Determinants of stock-bond market comovement in the Eurozone under model uncertainty

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Abstract

This paper examines the dynamic relationship between stock and bond returns in eleven Eurozone countries during the last seventeen years. The literature so far reports heterogeneous results with respect to the important determinants of the stock-bond relationship. To deal with model uncertainty we employ a Bayesian model averaging technique and examine various macroeconomic and financial variables which are likely to influence stock-bond comovement. Bond and stock market uncertainty, interest rate, inflation and state of the economy are important determinants of cross-asset correlations. Divergence in the dynamic patterns of stock-bond comovement as well as on the effect of economic variables on this comovement is reported during crisis periods and between different European regions. Our results are of high relevance for investment strategies as well as for policy decisions in the European context.

JEL classification: C58, E44, G15, C11

Keywords: stock-bond correlation, Bayesian Model Averaging, financial crisis

1. Introduction

Understanding time variations in stock-bond return comovement remains a fundamental question in financial economics. This issue has important implications for asset pricing, managing risk efficiently and allocating funds across assets successfully. It is widely recognized that correlations between stock and bond returns do not remain constant over time. For the US, and Glabadanidis (2003) claim that stock-bond correlations vary significantly over the post war period from negative in the late 1950s to positive since the mid 1960s. Kim at al. (2006) find that stock-bond correlations in most European countries, US and Japan have trended to zero and even negative since the mid 1990s. This study investigates the dynamics of the stock-bond correlations in the Eurozone countries and attempts to indentify the economic factors driving their time-series behavior.

During the last decade, may academic studies have examined the dynamic relationship between stock and bond returns (e.g. de Goeij and Marquering, 2004, Cappiello et al., 2006, Connolly et al., 2007). One of the most prominent issues within this stream of literature is related to exploring economic forces driving the time-varying stock-bond comovement. Stock and bond returns comove because the same economic factors are expected to influence their future cash flows and discount rates. The evidence in the literature on what determines the time variation in stock-bond comovement is mixed. Examining the predictive power of various economic variables for stock-bond correlation in the G7 countries, Li (2002) proposes a theoretical framework to support the examined relation and argues that uncertainty on expected inflation and real interest rate are the driving forces of the correlation between the two asset classes. Ilmanen (2003) argues that during periods of high inflation, changes in common discount rates dominate changes in cash-flow expectations and lead to positive stock-bond return correlation. Andersson et al. (2008) use data for the US, UK and Germany and argue that inflation expectations strongly affect the stock-bond comovement. Using a long dataset for both the US and the UK, Yang et al. (2009) provide evidence on the prominent role of macroeconomic conditions including the business cycle, the inflation environment and the monetary policy stance on the stock-bond comovement. In a more theoretical context, David and Veronesi (2013) provide a general equilibrium model which predicts that expected inflation drives the relation between stock and bond returns.

Another strand of literature provides contradictory evidence on the importance of the macroeconomic factors on cross-asset comovement. Early studies to investigate the stock-bond comovement (Shiller and Beltratti, 1992, Campbell and Ammer, 1993) conclude that the observed levels of stock-bond correlation cannot be explained by economic fundamentals. However, both studies assume time-invariance in the stock-bond comovement. More recently, Baele et al. (2010) use data for the US market and find that macroeconomic fundamentals play a minor role in explaining the stock-bond relationship.

Apart from the macroeconomic variables, another important driver of the stock-bond comovement is the stock market uncertainty. The rationale behind this is that during phases of financial turnoil investors rebalance their portfolios and transfer their money from the high-risk stocks to the low-risk bonds, thereby inducing negative stock-bond correlations. Evidence in favor of the so-called flight-to-quality phenomenon is provided in a number of studies including Conolly et al. (2005, 2007), Kim et al. (2006), Andersson et al. (2008).

Recent studies on the stock-bond comovement exploit the MIDAS-DCC econometric framework proposed by Colacito et al. (2012) to combine high-frequency asset returns with low-frequency macro variables. For the US case, Asgharian et al. (2015a) argue that forecasts of macro-finance factors are good predictors of the long-run stock-bond correlation both in-sample and out-of-sample. Moreover, Asgharian et al. (2015b) use the same MIDAS-DCC framework and provide evidence to support the flight-to-quality phenomenon when macroeconomic uncertainty is high.

Most of the aforementioned studies investigate the drivers of the comovement between the two asset classes for the US or the major developed markets. In the European context, Kim et al. (2006) find that real economic integration and the absence of currency risk induce increased stock-bond comovement. However, monetary policy convergence have created uncertainty about the economic prospects of the European monetary union and decreased comovement. Cappiello et al. (2006) introduce asymmetries in the stock-bond correlation in a sample of European, Australasian and North-American markets for the period 1987-2002. Regarding the stock-bond correlation in the Eurozone markets they find evidence of a stable positive correlation before and after the monetary union as well as evidence of the flight-to-quality phenomenon. A more recent study from Perego and Vermeulen (2016) focuses on the Euro-zone asset markets and provides evidence on the importance of macroeconomic factors on stock, bond and stock-bond correlation. However, their study focuses on cross-country and not within country stock-bond comovement. A modified DCC-MIDAS specification is used by Conrad and Loch (2016) to examine the determinants of stock-bond correlations in four European countries, France, Germany, Italy and UK. A limited number of studies including Boyer et al. (2006), Panchenco and Wu (2009), Dimic et al. (2016) focus on emerging markets.

This study contributes to the literature in three ways. First, to our knowledge this is the first study to use a Bayesian model selection technique to examine the driving forces of stock-bond comovements. The fact that there is no consensus in the existing literature on the determinants of the stock-bond relationship could indicate a high degree of uncertainty about the "true" empirical model. Bayesian Model Averaging (BMA) deals explicitly with model uncertainty by assuming that the "true" model is not known and analyses the entire model space, i.e. any possible combination of independent variables from a given set of potential determinants. BMA techniques have been used in the recent finance literature to explore the determinants of sovereign yield spreads in the Eurozone (Maltritz, 2012) and in emerging markets (Maltritz and Molchanov, 2013). Other studies are Avramov (2002) and Cremers (2002) to stock return predictability, Vrontos et al. (2008) to hedge funds, Bandiera et al. (2010) to sovereign defaults. Second, by examining the determinants of the stock-bond comovement in the Eurozone countries after the monetary union we provide important information for selecting the optimal monetary policy in a national and EU level. In addition, we shed more light on the divergent macro-finance behavior of Eurozone countries by examining whether core and peripheral countries exhibit different patterns on the cross-asset correlations and identifying the determinants of this divergence. Third, the time period examined in this study is characterized by high turbulence and incidents of global as well as regional financial crises. Specifically, the sample starts with the monetary union, includes the global financial crisis and continues with the ongoing EU debt crisis. The inclusion of a large crisis period enables us to examine thoroughly the effect of financial crises on the dynamics of the stock-bond relationship and the effect of macro-finance determinants.

A number of interesting finding emerge from this study. Stock-bond correlations in the Eurozone countries exhibit significant variation during the examined period. One of the most important determinants of stock-bond comovement is the bond market uncertainty. In periods of high domestic bond uncertainty the relationship between stock and bond returns strengthens. The dominant role of the bond market uncertainty is present in all European countries examined and during the whole sample period, but it is more pronounced during the crisis periods. In addition, this study complements on previous literature and documents the flight-to quality phenomenon. During periods of high stock market uncertainty, investors change their investments from stock to bonds thus decreasing stock-bond correlations. Interestingly, domestic stock market uncertainty drives stock-bond comovement in the core EE countries and during normal periods, while global stock market uncertainty is the driver in the peripheral EU countries and during turbulent periods. A general conclusion is that by differentiating among European regions, different patterns of cross-asset correlations in European markets appear. These findings provide important information for European policy makers as well as for the future of the monetary union. Finally, our results remain robust to using an alternative estimator for stock-bond comovement and to adding forecasts of macroeconomic variables.

The remainder of this article is organized as follows. Section 2 describes the data and the econometric methodology used in the empirical analysis. The empirical findings on the determinants of the stock-bond comovement are reported in Section 3. Section 4 presents some robustness checks and Section 5 concludes.

2. Data & Methodology

2.1 Data

The empirical analysis is focused on a sample of eleven European countries belonging to the Eurozone i.e. Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal and Spain. A combination of daily stock and bond returns and quarterly macroeconomic and financial variables is used. The data cover the sample period from the second quarter of 1999 until the second quarter of 2016 including 4501 daily observations and 69 quarterly observations for each country. In an attempt to investigate the question whether our results change between tranquil and turbulent times the sample is divided into two subsamples. The first sub-sample covers the non-crisis period including observations up to the second quarter of 2007 while the rest of the sample covers the crisis period including the global financial crisis and the EU debt crisis. In the subsequent empirical analysis we also divide our sample into core countries including Austria, Belgium, Finland, France, Germany and Netherlands and peripheral countries including Greece, Ireland, Italy, Portugal, Spain.[1]

Daily stock and bond returns are calculated based on the total return stock market indices and the 10-year benchmark bond market indices collected from Datastream. Table 1 depicts summary statistics for the daily stock and bond returns and the realized stock-bond correlation for the whole sample and the two sub-samples. On an average for the whole sample period, almost all countries exhibit negative stock-bond correlations except from Greece, Italy and Portugal that exhibit slightly positive average correlations. The lowest average correlation is found in Germany (-0.32), while the highest correlation is found in Greece (0.09). The global financial crisis leads to a decrease on average correlations for the core countries (except Belgium) and an increase for the peripheral countries. Furthermore, cross-asset correlations become more volatile after the crisis for all countries except from Belgium, Germany and Netherlands. It can also be noted from Table 1 that after the global crisis on average the bond returns increase on average for all countries (except Greece), stock returns decrease for all countries and both stock and bond returns become more volatility.

[1] A similar allocation of European countries to regions is used in Perego and Vermeulen (2016) and Fontana and Scheicher (2016).

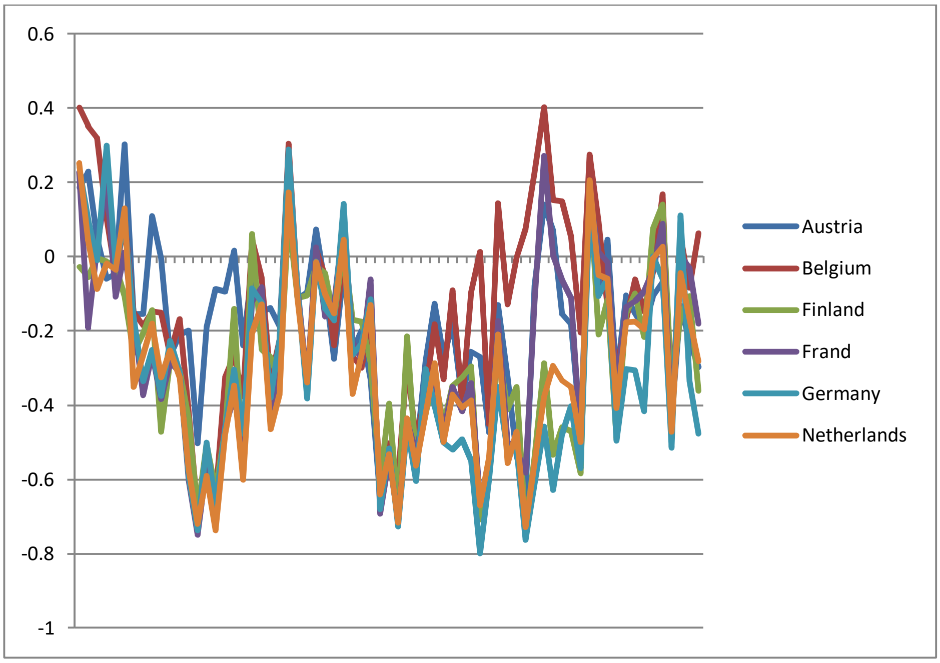
Table 1 Descriptive statistics of stock and bond market returns and realized correlations

		Whole sample		Pre-crisis period		Crisis period	
		Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Austria	Bond returns	0.010%	0.337%	0.000%	0.304%	0.020%	0.364%
	Stock returns	0.010%	1.160%	0.057%	0.743%	-0.033%	1.439%
	Correlations	-0.176	0.214	-0.088	0.174	-0.257	0.217
Belgium	Bond returns	0.010%	0.357%	0.000%	0.303%	0.019%	0.401%
	Stock returns	0.012%	1.172%	0.019%	0.988%	0.004%	1.319%
	Correlations	-0.132	0.259	-0.147	0.265	-0.119	0.257
Finland	Bond returns	0.008%	0.327%	-0.002%	0.291%	0.018%	0.356%
	Stock returns	0.002%	1.898%	0.023%	2.213%	-0.017%	1.553%
	Correlations	-0.282	0.224	-0.214	0.206	-0.343	0.226
France	Bond returns	0.010%	0.354%	-0.001%	0.333%	0.021%	0.371%
	Stock returns	0.007%	1.316%	0.025%	1.227%	-0.009%	1.393%
	Correlations	-0.252	0.256	-0.227	0.252	-0.275	0.261
Germany	Bond returns	0.010%	0.350%	-0.002%	0.306%	0.021%	0.386%
	Stock returns	0.007%	1.266%	0.017%	1.184%	-0.002%	1.336%
	Correlations	-0.316	0.269	-0.197	0.260	-0.425	0.230
Greece	Bond returns	-0.009%	1.642%	0.005%	0.292%	-0.021%	2.256%
	Stock returns	-0.061%	1.969%	0.012%	1.401%	-0.127%	2.371%
	Correlations	0.089	0.316	-0.083	0.199	0.246	0.324
Ireland	Bond returns	0.008%	0.512%	-0.001%	0.313%	0.016%	0.642%
	Stock returns	0.003%	1.357%	0.023%	1.053%	-0.016%	1.586%
	Correlations	-0.057	0.241	-0.153	0.163	0.031	0.269
Italy	Bond returns	0.009%	0.443%	0.000%	0.290%	0.017%	0.547%
	Stock returns	-0.011%	1.375%	0.012%	1.091%	-0.032%	1.591%
	Correlations	0.027	0.402	-0.183	0.258	0.219	0.417
Netherlands	Bond returns	0.010%	0.336%	0.000%	0.304%	0.020%	0.363%
	Stock returns	0.000%	1.300%	0.010%	1.203%	-0.009%	1.383%
	Correlations	-0.298	0.241	-0.239	0.249	-0.351	0.223
Portugal	Bond returns	0.007%	0.722%	0.001%	0.341%	0.012%	0.944%
	Stock returns	-0.013%	1.128%	0.019%	0.779%	-0.043%	1.372%
	Correlations	0.038	0.329	-0.118	0.200	0.181	0.360
Spain	Bond returns	0.010%	0.452%	0.002%	0.300%	0.017%	0.555%
	Stock returns	0.001%	1.345%	0.026%	1.105%	-0.022%	1.532%
	Correlations	-0.003	0.382	-0.176	0.259	0.156	0.409

Note: This table reports the mean and standard deviation of the daily bond and stock returns and the quarterly realized correlations between stock and bond returns. The whole sample covers the period from 1/4/1999 to 30/6/2016, the pre-crisis sample from 1/4/1999 to 30/6/2007 and the crisis sample from 1/7/2007 to 30/6/2016.

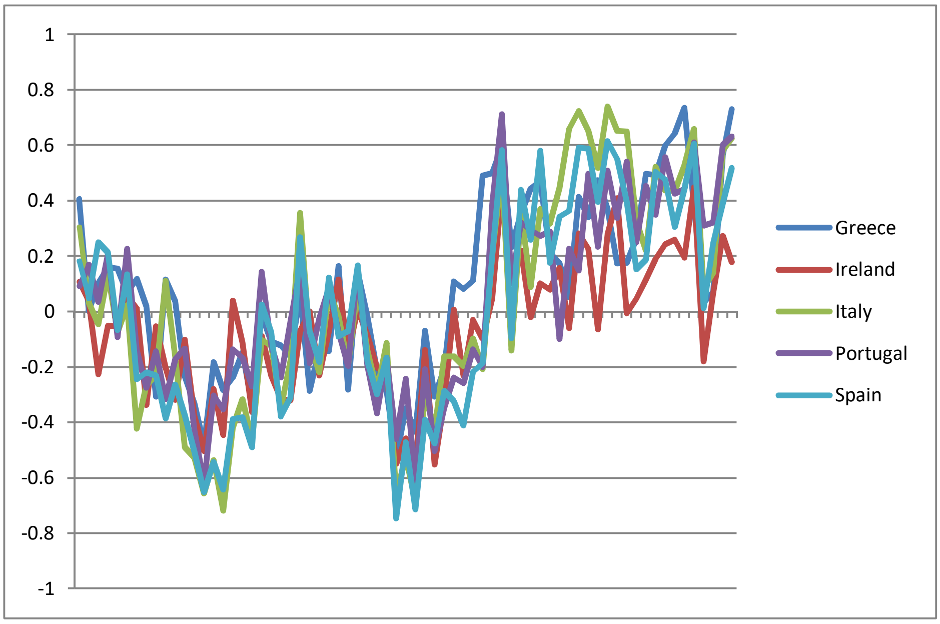
Developments of realized stock-bond correlations for the core and peripheral Eurozone countries are presented in Figures 1 and 2, respectively. Several interesting features emerge from these figures. Firstly, we observe that correlations vary substantially over time. Stock-bond comovement remains negative or slightly positive from the Euro introduction to the beginning of the Euro crisis. Although core and peripheral countries share similar patterns in the cross-asset correlation till the end of 2009, the peripheral Eurozone counties exhibit much higher and sudden increases in stock-bond correlations during the period following the Euro crisis. Interestingly, for the core countries the highest levels of correlation are found in Belgium (0.4 in the first quarter of 2012), while correlation in Germany remains relatively low up to the third quarter of 2013 when it exhibits a sudden increase, probably due to interest rate cuts by the European Central Bank.

Figure 1 Stock-bond correlations in the core Eurozone countries



Note: The figure plots quarterly realized stock-bond correlations for the core Eurozone countries

Figure 2 Stock-bond correlations in the peripheral Eurozone countries



Note: The figure plots quarterly realized stock-bond correlations for the peripheral Eurozone countries

Turning to economic factors we employ a variety of quarterly macroeconomic and financial variables as potential determinants of stock-bond correlations based on data availability and following previous research. These variable have been used by a number of researchers as potential determinants of stock-bond comovement e.g. Kim et al. (2006), Asgharian et al. (2016), Bale et al. (2010). A detailed description of the explaining variables, as well as their data sources, are presented in Table 2.

Table 2 Description of variables and data sources

Variable	Description	Source
Inflation	log difference of end of quarter harmonized consumer price index	Eurostat
Term spread	first difference in yield spread between the 10 year benchmark bond yield and the three month London interbank offer rate (LIBOR)	Datastream
Short interest rate	first difference of end-of-quarter three-month LIBOR	Datastream
Real GDP growth	log difference of quarterly seasonally adjusted real gross domestic prodcut (GDP)	Eurostat
Output gap	the percentage difference between GDP and its quadratic trend	Eurostat
Unemployment rate	first difference in quarterly unemployment rate	Eurostat
Composite leading indicator	log difference of end of quarter consumer leading indicator (CLI)	OECD
Consumer confidence indicator	log difference of end of quarter consumer confidence indicator (CCI)	OECD
VIX	(logarithm) of end-of-quarter VIX	CBOE
VSTOXX	(logarithm) of end-of-quarter VSTOXX	STOXX
Trade	first difference of (imports+exports) as a percentage of GDP	Eurostat
Stock market volatility	log of quarterly sum of daily squared stock returns	Datastream
Bond market volatility	log of quarterly sum of daily squared bond returns	Datastream

Note: This table presents a list of the explanatory variables used in BMA panel estimation, a brief description and data sources.

2.2 Methodology

The lack of consensus in the existing literature about the key determinants of stock-bond correlations and the appropriate model specification indicate a high degree of uncertainty about the "true empirical model". A stream of the literature including Kim et al. (2006), Panchenco and Wu (2009), Perego and Vermeulen (2016) use low-frequency data and panel regression techniques to explore the predictive power of macroeconomic fundamentals for the stock-bond comovement. Recent studies combine high-frequency asset market returns with low-frequency macroeconomic fundamentals exploiting the MIDAS-DCC econometric framework (e.g. Asgharian et al., 2015a, Conrad and Loch, 2016). While this specification is quite flexible allowing to model simultaneously asset correlations and the effect of their low-frequency determinants, its main shortcoming is that it is computationally difficult to include a large number of explanatory variables at a time without imposing further parameter restrictions. For example, Asgharian et al. (2015a) model the joint effect of all macro variables exploiting a principal component specification while Conrad and Loch (2016) impose the same beta weighting scheme on all economic variables.

A formal statistical framework that allows us to deal with both model and parameter uncertainty is the BMA methodology. BMA takes the model uncertainty explicitly into account, by analyzing the entire model space i.e. by comparing all possible models that could be constructed from a set of potential explanatory variables simultaneously. Moreover, it helps to identify the regressors that are most likely to influence the dependent variable by estimating the posterior probability of each model, i.e. the probability that a given model specification fits the data the best. In a classical linear regression framework, by contrast, the results are based on just one or a small number of models and only a small set of explanatory variables is included. Testing the full model (i.e. including all the potential regressors) in such a framework may lead to the false rejection of variables due to the multi-collinearity issue and the fact that parameter estimates are not robust to alternative model specifications. This is particularly an issue for small samples and a large number of regressors. The BMA methodology described below and applied in section 3 follows Fernandez et al. (2001).

Consider a set of possible linear regression models, where the *j*-th model, denoted by M_j, regresses the dependent variable, y, on a number of explanatory variables, k_j, chosen from a set of k variables ($0 \leq k_j \leq k$)

$$y = \alpha \iota_n + X_j \beta_j + \sigma \in \qquad (1)$$

where α is the intercept multiplied by an n-dimensional vector of 1's, ι_n, X_j is a n x k_j matrix with n observations of each of the k_j explanatory variables, β_j is a k_j x 1 vector including the regression coefficients for the selected regressors, $\in$ is a vector of residuals and σ is a scale parameter. Residuals are assumed to follow a multivariate normal distribution, with mean μ and covariance matrix Σ. By allowing for any subset of the k variables to appear in the model, 2^k models can be formulated.

In the BMA framework, two prior distributions need to be specified, the prior of the parameter distribution given a specific individual model, and the prior of inclusion of each explanatory variable in an individual model. For the prior distributions of the parameters in M_j (namely α, β_j and σ) we adopt non-informative priors based on the methodology of Fernandez et al. (2001) commonly used in the literature. They propose to use uninformative priors for the parameters that are common to all models, namely α and σ, and a *g*-prior structure for β_j.

$$p(\alpha,\sigma) \propto \sigma^{-1} \qquad (2)$$

and

$$p\left(\beta_j \middle| \alpha,\sigma,M_j\right) = N\left(\beta_j \middle| 0,\sigma^2\left(gX_j^{'}X_j\right)^{-1}\right) \qquad (3)$$

where N represent the multivariate normal distribution. By assuming a zero mean distribution we include no a-priori information regarding the sign of the regressors. Based on the empirical simulations of Fernandez et al. (2001) we set $g = 1/\max\{n,k^2\}$. For the a-priori distribution of model M_j over the model space

$$P(M_j) = p_j, \quad j = 1,\dots,2^k, \quad \text{with } p_j > 0 \quad \text{and} \quad \sum_{j=1}^{2^k} p_j = 1 \qquad (4)$$

we assume a uniform distribution i.e. $p_j = 2^{-k}$ implying a 50% a-priori probability of inclusion for a potential candidate variable.

For the assessment of the quality of a potential regressor, say *Z*, the BMA method accounts for model uncertainty by calculating the weighted average of the specific probabilities of inclusion over all models including the specific regressor, $P_{Z/y,\mathrm{M}_j}$, in each of the 2^k potential models, M_j, and using posterior probabilities, $P(M_j/y)$, as weights. Thus, the probability of inclusion of the selected regressor, is given by:

$$P_{Z/y} = \sum_{j=1}^{2^k} P_{Z/y,\mathrm{M}_j} P(M_j/y), \qquad (5)$$

Another quantity of interest is the sign of the regression coefficients since it hints the direction of influence. The average value of the regression coefficient, β_j, of regressor x_j, in equation (1) can be calculated as the weighted average of all coefficients estimated for models including the regresssor and using the respective model probabilities as weights. Due to the very large number of possible models (2^k possible models for *k* candidate independent variables) it is infeasible to estimate the entire model space. We search the model space approximately by applying the MC^3 Sampler (Markov Chain Monthe Carlo Model Composition) of Madigan et al. (1995) as commonly done in the BMA literature.

3. Empirical Results

We apply BMA as the model selection method to identify the determinants of stock-bond correlation in the Eurozone countries. Our dependent variable, stock-bond correlation, is the realized correlation between daily stock and bond market returns over a quarter. The inverse Fisher transformation of the original bounded correlation series, $\rho_{SB,t}$,, is used, i.e. $\rho^{*}_{SB,t} = \frac{1}{2}\ln\left(\frac{1+\rho_{SB,t}}{1-\rho_{SB,t}}\right)$ that is not bounded from minus one to one.

By combining quarterly data on realized correlations and the macroeconomic variable described in Table 2 from the second quarter of 1999 until the second quarter of 2016 for the eleven Eurozone countries we obtain a panel dataset of 748 observations (excluding lagged observations). We run BMA regressions with lagged independent variables following similar studies (Li, 2002, Perego and Vermeulen, 2016) and allowing for our model to be used for forecasting purposes. In addition, we include country dummies to exploit the panel structure of the data. Thus, our estimations are consistent with that of a country fixed effects panel estimation in a classical regression framework.

Table 3 presents the BMA estimation results for the whole sample period. The probabilities of inclusion are used to assess the importance of each regressor. These are marginal posterior probabilities computed as the weighted average of probability values from single models, using the model probabilities as weights in averaging. In a similar way, we infer the sign of the influence of each coefficient by averaging the coefficients obtained for a specific regressor in the single models and using the model probabilities as weights. Six variables display high marginal probabilities (higher than 50%). The highest probabilities of inclusion of 100% are obtained for domestic bond market volatility, VIX and inflation. While most of the previous studies on stock-market comovement focus solely on the impact of regional and global stock market uncertainty we also examine the influence of bond market uncertainty. Our results provide some significant and not previously reported evidence. Interestingly, domestic bond market uncertainty appears to have a prominent role in driving stock-bond market comovement in the Eurozone. The sign of the average coefficient is positive indicating that elevated levels of realized bond volatility significantly increase stock-bond correlations. A possible explanation is that in times of turbulent bond markets investors withdraw money from both domestic stocks and bonds and invest in other assets or safer countries.

Table 3 BMA estimation results for the whole sample period

	Probability of inclusion	Effect
Bond market volatility	1.000	Positive
VIX	1.000	Negative
Inflation	1.000	Negative
Short interest rate	0.858	Positive
Output gap	0.723	Negative
Term Spread	0.603	Negative
Consumer confidence indicator	0.443	Positive
Composite leading indicator	0.216	Positive
Unemployment rate	0.166	Negative
Stock market volatility	0.138	Negative
Trade	0.056	Positive
Real GDP growth	0.055	Positive
VSTOXX	0.027	Positive

Note: This table presents marginal posterior probabilities and the sign of the effect from the BMA estimation for the whole period i.e. from the third quarter of 1999 until the second quarter of 2016.

The well known flight-to-quality phenomenon documented in several studies (e.g. Fleming et al., 1998, Connolly et al., 2005, 2007, Asgharian et al., 2015a) is also reported in this study for European markets. Global stock market uncertainty, represented by VIX, is a significant driver of stock-bond comovements. The negative sign of the coefficient indicates that in times of increased stock market uncertainty investors transfer their money from stocks to bonds, thereby reducing stock-bond correlations. These results complement the work of De Goeij and Marquering (2004) on the asymmetric leverage effect in the stock-bond covariances. They argue that conditional covariances tend to be relatively low after bad news in the stock market and good news in the bond market. Interestingly, domestic stock market uncertainty has a negative effect on stock-bond market correlations but its probability of inclusion is low (14%).

Turning to the impact of monetary variables, we find a 100% probability of inclusion and a negative effect of inflation on the stock-bond comovement. An increase in inflation is expected to have a negative effect on bond prices by increasing discount rates. However, its effect on stock prices is rather ambiguous depending on whether the impact of elevated inflation on the discount rates or the future cash-flows will dominate. Previous studies investigating the effect of inflation on asset correlations provide mixing results. Campbell and Ammer (1993) and d' Addona and Kind (2006) provide evidence of a significant negative effect of inflation on stock-bond comovement. Other studies have shown that in periods of high inflation or inflation expectations the time-varying correlation between stock and bonds tends to rise (Ilmanen, 2003, Andersson et al., 2008, Yang et al., 2009), while Baele et al. (2010) and Aslanidis and Christiansen (2012) claim that inflation does not have a significant impact on the stock-bond comovement. Focusing on the impact of interest rate variables on bond risk, Viceira et al. (2012) support the hypothesis that the short interest rate proxies for both inflation and economic uncertainty and provide evidence for a significant positive effect of short rate on stock-bond covariance. Consistent with their findings, our results indicate a high probability of inclusion for short term interest rate. Moreover, increases in the short-term interest rate are associated with larger stock-bond correlations. This positive effect is also in line with previous evidence presented in d' Addona and King (2006), Christiansen and Aslanidis (2012) and Yang et al. (2009). Interestingly, term-structure also has a significant impact on correlations but the sign of the effect is in contrast with previous studies (see Aslanidis and Christiansen, 2012 and Viceira, 2012).

Finally, an improvement in economic conditions as expressed by a decrease in the output gap tends to increase stock-bond correlations although their effect is not that intense. The output gap seems to capture better the state of the economy compared to other variables commonly used in the literature such as the growth rate. The importance of output gap, a prime business cycle indicator, as a predictor of both stock and bond returns is highlighted in the study of Cooper and Priestley (2009). Furthermore, the positive effect of the state of the economy on stock-bond comovement is in line with Asgharian et al. (2015b) and in contrast with Andersson et al. (2008) and Conrad and Loch (2016) that report an insignificant impact. The rest of the variables do not exhibit high posterior probabilities i.e. higher than 0.5.

To shed more light on the effect of the recent financial crises on the stock-bond relation, we divide our sample into a non-crisis sample for the period starting with the monetary union until the global financial crisis and a crisis sample that starts with the global financial crisis and includes the recent and ongoing European sovereign debt crisis. Table 4 present the results from the two BMA regressions. We note several interesting findings from the comparison of the estimation results during the crisis and non-crisis periods. First, the factors that exhibit a high probability of inclusion both during non-crisis and crisis periods are the domestic bond market uncertainty and the unemployment rate.

Table 4 BMA estimation results for crisis and non-crisis periods

	Non crisis sample		Crisis sample	
	Probability of inclusion	Effect	Probability of inclusion	Effect
Stock market volatility	1.000	Negative	0.089	Positive
Unemployment rate	1.000	Negative	0.585	Negative
Bond market volatility	0.955	Positive	1.000	Positive
Short interest rate	0.656	Positive	0.309	Positive
Term spread	0.372	Negative	0.127	Negative
Trade	0.232	Positive	0.026	Positive
VSTOXX	0.209	Negative	0.098	Positive
VIX	0.192	Positive	1.000	Negative
Real GDP growth	0.156	Positive	0.697	Positive
Output gap	0.089	Positive	1.000	Negative
Inflation	0.059	Positive	1.000	Negative
Composite leading indicator	0.040	Positive	0.156	Positive
Consumer confidence indicator	0.025	Positive	0.065	Positive

Note: This table presents marginal posterior probabilities and the sign of the effect from the BMA estimations for the non-crisis period i.e. from the second quarter of 1999 until the second quarter of 2007 and the crisis period i.e. from the third quarter of 2007 until the second quarter of 2016.

In particular, domestic stock and bond market uncertainty and the state of the economy as represented by the unemployment rate are the most influential factors during the non crisis periods. A lower probability of inclusion of 66% is obtained for short-interest rates for the pre-crisis sample. During the crisis period the influence of financial market uncertainty as expressed by the domestic bond market volatility and the global stock market volatility (VIX), inflation and output gap dominate all other factors. Domestic stock market uncertainty is highly influential during the non-crisis period but its effect almost vanishes during the crisis period. It is rather the global stock market uncertainty that gives rise to the flight-to-safety phenomenon during turbulent periods. Interestingly, the unemployment rate becomes an important factor only in the sub-sample analysis. While its influence reduces substantially during the crisis period, the effect of bond market uncertainty remains highly significant during both normal and turbulent periods. A high probability of inclusion with a negative effect is exhibited for output gap also only during crisis periods.

Divergence in stock-bond correlations across different regions in the Eurozone is another interesting issue. Our aim is to examine whether our empirical results are consistent for both core and peripheral EU countries. Perego and Vermeulen (2016) use a similar segmentation of the Eurozone countries and argue that correlations in the Eurozone markets exhibit different patterns across different regions. Table 5 presents the results of the two separate BMA regressions for the core and peripheral EU countries. We fist note that the effect of the macro-finance variables on correlations differs significantly between the two regions. The only variable that exhibits a very high probability of inclusion of around 100% both for the core and peripheral EU countries is the bond market volatility confirming our previous results on the dominant role of bond uncertainty. For the core EU countries evidence supporting the flight-to-safety phenomenon is reported driven by the domestic stock market uncertainty. This effect is evident but rather limited for the peripheral countries. For the peripheral countries investors tend to exchange stocks for bonds during periods of global and not domestic financial uncertainty. Moreover, state-of-the economy and monetary variables are important drivers of stock bond comovement only in the peripheral Eurozone countries. More specifically, for the peripheral EU markets increases in short-term interest rates and decreases in inflation tend to elevate stock-bond comovement. Finally, the state-of-the-economy represented by the growth of the composite leading indicator appears to have a high probability of inclusion and a positive effect on the stock-bond correlation for this EU region.

Table 5 BMA estimation results for core and peripheral EU countries

	Core EU countries		Peripheral EU countries	
	Probability of inclusion	Effect	Probability of inclusion	Effect
Stock market volatility	0.999	Negative	0.571	Positive
Bond market volatility	0.999	Positive	1.000	Positive
Output gap	0.429	Negative	0.217	Negative
Real GDP growth	0.320	Positive	0.064	Negative
VIX	0.295	Negative	0.993	Negative
Term spread	0.288	Negative	0.271	Negative
Inflation	0.252	Negative	1.000	Negative
VSTOXX	0.144	Negative	0.058	Positive
Consumer confidence indicator	0.125	Positive	0.152	Positive
Composite leading indicator	0.088	Positive	0.752	Positive
Short interest rate	0.048	Positive	0.775	Positive
Trade	0.044	Positive	0.179	Positive
Unemployment rate	0.042	Negative	0.205	Negative

Note: This table presents marginal posterior probabilities and the sign of the effect from BMA estimations for the core EU countries (Austria, Belgium, Finland, France, Germany and Netherlands) and the peripheral EU counties (Greece, Italy, Ireland, Portugal, Spain) for the whole sample period i.e. from the second quarter of 1999 until the second quarter of 2016.

5. Robustness checks

Since the second moments of asset returns are not observable various methods have been developed for estimating correlations. We test the robustness of our results to alternative methods for estimating asset correlations by employing the time-varying dynamic conditional correlation (DCC) method proposed by Engle (2002). Firstly, for each country we estimate a univariate GARCH(1,1) model for stock and bond returns, r_{St} and r_{Bt}, respectively and obtain the standardized residuals, $z_{St} = \varepsilon_{St} / \sqrt{h_{St}}$ and $z_{Bt} = \varepsilon_{Bt} / \sqrt{h_{Bt}}$ where ε_{St}, ε_{Bt} are the residuals and h_{St}, h_{Bt} are the conditional variances from each GARH estimation. At a second step the conditional covariance matrix of the residuals, H_t=Var($\varepsilon_t | I_{t-1}$) is estimated. The DCC model develops as follows:

$$r_t | I_{t-1} \sim N(0, H_t), \quad r_t = [r_{st}, r_{b,t}]' \tag{6}$$

$$H_t = D_t R_t D_t \tag{7}$$

$$D_t = diag\left\{\sqrt{h_{i,t}}\right\} \tag{8}$$

$$z_t = [z_{St}, z_{Bt}]' = D^{-1}\varepsilon_t, \quad \varepsilon_t = [\varepsilon_{St}, \varepsilon_{Bt}]' \tag{9}$$

$$Q_t = (1 - \alpha_{SB} - \beta_{SB})\bar{Q} + \alpha_{SB} z_{t-1} z_{t-1}' + \beta_{SB} Q_{t-1} \tag{10}$$

$$\bar{Q} = E[z_{t-1} z_{t-1}'] \tag{11}$$

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{12}$$

The results of the BMA regression using DCC stock-bond correlations as a dependent variables are presented in Table 6. The results presented in this table do not differ significantly from the main results using realized stock-bond correlations (see Table 3). Local bond market uncertainty and global stock uncertainty as well as inflation, short interest rate and output gap remain amongst the most important drivers of stock-market comovement. Interestingly, local stock market uncertainty appears to have an important negative effect but its probability of inclusion remains lower than the probability of global stock uncertainty.

Table 6 BMA estimation results with DCC stock-bond correlations

	Probability of inclusion	Effect
Bond market volatility	1.000	Positive
Inflation	1.000	Negative
Short interest rate	0.970	Positive
Output gap	0.968	Negative
VIX	0.787	Negative
Stock market volatility	0.606	Negative
Unemployment rate	0.567	Negative
Composite leading indicator	0.444	Positive
Consumer confidence indicator	0.347	Positive
VSTOXX	0.268	Negative
Trade	0.068	Positive
Real GDP growth	0.065	Positive
Term spread	0.043	Negative

Note: This table presents marginal posterior probabilities and the sign of the effect from BMA estimation with DCC stock-bond correlations as the dependent variable for the whole period i.e. from the third quarter of 1999 until the second quarter of 2016.

A strand of the literature on the determinants of stock-bond comovement suggests that forecasts of macroeconomic variables such as GDP growth, inflation etc contain rich information for explaining the stock-bond relationship. For example, Asgharian et al. (2015a) use survey-based forecasts of inflation and interest rates and conclude that macro finance forecasts provide useful information. Since no survey-data are available for all the countries in the sample and for the whole sample period official forecasts of the European Commission[2] for real GDP growth and inflation are added as dependent variables in the BMA regression. We follow Dovern et al. (2012) and calculate one-year ahead fixed-horizon forecasts using current and next year forecasts as follows

$$\hat{Y}_t = \frac{q}{4}\hat{Y}_{t,current} + \frac{4-q}{4}\hat{Y}_{t,next} \qquad (10)$$

where q = 1,…,4 refers to the number of remaining quarters in the year.

[2] European Commission publishes forecasts twice per year. We convert semi-annual forecasts to quarterly using linear interpolation.

Table 7 BMA estimation results including European Commission's forecasts

	Probability of inclusion	Effect
Bond market volatility	1.000	Positive
Inflation forecast	1.000	Negative
VIX	0.978	Negative
Inflation	0.703	Negative
Term spread	0.678	Negative
Short interest rate	0.619	Positive
Stock market volatility	0.601	Negative
Unemployment	0.200	Negative
Output gap	0.053	Negative
VSTOXX	0.048	Positive
Real GDP growth	0.041	Positive
Trade	0.040	Positive
Real GDP growth forecast	0.038	Positive
Composite leading indicator	0.023	Positive
Consumer confidence indicator	0.019	Positive

Note: This table presents marginal posterior probabilities and the sign of the effect from BMA estimation including European Commission's forecasts for the whole period i.e. from the third quarter of 1999 until the second quarter of 2016.

Consistent with our previous findings inflation forecast as well as current inflation are important drivers with a negative effect on stock-bond comovement while the probability of inclusion of real GDP growth level and forecast are lower than 0.5. Employing the Internatonal Monetary Fund forecasts on real GDP growth and inflation using the same methodology does not alter our results significantly[3].

6. Conclusions

This article examines the dynamics of the comovement between stock and bond market returns in the Eurozone countries and the driving factors behind time-varying patterns. For this purpose a sample of eleven European countries extending from the beginning of the monetary union to the ongoing debt crisis is used. Naturally, a number of studies have addressed the question on what determines the time variation in stock-bond comovement, but the evidence on the literature is mixed. To face model uncertainty, the large number of determinants and multicollinearity issues a Bayesian model averaging technique is employed.

[3] Results are not reported for brevity but are available from the author upon request.

Our empirical results demonstrate that stock-bond market comovement in European countries has changed considerably over time and exhibits a substantial increase following the spreading of the financial turnoil and the recent sovereign debt crisis. Uncertainty measures including domestic stock and bond market uncertainty as well as global market uncertainty, represented by VIX, are key determinants of stock-bond comovement supporting the well documented flight-to quality phenomenon. Other important factors are inflation and interest rates variables and to a lesser extent variables representing the state of the economy. Only domestic bond market uncertainty and unemployment remain significant during normal and turbulent periods although the level of their significance changes. In addition, the effect of the domestic stock market uncertainty on the stock-bond relationship is evident only during normal periods and it appears to be substituted by the effect of global stock market uncertainty during the crisis periods. Different patterns on the impact of macro-finance drivers on stock-bond comovement are revealed when examining separately the core and peripheral EU countries. In the core countries, an increase in the domestic stock market uncertainty boosts up the segmentation of the stock and bond markets while no such effect exists in the peripheral EU countries. In the peripheral EU countries it is the global stock market uncertainty that gives rise to the flight-to-quality phenomenon.

These findings have important implications for both investors and policy makers. For investors, a continuing increase in bond market uncertainty for the Eurozone countries could elevate the degree of cross-asset integration in the Eurozone countries and reduce domestic diversification benefits. For policy makers, the divergence in the responses of stock-bond correlations across different Eurozone regions could imply that policy decisions could have asymmetric effects on the risk of stock-bond portfolios. In future work it would be interesting to exploit the information content of macroeconomic variables for forecasting stock and bond correlations in future periods.

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