

A direct approach to cross market spillovers

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Abstract

This paper introduces a framework that directly quantifies information spillovers between financial markets. Information spillovers occur when market specific information, defined as information that directly affects the return or volatility in one market only, indirectly affects returns or volatility in other markets through some channel(s) of transmission. By using market specific order flow as a measure of market specific information, we estimate the spillover effects from the stock market to the bond market and vice versa. We examine spillovers under different market conditions by employing a regime-switching framework. We find evidence of spillovers in returns and volatility across the two markets especially when the volatility in the stock market is high. Our findings are consistent with flight-to-quality and rebalancing as channels of transmission.

Keywords: Cross Market spillovers, Regime-switching, Market Microstructure.

JEL classifications: G12, G14.

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1 Introduction

Market specific information is defined as information that directly affects returns in one market only. Sometimes, however, market specific information indirectly affect returns and volatility in other markets. Falling prices in the U.S. housing market in 2006 are an example of this. This information was relevant for returns in the market for mortgage backed bonds, but turned out to affect financial markets worldwide. This indirect effect of market specific information is often referred to as cross market spillover or contagion. There is no consensus on the exact definition of spillovers and contagion in the literature. We follow Fleming, Kirby and Ostdiek (1998) and define spillovers as changes in returns or volatility in one market due to a transmission of market specific information from another market. In accordance with Allen and Gale (2000) we define contagion as strong spillover effects related to crisis periods. Market specific information spills over to other markets through different transmission mechanisms, often referred to as channels of transmission. Three possible channels of transmission will be considered in this paper; rebalancing, cross market hedging and flight-to-quality. We examine the extent of spillovers under different market conditions and relate our results to these three channels.

A better understanding of how and when spillovers occur is important as spillovers can contribute to significant comovements between assets and thus result in unexpected increases in portfolio risk. This can result in financial losses and stricter financing conditions for investors which in turn can lead to less investment, lower growth, and higher unemployment in the economy. However, empirically it is difficult to measure the effects of cross market spillovers. Many studies, for example Forbes and Rigobon (2002), define and measure spillovers indirectly as a significant increase in the level of correlation between markets. One problem related to the use of correlations is that both common information and spillovers of market specific information will influence the level of correlation. Since information flows are unobservable, the relative contribution of common information and the spillover of market specific information to changes in correlations is indiscernible. Bekaert, Harvey and Ng (2005) seek to eliminate the effect of common information by using a factor model reflecting economic fundamentals and measure spillovers as correlations in the model residuals. However, as there is no agreement in the literature

on which factors represent common information, there is a possibility that this indirect approach also can include some effects of common information.

This paper has two main contributions. First, it proposes an approach to measure spillover effects that overcomes the problems related to the use of correlations. We use market specific order flow as a measure of market specific information to capture spillovers in returns and volatility directly. We are thus able to isolate the effects of spillovers from the effects of common information. According to market microstructure theory order flow contains private information that can include heterogeneous interpretations of macroeconomic fundamentals as well as non-fundamental information held by market participants. To make sure we remove any private information that is common across markets we orthogonalize the order flow in each market and label this market specific order flow. This implies that heterogeneous interpretations of market specific public information is included in our measure. Second, our paper contributes by applying a dynamic framework to examine whether spillovers are stronger in periods of high volatility. Spillover effects are often associated with periods of uncertainty and financial crises. By using a regime-switching model we are able to compare the extent of spillovers in periods of high volatility with periods of normal volatility. We apply the proposed framework to the Norwegian stock and government bond markets and employ a data set covering all trades in Norwegian stocks and government bonds during the period September 1999 to March 2005. The bond market is divided into three different maturity segments for short, medium and long term bonds.

We define spillover effects in returns as positive when market specific order flow that leads to higher (lower) returns in the originating market also leads to higher (lower) returns in the other market. Spillover effects are negative when market specific order flow has opposite effects in the originating market and the affected market. Our results show that there are significant spillover effects across the stock and bond markets. We find negative spillover effects from the bond market to stock returns when stock market volatility is high. We also find that there are negative spillover effects from the stock market to bond returns when bond market volatility is normal and that periods of normal volatility in the bond market correspond to periods of high volatility in the stock market. Our results thus indicate that spillover effects are related to periods characterized by high risk in the

stock market. Our findings further indicate that while there are some spillover effects to volatility, these are of less significance than spillovers to returns in both markets.

Our results are consistent with flight-to-quality and portfolio rebalancing as channels of transmission. Flight-to-quality occurs when stock market uncertainty is high and refers to episodes when investors sell assets perceived as risky and buy the safest and most liquid assets, such as government bonds, instead. Episodes of flight-to-quality are often related to financial crises and imply negative spillover effects in returns across the stock and bond markets. Portfolio rebalancing refers to a change in the composition of a portfolio, for example to alter portfolio risk, and involves a purchase of one asset and a sale of another asset. If an investor becomes more risk averse and wants to reduce portfolio risk, she can sell stocks and buy bonds to increase the portfolio share in bonds. If she wants to increase the expected return of her portfolio she will do the opposite transaction. Thus, portfolio rebalancing also implies negative spillover effects in returns. The third channel of transmission we consider is cross market hedging, which refers to the purchase or sale of an asset in order to “insure” a position in another asset. Our results are not consistent with this channel. Stock and bond returns are negatively correlated in our sample period, and using bonds to hedge a stock position then implies positive spillover effects in returns.

Our results imply that the correlation between stock and bond returns becomes more negative when switching from the normal volatility regime to the high volatility regime in the stock market. By employing the dynamic conditional correlation (DCC) framework of Engle (2002) we document that the time varying correlation between returns on stocks and long bonds and stocks and medium term bonds become more negative when the volatility in the stock market switches from the normal to the high volatility regime. This is in line with the results of previous studies using changes in the level of correlation as a measure of spillover effects.

The paper is organized as follows: Section 2 discusses related literature, section 3 presents the framework for measuring cross-market spillovers, section 4 describes the data set and section 5 presents and discusses the results. Section 6 concludes.

2 Related literature

Our study is related to two fields of research. First, it is related to the literature on financial market linkages, including the literature on financial contagion. Second, it is related to the market microstructure literature focusing on the role of order flow as an information aggregator. From the first field our paper is related to several studies. Connolly, Stivers and Sun (2005) investigate the sources of the time varying correlation between stocks and bonds by examining whether the stock-bond return relation varies with two measures of stock market uncertainty suggested by the literature, namely the VIX index and abnormal stock turnover. They conclude that stock market uncertainty may generate important cross-market pricing influences, suggesting that stock market specific information could spill over to bond returns. Our study differs from theirs by directly quantifying the spillover effects. We also include spillovers from the bond market to the stock market and measure the spillover effects in both returns and volatility.

Forbes and Rigobon (2002) ask whether contagion can explain highly correlated stock market movements. They find no evidence of contagion during different periods of crises. Bekaert, Harvey and Ng (2005) examine changes in correlations in stock market returns between countries and investigate whether there has been episodes of contagion. They use a factor model reflecting economic fundamentals and measure contagion as the correlations in the model residuals. Our framework differs from these studies in a fundamental way because we do not examine the indirect measure of correlations, but quantify the informational spillover effects directly by using market specific order flow as a proxy for market specific information. Our approach captures the effects of market specific information in one market on returns and volatility in the other market by adding market specific order flow as an explanatory variable in regime-switching models.

As market specific information indirectly spills over to other markets, the literature is concerned with how this actually happens. A number of studies have investigated possible transmission mechanisms linking markets together. These mechanisms are often referred to as channels of transmission or channels of contagion. Pritsker (2001) and Longstaff (2010) provide a description of the main channels. Kodres and Pritsker (2002) focus on the channel of cross market rebalancing. Rebalancing refers to a change in the composition

of a portfolio and involves a purchase of one asset and a sale of another asset. Rebalancing occurs when new information affecting returns in one market makes an investor want to change portfolio holdings in that market. This change can lead to a change in portfolio holdings in other markets also even though there was no new information about these markets. Underwood (2009) finds evidence of cross market hedging as a channel of transmission. Hedging is undertaken to “insure” a position in an asset and involves the purchase or sale of a position in another asset which has a positive return when the insured position has a negative return and vice versa. If the correlation between the two assets is positive, and the investor has a long position in the asset to be hedged, the hedge will be established as a short position. If the correlation between the two assets is negative, and the investor has a long position in the asset to be hedged, the hedge will be established as a long position. Connolly, Stivers and Sun (2005) explore whether flight-to-quality can be a channel of transmission. Flight-to-quality occurs when market uncertainty is very high and refers to episodes when investors sell assets perceived as risky and buy the safest and most liquid assets instead. Examples of safe and liquid assets are short term government bonds. Episodes of flight-to-quality are often related to financial crises initiated by negative information in a high risk market. Our paper is related to these studies as we investigate whether our results are consistent with rebalancing, hedging or flight-to-quality as channels of transmission.

From the second field, the market microstructure literature, our paper is related to studies on the information content of order flow. A large number of studies document that order flow contains information about contemporaneous asset prices. Hasbrouck (1991) provides evidence that stock market order flow influences stock returns, Evans and Lyons (2002) document that currency market order flow has a strong effect on exchange rates and Brandt and Kavajecz (2004) show that Treasury market order flow explain bond yields. More recent studies show that order flow also contains information about future asset prices and future economic fundamentals. Evans and Lyons (2005) and Valseth (2011) show that order flow has out-of-sample predictive power for exchange rates and government bond yield changes, respectively. Evans and Lyons (2009) find that order flow in the foreign exchange market predicts future macro variables such as GDP growth and inflation. Beber, Brandt and Kavajecz (2010) provide evidence that stock market order flow predicts

economic fundamentals measured by the Chicago Fed National Activity Index. In all, these studies support a fundamental view in the market microstructure literature, namely that order flow contains private information about asset prices. This is important because while information flows are unobservable, order flows are observable. By using market specific order flow as a direct measure of market specific information we overcome the problem connected to the use of the indirect measure, correlation, which is that common information and spillover effects are indistinguishable as drivers of correlation.

Underwood (2009) employs stock and bond market order flow to explain cross market returns. He finds that the correlation between stock market order flow and bond market order flow is negative in periods of negative return correlation and positive in periods of positive return correlation. He concludes that cross market hedging is an important source of linkages between the two markets. Underwood (2009) does not differentiate between information spillover and common information. Our study differs from Underwood (2009) in that we focus on spillovers only and investigate the effects on both returns and volatility.

3 Framework for measuring cross market spillovers

3.1 Market specific order flow

We use market specific order flow as a proxy for market specific information. It is important that our proxy reflects market specific information only as this information should be independent from information that has a direct impact on the other market also. Our proxy for stock market specific information is therefore stock market specific order flow which is defined as the part of the stock market order flow that is orthogonal to the short, medium and long term order flow in the bond market. Common information that affects returns in both the stock market and the bond market is thus by construction removed from our proxy. Bond market specific information is defined by three variables; short term bond market specific order flow, medium term bond market specific order flow and long term bond market specific order flow. This is useful because returns on bonds with a long time to maturity could be determined by different factors than returns on bonds with shorter time to maturity. Investors could also specialize in different maturity bonds and spillover effects could therefore vary according to bond duration.

In order to identify the market specific part of stock market order flow, we orthogonalize stock market order flow by running the following regression

$$OF_t^S = \alpha_1 + \beta_1 OF_t^{BS} + \beta_2 OF_t^{BM} + \beta_3 OF_t^{BL} + e_t \quad (1)$$

where OF_t^S is the order flow in the stock market, α_1 is a constant, OF_t^{BS} is short term bond market order flow, OF_t^{BM} is medium term bond market order flow, OF_t^{BL} is long term bond market order flow and e_t is the residual. e_t is the part of the stock market order flow that is not related to bond market order flow and thus a measure of the stock market specific information. We label this part of the order flow $OF_t^{S,MS}$. In order to identify the market specific part of the three segments of bond market order flow, we orthogonalize short, medium and long term bond market order flow by running the following regressions

$$OF_t^{BS} = \alpha_2 + \beta_4 OF_t^S + \varepsilon_t \quad (2)$$

$$OF_t^{BM} = \alpha_3 + \beta_5 OF_t^S + \partial_t \quad (3)$$

$$OF_t^{BL} = \alpha_4 + \beta_6 OF_t^S + \pi_t \quad (4)$$

where ε_t , ∂_t and π_t are the bond market specific parts of the bond market order flows and thus a measure of short, medium and long term bond market specific information. We label the market specific order flow of the three segments $OF_t^{BS,MS}$, $OF_t^{BM,MS}$ and $OF_t^{BL,MS}$ respectively.

3.2 Informational spillover models

We use regime-switching models based on Gray (1996) to measure the degree of informational spillovers across different volatility regimes. Since we are investigating possible cross market spillovers in both returns and return volatilities at the same time, we consider two models that allow for changes in volatility. First, we estimate a constant variance regime-switching model which allows for different levels of volatility in each regime. Second, we estimate a regime-switching GARCH model which allows the levels of volatility in each regime to vary according to GARCH(1,1) processes. In the GARCH(1,1) model we include the market specific order flows as regressors in both the conditional mean and variance

equations.

We start by describing a conventional GARCH(1,1) model modified to include spillovers. The equations for a model including spillovers from the bond market to the stock market are

$$r_{s,t} = a_0 + a_1 OF_t^S + a_2 OF_t^{BL,MS} + a_3 OF_t^{BM,MS} + a_4 OF_t^{BS,MS} + u_{s,t}, \quad (5)$$

and

$$h_{s,t} = b_0 + b_1 u_{s,t-1}^2 + b_2 h_{s,t-1} + b_3 OF_t^{BL,MS} + b_4 OF_t^{BM,MS} + b_5 OF_t^{BS,MS} \quad (6)$$

where (5) is the mean equation, $r_{s,t}$ is daily stock market return, and $OF_t^{BL,MS}$, $OF_t^{BM,MS}$ and $OF_t^{BS,MS}$ are daily bond market specific order flows as defined in the previous section. Equation (6) is the conditional stock market variance modified to include the market specific order flows as regressors.

Accordingly, the equations in the GARCH(1,1) model for spillovers from the stock market to the different bond market segments, j , are

$$r_{bj,t} = a_o + a_1 r_{bj,t-1} + a_2 OF_t^{Bj} + a_3 OF_t^{S,MS} + u_{bj,t}, \quad (7)$$

and

$$h_{bj,t} = b_0 + b_1 u_{bj,t-1}^2 + b_2 h_{bj,t-1} + b_3 OF_t^{S,MS}. \quad (8)$$

where (7) is the mean equation with $r_{bj,t}$ as the daily market returns for the different bond segments, $j = s, m$ and l , and $OF_t^{S,MS}$ represents the stock market specific order flow as defined in the previous section. Equation (8) is the conditional bond market variance modified to include $OF_t^{S,MS}$ as a regressor.

These models are single regime models in the sense that they assume a single structure for the conditional mean and variance. The structural form of the conditional mean and variance equations, including the spillover coefficients, are assumed fixed and linear throughout the entire sample period. Hence, this model has the implicit assumption that any spillover effects are constant throughout the entire sample period. However, return

correlations exhibit a great deal of time variation as we will show in the results section. This time variation could be influenced by varying degrees of informational spillovers between the two markets. We therefore check whether the degree of informational spillover is different across volatility regimes, and in particular whether informational spillovers are more pronounced when return volatility is high. Since spillover effects imply changes in returns and volatility, we expect spillovers to occur in a market when the volatility in this market is high. Also, flight-to-quality is related to periods of high risk in the stock markets and we expect spillovers through this channel to occur when stock market volatility is high.

Prior research such as Clark (1973), Ross (1989) and Andersen (1996) argue that the level of information flows into a market is directly related to its level of return volatility. Also, following the works of Cai (1994) and Hamilton and Susmel (1994) several studies have supported the view that asset prices could be characterized by two regimes: a normal volatility regime and a high volatility regime. Shalen (1993) and Harris and Raviv (1993) provide theoretical arguments suggesting that high volatility periods are characterized by a dispersion of beliefs about asset values among investors. This dispersion may be due to asymmetric information or to heterogeneous interpretations of symmetric information. In addition to provide an explanation for increased volatility, the level of disagreement among investors could impact the role of order flow as an information aggregator. Order flow would be more informative when dispersion is large as it contains private information reflecting heterogeneous interpretations of public news. If this is the case one should see a larger impact of order flow on returns in periods of high volatility.¹ A larger impact on returns in the initiating market will provide a larger incentive for investors to change portfolio weights by rebalancing their portfolios. More rebalancing by investors would result in larger spillover effects .

Thus, if order flow carries more information in times of high volatility we would expect that the extent of informational spillovers is larger in high volatility regimes than in normal volatility regimes. We therefore want to relax the imposed linearity of the spillover effects of the single regime specifications above and let the coefficients of the above models be different in different volatility regimes if such exist. The regimes are never observed,

¹Pasquariello and Vega (2007) observe this in the U.S. Treasury bond market.

but probabilistic statements will be made about their relative likelihood of occurring, conditional on an information set. This is done according to an endogenous classification rule based on a Markov switching model. We follow the methodology developed by Gray (1996) which builds on Cai (1994), Hamilton (1994), and Hamilton and Susmel (1994).

First, we investigate if regime-switching alone could account for the observed conditional heteroscedasticity in the bond and stock markets. This is done by estimating a constant variance first-order Markov regime-switching model with two regimes. In this model, assuming conditional normality for each regime, the stock returns, $r_{si,t}$, and bond returns, $r_{bji,t}$, are distributed as

$$N(a_{0i} + a_{1i}OF_t^S + a_{2i}OF_t^{BL,MS} + a_{3i}OF_t^{BM,MS} + a_{4i}OF_t^{BS,MS}, b_{0i}) \quad (9)$$

and

$$N(a_{0i} + a_{1i}r_{bji,t-1} + a_{2i}OF_t^{Bj} + a_{3i}OF_t^{S,MS}, b_{0i}) \quad (10)$$

respectively in regime i where $i = 1, 2$. Hence, the variance is constant in each regime. We refer to this model as the constant variance regime-switching model. Any conditional heteroscedasticity can only be driven by switches between regimes.

We then relax the assumption of constant variances within each regime, allowing the conditional variances to be GARCH(1,1) processes. We follow Gray (1996) and assume conditional normality for each regime. The variance of the return series at time t is then given by

$$\begin{aligned} h_{k,t} &= E[r_{k,t}^2 | \Phi_{k,t}] - E[r_{k,t} | \Phi_{k,t}]^2 \\ &= p_{k,1t}(\mu_{k,1t}^2 + h_{k,1t}) + (1 - p_{k,1t})(\mu_{k,2t}^2 + h_{k,2t}) \\ &\quad - [p_{k,1t}\mu_{k,1t} + (1 - p_{k,1t})\mu_{k,2t}]^2, \end{aligned} \quad (11)$$

where $\mu_{k,it}$ is the conditional mean for market k , $k=S$ (stocks), BL (long term bonds), BM (medium term bonds), BS (short term bonds), in regime 1 and 2 respectively and $\Phi_{k,t}$ represents the information set available in market k at time t . The state probability $p_{k,1t}$

gives the probability that market k is in regime 1 at time t and is defined as

$$p_{k,1t} = (1 - Q_{k,t}) \left[\frac{g_{k,2t-1}(1 - p_{k,1t-1})}{g_{k,1t-1}p_{k,1t-1} + g_{k,2t-1}(1 - p_{k,1t-1})} \right] + P_{k,t} \left[\frac{g_{k,1t-1}p_{k,1t-1}}{g_{k,1t-1}p_{k,1t-1} + g_{k,2t-1}(1 - p_{k,1t-1})} \right], \quad (12)$$

where

$$\begin{aligned} p_{k,1t} &= \Pr(S_{k,t} = 1 | \Phi_{k,t}), \\ g_{k,1t} &= f(r_{k,t} | S_{k,t} = 1), \\ g_{k,2t} &= f(r_{k,t} | S_{k,t} = 2), \\ P_{k,t} &= \Phi(X_{k,t}/\beta_1), \\ Q_{k,t} &= \Phi(X_{k,t}/\beta_2). \end{aligned}$$

$S_{k,t}$ is the latent regime indicator while $P_{k,t}$ and $Q_{k,t}$ are probabilities of remaining in regime 1 and regime 2, respectively. The transition probabilities are time varying and dependent on the level of the explanatory variables in the conditional mean equations in the stock and bond market segments. β_1 and β_2 are matrices of unknown parameters to be estimated and $\Phi(\cdot)$ is the cumulative normal distribution function that guarantees $0 < P_{k,t}, Q_{k,t} < 1$. The terms in the square brackets in (12) represents $\Pr[S_{k,t-1} = 2 | \Phi_{k,t-1}]$ and $\Pr[S_{k,t-1} = 1 | \Phi_{k,t-1}]$, respectively.

Now $h_{k,t}$, which is path-independent, can be used as the lagged conditional variance in constructing $h_{k,1t+1}$ and $h_{k,2t+1}$ which follow GARCH(1,1) processes. Thus we have

$$\begin{aligned} h_{k,it} &= \omega_{k,i} + a_{k,i}\varepsilon_{k,t-1}^2 + b_{k,i}h_{k,t-1}, \\ h_{k,t-1} &= p_{k,1t-1}[\mu_{k,1t-1}^2 + h_{k,t-1}] + (1 - p_{k,1t-1})[\mu_{k,2t-1}^2 + h_{k,2t-1}] \\ &\quad - [p_{k,1t-1}\mu_{k,1t-1} + (1 - p_{k,1t-1})\mu_{k,2t-1}]^2, \\ \varepsilon_{k,t-1} &= r_{k,t} - E[r_{k,t} | \Phi_{k,t-1}] \\ &= r_{k,t} - [p_{k,1t} - \mu_{k,1t} + (1 - p_{k,1t})\mu_{k,2t}]. \end{aligned} \quad (13)$$

We refer to this model as the regime-switching GARCH model.

The regime-switching models for the stock market quantify any spillover effects from the bond market to stock returns when stock market volatility is high and when it is normal. The models for the bond market segments quantify any spillover effects from the stock market to bond returns when bond market volatility is high and when it is normal. The two regimes in our models thus capture the periods of high and normal volatility in the market where the spillover effects can occur, but not in the market where the spillover effects can be initiated. However, in some cases we would be interested in the volatility conditions in the market initiating the spillover effects also. For example, if stock market specific information leads to large changes in stock market returns, investors would be more prone to change their portfolio weight in stocks than otherwise. This implies that spillover effects from the stock market to bond returns would be more likely when the stock market is in the high volatility regime. Also, if there is flight-to-quality, high uncertainty in the stock market will initiate sales of risky stocks and purchases of safer assets such as government bonds. To identify whether flight-to-quality causes spillover effects we are interested in knowing whether spillover effects from stocks to bonds occur when stock market volatility is high.

Our regime-switching models will identify whether spillover effects from the stock market to bond returns occur in the high volatility or normal volatility regime in the bond market, but not whether they occur during the high volatility or normal volatility regime in the stock market. In order to investigate whether spillover effects from stocks to bonds occur when volatility in the stock market is high we estimate the following regression model:

$$r_{bj,t} = \alpha + \beta_1 r_{bj,t-1} + \beta_2 OF^{bj} + \beta_3 OF_t^{S,MS} * P_{s,t} + \beta_4 OF_t^{S,MS} * Q_{s,t} + \varepsilon_t, \quad (14)$$

where $OF_t^{S,MS} * P_{s,t}$ and $OF_t^{S,MS} * Q_{s,t}$ are interaction terms capturing the probability weighted spillover effects from the stock market to the bond segments. $P_{s,t}$ and $Q_{s,t}$ are the time-varying probabilities that the stock market is in a high volatility regime and a normal volatility regime respectively.

3.3 Testable predictions

We investigate whether spillovers occur across stock and bond markets, and whether they are consistent with portfolio rebalancing, hedging or flight-to-quality as possible channels of transmission. We can test whether spillover effects from the stock market to the bond market occur by estimating the effects of stock market specific order flow on bond returns and bond volatility. Similarly we can test whether spillover effects from the bond market to the stock market occur by estimating the effects of bond market specific order flows on stock returns and stock volatility.

The sign of the spillover effects will indicate which channel of transmission would be most likely. Rebalancing is consistent with negative spillover effects in returns as it involves a purchase of one asset and a sale of another asset. Hedging is consistent with positive spillover effects in returns if the hedging portfolio is established in a negatively correlated market. Hedging is consistent with negative spillover effects in returns if the hedging portfolio is established in a positively correlated market. Flight-to-quality as a channel of transmission is consistent with negative spillover effects from the stock market to bond returns when stock market volatility is high. We test for this by estimating whether spillovers from the stock market to bond returns depend on the regime probabilities in the stock market. The signs of any spillover effects to volatility are not clear for the transmission channels we discuss.

Positive spillover effects in returns contribute to positive correlation and negative spillover effects contribute to negative correlation between the two markets. According to this we expect any spillover effects to be positively related to the absolute level of return correlations. Also, Fleming, Kirby and Ostdiek (1998) argue that information spillovers should be strongest when hedging incentives are high which are in periods with a high absolute level of correlation. In order to check this we estimate the time varying return correlations between the stock market and the different bond market segments and compare the level of correlation to the probability for the stock market to be in the high volatility regime. The time varying return correlations are estimated using the dynamic conditional correlation (DCC) estimator of Engle (2002). The appendix explains how the DCC estimator is set up.

4 Data

We use data from the Norwegian stock and government bond markets for the years 1999 to 2005. The Norwegian stock market ranked as the 24th largest world equity market by market capitalization by the end of 2005. At that time 219 firms were listed on the Oslo Stock Exchange (OSE) with a total market value of about 1 402 billion NOK.² The Norwegian government bond market is organized in the same way as major government bond markets, but the number of bonds is smaller due to the oil driven financial surpluses of the Norwegian economy. In 2005, outstanding domestic government debt amounted to 207 billion NOK, of which six benchmark bonds accounted for 152 billion NOK. In September 1999, an electronic order book was established for trading in government bonds. Bond market trades can be agreed on either in the electronic order book or in the over-the-counter market. The share of electronic trading and the average electronic trade size in bonds increased gradually after the inception of the limit order book. In the interdealer market, electronic trades and over-the-counter trades constituted roughly one half each over the period. The OSE is the only regulated market place for securities trading in Norway and all trades are registered in the OSE trading system. In January 1999 the OSE introduced an electronic trading system for stocks. Since then a fully computerized centralized limit order book system has been in place for equity trading. The system is similar to the public limit order book in Paris, Toronto, Stockholm and Hong Kong. All trades are agreed upon within this system.

Our data set consists of daily return data and all transactions in stocks and government bonds over the period September 1999 to March 2005. The transactions data include date, time, price and amount in NOK. For stock transactions the initiating side of the trade is known. For government bond transactions, the method of Lee and Ready (1991) is used to identify the initiating dealer.³ We construct daily order flow series in stocks and bonds from the signed transactions data. Bond market order flow consists of three maturity groups. Short-term order flow is based on trades in bonds with a remaining time to

²Equivalent to a value of USD 207 billion. The USDNOK exchange rate was 6.77 at the end of 2005.

³According to this method, trades executed at a price above the middle of the bid-ask spread are classified as buyer-initiated trades. Trades executed at a price below the middle of the prevailing bid-ask spread are classified as seller-initiated trades. When trades are executed at the mid price, the tick rule is used. According to this rule the direction of change from the last transaction price determines whether the trade is classified as seller-initiated or buyer-initiated.

maturity from 1 year to 4 years, medium term order flow is based on trades in bonds with a remaining time to maturity greater than 4 years up to 7 years and long-term order flow is based on trades in bonds with a remaining time to maturity greater than 7 years up to 11 years. Daily order flow is the number of buyer-initiated trades minus the number of seller-initiated trades during a day and reflects the net buying pressure in the market. We use a stock market index including all stocks at the OSE and three bond total return indices to compute daily stock and bond returns. The indices are published by the OSE and the bond indices reflect the returns on government bonds with a constant duration of five years, three years and one year. The indices are constructed on the basis of the outstanding benchmark bonds, which are normally four to six bonds.⁴

Summary statistics for the return and order flow data are presented in Table 1, Panels A, B, and C. Panel A shows that the univariate properties of the return data contain the typical properties of financial return series. In other words, both stock and bond returns are leptokurtic with stock returns having a negative skew and bond returns having a positive skew. The annualized mean return for the stock market is 10.2 percent for the period while it ranges from 5.7 percent for the bonds with 1 year duration to 7.6 percent for the bonds with 5 year duration, in line with a typically upward sloping yield curve. According to the first order autocorrelation, bond returns, especially for the short and medium term durations, are persistent with coefficients between 9 and 14 percent. Stock market returns do not show any persistence. In addition there is clear evidence of conditional heteroscedasticity in all return series as the LM test for ARCH-effects systematically rejects the null of no such effects at a horizon up to at least a week.

Panel B shows the properties of the order flow variables. Average order flow in the stock market, OF_t^S , is positive indicating a net buying pressure in the market over the sample period. On average there have been 187 more buy-initiated trades per day than sell-initiated trades. The order flow variables for the bond market, OF_t^{BS} , OF_t^{BM} and OF_t^{BL} , all show a slight negative mean value indicating a small net selling pressure in the bond market in the sample period.

Panel C displays the unconditional correlations between returns and order flow. The

⁴The stock index data are from Datastream and are based on the total market index, TOTX, to the end of 2001, and the all share index, OSEAX, thereafter. Bond yield indices with a fixed duration of 1 year (ST3X), 3 years (ST4X) and 5 years (ST5X) are calculated daily by OSE.

correlation between the different maturity bond market returns and the stock market return is fairly low and negative, but increasing with duration. A low value of the unconditional correlation between bond and stock returns is in line with other studies like Connolly, Stivers and Sun (2005). As for the relationship between order flow and returns, we find that stock market order flow is negatively, but weakly related to bond returns. Short, medium and long term bond market order flows are weakly and negatively correlated to stock returns. The relationship between stock market order flow and stock market returns is strong and positive. The relationship between bond market order flow and bond market returns is also strong and positive, albeit weaker than in the case of the stock market.

Figures 1 to 4 display the cumulative order flow in the stock market and the three segments of the bond market. The cumulative order flow is constructed by adding up daily order flow. Figure 1 illustrates an almost homogenous buying pressure in the stock market through the whole sample period. At the end of the period the amount of buyer initiated trades in excess of seller initiated trades has accumulated to 250 000 trades which is equivalent to almost 90 billion Norwegian kroner. Figure 2 shows that there was a clear selling pressure in the market for long bonds from 2001 to mid 2003. Figure 3 displays a very different pattern for medium term bonds with net selling up to mid 2001 and net buying for most of the period from mid 2001 until early 2004. From mid 2001 to the beginning of 2004 long and medium term bonds were experiencing opposite net order flows. Figure 4, illustrating the short end of the bond market, shows that the amount of seller initiated trades in excess of buyer initiated trades accumulated to 1100 which in value equals 40 billion Norwegian kroner by spring 2005. Overall, these figures show that the active side of the bond market has been selling, except for the above mentioned buying period for medium term bonds, while the active side of the stock market has been buying.

5 Results

We investigate whether there are spillover effects across the stock market and the bond market and if so, whether they vary across volatility regimes. We do this by estimating the models presented in section 3.2. The results of these models are reported and discussed

below.

5.1 Constant variance models

We first estimate the constant variance regime-switching model and compare it with a standard single regime constant variance model. This will provide us with valuable insights into the characteristics of the two regimes and how spillover effects vary with the regimes. In addition, it will provide evidence on whether regime-switches can explain the ARCH effects found in stock and bond returns.

Panel A of Table 2 reports the results for the stock market. The first column gives the parameter estimates of a single regime constant variance model which is a conventional regression model. The spillover coefficients from the bond market, a_{21} , a_{31} and a_{41} , are all negative. The coefficients for the short and long term segments are significant and indicate that there are negative spillover effects from the short and long term bond markets to stock market returns. There is serial correlation in the squared residuals as indicated by the large ARCH test statistic. As expected, given the level of conditional heteroscedasticity in stock returns, this constant variance model does a poor job in modeling the volatility of stock returns.

The second column reports the results from the constant variance regime-switching model which allows for two possible levels of volatility, one for each regime. The volatility measured by the standard deviation in regime 1, b_{01} , is twice the size of the volatility in regime 2, b_{02} . The average daily returns in the stock market are also significantly negative in this regime while they are statistically zero under regime 2. Regime 1 is thus a high volatility negative return regime in the stock market. Regime 2 is a normal volatility regime. Although the spillover coefficient for the long term bond segment is marginally significant at the 10 percent level, the coefficients for the other segments are highly significant and economically much larger. This indicates that positive (negative) news in the bond market tends to reduce (increase) stock market returns. None of the spillover coefficients in the normal volatility regime, a_{22} , a_{32} and a_{42} are significant and the coefficients here are much smaller. In other words, spillover effects from the bond market to the stock market appear to be negative and restricted to periods of high stock market volatility. We also find that the high volatility regime is much less persistent than

the normal volatility regime. While the high volatility regime has an average duration of $1/(1-P) = 7.73$ days, the normal volatility regime has an average duration of $1/(1-Q) = 38.46$ days. This indicates that periods of high stock volatility usually are short. The ARCH test statistic is substantially lower in the regime-switching model indicating that this model is more adequate than the single regime model.

Panels B, C and D of Table 2 report the results for the short, medium, and long term bond market segments, respectively. The first column of Panel B shows that in the single regime model the spillover coefficient measuring the effects of stock market specific order flow on short bond returns, a_{31} , is negative and significant at the 5 percent level. The second column, presenting the results for the constant variance regime-switching model, shows that whereas the spillover coefficient in regime 1, a_{31} , is insignificant, the spillover coefficient in regime 2, a_{32} , is negative and highly significant. The size of the coefficient in regime 2 is considerably larger than the coefficient in the single regime model. Average daily short bond returns are positive in both regimes, but higher in regime 1. The volatility in regime 1 for short bonds, b_{01} , is 2.8 times higher than the volatility in regime 2, b_{02} .

Panel C reports the results for medium term bonds. The first column reveals that the spillover coefficient, a_{31} , is negative and significant at the 1 percent level in the single regime model. The second column shows that in regime 1 the spillover coefficient is insignificant while it is negative and highly significant in regime 2. The result for the spillover coefficient a_{32} implies that a one standard deviation increase (decrease) in stock market specific order flow reduces (increases) medium term bond returns by 1.1 basis points in regime 2. Daily medium bond returns are also positive in both regimes, but on average higher in regime 1. The volatility in regime 1 for medium term bonds is 2.4 times higher than the volatility in regime 2.

Finally, Panel D of Table 2 shows the results for long bonds. Also for long bonds the coefficient measuring the spillover from the stock market, a_{31} , is negative and significant in the single regime model. In the regime-switching model the coefficient is only significant in the normal volatility regime, and the value is higher than in the single regime model. Average daily long bond returns are positive and more than 2 times higher in regime 1 than in regime 2. The volatility in regime 1 for long term bonds is 2.3 times higher than the volatility in regime 2. In all three panels the ARCH test statistic is substantially lower

in the regime-switching model than in the single regime model. This indicates that the regime-switching model is more adequate for all three bond segments.

The results from the regime-switching model for the short, medium and long term bond segments indicate that regime 1 is a high volatility high return regime in the bond market. Regime 2 is a normal volatility regime. The spillover coefficient from the stock market in the high volatility regime, a_{31} , is not significant for any of the bond segments while the coefficient in the normal volatility regime, a_{32} , is highly significant and negative for all three segments. This implies that there are negative spillover effects from the stock market to the bond market only in 'normal times' which is opposite of what we find for the stock market, where there are spillover effects in the high volatility regime only. An explanation for this asymmetry between the stock and bond markets could be that spillovers from the stock market to the bond market are mainly related to the volatility regime in the stock market. If normal volatility regimes in the bond market coincides with periods of heightened volatility in the stock market it could explain the results in Table 2.

Figures 5 to 7 plot the probability that the stock market is in a high volatility regime against the probabilities that the different bond segments are in a high volatility regime. Figure 5 shows the probability that stocks and long term bonds will be in the high volatility regime and we see that the probabilities often are high at different times. This is more pronounced in Figure 6 which includes stocks and medium term bonds. It appears that when medium term bonds are in the high volatility regime the stock market is in a normal volatility regime and vice versa. Figure 7, including stocks and short term bonds, also shows that the high volatility regimes are not identical in the two markets. The figures thus confirm that the different bond segments frequently are in a normal volatility regime when the stock market is in a high volatility regime.

The results in Table 2 are based on a regime-switching model where the regimes reflect the volatility level in the market "receiving" the spillover effect. This model cannot address the question of whether spillover effects from stocks to bonds occur when volatility in the stock market is high. In order to investigate this question we therefore employ the regression model presented in equation (14). The results from this model are presented in Table 3. The first column reports the results for the long term bond segment. The coefficients for lagged returns and long term bond market order flow are positive and

significant. The coefficients for the interaction terms capturing the probability weighted spillover effects from the stock market to long bonds, $OF_t^{S,MS} * P_{s,t}$ and $OF_t^{S,MS} * Q_{s,t}$, are both negative and significant. The economic importance is much higher for the first term which indicates spillovers when the stock market is in the high volatility regime. The second column reports the results for the medium term bond segment. The coefficients for lagged returns and medium term bond market order flow are positive and significant. However, only the interaction term capturing the probability that the stock market is in the high volatility regime is significant. This implies that there is a negative spillover effect from the stock market only when the stock market is in a high volatility regime. The third column reports the results for the short term bond segment. Here, the coefficients for lagged returns and own order flow are also positive and significant, but only the coefficient for the interaction terms capturing the probability that the stock market is in the normal volatility regime is significant. Thus there are only negative spillover effects from the stock market to short bonds when the stock market is in a normal volatility regime. The explanatory power measured by R^2 is significantly higher for the long and medium term bonds models than for the short term bond model. The results in Table 3 document that there are negative spillover effects from stocks to medium and long term bonds when stock market volatility is high.⁵ This finding is consistent with flight-to-quality as a channel of transmission.

Another explanation for spillovers from stock to bonds in normal times only is that the normal volatility regime appears to be relatively much more persistent than the high volatility regime. Periods with high volatility only have an average duration between 1 and 6 days in the bond market. This can be due to the fact that we in this specification have forced the conditional variance into just two levels and thereby making the conditional variance mimic the regime probabilities. The regime-switching GARCH model in the next section overcomes this limitation with a richer parameterization of the conditional variance within each regime.

We construct a likelihood ratio test (LRT) to investigate whether the constant variance regime-switching model or a GARCH(1,1) regime-switching model is the most suitable

⁵The short term bond market, including government securities with an average duration of 1 year, was less liquid than the market for bonds with a duration over 1 year in our sample period.

model for each market. We then compare the significance of the regime switching GARCH model relative to the constant variance regime switching model. We find that the constant variance regime-switching model is most adequate for the three bond market segments, while the GARCH model is clearly best for the stock market.

5.2 GARCH models

We now drop the assumption of constant variances within each regime and allow the conditional variances to be GARCH(1,1) processes. The conditional variance equations will also contain market specific order flow variables as additional regressors. Table 4 reports the results for the stock market. The first column gives the parameter estimates of a conventional single regime GARCH(1,1) model. The spillover coefficients in the mean equation, a_{21} , a_{31} and a_{41} are all negative and the coefficients for the long and short term segments are significant. This is in line with the single regime model in Table 2. None of the spillover coefficients in the variance equation, b_{31} , b_{41} and b_{51} are significant. The second column of Table 4 reports estimates of the regime-switching GARCH(1,1) model. The spillover coefficients in the mean equation are all negative and significant in the high volatility regime. For example, we find that a one standard deviation increase (decrease) in medium term bond market specific order flow reduces (increases) stock returns by 14 basis points. This is in line with the constant variance regime-switching model in Panel A of Table 2. Note the almost identical economic impact in the spillover from all bond segments to the stock market returns. In the normal volatility regime only medium term bond market information spills over to the stock market. The coefficient, a_{32} , is positive and highly significant. Thus, in 'normal times' positive information in the medium term bond market increase stock market returns.

The conditional variance equation shows that there is no spillover to the conditional stock market volatility from any of the bond segments when the volatility is at a high level. None of the spillover coefficients, b_{31} , b_{41} and b_{51} are significant. In the normal volatility regime however, there are negative spillovers to the conditional volatility of the stock market from the long and medium term bond segments. The coefficients, b_{32} and b_{42} , are both significantly negative. This means that when the stock market is in a normal volatility regime, positive news in these bond segments will typically dampen

the conditional volatility in the stock market. Negative news in these bond segments will correspondingly increase the conditional volatility in the stock market.

By allowing for a time varying variance within each regime the conditional variance estimates are no longer forced to mimic the regime probabilities. Hence, the estimates of the transition probabilities P and Q should be more realistic if the GARCH specification is more adequate. The LRT statistic, which is distributed $\chi^2_{(10)}$ under the null, is 60.58. This is significant at any standard level, indicating that GARCH effects within each regime is an important feature of the stock market.⁶ The regimes now appear to be more persistent than was the case with the constant variance regime-switching model. The high volatility regime in the stock market now has an average duration of $1/(1 - P) = 21.60$ days while the normal volatility regime has an average duration of $1/(1 - Q) = 41.50$ days.

5.3 Discussion

Our results based on the regime-switching models document that there are significant negative spillover effects in returns across the stock and bond markets. In the stock market these spillovers occur in the high volatility regime and in the bond market segments they occur in the normal volatility regime. By comparing the time varying probabilities of being in the high volatility regime we find that the normal volatility regime in the bond market frequently coincides with high volatility regimes in the stock market. These findings indicate that spillover effects from the stock market to bond market returns occur when the stock market is in a high volatility regime. This is confirmed by the results from the regression model which separates spillovers from stocks to bonds according to the volatility regime in the stock market. They show that spillover effects from the stock market to medium and long term bond market returns are negative and significantly stronger when the stock market is in a high volatility regime than in a normal volatility regime. This is consistent with flight-to-quality as a channel of transmission. Episodes of flight-to-quality occur when the uncertainty in the stock market is very high. Risk averse

⁶It should be noted that the likelihood ratio test here is only indicative. This is because the parameters associated with the second regime is not identified under the null of a single regime. The LRT statistic can therefore only be assumed to be χ^2 distributed under the null. Hansen (1992) has developed a standardized LRT procedure that overcomes this difficulty. This procedure is however extremely troublesome unless the model is very simple. In our situation this procedure is practically infeasible. In practice, we are therefore judging the large difference in log-likelihood values as statistical evidence in favour of the regime switching GARCH model.

investors will then sell risky assets such as stocks and buy safer assets such as government bonds which imply negative spillovers from stocks to bonds.

Our results are also consistent with portfolio rebalancing as a channel of transmission. Rebalancing is undertaken by investors holding both stocks and bonds who want to change the relative weights of the two assets in their portfolios. Suppose that investors wish to change their portfolio weight in bonds because they expect a change in bond returns after acquiring private information about bonds from observing bond market specific order flow. Investors will then rebalance their portfolio by buying or selling bonds and doing the opposite trade in stocks thus initiating negative spillover effects from bonds to stocks. Correspondingly, there will be negative spillover effects from stocks to bonds if stock market specific order flow make investors want to change their stock holdings. When flight-to-quality or rebalancing are the channels of transmission, the spillover effects will continue until the new desired holdings in each asset are reached. This implies that spillover effects will have immediate, but not sustained effects on returns.

The sign of the spillover effects if hedging is the channel of transmission depends on the sign of the correlation between stock and bond returns when the hedge was established. Hedging a long stock position with bonds requires a long position in the bond market if the correlation is negative and a short position if the correlation is positive. Spillover effects in returns due to hedging should thus be positive when the correlation is negative and negative when the correlation is positive. Since the correlation between stock and bond returns has been negative during our sample period and we find negative spillover effects we conclude that hedging is not consistent with our results. We do not discuss the possibility of hedging a bond position with stocks as we consider this type of hedging an unlikely scenario. Our results further suggest that spillover effects to volatility are of less significance than spillovers to returns in both markets. In the bond market we find significant spillover effects from the stock market to volatility for long term bonds only, and the effect is positive in the high volatility regime. In the stock market we find negative spillover effects from long and medium term bonds to volatility in the normal stock market volatility regime. These results do not appear to be related to the channels of transmission considered in this paper.

Our results are consistent with the traditional measure of cross market spillovers as an

increase in the level of correlation. Negative spillover effects in periods of high volatility and no or positive effects in periods of normal volatility imply a change in return correlations when moving between these periods. This is documented in Figures 8 to 10 which show the probability of the stock market being in the high volatility regime and the correlation between stock returns and returns on long, medium and short term bonds, respectively. We see from the figures that the probability of being in the high volatility regime in the stock market coincides with an increase in the negative correlation between stock and bond returns. Our results thus confirm that the correlation between the stock and bond markets becomes more negative when switching from the normal volatility regime to the high volatility regime in the stock market.

6 Conclusion

We present a new approach to measure the extent of spillovers between financial markets. Contrary to previous studies on cross market spillovers we do not examine changes in correlations, but quantify the informational spillover effects directly. This is important because an increase in the correlation can reflect both common information and spillover of market specific information. We measure spillover effects by using market specific order flow as a proxy for market specific information. By employing this proxy in a regime-switching framework we are able to capture differences in spillovers under different market conditions. The approach is applied to the Norwegian stock and bond markets. We measure spillover effects in returns and volatility in a high volatility regime and a normal volatility regime. There are significant negative spillover effects in returns in periods of high volatility in the stock market. This is consistent with portfolio rebalancing and flight-to-quality as channels of transmission.

These results imply that there will be an increase in the level of negative correlation when moving from the normal volatility regime to the high volatility regime in the stock market. This is also consistent with the traditional measure of cross market spillovers as a significant increase in the absolute level of correlation. Our results thus confirm that spillovers of market specific information could be one source of the time variation in correlation empirically observed between the stock and bond markets.

Our findings have implications for asset pricing models since current models ignore any spillover effects between stocks and bonds. The importance of spillover effects during high volatility periods in the stock market may justify the inclusion of such effects, especially in studying financial crises. Our approach can be applied to all types of financial markets with access to order flow data. The extent of the recent financial crisis suggests that spillover effects have affected a number of asset markets and should encourage future applications of our approach.

Appendix

Dynamic Conditional Correlations

To estimate the time varying correlation between the two markets, we employ the dynamic, conditional correlation (DCC) framework of Engle (2002). The DCC estimator is a multivariate GARCH estimator and a generalization of Bollerslev (1990) constant conditional correlation (CCC) estimator developed mainly to overcome the dimensionality problem embedded in multivariate GARCH models. There is, however, no theoretical justification for assuming constant correlations and empirical evidence finds no indications of this. Rather, most recent studies finds the opposite and attempt to explain the determinants of time varying correlations. The DCC is a two step estimator of conditional variances and correlations.

To see how the estimator is set up, consider a vector of returns for our two markets, $\mathbf{r}_t = [r_{s,t}, r_{b,t}]'$ such that

$$\mathbf{r}_t = \mathbf{c} + \mathbf{u}_t, \quad (15)$$

and

$$\mathbf{u}_t = \mathbf{D}_t \boldsymbol{\varepsilon}_t, \quad (16)$$

where \mathbf{c} is the unconditional mean vector of \mathbf{r}_t , \mathbf{D}_t contains conditional standard deviations on the main diagonal and zeros elsewhere and $\boldsymbol{\varepsilon}_t$ are the innovations standardized by their conditional standard deviations. The conditioning information set is such that

$$\boldsymbol{\varepsilon}_t | \Psi_{t-1} \sim (\mathbf{0}, \mathbf{R}_t), \quad (17)$$

where Ψ_{t-1} represents the information set at time t . Observe that $E_{t-1}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') = \mathbf{R}_t$ is also the conditional correlation matrix of the standardized innovations. We can thus specify the conditional covariance matrix for the returns vector \mathbf{r}_t as

$$\text{Var}(\mathbf{r}_t | \Psi_{t-1}) = \text{Var}_{t-1}(\mathbf{r}_t) = E_{t-1} \left[(\mathbf{r}_t - \mathbf{c})(\mathbf{r}_t - \mathbf{c})' \right] = E_{t-1} \left[\mathbf{D}_t \boldsymbol{\varepsilon}_t (\mathbf{D}_t \boldsymbol{\varepsilon}_t)' \right] = E_{t-1} \left[\mathbf{D}_t \boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t' \mathbf{D}_t \right], \quad (18)$$

and since D_t is a function of information at $t - 1$ only, we can write the conditional

covariance matrix as

$$\mathbf{H}_t \equiv \text{Var}_{t-1}(\mathbf{r}_t) = \mathbf{D}_t E_{t-1}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}_t') \mathbf{D}_t \quad (19)$$

$$= \mathbf{D}_t \mathbf{R}_t \mathbf{D}_t. \quad (20)$$

The elements of the \mathbf{D}_t matrix are the conditional standard deviations, where

$$\mathbf{D}_t = \begin{bmatrix} \sqrt{h_{ss,t}} & 0 \\ 0 & \sqrt{h_{bb,t}} \end{bmatrix}. \quad (21)$$

When it comes to the specifications of the conditional variances a GARCH(1,1) structure is often chosen.

Once the univariate GARCH(1,1) models are estimated, the standardized residuals, $\mathbf{D}_t^{-1} u_t = \varepsilon_t$, are used to estimate the dynamics of the correlation. The standard model used in Engle (2002) for this process is again a GARCH(1,1) specification which in our cases could be written as

$$\mathbf{Q}_{s,b,t} = \omega_{s,b} + \alpha \varepsilon_{t-1}^s \varepsilon_{t-1}^b + \beta \mathbf{Q}_{s,b,t-1} \quad (22)$$

The matrix version of this is simply

$$\mathbf{Q}_t = \boldsymbol{\Omega} + \alpha \boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}_{t-1}' + \beta \mathbf{Q}_{t-1} \quad (23)$$

which yields two unknown dynamic parameters but $\frac{1}{2}n \times (n-1)$ parameters in the intercept matrix. However, applying simple correlation targeting leaves two remaining unknown parameters. This implies using an estimate of the unconditional correlations between the standardized random variables as follows

$$\hat{\boldsymbol{\Omega}} = (1 - \alpha - \beta) \bar{\mathbf{R}}, \quad \bar{\mathbf{R}} \equiv \frac{1}{T} \sum_{t=1}^T \varepsilon_t \varepsilon_t'. \quad (24)$$

Substituting (21) into (20) gives the basic form for the mean reverting DCC model

$$\mathbf{Q}_t = \bar{\mathbf{R}} + \alpha(\varepsilon_{t-1}\varepsilon'_{t-1} - \bar{\mathbf{R}}) + \beta(\mathbf{Q}_{t-1} - \bar{\mathbf{R}}), \quad (25)$$

or

$$\mathbf{Q}_t = (1 - \alpha - \beta)\bar{\mathbf{R}} + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta\mathbf{Q}_{t-1}, \quad (26)$$

where α and β are scalars. \mathbf{Q} is guaranteed to be a positive definite matrix as long as the initial value \mathbf{Q}_1 , α , β , and $(1 - \alpha - \beta)$ are all positive. This is because each subsequent value \mathbf{Q} is simply the sum of positive-definite or positive- semidefinite matrices and therefore must be positive definite. Notice the parsimony of this specification as only two parameters are being estimated regardless of the size of the system being modeled.

From (23) we can see how the conditional correlations behave. They are given by the off-diagonal elements of \mathbf{Q} and evolve through time in response to new information on the returns. When returns in the different markets move in the same direction the correlations will rise above their average level and stay there for while. Gradually, this information will decay and correlations will revert back to their long-run average. Similarly, when returns move in opposite direction, the correlations will temporarily fall below the unconditional level. The parameters α and β governs the speed of this adjustment process. The higher the value of β the more persistent are the correlation dynamics. Note that if $\alpha = \beta = 0$ then \mathbf{Q}_t is simply $\bar{\mathbf{R}}$, and the constant conditional correlation model of Bollerslev (1990) would be sufficient.

Although the GARCH(1,1) model specifies a process for the matrix \mathbf{Q} that gives a positive-definite quasi-correlation matrix for each period, it does not guarantee that \mathbf{Q} is a correlation matrix. Its diagonal elements will be one on average but will not be one for every observation. In order to convert the \mathbf{Q} processes into proper correlations they must be rescaled. The process is simply

$$\rho_{s,b,t} = \frac{\mathbf{Q}_{s,b,t}}{\sqrt{\mathbf{Q}_{s,s,t}\mathbf{Q}_{b,b,t}}}, \quad (27)$$

which in matrix form is given as

$$R_t = \text{diag}[\mathbf{Q}_t]^{-1} \mathbf{Q}_t \text{diag}[\mathbf{Q}_t]^{-1} \quad (28)$$

Again, since \mathbf{Q}_t is positive definite, \mathbf{R}_t is a correlation matrix with ones on the diagonal and every other element less than one in absolute value.

Estimation of the DCC model can be formulated as a maximum-likelihood problem with the following log-likelihood function

$$L = -0.5 \sum_{t=1}^T (n \log(2\pi) + \log(|H_t|) + r_t' H_t^{-1} r_t) \quad (29)$$

$$= -0.5 \sum_{t=1}^T (n \log(2\pi) + \log(|D_t R_t D_t|) + r_t' D_t^{-1} R_t^{-1} D_t^{-1} r_t) \quad (30)$$

$$= -0.5 \sum_{t=1}^T (n \log(2\pi) + 2 \log(|D_t|) + \log(|R_t|) + \varepsilon_t' R_t^{-1} \varepsilon_t). \quad (31)$$

In the likelihood function in (28) there are two components that are free to vary. The first is the volatility component and contains only terms in \mathbf{D}_t . The second is the correlation component and contains only terms in \mathbf{R}_t . Engle and Sheppard (2001) suggest to maximize L in two steps. In the first step, only the volatility component, \mathbf{D}_t , is maximized. This is done by replacing \mathbf{R}_t with a $n \times n$ identity matrix, giving the first-stage likelihood. Doing this means that the log likelihood is reduced to the sum of the likelihoods of univariate GARCH equations. The second step maximizes the correlation component \mathbf{R}_t , conditional on the estimated \mathbf{D}_t from the first step. The second step gives the DCC parameters, α and β .

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Table 1
Summary statistics

Panel A reports descriptive statistics, the first-order autocorrelation coefficient, and a test for ARCH effects for daily annualized returns on: Government bonds with 1-year constant duration, r_{bs} , 3- year constant duration, r_{bm} , 5- year constant duration, r_{bl} , and stock market returns, r_s . Panel B reports descriptive statistics for the daily order flow variables: Stock market order flow, OF^S , short term bond market order flow, OF^{BS} , medium term bond market order flow, OF^{BM} , and long term bond market order flow, OF^{BL} . Panel C reports the unconditional correlations between the return and order flow variables. Coefficients and test variables are in bold when significant at the 5 % level or better.

Panel A - Descriptive statistics, returns

| | r_{bs} | r_{bm} | r_{bl} | r_s |
|-------------------------------------|--------------|--------------|--------------|---------------|
| <i>Mean</i> | 0.0571 | 0.0674 | 0.0760 | 0.1021 |
| <i>Median</i> | 0.0539 | 0.0672 | 0.0760 | 0.1977 |
| <i>Std.Dev.</i> | 0.1185 | 0.4455 | 0.7667 | 16.142 |
| <i>Skewness</i> | 0.7319 | 0.3437 | 0.1178 | -0.5096 |
| <i>Kurtosis</i> | 8.4618 | 8.7489 | 7.6816 | 4.6586 |
| <i>AR(1)</i> | 0.14 | 0.11 | 0.09 | 0.02 |
| <i>ARCH($\chi^2(5)$)</i> | 27.61 | 49.37 | 96.95 | 136.56 |

Panel B - Descriptive statistics, order flow

| | OF^S | OF^{BS} | OF^{BM} | OF^{BL} |
|-----------------|----------|-----------|-----------|-----------|
| <i>Mean</i> | 33.9222 | -0.8151 | -0.1790 | -1.4057 |
| <i>Median</i> | 20 | 0 | 0 | -1 |
| <i>Std.Dev.</i> | 347.7180 | 3.9105 | 3.8380 | 4.6247 |
| <i>Skewness</i> | 0.2926 | -0.6050 | 0.0281 | -1.0889 |
| <i>Kurtosis</i> | 4.1449 | 10.1494 | 10.0281 | 8.9564 |

Panel C - Unconditional correlations, returns and order flow

| | r_{bs} | r_{bm} | r_{bl} | r_s | OF^S | OF^{BS} | OF^{BM} | OF^{BL} |
|-----------|---------------|---------------|---------------|---------------|--------|--------------|--------------|-----------|
| r_{bs} | 1 | | | | | | | |
| r_{bm} | 0.827 | 1 | | | | | | |
| r_{bl} | 0.719 | 0.932 | 1 | | | | | |
| r_s | -0.144 | -0.187 | -0.210 | 1 | | | | |
| OF^S | -0.072 | -0.075 | -0.108 | 0.555 | 1 | | | |
| OF^{BS} | 0.292 | 0.361 | 0.291 | -0.062 | -0.017 | 1 | | |
| OF^{BM} | 0.286 | 0.383 | 0.388 | -0.041 | -0.004 | 0.247 | 1 | |
| OF^{BL} | 0.229 | 0.333 | 0.403 | -0.091 | -0.047 | 0.190 | 0.239 | 1 |

Table 2

Panel A - Bond market spillovers to the stock market

Parameter estimates and related statistics for single regime and regime switching constant variance models. The sample contains daily observations and extends from 06/09/1999 to 09/03/2005, a total of 1363 observations.

| Parameter | Single regime | | Regime switching | |
|--------------------|---------------|---------|------------------|---------|
| | Estimate | p-value | Estimate | p-value |
| a_{01} | -0.0002303 | 0.3775 | -0.0027195 | 0.0167 |
| a_{02} | | | 0.0003721 | 0.2123 |
| a_{11} | 0.0000183 | 0.0000 | 0.0000228 | 0.0000 |
| a_{21} | -0.0001740 | 0.0048 | -0.0004540 | 0.1079 |
| a_{31} | -0.0001272 | 0.1777 | -0.0005815 | 0.0036 |
| a_{41} | -0.0001689 | 0.0370 | -0.0008088 | 0.0360 |
| a_{12} | | | 0.0000166 | 0.0000 |
| a_{22} | | | -0.0000978 | 0.1101 |
| a_{32} | | | 0.0000490 | 0.5580 |
| a_{42} | | | -0.0000110 | 0.8786 |
| b_{01} | 0.0094800 | | 0.0151000 | 0.0000 |
| b_{02} | | | 0.0075170 | 0.0000 |
| P | | | 0.8707 | 0.0000 |
| Q | | | 0.9740 | 0.0026 |
| $ARCH (\chi^2(5))$ | 148.66 | 0.0000 | 13.86 | 0.0166 |
| $Log - likelihood$ | 4418.13 | | 4500.14 | |

The single-regime model is estimated using OLS. The regime-switching model is estimated by maximum likelihood using Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm. p-values are based on heteroscedastic-consistent standard errors. Significance of P and Q is relative to 0.5. b_{01} in the single-regime model is the standard error of the estimate.

For the single-regime constant variance model:

$$r_{s,t}|\Phi_t \sim N(a_{01} + a_{11}OF_t^S + a_{21}OF_t^{BL,MS} + a_{31}OF_t^{BM,MS} + a_{41}OF_t^{BS,MS}, b_{01}).$$

For the regime-switching constant variance model:

$$r_{s,t}|\Phi_t \sim \begin{cases} N(a_{01} + a_{11}OF_t^S + a_{21}OF_t^{BL,MS} + a_{31}OF_t^{BM,MS} + a_{41}OF_t^{BS,MS}, b_{01}) \text{ w.p. } p_{1t} , \\ N(a_{02} + a_{12}OF_t^S + a_{22}OF_t^{BL,MS} + a_{32}OF_t^{BM,MS} + a_{42}OF_t^{BS,MS}, b_{02}) \text{ w.p. } 1 - p_{1t} , \end{cases}$$

$$p_{1t} = (1 - Q) \left[\frac{g_{2t-1}(1-p_{1t-1})}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] + P \left[\frac{g_{1t-1}p_{1t-1}}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] ,$$

$$g_{1t} = f(r_{s,t}|S_t = 1), \quad g_{2t} = f(r_{s,t}|S_t = 2).$$

Panel B - Stock market spillover to the short term bond market

Parameter estimates and related statistics for single regime and regime switching constant variance models. The sample contains daily observations and extends from 06/09/1999 to 09/03/2005, a total of 1363 observations.

| Parameter | Single regime | | Regime switching | |
|--------------------|---------------|---------|------------------|---------|
| | Estimate | p-value | Estimate | p-value |
| a_{01} | 0.0000225 | 0.0000 | 0.0000317 | 0.0001 |
| a_{02} | | | 0.0000216 | 0.0000 |
| a_{11} | 0.1065000 | 0.0034 | 0.1516000 | 0.1349 |
| a_{21} | 0.0000032 | 0.0000 | 0.0000289 | 0.0459 |
| a_{31} | -0.0000822 | 0.0137 | 0.0002336 | 0.3027 |
| a_{12} | | | 0.0811000 | 0.0026 |
| a_{22} | | | 0.0000033 | 0.0000 |
| a_{32} | | | -0.0001289 | 0.0001 |
| b_{01} | 0.0004251 | | 0.0000861 | 0.0000 |
| b_{02} | | | 0.0000303 | 0.0000 |
| P | | | 0.3993 | 0.0000 |
| Q | | | 0.9099 | 0.0001 |
| $ARCH (\chi^2(5))$ | 41.51 | 0.0000 | 19.61 | 0.0015 |
| $Log - likelihood$ | 11778.95 | | 11909.38 | |

The single-regime model is estimated using OLS. The regime-switching model is estimated by maximum likelihood using Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm. In order to facilitate convergence $r_{bs,t}$ is divided by 10 and $OF_t^{S,MS}$ is divided by 10000. p-values are based on heteroscedastic-consistent standard errors. Significance of P and Q is relative to 0.5. b_{01} in the single-regime model is the standard error of the estimate.

For the single-regime constant variance model:

$$r_{bs,t}|\Phi_t \sim N(a_{01} + a_{11}r_{bs,t-1} + a_{21}OF_t^{BS} + a_{31}OF_t^{S,MS}, b_{01}).$$

For the regime-switching constant variance model:

$$r_{bs,t}|\Phi_t \sim \begin{cases} N(a_{01} + a_{11}r_{bs,t-1} + a_{21}OF_t^{BS} + a_{31}OF_t^{S,MS}, b_{01}) \text{ w.p. } p_{1t} , \\ N(a_{02} + a_{12}r_{bs,t-1} + a_{22}OF_t^{BS} + a_{32}OF_t^{S,MS}, b_{02}) \text{ w.p. } 1 - p_{1t} , \end{cases}$$

$$p_{1t} = (1 - Q) \left[\frac{g_{2t-1}(1-p_{1t-1})}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] + P \left[\frac{g_{1t-1}p_{1t-1}}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] ,$$

$$g_{1t} = f(r_{bs,t}|S_t = 1), \quad g_{2t} = f(r_{bs,t}|S_t = 2).$$

Panel C - Stock market spillover to the medium term bond market

Parameter estimates and related statistics for single regime and regime switching constant variance models. The sample contains daily observations and extends from 06/09/1999 to 09/03/2005, a total of 1363 observations.

| Parameter | Single regime | | Regime switching | |
|--------------------|---------------|---------|------------------|---------|
| | Estimate | p-value | Estimate | p-value |
| a_{01} | 0.0000259 | 0.0000 | 0.0000376 | 0.0000 |
| a_{02} | | | 0.0000236 | 0.0000 |
| a_{11} | 0.1041000 | 0.0018 | 0.1010000 | 0.0190 |
| a_{21} | 0.0000146 | 0.0000 | 0.0000277 | 0.0000 |
| a_{31} | -0.0002677 | 0.0058 | -0.0000396 | 0.9202 |
| a_{12} | | | 0.1103000 | 0.0005 |
| a_{22} | | | 0.0000116 | 0.0000 |
| a_{32} | | | -0.0003295 | 0.0020 |
| b_{01} | 0.0001354 | | 0.0002409 | 0.0000 |
| b_{02} | | | 0.0000984 | 0.0000 |
| P | | | 0.8422 | 0.0000 |
| Q | | | 0.9689 | 0.0017 |
| $ARCH (\chi^2(5))$ | 26.02 | 0.0001 | 4.68 | 0.4558 |
| $Log - likelihood$ | 10201.53 | | 10337.78 | |

The single-regime model is estimated using OLS. The regime-switching model is estimated by maximum likelihood using Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm. In order to facilitate convergence $r_{bm,t}$ is divided by 10 and $OF_t^{S,MS}$ is divided by 10000. p-values are based on heteroscedastic-consistent standard errors. Significance of P and Q is relative to 0.5. b_{01} in the single-regime model is the standard error of the estimate.

For the single-regime constant variance model:

$$r_{bm,t}|\Phi_t \sim N(a_{01} + a_{11}r_{bm,t-1} + a_{21}OF_t^{BM} + a_{31}OF_t^{S,MS}, b_{01}).$$

For the regime-switching constant variance model:

$$r_{bm,t}|\Phi_t \sim \begin{cases} N(a_{01} + a_{11}r_{bm,t-1} + a_{21}OF_t^{BM} + a_{31}OF_t^{S,MS}, b_{01}) \text{ w.p. } p_{1t} , \\ N(a_{02} + a_{12}r_{bm,t-1} + a_{22}OF_t^{BM} + a_{32}OF_t^{S,MS}, b_{02}) \text{ w.p. } 1 - p_{1t} , \end{cases}$$

$$p_{1t} = (1 - Q) \left[\frac{g_{2t-1}(1-p_{1t-1})}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] + P \left[\frac{g_{1t-1}p_{1t-1}}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] ,$$

$$g_{1t} = f(r_{bm,t}|S_t = 1), \quad g_{2t} = f(r_{bm,t}|S_t = 2).$$

Panel D - Stock market spillover to the long term bond market

Parameter estimates and related statistics for single regime and regime switching constant variance models. The sample contains daily observations and extends from 06/09/1999 to 09/03/2005, a total of 1363 observations.

| Parameter | Single regime | | Regime switching | |
|--------------------|---------------|---------|------------------|---------|
| | Estimate | p-value | Estimate | p-value |
| a_{01} | 0.0005453 | 0.0000 | 0.0010075 | 0.0060 |
| a_{02} | | | 0.0004733 | 0.0000 |
| a_{11} | 0.0791518 | 0.0240 | 0.0782683 | 0.2790 |
| a_{21} | 0.0001972 | 0.0000 | 0.0003765 | 0.0000 |
| a_{31} | -0.0006123 | 0.0001 | 0.0000326 | 0.9748 |
| a_{12} | | | 0.0913704 | 0.0015 |
| a_{22} | | | 0.0001562 | 0.0000 |
| a_{32} | | | -0.0007176 | 0.0000 |
| b_{01} | 0.0020701 | | 0.0037915 | 0.0000 |
| b_{02} | | | 0.0016730 | 0.0000 |
| P | | | 0.7926 | 0.0000 |
| Q | | | 0.9736 | 0.0373 |
| $ARCH (\chi^2(5))$ | 64.45 | 0.0000 | 9.46 | 0.0922 |
| $Log - likelihood$ | 9622.90 | | 9713.53 | |

The single-regime model is estimated using OLS. The regime-switching model is estimated by maximum likelihood using Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm. In order to facilitate convergence $r_{bl,t}$ is divided by 10 and $OF_t^{S,MS}$ is divided by 10000. p-values are based on heteroscedastic-consistent standard errors. Significance of P and Q is relative to 0.5. b_{01} in the single-regime model is the standard error of the estimate.

For the single-regime constant variance model:

$$r_{bl,t}|\Phi_t \sim N(a_{01} + a_{11}r_{bl,t-1} + a_{21}OF_t^{BL} + a_{31}OF_t^{S,MS}, b_{01}).$$

For the regime-switching constant variance model:

$$r_{bl,t}|\Phi_t \sim \begin{cases} N(a_{01} + a_{11}r_{bl,t-1} + a_{21}OF_t^{BL} + a_{31}OF_t^{S,MS}, b_{01}) \text{ w.p. } p_{1t} , \\ N(a_{02} + a_{12}r_{bl,t-1} + a_{22}OF_t^{BL} + a_{32}OF_t^{S,MS}, b_{02}) \text{ w.p. } 1 - p_{1t} , \end{cases}$$

$$p_{1t} = (1 - Q) \left[\frac{g_{2t-1}(1-p_{1t-1})}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] + P \left[\frac{g_{1t-1}p_{1t-1}}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] ,$$

$$g_{1t} = f(r_{bl,t}|S_t = 1), \quad g_{2t} = f(r_{bl,t}|S_t = 2).$$

Table 3

Spillover effects from the stock market to long, medium, and short term bond returns when the stock market is in a high volatility regime (probability $P_{s,t}$) and in a normal volatility regime (probability $Q_{s,t}$). P-values in parenthesis.

| | \mathbf{r}_{bl} | \mathbf{r}_{bm} | \mathbf{r}_{bs} |
|---------------------------|---------------------------|---------------------------|---------------------------|
| <i>Constant</i> | 0.00054 (0.0000) | 0.00025 (0.0000) | 0.00023 (0.0000) |
| $r_{bl,t-1}$ | 0.07958 (0.0245) | | |
| $r_{bm,t-1}$ | | 0.10534 (0.0017) | |
| $r_{bs,t-1}$ | | | 0.10563 (0.0036) |
| OF_t^{BL} | 0.00020 (0.0000) | | |
| OF_t^{BM} | | 0.00015 (0.0000) | |
| OF_t^{BS} | | | 0.00003 (0.0000) |
| $OF_t^{S,MS} * Q_{s,t}$ | $-4.72E - 07$ (0.0145) | $-7.37E - 08$ (0.5755) | $-1.06E - 07$ (0.0135) |
| $OF_t^{S,MS} * P_{s,t}$ | $-9.34E - 07$ (0.0132) | $-7.01E - 07$ (0.0014) | $-3.06E - 08$ (0.7174) |
| <i>Adj. R²</i> | 0.1755 | 0.1611 | 0.0980 |

$$r_{bk} = c + \beta_1 r_{bk,t-1} + \beta_2 OF_t^{BK} + \beta_3 OF_t^{S,MS} * Q_{s,t} + \beta_4 OF_t^{S,MS} * P_{s,t} + \epsilon_{bk,t}$$

$k = l$ (long term), m (medium term), s (short term).

Table 4

Bond market spillovers to the stock market

Parameter estimates and related statistics for single-regime and regime-switching GARCH models. The sample contains daily observations and extends from 06/09/1999 to 09/03/2005, a total of 1363 observations.

| Parameter | Single regime | | Regime switching | |
|-------------------------|---------------|---------|------------------|---------|
| | Estimate | p-value | Estimate | p-value |
| a_{01} | 0.0001226 | 0.5997 | -0.0009299 | 0.0365 |
| a_{02} | | | 0.0008577 | 0.0009 |
| a_{11} | 0.0000172 | 0.0000 | 0.0000283 | 0.0000 |
| a_{21} | -0.0001648 | 0.0036 | -0.0003188 | 0.0065 |
| a_{31} | -0.0000551 | 0.4347 | -0.0003902 | 0.0211 |
| a_{41} | -0.0001083 | 0.0931 | -0.0003117 | 0.0172 |
| a_{12} | | | 0.0000130 | 0.0000 |
| a_{22} | | | -0.0000276 | 0.7371 |
| a_{32} | | | 0.0001845 | 0.0000 |
| a_{42} | | | 0.0000451 | 0.5538 |
| b_{01} | 0.0000040 | 0.0972 | 0.0000029 | 0.0000 |
| b_{11} | 0.0941000 | 0.0004 | 0.1246000 | 0.0000 |
| b_{21} | 0.8615000 | 0.0000 | 0.8181000 | 0.0000 |
| b_{31} | -0.0000004 | 0.2539 | -0.0000002 | 0.4489 |
| b_{41} | $8.37E - 08$ | 0.8343 | 0.0000007 | 0.5923 |
| b_{51} | $5.19E - 08$ | 0.8788 | $5.48E - 09$ | 0.9959 |
| b_{02} | | | 0.0000090 | 0.0000 |
| b_{12} | | | 0.0360000 | 0.0720 |
| b_{22} | | | 0.7530000 | 0.0000 |
| b_{32} | | | -0.0000011 | 0.0001 |
| b_{42} | | | -0.0000023 | 0.0000 |
| b_{52} | | | -0.0000001 | 0.4712 |
| P | | | 0.9537 | 0.0000 |
| Q | | | 0.9759 | 0.0000 |
| <i>Log - likelihood</i> | 4493.11 | | 4530.43 | |

The models are estimated by maximum likelihood using Broyden, Fletcher, Goldfarb, and Shanno (BFGS) algorithm. p-values are based on heteroscedastic-consistent standard errors. Significance of P and Q is relative to 0.5. b_{01} in the single-regime model is the standard error of the estimate.

For the single-regime GARCH model:

$$r_{s,t}|\Phi_t \sim N(a_{01} + a_{11}OF_t^S + a_{21}OF_t^{BL,MS} + a_{31}OF_t^{BM,MS} + a_{41}OF_t^{BS,MS}, h_{1t}).$$

For the regime-switching GARCH model:

$$r_{s,t}|\Phi_t \sim \begin{cases} N(a_{01} + a_{11}OF_t^S + a_{21}OF_t^{BL,MS} + a_{31}OF_t^{BM,MS} + a_{41}OF_t^{BS,MS}, h_{1t}) \text{ w.p. } p_{1t} , \\ N(a_{02} + a_{12}OF_t^S + a_{22}OF_t^{BL,MS} + a_{32}OF_t^{BM,MS} + a_{42}OF_t^{BS,MS}, h_{2t}) \text{ w.p. } 1 - p_{1t} , \end{cases}$$

$$h_{i,t} = b_{0i} + b_{1i}\varepsilon_{it-1}^2 + b_{2i}h_{it-1} + b_{3i}OF_{it}^{BL,MS} + b_{4i}OF_{it}^{BM,MS} + b_{5i}OF_{it}^{BS,MS},$$

$$\varepsilon_{t-1} = r_{s,t-1} - [p_{1,t-1}\mu_{1,t-1} + (1 - p_{1,t-1})\mu_{2,t-1}],$$

$$\mu_{i,t-1} = a_{0i} + a_{1i}r_{s,t-2},$$

$$h_{t-1} = p_{1,t-1}[\mu_{1,t-1}^2 - h_{1,t-2}] + (1 - p_{1,t-1})[\mu_{2,t-1}^2 - h_{2,t-2}] - [p_{1,t-1}\mu_{1,t-1} - (1 - p_{1,t-1})\mu_{2,t-1}]^2$$

$$p_{1t} = (1 - Q) \left[\frac{g_{2t-1}(1-p_{1t-1})}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right] + P \left[\frac{g_{1t-1}p_{1t-1}}{g_{1t-1}p_{1t-1} + g_{2t-1}(1-p_{1t-1})} \right],$$

$$g_{1t} = f(r_{s,t} | S_t = 1), \quad g_{2t} = f(r_{s,t} | S_t = 2).$$

Figure 1: Cumulative stock market order flow including all stocks registered at the Oslo Stock Exchange. The cumulative order flow is constructed by adding up daily order flow, OF_t^S , over the period September 1999 to March 2005.

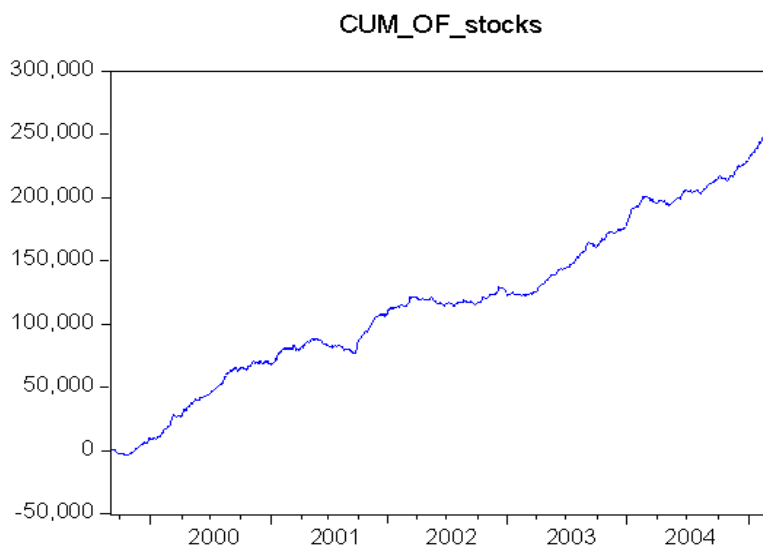


Figure 2: Cumulative order flow in long term government bonds with a remaining time to maturity from 7 to 11 years. The cumulative order flow is constructed by adding up daily order flow, OF_t^{BL} , over the period September 1999 to March 2005.

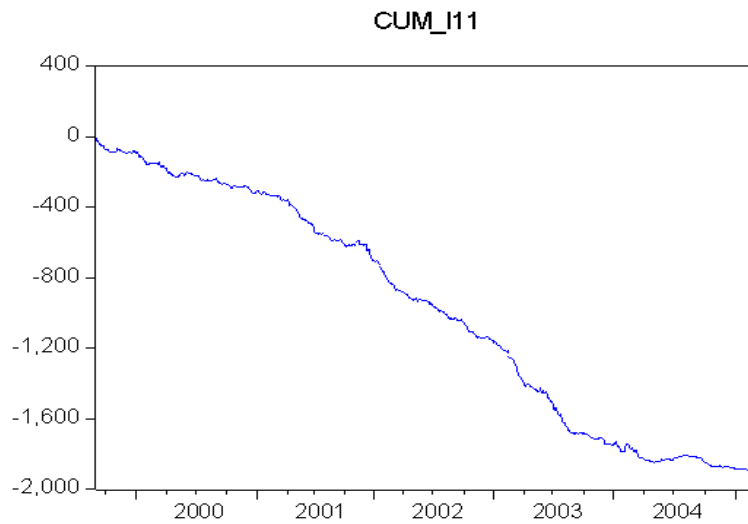


Figure 3: Cumulative order flow in medium term government bonds with a remaining time to maturity from 4 up to 7 years. The cumulative order flow is constructed by adding up daily order flow, OF_t^{BM} , over the period September 1999 to March 2005.

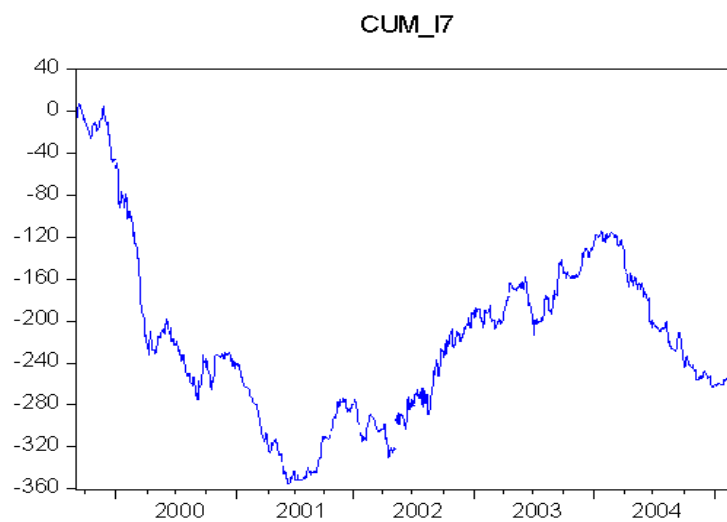


Figure 4: Cumulative order flow in short term government bonds with a remaining time to maturity from 1 up to 4 years. The cumulative order flow is constructed by adding up daily order flow, OF_t^{BS} , over the period September 1999 to March 2005.

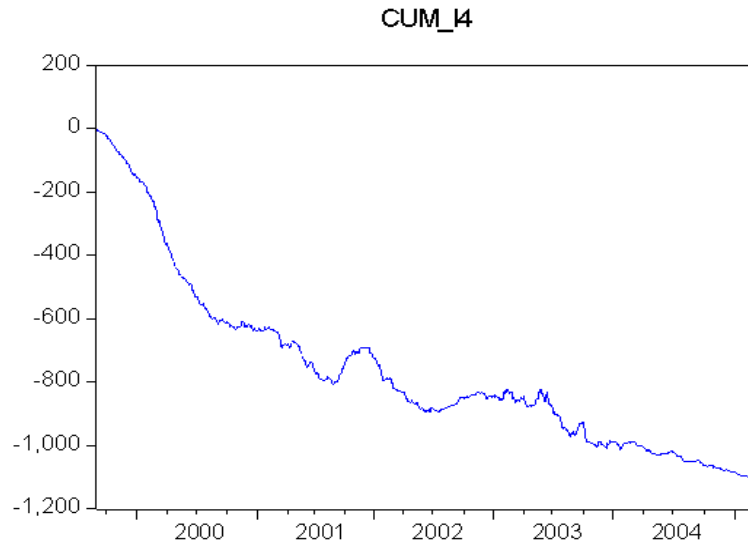


Figure 5: The figure shows the probability that the stock market is in a high volatility regime against the probability that the long term bond segment is in a high volatility regime. The dotted line represents the stock market while the solid line represents the long term bond market.

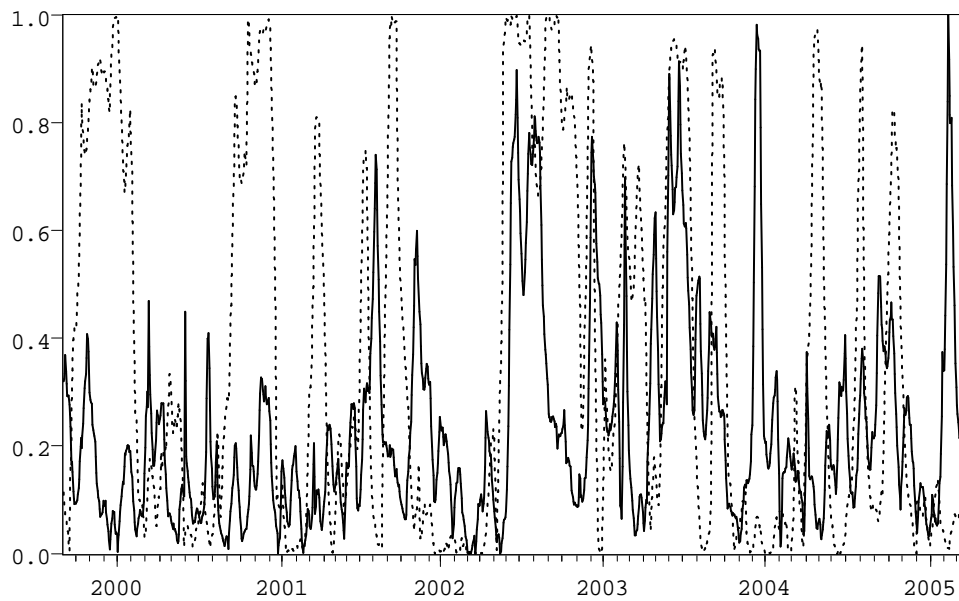


Figure 6: The figure shows the probability that the stock market is in a high volatility regime against the probability that the medium term bond segment is in a high volatility regime. The dotted line represents the stock market while the solid line represents the medium term bond market.

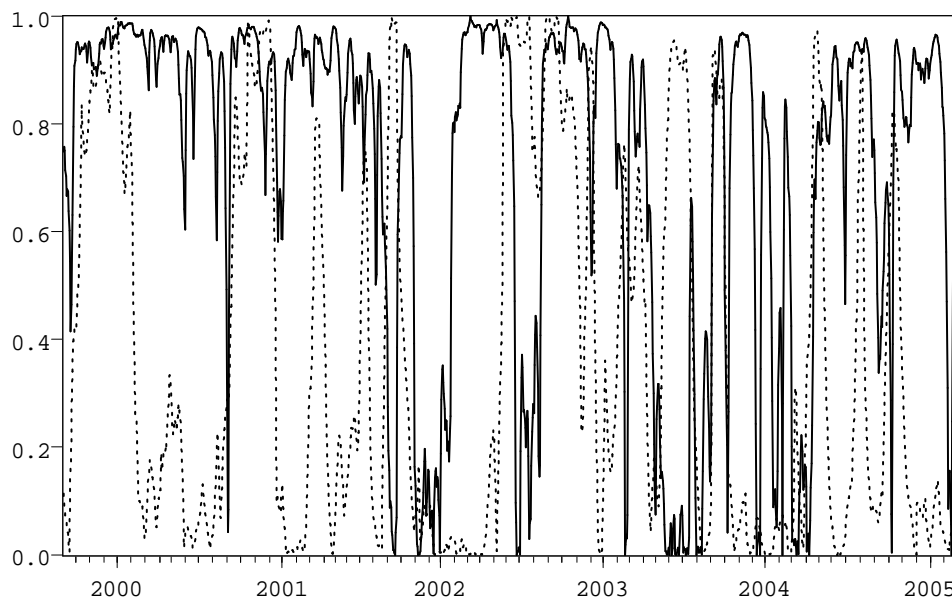


Figure 7: The figure shows the probability that the stock market is in a high volatility regime against the probability that the short term bond segment is in a high volatility regime. The dotted line represents the stock market while the solid line represents the short term bond market.

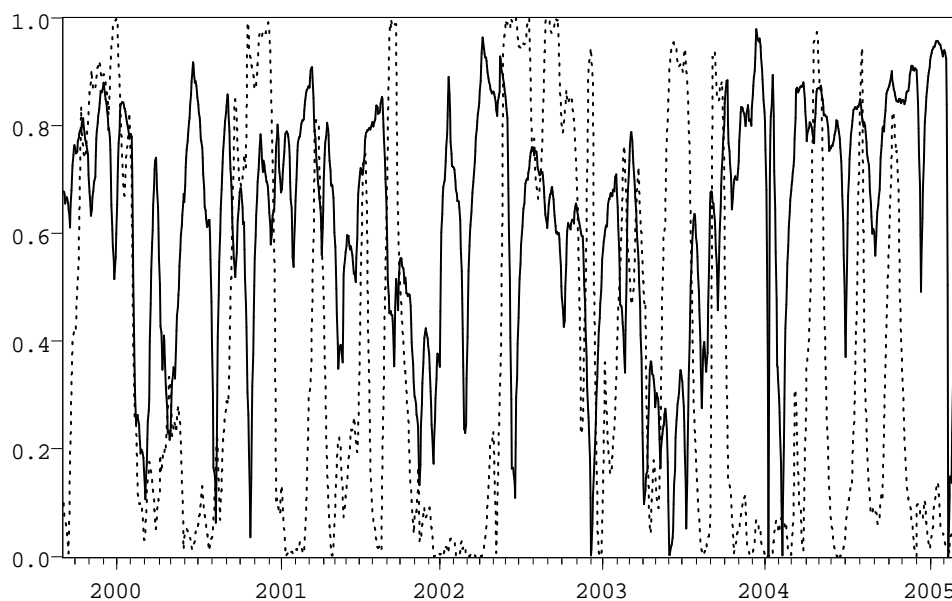


Figure 8: The figure shows the time varying correlation between returns on stocks and long term bonds against the probability that the stock market is in a high volatility regime. The dotted line represents the conditional correlation (DCC) while the solid line represents the probability of the stock market being in the high volatility regime.

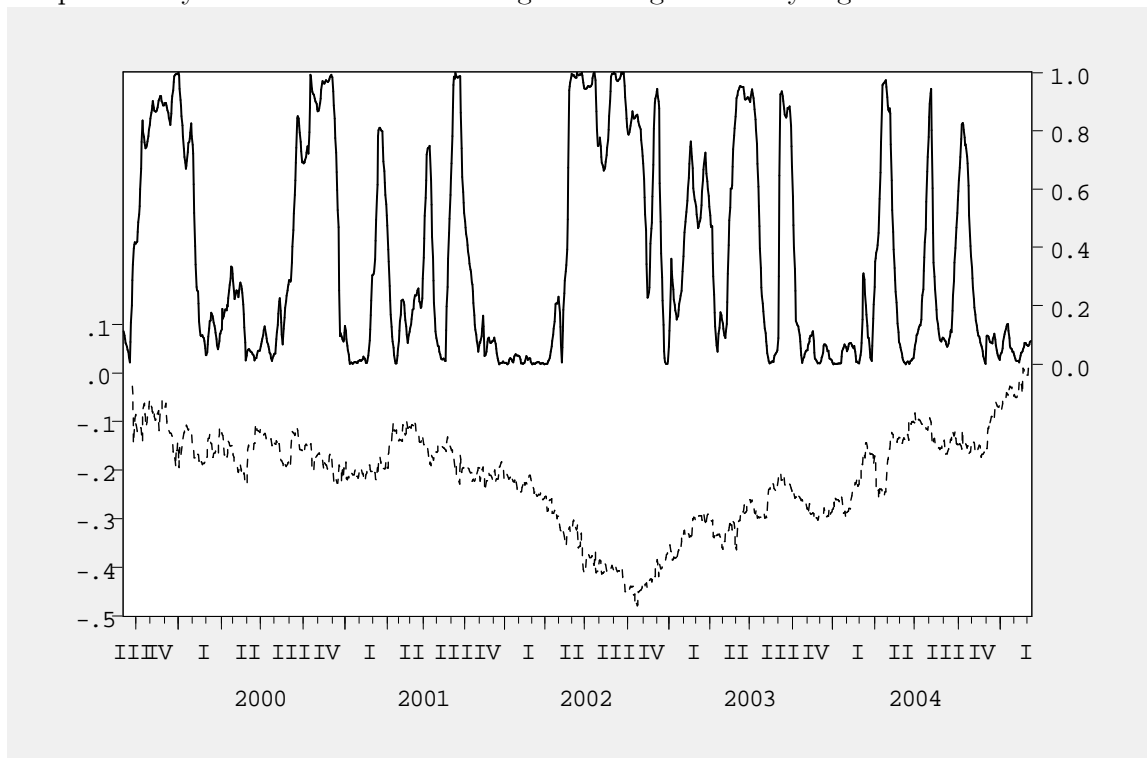


Figure 9: The figure shows the time varying correlation between returns on stocks and medium term bonds against the probability that the stock market is in a high volatility regime. The dotted line represents the conditional correlation (DCC) while the solid line represents the probability of the stock market being in the high volatility regime.

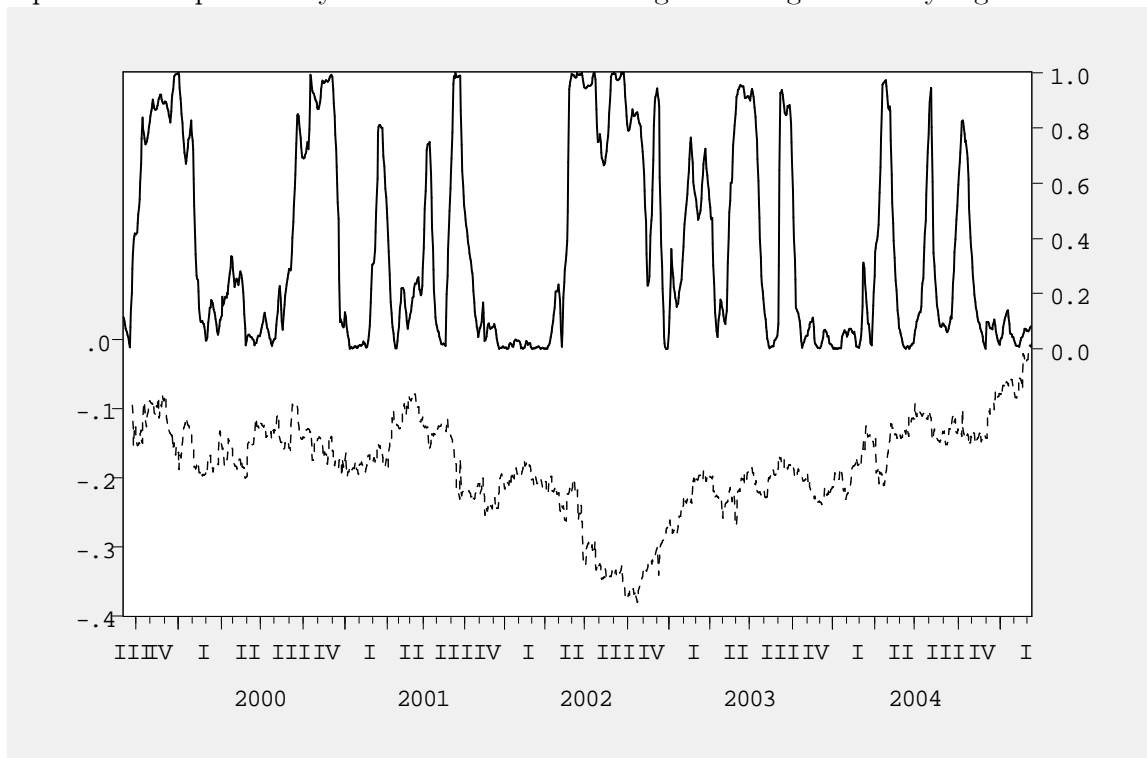


Figure 10: The figure shows the time varying correlation between returns on stocks and short term bonds against the probability that the stock market is in a high volatility regime. The dotted line represents the conditional correlation (DCC) while the solid line represents the probability of the stock market being in the high volatility regime.

