structure of the EGARCH model might sometimes overestimate the impact of outliers on volatility.

The set of univariate GARCH models includes the GARCH(1,1) model of Bollerslev (1986) given in (20), the GJR-GARCH(1,1) model of Glosten et al. (1993) also known as the Threshold ARCH (TARCH) given in (21) to allow for asymmetric effects of shocks, the Exponential GARCH(1,1) (EGARCH) model of Nelson (1991) given in (22) to allow for both size and sign effects to shocks in a non-linear formulation, and the Asymmetric Power ARCH(1,1) (APARCH) model of Ding et al. (1993) given in (23) to allow for asymmetric and long-memory effects of shocks. All of the univariate GARCH models are estimated with one lag of innovation, one lag of volatility, one order of asymmetry (where applicable), and assuming conditionally normally distributed errors irrespective of their originally proposed distributions.[33] In addition, all the standard restrictions for non-negativity of variances and stationarity are imposed. Let $h_{ii,t}$ be the conditional variance of the residuals, ω_i be the constant term, $\varepsilon_{i,t-1}$ be the news about volatility from the previous period, $h_{ii,t-1}$ be the last period's estimated conditional variance, γ_i be the coefficient for leverage effects, and λ_i be the power parameter of the standard deviation. The univariate GARCH models can be expressed as follows.

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \tag{20}$$

$$h_{ii,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \gamma_i I(\varepsilon_{i,t-1} < 0)\varepsilon_{i,t-1}^2 + \beta_i h_{ii,t-1} \tag{21}$$

$$\ln(h_{ii,t}) = \omega_i + \alpha_i \frac{|\varepsilon_{i,t-1}|}{\sqrt{h_{ii,t-1}}} + \gamma_i \frac{\varepsilon_{i,t-1}}{\sqrt{h_{ii,t-1}}} + \beta_i \ln(h_{ii,t-1}) \tag{22}$$

$$h_{ii,t}^{\lambda_i/2} = \omega_i + \alpha_i |\varepsilon_{i,t-1}|^{\lambda_i} + \gamma_i I(\varepsilon_{i,t-1} < 0)|\varepsilon_{i,t-1}|^{\lambda_i} + \beta_i h_{ii,t-1}^{\lambda_i/2} \tag{23}$$

[32] When the typical assumptions of non-negativity of parameters and covariance stationarity hold, the GARCH model is analogous to an infinite-order linear ARCH model of Engle (1982) with exponentially declining lag coefficients (Bollerslev et al., 1992), the GJR-GARCH model is analogous to the GARCH model when $\gamma_i = 0$, the APARCH model is analogous to the GARCH model when $\gamma_i = 0$ and $\lambda_i = 2$.

[33] For example, a modified version of EGARCH with normally distributed errors is adopted because Nelson (1991) originally proposes the Generalized Error Distribution (GED) for the error terms.

where I is an indicator function having the value 1 for all values satisfying the given conditions and the value 0 otherwise. Additionally, it is required that (20): $\omega, \alpha, \beta \geq 0$, $\alpha + \beta < 1$, (21): $\alpha + \gamma \geq 0$, $\beta + \left(\alpha + \frac{1}{2}\gamma\right) < 1$, and (23): $|\gamma| \leq 1$.

Generally, the estimated parameters α_i and β_i determine the short-run dynamics of the resulting volatility time series. The larger the news coefficient α_i, the more intensively the volatility reacts to shocks. The larger the lag coefficient β_i, the more persistent the volatility is meaning that the shocks to conditional variance take a long time to die out. The asymmetric effects are present in the conditional variance whenever $\gamma_i \neq 0$ meaning that good news has differential impact on the conditional variance than bad news. For example, in the case of the GJR-GARCH(1,1) model, good news $(\varepsilon_{i,t-1} > 0)$ has an impact of α_i, whereas bad news $(\varepsilon_{i,t-1} < 0)$ has an impact of $\alpha + \gamma$ on the conditional variance. Similarly, in the case of the EGARCH(1,1) model, good news $(\varepsilon_{i,t-1} > 0)$ has an impact of $\alpha_i(1 + \gamma_i)|\varepsilon_{i,t-1}|$, whereas bad news $(\varepsilon_{i,t-1} < 0)$ has an impact of $\alpha_i(1 - \gamma_i)|\varepsilon_{i,t-1}|$ on the conditional variance.

In the ML estimations of the univariate GARCH models, the presample covariance backcasting parameter is set to 0.7, and the Marquardt algorithm of Marquardt (1963) with maximum of 500 iterations and the convergence limit of 0.0001 is employed. To note, no convergence problems were encountered in the optimizations and only few runs were needed to obtain convergence. Because the estimation is done using the EViews built-in procedures, no further details on the estimations are given here. For further information on the estimation of the univariate GARCH models, refer to Bollerslev (1986), Glosten et al. (1993), Nelson (1991), Ding et al. (1993), EViews 7 Manuals, and the EViews code in Appendix 1.

Tables 6-7 report the parameter estimates and diagnostics of the selected univariate GARCH models together with the applicable Bollerslev and Wooldridge (1992) moment conditions. The Bollerslev and Wooldridge moment conditions signify that the QML estimates are consistent. Based on the lowest SIC criterion, all of the stock residual series prefer asymmetric GARCH models, whereas most of the bond residual series prefer the standard GARCH model with only a few exceptions in favor of the GJR-GARCH. This finding is well in line with the extensive literature on asymmetries in the conditional variances of stock and bond returns (see e.g. Schwert, 1989; Bekaert and Wu, 2000; de Goeij and Marquering, 2006). The descriptive statistics on standardized residuals show significant reduction in the skewness and the kurtosis compared to the logarithmic returns which indicates that a large part of the non-normality is attributable to conditional heteroskedasticity. The Ljung-Box Q-statistics on the standardized residuals and the squared standardized residuals point out that the performance of the selected univariate GARCH model of conditional second moments is satisfactory although some autocorrelation remains. It would be unreasonable to assume that an empirical model is able to capture all the autocorrelation because the daily returns are highly leptokurtic and sometimes daily returns display autocorrelation at relatively long lags (de Goeij and Marquering, 2004). To note, the conditional volatilities produced by the selected univariate GARCH models are shown in Appendix 2.

4.1.3.2 Second Stage: Bivariate DCC Specification Search

In the second stage, the DCC(1,1) model of Engle (2002) and the ADCC(1,1) model of Cappiello et al. (2006) are estimated using the standardized residuals from the first stage univariate GARCH estimations and the bivariate DCC models with the lowest SIC are selected to estimate the time-varying conditional intranational stock-bond correlations and test for the intranational flights between stocks and bonds. The purpose of the second stage specification search is to find out whether the dynamic adjustment process of conditional correlations is different for negative shocks than it is for positive shocks.

The standardized residuals, $u_{i,t}$, to be used in the second stage estimation are obtained as follows by dividing the residuals, $\varepsilon_{i,t}$, by their corresponding conditional standard deviations, $\sqrt{h_{ii,t}}$, of the selected univariate GARCH models.

$$u_{i,t} = \frac{\varepsilon_{i,t}}{\sqrt{h_{ii,t}}} \sim N(0,1) \tag{24}$$

In the bivariate DCC(1,1) and the ADCC(1,1,1) models where the estimated parameters are scalars, the conditional residual (co)variance matrix, H_t, can be modeled as follows.

$$H_t = D_t R_t D_t \tag{25}$$

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho_{12,t} \\ \rho_{21,t} & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & 0 \\ 0 & \sqrt{h_{22,t}} \end{bmatrix}$$

where D_t is a diagonal 2×2 matrix of time-varying standard deviations from univariate GARCH models and R_t is the time-varying correlation matrix with ones on the diagonal and time-varying correlations on the off-diagonal evolving as follows.

$$R_t = diag\,[\sqrt{Q_t}]^{-1} Q_t diag\,[\sqrt{Q_t}]^{-1} \tag{26}$$

$$R_t = \begin{bmatrix} \frac{1}{\sqrt{q_{11}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{22}}} \end{bmatrix} \begin{bmatrix} q_{11} & q_{12} \\ q_{21} & q_{22} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{q_{11}}} & 0 \\ 0 & \frac{1}{\sqrt{q_{22}}} \end{bmatrix}$$

where Q_t is a symmetric positive definite 2×2 (co)variance matrix of residuals, $\varepsilon_{i,t}$. The main difference between the DCC and the ADCC model is related to how Q_t is modeled over time. Next, both the DCC model and the ADCC model are specified in more detail.

First, in the scalar mean-reverting DCC(1,1) model of Engle (2002), Q_t evolves as follows.

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u'_{t-1} + \beta Q_{t-1} \tag{27}$$

where the estimated parameters α and β are scalars satisfying $\alpha, \beta \geq 0$, $\alpha + \beta < 1$, u_t is the standardized residual matrix from the first stage estimation, and $\bar{Q}$ is the 2×2 unconditional (co)variance matrix of u_t. Consequently, the conditional correlation of the above scalar DCC model is simply modeled as follows.

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11} q_{22}}} \tag{28}$$

where $q_{12,t}$ is $(1 - \alpha - \beta)\bar{q}_{12} + \alpha u_{1,t-1} u_{2,t-1} + \beta q_{12,t-1}$, q_{11} is $(1 - \alpha - \beta)\bar{q}_{11} + \alpha u^2_{1,t-1} + \beta q_{11,t-1}$, and q_{22} is $(1 - \alpha - \beta)\bar{q}_{22} + \alpha u^2_{2,t-1} + \beta q_{22,t-1}$.

To provide information about the persistency of the conditional correlations, Engle and Sheppard (2001) approximated the formula for the half-life of the DCC (HL_{DCC}) that is the time that it is expected to take for the shock to conditional correlation to be halfway dissipated.[34] The formula can be expressed as follows.

$$HL_{DCC} = \frac{\ln(0.5)}{\ln(\alpha^2 + \beta^2)} \tag{29}$$

where α and β are the estimated DCC parameters.

[34]The formula given in (29) does not apply to the ADCC model because the expectation of the cross product of the returns is not available.

Second, in the scalar mean-reverting ADCC(1,1,1) model of Cappiello et al. (2006), Q_t evolves as follows.

$$Q_{t,} = (1-\alpha-\beta)\bar{Q} - \eta\bar{N} + \alpha u_{t-1}u'_{t-1} + \beta Q_{t-1} + \eta n_{t-1}n'_{t-1} \tag{30}$$

where the estimated parameters α, β, and η are scalars satisfying $\alpha,\beta,\eta \geq 0$, $\alpha+\beta+\delta\eta < 1$, δ is the maximum eigenvalue of $\bar{Q}^{-\frac{1}{2}}\overline{(N)}\bar{Q}^{-\frac{1}{2}}$ as derived by Cappiello et al. (2006), u_t is the standardized residual matrix from the first stage estimation, $\bar{Q}$ is the 2×2 unconditional (co)variance matrix of u_t, $n_t = I(u_t < 0)\circ u_t$ is the matrix of asymmetric shocks, and $\bar{N}$ is the 2×2 unconditional (co)variance matrix of n_t. Consequently, the conditional correlation of the above scalar ADCC model is simply modeled as follows.

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11}q_{22}}} \tag{31}$$

where $q_{12,t}$ is $(1-\alpha-\beta)\bar{q}_{12} - \eta\bar{n}_{12} + \alpha u_{1,t-1}u_{2,t-1} + \beta q_{12,t-1} + \eta n_{12,t-1}$, q_{11} is $(1-\alpha-\beta)\bar{q}_{11} - \eta\bar{n}_{11} + \alpha u^2_{1,t-1} + \beta q_{11,t-1} + \eta n_{11,t-1}$, and q_{22} is $(1-\alpha-\beta)\bar{q}_{22} - \eta\bar{n}_{22} + \alpha u^2_{2,t-1} + \beta q_{22,t-1} + \eta n_{22,t-1}$.

In the second stage ML estimations of the DCC model and the ADCC models, the starting values for α, β and η are iteratively pre-selected to be reasonably close to a maximum point, and the BHHH gradient search algorithm of Berndt et al. (1974) with maximum of 100 iterations and the convergence limit of 0.0001 is employed. The advantages of using the BHHH algorithm are discussed in Engle and Kroner (1995). To note, no convergence problems were encountered in the optimizations and only few runs were needed to obtain convergence. As a robustness check, several different starting values for the estimated parameters were considered in the optimization to ensure that the algorithm is able to escape from (possible) local maxima. For further information on the estimation of the DCC models refer to Engle and Sheppard (2001), Engle (2002), Cappiello et al. (2006), EViews 7 Manuals, and the EViews code in Appendix 1.

As a performance measure for the time-varying correlation models, a test similar to Engle (2002) for the null of no autocorrelation in the squared standardized residuals is employed. Its purpose is to measure, how well the estimated MGARCH models are able to capture time-varying volatilities. In a bivariate setting, the test is implemented with a triangular square root. It is computed as an F-test from the regression of $v_{1,t}^2$ and $v_{2,t}^2$ on five lags of the squares and cross products of the triangular square root standardized residuals and an intercept. The number of rejections measures the performance of the estimator. Let $v_{1,t}$ and $v_{2,t}$ be the triangular square root standardized residuals for the test, respectively.

$$v_{1,t} = \frac{\varepsilon_{1,t}}{\sqrt{h_{11,t}}} \tag{32}$$

$$v_{2,t} = \frac{\varepsilon_{2,t}}{\sqrt{h_{22,t}(1-\hat{\rho}_t^2)}} - \frac{\varepsilon_{1,t}\hat{\rho}_t}{\sqrt{h_{11,t}(1-\hat{\rho}_t^2)}} \tag{33}$$

Table 8 reports the parameter estimates and diagnostics of the selected bivariate DCC model(s). Interestingly, based on the lowest SIC criterion, the DCC model is preferred to the ADCC model for all of the sample countries. One of the probable explanations for the preference for the DCC model is the allowance for the asymmetries already in the estimation of the conditional variances. The half-life of the estimated conditional correlations (HL_{DCC}) varies from 6.03 days to 19.27 days meaning that it takes one to three weeks for the shock to conditional correlation to be halfway dissipated. The F-tests on the squared and cross products of the triangular square root standardized residuals indicate that the scalar DCC(1,1) model provides adequate fit to the data.

Table 3: Selected Bivariate VAR Mean Equation Estimates and Diagnostics for Stocks

This table reports the parameter estimates and diagnostics of the vector autoregressive (VAR) model for the stock return series from January 1, 1999 to December 31, 2010 (3122-3129 observations with adjustments). To select the lag length (p), VAR models up to eight lags are estimated and the value of p that minimizes the Akaike information criterion (AIC) of Akaike (1974) is selected. For Germany and Japan the suggested lag length is zero but the VAR(1) model is applied to them for practical reasons. The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the cross products of residuals. The White's test statistics of White (1980) is employed to test the null of no heteroskedasticity in the levels and squares of residuals (no cross terms included). The reported White's test statistics is the LM chi-square statistics for the joint significance of all regressors in the system of test equations. For further information, refer to the above mentioned papers, EViews 7 Manuals and the EViews code in Appendix 1.*Indicates significance at the 5% level.

Country	μ_1	φ^1_{11}	φ^2_{11}	φ^3_{11}	φ^4_{11}	φ^5_{11}	φ^6_{11}	φ^7_{11}	φ^8_{11}	φ^1_{12}	φ^2_{12}	φ^3_{12}	φ^4_{12}	φ^5_{12}	φ^6_{12}	φ^7_{12}	φ^8_{12}	Obs	$Q_{\varepsilon1\varepsilon2}(12)$	White
Australia	0.0003	-0.0381*	-0.0146	-	-	-	-	-	-	-0.0357	-0.0028	-	-	-	-	-	-	3128	51.37	630.95*
	(1.83)	(-2.06)	(-0.79)							(-0.91)	(-0.07)									
Belgium	0.0001	0.1019*	-	-	-	-	-	-	-	0.0441	-	-	-	-	-	-	-	3129	56.40	353.88*
	(0.24)	(5.57)								(0.65)										
Canada	0.0004	-0.0141	-0.0568*	-	-	-	-	-	-	0.0691	-0.0362	-	-	-	-	-	-	3128	57.88	407.03*
	(1.70)	(-0.77)	(-3.11)							(1.18)	(-0.62)									
France	0.0002	-0.0113	-0.0329	-0.0665*	0.0387*	-0.0529*	-0.0359	-	-	-0.0337	0.0250	-0.1462	0.0254	-0.0184	0.0239	-	-	3124	20.72	931.60*
	(0.84)	(-0.60)	(-1.74)	(-3.52)	(2.05)	(-2.80)	(-1.90)			(-0.45)	(0.33)	(-1.93)	(0.34)	(-0.24)	(0.32)					
Germany	0.0001	0.0165	-	-	-	-	-	-	-	0.0315	-	-	-	-	-	-	-	3129	46.96	205.52*
	(0.43)	(0.88)								(0.43)										
Italy	0.0000	0.0060	-0.0059	-0.0173	0.0814*	-0.0634*	-	-	-	-0.0014	-0.1401	-0.0043	-0.0442	-0.0165	-	-	-	3125	38.68	1093.35*
	(0.17)	(0.33)	(-0.32)	(-0.95)	(4.48)	(-3.49)				(-0.02)	(-1.80)	(-0.06)	(-0.57)	(-0.21)						
Japan	0.0000	0.0318	-	-	-	-	-	-	-	-0.0169	-	-	-	-	-	-	-	3129	68.22*	202.57*
	(0.02)	(1.72)								(-0.19)										
Netherlands	0.0001	0.0140	0.0005	-0.0643*	0.0446*	-0.0503*	-0.0187	0.0315	0.0835*	0.0179	-0.0230	-0.0608	0.0066	-0.0046	-0.0071	-0.0243	0.0695	3122	12.74	1258.22*
	(0.30)	(0.73)	(0.03)	(-3.37)	(2.34)	(-2.63)	(-0.98)	(1.65)	(4.38)	(0.22)	(-0.28)	(-0.74)	(0.08)	(-0.06)	(-0.09)	(-0.30)	(0.85)			
Spain	0.0001	-0.0105	-0.0326	-0.0336	0.0206	-0.0373*	-0.0225	-	-	0.1301	-0.0542	-0.0537	-0.0427	-0.0234	0.0584	-	-	3124	28.27	947.36*
	(0.48)	(-0.58)	(-1.79)	(-1.84)	(1.13)	(-2.04)	(-1.24)			(1.82)	(-0.75)	(-0.75)	(-0.59)	(-0.33)	(0.82)					
Sweden	0.0003	-0.0031	-	-	-	-	-	-	-	0.0194	-	-	-	-	-	-	-	3129	45.82	300.33*
	(1.03)	(-0.17)								(0.21)										
Switzerland	0.0001	0.0295	-0.0299	-0.0459*	0.0546*	-0.0719*	-0.0528*	-0.0288	-	0.0122	0.0309	-0.0584	0.0886	-0.0509	0.0027	-0.1094	-	3123	20.94	1082.21*
	(0.51)	(1.58)	(-1.60)	(-2.46)	(2.93)	(-3.85)	(-2.82)	(-1.54)		(0.17)	(0.43)	(-0.82)	(1.24)	(-0.71)	(0.04)	(-1.54)				
UK	0.0001	-0.0270	-0.0328	-0.0752*	0.0679*	-0.0533*	-0.0417*	-	-	0.0856	0.1487*	0.0363	0.0215	0.0019	0.0283	-	-	3124	29.17	1117.67*
	(0.59)	(-1.44)	(-1.75)	(-4.02)	(3.63)	(-2.85)	(-2.23)			(1.39)	(2.41)	(0.59)	(0.35)	(0.03)	(0.46)					
US	0.0001	-0.0528*	-0.0678*	-	-	-	-	-	-	0.1157*	-0.0689	-	-	-	-	-	-	3128	59.72*	654.40*
	(0.38)	(-2.83)	(-3.64)							(2.31)	(-1.37)									

Table 4: Selected Bivariate VAR Mean Equation Estimates and Diagnostics for Bonds

This table reports the parameter estimates and diagnostics of the vector autoregressive (VAR) model for the bond return series from January 1, 1999 to December 31, 2010 (3122-3129 observations with adjustments). To select the lag length (p), VAR models up to eight lags are estimated and the value of p that minimizesthe Akaike information criterion (AIC) of Akaike (1974) is selected. For Germany and Japan the suggested lag length is zero but the VAR(1) model is applied to them for practical reasons. The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the cross products of residuals. The White's test statistics of White (1980) is employed to test the null of no heteroskedasticity in the levels and squares of residuals (no cross terms included). The reported White's test statistics is the LM chi-square statistics for the joint significance of all regressors in the system of test equations. For further information, refer to the above mentioned papers, EViews 7 Manuals and the EViews code in Appendix 1.*Indicates significance at the 5% level.

Country	μ_2	φ^1_{21}	φ^2_{21}	φ^3_{21}	φ^4_{21}	φ^5_{21}	φ^6_{21}	φ^7_{21}	φ^8_{21}	φ^1_{22}	φ^2_{22}	φ^3_{22}	φ^4_{22}	φ^5_{22}	φ^6_{22}	φ^7_{22}	φ^8_{22}	Obs	$Q_{\varepsilon1\varepsilon2}(12)$	White
Australia	0.0002*	0.0215*	-0.0051	-	-	-	-	-	-	-0.0559*	-0.0582*	-	-	-	-	-	-	3128	51.37	630.95*
	(2.72)	(2.49)	(-0.59)							(-3.03)	(-3.16)									
Belgium	0.0002*	0.0103*	-	-	-	-	-	-	-	0.0380*	-	-	-	-	-	-	-	3129	56.40	353.88*
	(3.19)	(2.07)								(2.07)										
Canada	0.0002*	0.0146*	-0.0018*	-	-	-	-	-	-	0.0148	-0.0550*	-	-	-	-	-	-	3128	57.88	407.03*
	(3.65)	(2.56)	(-0.32)							(0.81)	(-3.01)									
France	0.0002*	0.0098*	-0.0060	0.0049	-0.0036	0.0090	0.0146*	-	-	0.0055	-0.0319	-0.0082	0.0098	-0.0260	0.0311	-	-	3124	20.72	931.60*
	(2.98)	(2.07)	(-1.28)	(1.03)	(-0.77)	(1.90)	(3.10)			(0.29)	(-1.69)	(-0.44)	(0.52)	(-1.38)	(1.65)					
Germany	0.0002*	-0.0041	-	-	-	-	-	-	-	0.0363	-	-	-	-	-	-	-	3129	46.96	205.52*
	(2.98)	(-0.86)								(1.93)										
Italy	0.0002*	0.0201*	-0.0074	0.0091*	-0.0019	0.0119*	0.0935*			-	-0.0409*	-0.0228	0.0104	-0.0202	-	-	-	3125	38.68	1093.35*
	(3.13)	(4.72)	(-1.74)	(2.14)	(-0.44)	(2.80)	(5.15)				(-2.25)	(-1.25)	(0.57)	(-1.12)						
Japan	0.0001*	-0.0014	-	-	-	-	-	-	-	-0.0148	-	-	-	-	-	-	-	3129	68.22*	202.57*
	(2.23)	(-0.37)								(-0.80)										
Netherlands	0.0002*	0.0098*	-0.0026	0.0048	-0.0036	0.0087	0.0072	0.0025	-0.0083	0.0574*	-0.0168	0.0008	0.0144	-0.0072	0.0055	-0.0043	-0.0022	3122	12.74	1258.22*
	(3.13)	(2.19)	(-0.57)	(1.07)	(-0.81)	(1.94)	(1.62)	(0.56)	(-1.86)	(3.00)	(-0.88)	(0.04)	(0.75)	(-0.38)	(0.29)	(-0.22)	(-0.12)			
Spain	0.0001*	0.0220*	-0.0049	-0.0014	-0.0030	0.0149*	0.0138*	-	-	0.0934*	-0.0267	-0.0431*	0.0298	-0.0119	0.0089	-	-	3124	28.27	947.36*
	(2.31)	(4.77)	(-1.06)	(-0.31)	(-0.65)	(3.21)	(3.00)			(5.14)	(-1.46)	(-2.36)	(1.63)	(-0.65)	(0.49)					
Sweden	0.0002*	-0.0015	-	-	-	-	-	-	-	0.0900*	-	-	-	-	-	-	-	3129	45.82	300.33*
	(3.19)	(-0.40)								(4.86)										
Switzerland	0.0001*	-0.0117*	0.0047	-0.0001	0.0090	0.0103*	0.0043	0.0036	-	0.0188	0.0227	0.0423*	0.0208	-0.0129	-0.0239	-0.0342	-	3123	20.94	1082.21*
	(2.55)	(-2.39)	(0.95)	(-0.02)	(1.83)	(2.10)	(0.88)	(0.74)		(1.00)	(1.21)	(2.26)	(1.11)	(-0.69)	(-1.28)	(-1.83)				
UK	0.0002*	0.0019	0.0003	0.0043	-0.0020	0.0165*	0.0169*	-	-	0.0538*	-0.0252	-0.0272	0.0230	-0.0022	-0.0112	-	-	3124	29.17	1117.67*
	(2.86)	(0.34)	(0.06)	(0.76)	(-0.36)	(2.90)	(2.98)			(2.87)	(-1.35)	(-1.45)	(1.23)	(-0.12)	(-0.60)					
US	0.0002*	0.0056	-0.0013	-	-	-	-	-	-	0.0060	-0.0679*	-	-	-	-	-	-	3128	59.72*	654.40*
	(2.26)	(0.81)	(-0.18)							(0.32)	(-3.63)									

Table 5: Test Results for the Null of Constant Conditional Correlations

This table reports the parameter estimates and diagnostics of the CCC-GARCH(1,1) model of Bollerslev (1990) for the residual series from January 1, 1999 to December 31, 2010 (3122-3129 observations with adjustments) together with the test results for the null of constant correlations. In the ML estimations of the CCC-GARCH(1,1) model, the presample covariance backcasting parameter is set to 0.7, and the Marquardt algorithm of Marquardt (1963) with maximum of 500 iterations and the convergence limit of 0.0001 is employed. The Logl refers to the estimated log likelihood. The Bollerslev and Wooldridge (1992) moment conditions (MC) are employed to test the null of consistent quasi-maximum likelihood (QML) estimates. Under the null, the mean standardized residuals are zero (MC_1, MC_2) and the mean standardized products of residuals are one (MC_3, MC_4, MC_5). The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the residuals standardized by their inverse square root of the residual covariance matrix. The numbers in the brackets below the parameter estimates represent the t-statistics computed using the Bollerslev and Wooldridge (1992) robust standard errors to take into account possible departures from the normality assumption, whereas the numbers in the brackets below the moment conditions represent the ordinary t-statistics. The studentized information matrix test (IM_S) of Bera and Kim (2002) and the DCC-test (ES_{DCC}) of Engle and Sheppard (2001) are employed to test against the null of constant correlation and they are all based on the CCC-GARCH(1,1) model estimates. The lag length for the ES_{DCC} test is arbitrarily chosen to be one. For further information, refer to the above mentioned papers, EViews 7 Manuals and the EViews code in Appendix 1. *Indicates significance at the 5% level.

Country	m_1	a_1	b_1	m_2	a_2	b_2	ρ_{12}	Logl	Obs	MC_1	MC_2	MC_3	MC_4	MC_5	$Q_{u1u2}(12)$	IM_S	ES_{DCC}
Australia	0.0000*	0.0809*	0.9084*	0.0000*	0.0203*	0.9768*	-0.1923*	23120.23	3128	-0.0031	-0.0016	0.9993	0.9989	0.9983	40.77	22.36*	11.92*
	(3.77)	(5.91)	(74.18)	(1.98)	(3.98)	(179.29)	(-9.61)			(-0.17)	(-0.09)	(-0.02)	(-0.04)	(-0.02)			
Belgium	0.0000*	0.1291*	0.8607*	0.0000*	0.0455*	0.9451*	-0.2018*	23857.66	3129	-0.0159	-0.0022	1.0001	1.0028	1.0028	34.00	19.04*	34.59*
	(3.70)	(6.17)	(43.04)	(2.65)	(4.50)	(86.54)	(-10.69)			(-0.89)	(-0.12)	(0.00)	(0.09)	(0.03)			
Canada	0.0000*	0.0651*	0.9273*	0.0000*	0.0309*	0.9613*	-0.1795*	23476.30	3128	-0.0093	-0.0003	0.9990	1.0004	0.9994	49.18	12.48*	11.01*
	(3.14)	(5.75)	(78.35)	(2.33)	(4.66)	(108.09)	(-8.66)			(-0.52)	(-0.02)	(-0.03)	(0.01)	(-0.00)			
France	0.0000*	0.0893*	0.8980*	0.0000	0.0302*	0.9653*	-0.3058*	23202.78	3124	-0.0083	-0.0043	0.9995	1.0012	1.0006	37.82	29.73*	18.88*
	(3.89)	(6.06)	(62.18)	(1.74)	(5.04)	(128.26)	(-16.29)			(-0.47)	(-0.24)	(-0.02)	(0.04)	(0.01)			
Germany	0.0000*	0.0944*	0.8884*	0.0000*	0.0333*	0.9595*	-0.3015*	23371.28	3129	-0.0060	-0.0037	1.0006	1.0042	1.0044	36.41	32.90*	23.40*
	(2.84)	(6.54)	(63.33)	(2.31)	(4.66)	(106.12)	(-15.94)			(-0.34)	(-0.21)	(0.02)	(0.14)	(0.06)			
Italy	0.0000*	0.1122*	0.8791*	0.0000*	0.0516*	0.9293*	-0.1777*	23605.20	3125	-0.0031	-0.0009	0.9997	0.9996	0.9992	48.58	5.50*	17.10*
	(3.82)	(6.40)	(56.45)	(1.97)	(2.60)	(34.74)	(-8.26)			(-0.17)	(-0.05)	(-0.01)	(-0.01)	(-0.01)			
Japan	0.0000*	0.0855*	0.8991*	0.0000*	0.0778*	0.9063*	-0.3077*	23846.48	3129	0.0011	-0.0012	0.9997	1.0013	1.0010	38.12	18.90*	45.41*
	(3.59)	(6.24)	(60.99)	(2.86)	(4.54)	(46.40)	(-16.27)			(0.06)	(-0.07)	(-0.01)	(0.04)	(0.01)			
Netherlands	0.0000*	0.0941*	0.8915*	0.0000*	0.0354*	0.9568*	-0.3176*	23449.55	3122	-0.0060	-0.0027	1.0009	1.0026	1.0032	47.91	25.57*	23.43*
	(3.96)	(6.08)	(55.53)	(2.32)	(4.82)	(101.55)	(-16.79)			(-0.33)	(-0.15)	(0.03)	(0.09)	(0.05)			
Spain	0.0000*	0.1091*	0.8761*	0.0000*	0.0637*	0.9204*	-0.1867*	23286.29	3124	-0.0095	-0.0038	0.9985	0.9986	0.9972	45.85	2.51	17.01*
	(3.90)	(6.15)	(53.84)	(2.22)	(2.13)	(28.06)	(-7.69)			(-0.53)	(-0.21)	(-0.05)	(-0.04)	(-0.02)			
Sweden	0.0000*	0.0745*	0.9171*	0.0000*	0.0512*	0.9324*	-0.2647*	22734.16	3129	-0.0061	-0.0035	1.0008	1.0005	1.0012	31.46	20.82*	28.01*
	(3.16)	(6.55)	(77.65)	(2.85)	(5.15)	(70.20)	(-13.58)			(-0.34)	(-0.20)	(0.03)	(0.02)	(0.02)			
Switzerland	0.0000*	0.1037*	0.8740*	0.0000	0.0319*	0.9609*	-0.2587*	24231.76	3123	-0.0086	-0.0041	0.9986	0.9989	0.9977	47.31	18.25*	11.75*
	(4.02)	(6.40)	(50.48)	(1.88)	(4.10)	(100.66)	(-13.34)			(-0.48)	(-0.23)	(-0.04)	(-0.03)	(-0.03)			
UK	0.0000*	0.0999*	0.8897*	0.0000*	0.0262*	0.9706*	-0.2604*	23365.01	3124	-0.0059	0.0007	0.9999	1.0019	1.0017	44.50	14.41*	15.74*
	(4.10)	(7.45)	(68.76)	(1.98)	(5.16)	(177.53)	(-13.36)			(-0.33)	(0.04)	(-0.00)	(0.07)	(0.02)			
US	0.0000*	0.0675*	0.9233*	0.0000*	0.0340*	0.9610*	-0.2370*	22218.01	3128	-0.0027	-0.0014	0.9998	1.0013	1.0010	46.43	34.53*	14.76*
	(2.94)	(6.77)	(93.88)	(2.30)	(5.13)	(123.59)	(-11.28)			(-0.15)	(-0.08)	(-0.01)	(0.04)	(0.01)			

Table 6: Selected Univariate GARCH Parameter Estimates and Diagnostics for Stocks

This table reports the parameter estimates and diagnostics of the selected univariate GARCH models for the stock residual series from January 1, 1999 to December 31, 2010 (3122-3129 observations with adjustments). In the univariate GARCH specification search, the GARCH model of Bollerslev (1986), the GJR-GARCH model of Glosten et al. (1993), the EGARCH model of Nelson (1991), and the APARCH model of Ding et al. (1993) are estimated with one lag of innovation, one lag of volatility, one order of asymmetry (where applicable), and assuming conditionally normally distributed errors. Then the models with the lowest Schwartz information criterion (SIC) of Schwarz (1978) are employed to standardize the stock residual series. In the ML estimations of the univariate GARCH models, the presample covariance backcasting parameter is set to 0.7, and the Marquardt algorithm of Marquardt (1963) with maximum of 500 iterations and the convergence limit of 0.0001 is employed. The Logl refers to the estimated log likelihood. The Bollerslev and Wooldridge (1992) moment conditions (MC) are employed to test the null of consistent quasi-maximum likelihood (QML) estimates. Under the null, the mean standardized residuals are zero (MC_1, MC_2) and the mean standardized products of residuals are one (MC_3, MC_4). The descriptive statistics are computed to evaluate the properties of the standardized residuals. The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the standardized residuals and the squared standardized residuals. The numbers in the brackets below the parameter estimates represent the t-statistics computed using the Bollerslev and Wooldridge (1992) robust standard errors to take into account possible departures from the normality assumption, whereas the numbers in the brackets below the moment conditions represent the ordinary t-statistics. For further information, refer to the above mentioned papers, EViews 7 Manuals and the EViews code in Appendix 1. *Indicates significance at the 5% level.

Country	Selected model	ω_1	α_1	γ_1	β_1	λ_1	Logl	SIC	Obs	MC_1	SD	Skewness	Kurtosis	$Q_{u1}(12)$	MC_3	$Q_{u1u1}(12)$	$ARCH_{u1u1}(12)$
Australia	EGARCH	-0.3088*	0.1385*	-0.1107*	0.9790*	-	10620.70	-6.78	3128	0.0069	1.00	-0.39	4.12	7.37	0.9996	16.27	14.95
		(-7.98)	(6.29)	(-8.00)	(293.04)					(0.39)					(-0.01)		
Belgium	GJR-GARCH	0.0000*	0.0289*	0.1517*	0.8842*	-	10217.50	-6.52	3129	0.0177	1.00	-0.24	4.10	5.80	1.0001	6.22	6.17
		(5.73)	(2.07)	(5.61)	(61.50)					(0.99)					(0.00)		
Canada	GJR-GARCH	0.0000*	0.0166	0.0836*	0.9273*	-	10215.82	-6.52	3128	0.0101	1.00	-0.50	4.31	21.07*	0.9991	9.84	9.33
		(5.61)	(1.29)	(5.23)	(90.71)					(0.57)					(-0.03)		
France	EGARCH	-0.3126*	0.1479*	-0.0928*	0.9779*	-	9593.29	-6.13	3124	0.0134	1.00	-0.33	4.05	16.20	0.9991	16.78	17.00
		(-6.51)	(4.72)	(-4.30)	(251.28)					(0.75)					(-0.03)		
Germany	APARCH	0.0002	0.0803*	0.7164*	0.9067*	1.1459*	9734.01	-6.21	3129	0.0088	1.00	-0.43	5.08	12.10	1.0002	11.46	11.73
		(1.18)	(5.22)	(3.78)	(70.57)	(6.54)				(0.49)					(0.01)		
Italy	EGARCH	-0.3384*	0.1685*	-0.1021*	0.9771*		9807.62	-6.27	3125	0.0076	1.00	-0.42	3.82	21.17*	0.9994	28.48*	27.93*
		(-7.76)	(6.84)	(-6.34)	(243.41)	-				(0.42)					(-0.02)		
Japan	GJR-GARCH	0.0000*	0.0282	0.1023*	0.8941*		9365.31	-5.98	3129	-0.0009	1.00	-0.29	4.04	7.62	0.9994	22.02*	22.33*
		(4.70)	(1.94)	(4.20)	(63.40)					(-0.05)					(-0.02)		
Netherlands	APARCH	0.0001	0.0651*	0.7524	0.9267*	1.2357*	9710.46	-6.21	3122	0.0077	1.00	-0.42	4.53	27.42*	1.0008	21.95*	21.67*
		(0.93)	(2.91)	(1.83)	(66.75)	(5.88)				(0.43)					(0.02)		
Spain	APARCH	0.0001	0.0723*	0.8712*	0.9108*	1.1832*	9708.70	-6.20	3124	0.0164	1.00	-0.32	3.82	20.32	0.9980	22.68*	22.65*
		(1.28)	(5.79)	(4.70)	(95.72)	(7.34)				(0.92)					(-0.07)		
Sweden	EGARCH	-0.2786*	0.1537*	-0.0872*	0.9812*	-	9019.31	-5.75	3129	0.0058	1.00	-0.20	4.01	5.40	1.0002	7.81	7.91
		(-5.94)	(5.54)	(-4.43)	(239.13)					(0.32)					(0.01)		
Switzerland	APARCH	0.0002	0.0676*	1.0000*	0.9165*	1.0624*	10265.81	-6.56	3123	0.0149	1.00	-0.37	4.16	24.49*	0.9982	19.90	20.20
		(1.70)	(4.56)	(2.91)	(146.38)	(8.76)				(0.83)					(-0.06)		
UK	EGARCH	-0.2679*	0.1279*	-0.1000*	0.9818*	-	10030.29	-6.41	3124	0.0083	1.00	-0.38	3.87	20.87	0.9994	21.22*	20.13
		(-7.76)	(7.58)	(-6.67)	(327.18)					(0.46)					(-0.02)		
US	GJR-GARCH	0.0000*	-0.0167	0.1296*	0.9412*	-	9804.94	-6.26	3128	0.0041	1.00	-0.42	4.31	14.23	1.0001	21.27*	20.86
		(6.45)	(-1.67)	(8.44)	(127.65)					(0.23)					(0.00)		

Table 7: Selected Univariate GARCH Parameter Estimates and Diagnostics for Bonds

This table reports the parameter estimates and diagnostics of the selected univariate GARCH models for the bond residual series from January 1, 1999 to December 31, 2010 (3122-3129 observations with adjustments). In the univariate GARCH specification search, the GARCH model of Bollerslev (1986), the GJR-GARCH model of Glosten et al. (1993), the EGARCH model of Nelson (1991), and the APARCH model of Ding et al. (1993) are estimated with one lag of innovation, one lag of volatility, one order of asymmetry (where applicable), and assuming conditionally normally distributed errors. Then, the univariate GARCH models with the lowest Schwartz information criterion (SIC) of Schwarz (1978) are selected to standardize the bond residual series. In the ML estimations of the univariate GARCH models, the presample covariance backcasting parameter is set to 0.7, and the Marquardt algorithm of Marquardt (1963) with maximum of 500 iterations and the convergence limit of 0.0001 is employed. The Logl refers to the estimated log likelihood. The Bollerslev and Wooldridge (1992) moment conditions (MC) are employed to test the null of consistent quasi-maximum likelihood (QML) estimates. Under the null, the mean standardized residuals (MC_1, MC_2) are zero and the mean standardized products of residuals (MC_3, MC_4) are one. The descriptive statistics are computed to evaluate the properties of the standardized residuals. The Ljung-Box Q-statistics of Ljung and Box (1978) is employed to test the null of no serial correlation up to the twelfth lag in the standardized residuals and the squared standardized residuals. The numbers in the brackets below the parameter estimates represent the t-statistics computed using the Bollerslev and Wooldridge (1992) robust standard errors to take into account possible departures from the normality assumption, whereas the numbers in the brackets below the moment conditions represent the ordinary t-statistics. For further information, refer to the above mentioned papers, EViews 7 Manuals and the EViews code in Appendix 1. *Indicates significance at the 5% level.

Country	Selected model	ω_2	α_2	γ_2	β_2	λ_2	Logl	SIC	Obs	MC_2	SD	Skewness	Kurtosis	$Q_{u2}(12)$	MC_4	$Q_{u2u2}(12)$	$ARCH_{u2u2}(12)$
Australia	GARCH	0.0000	0.0215*	-	0.9758*	-	12502.37	-7.99	3128	0.0017	1.00	-0.03	4.22	5.21	0.9980	14.10	14.64
		(0.84)	(4.04)		(170.14)					(0.09)					(-0.06)		
Belgium	GARCH	0.0000	0.0443*	-	0.9466*	-	13625.02	-8.70	3129	0.0021	1.00	-0.01	3.98	9.07	1.0029	9.99	11.31
		(1.23)	(4.76)		(96.10)					(0.12)					(0.10)		
Canada	GARCH	0.0000	0.0322*	-	0.9601*	-	13232.66	-8.45	3128	0.0003	1.00	-0.18	3.83	6.72	1.0002	17.90	18.37
		(1.13)	(5.14)		(113.57)					(0.02)					(0.01)		
France	GARCH	0.0000	0.0306*	-	0.9641*	-	13510.51	-8.64	3124	0.0043	1.00	-0.15	3.91	8.41	1.0003	15.24	14.72
		(0.95)	(5.14)		(126.93)					(0.24)					(0.01)		
Germany	GARCH	0.0000	0.0349*	-	0.9588*	-	13548.59	-8.65	3129	0.0038	1.00	-0.15	3.67	7.34	1.0038	8.22	10.08
		(1.07)	(4.83)		(105.70)					(0.21)					(0.13)		
Italy	GJR-GARCH	0.0000	0.0297*	0.0334*	0.9328*	-	13804.88	-8.82	3125	0.0016	1.00	-0.25	4.14	7.18	0.9993	39.17*	37.86*
		(1.47)	(2.85)	(1.98)	(57.55)					(0.09)					(-0.02)		
Japan	GJR-GARCH	0.0000	0.0559*	0.0422	0.9042*	-	14358.41	-9.17	3129	0.0016	1.00	-0.36	5.19	15.42	1.0008	11.56	11.40
		(1.61)	(2.67)	(1.66)	(51.91)					(0.09)					(0.02)		
Netherlands	GARCH	0.0000	0.0352*	-	0.9579*	-	13630.91	-8.72	3122	0.0027	1.00	-0.13	3.61	5.72	1.0021	7.70	7.60
		(1.10)	(5.24)		(111.49)					(0.15)					(0.07)		
Spain	GJR-GARCH	0.0000	0.0355*	0.0370	0.9294*	-	13602.60	-8.70	3124	0.0041	1.00	-0.02	4.51	6.88	0.9983	24.58*	22.84*
		(1.76)	(3.34)	(1.46)	(50.59)					(0.23)					(-0.05)		
Sweden	GARCH	0.0000	0.0525*	-	0.9305*	-	13644.53	-8.71	3129	0.0035	1.00	-0.03	3.95	9.98	1.0001	10.46	10.54
		(1.55)	(5.58)		(73.57)					(0.19)					(0.00)		
Switzerland	GARCH	0.0000	0.0326*	-	0.9595*	-	13940.71	-8.92	3123	0.0040	1.00	-0.13	5.54	9.10	0.9985	8.16	7.98
		(0.89)	(4.04)		(95.49)					(0.22)					(-0.04)		
UK	GARCH	0.0000	0.0267*	-	0.9702*	-	13275.55	-8.49	3124	-0.0007	1.00	-0.10	3.57	5.86	1.0013	11.29	10.32
		(0.89)	(5.10)		(172.16)					(-0.04)					(0.04)		
US	GARCH	0.0000	0.0348*	-	0.9625*	-	12393.03	-7.92	3128	0.0014	1.00	-0.10	4.05	14.96	1.0012	15.54	15.47
		(0.84)	(5.54)		(141.94)					(0.08)					(0.04)		

Table 8: Selected Bivariate DCC Parameter Estimates and Diagnostics

This table reports the parameter estimates and diagnostics of the selected bivariate DCC model(s) for the standardized residual series from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). In the bivariate DCC specification search, the mean-reverting scalar DCC(1,1) model of Engle (2002) and the mean-reverting scalar ADCC(1,1,1) of Cappiello et al. (2006) are estimated in a two-stage estimation procedure by first estimating the selected univariate GARCH models for each residual series and then, estimating the parameters of the DCC models using the standardized residuals, the residuals standardized by their conditional standard deviations, from the first stage estimation. Then, the DCC model(s) with the lowest Schwartz information criterion (SIC) of Schwarz (1978) are selected to estimate time-varying conditional intranational stock-bond correlations. In the ML estimations of the DCC models, the starting values are arbitrarily chosen to be close to a maximum point, and the BHHH gradient search algorithm of Berndt et al. (1974) with maximum of 100 iterations and the convergence limit of 0.0001 is employed. As a robustness check, several different starting values were given for the optimization to ensure that the algorithm is able to escape from a (possible) local maximum. The Logl refers to the estimated log likelihood. The HL_{DCC} statistics suggested by Engle and Sheppard (2001) is employed to measure the approximate persistency (half-life) of a shock to the estimated conditional correlations. The F-tests suggested by Engle (2002) are employed to test the null of no serial correlation up to the fifth lag in the squared and cross products of the triangular square root standardized residuals. The numbers in the brackets below the parameter estimates represent the t-statistics on modified standard errors (Engle and Sheppard, 2001). For further information, refer to the above mentioned papers, EViews 7 Manuals and the EViews code in Appendix 1. *Indicates significance at the 5% level.

Country	Selected model	α	β	Logl	SIC	Obs	HL_{DCC}(days)	F_1	F_2
Australia	DCC	0.0408*	0.9442*	-2986.86	1.92	3127	6.14	1.46	1.22
		(6.34)	(100.98)						
Belgium	DCC	0.0340*	0.9523*	-2996.20	1.92	3128	7.18	0.86	1.75
		(5.48)	(102.37)						
Canada	DCC	0.0256*	0.9634*	-3020.66	1.94	3127	9.37	2.27*	0.59
		(6.32)	(148.05)						
France	DCC	0.0266*	0.9635*	-2893.90	1.86	3123	9.43	1.48	0.60
		(6.25)	(156.97)						
Germany	DCC	0.0238*	0.9694*	-2896.98	1.86	3128	11.25	1.27	0.90
		(5.96)	(178.27)						
Italy	DCC	0.0369*	0.9467*	-2995.39	1.92	3124	6.42	2.52*	3.95*
		(5.71)	(96.30)						
Japan	DCC	0.0178*	0.9755*	-2924.61	1.88	3128	14.08	1.02	2.18*
		(5.17)	(191.06)						
Netherlands	DCC	0.0237*	0.9683*	-2888.15	1.85	3121	10.87	1.84*	0.84
		(6.99)	(207.87)						
Spain	DCC	0.0396*	0.9434*	-2965.67	1.90	3123	6.04	2.47*	3.05*
		(6.48)	(100.15)						
Sweden	DCC	0.0145*	0.9807*	-2960.43	1.90	3128	17.93	0.38	0.94
		(4.51)	(225.44)						
Switzerland	DCC	0.0135*	0.9821*	-2972.76	1.91	3122	19.27	1.47	0.37
		(4.48)	(243.17)						
UK	DCC	0.0234*	0.9643*	-2964.67	1.90	3123	9.60	1.25	0.57
		(7.04)	(190.28)						
US	DCC	0.0432*	0.9431*	-2928.49	1.88	3127	6.03	1.83	1.27
		(8.33)	(125.00)						

4.2 Testing for the Flights between Stocks and Bonds

This paper distinguishes between four types of intranational cross-asset flights between stocks and bonds, namely flight-to-liquidity *(FTL)*, flight-to-quality *(FTQ),* flight-from-liquidity *(FFL)*, and flight-from-quality *(FFQ)*. They are defined in accordance with the literature (see e.g. Forbes and Rigobon, 2002; Baur and Lucey, 2006) without any explicit definitions for shocks as follows. The flight-to-liquidity from stocks and bonds (to alternative assets) is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds (from alternative assets) is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns.[35] The equations for the flights can be expressed as follows.

$$FTL = (\hat{\rho}_t - \hat{\rho}_{t-20}) * I\left(\hat{\rho}_t - \hat{\rho}_{t-20} > 1.000\sigma_{\hat{\rho}_t} \cap \sum_{s=t-19}^{t} r_{1,s} < 0 \cap \sum_{s=t-19}^{t} r_{2,s} < 0\right) \quad (34)$$

$$FTQ = (\hat{\rho}_t - \hat{\rho}_{t-20}) * I\left(\hat{\rho}_t - \hat{\rho}_{t-20} < 1.000\sigma_{\hat{\rho}_t} \cap \sum_{s=t-19}^{t} r_{1,s} < 0 \cap \sum_{s=t-19}^{t} r_{2,s} > 0\right) \quad (35)$$

$$FFL = (\hat{\rho}_t - \hat{\rho}_{t-20}) * I\left(\hat{\rho}_t - \hat{\rho}_{t-20} > 1.000\sigma_{\hat{\rho}_t} \cap \sum_{s=t-19}^{t} r_{1,s} > 0 \cap \sum_{s=t-19}^{t} r_{2,s} > 0\right) \quad (36)$$

$$FFQ = (\hat{\rho}_t - \hat{\rho}_{t-20}) * I\left(\hat{\rho}_t - \hat{\rho}_{t-20} < 1.000\sigma_{\hat{\rho}_t} \cap \sum_{s=t-19}^{t} r_{1,s} > 0 \cap \sum_{s=t-19}^{t} r_{2,s} < 0\right) \quad (37)$$

where $\hat{\rho}_t$ denotes the estimated time-varying conditional correlation, $r_{1,s}$ denotes return on stocks, $r_{2,s}$ denotes return on bonds, and I is an indicator function having the value 1 for all values satisfying the given conditions and the value 0 otherwise.

[35] Different window lengths (e.g. 10 and 30 days) and threshold levels (e.g. 1.28 and 1.645 standard deviations) were considered as a part of the robustness analysis. According to the analysis, flights become more (less) frequent when the window length is lengthened (shortened) and the threshold level is decreased (increased). The window length of 20 days and threshold level of one standard deviation is selected to maintain the comparability of the estimates with Baur and Lucey (2006) and to correspond to institutional risk horizons.

4.3 Modeling the CAViaR of Equally Weighted Stock-Bond Portfolios

In this paper, the CAViaR models considered for equally weighted intranational stock-bond portfolios include the Symmetric Absolute Value given in (38), the Indirect GARCH(1,1) given in (39), the Asymmetric Slope given in (40), and the Adaptive given in (41). The two former models are symmetric, whereas the two latter models are asymmetric. All of the models are mean-reverting in the sense that the estimated coefficient for the lagged VaR is not constrained to be one. The estimation of the CAViaR models is completed by first constructing the percentage returns of an equally weighted stock-bond portfolio for each country and then using the first 2,892 observations to estimate the models and the last 238 observations for out-of-sample testing.

Let y_t be a vector of portfolio returns, T the sample size, $\theta \in (0,1)$ the probability associated with VaR_t, $\Im_t$ information set at time t, x_t a vector of time t observable variables, β_0 a p-vector of unknown parameters, and $f_t(\boldsymbol{\beta}) \equiv f_t(x_{t-1}, \beta_\theta)$ the time t θ-quantile of the distribution of portfolio returns formed at time $t-1$. Suppressing the subscript θ for notational convenience, the problem of finding the VaR $Pr[y_t < -VaR_t | \Im_t] = \theta$, to which a generic CAViaR solution of Engle and Manganelli (2004) translates into $f_t(\boldsymbol{\beta}) = \beta_0 + \sum_{i=1}^{q} \beta_i f_{t-i}(\boldsymbol{\beta}) + \sum_{j=1}^{r} \beta_j l(x_{t-j})$, where $p = q + r + 1$ is the dimension of $\boldsymbol{\beta}$, and l is a function of a finite number of lagged values of observables. In this setting, the role of the autoregressive terms, $\beta_i f_{t-i}(\boldsymbol{\beta})$, where $i = 1, \dots q$ is to ensure that the quantile changes smoothly over time, and the role of $l(x_{t-j})$, where $j = 1, \dots r$ is to link $f_t(\boldsymbol{\beta})$ to observable variables belonging to the information set. A natural choice for x_{t-1} is lagged returns. Denoting $(x)^+ = max(x, 0)$ and $(x)^- = -min(x, 0)$, the CAViaR models of Engle and Manganelli (2004) are specified as follows.

$$f_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 f_{t-1}(\boldsymbol{\beta}) + \beta_3 |y_{t-1}| \tag{38}$$

$$f_t(\boldsymbol{\beta}) = (\beta_1 + \beta_2 f_{t-1}^2(\boldsymbol{\beta}) + \beta_3 y_{t-1}^2)^{1/2} \tag{39}$$

$$f_t(\boldsymbol{\beta}) = \beta_1 + \beta_2 f_{t-1}(\boldsymbol{\beta}) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^- \tag{40}$$

$$f_t(\beta_1) = f_{t-1}(\beta_1) + \beta_1\{[1 + \exp(G[y_{t-1} - f_{t-1}(\beta_1)]^{-1} - \theta\} \tag{41}$$

where G is set to 10 and the other parameters are estimated by regression quantiles, $\min_\beta \frac{1}{T}\sum_{t=1}^{T}[\theta - I(y_t < f_t(\beta))][y_t - f_t(\beta)]$, as introduced by Koenker and Bassett (1978).

The performance of the CAViaR models is evaluated by the in-sample and the out-of-sample dynamic quantile (DQ) tests as proposed by Engle and Manganelli (2004). Particularly, the in-sample DQ test (DQ_{IS}) serves as a model selection criterion, whereas the out-of-sample DQ test (DQ_{OOS}) allows for example regulators to examine whether a particular VaR satisfy requirements for the good quantile estimate. The DQ tests are specified as follows.

$$DQ_{IS} \equiv \frac{Hit'(\hat{\beta})X(\hat{\beta})\left(\widehat{M}_T\widehat{M}'_T\right)^{-1}X'(\hat{\beta})Hit'(\hat{\beta})}{\theta(1-\theta)} \sim \chi_q^2 \quad \text{as } T \to \infty \tag{42}$$

$$DQ_{OOS} \equiv N_R^{-1}Hit'(\hat{\beta}_{T_R})X(\hat{\beta}_{T_R})\left[X'(\hat{\beta}_{T_R}) \cdot X(\hat{\beta}_{T_R})\right]^{-1} * \frac{X'(\hat{\beta}_{T_R})Hit'(\hat{\beta}_{T_R})}{\left(\theta(1-\theta)\right)} \sim \chi_q^2 \quad \text{as } R \to \infty \tag{43}$$

where the test variable, Hit_t, is defined as $Hit_t(\beta^0) \equiv I\left(y_t < f_t(\beta^0)\right) - \theta$, which takes value $(1-\theta)$ when y_t is less than the quantile and $-\theta$ otherwise. Consequently, if $Hit_t(\beta^0)$ satisfies its moment conditions of zero expected value and independency from its own lagged values and $f_t(\beta^0)$, there should be only correct fraction of hits in the sample. Additionally, $\widehat{M}_T \equiv X'^{(\hat{\beta})} - \left\{(2T\hat{c}_T)^{-1}\sum_{t=1}^{T} I\left(\left|y_t - f_t(\hat{\beta})\right| < \hat{c}_T\right) * X'_t\left(\hat{\beta}\right)\nabla f_t\left(\hat{\beta}\right)\right\}\widehat{D}_T^{-1}\nabla' f\left(\hat{\beta}\right)$, N_R denotes the number of out-of-sample observations, and T_R the number of in-sample observations.

Tables 9-10 report the 1% and the 5% quantile parameter estimates of the selected CAViaR specifications together with the percentage of hits and the DQ-test statistics for in-sample ($Hits_{IS}, DQ_{IS}$) and for out-of-sample ($Hits_{OOS}, DQ_{OOS}$) estimation. Based on the DQ_{IS}, the Asymmetric Slope model is selected for the both quantiles and all countries. The statistics indicate that the performance of the Asymmetric Slope model is satisfactory. The parameter estimates and diagnostics for the other estimated CAViaR models are available from the Author upon request. For further details on the computation of CAViaR models and the DQ tests, refer to Engle and Manganelli (2004) and references therein.

Table 9: Selected 1% CAViaR Parameter Estimates and Diagnostics

This table reports the parameter estimates and diagnostics of the selected 1% CAViaR model(s) for the returns of equally weighted stock-bond portfolios from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). In the CAViaR specification search, the Symmetric Absolute Value, the Indirect GARCH(1,1), the Asymmetric Slope, and the Adaptive models of Engle and Manganelli (2004) are estimated. Then, the CAViaR model(s) with the lowest number of rejections in the in-sample dynamic quantile test (DQ_{IS}) of Engle and Manganelli (2004) are selected to estimate the market risk of equally weighted stock-bond portfolios. The parameters are estimated by regression quantiles as introduced by Koenker and Bassett (1978) to the 1% quantile for one day time period using the first 2,892 observations to estimate the models and the last 238 observations for out-of-sample testing similarly to Engle and Manganelli (2004). The regression quantile (RQ) refers to the optimized (minimized) value of the regression quantile objective function. The percentage of hits ($Hits_{IS}$) and out-of-sample ($Hits_{OOS}$), are employed to measure how many times the VaR is exceeded. In the optimal scenario, there should be 1% of hits. The out-of-sample dynamic quantile test (DQ_{OOS}) of Engle and Manganelli (2004) allows for example regulators to examine whether a particular VaR satisfy requirements for the good quantile estimate. The numbers in the brackets represent the standard errors of the parameter estimates. The MATLAB codes for the calculation of the CAViaR models are made available by Simone Manganelli at http://www.simonemanganelli.org/Simone/Research.html. For further information on the CAViaR models and the DQ tests, refer to Engle and Manganelli (2004) and references therein. *Indicates significance at the 5% level.

Country	Selected model	β_1	β_2	β_3	β_4	RQ	$Hits_{IS}$	$Hits_{OOS}$	DQ_{IS} (p-value)	DQ_{OOS} (p-value)
Australia	Asymmetric Slope	0.0815*	0.8495*	-0.0305	0.6588*	42.27	1.00 %	0.41 %	0.92	0.96
		[0.04]	[0.08]	[0.15]	[0.38]					
Belgium	Asymmetric Slope	0.0953*	0.7959*	0.1624	0.6560*	42.89	1.04 %	2.47 %	0.71	0.39
		[0.04]	[0.08]	[0.13]	[0.35]					
Canada	Asymmetric Slope	0.0333*	0.9118*	0.1180	0.3320*	49.30	1.00 %	0.00 %	0.76	NaN
		[0.01]	[0.03]	[0.09]	[0.09]					
France	Asymmetric Slope	0.0344*	0.9258*	0.0456	0.2685*	51.05	0.97 %	1.65 %	0.64	0.95
		[0.01]	[0.02]	[0.05]	[0.12]					
Germany	Asymmetric Slope	0.1162*	0.8241*	0.1431	0.4175*	48.71	1.00 %	0.41 %	0.87	0.99
		[0.05]	[0.07]	[0.15]	[0.13]					
Italy	Asymmetric Slope	0.0544*	0.8746*	0.1769*	0.4198*	52.06	1.04 %	1.65 %	0.56	0.95
		[0.02]	[0.03]	[0.08]	[0.10]					
Japan	Asymmetric Slope	0.1112*	0.8349*	0.1587	0.5270*	58.87	0.97 %	0.82 %	0.66	1.00
		[0.04]	[0.05]	[0.13]	[0.11]					
Netherlands	Asymmetric Slope	0.0400*	0.8961*	0.0783	0.3966*	48.87	1.00 %	1.23 %	0.03	0.93
		[0.02]	[0.02]	[0.06]	[0.12]					
Spain	Asymmetric Slope	0.1183*	0.8232*	0.0917	0.5247*	49.82	0.97 %	1.65 %	0.49	0.99
		[0.02]	[0.04]	[0.09]	[0.14]					
Sweden	Asymmetric Slope	0.0541*	0.9235*	0.0425	0.2587*	64.36	1.00 %	0.82 %	0.05	1.00
		[0.02]	[0.02]	[0.04]	[0.10]					
Switzerland	Asymmetric Slope	0.0349*	0.9169*	0.0002	0.3541*	44.05	1.07 %	0.41 %	0.71	NaN
		[0.01]	[0.02]	[0.06]	[0.06]					
UK	Asymmetric Slope	0.0480*	0.8746*	0.1053	0.5369*	48.07	0.97 %	0.41 %	0.50	0.99
		[0.03]	[0.04]	[0.14]	[0.12]					
US	Asymmetric Slope	0.0398*	0.9156*	0.0450	0.3170*	50.34	1.00 %	1.65 %	0.03	0.77
		[0.01]	[0.02]	[0.05]	[0.03]					

Table 10: Selected 5% CAViaR Parameter Estimates and Diagnostics

This table reports the parameter estimates and diagnostics of the selected 5% CAViaR model(s) for the returns of equally weighted stock-bond portfolios from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). In the CAViaR specification search, the Symmetric Absolute Value, the Indirect GARCH(1,1), the Asymmetric Slope, and the Adaptive models of Engle and Manganelli (2004) are estimated. Then, the CAViaR model(s) with the lowest number of rejections in the in-sample dynamic quantile test (DQ_{IS}) of Engle and Manganelli (2004) are selected to estimate the market risk of equally weighted stock-bond portfolios. The parameters are estimated by regression quantiles as introduced by Koenker and Bassett (1978) to the 5% quantile for one day time period using the first 2,892 observations to estimate the models and the last 238 observations for out-of-sample testing similarly to Engle and Manganelli (2004). The regression quantile (RQ) refers to the optimized (minimized) value of the regression quantile objective function. The percentage of hits ($Hits_{IS}$) and out-of-sample ($Hits_{OOS}$), are employed to measure how many times the VaR is exceeded. In the optimal scenario, there should be 5% of hits. The out-of-sample dynamic quantile test (DQ_{OOS}) of Engle and Manganelli (2004) allows for example regulators to examine whether a particular VaR satisfy requirements for the good quantile estimate. The numbers in the brackets represent the standard errors of the parameter estimates. The MATLAB codes for the calculation of the CAViaR models are made available by Simone Manganelli at http://www.simonemanganelli.org/Simone/Research.html. For further information on the CAViaR models and the DQ tests, refer to Engle and Manganelli (2004) and references therein. *Indicates significance at the 5% level.

Country	Selected model	β_1	β_2	β_3	β_4	RQ	$Hits_{IS}$	$Hits_{OOS}$	DQ_{IS} (p-value)	DQ_{OOS} (p-value)
Australia	Asymmetric Slope	0.0279*	0.9107*	0.0057	0.2294*	150.42	4.98 %	3.70 %	0.68	0.82
		[0.01]	[0.04]	[0.04]	[0.08]					
Belgium	Asymmetric Slope	0.0240*	0.8800*	0.0658*	0.3227*	160.25	5.05 %	7.00 %	0.13	0.25
		[0.01]	[0.02]	[0.03]	[0.05]					
Canada	Asymmetric Slope	0.0065	0.9351*	0.0609	0.1897*	172.90	4.98 %	4.94 %	0.38	0.28
		[0.01]	[0.02]	[0.04]	[0.05]					
France	Asymmetric Slope	0.0196*	0.9206*	0.0263	0.2280*	183.49	5.05 %	6.17 %	0.61	0.91
		[0.00]	[0.01]	[0.03]	[0.03]					
Germany	Asymmetric Slope	0.0334*	0.8827*	0.0489	0.3158*	180.00	5.01 %	4.53 %	0.76	0.91
		[0.01]	[0.03]	[0.06]	[0.07]					
Italy	Asymmetric Slope	0.0171*	0.9153*	0.0573	0.2456*	185.72	5.01 %	6.58 %	0.29	0.02
		[0.00]	[0.03]	[0.07]	[0.06]					
Japan	Asymmetric Slope	0.0273*	0.9101*	0.0428	0.2435*	204.77	5.08 %	4.53 %	0.89	0.83
		[0.01]	[0.02]	[0.03]	[0.04]					
Netherlands	Asymmetric Slope	0.0244*	0.8916*	0.0655	0.2969*	183.35	5.05 %	4.53 %	0.26	0.71
		[0.01]	[0.03]	[0.06]	[0.08]					
Spain	Asymmetric Slope	0.0221*	0.9296*	0.0138	0.1902*	182.04	5.01 %	7.41 %	0.56	0.00
		[0.00]	[0.02]	[0.04]	[0.03]					
Sweden	Asymmetric Slope	0.0205*	0.9311*	0.0392	0.1792*	229.62	5.05 %	4.12 %	0.47	0.18
		[0.01]	[0.01]	[0.03]	[0.02]					
Switzerland	Asymmetric Slope	0.0211*	0.9318*	-0.0404	0.2313*	160.47	5.01 %	5.35 %	0.84	0.88
		[0.01]	[0.02]	[0.03]	[0.05]					
UK	Asymmetric Slope	0.0186*	0.9249*	-0.0129	0.2581*	173.31	5.01 %	4.94 %	0.55	0.85
		[0.00]	[0.02]	[0.03]	[0.06]					
US	Asymmetric Slope	0.0179*	0.9538*	-0.0139	0.1334*	184.21	5.05 %	6.17 %	0.94	0.61
		[0.00]	[0.01]	[0.02]	[0.02]					

5. Empirical Results

The underlying hypothesis of this paper is that the financial markets of the world's most advanced economies exhibit financial market stability even under extreme market conditions and potentially systemic events. The econometric framework employed to assess whether a country exhibits financial market stability or not includes modeling the time-varying conditional intranational stock-bond correlations, testing for the intranational flights between stocks and bonds, and modeling the conditional autoregressive value at risk (CAViaR) of equally weighted intranational stock-bond portfolios. This section presents the empirical results and discusses their implications on the validity of the hypothesis.

First, Table 11 reports the monthly, and total period averages of the daily conditional intranational stock-bond correlation estimates. Additionally, the annual averages of the daily conditional intranational stock-bond correlation estimates and the selected percentiles of the daily conditional intranational stock-bond correlation estimates are given in Appendices 3-4. The conditional intranational stock-bond correlation estimates show relatively similar patterns across the sample countries, varying mostly below zero throughout the sample period. The lowest total period average conditional intranational stock-bond correlations are reported in the Netherlands (-0.31) and in Japan (-0.30), whereas the highest total period average conditional intranational stock-bond correlations are reported in Canada (-0.17) and Australia (-0.18). Thus, even the highest total period average conditional intranational stock-bond correlations are highly negative. Interestingly, the periods of extremely negative conditional intranational stock-bond correlations take place around the South American economic crisis in 2002, the global financial crisis starting from February, 2007, and the European sovereign debt crisis starting from April, 2010. The finding of pervasive negative correlation is in contrast with the fundamental line of research trying to explain stock-bond return relation based on the rational expectations present value models (see e.g. Shiller and Beltratti, 1992; Campbell and Ammer, 1993). However, it is well in line with the empirical line of research trying to explain stock-bond return relation based on the observed data (see e.g. Ilmanen, 2003; Connolly et al., 2005). For example, Ilmanen (2003) finds that the correlation turns negative at the end of the 1990s and concludes that 'the negative relation (between stocks and bonds) is so pervasive that the new generation of market participants cannot even fathom that positive correlation was the standard only a few years ago'. Overall, the pervasive negative relation between stocks and bonds implies that the bonds are excellent safe havens against major systematic risks (Ilmanen, 2003). The largest differences between the monthly average intranational stock-bond correlations are reported in May and June 2010, after the early signs of the European sovereign debt crisis had emerged. At the time, the lowest monthly average conditional intranational stock-bond correlations are found in the US (-0.64 and -0.67) and Germany (-0.64 and -0.66), whereas the highest monthly average intranational stock-bond correlations are found in Spain (0.45 and 0.32) and Italy (0.31 and 0.22). In the context of financial market stability, these extreme differences between the conditional intranational stock-bond correlations are alarming because they imply that the Italian and Spanish stock and bonds are becoming more ‘equity like’ and losing their safe haven status. Earlier, Kim et al. (2006) has found signs that the stock and bond markets in Italy have become more integrated compared to the stock and bond markets in other major developed markets.

Second, Tables 12-15 report the monthly intranational flight-to-liquidity, flight-to-quality, flight-from-liquidity, and flight-from-quality estimates and the threshold levels employed to compute them. Additionally, Tables 16-19 report the annual and total period frequencies of the intranational flight-to-liquidity, flight-to-quality, flight-from-liquidity, and flight-from-quality. The intranational flights between stocks and bonds are relatively common phenomena occurring almost throughout the sample and being frequently associated with extreme market conditions and potentially systemic events, although the frequencies of flights vary considerable between the sample countries. In the sample, there are altogether 553 days of flight-to-liquidity, 982 days of flight-to-quality, 671 days of flight-from-liquidity, and 367 days of flight-from-quality. The flight-to-quality turns out to be the only flight that is more common in extreme market conditions between 2007 and 2010 than in normal market conditions between 1999 and 2006 indicating that bonds are considered as safe haven under extreme market conditions. The flight-to-liquidity is the most frequent in Italy (78 days) and Spain (71 days) and the least frequent in the Netherlands (8 days) and Switzerland (18 days). On aggregate level, the flight-to-liquidity is the most pronounced around the South American economic crisis in 1999 and the 10-year US Treasury yield rise in May, 2004. Importantly, the flight-to-liquidity is not the most prevalent flight around the global financial crisis starting from February, 2007, and the European sovereign debt crisis starting from April, 2010, expect in Italy and Spain, where altogether 68 days of flight-to-liquidity were recorded only in 2010. This finding indicates that the flight-to-liquidity, commonly attributable to developing countries, has recently arrived in the heart of Europe with the potential to increase the propagation of shocks and contribute negatively to the resiliency of stock-bond diversification benefits, thus weakening financial market stability. The flight-to-quality is the most frequent in Australia (143 days) and the US (136 days) and the least frequent in Germany (18 days) and Japan (29 days). On aggregate level, the flight-to-quality is the most pronounced around the South American economic crisis between 2000 and 2002, the September 11 terrorist attacks in 2001, the global financial crisis starting from February, 2007, and the European sovereign debt crisis starting from April, 2010. The prevalence of flight-to-quality around the global financial crisis starting from February, 2007, and the European sovereign debt crisis starting from April, 2010 indicates that investors rely on the safe haven property of government bonds under extreme market conditions and potentially systemic events. This has the potential to limit the propagation of shocks and contribute positively to the resiliency of stock-bond diversification benefits, thus improving financial market stability. The flight-from-liquidity is the most frequent in Australia (112 days) and Belgium (93 days) and the least frequent in Sweden (9 days) and Switzerland (16 days). The flight-from-quality is the most frequent in Spain (55 days) and Belgium (47 days) and the least frequent in Japan (5 days) and Switzerland (6 days). On aggregate level, neither the flight-from-liquidity, nor the flight-from-quality is clearly associated with extreme market conditions or potentially systemic events and thus they are not considered important for the assessment of financial market stability. Overall, the dominance of flight-to-quality between stocks and bonds under extreme market conditions and potentially systemic events is in line with the literature (see e.g. Hartmann et al., 2004; Baur and Lucey, 2009).

Third, Tables 20-21 report the monthly and total period averages of the daily 1% and 5% CAViaR estimates of equally weighted intranational stock-bond portfolios. Additionally, the annual averages of the daily 1% and 5% CAViaR estimates of equally weighted intranational stock-bond portfolios and the selected percentiles of the daily 1% and 5% CAViaR estimates of equally weighted intranational stock-bond portfolios are given in Appendices 5-8. The 1% and 5% CAViaR estimates of equally weighted intranational stock-bond portfolio show fairly similar patterns across the sample countries by varying mostly around their means, and occasionally spiking as an indication of increased market risk for example around the September 11 terrorist attacks in 2001, the South American economic crisis in 2002 and after the peak of the global financial crisis in 2008. These spikes are most often associated with flight-to-quality effect indicating that investors turn to bonds in the face of high market risk. The lowest total period average 1% CAViaR are reported in Switzerland (1.20%) and Australia (1.24%), whereas the highest total period average 1% CAViaR are reported in Sweden (1.75%) and Japan (1.63%). The lowest total period average 5% CAViaR are reported in Australia (0.76%) and Switzerland (0.82%), whereas the highest total period average 5% CAViaR are reported in Sweden (1.15%) and Japan (1.04%). The most excessive divergent spillover effects take place in Italy and Spain around the beginning of the European sovereign debt crisis starting in April, 2010, which implies that Italy and Spain do not exhibit financial market stability to a similar degree than the other sample countries do.

Finally, Figures 1-13 show the daily estimates of the conditional intranational stock-bond correlations, the intranational flights between stocks and bonds, and the 1% and 5% CAViaR of equally weighted intranational stock-bond portfolios. These figures are especially useful in summing up the empirical results in an easily understandable format and enabling chronologically flexible interpretation of results. Furthermore, they are equally scaled to ensure full comparability between the sample countries. To sum up, the empirical results show that the world's most advanced economies, except Italy and Spain, exhibit financial market stability under extreme market conditions and potentially systemic events as assessed by their intranational stock-bond return relations. In the financially stable countries under extreme market conditions and potentially systemic events, the conditional intranational stock-bond correlations tend to stay below or close to zero, the intranational flights between stocks and bonds tend to rather reduce than aggravate the propagation of shocks, and the CAViaR of equally weighted intranational stock-bond portfolios resemble each other to a high degree without showing hardly any excessive divergent spillover effects. In Italy and Spain, the conditional intranational stock-bond correlations have recently turned from negative to positive, the intranational flights between stocks and bonds tend to rather aggravate than reduce the propagation of shocks, and the CAViaR of equally weighted intranational stock-bond portfolios show excessive divergent spillover effects. It is hardly surprising that Italy and Spain prove out to be the only exceptions that do not exhibit financial market stability as assessed by their intranational stock-bond return relations given their inferior credit ratings compared to the 'AAA' rated countries (see Appendix 9). In addition to their inferior credit ratings, Italy and Spain have been facing increasingly widening credit default swap (CDS) premium differentials and government bond yield spreads compared to traditionally more stable nations such as Germany, Switzerland, and the United States (see Appendices 10-11). Overall, these results in favor of prevailing financial market stability even under extreme market conditions and potentially systemic events are relatively well in line with the rare empirical literature on financial market stability with the emphasis on cross-asset linkages in developed markets.

Table 11: Conditional Correlation Estimates (Monthly Averages)

This table reports the monthly and total period averages of the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). Note that the table continues on the next page. For further information, refer to Section 4.1.

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
January 1999	0.00	-0.29	-0.35	-0.52	-0.30	-0.23	0.07	-0.10	-0.44	0.09	-0.69	-0.40	-0.48
February 1999	-0.09	-0.37	-0.14	-0.21	-0.26	-0.16	0.00	-0.29	-0.22	-0.22	-0.30	-0.28	-0.11
March 1999	0.08	0.07	0.05	0.06	0.05	-0.13	-0.09	0.13	-0.09	0.07	0.09	0.04	0.12
April 1999	-0.07	0.08	0.11	0.07	0.08	-0.13	-0.07	0.11	0.02	0.09	0.16	0.00	0.08
May 1999	0.27	0.01	0.24	-0.03	0.08	0.09	-0.02	0.08	0.03	0.07	0.06	-0.06	0.18
June 1999	0.23	0.21	0.24	0.09	0.07	0.19	-0.11	0.14	0.08	0.09	0.11	0.01	0.20
July 1999	0.17	0.30	0.14	0.04	0.04	0.07	-0.03	-0.02	0.08	0.07	0.07	-0.10	0.22
August 1999	0.26	0.22	0.17	-0.04	0.03	-0.06	-0.15	-0.05	0.01	0.03	0.07	0.00	0.35
September 1999	0.17	0.26	0.16	-0.19	0.08	0.04	-0.20	0.05	0.02	0.08	0.14	0.11	0.41
October 1999	0.06	0.14	0.12	-0.10	0.00	0.03	-0.26	-0.04	0.00	0.04	0.05	0.07	0.15
November 1999	0.07	0.32	0.17	0.07	0.07	0.02	-0.25	-0.01	0.14	0.07	0.09	0.08	0.21
December 1999	0.00	0.19	0.13	-0.12	-0.07	-0.10	-0.24	-0.16	0.07	0.04	0.00	-0.08	0.10
January 2000	0.06	0.19	0.21	-0.06	0.11	0.03	-0.17	-0.10	0.15	-0.02	0.06	0.16	-0.07
February 2000	-0.01	0.08	0.00	-0.03	0.11	0.00	-0.15	-0.13	0.07	-0.03	0.07	0.04	-0.10
March 2000	-0.02	-0.11	-0.14	-0.04	0.09	0.02	-0.15	-0.20	-0.03	-0.02	0.01	-0.05	-0.04
April 2000	-0.21	-0.12	-0.21	0.02	-0.06	-0.09	-0.21	-0.28	-0.16	-0.07	-0.13	-0.10	-0.11
May 2000	-0.20	-0.14	-0.20	-0.06	-0.11	-0.11	-0.32	-0.20	-0.10	-0.08	-0.17	-0.07	-0.18
June 2000	-0.05	-0.13	-0.11	-0.08	0.00	0.01	-0.37	0.01	0.00	-0.02	-0.09	0.04	-0.08
July 2000	0.14	0.00	-0.05	-0.17	-0.06	-0.12	-0.29	-0.03	-0.06	-0.07	-0.04	-0.08	-0.04
August 2000	0.08	-0.11	0.02	-0.20	-0.07	-0.12	-0.31	-0.08	-0.09	-0.09	-0.03	-0.15	0.01
September 2000	0.09	-0.03	0.10	-0.01	0.12	-0.01	-0.24	0.01	0.07	-0.01	-0.03	0.08	0.14
October 2000	0.00	-0.06	0.02	-0.13	0.03	-0.08	-0.19	-0.15	-0.07	-0.09	-0.13	-0.07	-0.09
November 2000	-0.07	-0.16	-0.02	-0.15	-0.12	-0.12	-0.32	-0.27	-0.19	-0.19	-0.18	-0.24	-0.23
December 2000	-0.23	-0.05	-0.11	-0.18	-0.16	-0.32	-0.39	-0.24	-0.16	-0.26	-0.23	-0.26	-0.31
January 2001	-0.32	-0.06	-0.35	-0.29	-0.20	-0.44	-0.41	-0.24	-0.15	-0.33	-0.21	-0.29	-0.54
February 2001	0.02	-0.07	-0.30	-0.27	-0.20	-0.23	-0.31	-0.21	-0.11	-0.28	-0.16	-0.24	-0.33
March 2001	0.00	-0.13	-0.25	-0.32	-0.24	-0.12	-0.20	-0.24	-0.22	-0.27	-0.26	-0.26	-0.29
April 2001	-0.10	-0.22	-0.28	-0.39	-0.34	-0.16	-0.06	-0.32	-0.37	-0.28	-0.40	-0.35	-0.39
May 2001	-0.13	-0.25	-0.19	-0.32	-0.30	-0.20	-0.14	-0.24	-0.23	-0.31	-0.38	-0.22	-0.21
June 2001	-0.09	-0.09	-0.06	-0.20	-0.19	-0.25	-0.22	-0.18	-0.17	-0.20	-0.31	-0.08	-0.05
July 2001	-0.04	-0.21	-0.14	-0.28	-0.27	-0.22	-0.17	-0.27	-0.20	-0.17	-0.31	-0.19	-0.17
August 2001	0.12	-0.28	-0.25	-0.31	-0.28	-0.13	-0.15	-0.31	-0.30	-0.18	-0.29	-0.29	-0.32
September 2001	-0.15	-0.37	-0.37	-0.45	-0.43	0.05	-0.09	-0.45	-0.49	-0.17	-0.40	-0.41	-0.30
October 2001	-0.15	-0.26	-0.34	-0.37	-0.33	0.06	-0.07	-0.38	-0.30	-0.15	-0.34	-0.34	-0.14
November 2001	-0.12	-0.26	-0.21	-0.31	-0.23	-0.03	-0.12	-0.29	-0.25	-0.20	-0.35	-0.32	-0.12
December 2001	-0.01	-0.20	-0.21	-0.31	-0.27	-0.18	-0.16	-0.29	-0.27	-0.26	-0.32	-0.33	-0.09
January 2002	0.00	-0.25	-0.13	-0.36	-0.32	-0.29	-0.20	-0.31	-0.34	-0.26	-0.33	-0.28	-0.20
February 2002	-0.25	-0.22	-0.19	-0.33	-0.32	-0.41	-0.01	-0.35	-0.34	-0.26	-0.34	-0.22	-0.36
March 2002	-0.16	-0.12	-0.16	-0.32	-0.32	-0.40	0.04	-0.32	-0.24	-0.32	-0.32	-0.16	-0.25
April 2002	0.05	-0.04	-0.14	-0.33	-0.29	-0.31	0.03	-0.35	-0.20	-0.26	-0.25	-0.23	-0.26
May 2002	-0.18	-0.13	-0.30	-0.42	-0.33	-0.28	-0.05	-0.35	-0.23	-0.29	-0.28	-0.26	-0.43
June 2002	-0.28	-0.31	-0.41	-0.48	-0.45	-0.42	-0.06	-0.42	-0.42	-0.35	-0.35	-0.37	-0.43
July 2002	-0.45	-0.53	-0.50	-0.61	-0.58	-0.56	-0.11	-0.58	-0.57	-0.43	-0.46	-0.51	-0.49
August 2002	-0.51	-0.56	-0.47	-0.60	-0.59	-0.49	-0.07	-0.57	-0.48	-0.49	-0.51	-0.52	-0.47
September 2002	-0.42	-0.57	-0.44	-0.63	-0.63	-0.48	-0.06	-0.59	-0.50	-0.48	-0.52	-0.55	-0.51
October 2002	-0.36	-0.51	-0.48	-0.59	-0.58	-0.49	-0.03	-0.59	-0.44	-0.46	-0.54	-0.52	-0.64
November 2002	-0.42	-0.47	-0.48	-0.51	-0.48	-0.39	-0.05	-0.53	-0.38	-0.49	-0.53	-0.42	-0.64
December 2002	-0.47	-0.51	-0.48	-0.55	-0.54	-0.48	-0.11	-0.57	-0.54	-0.49	-0.51	-0.42	-0.59
January 2003	-0.31	-0.53	-0.39	-0.63	-0.62	-0.61	-0.17	-0.63	-0.56	-0.50	-0.46	-0.43	-0.63
February 2003	-0.20	-0.48	-0.29	-0.60	-0.58	-0.55	-0.21	-0.62	-0.48	-0.46	-0.39	-0.42	-0.52
March 2003	-0.31	-0.51	-0.38	-0.56	-0.52	-0.48	-0.28	-0.58	-0.46	-0.47	-0.35	-0.35	-0.56
April 2003	-0.46	-0.58	-0.44	-0.62	-0.57	-0.52	-0.36	-0.64	-0.52	-0.50	-0.35	-0.49	-0.62
May 2003	-0.40	-0.36	-0.26	-0.51	-0.50	-0.34	-0.28	-0.55	-0.44	-0.49	-0.34	-0.41	-0.34
June 2003	-0.15	-0.32	-0.21	-0.46	-0.48	-0.36	-0.21	-0.49	-0.36	-0.47	-0.35	-0.37	-0.26
July 2003	0.03	-0.24	-0.27	-0.37	-0.40	-0.25	-0.27	-0.37	-0.23	-0.42	-0.26	-0.27	-0.16
August 2003	0.01	-0.26	-0.18	-0.36	-0.36	-0.27	-0.32	-0.33	-0.30	-0.38	-0.20	-0.26	0.08
September 2003	-0.11	-0.18	-0.19	-0.32	-0.32	-0.20	-0.41	-0.29	-0.27	-0.33	-0.28	-0.20	-0.16
October 2003	-0.26	-0.32	-0.26	-0.42	-0.35	-0.31	-0.39	-0.42	-0.38	-0.37	-0.32	-0.30	-0.35
November 2003	-0.19	-0.30	-0.28	-0.43	-0.40	-0.33	-0.45	-0.46	-0.38	-0.38	-0.34	-0.27	-0.31
December 2003	-0.10	-0.29	-0.22	-0.43	-0.42	-0.40	-0.48	-0.48	-0.33	-0.38	-0.34	-0.25	-0.29
January 2004	-0.02	-0.20	-0.19	-0.39	-0.39	-0.25	-0.47	-0.49	-0.20	-0.33	-0.33	-0.30	-0.22
February 2004	0.10	-0.01	-0.06	-0.15	-0.16	-0.08	-0.43	-0.28	0.12	-0.22	-0.24	-0.14	0.00
March 2004	0.10	-0.02	0.00	-0.17	-0.16	-0.13	-0.42	-0.26	-0.01	-0.23	-0.29	-0.17	-0.01
April 2004	0.03	-0.17	-0.12	-0.30	-0.28	-0.36	-0.42	-0.34	-0.26	-0.25	-0.29	-0.26	-0.14
May 2004	0.18	-0.09	0.03	-0.18	-0.17	-0.13	-0.32	-0.22	-0.10	-0.17	-0.20	-0.10	0.10
June 2004	0.12	0.01	0.02	-0.07	-0.08	0.00	-0.33	-0.11	0.00	-0.13	-0.16	-0.05	0.12
July 2004	0.03	-0.08	-0.02	-0.14	-0.12	-0.08	-0.29	-0.17	-0.10	-0.14	-0.12	-0.14	-0.04
August 2004	-0.15	-0.19	-0.12	-0.24	-0.22	-0.18	-0.35	-0.28	-0.19	-0.20	-0.18	-0.19	-0.32
September 2004	0.09	-0.32	-0.08	-0.35	-0.30	-0.35	-0.39	-0.38	-0.35	-0.23	-0.20	-0.25	-0.24

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
October 2004	-0.01	-0.43	-0.17	-0.45	-0.40	-0.39	-0.50	-0.45	-0.40	-0.32	-0.23	-0.32	-0.40
November 2004	-0.05	-0.37	-0.11	-0.40	-0.35	-0.30	-0.51	-0.45	-0.40	-0.35	-0.18	-0.29	-0.23
December 2004	-0.02	-0.20	-0.04	-0.27	-0.25	-0.12	-0.42	-0.32	-0.21	-0.33	-0.17	-0.23	0.02
January 2005	-0.08	-0.01	0.04	-0.06	-0.05	0.02	-0.35	-0.13	-0.04	-0.15	-0.05	-0.10	0.01
February 2005	-0.05	-0.01	-0.01	-0.02	0.04	0.11	-0.31	-0.09	0.04	-0.10	-0.04	-0.03	-0.05
March 2005	-0.16	0.13	0.13	-0.04	0.03	0.16	-0.36	-0.06	0.08	-0.07	-0.08	-0.01	0.25
April 2005	-0.16	0.04	0.15	-0.10	-0.06	0.02	-0.37	-0.10	-0.09	-0.06	-0.09	-0.11	0.03
May 2005	-0.25	-0.14	-0.11	-0.23	-0.20	-0.15	-0.32	-0.20	-0.21	-0.13	-0.08	-0.20	-0.19
June 2005	-0.11	-0.05	-0.09	-0.04	-0.02	-0.06	-0.27	-0.10	0.01	-0.15	0.01	-0.10	-0.04
July 2005	-0.18	-0.18	-0.16	-0.15	-0.12	-0.19	-0.29	-0.22	-0.17	-0.15	-0.06	-0.25	-0.20
August 2005	-0.16	-0.23	-0.17	-0.21	-0.18	-0.17	-0.37	-0.21	-0.12	-0.14	-0.19	-0.27	0.09
September 2005	-0.16	-0.23	-0.07	-0.22	-0.23	-0.13	-0.40	-0.26	-0.11	-0.13	-0.17	-0.28	-0.11
October 2005	-0.29	-0.23	-0.12	-0.28	-0.25	-0.18	-0.48	-0.30	-0.13	-0.20	-0.15	-0.25	-0.18
November 2005	-0.27	-0.14	-0.13	-0.15	-0.16	-0.08	-0.48	-0.20	-0.07	-0.23	-0.24	-0.20	-0.13
December 2005	-0.01	-0.03	-0.01	-0.11	-0.19	-0.02	-0.49	-0.13	-0.01	-0.14	-0.17	-0.15	-0.06
January 2006	-0.07	-0.09	-0.10	-0.11	-0.16	-0.04	-0.44	-0.13	-0.08	-0.13	-0.17	-0.14	-0.13
February 2006	-0.25	-0.24	-0.16	-0.24	-0.24	-0.18	-0.44	-0.23	-0.21	-0.20	-0.20	-0.19	-0.20
March 2006	-0.24	-0.09	-0.08	-0.21	-0.18	-0.08	-0.41	-0.17	-0.09	-0.22	-0.23	-0.15	-0.04
April 2006	-0.13	-0.10	-0.04	-0.19	-0.17	-0.04	-0.42	-0.13	-0.07	-0.29	-0.27	-0.13	0.13
May 2006	0.01	-0.15	-0.06	-0.15	-0.09	-0.08	-0.36	-0.07	-0.02	-0.21	-0.22	-0.11	0.21
June 2006	0.02	-0.16	-0.06	-0.14	-0.12	-0.15	-0.32	-0.12	-0.06	-0.20	-0.22	-0.11	0.07
July 2006	0.02	-0.20	-0.06	-0.16	-0.13	-0.13	-0.32	-0.18	-0.10	-0.21	-0.21	-0.12	0.05
August 2006	0.24	-0.06	0.03	-0.04	-0.05	0.04	-0.33	-0.11	0.08	-0.16	-0.12	-0.01	0.20
September 2006	0.12	-0.03	0.01	-0.02	0.03	0.05	-0.33	-0.02	0.07	-0.08	-0.07	-0.06	0.11
October 2006	-0.02	-0.09	-0.04	-0.11	-0.07	-0.17	-0.38	-0.13	-0.09	-0.11	-0.13	-0.20	-0.02
November 2006	-0.12	-0.15	-0.16	-0.19	-0.13	-0.11	-0.38	-0.23	-0.12	-0.14	-0.19	-0.24	-0.07
December 2006	-0.33	-0.27	-0.15	-0.26	-0.22	-0.17	-0.33	-0.30	-0.21	-0.14	-0.16	-0.25	-0.11
January 2007	-0.29	-0.15	-0.23	-0.14	-0.15	-0.08	-0.28	-0.19	-0.02	-0.10	-0.13	-0.27	-0.16
February 2007	-0.02	-0.09	-0.14	-0.13	-0.11	-0.06	-0.24	-0.15	-0.07	-0.03	-0.10	-0.23	0.07
March 2007	-0.37	-0.27	-0.24	-0.27	-0.22	-0.25	-0.28	-0.28	-0.30	-0.07	-0.21	-0.29	-0.42
April 2007	-0.30	-0.30	-0.25	-0.33	-0.27	-0.32	-0.30	-0.31	-0.34	-0.17	-0.24	-0.35	-0.24
May 2007	-0.18	-0.29	-0.30	-0.20	-0.24	-0.15	-0.35	-0.21	-0.19	-0.21	-0.24	-0.23	-0.30
June 2007	0.00	-0.17	0.02	-0.15	-0.19	-0.13	-0.24	-0.21	-0.19	-0.09	-0.16	-0.21	0.14
July 2007	-0.19	-0.32	0.03	-0.29	-0.28	-0.26	-0.24	-0.28	-0.32	-0.14	-0.12	-0.34	-0.09
August 2007	-0.59	-0.43	-0.16	-0.50	-0.46	-0.47	-0.46	-0.45	-0.55	-0.32	-0.24	-0.47	-0.45
September 2007	-0.57	-0.51	-0.28	-0.57	-0.55	-0.55	-0.54	-0.55	-0.62	-0.38	-0.27	-0.49	-0.48
October 2007	-0.38	-0.39	-0.19	-0.47	-0.50	-0.40	-0.53	-0.50	-0.47	-0.37	-0.26	-0.42	-0.35
November 2007	-0.50	-0.47	-0.36	-0.49	-0.51	-0.44	-0.55	-0.49	-0.46	-0.41	-0.29	-0.43	-0.54
December 2007	-0.42	-0.45	-0.44	-0.53	-0.52	-0.47	-0.53	-0.53	-0.42	-0.38	-0.26	-0.41	-0.55
January 2008	-0.45	-0.41	-0.35	-0.55	-0.56	-0.49	-0.55	-0.55	-0.45	-0.42	-0.31	-0.42	-0.52
February 2008	-0.58	-0.51	-0.30	-0.58	-0.58	-0.52	-0.63	-0.59	-0.55	-0.49	-0.36	-0.50	-0.32
March 2008	-0.40	-0.43	-0.37	-0.59	-0.61	-0.54	-0.58	-0.60	-0.53	-0.48	-0.38	-0.54	-0.58
April 2008	-0.40	-0.37	-0.38	-0.57	-0.60	-0.46	-0.50	-0.58	-0.52	-0.49	-0.37	-0.52	-0.57
May 2008	-0.29	-0.33	-0.21	-0.51	-0.49	-0.35	-0.53	-0.51	-0.41	-0.44	-0.35	-0.34	-0.39
June 2008	-0.24	-0.26	-0.01	-0.37	-0.42	-0.22	-0.48	-0.43	-0.28	-0.32	-0.31	-0.28	-0.44
July 2008	-0.24	-0.27	-0.10	-0.31	-0.38	-0.25	-0.47	-0.35	-0.25	-0.27	-0.32	-0.28	-0.45
August 2008	-0.32	-0.27	-0.18	-0.25	-0.36	-0.18	-0.45	-0.29	-0.20	-0.25	-0.27	-0.25	-0.49
September 2008	-0.42	-0.43	-0.35	-0.41	-0.48	-0.37	-0.28	-0.43	-0.44	-0.32	-0.31	-0.42	-0.55
October 2008	-0.42	-0.48	-0.46	-0.54	-0.57	-0.42	-0.35	-0.54	-0.41	-0.41	-0.44	-0.52	-0.46
November 2008	-0.44	-0.42	-0.44	-0.49	-0.44	-0.28	-0.37	-0.50	-0.35	-0.39	-0.43	-0.42	-0.37
December 2008	-0.39	-0.38	-0.45	-0.42	-0.41	-0.15	-0.38	-0.46	-0.27	-0.34	-0.39	-0.39	-0.41
January 2009	-0.26	-0.20	-0.27	-0.32	-0.31	-0.13	-0.32	-0.36	-0.19	-0.26	-0.38	-0.27	-0.37
February 2009	-0.24	-0.23	-0.26	-0.27	-0.27	-0.11	-0.37	-0.27	-0.18	-0.29	-0.36	-0.24	-0.33
March 2009	-0.28	-0.29	-0.31	-0.38	-0.39	-0.33	-0.32	-0.35	-0.40	-0.35	-0.35	-0.32	-0.26
April 2009	-0.36	-0.15	-0.23	-0.39	-0.44	-0.16	-0.26	-0.39	-0.42	-0.34	-0.30	-0.36	-0.22
May 2009	-0.34	-0.22	-0.20	-0.37	-0.38	-0.14	-0.34	-0.42	-0.38	-0.36	-0.35	-0.33	-0.25
June 2009	-0.32	-0.26	-0.14	-0.42	-0.43	-0.22	-0.37	-0.45	-0.38	-0.37	-0.35	-0.34	-0.19
July 2009	-0.34	-0.31	-0.24	-0.44	-0.49	-0.15	-0.38	-0.45	-0.30	-0.39	-0.33	-0.34	-0.27
August 2009	-0.41	-0.13	-0.33	-0.37	-0.49	-0.19	-0.45	-0.43	-0.21	-0.38	-0.25	-0.32	-0.38
September 2009	-0.29	-0.08	-0.30	-0.30	-0.45	-0.11	-0.43	-0.31	-0.14	-0.40	-0.25	-0.32	-0.36
October 2009	-0.43	-0.25	-0.24	-0.34	-0.46	-0.22	-0.42	-0.35	-0.16	-0.39	-0.29	-0.35	-0.39
November 2009	-0.40	-0.35	-0.19	-0.34	-0.44	-0.25	-0.36	-0.35	-0.26	-0.35	-0.29	-0.27	-0.30
December 2009	-0.42	-0.31	-0.20	-0.39	-0.47	-0.10	-0.31	-0.39	-0.17	-0.37	-0.26	-0.36	-0.38
January 2010	-0.34	-0.26	-0.28	-0.38	-0.46	-0.10	-0.36	-0.40	-0.15	-0.38	-0.29	-0.32	-0.37
February 2010	-0.46	-0.21	-0.36	-0.41	-0.51	0.00	-0.36	-0.44	0.04	-0.40	-0.29	-0.28	-0.45
March 2010	-0.31	-0.10	-0.27	-0.35	-0.49	0.03	-0.32	-0.39	-0.03	-0.36	-0.25	-0.26	-0.33
April 2010	-0.38	-0.24	-0.18	-0.40	-0.48	-0.11	-0.29	-0.44	-0.08	-0.37	-0.26	-0.32	-0.34
May 2010	-0.55	-0.06	-0.28	-0.60	-0.64	0.31	-0.38	-0.57	0.45	-0.55	-0.41	-0.52	-0.64
June 2010	-0.62	-0.08	-0.40	-0.57	-0.66	0.22	-0.48	-0.56	0.32	-0.58	-0.44	-0.52	-0.67
July 2010	-0.58	-0.14	-0.43	-0.53	-0.61	0.03	-0.48	-0.56	0.04	-0.52	-0.41	-0.41	-0.57
August 2010	-0.39	-0.31	-0.43	-0.50	-0.55	-0.08	-0.48	-0.54	-0.01	-0.46	-0.43	-0.44	-0.53
September 2010	-0.40	-0.41	-0.38	-0.55	-0.60	-0.14	-0.45	-0.57	-0.14	-0.49	-0.46	-0.48	-0.56
October 2010	-0.33	-0.33	-0.23	-0.45	-0.53	-0.16	-0.31	-0.46	-0.23	-0.43	-0.44	-0.34	-0.31
November 2010	-0.09	-0.16	0.03	-0.26	-0.36	0.02	-0.29	-0.28	0.07	-0.36	-0.39	-0.07	0.07
December 2010	-0.21	0.03	-0.05	-0.20	-0.38	0.21	-0.32	-0.28	0.25	-0.42	-0.44	-0.22	-0.17
Total	-0.18	-0.20	-0.17	-0.30	-0.29	-0.18	-0.30	-0.31	-0.20	-0.25	-0.24	-0.25	-0.22

Table 12: Flight-to-Liquidity Estimates and Threshold Levels

This table reports the monthly intranational flight-to-liquidity estimates and threshold levels employed to compute them based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-to-liquidity is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns during the corresponding period. Note that the table continues on the next page. For further information, refer to Section 4.2.

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
January 1999	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
February 1999	-	-	FTL	FTL	FTL	FTL	-	-	FTL	-	-	FTL	FTL
March 1999	-	FTL	FTL	FTL	FTL	-	-	FTL	FTL	FTL	FTL	FTL	FTL
April 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
May 1999	FTL	-	FTL	-	-	FTL	-	-	FTL	-	-	FTL	FTL
June 1999	FTL	FTL	FTL	-	-	FTL	-	-	-	-	-	FTL	-
July 1999	-	FTL	-	-	-	-	-	-	-	-	-	-	-
August 1999	-	-	-	-	-	-	-	-	-	-	-	FTL	FTL
September 1999	-	-	-	-	-	-	-	-	-	-	-	FTL	-
October 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
November 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
December 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2000	-	-	-	-	-	FTL	-	FTL	-	-	FTL	FTL	-
February 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2000	-	FTL	-	FTL	FTL	FTL	-	-	-	-	-	FTL	FTL
October 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2001	-	-	-	FTL	-	-	-	-	FTL	-	-	FTL	-
June 2001	-	-	-	FTL	FTL	-	-	-	FTL	-	-	FTL	FTL
July 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2001	FTL	-	-	-	-	-	-	-	-	-	-	-	-
January 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2002	-	-	-	-	-	-	FTL	-	-	-	-	-	-
March 2002	FTL	-	-	-	-	-	-	-	-	-	-	-	-
April 2002	FTL	-	-	-	-	-	-	-	-	-	-	-	FTL
May 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2003	FTL	-	-	-	-	-	-	-	-	-	-	-	-
July 2003	FTL	-	-	-	-	-	-	-	-	-	-	-	FTL
August 2003	-	-	-	-	-	-	-	-	-	-	-	-	FTL
September 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2004	FTL	-	-	-	-	-	-	-	-	-	-	-	-
February 2004	-	-	-	-	FTL	-	-	-	-	-	-	FTL	-
March 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2004	-	-	FTL	-	-	-	-	-	-	-	-	-	FTL
May 2004	FTL	FTL	FTL	FTL	FTL	FTL	FTL	FTL	FTL	-	-	FTL	FTL
June 2004	-	-	-	-	-	FTL	-	-	-	-	-	-	-
July 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2004	-	-	-	-	-	-	-	-	-	-	-	-	-

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
October 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2005	-	FTL	FTL	-	-	-	-	-	-	-	-	-	FTL
April 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2005	-	-	-	-	-	-	FTL	-	-	-	-	-	-
June 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2005	-	-	-	-	-	-	-	-	-	-	-	-	FTL
September 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2005	-	-	-	-	FTL	FTL	-	-	FTL	-	-	-	-
November 2005	-	-	-	FTL	FTL	FTL	-	-	FTL	-	-	FTL	-
December 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2006	-	-	-	-	FTL	-	-	-	FTL	FTL	-	FTL	-
June 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2007	-	-	-	-	-	-	-	-	FTL	-	-	-	-
February 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2007	-	-	-	-	-	-	-	-	FTL	-	-	-	-
June 2007	FTL	-	FTL	-	-	-	-	-	-	FTL	FTL	-	FTL
July 2007	-	-	FTL	-	-	-	-	-	-	FTL	FTL	-	FTL
August 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2007	FTL	-	-	-	-	-	-	-	-	-	-	-	-
January 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2008	-	-	-	-	-	-	-	-	-	-	-	FTL	-
June 2008	-	-	FTL	FTL	-	FTL	-	-	-	-	-	-	-
July 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2008	-	-	-	-	-	-	FTL	-	-	-	-	-	-
October 2008	-	-	-	-	-	-	-	-	FTL	-	-	-	FTL
November 2008	FTL	-	-	-	FTL	-	-	-	FTL	-	-	FTL	FTL
December 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2009	-	-	-	-	-	FTL	-	-	-	-	-	-	-
March 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2010	-	-	-	-	-	-	-	-	FTL	-	-	-	-
May 2010	-	-	-	-	-	FTL	-	-	FTL	-	-	-	-
June 2010	-	-	-	-	-	FTL	-	-	-	-	-	-	-
July 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2010	FTL	FTL	-	FTL	-	FTL	-	-	FTL	-	-	FTL	-
December 2010	-	FTL	-	FTL	-	FTL	-	-	FTL	-	-	-	-
Threshold	0.2170	0.1953	0.1795	0.1875	0.2109	0.1934	0.1505	0.1873	0.2107	0.1662	0.1561	0.1620	0.2549

Table 13: Flight-to-Quality Estimates and Threshold Levels

This table reports the monthly intranational flight-to-quality estimates and threshold levels employed to compute them based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-to-quality is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns during the corresponding period. Note that the table continues on the next page. For further information, refer to Section 4.2.

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
January 1999	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
February 1999	-	FTQ	-	-	FTQ	FTQ	-	-	-	-	-	-	-
March 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
April 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
May 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
June 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
July 1999	-	-	-	-	-	FTQ	-	FTQ	-	-	FTQ	FTQ	-
August 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
September 1999	FTQ	-	-	-	-	-	-	-	-	-	-	-	FTQ
October 1999	FTQ	-	-	-	-	-	-	-	-	-	-	-	FTQ
November 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
December 1999	-	FTQ	-	-	-	-	-	-	-	-	-	-	-
January 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2000	FTQ	-	-	-	-	-	-	-	-	-	-	FTQ	-
March 2000	-	FTQ	FTQ	-	-	-	-	-	-	-	-	-	-
April 2000	FTQ	-	-	-	-	-	FTQ	-	-	-	-	-	FTQ
May 2000	-	-	-	-	-	-	FTQ	-	-	-	-	-	-
June 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2000	FTQ	-	FTQ	FTQ	-	FTQ	-	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ
November 2000	-	-	FTQ	-	FTQ	-	FTQ	-	FTQ	FTQ	-	FTQ	FTQ
December 2000	FTQ	-	FTQ	-	-	FTQ	-	-	-	-	-	-	-
January 2001	FTQ	FTQ	FTQ	FTQ	-	FTQ	-	-	-	-	-	-	FTQ
February 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2001	FTQ	FTQ	-	-	-	FTQ	-	-	FTQ	-	FTQ	FTQ	-
April 2001	-	FTQ	-	-	-	-	-	-	FTQ	-	FTQ	FTQ	FTQ
May 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2001	-	-	-	-	-	-	-	-	-	-	-	FTQ	-
August 2001	-	FTQ	-	FTQ	FTQ	-	-	FTQ	FTQ	-	-	-	FTQ
September 2001	FTQ	FTQ	-	FTQ	FTQ	-	-	FTQ	FTQ	-	FTQ	-	FTQ
October 2001	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
November 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2002	-	-	-	-	-	-	-	-	-	-	-	-	FTQ
February 2002	FTQ	-	-	-	-	FTQ	-	-	FTQ	-	-	-	FTQ
March 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2002	FTQ	FTQ	FTQ	-	-	-	-	-	-	-	-	-	FTQ
June 2002	-	FTQ	-	-	-	FTQ	-	-	FTQ	-	-	FTQ	FTQ
July 2002	FTQ	FTQ	-	-	-	FTQ	-	-	FTQ	-	-	FTQ	-
August 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2002	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
January 2003	-	-	-	-	-	FTQ	-	-	-	-	-	-	-
February 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2003	-	-	-	-	-	-	-	-	-	-	-	-	FTQ
October 2003	FTQ	-	-	-	-	-	-	FTQ	FTQ	-	-	-	-
November 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2004	-	-	-	-	-	-	-	-	FTQ	-	-	-	-
May 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2004	-	FTQ	-	FTQ	FTQ	FTQ	-	FTQ	FTQ	-	-	FTQ	FTQ
August 2004	FTQ	-	-	-	-	FTQ	-	-	-	-	-	-	FTQ
September 2004	-	-	-	-	-	-	-	-	-	-	-	-	-

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
October 2004	-	-	-	-	-	-	-	-	-	-	-	-	FTQ
November 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2005	FTQ	FTQ	-	FTQ	FTQ	FTQ	-	-	FTQ	-	-	FTQ	FTQ
May 2005	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	-	-	FTQ	-	-	-	FTQ
June 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2005	-	-	-	-	-	-	-	-	-	-	-	-	FTQ
October 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2005	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
December 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2006	-	-	-	-	-	FTQ	-	FTQ	FTQ	-	-	-	-
July 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2006	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
October 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2006	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
January 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2007	-	-	-	-	-	-	-	-	-	-	-	-	FTQ
March 2007	FTQ	FTQ	FTQ	FTQ	-	FTQ	-	FTQ	FTQ	-	-	-	FTQ
April 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2007	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	-	FTQ	FTQ	-	FTQ	FTQ
August 2007	FTQ	-	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ
September 2007	-	-	-	-	-	-	FTQ	-	-	-	-	-	-
October 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2007	FTQ	-	FTQ	-	-	-	-	-	-	-	-	-	-
December 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2008	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
February 2008	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
March 2008	-	-	-	-	-	-	-	-	-	-	-	-	FTQ
April 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2008	-	-	FTQ	-	-	-	-	-	-	-	-	-	-
August 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2008	FTQ	FTQ	FTQ	FTQ	FTQ	FTQ	-	FTQ	FTQ	FTQ	FTQ	FTQ	-
October 2008	FTQ	-	FTQ	FTQ	FTQ	-	-	FTQ	FTQ	FTQ	FTQ	FTQ	-
November 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2009	-	-	-	-	-	FTQ	-	-	FTQ	-	-	-	-
March 2009	-	-	FTQ	FTQ	-	FTQ	-	-	FTQ	-	-	-	-
April 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2009	-	FTQ	-	-	-	-	-	-	-	-	-	-	-
December 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2010	FTQ	-	-	-	-	-	-	-	-	-	-	-	-
March 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2010	FTQ	FTQ	-	FTQ	-	FTQ	-	-	-	-	-	FTQ	-
May 2010	FTQ	-	FTQ	FTQ	-	-	-	-	-	FTQ	FTQ	FTQ	FTQ
June 2010	-	-	FTQ	-	-	-	-	-	-	-	-	-	-
July 2010	-	-	-	-	-	FTQ	-	-	FTQ	-	-	-	-
August 2010	-	FTQ	-	-	-	FTQ	-	-	-	-	-	-	-
September 2010	-	FTQ	-	-	-	-	-	-	-	-	-	-	-
October 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
Threshold	-0.2170	-0.1953	-0.1795	-0.1875	-0.2109	-0.1934	-0.1505	-0.1873	-0.2107	-0.1662	-0.1561	-0.1620	-0.2549

Table 14: Flight-from-Liquidity Estimates and Threshold Levels

This table reports the monthly intranational flight-from-liquidity estimates and threshold levels employed to compute them based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-from-liquidity is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns during the corresponding period. Note that the table continues on the next page. For further information, refer to Section 4.2.

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
January 1999	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
February 1999	-	-	-	-	-	-	-	-	FFL	-	FFL	-	-
March 1999	FFL	-	FFL	FFL	FFL	-	-	FFL	-	-	FFL	FFL	-
April 1999	-	-	-	-	-	-	-	-	-	-	FFL	-	-
May 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
June 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
July 1999	-	-	-	-	-	-	FFL	-	-	-	-	-	-
August 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
September 1999	-	-	-	-	-	FFL	-	FFL	-	-	-	-	FFL
October 1999	-	-	-	FFL	-	-	-	-	-	-	-	-	-
November 1999	-	FFL	-	FFL	-	-	-	-	FFL	-	-	-	-
December 1999	-	FFL	-	-	-	-	-	-	-	-	-	-	-
January 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2000	FFL	-	FFL	-	-	FFL	-	FFL	-	-	-	FFL	-
July 2000	FFL	-	-	-	-	-	-	-	-	-	-	-	-
August 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2000	-	-	-	FFL	FFL	-	-	-	FFL	-	-	FFL	-
October 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2001	FFL	-	-	-	-	-	FFL	-	-	-	-	-	FFL
March 2001	FFL	-	-	-	-	-	FFL	-	-	-	-	-	-
April 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2001	-	-	-	-	-	-	-	-	-	-	-	FFL	-
June 2001	-	FFL	FFL	-	-	-	-	-	-	-	-	-	FFL
July 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2001	FFL	-	-	-	-	FFL	-	-	-	-	-	-	-
September 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2001	-	FFL	-	-	-	-	-	-	FFL	-	-	-	FFL
November 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2002	-	-	FFL	-	-	-	-	-	-	-	-	-	-
February 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2002	-	-	-	-	-	-	FFL	-	-	-	-	-	-
April 2002	-	FFL	-	-	-	FFL	-	-	-	-	-	-	-
May 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2002	FFL	-	-	-	-	-	-	-	-	-	-	-	-
October 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2002	FFL	-	-	-	-	-	-	-	-	-	-	-	-
December 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2003	-	-	-	-	-	-	-	-	-	-	-	FFL	-
April 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2003	FFL	FFL	FFL	-	-	FFL	-	-	-	-	-	-	FFL
June 2003	FFL	-	FFL	-	-	-	-	-	-	-	-	-	-
July 2003	FFL	-	-	-	-	-	-	-	-	-	-	-	-
August 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2003	-	-	FFL	-	-	-	-	-	-	-	-	-	-
January 2004	-	FFL	FFL	FFL	FFL	FFL	-	FFL	FFL	-	-	-	-
February 2004	-	FFL	FFL	FFL	FFL	FFL	-	FFL	FFL	-	-	-	FFL
March 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2004	-	FFL	-	FFL	-	FFL	-	-	FFL	-	-	-	-
July 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2004	FFL	-	-	-	-	-	-	-	-	-	-	-	FFL

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
October 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2004	FFL	FFL	-	-	-	-	-	-	FFL	-	-	-	-
December 2004	FFL	FFL	-	-	-	FFL	-	-	FFL	-	-	-	FFL
January 2005	-	FFL	-	FFL	FFL	-	-	FFL	FFL	FFL	-	FFL	-
February 2005	-	-	-	-	-	-	-	-	FFL	-	-	-	-
March 2005	-	FFL	-	-	-	-	-	-	-	-	-	-	-
April 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2005	-	-	-	-	-	-	FFL	-	-	-	-	-	-
June 2005	FFL	-	-	FFL	FFL	-	-	-	FFL	-	-	FFL	FFL
July 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2005	FFL	-	-	-	-	-	-	-	-	-	-	-	-
December 2005	FFL	FFL	FFL	-	-	-	-	-	-	-	-	-	-
January 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2006	FFL	FFL	-	FFL	-	FFL	-	-	FFL	-	-	-	-
September 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2007	FFL	-	-	-	-	-	-	-	-	-	-	-	-
February 2007	FFL	-	FFL	-	-	-	-	-	-	-	-	-	FFL
March 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2007	-	-	-	-	-	FFL	-	-	-	-	-	FFL	-
June 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2007	FFL	FFL	FFL	-	-	FFL	-	-	FFL	-	-	-	FFL
November 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2008	-	-	FFL	-	-	-	-	-	-	-	-	FFL	-
June 2008	-	-	FFL	-	-	-	-	-	-	-	-	-	-
July 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2008	-	-	-	-	FFL	-	-	-	-	-	-	-	-
December 2008	-	-	FFL	-	-	FFL	-	-	-	-	-	-	-
January 2009	FFL	FFL	FFL	-	-	FFL	FFL	-	FFL	-	-	FFL	-
February 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2009	-	-	FFL	-	-	FFL	-	-	-	-	-	-	FFL
April 2009	-	FFL	FFL	-	-	FFL	-	-	-	-	-	-	FFL
May 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2009	-	-	-	-	-	FFL	-	-	-	-	-	-	-
August 2009	-	FFL	-	-	-	-	-	-	FFL	-	-	-	-
September 2009	FFL	-	-	-	-	-	-	FFL	-	-	-	-	-
October 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2009	-	-	-	-	-	FFL	-	-	-	-	-	-	-
January 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2010	FFL	-	-	-	-	-	-	-	-	-	-	-	-
September 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2010	-	-	FFL	-	-	-	FFL	-	-	-	-	-	FFL
November 2010	-	-	FFL	-	-	-	-	-	-	-	-	-	-
December 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
Threshold	0.2170	0.1953	0.1795	0.1875	0.2109	0.1934	0.1505	0.1873	0.2107	0.1662	0.1561	0.1620	0.2549

Table 15: Flight-from-Quality Estimates and Threshold Levels

This table reports the monthly intranational flight-from-quality estimates and threshold levels employed to compute them based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-from-quality is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns during the corresponding period. Note that the table continues on the next page. For further information, refer to Section 4.2.

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
January 1999	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
February 1999	FFQ	-	-	-	-	-	FFQ	-	-	FFQ	-	-	-
March 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
April 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
May 1999	-	-	-	FFQ	-	-	-	-	-	-	-	FFQ	-
June 1999	-	-	-	-	-	-	FFQ	-	-	-	-	-	-
July 1999	-	-	-	FFQ	-	-	-	FFQ	-	-	-	-	-
August 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
September 1999	-	-	-	FFQ	-	-	-	-	-	-	-	-	-
October 1999	-	-	-	-	-	-	-	-	-	-	-	-	-
November 1999	-	-	-	-	-	FFQ	-	-	-	-	-	-	-
December 1999	FFQ	FFQ	-	FFQ	FFQ	FFQ	-	FFQ	FFQ	-	FFQ	FFQ	-
January 2000	-	-	-	-	-	-	-	-	-	-	-	-	FFQ
February 2000	-	-	FFQ	-	-	-	-	-	-	-	-	-	-
March 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2000	-	-	-	-	-	-	-	-	-	-	FFQ	-	-
May 2000	-	-	-	-	FFQ	FFQ	-	-	FFQ	-	-	-	-
June 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2000	FFQ	FFQ	-	-	-	-	-	-	-	-	-	-	-
September 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2000	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2001	-	-	FFQ	-	-	-	-	-	-	-	-	-	FFQ
February 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2001	-	-	-	-	-	-	-	-	FFQ	-	-	-	-
May 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2001	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2001	-	-	-	-	-	FFQ	-	-	-	-	-	-	-
January 2002	-	-	-	-	-	FFQ	-	-	-	-	-	-	-
February 2002	FFQ	-	-	-	-	-	-	-	-	-	-	-	-
March 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2002	-	FFQ	-	-	-	-	-	-	-	-	-	-	-
June 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2002	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2002	FFQ	-	-	-	-	-	-	-	-	-	-	-	-
December 2002	FFQ	-	-	-	-	-	-	-	-	-	-	-	-
January 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2003	-	FFQ	-	-	-	-	-	-	-	-	-	FFQ	-
April 2003	FFQ	FFQ	FFQ	-	-	-	-	-	FFQ	-	-	FFQ	FFQ
May 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2003	-	FFQ	-	-	-	-	-	-	-	-	-	FFQ	-
November 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2003	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2004	-	FFQ	FFQ	FFQ	-	FFQ	-	-	FFQ	-	-	-	FFQ
May 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2004	-	-	-	-	-	-	-	-	-	-	-	-	-

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
October 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2004	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2005	FFQ	-	-	FFQ	-	-	-	-	-	-	-	-	-
April 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2005	-	FFQ	-	FFQ	FFQ	FFQ	-	FFQ	FFQ	-	-	FFQ	FFQ
August 2005	-	FFQ	-	FFQ	-	-	-	-	-	-	FFQ	-	-
September 2005	-	-	-	FFQ	-	FFQ	-	FFQ	FFQ	-	-	-	FFQ
October 2005	-	-	-	FFQ	-	FFQ	-	FFQ	FFQ	-	-	-	FFQ
November 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2005	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2006	FFQ	FFQ	-	-	-	-	-	-	-	-	-	-	-
February 2006	FFQ	FFQ	-	FFQ	-	FFQ	-	FFQ	FFQ	-	-	FFQ	-
March 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2006	-	FFQ	-	-	-	-	-	-	-	-	-	-	-
May 2006	-	FFQ	-	-	-	-	-	-	-	-	-	-	-
June 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2006	-	FFQ	-	-	-	FFQ	-	FFQ	FFQ	-	-	FFQ	-
November 2006	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2006	FFQ	-	-	-	-	-	-	-	-	-	-	-	-
January 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2007	-	-	-	-	-	FFQ	-	-	-	-	-	-	-
April 2007	-	-	-	-	-	FFQ	-	-	-	-	-	-	-
May 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2007	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2008	-	FFQ	-	-	-	-	-	-	-	-	-	-	-
October 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2008	-	-	-	-	-	-	-	-	-	-	-	-	-
January 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
May 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
July 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
August 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
October 2009	FFQ	-	-	-	-	-	-	-	-	-	-	-	-
November 2009	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2009	-	-	-	-	-	-	-	-	-	-	-	-	FFQ
January 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
February 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
March 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
April 2010	FFQ	-	-	-	-	-	-	-	-	-	-	-	-
May 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
June 2010	-	-	FFQ	-	-	-	-	-	FFQ	-	-	-	-
July 2010	-	-	-	-	-	-	-	-	FFQ	-	-	-	-
August 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
September 2010	-	-	-	-	-	-	-	-	FFQ	-	-	-	-
October 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
November 2010	-	-	-	-	-	-	-	-	-	-	-	-	-
December 2010	FFQ	-	-	-	-	FFQ	-	-	FFQ	-	-	FFQ	FFQ
Threshold	-0.2170	-0.1953	-0.1795	-0.1875	-0.2109	-0.1934	-0.1505	-0.1873	-0.2107	-0.1662	-0.1561	-0.1620	-0.2549

Table 16: Frequencies of Flight-to-Liquidity

This table reports the annual and total period number of flight-to-liquidity days based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-to-liquidity is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns during the corresponding period. For further information, refer to Section 4.2.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Australia	17	0	1	2	5	6	0	0	13	1	0	2	47
Belgium	30	3	0	0	0	3	2	0	0	0	0	10	48
Canada	27	0	0	0	0	9	2	0	13	4	0	0	55
France	10	2	3	0	0	4	2	0	0	1	0	6	28
Germany	15	2	1	0	0	2	3	1	0	1	0	0	25
Italy	16	5	0	0	0	19	5	0	0	5	2	26	78
Japan	0	0	0	14	0	1	1	0	0	6	0	0	22
Netherlands	4	2	0	0	0	2	0	0	0	0	0	0	8
Spain	5	0	5	0	0	6	6	1	4	2	0	42	71
Sweden	8	0	0	0	0	0	0	1	11	0	0	0	20
Switzerland	2	7	0	0	0	0	0	0	9	0	0	0	18
UK	12	24	5	0	0	12	2	1	0	3	0	4	63
US	17	1	1	2	10	12	11	0	10	6	0	0	70

Table 17: Frequencies of Flight-to-Quality

This table reports the annual and total period number of flight-to-quality days based on the selected bivariate DCC model(s), scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-to-quality is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns during the corresponding period. For further information, refer to Section 4.2.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Australia	5	17	21	13	1	5	10	5	38	20	0	8	143
Belgium	4	4	18	20	0	5	16	0	13	3	1	13	97
Canada	0	13	8	5	0	0	10	0	17	7	3	3	66
France	0	4	12	0	0	5	15	0	20	12	3	11	82
Germany	2	2	4	0	0	1	5	0	2	2	0	0	18
Italy	3	11	5	5	3	7	18	2	20	7	16	4	101
Japan	0	8	0	0	0	0	0	0	21	0	0	0	29
Netherlands	1	6	4	0	1	4	0	1	5	11	0	0	33
Spain	0	15	21	5	1	5	17	2	23	7	15	1	112
Sweden	0	2	0	0	0	0	0	0	10	10	0	10	32
Switzerland	3	2	19	0	0	0	0	0	2	7	0	4	37
UK	1	16	13	14	0	4	8	0	11	14	0	15	96
US	5	14	12	9	2	19	17	0	35	11	0	12	136

Table 18: Frequencies of Flight-from-Liquidity

This table reports the annual and total period number of flight-from-liquidity days based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-from-liquidity is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns during the corresponding period. For further information, refer to Section 4.2.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Australia	3	7	17	2	11	20	19	6	13	0	12	2	112
Belgium	12	0	3	4	16	17	10	3	2	0	26	0	93
Canada	3	2	3	2	17	7	4	0	7	13	16	4	78
France	10	3	0	0	0	17	19	1	0	0	0	0	50
Germany	2	2	0	0	0	13	11	0	0	1	0	0	29
Italy	2	7	2	2	4	15	0	10	2	1	16	0	61
Japan	1	0	6	7	0	0	1	0	0	0	2	4	21
Netherlands	5	13	0	0	0	14	13	0	0	0	2	0	47
Spain	10	5	6	0	0	23	20	8	6	0	2	0	80
Sweden	0	0	0	0	0	0	9	0	0	0	0	0	9
Switzerland	16	0	0	0	0	0	0	0	0	0	0	0	16
UK	2	8	3	0	1	0	4	0	1	1	3	0	23
US	1	0	4	0	14	10	4	0	9	0	6	4	52

Table 19: Frequencies of Flight-from-Quality

This table reports the annual and total period number of flight-from-quality days based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). For this thesis, the flight-from-quality is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns during the corresponding period. For further information, refer to Section 4.2.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Australia	5	1	0	9	1	0	1	14	0	0	2	5	38
Belgium	2	1	0	2	9	4	10	18	0	1	0	0	47
Canada	0	2	4	0	1	7	0	0	0	0	0	1	15
France	17	0	0	0	0	1	13	6	0	0	0	0	37
Germany	4	2	0	0	0	0	3	0	0	0	0	0	9
Italy	2	1	3	1	0	10	10	11	3	0	0	2	43
Japan	5	0	0	0	0	0	0	0	0	0	0	0	5
Netherlands	5	0	0	0	0	0	7	3	0	0	0	0	15
Spain	3	1	1	0	1	8	13	12	0	0	0	16	55
Sweden	8	0	0	0	0	0	0	0	0	0	0	0	8
Switzerland	3	1	0	0	0	0	2	0	0	0	0	0	6
UK	12	0	0	0	15	0	3	7	0	0	0	9	46
US	0	1	1	0	5	7	12	0	0	0	3	14	43

Table 20: 1% CAViaR Estimates (Monthly Averages)

This table reports the monthly and total period averages of the daily 1% conditional autoregressive value at risk (CAViaR) estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the table continues on the next page. For further information, refer to Section 4.3.

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
January 1999	1.33 %	1.64 %	1.39 %	1.75 %	1.79 %	2.20 %	1.84 %	2.22 %	2.13 %	1.71 %	1.60 %	1.70 %	1.42 %
February 1999	1.36 %	1.07 %	1.56 %	1.67 %	1.62 %	1.92 %	1.59 %	1.76 %	1.46 %	1.59 %	1.38 %	1.39 %	1.72 %
March 1999	1.26 %	1.82 %	1.47 %	1.54 %	1.84 %	1.82 %	1.58 %	1.59 %	1.52 %	1.79 %	1.28 %	1.49 %	1.52 %
April 1999	0.88 %	1.16 %	1.21 %	1.19 %	1.29 %	1.26 %	1.41 %	1.16 %	1.32 %	1.51 %	1.18 %	1.12 %	1.41 %
May 1999	2.13 %	1.23 %	1.43 %	1.28 %	1.36 %	1.60 %	1.46 %	1.24 %	1.21 %	1.53 %	1.33 %	1.59 %	1.72 %
June 1999	1.30 %	1.46 %	1.37 %	1.30 %	1.33 %	1.54 %	1.27 %	1.22 %	1.24 %	1.51 %	1.40 %	1.20 %	1.69 %
July 1999	1.21 %	1.52 %	1.35 %	1.34 %	1.44 %	1.54 %	1.58 %	1.31 %	1.70 %	1.63 %	1.39 %	1.42 %	1.29 %
August 1999	1.69 %	1.51 %	1.58 %	1.46 %	1.55 %	1.75 %	1.52 %	1.57 %	1.56 %	1.56 %	1.36 %	1.74 %	1.80 %
September 1999	1.50 %	1.28 %	1.41 %	1.20 %	1.50 %	1.50 %	1.65 %	1.55 %	1.56 %	1.65 %	1.33 %	1.91 %	1.74 %
October 1999	1.78 %	1.44 %	1.50 %	1.39 %	1.41 %	1.46 %	1.67 %	1.60 %	1.52 %	1.52 %	1.39 %	1.70 %	1.73 %
November 1999	0.99 %	1.32 %	1.26 %	1.09 %	1.16 %	1.15 %	1.31 %	1.05 %	1.12 %	1.37 %	0.95 %	1.15 %	1.31 %
December 1999	1.06 %	1.61 %	1.43 %	1.02 %	1.13 %	1.28 %	1.52 %	0.85 %	1.15 %	1.61 %	0.90 %	1.06 %	1.16 %
January 2000	1.59 %	2.11 %	1.68 %	1.72 %	1.77 %	1.97 %	1.95 %	1.67 %	1.74 %	1.72 %	1.33 %	1.94 %	1.56 %
February 2000	1.07 %	1.57 %	1.64 %	1.62 %	1.72 %	1.89 %	1.56 %	1.62 %	1.31 %	1.71 %	1.51 %	1.74 %	1.67 %
March 2000	1.05 %	1.47 %	1.54 %	1.79 %	1.46 %	1.96 %	1.99 %	1.21 %	1.21 %	1.94 %	1.24 %	1.42 %	1.59 %
April 2000	1.65 %	1.39 %	2.37 %	2.14 %	1.64 %	2.08 %	2.24 %	1.53 %	1.51 %	2.61 %	1.00 %	1.92 %	2.01 %
May 2000	1.57 %	0.92 %	2.14 %	1.89 %	1.88 %	1.85 %	1.97 %	1.32 %	1.95 %	2.43 %	0.85 %	1.63 %	2.20 %
June 2000	0.93 %	1.01 %	1.57 %	1.56 %	1.38 %	1.58 %	1.63 %	0.99 %	1.52 %	2.51 %	0.94 %	1.33 %	1.58 %
July 2000	0.96 %	0.86 %	1.33 %	1.31 %	1.23 %	1.15 %	1.67 %	0.98 %	1.29 %	2.37 %	0.74 %	1.19 %	1.41 %
August 2000	0.84 %	0.74 %	1.29 %	1.20 %	1.22 %	1.20 %	1.48 %	0.89 %	1.32 %	2.18 %	0.67 %	0.88 %	1.31 %
September 2000	1.52 %	0.99 %	1.69 %	1.43 %	1.53 %	1.27 %	1.62 %	1.03 %	1.47 %	1.90 %	0.94 %	1.37 %	1.27 %
October 2000	1.22 %	0.86 %	2.17 %	1.64 %	1.47 %	1.39 %	1.76 %	1.02 %	1.85 %	2.59 %	1.18 %	1.33 %	1.81 %
November 2000	0.99 %	0.92 %	2.14 %	1.60 %	1.50 %	1.29 %	1.59 %	1.07 %	1.92 %	2.42 %	0.86 %	1.25 %	1.78 %
December 2000	0.97 %	0.88 %	1.76 %	1.75 %	1.68 %	1.72 %	1.74 %	1.51 %	2.04 %	2.27 %	1.04 %	1.46 %	1.79 %
January 2001	0.97 %	0.79 %	1.57 %	1.47 %	1.13 %	1.33 %	1.47 %	1.14 %	1.19 %	2.26 %	0.94 %	1.16 %	1.58 %
February 2001	1.12 %	0.74 %	1.61 %	1.43 %	1.31 %	1.44 %	1.45 %	1.04 %	1.59 %	2.52 %	1.03 %	1.14 %	1.52 %
March 2001	1.17 %	1.43 %	1.83 %	1.87 %	1.96 %	1.94 %	2.02 %	1.57 %	1.76 %	3.02 %	1.58 %	1.88 %	2.05 %
April 2001	1.17 %	1.20 %	1.71 %	1.64 %	1.62 %	1.60 %	1.96 %	1.52 %	1.60 %	3.19 %	1.54 %	1.63 %	2.05 %
May 2001	0.95 %	0.95 %	1.22 %	1.29 %	1.23 %	1.21 %	1.49 %	1.24 %	1.38 %	2.13 %	0.91 %	1.38 %	1.47 %
June 2001	1.03 %	1.00 %	1.36 %	1.41 %	1.33 %	1.36 %	1.51 %	1.23 %	1.44 %	2.10 %	1.09 %	1.34 %	1.53 %
July 2001	1.45 %	0.75 %	1.25 %	1.57 %	1.38 %	1.35 %	2.00 %	1.30 %	1.71 %	2.04 %	1.50 %	1.39 %	1.45 %
August 2001	1.13 %	0.79 %	0.92 %	1.46 %	1.41 %	1.17 %	1.91 %	1.24 %	1.31 %	1.80 %	1.38 %	1.07 %	1.27 %
September 2001	2.11 %	2.06 %	1.47 %	2.46 %	2.61 %	3.26 %	2.76 %	2.81 %	2.49 %	2.88 %	2.80 %	2.68 %	1.87 %
October 2001	1.22 %	1.36 %	1.36 %	2.01 %	1.71 %	2.85 %	2.01 %	2.53 %	1.79 %	2.48 %	1.89 %	2.00 %	1.63 %
November 2001	1.22 %	1.22 %	1.29 %	1.83 %	1.65 %	2.08 %	1.70 %	1.92 %	1.75 %	2.06 %	1.34 %	1.46 %	1.52 %
December 2001	1.27 %	1.03 %	1.28 %	1.56 %	1.49 %	1.70 %	1.94 %	1.53 %	1.66 %	1.92 %	1.37 %	1.36 %	1.55 %
January 2002	1.08 %	1.04 %	1.14 %	1.30 %	1.21 %	1.29 %	1.72 %	1.27 %	1.53 %	1.89 %	1.05 %	1.14 %	1.15 %
February 2002	0.93 %	1.25 %	1.11 %	1.49 %	1.40 %	1.28 %	1.89 %	1.31 %	1.56 %	1.82 %	1.18 %	1.33 %	1.40 %
March 2002	1.42 %	1.00 %	1.12 %	1.19 %	1.18 %	1.14 %	1.77 %	1.04 %	1.24 %	1.59 %	0.89 %	1.15 %	1.38 %
April 2002	1.18 %	0.92 %	1.09 %	1.19 %	1.15 %	1.15 %	1.63 %	1.02 %	1.26 %	1.78 %	0.75 %	0.96 %	1.26 %
May 2002	0.97 %	1.24 %	0.99 %	1.22 %	1.27 %	1.31 %	1.18 %	1.23 %	1.29 %	1.88 %	0.87 %	1.05 %	1.47 %
June 2002	1.01 %	1.73 %	0.99 %	1.77 %	1.67 %	1.75 %	1.94 %	1.97 %	1.83 %	2.00 %	1.68 %	1.62 %	1.54 %
July 2002	1.28 %	2.69 %	1.38 %	2.77 %	2.19 %	2.30 %	2.07 %	3.36 %	2.31 %	2.60 %	2.82 %	3.14 %	2.20 %
August 2002	0.99 %	1.98 %	1.33 %	2.57 %	1.92 %	2.05 %	1.84 %	3.00 %	2.14 %	2.78 %	2.37 %	2.37 %	2.18 %
September 2002	1.11 %	2.37 %	1.31 %	2.74 %	2.06 %	2.30 %	2.11 %	2.95 %	2.15 %	2.34 %	2.38 %	2.36 %	1.87 %
October 2002	1.33 %	2.09 %	1.63 %	2.80 %	2.38 %	2.27 %	2.13 %	2.77 %	1.86 %	2.84 %	2.23 %	2.39 %	2.16 %
November 2002	0.91 %	1.16 %	1.21 %	2.10 %	1.74 %	1.75 %	1.88 %	1.97 %	1.35 %	2.12 %	1.50 %	1.72 %	1.37 %
December 2002	0.96 %	1.41 %	1.04 %	1.75 %	1.61 %	1.64 %	1.61 %	1.71 %	1.48 %	1.90 %	1.33 %	1.64 %	1.32 %
January 2003	1.05 %	1.34 %	0.91 %	1.48 %	1.46 %	1.38 %	1.34 %	1.54 %	1.36 %	1.66 %	1.47 %	1.54 %	1.24 %
February 2003	1.51 %	1.91 %	0.95 %	1.84 %	1.83 %	1.51 %	1.38 %	2.20 %	1.67 %	2.05 %	2.00 %	1.84 %	1.50 %
March 2003	1.42 %	2.42 %	1.04 %	2.29 %	1.95 %	2.05 %	1.74 %	2.76 %	1.80 %	1.88 %	2.14 %	2.20 %	1.44 %
April 2003	0.73 %	1.28 %	0.80 %	1.88 %	1.48 %	1.37 %	1.71 %	1.89 %	1.20 %	1.69 %	1.54 %	1.53 %	1.23 %
May 2003	0.84 %	1.19 %	0.74 %	1.31 %	1.27 %	1.09 %	1.42 %	1.42 %	1.26 %	1.39 %	1.19 %	1.21 %	1.00 %
June 2003	0.85 %	1.12 %	0.89 %	1.13 %	1.16 %	1.02 %	1.31 %	1.35 %	1.15 %	1.31 %	1.07 %	1.09 %	1.07 %
July 2003	1.26 %	1.21 %	0.91 %	1.41 %	1.33 %	1.33 %	1.52 %	1.66 %	1.44 %	1.40 %	1.22 %	1.26 %	1.55 %
August 2003	1.02 %	0.91 %	0.92 %	1.22 %	1.14 %	0.99 %	1.32 %	1.16 %	1.04 %	1.28 %	1.05 %	1.00 %	1.66 %
September 2003	0.91 %	1.00 %	0.73 %	1.16 %	1.35 %	1.04 %	1.36 %	1.17 %	1.19 %	1.34 %	0.96 %	1.08 %	1.08 %
October 2003	0.92 %	0.86 %	0.89 %	1.19 %	1.39 %	1.04 %	1.64 %	1.27 %	1.06 %	1.44 %	1.01 %	1.09 %	1.03 %
November 2003	1.13 %	0.85 %	0.84 %	1.06 %	1.12 %	0.96 %	2.03 %	1.09 %	0.95 %	1.33 %	1.02 %	0.99 %	0.97 %
December 2003	0.96 %	0.72 %	0.82 %	0.87 %	0.94 %	0.88 %	1.56 %	0.84 %	0.82 %	1.17 %	0.79 %	0.88 %	0.91 %
January 2004	0.94 %	0.70 %	0.83 %	0.73 %	0.90 %	0.95 %	1.11 %	0.73 %	0.89 %	1.05 %	0.67 %	0.69 %	0.86 %
February 2004	0.94 %	0.84 %	1.11 %	0.96 %	1.11 %	0.96 %	1.22 %	0.91 %	1.14 %	1.18 %	0.73 %	0.89 %	1.03 %
March 2004	0.82 %	1.27 %	1.25 %	1.22 %	1.42 %	1.13 %	1.26 %	1.28 %	1.50 %	1.48 %	1.03 %	1.13 %	1.22 %
April 2004	1.13 %	0.82 %	1.22 %	1.08 %	1.05 %	0.86 %	1.27 %	0.94 %	1.05 %	1.38 %	0.93 %	0.87 %	1.29 %
May 2004	1.17 %	1.25 %	1.53 %	1.40 %	1.48 %	1.30 %	2.14 %	1.43 %	1.56 %	1.94 %	1.29 %	1.39 %	1.46 %
June 2004	0.75 %	0.94 %	1.18 %	1.18 %	1.12 %	1.02 %	1.46 %	1.05 %	1.14 %	1.41 %	1.10 %	0.99 %	1.09 %
July 2004	0.85 %	0.81 %	0.97 %	0.99 %	1.07 %	0.89 %	1.54 %	0.96 %	1.08 %	1.34 %	1.04 %	1.03 %	1.05 %
August 2004	0.80 %	0.83 %	1.01 %	1.09 %	1.17 %	1.01 %	1.35 %	1.12 %	1.17 %	1.45 %	1.04 %	1.04 %	1.02 %
September 2004	0.84 %	0.64 %	0.89 %	0.84 %	0.96 %	0.70 %	1.17 %	0.78 %	0.85 %	1.11 %	0.79 %	0.62 %	0.92 %

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
October 2004	0.78 %	0.73 %	0.86 %	0.90 %	0.98 %	0.72 %	1.26 %	0.88 %	0.90 %	1.15 %	0.97 %	0.74 %	0.92 %
November 2004	0.79 %	0.73 %	0.83 %	0.86 %	0.92 %	0.74 %	1.23 %	0.73 %	0.88 %	1.14 %	0.90 %	0.77 %	0.94 %
December 2004	0.79 %	0.75 %	0.88 %	0.84 %	0.92 %	0.80 %	1.21 %	0.73 %	0.87 %	1.06 %	0.81 %	0.78 %	1.02 %
January 2005	0.84 %	0.79 %	0.99 %	0.85 %	1.01 %	0.84 %	1.06 %	0.79 %	0.93 %	1.26 %	0.76 %	0.86 %	1.08 %
February 2005	0.79 %	0.88 %	0.75 %	0.81 %	0.98 %	0.96 %	0.97 %	0.72 %	1.00 %	1.31 %	0.67 %	0.80 %	0.94 %
March 2005	1.01 %	1.05 %	1.08 %	0.94 %	1.00 %	1.05 %	0.99 %	0.96 %	1.26 %	1.23 %	0.87 %	1.06 %	1.31 %
April 2005	1.18 %	0.97 %	1.17 %	0.94 %	1.02 %	1.07 %	1.44 %	0.94 %	1.12 %	1.17 %	0.81 %	0.91 %	1.20 %
May 2005	1.02 %	0.83 %	0.95 %	0.83 %	0.91 %	0.94 %	1.20 %	0.83 %	0.92 %	1.24 %	0.80 %	0.74 %	1.07 %
June 2005	0.73 %	0.86 %	0.86 %	0.83 %	0.97 %	0.91 %	1.04 %	0.78 %	1.00 %	1.01 %	0.71 %	0.78 %	0.93 %
July 2005	0.93 %	0.80 %	0.87 %	0.88 %	0.91 %	1.00 %	0.90 %	0.80 %	0.97 %	1.13 %	0.67 %	0.86 %	0.91 %
August 2005	0.90 %	0.78 %	0.98 %	0.86 %	0.99 %	0.95 %	1.06 %	0.82 %	1.01 %	1.15 %	0.62 %	0.72 %	1.09 %
September 2005	0.93 %	0.66 %	1.00 %	0.87 %	1.05 %	0.87 %	1.06 %	0.73 %	0.95 %	1.11 %	0.71 %	0.69 %	0.97 %
October 2005	1.44 %	0.98 %	1.49 %	1.13 %	1.23 %	1.27 %	1.34 %	1.14 %	1.29 %	1.25 %	0.96 %	1.18 %	1.27 %
November 2005	0.92 %	0.85 %	1.18 %	1.11 %	1.02 %	1.13 %	1.09 %	0.92 %	1.13 %	1.13 %	0.90 %	0.91 %	1.05 %
December 2005	1.01 %	0.84 %	0.98 %	0.83 %	0.85 %	0.85 %	1.28 %	0.68 %	0.94 %	1.08 %	0.76 %	0.86 %	0.94 %
January 2006	0.76 %	0.79 %	0.82 %	0.86 %	1.06 %	0.97 %	1.61 %	0.92 %	1.01 %	1.12 %	0.76 %	0.80 %	0.89 %
February 2006	1.11 %	0.75 %	1.13 %	0.89 %	0.99 %	0.95 %	1.87 %	0.79 %	0.93 %	1.11 %	0.73 %	0.87 %	0.96 %
March 2006	0.88 %	0.99 %	1.07 %	0.98 %	1.10 %	1.15 %	1.46 %	0.98 %	1.09 %	1.15 %	0.85 %	1.00 %	1.00 %
April 2006	0.94 %	0.81 %	1.10 %	1.01 %	0.98 %	1.26 %	1.34 %	0.95 %	1.09 %	1.21 %	0.86 %	0.97 %	1.04 %
May 2006	1.45 %	1.38 %	1.26 %	1.35 %	1.48 %	1.48 %	1.63 %	1.43 %	1.43 %	1.80 %	1.27 %	1.65 %	1.14 %
June 2006	1.79 %	1.47 %	1.65 %	1.80 %	1.54 %	1.63 %	2.18 %	1.74 %	1.52 %	2.44 %	1.59 %	1.78 %	1.38 %
July 2006	1.36 %	1.07 %	1.35 %	1.33 %	1.32 %	1.18 %	1.78 %	1.23 %	1.20 %	1.85 %	1.12 %	1.17 %	1.23 %
August 2006	1.36 %	0.88 %	1.07 %	1.18 %	1.10 %	1.10 %	1.33 %	1.00 %	1.15 %	1.55 %	0.86 %	1.19 %	1.02 %
September 2006	1.13 %	0.91 %	1.11 %	1.00 %	1.02 %	0.95 %	1.35 %	0.96 %	1.02 %	1.29 %	0.75 %	0.99 %	0.83 %
October 2006	0.98 %	0.84 %	1.21 %	0.84 %	0.85 %	0.84 %	1.23 %	0.75 %	0.96 %	1.20 %	0.69 %	0.83 %	0.77 %
November 2006	0.91 %	0.86 %	1.00 %	0.83 %	0.94 %	0.84 %	1.38 %	0.77 %	0.97 %	1.17 %	0.70 %	0.82 %	0.82 %
December 2006	0.90 %	0.77 %	0.86 %	0.91 %	0.98 %	0.89 %	1.16 %	0.88 %	1.17 %	1.32 %	0.92 %	0.81 %	0.84 %
January 2007	0.94 %	0.83 %	0.98 %	0.94 %	0.95 %	0.91 %	1.13 %	0.83 %	1.06 %	1.19 %	0.71 %	0.88 %	0.82 %
February 2007	0.79 %	0.87 %	0.94 %	0.90 %	0.95 %	0.95 %	1.07 %	0.83 %	0.97 %	1.23 %	0.78 %	0.89 %	0.85 %
March 2007	1.29 %	1.36 %	1.21 %	1.24 %	1.31 %	1.38 %	1.83 %	1.29 %	1.52 %	1.72 %	1.32 %	1.41 %	1.16 %
April 2007	0.94 %	0.88 %	0.92 %	0.91 %	0.94 %	0.95 %	1.43 %	0.94 %	1.09 %	1.32 %	0.86 %	0.84 %	0.92 %
May 2007	1.04 %	0.88 %	0.92 %	0.84 %	0.98 %	1.04 %	1.15 %	0.87 %	1.13 %	1.34 %	0.81 %	0.88 %	0.85 %
June 2007	1.34 %	1.17 %	1.31 %	1.13 %	1.30 %	1.23 %	1.25 %	1.03 %	1.42 %	1.55 %	1.16 %	1.21 %	1.24 %
July 2007	1.04 %	0.98 %	1.23 %	1.06 %	1.25 %	1.13 %	1.25 %	0.90 %	1.09 %	1.34 %	1.09 %	1.11 %	1.07 %
August 2007	1.78 %	1.59 %	1.53 %	1.66 %	1.35 %	1.67 %	1.95 %	1.72 %	1.51 %	2.01 %	1.55 %	2.04 %	1.48 %
September 2007	1.04 %	1.25 %	1.12 %	1.44 %	1.12 %	1.36 %	1.68 %	1.27 %	1.43 %	1.94 %	1.28 %	1.53 %	1.13 %
October 2007	1.01 %	1.07 %	1.00 %	1.02 %	0.96 %	1.02 %	1.49 %	1.02 %	1.05 %	1.72 %	0.97 %	1.16 %	1.01 %
November 2007	1.42 %	1.85 %	1.34 %	1.22 %	1.20 %	1.33 %	1.93 %	1.48 %	1.10 %	1.91 %	1.42 %	1.71 %	1.45 %
December 2007	1.46 %	1.22 %	1.10 %	1.20 %	1.09 %	1.14 %	1.49 %	1.23 %	1.22 %	1.72 %	1.37 %	1.60 %	1.33 %
January 2008	2.06 %	1.76 %	1.48 %	1.49 %	1.57 %	1.45 %	2.49 %	1.79 %	1.83 %	2.05 %	1.73 %	1.80 %	1.47 %
February 2008	2.09 %	1.71 %	1.48 %	1.85 %	1.51 %	1.68 %	2.11 %	1.78 %	1.67 %	2.04 %	1.73 %	1.96 %	1.57 %
March 2008	2.28 %	1.57 %	1.57 %	1.72 %	1.44 %	1.97 %	2.48 %	1.51 %	1.47 %	2.06 %	1.94 %	1.77 %	1.35 %
April 2008	1.36 %	1.18 %	1.26 %	1.28 %	1.15 %	1.34 %	2.00 %	1.11 %	1.45 %	1.81 %	1.56 %	1.32 %	1.19 %
May 2008	1.12 %	1.28 %	1.27 %	1.07 %	1.08 %	1.15 %	1.52 %	1.06 %	1.23 %	1.57 %	1.15 %	1.35 %	1.12 %
June 2008	1.77 %	1.96 %	1.55 %	1.62 %	1.34 %	1.63 %	1.76 %	1.60 %	1.79 %	1.89 %	1.44 %	1.76 %	1.32 %
July 2008	2.07 %	2.26 %	1.78 %	1.97 %	1.36 %	1.79 %	1.58 %	2.13 %	2.06 %	2.39 %	1.49 %	2.17 %	1.45 %
August 2008	1.43 %	1.68 %	1.49 %	1.49 %	1.20 %	1.37 %	1.92 %	1.47 %	1.61 %	1.94 %	1.03 %	1.37 %	1.34 %
September 2008	1.92 %	2.50 %	2.28 %	1.98 %	1.47 %	2.17 %	2.45 %	2.27 %	2.08 %	2.36 %	1.62 %	2.46 %	1.94 %
October 2008	4.31 %	4.88 %	4.80 %	3.88 %	3.42 %	4.72 %	5.11 %	5.47 %	3.91 %	4.04 %	3.75 %	5.18 %	4.66 %
November 2008	3.38 %	3.03 %	4.50 %	3.48 %	2.99 %	3.78 %	4.39 %	4.06 %	2.66 %	3.83 %	3.19 %	3.78 %	4.54 %
December 2008	1.96 %	1.83 %	3.73 %	2.74 %	1.71 %	2.72 %	2.43 %	2.70 %	1.85 %	2.98 %	2.21 %	2.40 %	3.22 %
January 2009	1.92 %	1.70 %	2.58 %	1.95 %	1.71 %	2.09 %	2.14 %	2.05 %	1.93 %	2.37 %	1.45 %	2.17 %	2.18 %
February 2009	1.82 %	1.88 %	2.31 %	2.12 %	1.95 %	2.30 %	2.11 %	2.58 %	1.96 %	2.48 %	1.71 %	2.25 %	2.61 %
March 2009	1.51 %	2.13 %	2.60 %	2.11 %	1.73 %	3.16 %	2.17 %	2.56 %	1.98 %	2.62 %	2.02 %	2.47 %	2.91 %
April 2009	1.24 %	1.60 %	2.11 %	1.63 %	1.51 %	2.24 %	1.99 %	1.69 %	1.51 %	2.21 %	1.42 %	1.96 %	2.24 %
May 2009	1.72 %	1.49 %	2.10 %	1.46 %	1.53 %	1.94 %	1.72 %	1.47 %	1.39 %	2.16 %	1.03 %	1.57 %	1.89 %
June 2009	1.69 %	1.26 %	2.07 %	1.39 %	1.42 %	1.88 %	1.44 %	1.56 %	1.43 %	1.85 %	1.13 %	1.53 %	1.79 %
July 2009	1.28 %	1.10 %	1.79 %	1.46 %	1.39 %	1.89 %	1.58 %	1.51 %	1.34 %	1.61 %	1.06 %	1.40 %	1.44 %
August 2009	0.87 %	1.08 %	1.47 %	1.07 %	1.30 %	1.46 %	1.37 %	1.08 %	1.17 %	1.62 %	0.78 %	1.06 %	1.10 %
September 2009	1.01 %	1.23 %	1.23 %	1.12 %	1.18 %	1.35 %	1.55 %	1.22 %	1.24 %	1.62 %	0.82 %	1.03 %	0.98 %
October 2009	1.24 %	1.40 %	1.50 %	1.30 %	1.36 %	1.45 %	1.59 %	1.43 %	1.52 %	1.56 %	1.00 %	1.44 %	1.19 %
November 2009	1.42 %	1.47 %	1.47 %	1.48 %	1.39 %	1.80 %	1.42 %	1.54 %	1.39 %	1.52 %	1.03 %	1.56 %	1.36 %
December 2009	1.18 %	1.21 %	1.20 %	1.27 %	1.13 %	1.50 %	1.42 %	1.21 %	1.35 %	1.55 %	0.96 %	1.38 %	1.03 %
January 2010	0.97 %	0.97 %	0.94 %	1.03 %	1.14 %	1.15 %	1.30 %	0.92 %	1.34 %	1.22 %	0.84 %	1.06 %	0.99 %
February 2010	1.43 %	1.32 %	1.23 %	1.45 %	1.31 %	1.81 %	1.66 %	1.30 %	2.14 %	1.43 %	1.03 %	1.45 %	1.30 %
March 2010	0.95 %	1.00 %	0.93 %	1.05 %	0.98 %	1.28 %	1.21 %	1.02 %	1.33 %	1.18 %	0.72 %	0.90 %	0.88 %
April 2010	0.91 %	1.07 %	0.92 %	0.99 %	1.00 %	1.32 %	1.25 %	0.98 %	1.58 %	1.09 %	0.82 %	0.98 %	0.83 %
May 2010	1.90 %	2.32 %	1.28 %	2.08 %	1.72 %	3.40 %	1.91 %	2.13 %	3.67 %	2.01 %	1.53 %	2.18 %	1.61 %
June 2010	1.30 %	1.47 %	1.22 %	1.76 %	1.16 %	2.36 %	1.62 %	1.52 %	2.30 %	1.64 %	1.18 %	1.46 %	1.58 %
July 2010	1.21 %	1.40 %	1.25 %	1.64 %	1.21 %	1.87 %	1.59 %	1.56 %	1.54 %	1.70 %	1.26 %	1.53 %	1.40 %
August 2010	1.15 %	1.21 %	0.98 %	1.27 %	1.11 %	1.50 %	1.53 %	1.29 %	1.70 %	1.53 %	0.94 %	1.21 %	1.16 %
September 2010	1.02 %	0.96 %	0.92 %	1.07 %	0.92 %	1.32 %	1.38 %	0.92 %	1.36 %	1.36 %	0.88 %	0.91 %	0.94 %
October 2010	1.17 %	1.03 %	0.90 %	1.01 %	0.97 %	1.14 %	1.54 %	1.00 %	1.13 %	1.30 %	0.77 %	1.02 %	0.97 %
November 2010	1.35 %	1.47 %	1.18 %	1.20 %	1.11 %	1.65 %	1.24 %	1.16 %	2.14 %	1.38 %	0.86 %	1.47 %	1.28 %
December 2010	0.90 %	1.25 %	0.98 %	1.21 %	1.09 %	1.72 %	1.10 %	1.02 %	1.97 %	1.22 %	0.94 %	1.09 %	1.20 %
Total	1.24 %	1.27 %	1.35 %	1.42 %	1.35 %	1.49 %	1.64 %	1.40 %	1.45 %	1.75 %	1.21 %	1.40 %	1.41 %

Table 21: 5% CAViaR Estimates (Monthly Averages)

This table reports the monthly and total period averages of the daily 5% conditional autoregressive value at risk (CAViaR) estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the table continues on the next page. For further information, refer to Section 4.3.

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
January 1999	0.89 %	1.15 %	0.79 %	1.13 %	1.27 %	1.39 %	1.15 %	1.41 %	1.35 %	1.18 %	1.02 %	1.03 %	0.98 %
February 1999	0.83 %	0.76 %	0.95 %	1.14 %	1.24 %	1.35 %	1.03 %	1.21 %	1.14 %	1.04 %	0.95 %	0.91 %	1.10 %
March 1999	0.80 %	1.22 %	0.94 %	1.05 %	1.43 %	1.23 %	0.90 %	1.11 %	1.03 %	1.16 %	0.86 %	0.93 %	1.03 %
April 1999	0.57 %	0.82 %	0.74 %	0.77 %	0.92 %	0.86 %	0.84 %	0.80 %	0.91 %	0.98 %	0.79 %	0.67 %	0.93 %
May 1999	1.15 %	0.83 %	0.87 %	0.86 %	0.98 %	1.06 %	0.87 %	0.85 %	0.79 %	0.97 %	0.92 %	0.99 %	1.10 %
June 1999	0.87 %	0.97 %	0.86 %	0.88 %	0.93 %	1.07 %	0.78 %	0.84 %	0.79 %	0.95 %	0.96 %	0.81 %	1.15 %
July 1999	0.76 %	1.04 %	0.82 %	0.91 %	1.02 %	1.06 %	0.91 %	0.90 %	1.07 %	1.04 %	0.97 %	0.90 %	0.90 %
August 1999	1.00 %	1.07 %	1.00 %	1.01 %	1.19 %	1.22 %	0.97 %	1.09 %	1.14 %	0.99 %	0.94 %	1.11 %	1.16 %
September 1999	0.92 %	0.87 %	0.90 %	0.80 %	1.11 %	1.02 %	0.99 %	1.08 %	1.04 %	1.05 %	0.91 %	1.25 %	1.16 %
October 1999	1.02 %	0.99 %	0.94 %	0.96 %	1.03 %	1.01 %	1.06 %	1.11 %	1.01 %	0.95 %	0.98 %	1.14 %	1.17 %
November 1999	0.72 %	0.83 %	0.78 %	0.69 %	0.71 %	0.74 %	0.81 %	0.72 %	0.76 %	0.88 %	0.61 %	0.66 %	0.89 %
December 1999	0.64 %	1.15 %	0.88 %	0.64 %	0.69 %	0.72 %	0.93 %	0.57 %	0.69 %	1.06 %	0.60 %	0.64 %	0.81 %
January 2000	0.91 %	1.47 %	1.04 %	1.21 %	1.26 %	1.27 %	1.19 %	1.18 %	1.09 %	1.13 %	0.88 %	1.19 %	0.98 %
February 2000	0.70 %	1.17 %	1.05 %	1.10 %	1.26 %	1.18 %	1.00 %	1.13 %	0.91 %	1.15 %	1.04 %	1.17 %	1.09 %
March 2000	0.66 %	0.98 %	0.97 %	1.23 %	1.03 %	1.28 %	1.28 %	0.83 %	0.76 %	1.30 %	0.84 %	0.84 %	1.00 %
April 2000	0.94 %	0.97 %	1.51 %	1.53 %	1.29 %	1.50 %	1.45 %	1.07 %	0.95 %	1.79 %	0.68 %	1.20 %	1.20 %
May 2000	0.97 %	0.62 %	1.46 %	1.32 %	1.45 %	1.26 %	1.34 %	0.90 %	1.26 %	1.68 %	0.58 %	1.09 %	1.43 %
June 2000	0.65 %	0.62 %	1.05 %	1.05 %	1.04 %	1.10 %	1.11 %	0.67 %	1.12 %	1.76 %	0.63 %	0.82 %	1.10 %
July 2000	0.59 %	0.54 %	0.84 %	0.88 %	0.85 %	0.76 %	1.08 %	0.66 %	0.91 %	1.65 %	0.49 %	0.77 %	0.97 %
August 2000	0.54 %	0.42 %	0.81 %	0.80 %	0.85 %	0.79 %	0.99 %	0.60 %	0.85 %	1.50 %	0.43 %	0.59 %	0.92 %
September 2000	0.83 %	0.59 %	1.03 %	0.99 %	1.11 %	0.81 %	1.00 %	0.70 %	0.91 %	1.26 %	0.65 %	0.81 %	0.87 %
October 2000	0.77 %	0.54 %	1.39 %	1.15 %	1.11 %	0.93 %	1.14 %	0.69 %	1.20 %	1.77 %	0.81 %	0.86 %	1.15 %
November 2000	0.65 %	0.54 %	1.47 %	1.11 %	1.09 %	0.81 %	1.05 %	0.73 %	1.32 %	1.67 %	0.57 %	0.78 %	1.18 %
December 2000	0.59 %	0.55 %	1.18 %	1.22 %	1.31 %	1.17 %	1.09 %	1.05 %	1.48 %	1.56 %	0.69 %	0.92 %	1.18 %
January 2001	0.61 %	0.46 %	1.03 %	1.00 %	0.78 %	0.92 %	0.99 %	0.77 %	0.92 %	1.56 %	0.64 %	0.77 %	1.09 %
February 2001	0.66 %	0.41 %	1.02 %	0.99 %	0.89 %	0.96 %	0.91 %	0.70 %	0.98 %	1.73 %	0.72 %	0.73 %	1.05 %
March 2001	0.68 %	0.88 %	1.20 %	1.34 %	1.52 %	1.33 %	1.22 %	1.09 %	1.16 %	2.11 %	1.11 %	1.17 %	1.34 %
April 2001	0.73 %	0.85 %	1.13 %	1.12 %	1.30 %	1.12 %	1.32 %	1.05 %	1.14 %	2.29 %	1.07 %	1.12 %	1.36 %
May 2001	0.59 %	0.61 %	0.79 %	0.85 %	0.86 %	0.82 %	0.95 %	0.85 %	0.97 %	1.49 %	0.62 %	0.88 %	1.04 %
June 2001	0.62 %	0.63 %	0.83 %	0.98 %	0.95 %	0.92 %	0.98 %	0.84 %	0.95 %	1.41 %	0.76 %	0.90 %	1.05 %
July 2001	0.84 %	0.44 %	0.78 %	1.10 %	1.00 %	0.93 %	1.28 %	0.89 %	1.16 %	1.37 %	1.05 %	0.95 %	1.02 %
August 2001	0.73 %	0.46 %	0.54 %	1.00 %	1.06 %	0.77 %	1.29 %	0.85 %	0.93 %	1.19 %	0.97 %	0.71 %	0.92 %
September 2001	1.13 %	1.31 %	0.87 %	1.84 %	2.21 %	2.21 %	1.84 %	2.00 %	1.55 %	1.95 %	1.93 %	1.62 %	1.21 %
October 2001	0.87 %	1.03 %	0.86 %	1.39 %	1.34 %	2.04 %	1.42 %	1.79 %	1.35 %	1.75 %	1.30 %	1.31 %	1.10 %
November 2001	0.74 %	0.81 %	0.78 %	1.26 %	1.20 %	1.48 %	1.15 %	1.35 %	1.21 %	1.43 %	0.89 %	0.92 %	1.00 %
December 2001	0.80 %	0.70 %	0.79 %	1.07 %	1.12 %	1.20 %	1.27 %	1.06 %	1.17 %	1.30 %	0.96 %	0.92 %	1.04 %
January 2002	0.67 %	0.65 %	0.69 %	0.88 %	0.82 %	0.89 %	1.12 %	0.87 %	1.07 %	1.25 %	0.73 %	0.75 %	0.86 %
February 2002	0.58 %	0.81 %	0.66 %	1.04 %	1.02 %	0.86 %	1.27 %	0.90 %	1.08 %	1.19 %	0.82 %	0.85 %	0.95 %
March 2002	0.80 %	0.67 %	0.65 %	0.78 %	0.77 %	0.71 %	1.08 %	0.71 %	0.84 %	1.03 %	0.60 %	0.75 %	0.92 %
April 2002	0.75 %	0.55 %	0.64 %	0.80 %	0.77 %	0.72 %	1.07 %	0.69 %	0.81 %	1.14 %	0.50 %	0.63 %	0.90 %
May 2002	0.60 %	0.79 %	0.58 %	0.82 %	0.91 %	0.88 %	0.73 %	0.84 %	0.84 %	1.23 %	0.59 %	0.67 %	0.99 %
June 2002	0.60 %	1.15 %	0.57 %	1.28 %	1.28 %	1.18 %	1.15 %	1.39 %	1.13 %	1.30 %	1.15 %	1.03 %	1.05 %
July 2002	0.72 %	1.88 %	0.82 %	2.05 %	1.78 %	1.60 %	1.39 %	2.41 %	1.55 %	1.77 %	1.92 %	1.95 %	1.40 %
August 2002	0.65 %	1.56 %	0.84 %	1.83 %	1.59 %	1.43 %	1.27 %	2.13 %	1.61 %	1.96 %	1.63 %	1.59 %	1.39 %
September 2002	0.65 %	1.65 %	0.80 %	2.00 %	1.70 %	1.61 %	1.38 %	2.09 %	1.53 %	1.61 %	1.66 %	1.57 %	1.28 %
October 2002	0.79 %	1.61 %	1.03 %	2.02 %	1.98 %	1.62 %	1.45 %	1.97 %	1.42 %	2.00 %	1.54 %	1.55 %	1.40 %
November 2002	0.59 %	0.83 %	0.77 %	1.44 %	1.38 %	1.22 %	1.25 %	1.38 %	0.98 %	1.50 %	1.01 %	1.15 %	1.01 %
December 2002	0.58 %	0.95 %	0.62 %	1.21 %	1.24 %	1.11 %	1.09 %	1.19 %	0.97 %	1.27 %	0.93 %	1.09 %	0.94 %
January 2003	0.62 %	0.89 %	0.51 %	1.01 %	1.08 %	0.94 %	0.83 %	1.06 %	0.88 %	1.07 %	1.02 %	1.03 %	0.87 %
February 2003	0.86 %	1.30 %	0.54 %	1.31 %	1.44 %	1.01 %	0.87 %	1.56 %	1.11 %	1.36 %	1.41 %	1.18 %	1.03 %
March 2003	0.88 %	1.76 %	0.59 %	1.65 %	1.55 %	1.37 %	1.07 %	1.96 %	1.20 %	1.24 %	1.48 %	1.36 %	0.96 %
April 2003	0.53 %	0.96 %	0.44 %	1.29 %	1.08 %	0.95 %	1.11 %	1.32 %	0.89 %	1.11 %	1.02 %	0.99 %	0.84 %
May 2003	0.51 %	0.77 %	0.37 %	0.86 %	0.85 %	0.66 %	0.89 %	0.98 %	0.78 %	0.87 %	0.78 %	0.71 %	0.66 %
June 2003	0.51 %	0.70 %	0.46 %	0.73 %	0.70 %	0.59 %	0.76 %	0.94 %	0.67 %	0.81 %	0.67 %	0.63 %	0.64 %
July 2003	0.73 %	0.84 %	0.50 %	0.97 %	0.91 %	0.87 %	0.92 %	1.16 %	0.92 %	0.87 %	0.80 %	0.80 %	0.95 %
August 2003	0.65 %	0.56 %	0.51 %	0.80 %	0.75 %	0.65 %	0.82 %	0.79 %	0.71 %	0.78 %	0.70 %	0.64 %	1.10 %
September 2003	0.56 %	0.64 %	0.38 %	0.76 %	0.92 %	0.65 %	0.78 %	0.80 %	0.71 %	0.82 %	0.63 %	0.66 %	0.80 %
October 2003	0.56 %	0.51 %	0.47 %	0.80 %	0.99 %	0.66 %	0.98 %	0.87 %	0.68 %	0.89 %	0.69 %	0.69 %	0.73 %
November 2003	0.66 %	0.51 %	0.45 %	0.69 %	0.73 %	0.57 %	1.32 %	0.74 %	0.56 %	0.81 %	0.68 %	0.63 %	0.68 %
December 2003	0.60 %	0.42 %	0.43 %	0.54 %	0.54 %	0.52 %	1.05 %	0.56 %	0.46 %	0.69 %	0.52 %	0.55 %	0.63 %
January 2004	0.56 %	0.36 %	0.43 %	0.43 %	0.46 %	0.55 %	0.67 %	0.49 %	0.44 %	0.60 %	0.42 %	0.40 %	0.57 %
February 2004	0.58 %	0.49 %	0.62 %	0.62 %	0.69 %	0.58 %	0.73 %	0.61 %	0.64 %	0.69 %	0.45 %	0.54 %	0.66 %
March 2004	0.51 %	0.78 %	0.73 %	0.82 %	0.99 %	0.69 %	0.70 %	0.88 %	0.87 %	0.91 %	0.69 %	0.66 %	0.76 %
April 2004	0.66 %	0.54 %	0.73 %	0.71 %	0.70 %	0.53 %	0.73 %	0.63 %	0.72 %	0.85 %	0.64 %	0.58 %	0.87 %
May 2004	0.70 %	0.80 %	0.96 %	0.97 %	1.09 %	0.83 %	1.32 %	0.99 %	0.98 %	1.26 %	0.88 %	0.87 %	1.01 %
June 2004	0.50 %	0.61 %	0.73 %	0.78 %	0.74 %	0.65 %	1.00 %	0.71 %	0.78 %	0.89 %	0.78 %	0.66 %	0.80 %
July 2004	0.50 %	0.48 %	0.57 %	0.64 %	0.70 %	0.56 %	0.96 %	0.65 %	0.67 %	0.81 %	0.75 %	0.67 %	0.76 %
August 2004	0.50 %	0.50 %	0.59 %	0.72 %	0.79 %	0.63 %	0.88 %	0.76 %	0.75 %	0.90 %	0.73 %	0.65 %	0.73 %
September 2004	0.51 %	0.34 %	0.49 %	0.52 %	0.56 %	0.39 %	0.69 %	0.52 %	0.51 %	0.65 %	0.53 %	0.38 %	0.63 %

Month	Australia	Belgium	Canada	France	Germany	Italy	Japan	Netherlands	Spain	Sweden	Switzerland	UK	US
October 2004	0.48 %	0.39 %	0.47 %	0.57 %	0.59 %	0.38 %	0.74 %	0.59 %	0.48 %	0.66 %	0.65 %	0.41 %	0.64 %
November 2004	0.49 %	0.40 %	0.44 %	0.53 %	0.50 %	0.38 %	0.74 %	0.48 %	0.47 %	0.66 %	0.59 %	0.42 %	0.62 %
December 2004	0.49 %	0.41 %	0.47 %	0.52 %	0.50 %	0.42 %	0.72 %	0.48 %	0.46 %	0.60 %	0.53 %	0.46 %	0.67 %
January 2005	0.50 %	0.45 %	0.55 %	0.53 %	0.60 %	0.46 %	0.59 %	0.53 %	0.50 %	0.74 %	0.49 %	0.51 %	0.73 %
February 2005	0.48 %	0.49 %	0.39 %	0.50 %	0.57 %	0.55 %	0.54 %	0.48 %	0.52 %	0.79 %	0.43 %	0.46 %	0.66 %
March 2005	0.58 %	0.67 %	0.60 %	0.60 %	0.62 %	0.66 %	0.52 %	0.65 %	0.76 %	0.73 %	0.58 %	0.67 %	0.85 %
April 2005	0.70 %	0.58 %	0.69 %	0.60 %	0.61 %	0.65 %	0.83 %	0.63 %	0.70 %	0.68 %	0.54 %	0.58 %	0.83 %
May 2005	0.65 %	0.53 %	0.55 %	0.51 %	0.53 %	0.59 %	0.74 %	0.55 %	0.57 %	0.73 %	0.54 %	0.47 %	0.75 %
June 2005	0.48 %	0.50 %	0.47 %	0.51 %	0.52 %	0.53 %	0.60 %	0.52 %	0.55 %	0.56 %	0.45 %	0.43 %	0.65 %
July 2005	0.55 %	0.49 %	0.46 %	0.55 %	0.51 %	0.59 %	0.49 %	0.53 %	0.56 %	0.66 %	0.43 %	0.48 %	0.64 %
August 2005	0.55 %	0.44 %	0.54 %	0.54 %	0.57 %	0.57 %	0.56 %	0.54 %	0.57 %	0.66 %	0.41 %	0.44 %	0.73 %
September 2005	0.57 %	0.36 %	0.56 %	0.54 %	0.63 %	0.50 %	0.55 %	0.48 %	0.54 %	0.63 %	0.45 %	0.40 %	0.69 %
October 2005	0.81 %	0.56 %	0.89 %	0.76 %	0.83 %	0.81 %	0.77 %	0.78 %	0.71 %	0.72 %	0.62 %	0.72 %	0.85 %
November 2005	0.61 %	0.53 %	0.73 %	0.73 %	0.65 %	0.75 %	0.60 %	0.62 %	0.76 %	0.66 %	0.58 %	0.56 %	0.74 %
December 2005	0.63 %	0.49 %	0.58 %	0.51 %	0.45 %	0.51 %	0.70 %	0.44 %	0.59 %	0.61 %	0.49 %	0.51 %	0.66 %
January 2006	0.48 %	0.45 %	0.44 %	0.53 %	0.61 %	0.55 %	0.92 %	0.63 %	0.55 %	0.63 %	0.49 %	0.44 %	0.62 %
February 2006	0.64 %	0.43 %	0.64 %	0.56 %	0.59 %	0.56 %	1.20 %	0.52 %	0.54 %	0.63 %	0.49 %	0.51 %	0.68 %
March 2006	0.57 %	0.60 %	0.63 %	0.63 %	0.69 %	0.70 %	0.98 %	0.67 %	0.62 %	0.66 %	0.58 %	0.59 %	0.69 %
April 2006	0.57 %	0.51 %	0.64 %	0.66 %	0.61 %	0.82 %	0.80 %	0.64 %	0.66 %	0.70 %	0.60 %	0.61 %	0.73 %
May 2006	0.82 %	0.83 %	0.75 %	0.94 %	1.04 %	0.97 %	1.01 %	1.00 %	0.82 %	1.13 %	0.88 %	1.00 %	0.78 %
June 2006	1.05 %	1.08 %	1.03 %	1.28 %	1.23 %	1.14 %	1.45 %	1.21 %	1.05 %	1.66 %	1.11 %	1.20 %	0.92 %
July 2006	0.86 %	0.69 %	0.86 %	0.88 %	0.92 %	0.78 %	1.19 %	0.84 %	0.80 %	1.24 %	0.77 %	0.76 %	0.85 %
August 2006	0.87 %	0.55 %	0.66 %	0.77 %	0.71 %	0.69 %	0.86 %	0.68 %	0.74 %	1.01 %	0.56 %	0.76 %	0.73 %
September 2006	0.71 %	0.54 %	0.65 %	0.64 %	0.61 %	0.57 %	0.82 %	0.65 %	0.61 %	0.80 %	0.47 %	0.62 %	0.60 %
October 2006	0.63 %	0.50 %	0.72 %	0.52 %	0.45 %	0.49 %	0.73 %	0.50 %	0.54 %	0.72 %	0.44 %	0.51 %	0.54 %
November 2006	0.57 %	0.50 %	0.58 %	0.52 %	0.51 %	0.47 %	0.83 %	0.51 %	0.51 %	0.69 %	0.44 %	0.48 %	0.55 %
December 2006	0.56 %	0.46 %	0.47 %	0.58 %	0.58 %	0.53 %	0.69 %	0.59 %	0.68 %	0.80 %	0.61 %	0.51 %	0.56 %
January 2007	0.57 %	0.47 %	0.55 %	0.60 %	0.55 %	0.54 %	0.64 %	0.55 %	0.65 %	0.70 %	0.46 %	0.55 %	0.59 %
February 2007	0.50 %	0.51 %	0.53 %	0.57 %	0.53 %	0.56 %	0.60 %	0.55 %	0.56 %	0.73 %	0.50 %	0.53 %	0.58 %
March 2007	0.74 %	0.88 %	0.70 %	0.84 %	0.90 %	0.89 %	1.10 %	0.89 %	0.93 %	1.10 %	0.90 %	0.85 %	0.74 %
April 2007	0.61 %	0.57 %	0.53 %	0.56 %	0.55 %	0.59 %	0.93 %	0.63 %	0.69 %	0.82 %	0.59 %	0.56 %	0.65 %
May 2007	0.62 %	0.52 %	0.51 %	0.52 %	0.58 %	0.64 %	0.70 %	0.58 %	0.73 %	0.81 %	0.56 %	0.55 %	0.60 %
June 2007	0.79 %	0.75 %	0.76 %	0.76 %	0.87 %	0.81 %	0.73 %	0.69 %	0.87 %	0.96 %	0.80 %	0.74 %	0.79 %
July 2007	0.65 %	0.61 %	0.74 %	0.70 %	0.85 %	0.74 %	0.74 %	0.60 %	0.72 %	0.81 %	0.77 %	0.70 %	0.74 %
August 2007	1.03 %	1.08 %	0.95 %	1.18 %	0.98 %	1.11 %	1.20 %	1.20 %	0.95 %	1.31 %	1.06 %	1.25 %	0.94 %
September 2007	0.72 %	0.84 %	0.70 %	0.98 %	0.74 %	0.92 %	1.14 %	0.87 %	0.95 %	1.29 %	0.87 %	0.98 %	0.79 %
October 2007	0.63 %	0.71 %	0.58 %	0.65 %	0.56 %	0.66 %	0.93 %	0.69 %	0.70 %	1.12 %	0.66 %	0.72 %	0.70 %
November 2007	0.83 %	1.25 %	0.80 %	0.83 %	0.79 %	0.87 %	1.25 %	1.03 %	0.65 %	1.24 %	0.98 %	1.05 %	0.91 %
December 2007	0.86 %	0.89 %	0.67 %	0.80 %	0.71 %	0.77 %	0.98 %	0.84 %	0.75 %	1.12 %	0.94 %	1.03 %	0.88 %
January 2008	1.13 %	1.13 %	0.88 %	1.06 %	1.13 %	0.96 %	1.55 %	1.26 %	1.11 %	1.35 %	1.22 %	1.16 %	0.99 %
February 2008	1.33 %	1.28 %	0.95 %	1.31 %	1.18 %	1.17 %	1.54 %	1.24 %	1.24 %	1.38 %	1.22 %	1.29 %	1.05 %
March 2008	1.37 %	1.12 %	0.98 %	1.21 %	1.09 %	1.36 %	1.67 %	1.05 %	1.05 %	1.38 %	1.36 %	1.18 %	0.95 %
April 2008	0.94 %	0.80 %	0.80 %	0.85 %	0.78 %	0.93 %	1.36 %	0.75 %	0.95 %	1.20 %	1.08 %	0.85 %	0.84 %
May 2008	0.72 %	0.83 %	0.77 %	0.69 %	0.68 %	0.75 %	0.99 %	0.72 %	0.82 %	1.01 %	0.78 %	0.83 %	0.78 %
June 2008	1.01 %	1.34 %	0.95 %	1.16 %	0.98 %	1.13 %	1.12 %	1.11 %	1.16 %	1.22 %	1.02 %	1.19 %	0.91 %
July 2008	1.22 %	1.69 %	1.15 %	1.42 %	1.01 %	1.27 %	1.04 %	1.49 %	1.44 %	1.61 %	1.06 %	1.44 %	1.01 %
August 2008	0.97 %	1.22 %	0.97 %	1.00 %	0.80 %	0.92 %	1.23 %	1.02 %	1.19 %	1.31 %	0.67 %	0.91 %	0.91 %
September 2008	1.11 %	1.68 %	1.45 %	1.42 %	1.05 %	1.42 %	1.61 %	1.61 %	1.36 %	1.61 %	1.06 %	1.45 %	1.17 %
October 2008	2.35 %	3.64 %	3.19 %	2.93 %	2.87 %	3.31 %	3.35 %	3.94 %	2.57 %	2.86 %	2.52 %	3.25 %	2.64 %
November 2008	2.16 %	2.46 %	3.23 %	2.53 %	2.70 %	2.87 %	3.40 %	2.89 %	2.32 %	2.81 %	2.21 %	2.58 %	2.85 %
December 2008	1.42 %	1.51 %	2.75 %	1.94 %	1.44 %	2.10 %	1.93 %	1.90 %	1.56 %	2.19 %	1.57 %	1.66 %	2.22 %
January 2009	1.16 %	1.14 %	1.87 %	1.37 %	1.30 %	1.49 %	1.46 %	1.44 %	1.32 %	1.65 %	1.04 %	1.39 %	1.63 %
February 2009	1.15 %	1.33 %	1.63 %	1.52 %	1.57 %	1.66 %	1.51 %	1.83 %	1.44 %	1.74 %	1.23 %	1.51 %	1.77 %
March 2009	1.00 %	1.54 %	1.77 %	1.50 %	1.40 %	2.26 %	1.44 %	1.80 %	1.51 %	1.84 %	1.42 %	1.60 %	1.89 %
April 2009	0.78 %	1.15 %	1.46 %	1.09 %	1.05 %	1.52 %	1.31 %	1.18 %	1.04 %	1.56 %	0.92 %	1.21 %	1.49 %
May 2009	0.98 %	0.99 %	1.39 %	0.98 %	1.11 %	1.26 %	1.09 %	1.03 %	0.94 %	1.48 %	0.67 %	0.93 %	1.28 %
June 2009	1.04 %	0.87 %	1.39 %	0.95 %	1.03 %	1.30 %	0.89 %	1.09 %	0.92 %	1.24 %	0.76 %	1.01 %	1.23 %
July 2009	0.88 %	0.74 %	1.21 %	0.99 %	0.98 %	1.29 %	1.01 %	1.05 %	0.89 %	1.06 %	0.68 %	0.89 %	1.02 %
August 2009	0.59 %	0.65 %	0.96 %	0.66 %	0.85 %	0.92 %	0.80 %	0.74 %	0.70 %	1.06 %	0.44 %	0.56 %	0.76 %
September 2009	0.64 %	0.81 %	0.77 %	0.72 %	0.78 %	0.85 %	0.97 %	0.84 %	0.77 %	1.05 %	0.52 %	0.56 %	0.67 %
October 2009	0.71 %	0.89 %	0.92 %	0.88 %	0.91 %	0.91 %	1.03 %	1.00 %	0.92 %	1.00 %	0.65 %	0.78 %	0.74 %
November 2009	0.88 %	1.04 %	0.93 %	1.02 %	1.01 %	1.21 %	0.93 %	1.07 %	0.94 %	0.97 %	0.69 %	0.98 %	0.86 %
December 2009	0.75 %	0.83 %	0.75 %	0.85 %	0.75 %	1.03 %	0.86 %	0.83 %	0.90 %	0.99 %	0.64 %	0.91 %	0.75 %
January 2010	0.59 %	0.60 %	0.55 %	0.67 %	0.73 %	0.74 %	0.74 %	0.62 %	0.82 %	0.73 %	0.57 %	0.67 %	0.70 %
February 2010	0.83 %	0.86 %	0.72 %	1.01 %	0.95 %	1.23 %	1.05 %	0.89 %	1.44 %	0.87 %	0.70 %	0.94 %	0.86 %
March 2010	0.62 %	0.65 %	0.53 %	0.67 %	0.57 %	0.85 %	0.75 %	0.70 %	0.97 %	0.71 %	0.47 %	0.52 %	0.63 %
April 2010	0.55 %	0.63 %	0.51 %	0.64 %	0.56 %	0.82 %	0.70 %	0.67 %	0.96 %	0.62 %	0.55 %	0.55 %	0.58 %
May 2010	1.02 %	1.60 %	0.74 %	1.51 %	1.27 %	2.30 %	1.18 %	1.51 %	2.39 %	1.30 %	1.04 %	1.31 %	0.95 %
June 2010	0.86 %	1.09 %	0.74 %	1.22 %	0.81 %	1.77 %	1.09 %	1.05 %	1.93 %	1.07 %	0.81 %	1.00 %	1.04 %
July 2010	0.76 %	0.97 %	0.76 %	1.13 %	0.82 %	1.33 %	1.03 %	1.09 %	1.28 %	1.10 %	0.87 %	0.96 %	0.96 %
August 2010	0.70 %	0.81 %	0.57 %	0.84 %	0.70 %	1.01 %	0.97 %	0.88 %	1.10 %	0.97 %	0.64 %	0.73 %	0.81 %
September 2010	0.65 %	0.62 %	0.52 %	0.69 %	0.53 %	0.88 %	0.88 %	0.62 %	0.96 %	0.85 %	0.61 %	0.54 %	0.67 %
October 2010	0.70 %	0.64 %	0.49 %	0.65 %	0.54 %	0.72 %	0.93 %	0.68 %	0.77 %	0.79 %	0.53 %	0.57 %	0.62 %
November 2010	0.79 %	0.95 %	0.68 %	0.82 %	0.68 %	1.08 %	0.77 %	0.79 %	1.27 %	0.84 %	0.57 %	0.89 %	0.78 %
December 2010	0.60 %	0.91 %	0.57 %	0.81 %	0.70 %	1.21 %	0.64 %	0.69 %	1.52 %	0.72 %	0.65 %	0.73 %	0.82 %
Total	0.76 %	0.85 %	0.83 %	0.96 %	0.95 %	0.99 %	1.04 %	0.97 %	0.96 %	1.15 %	0.82 %	0.89 %	0.95 %

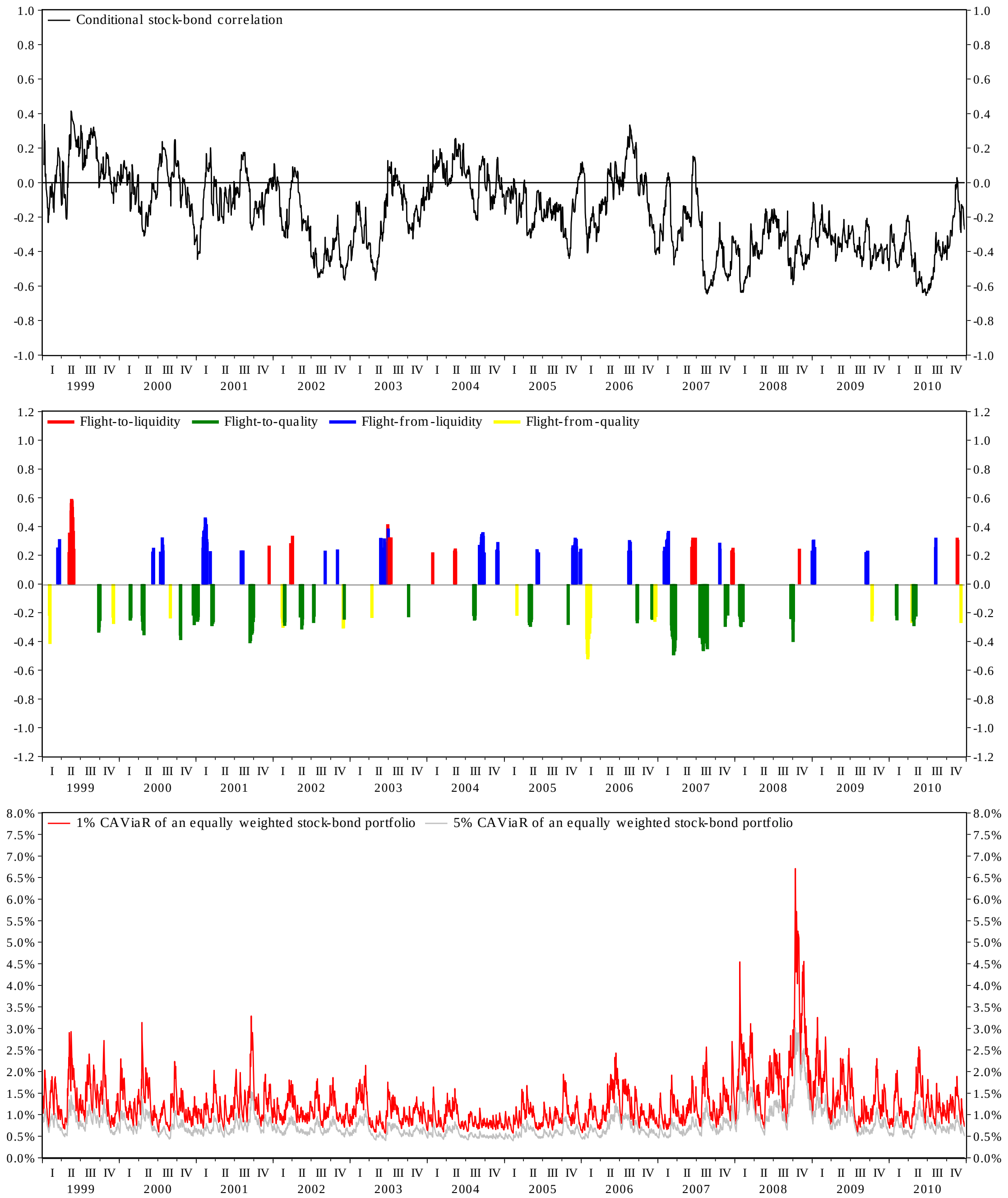


Figure 1: Conditional Correlation, Flight and CAViaR Estimates in Australia

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

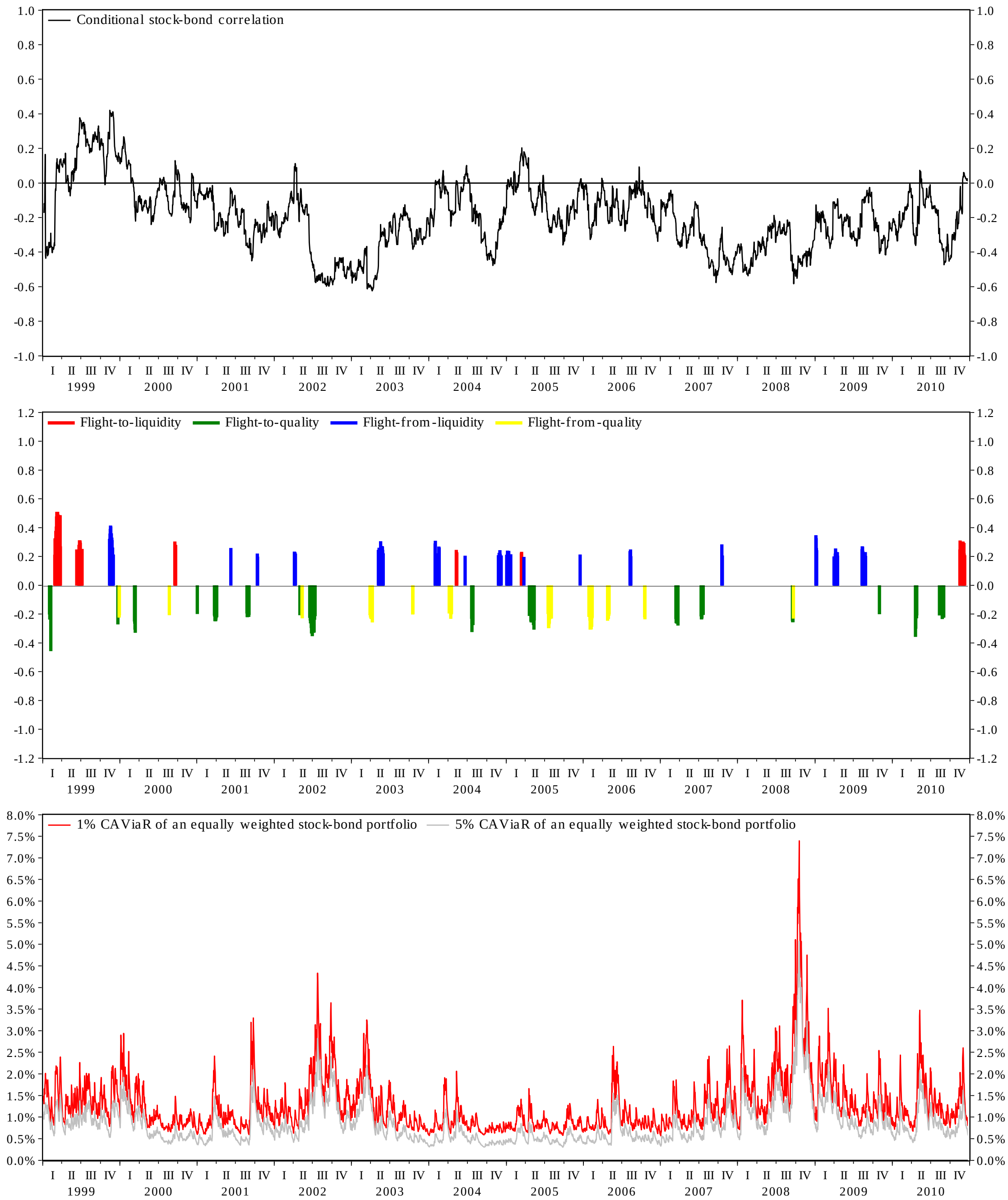


Figure 2: Conditional Correlation, Flight and CAViaR Estimates in Belgium

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

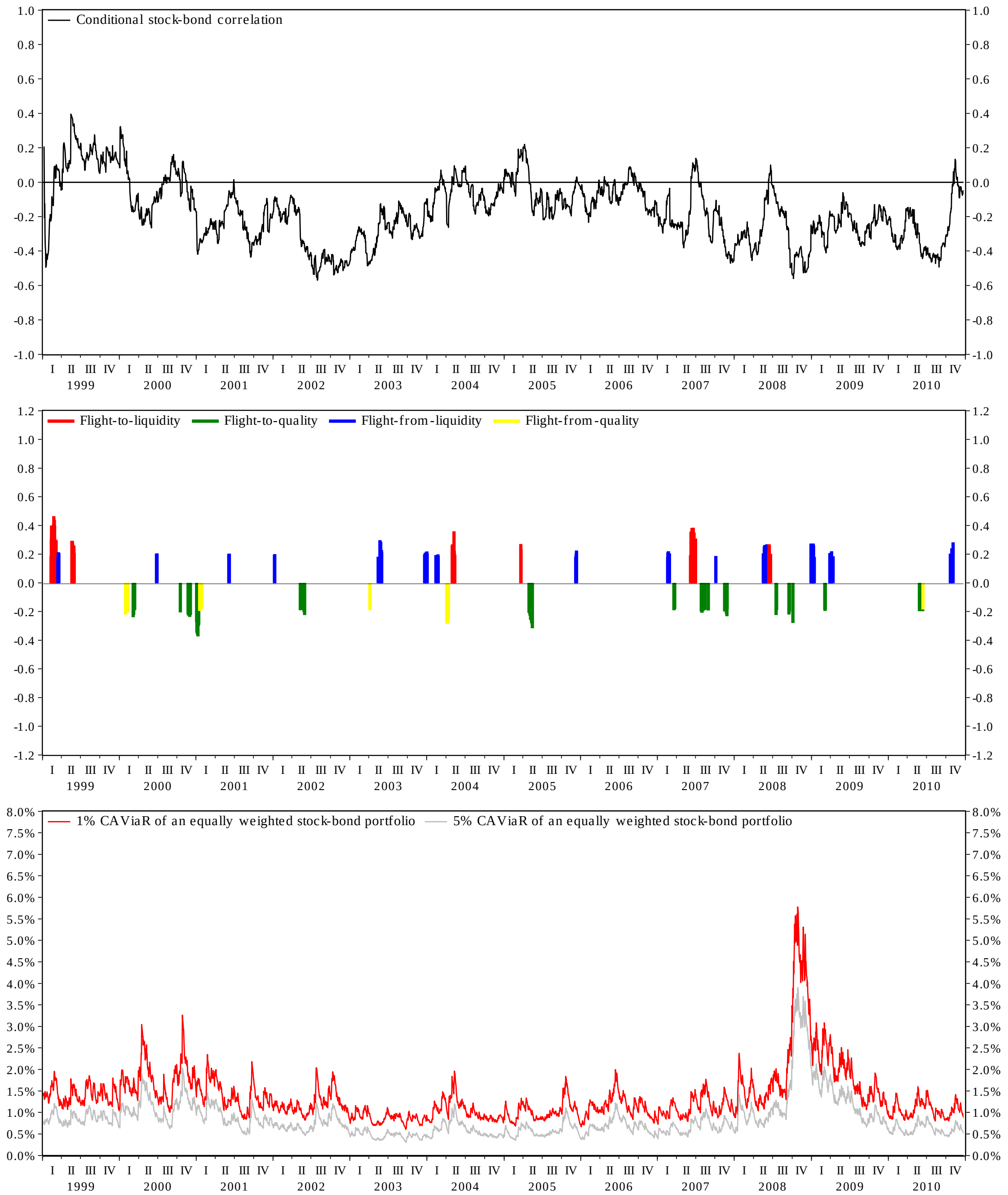


Figure 3: Conditional Correlation, Flight and CAViaR Estimates in Canada

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

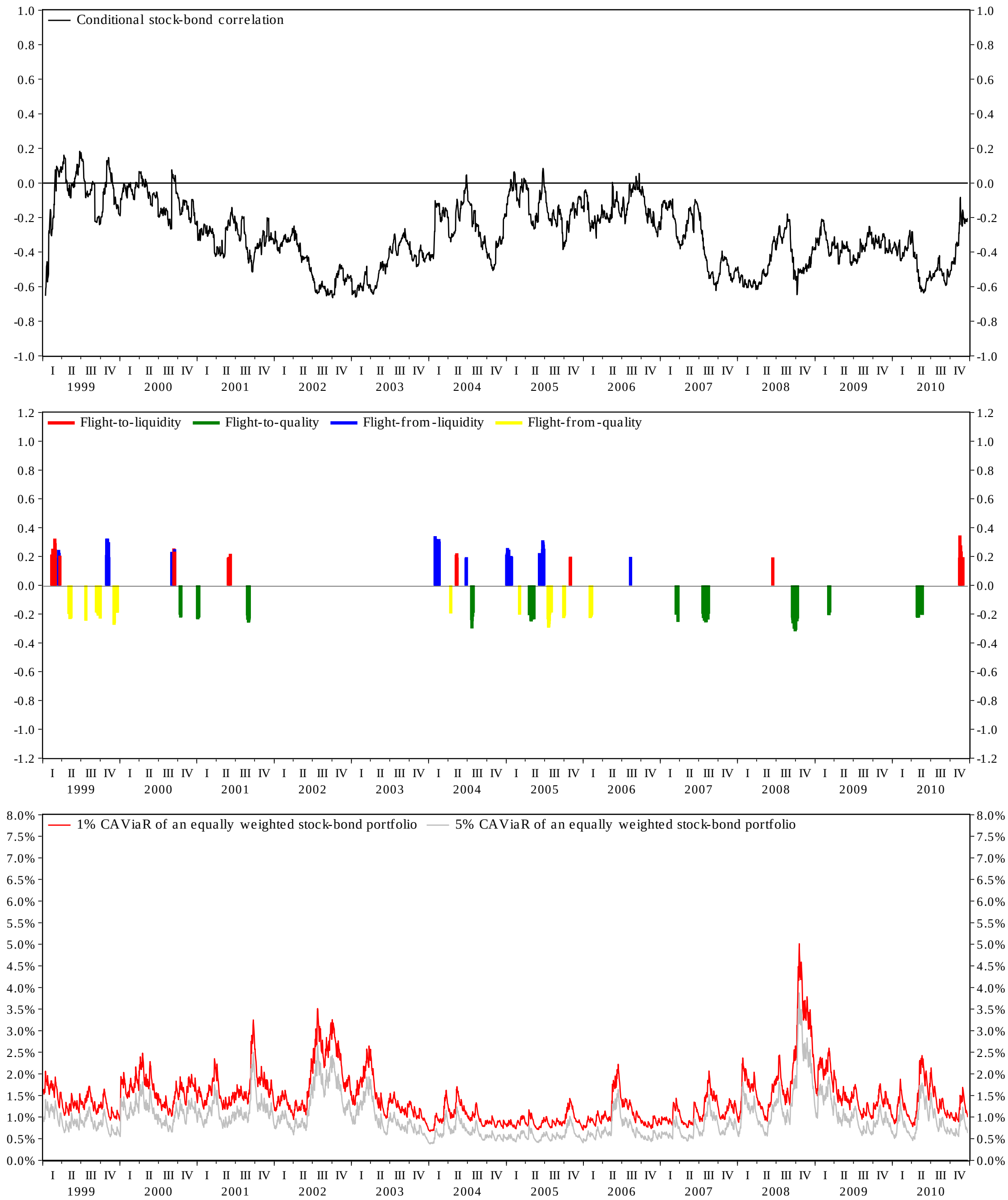


Figure 4: Conditional Correlation, Flight and CAViaR Estimates in France

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

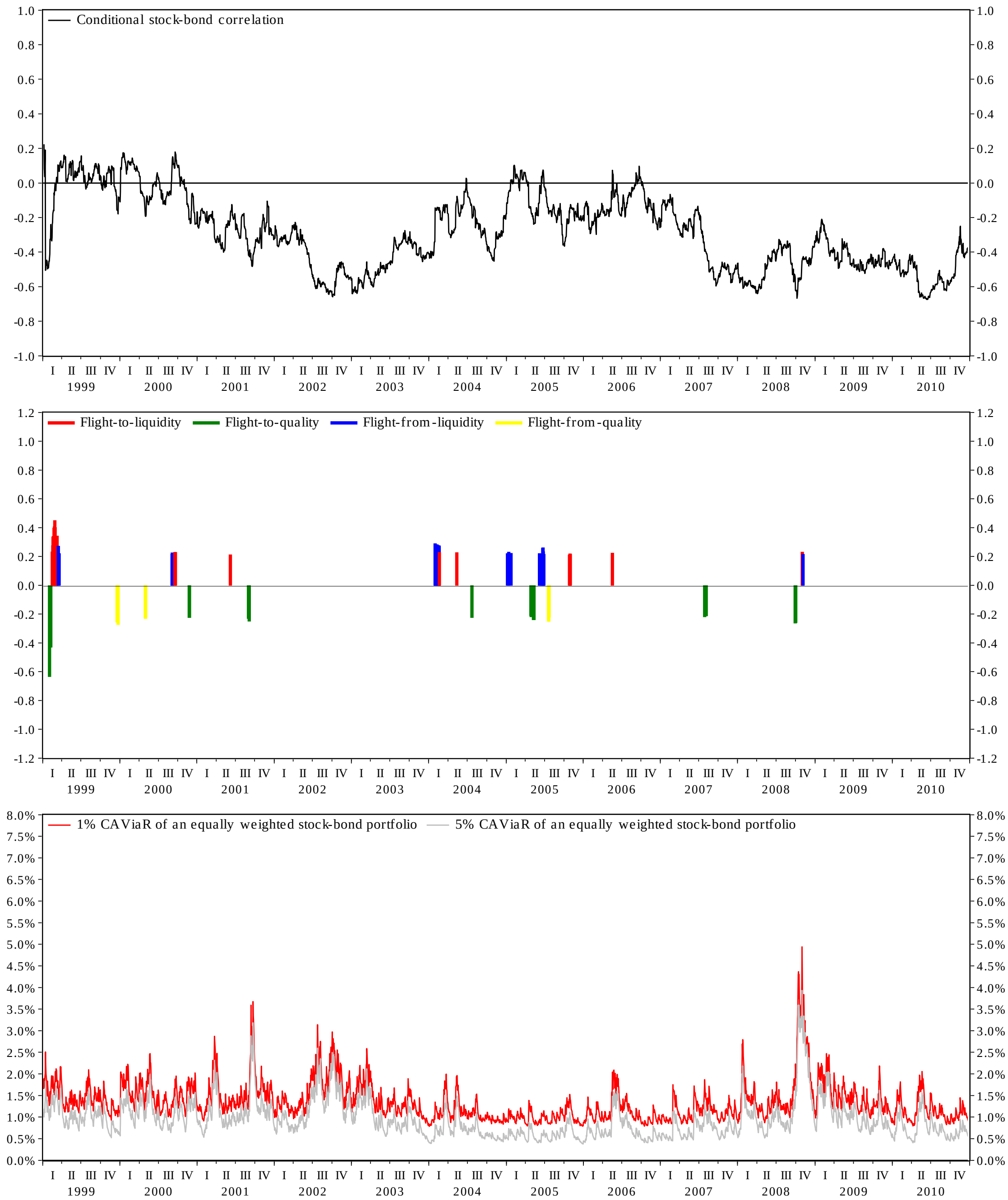


Figure 5: Conditional Correlation, Flight and CAViaR Estimates in Germany

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

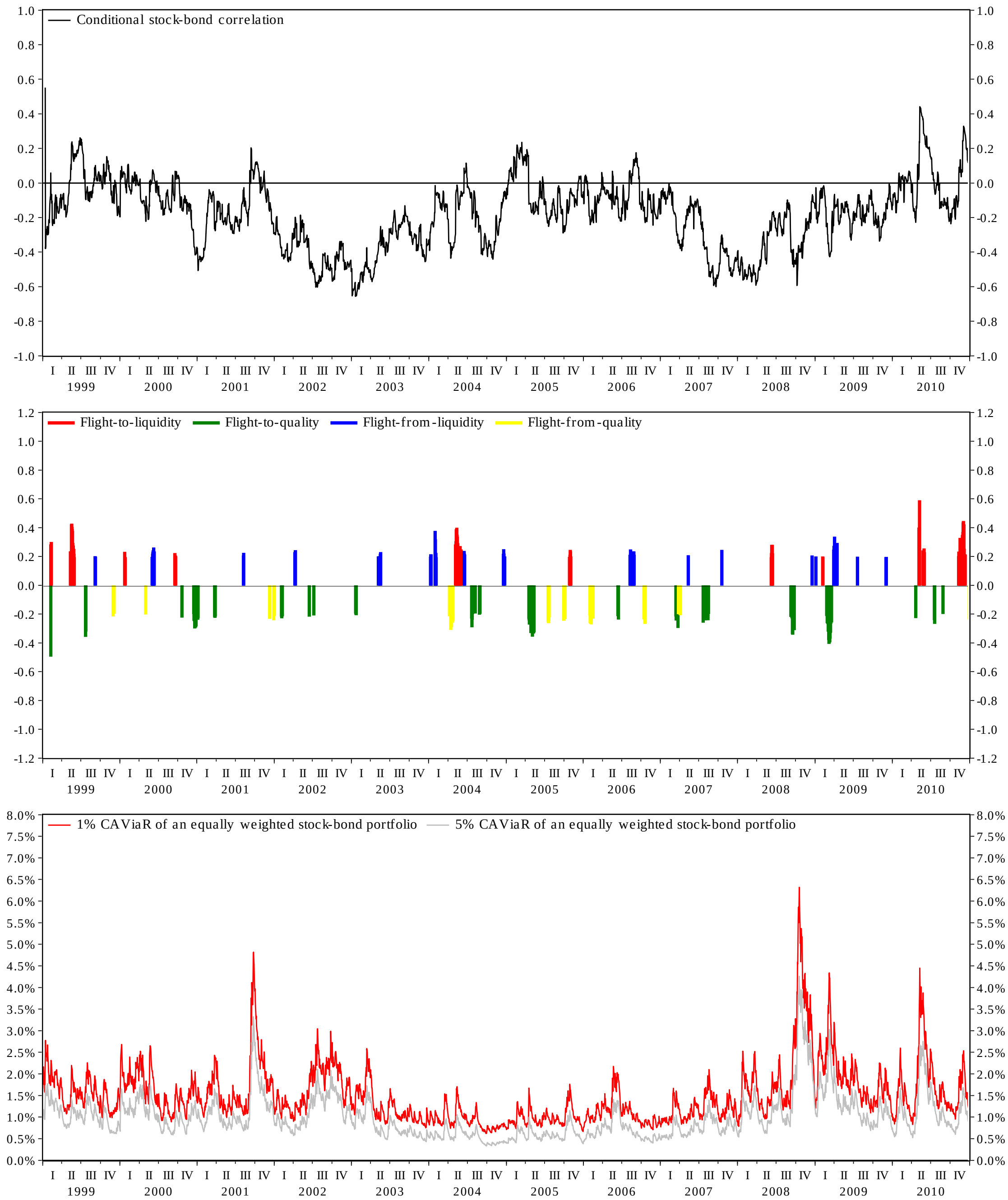


Figure 6: Conditional Correlation, Flight and CAViaR Estimates in Italy

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

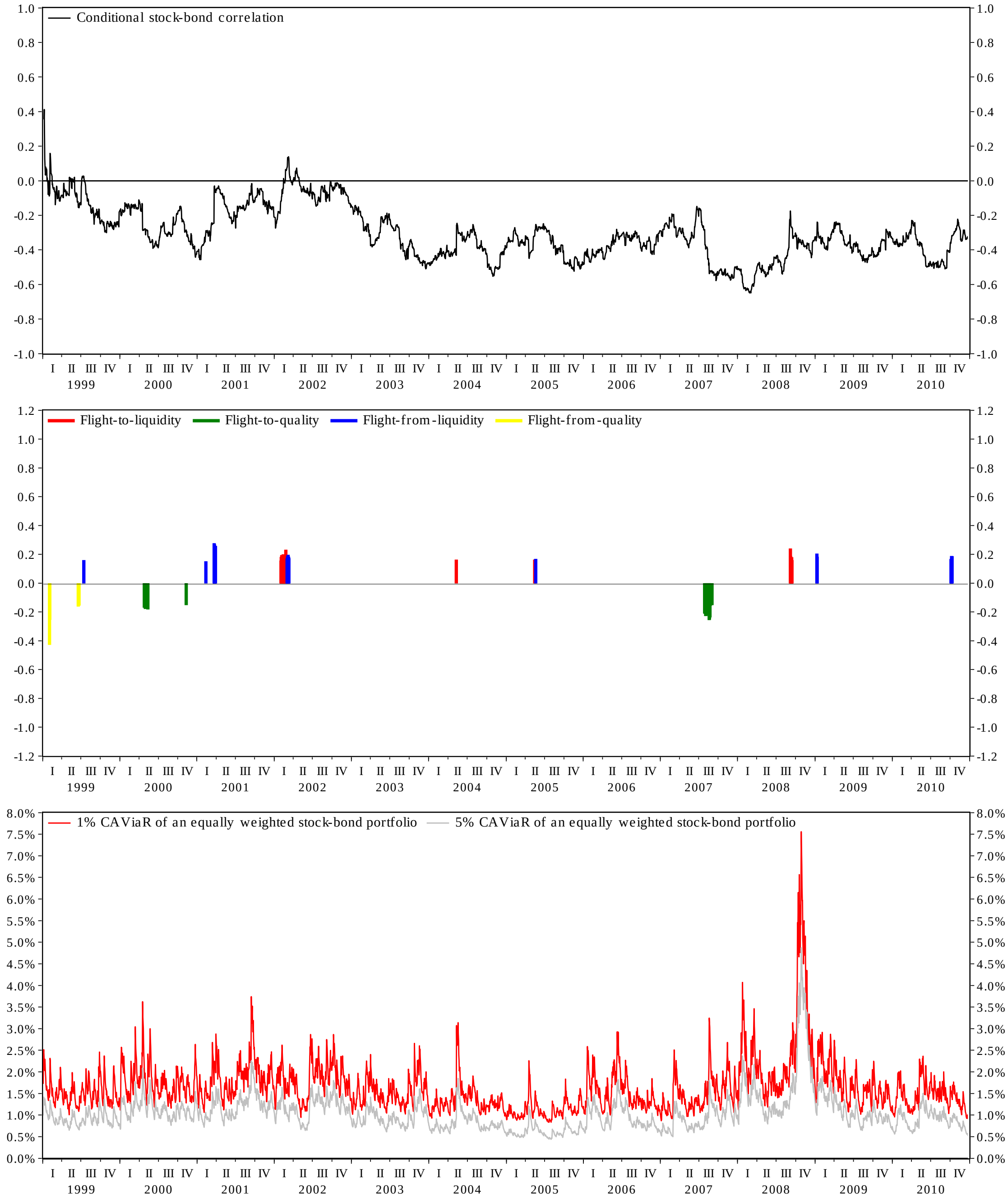


Figure 7: Conditional Correlation, Flight and CAViaR Estimates in Japan

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

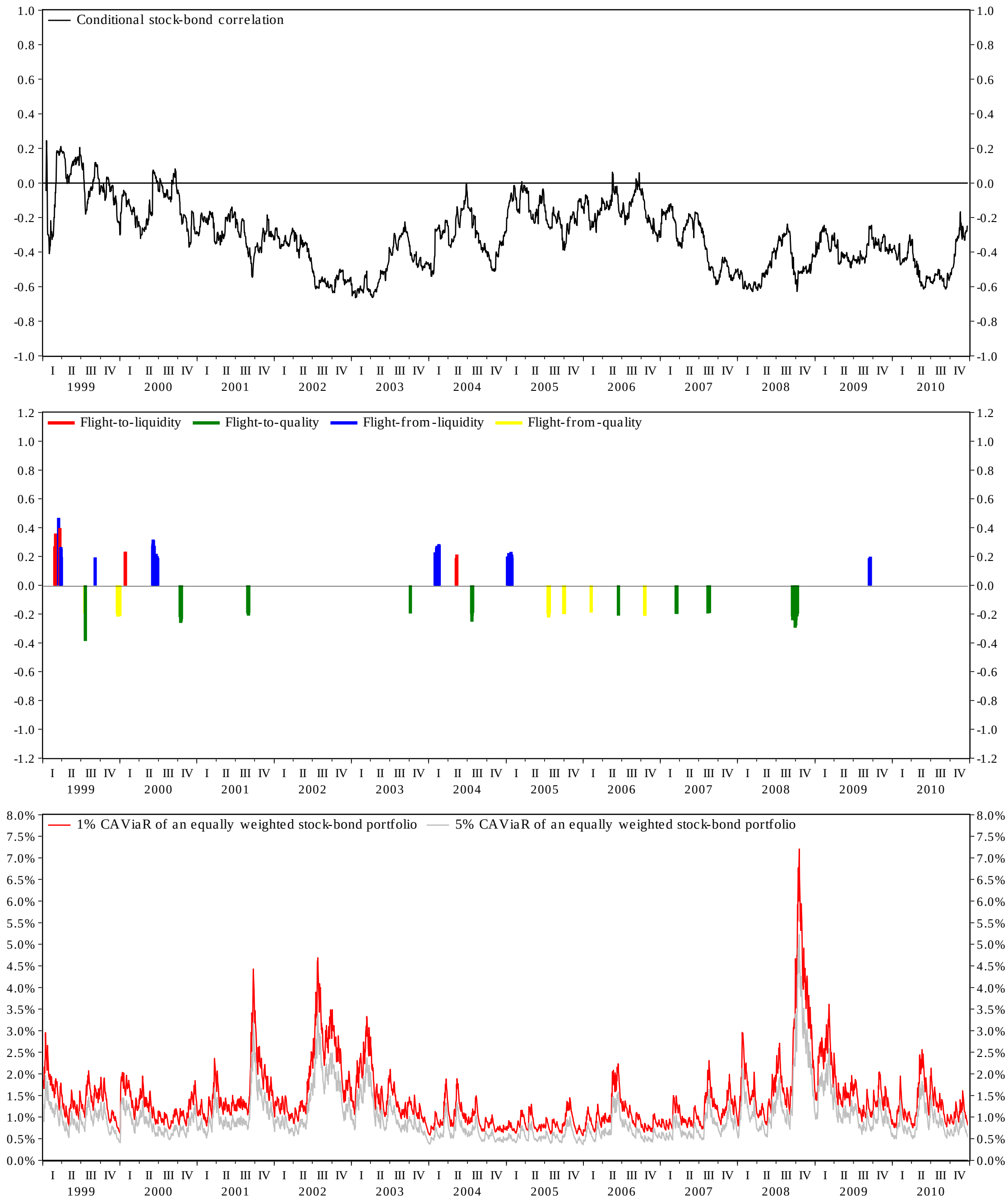


Figure 8: Conditional Correlation, Flight and CAViaR Estimates in the Netherlands

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

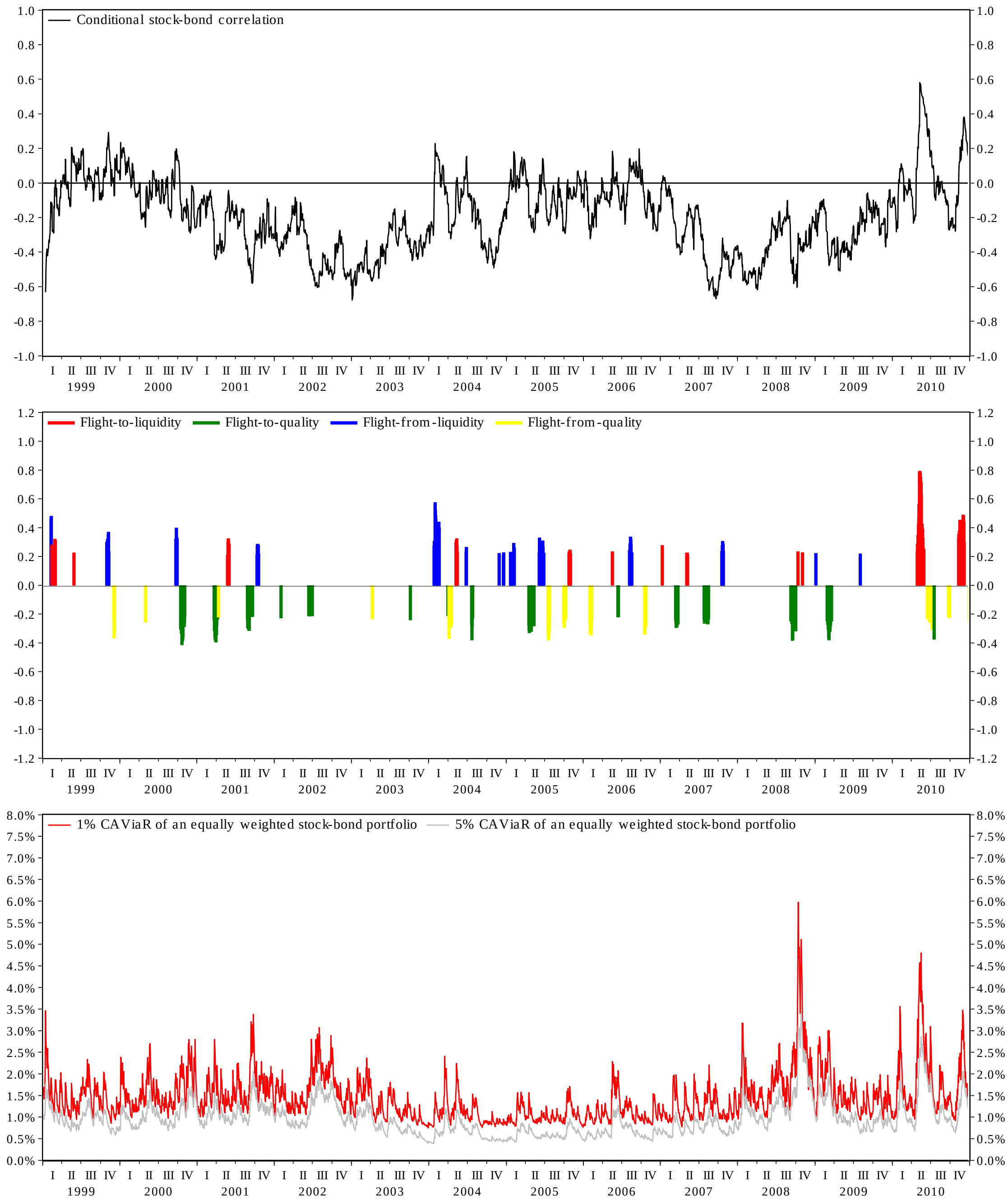


Figure 9: Conditional Correlation, Flight and CAViaR Estimates in Spain

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

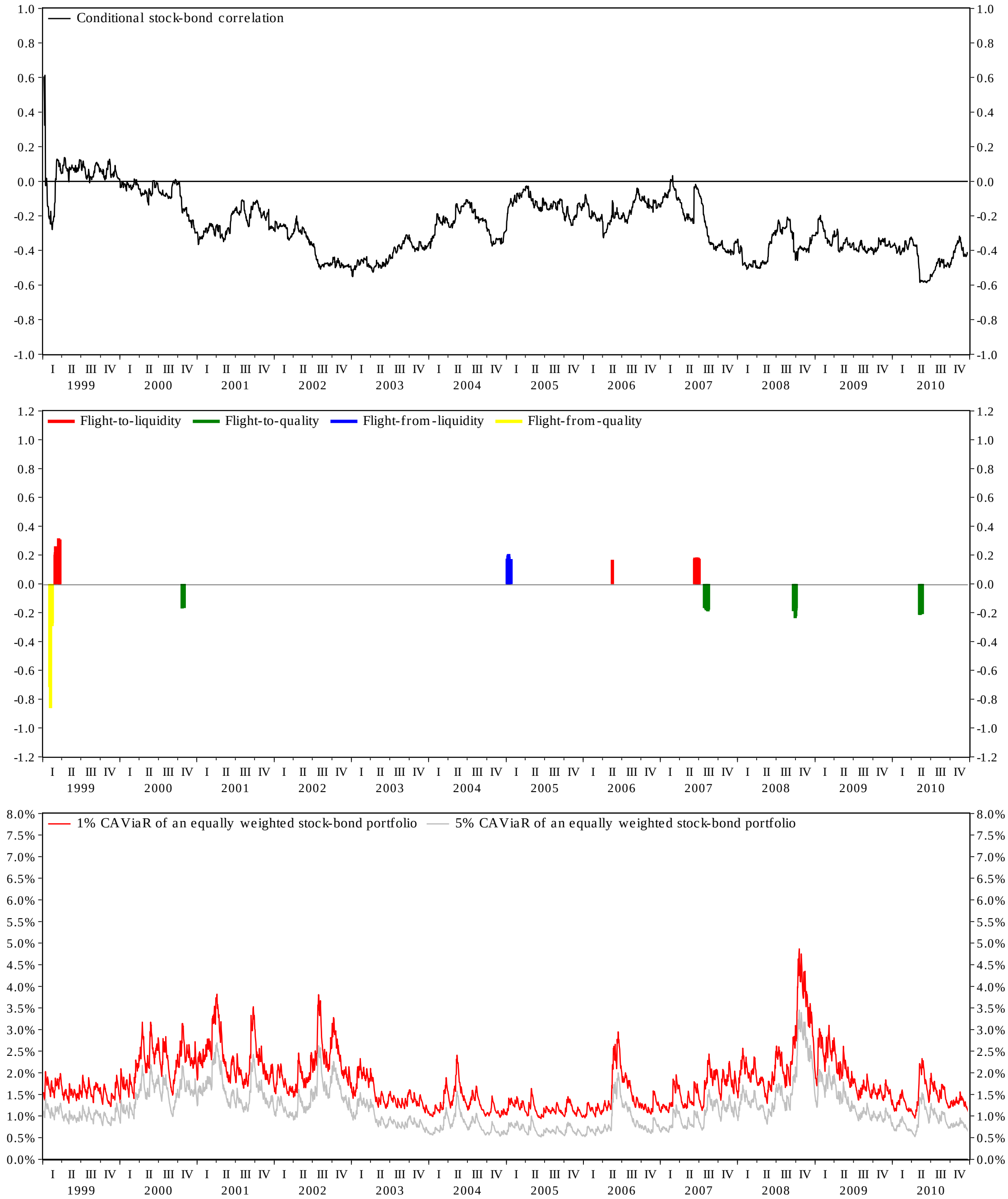


Figure 10: Conditional Correlation, Flight and CAViaR Estimates in Sweden

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

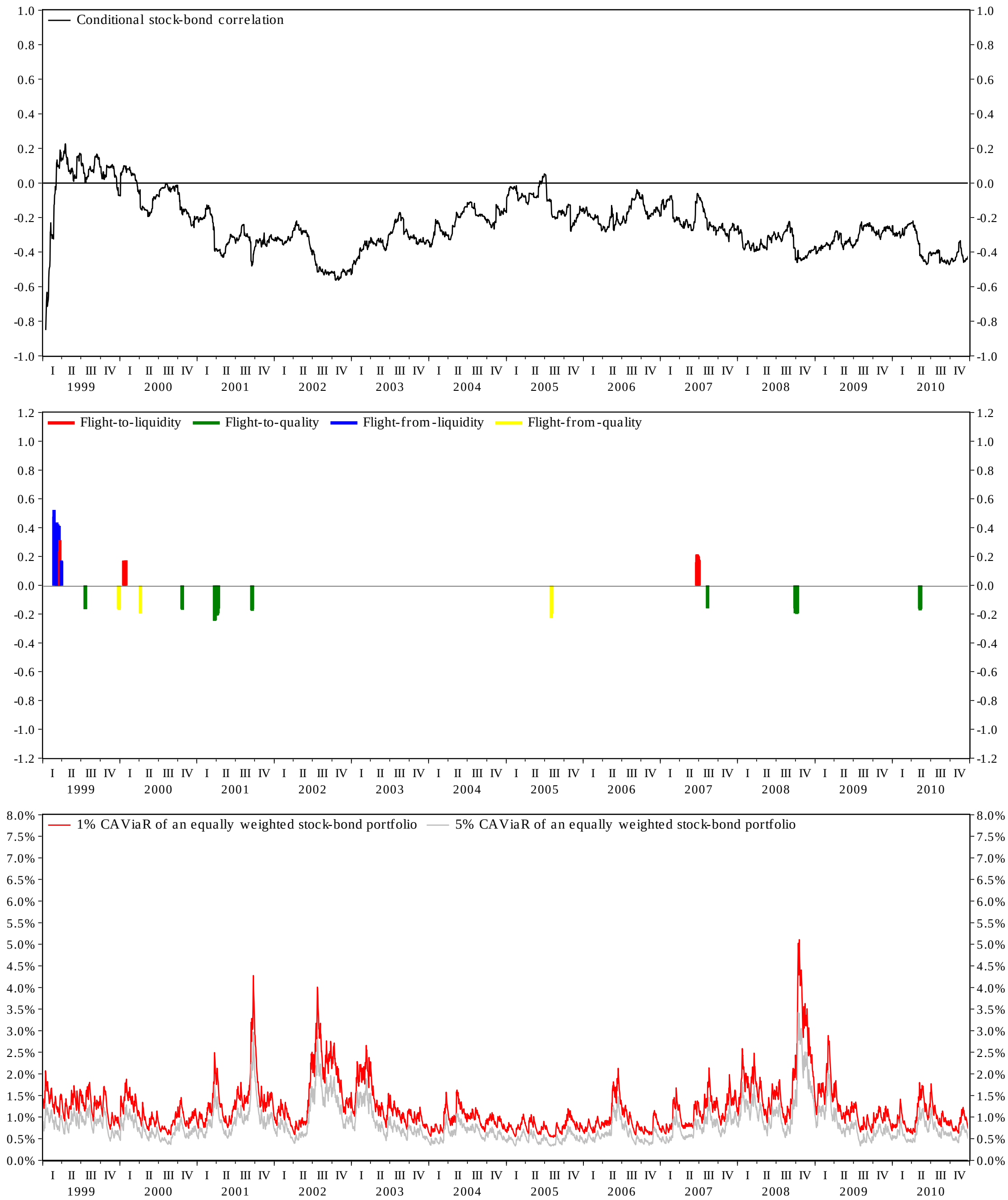


Figure 11: Conditional Correlation, Flight and CAViaR Estimates in Switzerland

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

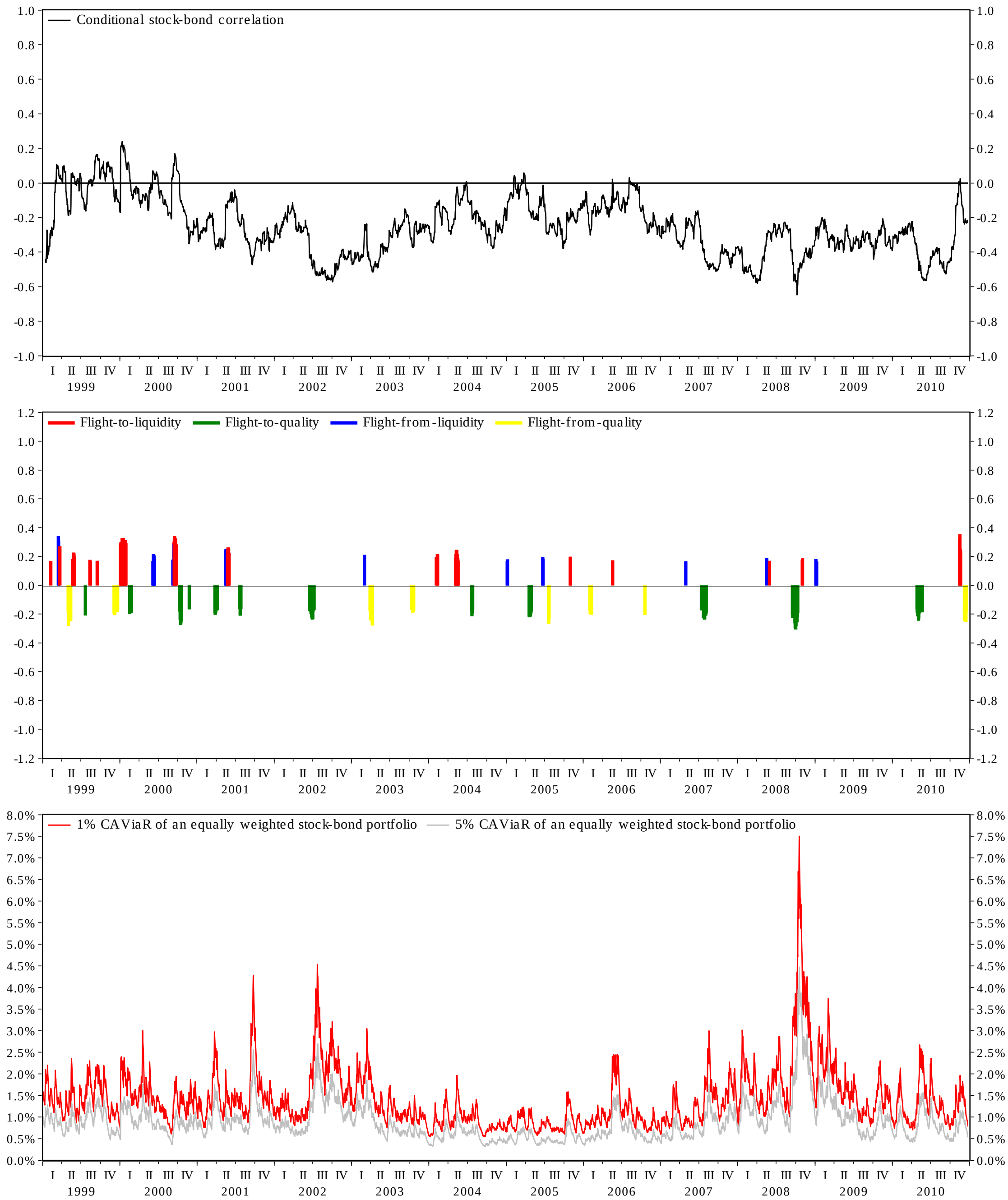


Figure 12: Conditional Correlation, Flight and CAViaR Estimates in the UK

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

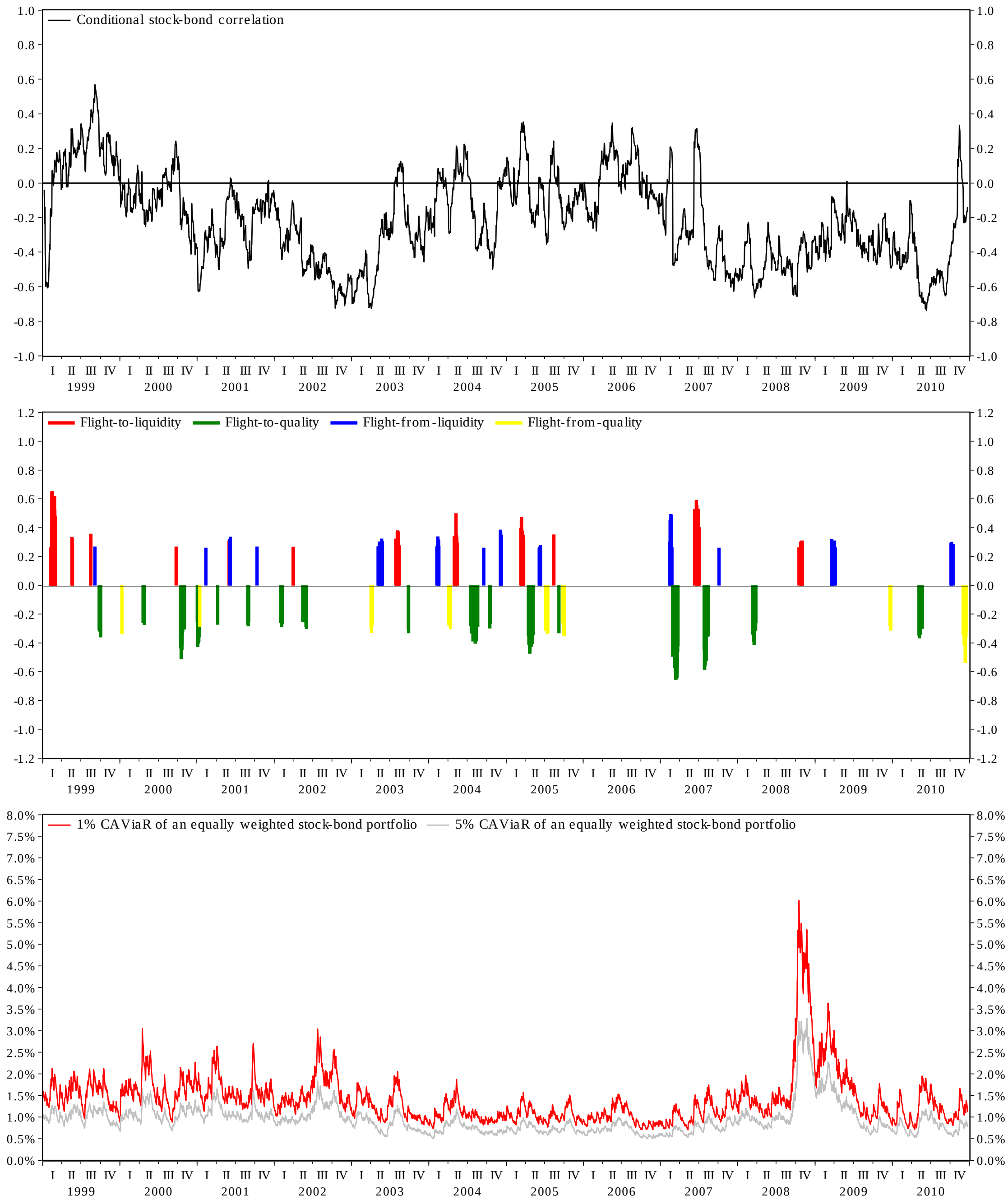


Figure 13: Conditional Correlation, Flight and CAViaR Estimates in the US

The first figure (from above) shows the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). The second figure (from above) shows the intranational flight-to-liquidity (red), flight-to-quality (green), flight-from-liquidity (blue), and the flight-from-quality (yellow) estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3101-3108 observations with adjustments). The flight-to-liquidity from stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly negative stock and bond returns. The flight-to-quality from stocks to bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving negative stock and positive bond returns. The flight-from-liquidity to stocks and bonds is defined as over one standard deviation increase in the conditional stock-bond correlation in a 20-day period involving jointly positive stock and bond returns. The flight-from-quality to stocks from bonds is defined as over one standard deviation decrease in the conditional stock-bond correlation in a 20-day period involving positive stock and negative bond returns. The third figure (from above) shows the daily 1% (red) and 5% (gray) CAViaR estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR model of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Note that the conditional correlation and flight estimates at the beginning of the sample period may not be reliable because the bivariate DCC model(s) may require 10-40 observations to converge. For further information, refer to Section 4.

6. Conclusions

This paper investigated the intranational dynamic relationship between daily stock and government bond returns of selected countries between January 1, 1999 and December 31, 2010 to assess financial market stability in different countries and market conditions. The underlying hypothesis of this paper was that the financial markets of the world's most advanced economies exhibit financial market stability even under extreme market conditions and potentially systemic events. The econometric framework employed to assess whether a country exhibits financial market stability or not included modeling the time-varying conditional intranational stock-bond correlations, testing for the intranational flights between stocks and bonds, and modeling the conditional autoregressive value at risk (CAViaR) of equally weighted intranational stock-bond portfolios.

The empirical results showed that the world's most advanced economies, except Italy and Spain, exhibit financial market stability under extreme market conditions and potentially systemic events as assessed by their intranational stock-bond return relations. In the financially stable countries under extreme market conditions and potentially systemic events, the conditional intranational stock-bond correlations tend to stay below or close to zero, the intranational flights between stocks and bonds tend to rather reduce than aggravate the propagation of shocks, and the CAViaR of equally weighted intranational stock-bond portfolios resembled each other to a high degree without showing hardly any excessive divergent spillover effects. In Italy and Spain, the reverse applied. Overall, these results in favor of prevailing financial market stability even under extreme market conditions and potentially systemic events are relatively well in line with the rare empirical literature on financial market stability with the emphasis on cross-asset linkages in developed markets.

As I am writing this thesis in September, 2011, the prevailing global economic and political uncertainty is seriously threatening the continuation of the global economic rehabilitation because even many of the world's most developed economies now face over-stretched public finances and thus have little room for fiscal manoeuvre (see Appendices 13-14). Interestingly, during the last two decades, emerging markets have both advanced close to the point that they no longer depend on the developed markets for growth and gradually abolished restrictions on foreign ownership of assets. Particularly, emerging stock markets have become less segmented from developed stock markets, which has enhanced risk sharing between domestic and foreign investors and decreased the cost of capital (Chari and Henry, 2004). Now it seems that certain emerging market countries are close to overtake many developed ones in terms of credit quality and become core investment propositions in international investors' portfolios. However, relatively little is known about the joint behavior of stock and bond returns in emerging markets because of the lack of high quality data. Given the substantial growth in funds invested in emerging market securities, future research could extend the cross-asset approach for assessing financial market stability in emerging markets. An interesting research question could relate to the question on whether certain emerging market countries are already considered more financially stable under extreme market conditions and potentially systemic events than some of the more developed ones. The econometric analysis could include both macroeconomic and financial variables, such as liquidity proxies as suggested by Baele et al. (2010). In particular, a new class of GARCH-MIDAS models of Engle et al. (2008) is designed to allow for analyzing high frequency daily returns together with low frequency macroeconomic or financial variables by employing a mean reverting unit daily GARCH process for daily returns and a MIDAS polynomial for low frequency data. For an application of a GARCH-MIDAS methodology in the stock-bond context, refer to Baele et al. (2010).

Financial market stability is difficult to study thoroughly and the fact that it has largely been ignored by the academic society does not make it any easier. The critics of this study might argue that the cross-asset framework employed in this paper for assessing financial market stability is too narrow because it is based on a microeconomic analysis of a macroeconomic phenomenon. However, the proponents of this study might claim that extreme cross-asset linkages are at the core of systemic risk and thus cannot be disregarded in the assessment of financial market stability (see e.g. Hartmann et al., 2004; Baur and Schulze, 2009).

It is clear that investors, policy makers and regulatory authorities should not assume that the results in favor of prevailing financial market stability even under extreme market conditions and potentially systemic events given in this paper will hold in the future since the next crisis might turn out to be broad and different. As a matter of fact, this paper already shows that even the world's most developed economies may become financially unstable when markets lose faith in their ability to manage their economies or service their debts. To conclude, the overall idea of this paper was to emphasize the importance of studying time-varying differences in intranational propagation mechanisms across asset classes for assessing financial market stability. If this paper encourages the academic society to focus more on the commonly disregarded extreme cross-asset linkages for assessing financial market stability, then I have achieved what I could hope for.

7. Appendices

Appendix 1: EViews Code

This appendix shows the Author's EViews 7 codes for the calculation of all the statistics, tests, models, and diagnostics presented in this paper except the CAViaR models of Engle and Manganelli (2004).

```
'SPECIFYING THE INPUTS FOR THE CODE

'Specifying the frequency and sample range of the workfile and the name of the database
close @objects
%frequency = "d5"
%sample ="01/01/1999 31/12/2010"
%database = "database_d"

'Specifying the coefficient starting values and the maximum number of iterations for the ML estimations of the DCC and the ADCC models
!dcc_alpha = 0.03
!dcc_beta = 0.96
!adcc_alpha = 0.02
!adcc_beta = 0.96
!adcc_eta = 0.01
!itermle = 100

'Specifying the presample residual variance backcast coefficient for the estimations of the CCC and the GARCH models (default is 0.7)
!bc = 0.7

'Specifying the interval, threshold level, and performance constraints for the computations of flights (see e.g. Baur and Lucey, 2006)
!flight_interval = 20
!flight_threshold = 1.00
!outperformance = 0.00
!positivity = 0.00
!negativity = 0.00

'Specifying the lag lengths for the residual diagnostics
!qlength = 12
!archlength = 12

'Creating new workpage
pagecreate(page = all) {%frequency} {%sample}

'Specifying the countries (or actually the prefixes of the file names) for which the estimation is to be done
%countries = "aus bel can fra ger ita jap net spa swe swi uk us"
for %country {%countries}

'Measuring the workfile length
scalar {%country}_obslength = @obsrange
'Fetching the data from the predefined database
fetch(d={%database}) {%country}_stocks_ds
fetch(d={%database}) {%country}_bonds_ds10
fetch(d={%database}) {%country}_port_asl_1
fetch(d={%database}) {%country}_port_asl_5

'Calculating log returns (r1, r2) and indexed log returns(r1_indx, r2_indx)
series {%country}_r1 = dlog({%country}_stocks_ds)
series {%country}_r2 = dlog({%country}_bonds_ds10)
vector({%country}_obslength) {%country}_r1_vector = {%country}_r1
vector({%country}_obslength) {%country}_r1_ind
{%country}_r1_ind(1) = 100
for !a = 2 to {%country}_obslength
{%country}_r1_ind(!a) =  ({%country}_r1_ind(!a-1)* {%country}_r1_vector(!a-1))+ {%country}_r1_ind(!a-1)
next
mtos({%country}_r1_ind, {%country}_r1_indx)
delete {%country}_r1_vector {%country}_r1_ind
vector({%country}_obslength) {%country}_r2_vector = {%country}_r2
vector({%country}_obslength) {%country}_r2_ind
{%country}_r2_ind(1) = 100
for !a = 2 to {%country}_obslength
{%country}_r2_ind(!a) =  ({%country}_r2_ind(!a-1)* {%country}_r2_vector(!a-1))+ {%country}_r2_ind(!a-1)
next
mtos({%country}_r2_ind, {%country}_r2_indx)
delete {%country}_r2_vector {%country}_r2_ind

'MODELING THE CONDITIONAL MEANS OF THE STOCK AND BOND RETURNS

'Employing a VAR(p) filter with constant and selecting the optimal lag length (max.8) based on the AIC to demean and filter the log returns (if the suggested lag length is zero, arbitrarily using one lag)
```

```
var {%country}_var_test.ls() 1 8 {%country}_r1 {%country}_r2
{%country}_var_test.laglen(8, vname={%country}_var_ret_lag)
!meanlaglength={%country}_var_ret_lag(3)
if !meanlaglength > 0 then
group {%country}_ret {%country}_r1 {%country}_r2
{%country}_ret.makewhiten(lag=a, info=aic, maxlag=8, gname = {%country}_r12_whitened) {%country}_r1w {%country}_r2w
var {%country}_var_ret.ls() 1 !meanlaglength {%country}_r1 {%country}_r2
{%country}_var_ret.results()
delete {%country}_ret
else
!meanlaglength = 1
group {%country}_ret {%country}_r1 {%country}_r2
{%country}_ret.makewhiten(lag=1) {%country}_r1w {%country}_r2w
var {%country}_var_ret.ls() 1 !meanlaglength {%country}_r1 {%country}_r2
{%country}_var_ret.results()
delete {%country}_ret
endif
delete {%country}_var_test

'Adjusting the samples for the estimations
!s0 = 1
!s1 = 2
!sf = 3
sample {%country}_s0        @first+!s0+!meanlaglength @last
sample {%country}_s1        @first+!s1+!meanlaglength @last
sample {%country}_sf        @first+!sf+!meanlaglength @last

'Evaluating the need and suitability for the VAR- and the GARCH-type of modeling
{%country}_r1.uroot(adf)
{%country}_r2.uroot(adf)
equation {%country}_r1_correl.ls {%country}_r1 c
equation {%country}_r2_correl.ls {%country}_r2 c
{%country}_r1_correl.correl(!qlength)
{%country}_r2_correl.correl(!qlength)
equation {%country}_r1_correlsq.ls {%country}_r1 c
equation {%country}_r2_correlsq.ls {%country}_r2 c
{%country}_r1_correlsq.correlsq(!qlength)
{%country}_r2_correlsq.correlsq(!qlength)
equation {%country}_r1_arch.ls {%country}_r1 c
equation {%country}_r2_arch.ls {%country}_r2 c
{%country}_r1_arch.archtest(!archlength)
{%country}_r2_arch.archtest(!archlength)
system {%country}_r12_portm
{%country}_r12_portm.append {%country}_r1 = c(1)
{%country}_r12_portm.append {%country}_r2 = c(2)
{%country}_r12_portm.ls()
{%country}_r12_portm.qstats(!qlength)
{%country}_var_ret.qstats(!qlength, name = {%country}_var_ret_portm)
{%country}_var_ret.white(name = {%country}_var_ret_white)
```

'TESTING FOR THE NULL OF CONSTANT CONDITIONAL STOCK-BOND CORRELATIONS

```
'Estimating the CCC model of Bollerslev (1990)
smpl {%country}_s0
system {%country}_ccc
{%country}_ccc.append {%country}_r1w
{%country}_ccc.append {%country}_r2w
{%country}_ccc.arch(h, backcast = !bc) @ccc c(scalar) arch(1) garch(1)
{%country}_ccc.makeresids(o,bn = {%country}_ccc_e)
rename {%country}_ccc_e01 {%country}_ccc_e1
rename {%country}_ccc_e02 {%country}_ccc_e2
{%country}_ccc.makeresids(cov,bn = {%country}_ccc_en_cov)
rename {%country}_ccc_en_cov01 {%country}_ccc_e1n_cov
rename {%country}_ccc_en_cov02 {%country}_ccc_e2n_cov
{%country}_ccc.makeresids(cor,bn = {%country}_ccc_en_cor)
rename {%country}_ccc_en_cor01 {%country}_ccc_e1n_cor
rename {%country}_ccc_en_cor02 {%country}_ccc_e2n_cor
{%country}_ccc.makegarch(cor, name = {%country}_ccc_rt)
rename {%country}_ccc_rt01_02 {%country}_ccc_rt
{%country}_ccc.makegarch(cov, name={%country}_ccc_q)
rename {%country}_ccc_q01 {%country}_ccc_q11
rename {%country}_ccc_q02 {%country}_ccc_q22
rename {%country}_ccc_q01_02 {%country}_ccc_q12
{%country}_ccc.qstats(!qlength,cov)

'Calculating the Bollerslev-Wooldridge (1992) moment conditions for the CCC model
```

```
series {%country}_ccc_mc_1 = {%country}_ccc_e1/({%country}_ccc_q11^0.5)
series {%country}_ccc_mc_2 = {%country}_ccc_e2/({%country}_ccc_q22^0.5)
series {%country}_ccc_mc_3 = {%country}_ccc_mc_1^2
series {%country}_ccc_mc_4 = {%country}_ccc_mc_2^2
series {%country}_ccc_mc_5 = ({%country}_ccc_e1*{%country}_ccc_e2)/({%country}_ccc_q12)
{%country}_ccc_mc_1.teststat(mean=0)
{%country}_ccc_mc_2.teststat(mean=0)
{%country}_ccc_mc_3.teststat(mean=1)
{%country}_ccc_mc_4.teststat(mean=1)
{%country}_ccc_mc_5.teststat(mean=1)

'Testing for the null of constant of correlation using the studentized versions of the IM test proposed by Bera and Kim (2002)
smpl {%country}_s0
series {%country}_imc_nominator = ((@sum(((({%country}_ccc_e1n_cov-{%country}_ccc_rt*{%country}_ccc_e2n_cov)/(sqr(1-
{%country}_ccc_rt^2)))^2)*((({%country}_ccc_e2n_cov-{%country}_ccc_rt*{%country}_ccc_e1n_cov)/(sqr(1-
{%country}_ccc_rt^2)))^2)-1-2*{%country}_ccc_rt^2))^2)
series {%country}_imc_denominator_s = @sum((((((({%country}_ccc_e1n_cov-{%country}_ccc_rt*{%country}_ccc_e2n_cov)/(sqr(1-
{%country}_ccc_rt^2)))^2)*((( {%country}_ccc_e2n_cov-{%country}_ccc_rt*{%country}_ccc_e1n_cov)/(sqr(1-
{%country}_ccc_rt^2)))^2)-1-2*{%country}_ccc_rt^2))-(@mean((((({%country}_ccc_e1n_cov-
{%country}_ccc_rt*{%country}_ccc_e2n_cov)/(sqr(1-{%country}_ccc_rt^2)))^2)*((( {%country}_ccc_e2n_cov-
{%country}_ccc_rt*{%country}_ccc_e1n_cov)/(sqr(1-{%country}_ccc_rt^2)))^2)-1-2*{%country}_ccc_rt^2))))^2)
series {%country}_imc_stat_s = {%country}_imc_nominator/{%country}_imc_denominator_s
scalar(1) {%country}_imc_stat = {%country}_imc_stat_s(12)
scalar(1) {%country}_imc_pval = 1-@cchisq({%country}_imc_stat_s(12),1)

'Testing for the null of constant of correlation using the dynamic conditional correlation test proposed by Engle and Sheppard (2001)
smpl {%country}_s0
series {%country}_ccc_e12n_cor = {%country}_ccc_e1n_cor*{%country}_ccc_e2n_cor
matrix(@obssmpl,1) {%country}_outerprods
{%country}_outerprods = {%country}_ccc_e12n_cor
matrix(@obssmpl,2) {%country}_regressors
for !i = 1 to @obssmpl
{%country}_regressors(!i,1) = 1
{%country}_regressors(!i,2) = {%country}_outerprods(!i,1)
next
for !i = 2 to @obssmpl
vector(@obssmpl) {%country}_regressand = {%country}_outerprods(!i)
for !i = 2 to @obssmpl
{%country}_regressand(!i-1) = {%country}_outerprods(!i)
next
next
mtos({%country}_regressand, {%country}_help8)
mtos({%country}_regressors, {%country}_help)
{%country}_help.drop ser01 ser02
rename ser01 {%country}_help9
rename ser02 {%country}_help10
equation {%country}_beta1.ls {%country}_help8 {%country}_help9
equation {%country}_beta2.ls {%country}_help8 {%country}_help10
vector(2) {%country}_beta
{%country}_beta(1) = {%country}_beta1.c(1)
{%country}_beta(2) = {%country}_beta2.c(1)
matrix {%country}_xPx = @transpose({%country}_regressors)* {%country}_regressors
matrix {%country}_e = {%country}_regressand-{%country}_regressors*{%country}_beta
matrix {%country}_sig = @transpose({%country}_e)*( {%country}_e/(@obssmpl-1-1))
matrix {%country}_help11 = @transpose({%country}_beta)
matrix {%country}_help12 = {%country}_help11*{%country}_xPx
matrix {%country}_help14 =sqr({%country}_sig)
vector(2) {%country}_help15
{%country}_help15(1) = {%country}_help14(1,1)
{%country}_help15(2) = {%country}_help14(1,1)
matrix {%country}_help16 = @ediv({%country}_beta, {%country}_help15)
matrix {%country}_stat = {%country}_help12*{%country}_help16
scalar {%country}_help17 = {%country}_stat(1,1)
matrix {%country}_pval = 1-@cchisq({%country}_help17, 1+1)
smpl {%country}_s0
delete {%country}_beta* {%country}_hel* {%country}_imc* {%country}_xPx {%country}_e {%country}_sig {%country}_stat
{%country}_pval {%country}_regressand {%country}_regressors {%country}_outerprods
```

'MODELING THE TIME-VARYING CONDITIONAL STOCK-BOND CORRELATIONS

'FIRST STAGE: UNIVARIATE GARCH SPECIFICATION SEARCH

```
'Estimating the GARCH(1,1) model of Bollerslev(1986), the GJR-GARCH(1,1,1) model of (Glosten et al., 1993), the EGARCH(1,1,1)
model of Nelson (1991), and the APARCH model of Ding et al. (1993)
equation {%country}_r1w_garch.arch(1,1,m=500,c=1e-5,h, backcast = !bc) {%country}_r1w
equation {%country}_r1w_tarch.arch(1,1,m=500,c=1e-5,h,thrsh=1, backcast = !bc) {%country}_r1w
```

```
equation {%country}_r1w_egarch.arch(1,1,m=500,c=1e-5,h,egarch,asy=1, backcast = !bc) {%country}_r1w
equation {%country}_r1w_aparch.arch(1,1,m=500,c=1e-5,h,parch,asy=1, backcast = !bc) {%country}_r1w
equation {%country}_r2w_garch.arch(1,1,m=500,c=1e-5,h, backcast = !bc) {%country}_r2w
equation {%country}_r2w_tarch.arch(1,1,m=500,c=1e-5,h,thrsh=1, backcast = !bc) {%country}_r2w
equation {%country}_r2w_egarch.arch(1,1,m=500,c=1e-5,h,egarch, asy=1, backcast = !bc) {%country}_r2w
equation {%country}_r2w_aparch.arch(1,1,m=500,c=1e-5,h,parch,asy=1, backcast = !bc) {%country}_r2w

'Selecting between the univariate GARCH models based on the AIC
vector(4) {%country}_r1w_garch_sic
{%country}_r1w_garch_sic(1) = {%country}_r1w_garch.@schwarz
{%country}_r1w_garch_sic(2) = {%country}_r1w_tarch.@schwarz
{%country}_r1w_garch_sic(3) = {%country}_r1w_egarch.@schwarz
{%country}_r1w_garch_sic(4) = {%country}_r1w_aparch.@schwarz
vector(4) {%country}_r1w_garch_sicr
{%country}_r1w_garch_sicr = @ranks({%country}_r1w_garch_sic, "a")
if {%country}_r1w_garch_sicr(1) = 1 then
%r1w_selected = "garch"
%r1w_selected_name = "GARCH(1,1)"
delete {%country}_r1w_tarch {%country}_r1w_egarch {%country}_r1w_aparch
endif
if {%country}_r1w_garch_sicr(2) = 1 then
%r1w_selected = "tarch"
%r1w_selected_name = "GJR-GARCH(1,1,1)"
delete {%country}_r1w_garch {%country}_r1w_egarch {%country}_r1w_aparch
endif
if {%country}_r1w_garch_sicr(3) = 1 then
%r1w_selected = "egarch"
%r1w_selected_name = "EGARCH(1,1,1)"
delete {%country}_r1w_garch {%country}_r1w_tarch {%country}_r1w_aparch
endif
if {%country}_r1w_garch_sicr(4) = 1 then
%r1w_selected = "aparch"
%r1w_selected_name = "APARCH(1,1,1)"
delete {%country}_r1w_garch {%country}_r1w_tarch {%country}_r1w_egarch
endif
{%country}_r1w_{%r1w_selected}.makegarch {%country}_r1w_{%r1w_selected}_h11
series {%country}_r1w_{%r1w_selected}_d11 = {%country}_r1w_{%r1w_selected}_h11^0.5
{%country}_r1w_{%r1w_selected}.makeresids(o) {%country}_r1w_{%r1w_selected}_e1
{%country}_r1w_{%r1w_selected}.makeresids(s) {%country}_r1w_{%r1w_selected}_e1n
vector(4) {%country}_r2w_garch_sic
{%country}_r2w_garch_sic(1) = {%country}_r2w_garch.@schwarz
{%country}_r2w_garch_sic(2) = {%country}_r2w_tarch.@schwarz
{%country}_r2w_garch_sic(3) = {%country}_r2w_egarch.@schwarz
{%country}_r2w_garch_sic(4) = {%country}_r2w_aparch.@schwarz
vector(4) {%country}_r2w_garch_sicr
{%country}_r2w_garch_sicr = @ranks({%country}_r2w_garch_sic, "a")
if {%country}_r2w_garch_sicr(1) = 1 then
%r2w_selected = "garch"
%r2w_selected_name = "GARCH(1,1)"
delete {%country}_r2w_tarch {%country}_r2w_egarch {%country}_r2w_aparch
endif
if {%country}_r2w_garch_sicr(2) = 1 then
%r2w_selected = "tarch"
%r2w_selected_name = "GJR-GARCH(1,1,1)"
delete {%country}_r2w_garch {%country}_r2w_egarch {%country}_r2w_aparch
endif
if {%country}_r2w_garch_sicr(3) = 1 then
%r2w_selected = "egarch"
%r2w_selected_name = "EGARCH(1,1,1)"
delete {%country}_r2w_garch {%country}_r2w_tarch {%country}_r2w_aparch
endif
if {%country}_r2w_garch_sicr(4) = 1 then
%r2w_selected = "aparch"
%r2w_selected_name = "APARCH(1,1,1)"
delete {%country}_r2w_garch {%country}_r2w_tarch {%country}_r2w_egarch
endif
{%country}_r2w_{%r2w_selected}.makegarch {%country}_r2w_{%r2w_selected}_h22
series {%country}_r2w_{%r2w_selected}_d22 = {%country}_r2w_{%r2w_selected}_h22^0.5
{%country}_r2w_{%r2w_selected}.makeresids(o) {%country}_r2w_{%r2w_selected}_e2
{%country}_r2w_{%r2w_selected}.makeresids(s) {%country}_r2w_{%r2w_selected}_e2n

'Calculating the Bollerslev-Wooldridge (1992) moment conditions for the selected GARCH models
series {%country}_{%r1w_selected}_mc_1 = {%country}_r1w_{%r1w_selected}_e1/({%country}_r1w_{%r1w_selected}_d11)
series {%country}_{%r2w_selected}_mc_2 = {%country}_r2w_{%r2w_selected}_e2/({%country}_r2w_{%r2w_selected}_d22)
series {%country}_{%r1w_selected}_mc_3 = {%country}_{%r1w_selected}_mc_1^2
```

```
series {%country}_{%r2w_selected}_mc_4 = {%country}_{%r2w_selected}_mc_2^2
{%country}_{%r1w_selected}_mc_1.teststat(mean=0)
{%country}_{%r2w_selected}_mc_2.teststat(mean=0)
{%country}_{%r1w_selected}_mc_3.teststat(mean=1)
{%country}_{%r2w_selected}_mc_4.teststat(mean=1)
```

'SECOND STAGE: BIVARIATE DCC SPECIFICATION SEARCH

```
'Specifying the elements of the matrices for the estimation of the DCC model of Engle (2002)
smpl {%country}_s0
series {%country}_dcc_e11n = {%country}_r1w_{%r1w_selected}_e1n*{%country}_r1w_{%r1w_selected}_e1n
series {%country}_dcc_e12n = {%country}_r1w_{%r1w_selected}_e1n*{%country}_r2w_{%r2w_selected}_e2n
series {%country}_dcc_e21n = {%country}_r2w_{%r2w_selected}_e2n*{%country}_r1w_{%r1w_selected}_e1n
series {%country}_dcc_e22n = {%country}_r2w_{%r2w_selected}_e2n*{%country}_r2w_{%r2w_selected}_e2n
series {%country}_dcc_qbar11 = @mean({%country}_r1w_{%r1w_selected}_e1n*{%country}_r1w_{%r1w_selected}_e1n)
series {%country}_dcc_qbar12 = @mean({%country}_r1w_{%r1w_selected}_e1n*{%country}_r2w_{%r2w_selected}_e2n)
series {%country}_dcc_qbar21 = @mean({%country}_r2w_{%r2w_selected}_e2n*{%country}_r1w_{%r1w_selected}_e1n)
series {%country}_dcc_qbar22 = @mean({%country}_r2w_{%r2w_selected}_e2n*{%country}_r2w_{%r2w_selected}_e2n)
series {%country}_dcc_q11 = @var({%country}_r1w_{%r1w_selected}_e1)
series {%country}_dcc_q12 = @cov({%country}_r1w_{%r1w_selected}_e1,{%country}_r2w_{%r2w_selected}_e2)
series {%country}_dcc_q21 = @cov({%country}_r2w_{%r2w_selected}_e2,{%country}_r1w_{%r1w_selected}_e1)
series {%country}_dcc_q22 = @var({%country}_r2w_{%r2w_selected}_e2)

'Defining the coefficients and their starting values for the second stage ML estimation of the DCC model
coef(1) {%country}_dcc_alpha
coef(1) {%country}_dcc_beta
{%country}_dcc_alpha(1) = !dcc_alpha
{%country}_dcc_beta(1) = !dcc_beta

'Setting up and estimating the log likelihood function of the DCC model
logl {%country}_dcc
{%country}_dcc.append @logl {%country}_dcc_logl
{%country}_dcc.append  {%country}_dcc_q11 = {%country}_dcc_qbar11-{%country}_dcc_alpha(1)*{%country}_dcc_qbar11-
{%country}_dcc_beta(1)*{%country}_dcc_qbar11+{%country}_dcc_alpha(1)*{%country}_dcc_e11n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q11(-1)
{%country}_dcc.append  {%country}_dcc_q12 = {%country}_dcc_qbar12-{%country}_dcc_alpha(1)*{%country}_dcc_qbar12-
{%country}_dcc_beta(1)*{%country}_dcc_qbar12+{%country}_dcc_alpha(1)*{%country}_dcc_e12n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q12(-1)
{%country}_dcc.append  {%country}_dcc_q21 = {%country}_dcc_qbar21-{%country}_dcc_alpha(1)*{%country}_dcc_qbar21-
{%country}_dcc_beta(1)*{%country}_dcc_qbar21+{%country}_dcc_alpha(1)*{%country}_dcc_e21n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q21(-1)
{%country}_dcc.append  {%country}_dcc_q22 = {%country}_dcc_qbar22-{%country}_dcc_alpha(1)*{%country}_dcc_qbar22-
{%country}_dcc_beta(1)*{%country}_dcc_qbar22+{%country}_dcc_alpha(1)*{%country}_dcc_e22n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q22(-1)
{%country}_dcc.append  {%country}_dcc_q12n = ({%country}_dcc_qbar12-{%country}_dcc_alpha(1)*{%country}_dcc_qbar12-
{%country}_dcc_beta(1)*{%country}_dcc_qbar12+{%country}_dcc_alpha(1)*{%country}_dcc_e12n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q12(-1))/((abs({%country}_dcc_q11)^0.5)*(abs({%country}_dcc_q22)^0.5))
{%country}_dcc.append  {%country}_dcc_q21n = ({%country}_dcc_qbar21-{%country}_dcc_alpha(1)*{%country}_dcc_qbar21-
{%country}_dcc_beta(1)*{%country}_dcc_qbar21+{%country}_dcc_alpha(1)*{%country}_dcc_e21n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q21(-1))/((abs({%country}_dcc_q22)^0.5)*(abs({%country}_dcc_q11)^0.5))
{%country}_dcc.append  {%country}_dcc_detQQQ = 1-{%country}_dcc_q12n*{%country}_dcc_q21n
{%country}_dcc.append  {%country}_dcc_cofact11 = 1*1
{%country}_dcc.append  {%country}_dcc_cofact12 =(-1)*{%country}_dcc_q21n
{%country}_dcc.append  {%country}_dcc_cofact21 =(-1)*{%country}_dcc_q12n
{%country}_dcc.append  {%country}_dcc_cofact22 = 1*1
{%country}_dcc.append  {%country}_dcc_invQQQ11 = {%country}_dcc_cofact11/ {%country}_dcc_detQQQ
{%country}_dcc.append  {%country}_dcc_invQQQ12 = {%country}_dcc_cofact12/ {%country}_dcc_detQQQ
{%country}_dcc.append  {%country}_dcc_invQQQ21 = {%country}_dcc_cofact21/ {%country}_dcc_detQQQ
{%country}_dcc.append  {%country}_dcc_invQQQ22 = {%country}_dcc_cofact22/ {%country}_dcc_detQQQ
{%country}_dcc.append  {%country}_dcc_enQQQen11 =
{%country}_r1w_{%r1w_selected}_e1n*{%country}_dcc_invQQQ11*{%country}_r1w_{%r1w_selected}_e1n
{%country}_dcc.append  {%country}_dcc_enQQQen12 =
{%country}_r1w_{%r1w_selected}_e1n*{%country}_dcc_invQQQ12*{%country}_r2w_{%r2w_selected}_e2n
{%country}_dcc.append  {%country}_dcc_enQQQen21 =
{%country}_r2w_{%r2w_selected}_e2n*{%country}_dcc_invQQQ21*{%country}_r1w_{%r1w_selected}_e1n
{%country}_dcc.append  {%country}_dcc_enQQQen22 =
{%country}_r2w_{%r2w_selected}_e2n*{%country}_dcc_invQQQ22*{%country}_r2w_{%r2w_selected}_e2n
{%country}_dcc.append {%country}_dcc_logl = -0.5*(log(abs({%country}_dcc_detQQQ)) + ({%country}_dcc_enQQQen11+
{%country}_dcc_enQQQen21+ {%country}_dcc_enQQQen12+ {%country}_dcc_enQQQen22))
smpl {%country}_s1
{%country}_dcc.ml(b,showopts, m=!itermle, c=1e-5)
series {%country}_dcc_count = ({%country}_dcc_detQQQ<=0)
scalar {%country}_dcc_detQQQnpd = @sum({%country}_dcc_count)

'Initializing the output series and estimating the conditional correlation using the estimated DCC model parameter coefficients
series  {%country}_dcc_q11f = 0
```

```
series  {%country}_dcc_q12f = 0
series  {%country}_dcc_q21f = 0
series  {%country}_dcc_q22f = 0
smpl {%country}_sf
series  {%country}_dcc_q11f = {%country}_dcc_qbar11-{%country}_dcc_alpha(1)*{%country}_dcc_qbar11-
{%country}_dcc_beta(1)*{%country}_dcc_qbar11+{%country}_dcc_alpha(1)*{%country}_dcc_e11n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q11(-1)
series  {%country}_dcc_q12f = {%country}_dcc_qbar12-{%country}_dcc_alpha(1)*{%country}_dcc_qbar12-
{%country}_dcc_beta(1)*{%country}_dcc_qbar12+{%country}_dcc_alpha(1)*{%country}_dcc_e12n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q12(-1)
series  {%country}_dcc_q21f = {%country}_dcc_qbar21-{%country}_dcc_alpha(1)*{%country}_dcc_qbar21-
{%country}_dcc_beta(1)*{%country}_dcc_qbar21+{%country}_dcc_alpha(1)*{%country}_dcc_e21n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q21(-1)
series  {%country}_dcc_q22f = {%country}_dcc_qbar22-{%country}_dcc_alpha(1)*{%country}_dcc_qbar22-
{%country}_dcc_beta(1)*{%country}_dcc_qbar22+{%country}_dcc_alpha(1)*{%country}_dcc_e22n(-
1)+{%country}_dcc_beta(1)*{%country}_dcc_q22(-1)
series {%country}_dcc_rt = {%country}_dcc_q12f/(@sqr({%country}_dcc_q11f)*@sqr({%country}_dcc_q22f))

'Diagnosing the minimum eigenvalues of the DCC estimates (must be positive for all t)
series {%country}_dcc_eigmins
scalar {%country}_dcc_eigmin
for !j = !sf+!meanlaglength to {%country}_obslength
sym(2) {%country}_dcc_Q
{%country}_dcc_Q(1,1) = {%country}_dcc_q11f(!j)
{%country}_dcc_Q(1,2) = {%country}_dcc_q12f(!j)
{%country}_dcc_Q(2,2) = {%country}_dcc_q22f(!j)
vector(4) {%country}_dcc_Qeigenval
{%country}_dcc_Qeigenval = @eigenvalues({%country}_dcc_Q)
{%country}_dcc_eigmins(!j) = @min({%country}_dcc_Qeigenval)
next
{%country}_dcc_eigmin = @min({%country}_dcc_eigmins)

'Computing the half-life of the DCC estimates (see Cappiello et al., 2006)
scalar {%country}_dcc_rt_hl = @log(0.5)/@log({%country}_dcc_alpha(1)^2+{%country}_dcc_beta(1)^2)

'Specifying the elements of the matrices for the estimation of the ADCC model of Cappiello et al. (2006)
smpl {%country}_s0
series {%country}_adcc_e11n = {%country}_r1w_{%r1w_selected}_e1n*{%country}_r1w_{%r1w_selected}_e1n
series {%country}_adcc_e12n = {%country}_r1w_{%r1w_selected}_e1n*{%country}_r2w_{%r2w_selected}_e2n
series {%country}_adcc_e21n = {%country}_r2w_{%r2w_selected}_e2n*{%country}_r1w_{%r1w_selected}_e1n
series {%country}_adcc_e22n = {%country}_r2w_{%r2w_selected}_e2n*{%country}_r2w_{%r2w_selected}_e2n
series {%country}_adcc_qbar11 = @mean({%country}_r1w_{%r1w_selected}_e1n*{%country}_r1w_{%r1w_selected}_e1n)
series {%country}_adcc_qbar12 = @mean({%country}_r1w_{%r1w_selected}_e1n*{%country}_r2w_{%r2w_selected}_e2n)
series {%country}_adcc_qbar21 = @mean({%country}_r2w_{%r2w_selected}_e2n*{%country}_r1w_{%r1w_selected}_e1n)
series {%country}_adcc_qbar22 = @mean({%country}_r2w_{%r2w_selected}_e2n*{%country}_r2w_{%r2w_selected}_e2n)
series {%country}_adcc_q11 = @var({%country}_r1w_{%r1w_selected}_e1)
series {%country}_adcc_q12 = @cov({%country}_r1w_{%r1w_selected}_e1, {%country}_r2w_{%r2w_selected}_e2)
series {%country}_adcc_q21 = @cov({%country}_r2w_{%r2w_selected}_e2, {%country}_r1w_{%r1w_selected}_e1)
series {%country}_adcc_q22 = @var({%country}_r2w_{%r2w_selected}_e2)
series {%country}_adcc_n1 = {%country}_r1w_{%r1w_selected}_e1n*({%country}_r1w_{%r1w_selected}_e1<0)
series {%country}_adcc_n2 = {%country}_r2w_{%r2w_selected}_e2n*({%country}_r2w_{%r2w_selected}_e2<0)
series {%country}_adcc_n11 = {%country}_adcc_n1*{%country}_adcc_n1
series {%country}_adcc_n12 = {%country}_adcc_n1*{%country}_adcc_n2
series {%country}_adcc_n21 = {%country}_adcc_n2*{%country}_adcc_n1
series {%country}_adcc_n22 = {%country}_adcc_n2*{%country}_adcc_n2
series  {%country}_adcc_nbar11 = @mean({%country}_adcc_n1*{%country}_adcc_n1)
series  {%country}_adcc_nbar12 = @mean({%country}_adcc_n1*{%country}_adcc_n2)
series  {%country}_adcc_nbar21 = @mean({%country}_adcc_n2*{%country}_adcc_n1)
series  {%country}_adcc_nbar22 = @mean({%country}_adcc_n2*{%country}_adcc_n2)

'Defining the coefficients and their starting values for the second stage ML estimation of the ADCC model
coef(1) {%country}_adcc_alpha
coef(1) {%country}_adcc_beta
coef(1) {%country}_adcc_eta
{%country}_adcc_alpha(1) = !adcc_alpha
{%country}_adcc_beta(1) = !adcc_beta
{%country}_adcc_eta(1) = !adcc_eta

'Setting up and estimating the log likelihood function of the ADCC model
logl {%country}_adcc
{%country}_adcc.append @logl {%country}_adcc_logl
{%country}_adcc.append  {%country}_adcc_q11 = {%country}_adcc_qbar11-{%country}_adcc_alpha(1)*{%country}_adcc_qbar11-
{%country}_adcc_beta(1)*{%country}_adcc_qbar11-
{%country}_adcc_eta(1)*{%country}_adcc_nbar11+{%country}_adcc_alpha(1)*{%country}_adcc_e11n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q11(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n11(-1)
```

```
{%country}_adcc.append {%country}_adcc_q12 = {%country}_adcc_qbar12-{%country}_adcc_alpha(1)*{%country}_adcc_qbar12-
{%country}_adcc_beta(1)*{%country}_adcc_qbar12-
{%country}_adcc_eta(1)*{%country}_adcc_nbar12+{%country}_adcc_alpha(1)*{%country}_adcc_e12n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q12(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n12(-1)
{%country}_adcc.append {%country}_adcc_q21 = {%country}_adcc_qbar21-{%country}_adcc_alpha(1)*{%country}_adcc_qbar21-
{%country}_adcc_beta(1)*{%country}_adcc_qbar21-
{%country}_adcc_eta(1)*{%country}_adcc_nbar21+{%country}_adcc_alpha(1)*{%country}_adcc_e21n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q21(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n21(-1)
{%country}_adcc.append {%country}_adcc_q22 = {%country}_adcc_qbar22-{%country}_adcc_alpha(1)*{%country}_adcc_qbar22-
{%country}_adcc_beta(1)*{%country}_adcc_qbar22-
{%country}_adcc_eta(1)*{%country}_adcc_nbar22+{%country}_adcc_alpha(1)*{%country}_adcc_e22n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q22(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n22(-1)
{%country}_adcc.append {%country}_adcc_q12n = ({%country}_adcc_qbar12-{%country}_adcc_alpha(1)*{%country}_adcc_qbar12-
{%country}_adcc_beta(1)*{%country}_adcc_qbar12-
{%country}_adcc_eta(1)*{%country}_adcc_nbar12+{%country}_adcc_alpha(1)*{%country}_adcc_e12n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q12(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n12(-
1))/((abs({%country}_adcc_q11)^0.5)*(abs({%country}_adcc_q22)^0.5))
{%country}_adcc.append {%country}_adcc_q21n = ({%country}_adcc_qbar21-{%country}_adcc_alpha(1)*{%country}_adcc_qbar21-
{%country}_adcc_beta(1)*{%country}_adcc_qbar21-
{%country}_adcc_eta(1)*{%country}_adcc_nbar21+{%country}_adcc_alpha(1)*{%country}_adcc_e21n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q21(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n21(-
1))/((abs({%country}_adcc_q22)^0.5)*(abs({%country}_adcc_q11)^0.5))
{%country}_adcc.append {%country}_adcc_detQQQ = 1 - {%country}_adcc_q12n* {%country}_adcc_q21n
{%country}_adcc.append {%country}_adcc_cofact11 =  1*1
{%country}_adcc.append {%country}_adcc_cofact12 =(-1)*{%country}_adcc_q21n
{%country}_adcc.append {%country}_adcc_cofact21 =(-1)*{%country}_adcc_q12n
{%country}_adcc.append {%country}_adcc_cofact22 =  1*1
{%country}_adcc.append {%country}_adcc_invQQQ11 = {%country}_adcc_cofact11/ {%country}_adcc_detQQQ
{%country}_adcc.append {%country}_adcc_invQQQ12 = {%country}_adcc_cofact12/ {%country}_adcc_detQQQ
{%country}_adcc.append {%country}_adcc_invQQQ21 = {%country}_adcc_cofact21/ {%country}_adcc_detQQQ
{%country}_adcc.append {%country}_adcc_invQQQ22 = {%country}_adcc_cofact22/ {%country}_adcc_detQQQ
{%country}_adcc.append {%country}_adcc_enQQQen11 =
{%country}_r1w_{%r1w_selected}_e1n*{%country}_adcc_invQQQ11*{%country}_r1w_{%r1w_selected}_e1n
{%country}_adcc.append {%country}_adcc_enQQQen12 =
{%country}_r1w_{%r1w_selected}_e1n*{%country}_adcc_invQQQ12*{%country}_r2w_{%r2w_selected}_e2n
{%country}_adcc.append {%country}_adcc_enQQQen21 =
{%country}_r2w_{%r2w_selected}_e2n*{%country}_adcc_invQQQ21*{%country}_r1w_{%r1w_selected}_e1n
{%country}_adcc.append {%country}_adcc_enQQQen22 =
{%country}_r2w_{%r2w_selected}_e2n*{%country}_adcc_invQQQ22*{%country}_r2w_{%r2w_selected}_e2n
{%country}_adcc.append {%country}_adcc_logl = -0.5*(log(abs({%country}_adcc_detQQQ)) + ({%country}_adcc_enQQQen11+
{%country}_adcc_enQQQen21+ {%country}_adcc_enQQQen12+ {%country}_adcc_enQQQen22))
smpl {%country}_s1
{%country}_adcc.ml(b, showopts, m=!itermle, c=1e-5)
series {%country}_adcc_count = ({%country}_adcc_detQQQ<=0)
scalar {%country}_adcc_detQQQnpd = @sum({%country}_adcc_count)

'Initializing the output series and estimating the conditional correlation using the estimated ADCC model parameter coefficients
series {%country}_adcc_q11f = 0
series {%country}_adcc_q12f = 0
series {%country}_adcc_q21f = 0
series {%country}_adcc_q22f = 0
smpl {%country}_sf
series {%country}_adcc_q11f = {%country}_adcc_qbar11-{%country}_adcc_alpha(1)*{%country}_adcc_qbar11-
{%country}_adcc_beta(1)*{%country}_adcc_qbar11-
{%country}_adcc_eta(1)*{%country}_adcc_nbar11+{%country}_adcc_alpha(1)*{%country}_adcc_e11n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q11(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n11(-1)
series {%country}_adcc_q12f = {%country}_adcc_qbar12-{%country}_adcc_alpha(1)*{%country}_adcc_qbar12-
{%country}_adcc_beta(1)*{%country}_adcc_qbar12-
{%country}_adcc_eta(1)*{%country}_adcc_nbar12+{%country}_adcc_alpha(1)*{%country}_adcc_e12n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q12(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n12(-1)
series {%country}_adcc_q21f = {%country}_adcc_qbar21-{%country}_adcc_alpha(1)*{%country}_adcc_qbar21-
{%country}_adcc_beta(1)*{%country}_adcc_qbar21-
{%country}_adcc_eta(1)*{%country}_adcc_nbar21+{%country}_adcc_alpha(1)*{%country}_adcc_e21n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q21(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n21(-1)
series {%country}_adcc_q22f = {%country}_adcc_qbar22-{%country}_adcc_alpha(1)*{%country}_adcc_qbar22-
{%country}_adcc_beta(1)*{%country}_adcc_qbar22-
{%country}_adcc_eta(1)*{%country}_adcc_nbar22+{%country}_adcc_alpha(1)*{%country}_adcc_e22n(-
1)+{%country}_adcc_beta(1)*{%country}_adcc_q22(-1)+{%country}_adcc_eta(1)*{%country}_adcc_n22(-1)
series {%country}_adcc_rt = {%country}_adcc_q12f/(@sqr({%country}_adcc_q11f)*@sqr({%country}_adcc_q22f))

'Diagnosing the minimum eigenvalues of the ADCC estimates (must be positive for all t)
series {%country}_adcc_eigmins
scalar {%country}_adcc_eigmin
for !j = !sf+!meanlaglength to {%country}_obslength
sym(2) {%country}_adcc_Q
```

```
{%country}_adcc_Q(1,1) = {%country}_adcc_q11f(!j)
{%country}_adcc_Q(1,2) = {%country}_adcc_q12f(!j)
{%country}_adcc_Q(2,2) = {%country}_adcc_q22f(!j)
vector(4) {%country}_adcc_Qeigenval
{%country}_adcc_Qeigenval = @eigenvalues({%country}_adcc_Q)
{%country}_adcc_eigmins(!j) = @min({%country}_adcc_Qeigenval)
next
{%country}_adcc_eigmin = @min({%country}_adcc_eigmins)
smpl {%country}_s0

'Selecting between the DCC and the ADCC models based on the SIC
vector(2) {%country}_dcc_sic
{%country}_dcc_sic(1) = {%country}_dcc.@schwarz
{%country}_dcc_sic(2) = {%country}_adcc.@schwarz
vector(2) {%country}_dcc_sicr = @ranks({%country}_dcc_sic, "a")
if {%country}_dcc_sicr(1) = 1 then
%dcc_selected ="dcc"
delete {%country}_adcc*
else
%dcc_selected ="adcc"
delete {%country}_dcc*
endif
delete {%country}_dcc_sic

'Calculating the F-test for remaining time-varying volatility in squared standardized residuals and cross-products of the standardized
residuals of the selected bivariate DCC model (see Engle, 2002)
series {%country}_{%dcc_selected}_v1 = ({%country}_r1w_{%r1w_selected}_e1)/(sqr({%country}_r1w_{%r1w_selected}_h11))
series {%country}_{%dcc_selected}_v2 = ({%country}_r2w_{%r2w_selected}_e2)/(sqr({%country}_r2w_{%r2w_selected}_h22*(1-
{%country}_{%dcc_selected}_rt^2)))-
(({%country}_r1w_{%r1w_selected}_e1*{%country}_{%dcc_selected}_rt)/(sqr({%country}_r1w_{%r1w_selected}_h11*(1-
{%country}_{%dcc_selected}_rt^2))))
series {%country}_{%dcc_selected}_v11 = {%country}_{%dcc_selected}_v1^2
series {%country}_{%dcc_selected}_v22 = {%country}_{%dcc_selected}_v2^2
series {%country}_{%dcc_selected}_v12 = {%country}_{%dcc_selected}_v1*{%country}_{%dcc_selected}_v2
equation {%country}_{%dcc_selected}_ftest1.ls {%country}_{%dcc_selected}_v11 c {%country}_{%dcc_selected}_v11(-1)
{%country}_{%dcc_selected}_v11(-2) {%country}_{%dcc_selected}_v11(-3) {%country}_{%dcc_selected}_v11(-4)
{%country}_{%dcc_selected}_v11(-5) {%country}_{%dcc_selected}_v12(-1) {%country}_{%dcc_selected}_v12(-2)
{%country}_{%dcc_selected}_v12(-3) {%country}_{%dcc_selected}_v12(-4) {%country}_{%dcc_selected}_v12(-5)
equation {%country}_{%dcc_selected}_ftest2.ls {%country}_{%dcc_selected}_v22 c {%country}_{%dcc_selected}_v22(-1)
{%country}_{%dcc_selected}_v22(-2) {%country}_{%dcc_selected}_v22(-3) {%country}_{%dcc_selected}_v22(-4)
{%country}_{%dcc_selected}_v22(-5) {%country}_{%dcc_selected}_v12(-1) {%country}_{%dcc_selected}_v12(-2)
{%country}_{%dcc_selected}_v12(-3) {%country}_{%dcc_selected}_v12(-4) {%country}_{%dcc_selected}_v12(-5)
scalar {%country}_{%dcc_selected}_f1 = {%country}_{%dcc_selected}_ftest1.@f
scalar {%country}_{%dcc_selected}_f2 = {%country}_{%dcc_selected}_ftest2.@f
```

'TESTING FOR THE FLIGHTS BETWEEN STOCKS AND BONDS

```
smpl @all
series {%country}_r1_movs = @movsum({%country}_r1,!flight_interval)
series {%country}_r2_movs = @movsum({%country}_r2,!flight_interval)
series  {%country}_{%dcc_selected}_rt_ccc = {%country}_{%dcc_selected}_rt - {%country}_{%dcc_selected}_rt(-!flight_interval+1)
series {%country}_{%dcc_selected}_rt_cacc = {%country}_{%dcc_selected}_rt_ccc
*(abs({%country}_{%dcc_selected}_rt_ccc)>@stdev({%country}_{%dcc_selected}_rt)*!flight_threshold)
series {%country}_{%dcc_selected}_ftl = {%country}_{%dcc_selected}_rt_cacc*({%country}_{%dcc_selected}_rt_cacc>0 and
{%country}_r1_movs<!negativity and {%country}_r2_movs<!negativity)
series {%country}_{%dcc_selected}_ftq = {%country}_{%dcc_selected}_rt_cacc*({%country}_{%dcc_selected}_rt_cacc<0 and
{%country}_r1_movs-{%country}_r2_movs<!outperformance and {%country}_r1_movs<0 and {%country}_r2_movs>0)
series {%country}_{%dcc_selected}_ffl = {%country}_{%dcc_selected}_rt_cacc*({%country}_{%dcc_selected}_rt_cacc>0 and
{%country}_r1_movs>!positivity and {%country}_r2_movs>!positivity)
series {%country}_{%dcc_selected}_ffq = {%country}_{%dcc_selected}_rt_cacc*({%country}_{%dcc_selected}_rt_cacc<0 and
{%country}_r1_movs-{%country}_r2_movs>!outperformance and {%country}_r1_movs>0 and {%country}_r2_movs<0)
```

'SPECIFYING THE OUTPUTS FOR THE THESIS

```
'Drawing figures for the thesis
smpl @all
!lw = 1
series {%country}_blackzero = 0
graph {%country}_graph_rt.line(x) {%country}_{%dcc_selected}_rt {%country}_blackzero
{%country}_graph_rt.legend display columns(4)
{%country}_graph_rt.name(1) Conditional stock-bond correlation
{%country}_graph_rt.name(2)  'Leave this empty
{%country}_graph_rt.setelem(1) linecolor(black) linepattern(1) axis(l) linewidth(!lw)
{%country}_graph_rt.setelem(2) linecolor(black) linepattern(1) axis(l) linewidth(!lw)
{%country}_graph_rt.axis(l) range(-1.0,1.0) format(dec=1)
{%country}_graph_rt.axis(r) range(-1.0,1.0) format(dec=1)
```

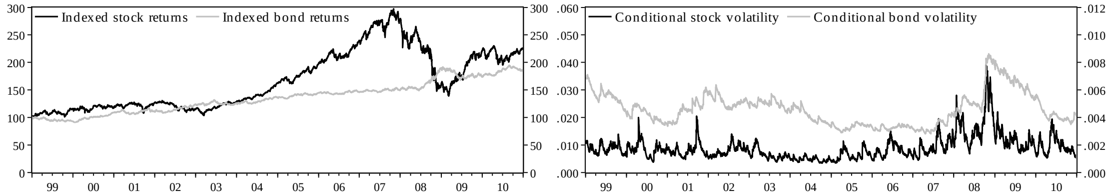
```
{%country}_graph_rt.options size(16.00,6.25)
graph {%country}_graph_flights.spike(x) {%country}_{%dcc_selected}_ftl {%country}_{%dcc_selected}_ftq
{%country}_{%dcc_selected}_ffl {%country}_{%dcc_selected}_ffq {%country}_blackzero
{%country}_graph_flights.legend display columns(5)
{%country}_graph_flights.name(1) Flight-to-liquidity
{%country}_graph_flights.name(2) Flight-to-quality
{%country}_graph_flights.name(3) Flight-from-liquidity
{%country}_graph_flights.name(4) Flight-from-quality
{%country}_graph_flights.name(5) 'Leave this empty
{%country}_graph_flights.setelem(1) linecolor(red) linepattern(1) axis(l) linewidth(4.0)
{%country}_graph_flights.setelem(2) linecolor(green) linepattern(1) axis(l) linewidth(4.0)
{%country}_graph_flights.setelem(3) linecolor(blue) linepattern(1) axis(l) linewidth(4.0)
{%country}_graph_flights.setelem(4) linecolor(yellow) linepattern(1) axis(l) linewidth(4.0)
{%country}_graph_flights.setelem(5) linecolor(@rgb(0,0,0)) linepattern(1) axis(l) linewidth(4.0)
{%country}_graph_flights.axis(l) range(-1.2, 1.2) format(dec=1)
{%country}_graph_flights.axis(r) range(-1.2, 1.2) format(dec=1)
{%country}_graph_flights.options size(16.00,6.25)
graph {%country}_graph_CAViaR.line(x) {%country}_port_asl_1 {%country}_port_asl_5  {%country}_blackzero
{%country}_graph_CAViaR.legend display columns(4)
{%country}_graph_CAViaR.name(1) 1% CAViaR of an equally weighted stock-bond portfolio
{%country}_graph_CAViaR.name(2) 5% CAViaR of an equally weighted stock-bond portfolio
{%country}_graph_CAViaR.name(3)  'Leave this empty
{%country}_graph_CAViaR.setelem(1) linecolor(red) linepattern(1) axis(l) linewidth(!lw)
{%country}_graph_CAViaR.setelem(2) linecolor(ltgray) linepattern(7) axis(l) linewidth(!lw)
{%country}_graph_CAViaR.setelem(3) linecolor(black) linepattern(1) axis(l) linewidth(!lw)
{%country}_graph_CAViaR.axis(l) range(0.0, 8.0) format(suffix=%, dec=1)
{%country}_graph_CAViaR.axis(r) range(0.0, 8.0) format(suffix=%, dec=1)
{%country}_graph_CAViaR.options size(16.00,6.25)
graph {%country}_graph_1.merge {%country}_graph_rt {%country}_graph_flights {%country}_graph_CAViaR
{%country}_graph_1.align(1,1.00,1.00)
{%country}_graph_1.save(t=emf, u=cm, w=16.00, h=18.75, c, -trans) {%country}_graph_1
graph {%country}_graph_indx.line(x) {%country}_r1_indx  {%country}_r2_indx
{%country}_graph_indx.legend display columns(4)
{%country}_graph_indx.name(1) Indexed stock returns
{%country}_graph_indx.name(2) Indexed bond returns
{%country}_graph_indx.setelem(1) linecolor(black) linepattern(1) axis(l) linewidth(!lw)
{%country}_graph_indx.setelem(2) linecolor(ltgray) linepattern(1) axis(r) linewidth(!lw)
{%country}_graph_indx.axis(l) range(0,300) format(dec=0)
{%country}_graph_indx.axis(r) range(0,300) format(dec=0)
{%country}_graph_indx.options size(8.00,3.10)
graph {%country}_graph_vola.line(x) {%country}_r1w_{%r1w_selected}_d11 {%country}_r2w_{%r2w_selected}_d22
{%country}_graph_vola.legend display columns(4)
{%country}_graph_vola.name(1) Conditional stock volatility
{%country}_graph_vola.name(2) Conditional bond volatility
{%country}_graph_vola.setelem(1) linecolor(black) linepattern(1) axis(l) linewidth(!lw)
{%country}_graph_vola.setelem(2) linecolor(ltgray) linepattern(1) axis(r) linewidth(!lw)
{%country}_graph_vola.axis(l) range(0.00,0.060) format(dec=3)
{%country}_graph_vola.axis(r) range(0.00,0.012) format(dec=3)
{%country}_graph_vola.options size(8.00,3.10)
graph {%country}_graph_2.merge {%country}_graph_indx {%country}_graph_vola
{%country}_graph_2.align(2,1.00,1.00)
{%country}_graph_2.save(t=emf, u=cm, w=16.00, h=3.10, c, -trans) {%country}_graph_2
smpl @all
close @objects
next

'Grouping all relevant output series and saving each country as an individual workfile page and the workfile in the default directory
group output_series *r1 *r2 *r1_indx *r2_indx *r1w *r2w *r1_movs *r2_movs *d11 *d22 *dcc_rt *_rt_ccc *_rt_cacc *dcc_ftl *dcc_ftq
*dcc_ffl *dcc_ffq *asl_1 *asl_5
for %country {%countries}
pagecreate(page={%country}) {%frequency} {%sample}
copy() all\{%country}* {%country}\{%country}*
next
wfsave(2) "all"
```

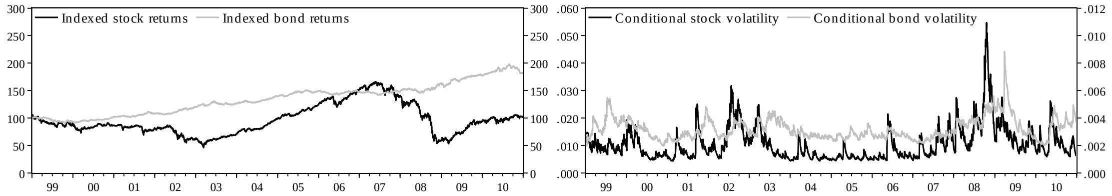
Appendix 2: Indexed Returns and Conditional Volatilities

On the left hand side, this appendix shows the indexed daily local currency denominated logarithmic total stock (black) and bond (light gray) returns from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). The returns are indexed to 100 at the beginning of the sample period on the January 1, 1999 to facilitate their comparison. On the right hand side, this appendix shows the daily conditional volatility estimates of the stock (black) and bond (light gray) residuals based on the selected GARCH specifications from January 1, 1999 to December 31, 2010 (3122-3129 observations with adjustments). For the list selected GARCH specifications refer to Tables 6-7. Note that the axis scaling differs in the figures on the right hand side. All the left and right hand side figures are equally scaled between countries to ensure full comparability between them. For further information, refer to Section 4.1.

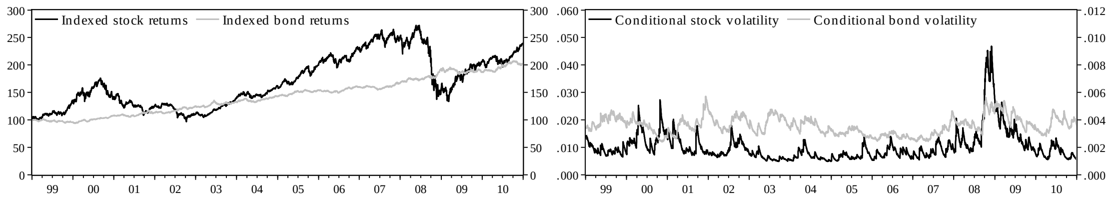
Australia



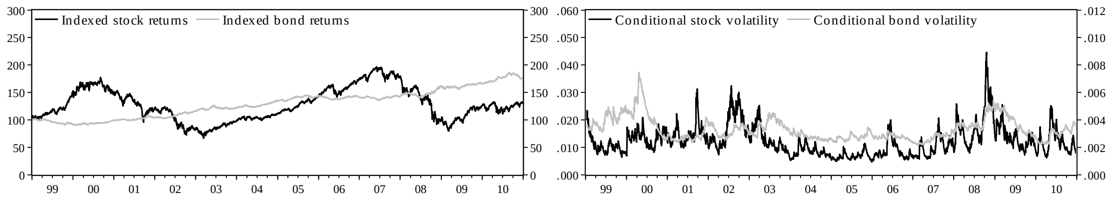
Belgium



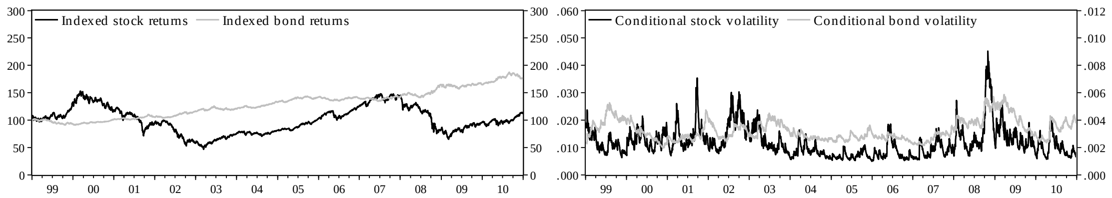
Canada



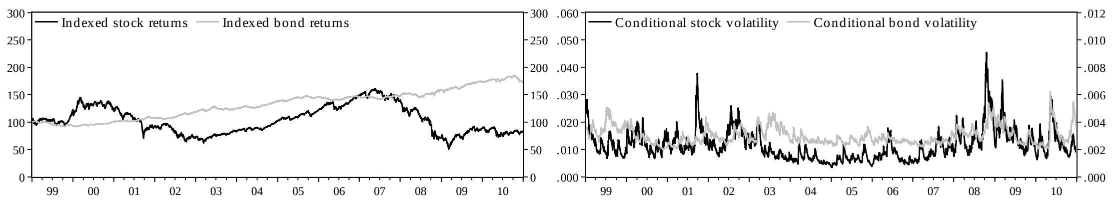
France



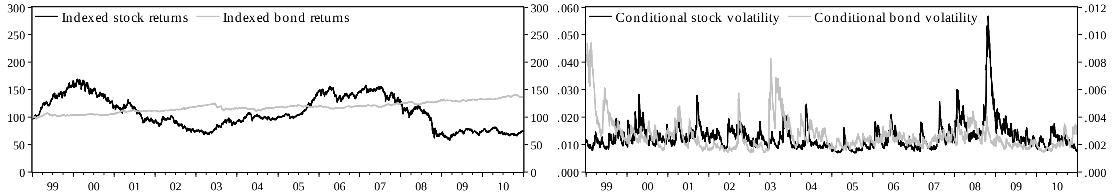
Germany



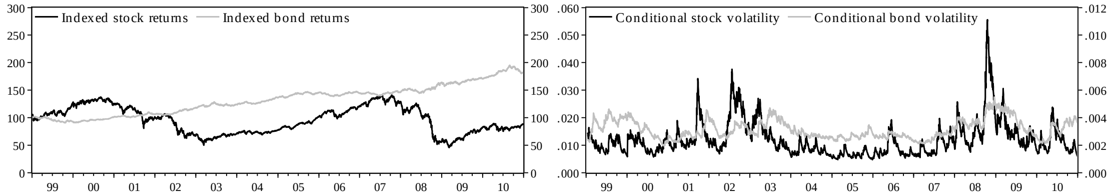
Italy



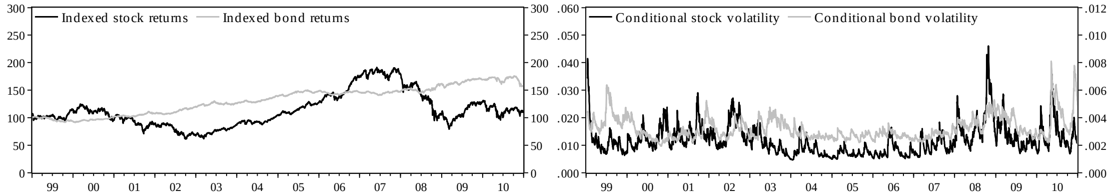
Japan



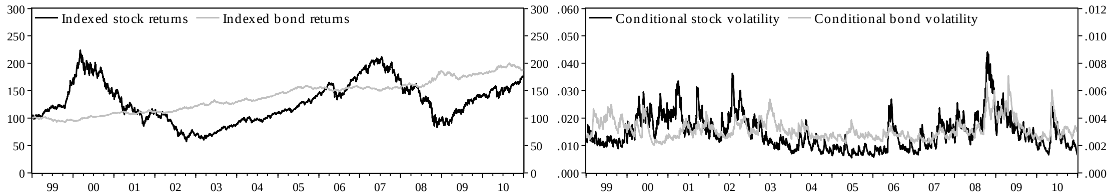
The Netherlands



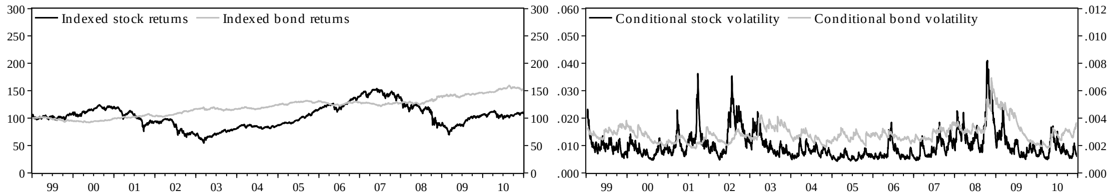
Spain



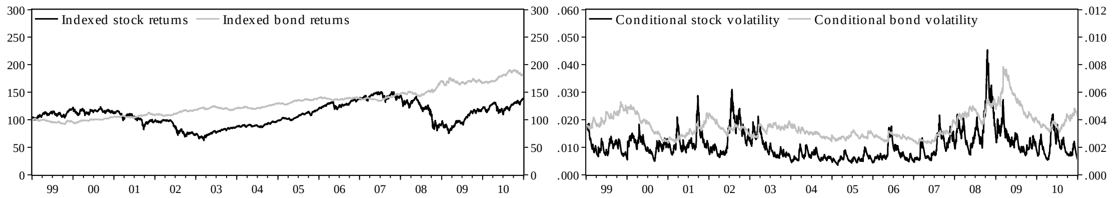
Sweden



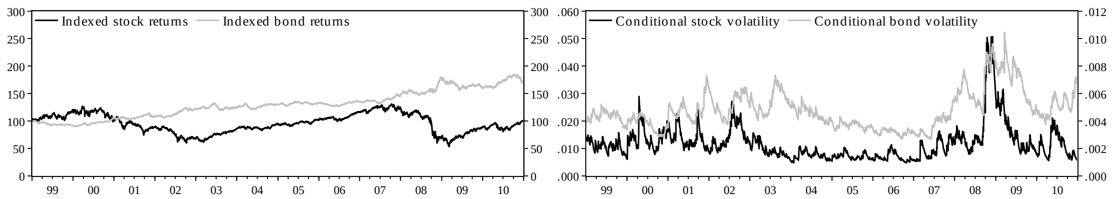
Switzerland



UK



US



Appendix 3: Conditional Correlation Estimates (Annual Averages)

This appendix reports the annual and total period averages of the daily conditional intranational stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest correlation gets the ranking number 1, the country with the second lowest correlation gets the ranking number 2, and so on). The numbers in the brackets represent the country rankings. For further information, refer to Section 4.1.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Australia	0.10	-0.03	-0.08	-0.29	-0.21	0.03	-0.16	-0.06	-0.32	-0.38	-0.34	-0.39	-0.18
	(11)	(12)	(13)	(12)	(13)	(13)	(4)	(12)	(8)	(9)	(6)	(6)	(12)
Belgium	0.11	-0.06	-0.20	-0.35	-0.36	-0.17	-0.09	-0.14	-0.32	-0.38	-0.23	-0.19	-0.20
	(12)	(9)	(10)	(10)	(7)	(10)	(9)	(7)	(7)	(10)	(12)	(11)	(9)
Canada	0.10	-0.04	-0.24	-0.35	-0.28	-0.07	-0.05	-0.07	-0.21	-0.30	-0.24	-0.27	-0.17
	(10)	(11)	(8)	(11)	(12)	(12)	(12)	(11)	(12)	(13)	(11)	(10)	(13)
France	-0.05	-0.09	-0.32	-0.48	-0.47	-0.26	-0.14	-0.15	-0.34	-0.47	-0.36	-0.43	-0.30
	(2)	(4)	(1)	(1)	(2)	(3)	(6)	(5)	(4)	(3)	(3)	(4)	(3)
Germany	0.00	-0.01	-0.27	-0.45	-0.46	-0.24	-0.12	-0.13	-0.33	-0.49	-0.42	-0.52	-0.29
	(7)	(13)	(5)	(3)	(3)	(5)	(7)	(8)	(5)	(1)	(1)	(1)	(4)
Italy	-0.02	-0.08	-0.16	-0.42	-0.38	-0.20	-0.06	-0.09	-0.30	-0.35	-0.18	0.02	-0.18
	(4)	(6)	(12)	(5)	(6)	(8)	(11)	(9)	(9)	(12)	(13)	(12)	(11)
Japan	-0.12	-0.26	-0.17	-0.06	-0.32	-0.41	-0.38	-0.37	-0.38	-0.46	-0.36	-0.38	-0.30
	(1)	(1)	(11)	(13)	(11)	(1)	(1)	(1)	(1)	(4)	(4)	(7)	(2)
Netherlands	-0.01	-0.14	-0.28	-0.46	-0.49	-0.31	-0.17	-0.15	-0.35	-0.49	-0.38	-0.46	-0.31
	(6)	(2)	(3)	(2)	(1)	(2)	(2)	(4)	(2)	(2)	(2)	(2)	(1)
Spain	-0.01	-0.05	-0.25	-0.39	-0.39	-0.18	-0.07	-0.07	-0.33	-0.39	-0.27	0.04	-0.20
	(5)	(10)	(6)	(7)	(5)	(9)	(10)	(10)	(6)	(7)	(10)	(13)	(10)
Sweden	0.04	-0.08	-0.23	-0.38	-0.43	-0.24	-0.14	-0.17	-0.22	-0.38	-0.35	-0.44	-0.25
	(9)	(5)	(9)	(8)	(4)	(4)	(5)	(3)	(11)	(8)	(5)	(3)	(5)
Switzerland	0.02	-0.07	-0.31	-0.41	-0.33	-0.22	-0.11	-0.18	-0.21	-0.35	-0.31	-0.38	-0.24
	(8)	(7)	(2)	(6)	(10)	(6)	(8)	(2)	(13)	(11)	(8)	(8)	(7)
UK	-0.03	-0.06	-0.28	-0.37	-0.34	-0.20	-0.16	-0.14	-0.35	-0.41	-0.32	-0.35	-0.25
	(3)	(8)	(4)	(9)	(9)	(7)	(3)	(6)	(3)	(6)	(7)	(9)	(6)
US	0.13	-0.09	-0.25	-0.44	-0.34	-0.11	-0.05	0.02	-0.28	-0.46	-0.31	-0.40	-0.22
	(13)	(3)	(7)	(4)	(8)	(11)	(13)	(13)	(10)	(5)	(9)	(5)	(8)

Appendix 4: Conditional Correlation Estimates by Percentiles

This appendix reports the selected percentiles of the daily conditional stock-bond correlation estimates based on the selected bivariate DCC model(s), the scalar DCC(1,1) model of Engle (2002), from January 1, 1999 to December 31, 2010 (3121-3128 observations with adjustments). For further information, refer to Section 4.1.

Country	1 %	5 %	10 %	20 %	30 %	40 %	50 %	60 %	70 %	80 %	90 %	95 %	99 %
Australia	-0.63	-0.53	-0.46	-0.38	-0.31	-0.25	-0.18	-0.11	-0.04	0.03	0.10	0.17	0.28
Belgium	-0.58	-0.52	-0.46	-0.36	-0.30	-0.25	-0.20	-0.16	-0.11	-0.05	0.04	0.15	0.32
Canada	-0.52	-0.46	-0.41	-0.33	-0.27	-0.22	-0.17	-0.13	-0.08	-0.02	0.07	0.14	0.25
France	-0.64	-0.60	-0.55	-0.48	-0.41	-0.36	-0.31	-0.24	-0.19	-0.12	-0.04	0.00	0.11
Germany	-0.65	-0.60	-0.56	-0.49	-0.44	-0.37	-0.30	-0.23	-0.16	-0.09	0.02	0.08	0.13
Italy	-0.59	-0.52	-0.46	-0.37	-0.27	-0.21	-0.17	-0.12	-0.08	-0.04	0.05	0.13	0.26
Japan	-0.61	-0.52	-0.49	-0.43	-0.39	-0.36	-0.32	-0.29	-0.25	-0.16	-0.08	-0.04	0.04
Netherlands	-0.63	-0.60	-0.56	-0.49	-0.42	-0.36	-0.31	-0.26	-0.21	-0.15	-0.05	0.01	0.16
Spain	-0.60	-0.53	-0.48	-0.39	-0.32	-0.25	-0.20	-0.14	-0.08	-0.01	0.07	0.14	0.33
Sweden	-0.57	-0.49	-0.47	-0.40	-0.37	-0.32	-0.26	-0.21	-0.16	-0.11	-0.02	0.04	0.11
Switzerland	-0.54	-0.47	-0.42	-0.36	-0.33	-0.29	-0.26	-0.22	-0.18	-0.11	-0.02	0.07	0.15
UK	-0.56	-0.51	-0.47	-0.39	-0.34	-0.29	-0.26	-0.23	-0.17	-0.11	-0.02	0.04	0.14
US	-0.69	-0.61	-0.55	-0.46	-0.38	-0.31	-0.23	-0.15	-0.08	0.02	0.14	0.21	0.35

Appendix 5: 1% CAViaR Estimates (Annual Averages)

This appendix reports the annual and total period averages of the daily 1% conditional autoregressive value at risk (CAViaR) estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest CAViaR gets the ranking number 1, the country with the second lowest CAViaR gets the ranking number 2, and so on). The numbers in the brackets represent the country rankings. For further information, refer to Section 4.3.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Australia	1.37 %	1.19 %	1.23 %	1.10 %	1.05 %	0.88 %	0.97 %	1.13 %	1.18 %	2.15 %	1.41 %	1.18 %	1.24 %
	(3)	(3)	(2)	(1)	(2)	(2)	(6)	(10)	(9)	(7)	(2)	(5)	(2)
Belgium	1.42 %	1.14 %	1.11 %	1.58 %	1.23 %	0.86 %	0.86 %	0.97 %	1.16 %	2.14 %	1.46 %	1.29 %	1.27 %
	(6)	(2)	(1)	(3)	(5)	(1)	(3)	(2)	(7)	(6)	(3)	(8)	(3)
Canada	1.41 %	1.77 %	1.40 %	1.20 %	0.87 %	1.05 %	1.02 %	1.14 %	1.13 %	2.27 %	1.87 %	1.06 %	1.35 %
	(4)	(12)	(3)	(2)	(1)	(8)	(9)	(11)	(6)	(10)	(11)	(2)	(5)
France	1.35 %	1.63 %	1.66 %	1.91 %	1.40 %	1.01 %	0.91 %	1.08 %	1.13 %	2.05 %	1.53 %	1.31 %	1.41 %
	(2)	(9)	(10)	(11)	(10)	(7)	(5)	(6)	(5)	(4)	(6)	(9)	(9)
Germany	1.45 %	1.54 %	1.56 %	1.65 %	1.36 %	1.09 %	1.00 %	1.12 %	1.12 %	1.69 %	1.46 %	1.14 %	1.35 %
	(7)	(6)	(6)	(6)	(9)	(11)	(8)	(8)	(3)	(1)	(4)	(3)	(4)
Italy	1.58 %	1.61 %	1.77 %	1.69 %	1.22 %	0.92 %	0.99 %	1.11 %	1.18 %	2.15 %	1.92 %	1.71 %	1.49 %
	(12)	(8)	(11)	(8)	(3)	(4)	(7)	(7)	(8)	(8)	(12)	(12)	(11)
Japan	1.53 %	1.77 %	1.85 %	1.81 %	1.52 %	1.35 %	1.12 %	1.53 %	1.47 %	2.52 %	1.71 %	1.44 %	1.63 %
	(10)	(11)	(12)	(10)	(13)	(13)	(12)	(13)	(12)	(13)	(9)	(11)	(12)
Netherlands	1.42 %	1.23 %	1.58 %	1.97 %	1.52 %	0.96 %	0.84 %	1.04 %	1.12 %	2.25 %	1.65 %	1.23 %	1.40 %
	(5)	(4)	(7)	(12)	(12)	(6)	(2)	(4)	(4)	(9)	(8)	(6)	(7)
Spain	1.45 %	1.59 %	1.63 %	1.67 %	1.24 %	1.09 %	1.04 %	1.13 %	1.21 %	1.97 %	1.52 %	1.84 %	1.45 %
	(8)	(7)	(9)	(7)	(6)	(10)	(10)	(9)	(10)	(3)	(5)	(13)	(10)
Sweden	1.58 %	2.22 %	2.36 %	2.14 %	1.49 %	1.31 %	1.17 %	1.44 %	1.58 %	2.42 %	1.93 %	1.42 %	1.75 %
	(13)	(13)	(13)	(13)	(11)	(12)	(13)	(12)	(13)	(12)	(13)	(10)	(13)
Switzerland	1.28 %	1.02 %	1.44 %	1.59 %	1.28 %	0.94 %	0.77 %	0.93 %	1.11 %	1.91 %	1.20 %	0.98 %	1.20 %
	(1)	(1)	(4)	(4)	(7)	(5)	(1)	(1)	(1)	(2)	(1)	(1)	(1)
UK	1.45 %	1.45 %	1.53 %	1.74 %	1.30 %	0.91 %	0.86 %	1.08 %	1.27 %	2.28 %	1.65 %	1.27 %	1.40 %
	(9)	(5)	(5)	(9)	(8)	(3)	(4)	(5)	(11)	(11)	(7)	(7)	(6)
US	1.54 %	1.66 %	1.62 %	1.61 %	1.22 %	1.07 %	1.06 %	1.00 %	1.11 %	2.10 %	1.72 %	1.17 %	1.41 %
	(11)	(10)	(8)	(5)	(4)	(9)	(11)	(3)	(2)	(5)	(10)	(4)	(8)

Appendix 6: 1% CAViaR Estimates by Percentiles

This appendix reports the selected percentiles of the daily 1% conditional autoregressive value at risk (CAViaR) estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). For further information, refer to Section 4.3.

Country	1 %	5 %	10 %	20 %	30 %	40 %	50 %	60 %	70 %	80 %	90 %	95 %	99 %
Australia	0.63 %	0.71 %	0.76 %	0.84 %	0.92 %	1.00 %	1.09 %	1.19 %	1.34 %	1.53 %	1.85 %	2.20 %	3.28 %
Belgium	0.62 %	0.68 %	0.73 %	0.80 %	0.88 %	0.97 %	1.07 %	1.19 %	1.37 %	1.65 %	2.03 %	2.42 %	3.60 %
Canada	0.71 %	0.81 %	0.86 %	0.93 %	1.02 %	1.11 %	1.20 %	1.30 %	1.43 %	1.62 %	1.92 %	2.38 %	4.38 %
France	0.74 %	0.81 %	0.87 %	0.96 %	1.06 %	1.19 %	1.30 %	1.42 %	1.56 %	1.75 %	2.10 %	2.47 %	3.45 %
Germany	0.82 %	0.87 %	0.92 %	1.00 %	1.08 %	1.15 %	1.24 %	1.34 %	1.46 %	1.62 %	1.89 %	2.14 %	3.08 %
Italy	0.71 %	0.81 %	0.87 %	0.97 %	1.07 %	1.20 %	1.32 %	1.46 %	1.65 %	1.88 %	2.26 %	2.62 %	4.09 %
Japan	0.91 %	1.02 %	1.10 %	1.21 %	1.31 %	1.41 %	1.51 %	1.64 %	1.78 %	1.96 %	2.24 %	2.56 %	3.92 %
Netherlands	0.65 %	0.72 %	0.78 %	0.89 %	1.00 %	1.10 %	1.21 %	1.33 %	1.49 %	1.73 %	2.25 %	2.82 %	4.26 %
Spain	0.80 %	0.87 %	0.93 %	1.02 %	1.11 %	1.21 %	1.32 %	1.43 %	1.59 %	1.78 %	2.10 %	2.46 %	3.47 %
Sweden	0.99 %	1.07 %	1.13 %	1.25 %	1.36 %	1.50 %	1.63 %	1.78 %	1.95 %	2.19 %	2.50 %	2.84 %	3.75 %
Switzerland	0.59 %	0.66 %	0.72 %	0.80 %	0.88 %	0.97 %	1.06 %	1.18 %	1.31 %	1.49 %	1.82 %	2.25 %	3.36 %
UK	0.61 %	0.71 %	0.78 %	0.90 %	1.00 %	1.12 %	1.24 %	1.38 %	1.55 %	1.78 %	2.16 %	2.59 %	3.97 %
US	0.75 %	0.84 %	0.89 %	0.98 %	1.07 %	1.19 %	1.29 %	1.40 %	1.52 %	1.68 %	1.96 %	2.38 %	4.34 %

Appendix 7: 5% CAViaR Estimates (Annual Averages)

This appendix reports the annual and total period averages of the daily 5% conditional autoregressive value at risk (CAViaR) estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest CAViaR gets the ranking number 1, the country with the second lowest CAViaR gets the ranking number 2, and so on). The numbers in the brackets represent the country rankings. For further information, refer to Section 4.3.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	Total
Australia	0.85 %	0.73 %	0.75 %	0.67 %	0.64 %	0.54 %	0.59 %	0.70 %	0.72 %	1.31 %	0.88 %	0.72 %	0.76 %
	(1)	(2)	(2)	(1)	(2)	(2)	(7)	(8)	(2)	(2)	(2)	(3)	(1)
Belgium	0.98 %	0.75 %	0.71 %	1.10 %	0.82 %	0.51 %	0.51 %	0.60 %	0.76 %	1.56 %	0.99 %	0.86 %	0.85 %
	(9)	(3)	(1)	(5)	(5)	(1)	(2)	(1)	(7)	(10)	(3)	(8)	(4)
Canada	0.87 %	1.15 %	0.88 %	0.72 %	0.47 %	0.60 %	0.58 %	0.67 %	0.67 %	1.51 %	1.25 %	0.61 %	0.83 %
	(2)	(12)	(3)	(2)	(1)	(5)	(6)	(4)	(1)	(8)	(11)	(1)	(3)
France	0.90 %	1.13 %	1.16 %	1.35 %	0.95 %	0.65 %	0.58 %	0.71 %	0.75 %	1.46 %	1.04 %	0.88 %	0.96 %
	(4)	(9)	(9)	(11)	(10)	(9)	(5)	(10)	(5)	(6)	(6)	(10)	(9)
Germany	1.04 %	1.13 %	1.18 %	1.27 %	0.96 %	0.69 %	0.59 %	0.71 %	0.72 %	1.31 %	1.06 %	0.74 %	0.95 %
	(12)	(10)	(10)	(10)	(12)	(10)	(8)	(11)	(3)	(1)	(7)	(4)	(7)
Italy	1.06 %	1.07 %	1.22 %	1.15 %	0.79 %	0.55 %	0.60 %	0.69 %	0.76 %	1.52 %	1.31 %	1.16 %	0.99 %
	(13)	(7)	(12)	(8)	(3)	(3)	(9)	(7)	(8)	(9)	(13)	(12)	(11)
Japan	0.93 %	1.14 %	1.22 %	1.19 %	0.95 %	0.82 %	0.62 %	0.96 %	0.91 %	1.73 %	1.11 %	0.89 %	1.04 %
	(6)	(11)	(11)	(9)	(11)	(13)	(11)	(13)	(12)	(13)	(8)	(11)	(12)
Netherlands	0.97 %	0.85 %	1.10 %	1.39 %	1.06 %	0.65 %	0.56 %	0.71 %	0.76 %	1.59 %	1.16 %	0.85 %	0.97 %
	(7)	(4)	(7)	(12)	(13)	(8)	(4)	(9)	(10)	(11)	(9)	(7)	(10)
Spain	0.97 %	1.06 %	1.12 %	1.15 %	0.79 %	0.65 %	0.61 %	0.68 %	0.76 %	1.40 %	1.02 %	1.28 %	0.96 %
	(8)	(6)	(8)	(7)	(4)	(7)	(10)	(5)	(9)	(5)	(4)	(13)	(8)
Sweden	1.02 %	1.52 %	1.63 %	1.44 %	0.94 %	0.79 %	0.68 %	0.89 %	1.00 %	1.66 %	1.30 %	0.88 %	1.15 %
	(10)	(13)	(13)	(13)	(9)	(12)	(12)	(12)	(13)	(12)	(12)	(9)	(13)
Switzerland	0.87 %	0.69 %	0.99 %	1.09 %	0.86 %	0.64 %	0.50 %	0.62 %	0.76 %	1.31 %	0.80 %	0.67 %	0.82 %
	(3)	(1)	(4)	(4)	(8)	(6)	(1)	(2)	(6)	(3)	(1)	(2)	(2)
UK	0.92 %	0.92 %	1.00 %	1.14 %	0.82 %	0.56 %	0.52 %	0.67 %	0.79 %	1.48 %	1.03 %	0.78 %	0.88 %
	(5)	(5)	(5)	(6)	(6)	(4)	(3)	(3)	(11)	(7)	(5)	(5)	(5)
US	1.03 %	1.09 %	1.10 %	1.09 %	0.82 %	0.73 %	0.73 %	0.69 %	0.74 %	1.36 %	1.17 %	0.78 %	0.95 %
	(11)	(8)	(6)	(3)	(7)	(11)	(13)	(6)	(4)	(4)	(10)	(6)	(6)

Appendix 8: 5% CAViaR Estimates by Percentiles

This appendix reports the selected percentiles of the daily 5% conditional autoregressive value at risk (CAViaR) estimates of equally weighted intranational stock-bond portfolios based on the selected CAViaR model(s), the Asymmetric Slope CAViaR of Engle and Manganelli (2004), from January 1, 1999 to December 31, 2010 (3130 observations with adjustments). For further information, refer to Section 4.3.

Country	1 %	5 %	10 %	20 %	30 %	40 %	50 %	60 %	70 %	80 %	90 %	95 %	99 %
Australia	0.44 %	0.48 %	0.51 %	0.56 %	0.60 %	0.64 %	0.68 %	0.73 %	0.81 %	0.91 %	1.07 %	1.25 %	1.99 %
Belgium	0.34 %	0.39 %	0.43 %	0.49 %	0.55 %	0.63 %	0.71 %	0.81 %	0.95 %	1.13 %	1.40 %	1.71 %	2.59 %
Canada	0.37 %	0.43 %	0.47 %	0.53 %	0.59 %	0.66 %	0.73 %	0.80 %	0.88 %	1.02 %	1.24 %	1.59 %	3.15 %
France	0.43 %	0.50 %	0.54 %	0.61 %	0.69 %	0.79 %	0.87 %	0.96 %	1.08 %	1.23 %	1.50 %	1.77 %	2.52 %
Germany	0.42 %	0.47 %	0.52 %	0.60 %	0.69 %	0.76 %	0.86 %	0.95 %	1.07 %	1.21 %	1.46 %	1.71 %	2.66 %
Italy	0.38 %	0.47 %	0.52 %	0.61 %	0.69 %	0.79 %	0.87 %	0.98 %	1.12 %	1.28 %	1.55 %	1.84 %	2.91 %
Japan	0.50 %	0.58 %	0.65 %	0.73 %	0.81 %	0.89 %	0.97 %	1.05 %	1.15 %	1.26 %	1.44 %	1.64 %	3.01 %
Netherlands	0.42 %	0.47 %	0.52 %	0.59 %	0.67 %	0.75 %	0.83 %	0.92 %	1.03 %	1.21 %	1.59 %	2.00 %	3.05 %
Spain	0.43 %	0.49 %	0.55 %	0.65 %	0.73 %	0.81 %	0.88 %	0.96 %	1.07 %	1.20 %	1.45 %	1.67 %	2.47 %
Sweden	0.55 %	0.61 %	0.66 %	0.75 %	0.84 %	0.95 %	1.05 %	1.17 %	1.30 %	1.49 %	1.74 %	1.99 %	2.69 %
Switzerland	0.37 %	0.42 %	0.46 %	0.53 %	0.59 %	0.65 %	0.72 %	0.80 %	0.90 %	1.03 %	1.27 %	1.56 %	2.30 %
UK	0.36 %	0.42 %	0.47 %	0.56 %	0.63 %	0.71 %	0.79 %	0.88 %	0.99 %	1.14 %	1.37 %	1.63 %	2.57 %
US	0.54 %	0.58 %	0.62 %	0.68 %	0.74 %	0.82 %	0.89 %	0.95 %	1.02 %	1.11 %	1.28 %	1.54 %	2.70 %

Appendix 9: Standard & Poor's Sovereign Local Currency Ratings and Outlooks

This appendix reports the end-of-year Standard & Poor's sovereign local currency based ratings and outlooks. The rating 'AAA' is the highest rating and indicates extremely strong capacity to meet financial commitments, the rating 'AA' indicates very strong capacity to meet financial commitments, and the rating 'A' indicates strong capacity to meet financial commitments, but somewhat susceptible to adverse economic conditions and changes in circumstances, . Ratings below 'AAA' may be modified by the addition of a plus (+) or minus (-) sign to show relative standing within the major rating categories. The data is retrieved from http://www.standardandpoors.com/ratings/articles/en/eu/?assetID=1245268586992 on January 25, 2011. The text in the brackets represents the outlooks. For further information, refer to the Standard & Poor's (2010) or http://www.standardandpoors.com. *The ratings and outlooks as of November 30, 2010.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010*
Australia	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
Belgium	AA+	AA+	AA+	AA+	AA+	AA+	AA+	AA+	AA+	AA+	AA+	AA+
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
Canada	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
France	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
Germany	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
Italy	AA	AA	AA	AA	AA	AA-	AA-	A+	A+	A+	A+	A+
	(Stable)	(Stable)	(Stable)	(Stable)	(Negative)	(Stable)	(Negative)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
Japan	AAA	AAA	AA	AA-	AA-	AA-	AA-	AA-	AA	AA	AA	AA
	(Stable)	(Stable)	(Negative)	(Negative)	(Negative)	(Stable)	(Stable)	(Positive)	(Stable)	(Stable)	(Stable)	(Negative)
Netherlands	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
Spain	AA+	AA+	AA+	AA+	AA+	AAA	AAA	AAA	AAA	AAA	AA+	AA
	(Stable)	(Stable)	(Stable)	(Stable)	(Positive)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Negative)	(Negative)
Sweden	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
Switzerland	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)
UK	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Negative)	(Stable)
US	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA	AAA
	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)	(Stable)

Appendix 10: 10-year Senior CDS Premiums

This appendix reports the annual averages of the daily 10-year senior credit default swap (CDS) US dollar denominated (except for Sweden and Switzerland euro denominated) premium mid quotes. Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest CDS premium gets the ranking number 1, the country with the second lowest CDS premium gets the ranking number 2, and so on). All the series are retrieved from Datastream and provided by Credit Market Analysis Ltd (CMA). The numbers in the brackets represent the country rankings. For further information, refer to http://www.cmavision.com. *The CDS premiums as of September 30, 2010.

Country	DS code	First quote	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010*
Australia	AUGVTSX(SM)	January 2, 2003	#NA	#NA	#NA	#NA	33.99	14.73	29.96	11.71	15.71	45.57	81.84	53.83
			-	-	-	-	(2)	(4)	(8)	(8)	(9)	(9)	(9)	(6)
Belgium	BGGVTSX(SM)	January 2, 2006	#NA	#NA	#NA	#NA	#NA	#NA	#NA	3.92	6.33	38.02	68.37	96.37
			-	-	-	-	-	-	-	(3)	(3)	(8)	(5)	(9)
Canada	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA
			-	-	-	-	-	-	-	-	-	-	-	-
France	FRGVTSX(SM)	August 16, 2005	#NA	#NA	#NA	#NA	#NA	#NA	3.54	3.14	5.24	23.69	43.44	70.31
			-	-	-	-	-	-	(1)	(1)	(2)	(2)	(2)	(7)
Germany	BDGVTSX(SM)	August 1, 2005	#NA	#NA	#NA	#NA	#NA	#NA	3.80	3.31	4.30	17.81	39.68	44.02
			-	-	-	-	-	-	(2)	(2)	(1)	(1)	(1)	(1)
Italy	ITGVTSX(SM)	January 20, 2004	#NA	#NA	#NA	#NA	#NA	13.98	19.26	23.34	17.81	68.57	111.34	154.18
			-	-	-	-	-	(3)	(5)	(10)	(10)	(11)	(12)	(11)
Japan	JPGVTSX(SM)	January 1, 2004	#NA	#NA	#NA	#NA	#NA	11.74	9.61	6.02	12.01	30.13	68.73	97.65
			-	-	-	-	-	(2)	(3)	(4)	(7)	(5)	(6)	(10)
Netherlands	NLGVTSX(SM)	September 7, 2005	#NA	#NA	#NA	#NA	#NA	#NA	19.76	6.48	10.74	25.78	58.03	47.00
			-	-	-	-	-	-	(6)	(6)	(5)	(4)	(4)	(4)
Spain	ESGVTSX(SM)	April 27, 2005	#NA	#NA	#NA	#NA	#NA	#NA	15.28	6.19	11.10	55.96	96.06	175.92
			-	-	-	-	-	-	(4)	(5)	(6)	(10)	(11)	(12)
Sweden	SDGVTSX(SM)	August 11, 2003	#NA	#NA	#NA	#NA	5.39	4.70	23.66	8.45	47.58	33.31	73.79	44.42
			-	-	-	-	(1)	(1)	(7)	(7)	(11)	(6)	(7)	(2)
Switzerland	SWGVTSX(SM)	January 16, 2009	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	76.00	52.11
			-	-	-	-	-	-	-	-	-	-	(8)	(5)
UK	UKGVTSX(SM)	November 13, 2007	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	8.88	35.85	87.18	80.17
			-	-	-	-	-	-	-	-	(4)	(7)	(10)	(8)
US	USGVTSX(SM)	June 19, 2006	#NA	#NA	#NA	#NA	#NA	#NA	#NA	12.26	14.66	23.84	45.19	46.64
			-	-	-	-	-	-	-	(9)	(8)	(3)	(3)	(3)

Appendix 11: 10-year Sovereign Bond Redemption Yields

This appendix reports the annual averages of the daily 10-year local currency denominated government bond redemption yield bid quotes. Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest yield gets the ranking number 1, the country with the second lowest yield gets the ranking number 2, and so on). All the series are retrieved from Datastream and provided by CMA. The numbers in the brackets represent the country rankings. *The first date included for Belgium is February 14, 2003.

Country	DS code	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Australia	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA	#NA
		-	-	-	-	-	-	-	-	-	-	-	-
Belgium*	TRBE10T	#NA	#NA	#NA	#NA	4.18 %	4.15 %	3.43 %	3.82 %	4.33 %	4.42 %	3.91 %	3.47 %
		-	-	-	-	(8)	(7)	(8)	(8)	(9)	(10)	(10)	(9)
Canada	TRCA10T	5.55 %	5.93 %	5.48 %	5.30 %	4.81 %	4.58 %	4.07 %	4.20 %	4.27 %	3.61 %	3.24 %	3.24 %
		(10)	(10)	(11)	(10)	(12)	(11)	(10)	(10)	(5)	(3)	(3)	(8)
France	TRFR10T	4.62 %	5.40 %	4.95 %	4.88 %	4.14 %	4.10 %	3.41 %	3.80 %	4.30 %	4.23 %	3.64 %	3.12 %
		(4)	(6)	(5)	(6)	(6)	(5)	(7)	(6)	(7)	(7)	(8)	(6)
Germany	TRDE10T	4.51 %	5.26 %	4.82 %	4.79 %	4.10 %	4.06 %	3.38 %	3.78 %	4.23 %	4.00 %	3.27 %	2.78 %
		(3)	(3)	(3)	(4)	(4)	(3)	(4)	(4)	(4)	(6)	(6)	(3)
Italy	TRIT10T	4.76 %	5.60 %	5.19 %	5.03 %	4.25 %	4.24 %	3.55 %	4.05 %	4.48 %	4.66 %	4.28 %	4.04 %
		(7)	(9)	(10)	(9)	(9)	(8)	(9)	(9)	(10)	(12)	(12)	(11)
Japan	TRJP10T	1.74 %	1.75 %	1.34 %	1.27 %	0.99 %	1.50 %	1.39 %	1.74 %	1.67 %	1.49 %	1.35 %	1.18 %
		(1)	(1)	(1)	(1)	(2)	(2)	(2)	(1)	(1)	(1)	(2)	(2)
Netherlands	TRNL10T	4.65 %	5.41 %	4.97 %	4.90 %	4.14 %	4.10 %	3.38 %	3.79 %	4.29 %	4.25 %	3.71 %	3.01 %
		(5)	(7)	(6)	(7)	(7)	(6)	(3)	(5)	(6)	(8)	(9)	(5)
Spain	TRES10T	4.75 %	5.53 %	5.11 %	4.94 %	4.13 %	4.08 %	3.38 %	3.80 %	4.31 %	4.38 %	4.02 %	4.30 %
		(6)	(8)	(9)	(8)	(5)	(4)	(6)	(7)	(8)	(9)	(11)	(12)
Sweden	TRSE10T	4.99 %	5.37 %	5.11 %	5.30 %	4.64 %	4.43 %	3.38 %	3.70 %	4.17 %	3.89 %	3.25 %	2.89 %
		(8)	(5)	(8)	(11)	(11)	(10)	(5)	(3)	(3)	(5)	(5)	(4)
Switzerland	TRCH10T	1.99 %	3.49 %	2.82 %	1.75 %	0.55 %	1.05 %	1.13 %	1.93 %	2.56 %	2.08 %	0.55 %	0.77 %
		(2)	(2)	(2)	(2)	(1)	(1)	(1)	(2)	(2)	(2)	(1)	(1)
UK	TRGB10T	4.99 %	5.27 %	4.91 %	4.87 %	4.48 %	4.87 %	4.41 %	4.50 %	5.02 %	4.49 %	3.60 %	3.53 %
		(9)	(4)	(4)	(5)	(10)	(12)	(12)	(11)	(12)	(11)	(7)	(10)
US	TRUS10T	5.64 %	6.02 %	5.00 %	4.59 %	4.00 %	4.26 %	4.28 %	4.79 %	4.63 %	3.64 %	3.24 %	3.20 %
		(11)	(11)	(7)	(3)	(3)	(9)	(11)	(12)	(11)	(4)	(4)	(7)

Appendix 12: Inflations

This appendix reports the annual averages of the quarterly average local currency denominated seasonally unadjusted inflations. Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest inflation gets the ranking number 1, the country with the second lowest inflation gets the ranking number 2, and so on). All the series are retrieved from Datastream and provided by IFO World Economic Survey (WES). The numbers in the brackets represent the country rankings.

Country	DS code	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Australia	AUIFPR04	2.00 %	4.35 %	2.95 %	3.10 %	2.20 %	2.70 %	4.05 %	4.20 %	5.00 %	6.65 %	2.05 %	4.65 %
		(9)	(11)	(10)	(9)	(7)	(11)	(11)	(12)	(12)	(12)	(12)	(13)
Belgium	BGIFPR04	1.00 %	2.95 %	2.55 %	2.00 %	1.50 %	1.70 %	2.40 %	1.90 %	1.70 %	5.95 %	1.85 %	2.10 %
		(1)	(4)	(6)	(4)	(3)	(6)	(5)	(3)	(3)	(10)	(7)	(7)
Canada	CNIFPR04	1.90 %	3.00 %	2.15 %	2.05 %	3.75 %	1.85 %	2.65 %	3.40 %	3.20 %	2.55 %	1.80 %	2.70 %
		(8)	(6)	(3)	(5)	(11)	(7)	(7)	(10)	(9)	(1)	(5)	(11)
France	FRIFPR04	1.00 %	2.00 %	2.55 %	2.20 %	2.40 %	1.65 %	2.50 %	1.60 %	1.50 %	4.60 %	1.80 %	1.40 %
		(1)	(2)	(6)	(6)	(9)	(5)	(6)	(2)	(1)	(5)	(5)	(1)
Germany	BDIFPR04	1.15 %	3.25 %	2.75 %	1.95 %	1.20 %	1.25 %	1.60 %	1.90 %	2.50 %	5.35 %	1.50 %	1.55 %
		(5)	(8)	(9)	(3)	(1)	(1)	(2)	(3)	(6)	(8)	(1)	(2)
Italy	ITIFPR04	1.85 %	4.35 %	3.60 %	3.75 %	4.15 %	4.30 %	3.45 %	2.65 %	3.15 %	5.75 %	1.95 %	2.30 %
		(7)	(12)	(11)	(11)	(12)	(12)	(10)	(7)	(8)	(9)	(8)	(9)
Japan	JPIFPR04	1.00 %	1.05 %	2.20 %	3.00 %	2.60 %	2.60 %	2.70 %	2.95 %	2.40 %	3.45 %	2.25 %	2.57 %
		(1)	(1)	(4)	(8)	(10)	(10)	(8)	(8)	(5)	(2)	(13)	(10)
Netherlands	NLIFPR04	2.85 %	3.45 %	6.65 %	5.30 %	1.85 %	1.40 %	1.75 %	2.10 %	1.70 %	4.40 %	1.95 %	1.75 %
		(12)	(10)	(13)	(12)	(4)	(3)	(3)	(6)	(3)	(4)	(8)	(5)
Spain	ESIFPR04	6.55 %	6.80 %	6.40 %	5.80 %	6.40 %	4.90 %	6.75 %	7.10 %	5.10 %	7.45 %	1.95 %	2.05 %
		(13)	(13)	(12)	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(8)	(6)
Sweden	SDIFPR04	1.30 %	2.30 %	2.55 %	3.25 %	2.25 %	1.60 %	2.25 %	2.05 %	2.55 %	5.25 %	2.00 %	1.60 %
		(6)	(3)	(5)	(10)	(8)	(4)	(4)	(5)	(7)	(7)	(11)	(3)
Switzerland	SWIFPR04	1.00 %	3.25 %	1.65 %	1.35 %	1.40 %	1.40 %	1.45 %	1.40 %	1.65 %	3.75 %	1.60 %	1.70 %
		(1)	(7)	(2)	(1)	(2)	(2)	(1)	(1)	(2)	(3)	(2)	(4)
UK	UKIFPR04	2.75 %	2.95 %	1.60 %	1.55 %	1.90 %	2.30 %	2.75 %	3.00 %	4.10 %	6.00 %	1.80 %	3.15 %
		(11)	(4)	(1)	(2)	(5)	(9)	(9)	(9)	(11)	(11)	(4)	(12)
US	USIFPR04	2.20 %	3.35 %	2.65 %	2.30 %	2.05 %	2.15 %	4.35 %	4.05 %	3.50 %	4.70 %	1.75 %	2.25 %
		(10)	(9)	(8)	(7)	(6)	(8)	(12)	(11)	(10)	(6)	(3)	(8)

Appendix 13: Gross Financial Liabilities

This appendix reports the annual averages of the local currency denominated general government gross financial liabilities per cent of nominal GDP. Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest gross financial liabilities relative to its nominal GDP gets the ranking number 1, the country with the second lowest gross financial liabilities relative to its nominal GDP gets the ranking number 2, and so on). All the series are retrieved from the OECD Economic Outlook 88 database. Note that the gross debt data is not always comparable across countries due to different definitions or treatment of debt components. Notably, they include the funded portion of government employee pension liabilities for some OECD countries, including Australia and the United States. The debt position of these countries is thus overstated relative to countries that have large unfunded liabilities for such pensions which according to ESA95/SNA93 are not counted in the debt figures, but rather as a memorandum item to the debt. The numbers in the brackets represent the country rankings. For further information, refer to OECD Economic Outlook Sources and Methods at http://www.oecd.org/eco/sources-and-methods.

Country	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Australia	27.60 %	24.65 %	21.75 %	19.77 %	18.29 %	16.55 %	16.08 %	15.32 %	14.25 %	13.64 %	19.25 %	23.58 %
	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Belgium	119.66 %	113.69 %	112.03 %	108.41 %	103.42 %	98.45 %	95.86 %	91.63 %	88.02 %	93.36 %	100.38 %	102.53 %
	(11)	(11)	(11)	(11)	(11)	(11)	(11)	(11)	(11)	(11)	(11)	(11)
Canada	91.37 %	82.13 %	82.66 %	80.55 %	76.56 %	72.60 %	71.61 %	70.26 %	66.52 %	71.28 %	83.39 %	84.43 %
	(10)	(10)	(10)	(10)	(10)	(9)	(9)	(9)	(9)	(9)	(8)	(8)
France	66.80 %	65.65 %	64.26 %	67.29 %	71.43 %	73.93 %	75.69 %	70.87 %	69.97 %	75.86 %	87.14 %	92.36 %
	(6)	(8)	(9)	(9)	(9)	(10)	(10)	(10)	(10)	(10)	(10)	(9)
Germany	61.49 %	60.41 %	59.78 %	62.18 %	65.38 %	68.79 %	71.22 %	69.32 %	65.31 %	69.43 %	76.52 %	79.94 %
	(5)	(5)	(6)	(8)	(8)	(8)	(8)	(8)	(8)	(7)	(7)	(6)
Italy	126.41 %	121.62 %	120.80 %	119.36 %	116.84 %	117.30 %	119.86 %	117.23 %	112.66 %	115.13 %	127.70 %	131.26 %
	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)	(12)
Japan	127.07 %	135.40 %	143.69 %	152.28 %	157.98 %	165.52 %	175.27 %	172.15 %	167.06 %	173.86 %	192.76 %	198.39 %
	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)	(13)
Netherlands	71.57 %	63.89 %	59.43 %	60.27 %	61.87 %	62.20 %	61.12 %	54.90 %	51.96 %	66.02 %	69.36 %	74.60 %
	(8)	(6)	(5)	(6)	(7)	(7)	(6)	(6)	(6)	(6)	(5)	(5)
Spain	69.39 %	66.47 %	61.86 %	60.33 %	55.35 %	53.36 %	50.69 %	46.20 %	42.26 %	47.43 %	62.39 %	72.18 %
	(7)	(9)	(7)	(7)	(3)	(3)	(3)	(3)	(2)	(4)	(4)	(4)
Sweden	73.20 %	64.29 %	62.67 %	60.23 %	59.34 %	59.23 %	59.92 %	52.84 %	47.38 %	46.67 %	51.86 %	51.25 %
	(9)	(7)	(8)	(5)	(5)	(5)	(5)	(5)	(5)	(3)	(3)	(3)
Switzerland	51.89 %	52.43 %	51.23 %	57.15 %	56.95 %	57.88 %	56.43 %	50.25 %	46.46 %	44.30 %	42.16 %	42.08 %
	(3)	(3)	(3)	(4)	(4)	(4)	(4)	(4)	(3)	(2)	(2)	(2)
UK	47.40 %	45.14 %	40.39 %	40.83 %	41.49 %	43.77 %	46.39 %	46.05 %	47.20 %	56.96 %	72.43 %	81.33 %
	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(2)	(4)	(5)	(6)	(7)
US	60.50 %	54.52 %	54.45 %	56.82 %	60.16 %	61.18 %	61.43 %	60.91 %	61.95 %	71.05 %	84.40 %	92.78 %
	(4)	(4)	(4)	(3)	(6)	(6)	(7)	(7)	(7)	(8)	(9)	(10)

Appendix 14: Public Deficits

This appendix reports the annual averages of the quarterly average local currency denominated seasonally unadjusted public deficits per cent of nominal GDP. Furthermore, the countries are ranked in an ascending order relative to the other countries (the country with the lowest public deficit relative to its nominal GDP gets the ranking number 1, the country with the second lowest public deficit gets the ranking number 2, and so on). All the series are retrieved from Datastream and provided by IFO World Economic Survey (WES). The numbers in the brackets represent the country rankings.

Country	DS code	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Australia	AUIFPR08	3.20 %	2.75 %	2.65 %	2.55 %	2.35 %	2.70 %	1.90 %	2.45 %	2.10 %	2.05 %	4.70 %	1.95 %
		(6)	(6)	(7)	(3)	(2)	(1)	(3)	(5)	(3)	(4)	(5)	(2)
Belgium	BGIFPR08	7.15 %	4.25 %	3.25 %	3.80 %	3.75 %	4.15 %	4.25 %	3.20 %	3.65 %	3.90 %	6.85 %	7.05 %
		(13)	(10)	(9)	(9)	(6)	(6)	(6)	(6)	(7)	(8)	(11)	(10)
Canada	CNIFPR08	1.95 %	1.85 %	2.25 %	3.10 %	3.15 %	3.40 %	1.80 %	1.90 %	2.10 %	1.80 %	3.95 %	5.15 %
		(3)	(3)	(4)	(7)	(5)	(4)	(2)	(3)	(3)	(3)	(3)	(4)
France	FRIFPR08	5.60 %	4.40 %	4.35 %	5.80 %	6.70 %	7.20 %	6.50 %	5.75 %	6.95 %	6.75 %	7.25 %	7.60 %
		(11)	(11)	(11)	(11)	(13)	(13)	(10)	(10)	(12)	(13)	(12)	(12)
Germany	BDIFPR08	4.40 %	3.25 %	3.65 %	5.80 %	6.45 %	6.35 %	6.20 %	5.65 %	3.95 %	3.65 %	5.75 %	6.20 %
		(8)	(7)	(10)	(12)	(12)	(10)	(9)	(9)	(8)	(7)	(7)	(6)
Italy	ITIFPR08	5.95 %	6.00 %	6.50 %	5.75 %	5.40 %	6.05 %	6.80 %	7.55 %	7.10 %	6.40 %	6.20 %	6.45 %
		(12)	(12)	(12)	(10)	(10)	(9)	(11)	(13)	(13)	(12)	(8)	(7)
Japan	JPIFPR08	5.45 %	6.50 %	6.50 %	6.40 %	6.20 %	6.95 %	7.30 %	7.50 %	6.60 %	5.40 %	5.45 %	6.60 %
		(10)	(13)	(12)	(13)	(11)	(12)	(13)	(12)	(11)	(10)	(6)	(9)
Netherlands	NLIFPR08	2.85 %	2.05 %	1.90 %	1.50 %	2.70 %	3.70 %	1.40 %	1.75 %	2.20 %	1.55 %	4.25 %	5.80 %
		(5)	(4)	(2)	(1)	(4)	(5)	(1)	(1)	(5)	(2)	(4)	(5)
Spain	ESIFPR08	3.65 %	3.55 %	3.10 %	2.60 %	1.95 %	2.95 %	2.85 %	2.40 %	1.95 %	3.30 %	6.20 %	7.40 %
		(7)	(9)	(8)	(4)	(1)	(2)	(5)	(4)	(2)	(6)	(9)	(11)
Sweden	SDIFPR08	1.95 %	1.60 %	2.25 %	2.50 %	2.65 %	3.05 %	2.30 %	1.85 %	1.20 %	1.35 %	2.40 %	1.30 %
		(3)	(2)	(4)	(2)	(3)	(3)	(4)	(2)	(1)	(1)	(1)	(1)
Switzerland	SWIFPR08	5.00 %	3.30 %	2.15 %	3.60 %	4.50 %	4.50 %	5.00 %	4.15 %	3.40 %	2.15 %	3.35 %	2.90 %
		(9)	(8)	(3)	(8)	(8)	(8)	(8)	(8)	(6)	(5)	(2)	(3)
UK	UKIFPR08	1.30 %	1.35 %	1.55 %	2.80 %	4.40 %	4.40 %	4.65 %	3.95 %	4.15 %	4.85 %	7.50 %	8.40 %
		(1)	(1)	(1)	(5)	(7)	(7)	(7)	(7)	(9)	(9)	(13)	(13)
US	USIFPR08	1.55 %	2.05 %	2.25 %	3.00 %	5.35 %	6.75 %	6.85 %	6.80 %	5.40 %	5.65 %	6.65 %	6.50 %
		(2)	(4)	(4)	(6)	(9)	(11)	(12)	(11)	(10)	(11)	(10)	(8)

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