High- and Low-Frequency Correlations in European Government Bond Spreads and Their Macroeconomic Drivers *

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October 13, 2013

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*We wish to thank Jan Novotny for insightful discussions and very useful comments on a previous version of the paper. The usual disclaimer applies. Special thanks to Morningstar, in particular to Richard Barden, for having made available the rich and unique data set used in this paper. Simona Boffelli acknowledges financial support from the Centre for Econometric Analysis, Cass Business School, London, UK.

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Abstract

We propose high-frequency MIDAS regression models to estimate high- and low-frequency correlations in the 10-year government bond spreads for Belgium, France, Italy, the Netherlands and Spain relative to Germany, from 1-June-2007 to the 31-May-2012. The high-frequency component, reflecting financial market conditions, is evaluated at 15-minute frequency, while the low-frequency component, fixed through a month, depends on country specific macroeconomic conditions. We find strong links between spreads volatility and worsening macroeconomic fundamentals; in presence of similar macroeconomic fundamentals relative spreads move together; the increasing correlation in spreads during the pick of the sovereign debt crisis cannot be ascribed to macroeconomic factors.

Keywords: High-Frequency MIDAS Models, Government Bond Spreads, Macroeconomic Variables, Correlations, Volatilities.

J.E.L. Classification Numbers: E44, G12, H63, C32, C58.

1 Introduction

According to the covered interest parity condition, two otherwise equivalent bonds issued in two different currencies should have the same yield expressed in one currency. However, deviations from covered interest parity condition evaluated on sovereign bond yields may occur because of different default risk of the issuer, different liquidity conditions and characteristics of the bonds, and also because of imperfect market integration either preventing or slowing down trading arbitrage to eliminate yield differences. If we consider European government bonds of a same maturity, and similar liquidity, any difference between two or more countries should be ascribed to credit risk which itself depends on country-specific macroeconomic and financial fundamentals. Therefore there should exists a linkage between macroeconomic fundamentals and government bond spreads.

Investigating the existence and the nature of the relationship between market volatility and macroeconomic fundamentals is crucial in understanding issues relevant to policy makers and institutional investors. For instance, by analyzing the comovements during the current sovereign debt crisis, we could assess market perception of sovereign debt risk. In particular, one would expect countries with larger fiscal deficits or with worst economic fundamentals to be characterized by higher volatility in their bond markets with respect to more stable countries, with this differential becoming more pronounced during crisis periods. In addition, we may verify whether all countries experience a worsening in government bond spreads because of a regime shift in the market pricing of government credit risk during a turmoil period. These issues are relevant not only to macroeconomists and policy makers studying systemic risk but are also of interest to financial investors working in derivatives pricing, portfolio selection and risk management since they help to uncover linkages between price movements and underlying risk factors or business cycle state variables.

There is a rich empirical literature investigating the impact of macroeconomic fundamentals on stock market volatility since the seminal paper by Schwert (1989). Focusing on longer horizon bond returns, Attinasi et al. (2011) identify several important factors as possible determinants of risk premia paid by governments relative to the benchmark country, the most relevant being the country's creditworthiness as reflected by its fiscal and macroeconomic position. Other factors affecting government bond spreads are liquidity risk, international risk aversion, macroannouncements and fiscal policy events. Bikbov and Chernov (2010) also find that the 10-year premium is more responsive to macroeconomic conditions than the 1-year premium, while the term premia declines in response to good economic conditions, captured by the increase in either real activity or inflation. Aizenman et al. (2013) estimate the pricing of sovereign risk for sixty countries based on fiscal space and other economic fundamentals showing that, although these variables significantly determine market-based sovereign risk, the explanatory power of fiscal stance measures (e.g. debt-to-GDP) drops during the crisis period. In particular, risk pricing of the peripheral countries such as Greece, Ireland, Italy, Portugal and Spain is not predicted accurately with the periphery default risk being priced much higher than the risk for other European countries.

An alternative interpretation given by Aizenman et al. (2013) to the failure of macroeconomic fundamentals to explain volatilities is that market is not pricing on current but on expected (future outlook of) fundamentals and therefore the inability of models to capture such high spreads is due to the market expectation that peripheral countries fundamentals will deteriorate. Thus, Aizenman et al. (2013) suggest to incorporate in the model not only real economy measures but also forward looking indicators. Similarly, von Hagen et al. (2011) show that bond yield spreads before and during the crisis are largely explained by the impact of fiscal imbalances becoming more relevant after the Lehman & Brothers default in September 2008, identifying the higher general risk aversion, measured by corporate credit spreads, as the main cause of the increase in the spread on non-benchmark bonds. Mody (2009), investigating the drivers of European government bond spreads, shows that before the start of the subprime crisis in July 2007, the weekly changes in spreads were essentially random with no obvious determinants while, once that the crisis burst and through to the rescue of Bear Stearns, the movements in spreads reflect global factors, in particular a flight to quality and global financial sector instability. Attinasi et al. (2011) analyze the impact of unemployment, industrial production and inflation measures on European spreads concluding that real activity is only weakly correlated with yields while inflation strongly contributes to explain spreads. This result is in contrast with Ludvigson and Ng (2009) and Lustig et al. (2012) where the importance of industrial production in explaining returns for both bonds and foreign exchange is assessed[1]. Ang and Piazzesi (2003) are the first to analyze the sensitivity of the entire term structure to macroeconomic fundamentals providing evidence that macro factors explain the 85% of bond yields variance. Finally, in the analysis of the link between macroeconomic fundamentals and government bond spreads, a great attention has been devoted to countries fiscal conditions. Barrios et al. (2009) present empirical evidence of the strong positive relationship between current account deficits, foreign debt and risk aversion with sovereign risk premium, while Gros (2011) shows that foreign debt is more important than public debt.

In this paper, we assess whether and how the 10-year European government bond spreads intraday movements were driven by macroeconomic fundamentals, both in terms of volatility and correlations. The main issue we focus on is of relevance given the strong increase in government bond spreads, especially of peripheral countries, experienced during the recent European sovereign crisis; this has generated ample debate between economists about whether spreads reflect worsening economic conditions or rather speculative trading activity leading to an overshooting of spreads.

This paper also offers a methodological contribution. In order to jointly model high-

[1] The role of macroeconomic drivers is also important in modelling other asset classes. Paye (2012) shows that macroeconomic variables (including commercial paper-to-Treasury spread, default return, default spread and the investment-to-capital ratio) significantly explain S&P 500 market volatility, particularly pronounced during recession periods. Christiansen et al. (2012) evaluate the dependence of volatility of a broad range of asset classes (equity, bond, commodities and foreign exchange) on macroeconomic and financial variables providing evidence of the significant role played by proxies for credit risk, funding liquidity and time-varying risk premia, while inflation and industrial production turned out to be less informative. A similar result is reported in Baele et al. (2010) where, using a dynamic factor model to study comovements between stock and bond returns, the authors report that macroeconomic factors (output gap, inflation and short rate) mildly contribute to explain stock and bond return correlations while other factors, such as liquidity proxies, play an important role. Finally, relationship between volatile fundamentals and volatile stock markets in a cross-section of countries is also reported in Diebold and Yilmaz (2010) and Hilscher and Nosbusch (2010).

and low-frequency multivariate time series, we adopt and extend the MIxed Data Sampling (MIDAS) approach, proposed in the seminal papers by Ghysels, Santa-Clara and Valkanov (2004, 2005, 2006) and Ghysels, Sinko, and Valkanov (2007). The MIDAS framework allows linking financial market data, sampled at high-frequency, in general daily, and data on macroeconomic fundamentals recorded at lower frequency, in general monthly or quarterly[2]. This paper makes two contributions to MIDAS literature. First, the MIDAS approach is extended to the case when tick-by-tick financial market data are available though resampled at an appropriate frequency, in particular we combine 15-minute frequency data on spreads with monthly macroeconomic data. To the best of our knowledge, there has been no previous attempt to apply MIDAS framework to high-frequency data. Second, we extend the Colacito et al. (2011) DCC-MIDAS based upon a pure time series approach by allowing the low-frequency (monthly) correlation to be driven by country macroeconomic fundamentals. Finally, another important contribution of the paper is that, by exploiting high- and low-frequency correlations, we evaluate time-varying possible phenomenon of ongoing economic and financial markets integration amongst European countries.

The remainder of the paper is organized as follows. In Section 2, we discuss the dataset and the macroeconomic variables. Section 3 presents the high-frequency MIDAS regression models and discusses some data preparation procedures. In Section 4, we report the results for both univariate and multivariate GARCH-MIDAS models. Section 5 concludes.

[2]Recent developments in the mixed-frequency literature are Andreou, Ghysels and Kourtellos (2010) and Ghysels (2012) for regression and VAR models, Ghysels, Hill and Motegi (2013) in testing for Granger causality, Andreou, Ghysels and Kourtellos (2013) and Galvao (2013) for the evaluation of the predictive ability of financial variables.

2 Data Description

2.1 Spreads

We use data for the 10-year government bonds of Belgium, France, Germany, Italy, Spain and the Netherlands over the period 1st June 2007 - 31st May 2012. We consider bid data. The 10-year bonds are bond market benchmarks at the most active maturities. Morningstar provided us with this unique tick-by-tick data sample that we resampled at the microstructure noise robust 15-minute frequency using calendar time, excluding time intervals with missing values for at least one country.

The trading period considered is 8 a.m.-3:30 p.m. coordinated universal time (UTC). We detect and remove holidays and outliers by applying a filter which is a modification of the procedure to remove outliers proposed in Brownlees and Gallo (2006). Following the steps suggested by Barndorff-Nielsen et al. (2011, p. 156), the implementation can be summarized as follows.

Let $p_{t,i}$ be a tick-by-tick time series of prices, where $t = 1, ..., T$ denotes day and $i = 1, ..., N$ the time interval within day t, then an observation is removed iff:

$$\left|p_{t,i} - \overline{p}_{t,i}\left(k^L\right)\right| > \max\left\{4MD_{t,i}(k), n\gamma\right\} \quad \wedge \quad \left|p_{t,i} - \overline{p}_{t,i}\left(k^R\right)\right| > \max\left\{4MD_{t,i}(k), n\gamma\right\} \qquad (1)$$

where k is the bandwidth, $\overline{p}_{t,i}\left(k^L\right)$ and $\overline{p}_{t,i}\left(k^R\right)$ are sample medians of the $k/2$ observations before (L for left) and after (R for right) (t, i), respectively, $MD_{t,i}(k)$ is the mean absolute deviation from the median of the whole neighborhood, $\wedge$ is the logical conjuction operator and n $\gamma-$multiplier.

The advantage of this rule lies in the separate comparison of the $(t, i)-$th trade against the left and right neighbours while the measure of dispersion is calculated on the whole bunch of k trades. This approach is specifically designed to avoid detecting jumps as false outliers.

Finally, we also remove the first return of the day that occurs at 8 a.m. as it largely reflects the adjustment to information accumulated overnight and hence exhibits a spurious excess variability compared to any other 15-minute interval. The data selection procedure is summarized in Table 1.

[Insert here Table 1]

For each time series, we report the overall number of ticks available from which we remove holidays, weekends and trades occurred outside the trading period 8 a.m. - 3:30 p.m. UTC. Following the filtering procedure in (1), we detect a percentage of outliers ranging from 0.09% for Germany to the 0.16% for Belgium. In addition, we also report some descriptive statistics to get useful insights about market liquidity. In particular, we compute the mean number of trades per day and the time elapsed between two consecutive trades, where both statistics indicate that the most liquid market is the German one with a daily average number of trades of 2,345 and a trade duration of 14 seconds, followed by France (828 trades, 38 seconds), Spain (764 trades, 38 seconds), Italy (736 trades, 43 seconds), Belgium (659 trades, 47 seconds) and the Netherlands (513 trades, 60 seconds). After resampling at the 15-minute frequency and removing the 8 a.m. return for each day, we end up with 38,370 returns, covering 1,279 days corresponding to 30 observations per day. In Table 1, we also report descriptive statistics about yields and spreads with respect to German Bund: Italy has the highest average yield (4.66%), while Germany has the lowest equal to 3.18%; the average bid spread with respect to Germany is equal to 150 bps for Italy, 140 for Spain, 83 for Belgium, 42 for France and 30 for the Netherlands. The information that the average indicator offers is limited in the light that government bond spreads vary a lot throughout our sample period as it is evidenced in Figure 1.

[Insert here Figure 1]

Government bond spreads move very closely until May 2010, when markets start to pay more attention to sovereign debt risk as a response to the burst of Greek crisis. In

May 2010, the Greek government deficit was revised and estimated to be 13.6% of GDP leading to reduction of confidence in Greece's ability to repay its debt. Despite the first rescue package was then approved by European countries and the IMF, concerns about Euro countries solvability began to raise together with spreads.

2.2 Macroeconomic Variables

We select two real economy variables, employment and industrial production, and a forward looking indicator, the economic sentiment. Our choice is motivated by the existing literature such as, amongst others, Mody (2009) and Aizenman et al. (2013). Macroeconomic data are available at monthly frequency and were obtained from the Eurostat website, starting from January 2005 up to May 2012. The economic sentiment is also provided by Eurostat and it is composed of five sectoral confidence indicators with different weights: industrial, services, consumer, construction and retail trade.

Given that the dependent variable in our study is expressed in terms of difference of the 10-year government bond yields of each country and Germany, also the macrovariables, reported in Figures 2-4, are expressed in terms of difference between each country and Germany macrovariables.

[**Insert here Figures 2-4**]

All the macroeconomic variables considered capture very well the worsening macroeconomic conditions starting from the last quarter of 2008, with the dramatic drop of the level of employment for Spain and the strong contraction of industrial production, especially evident for Spain, Italy and France. It is worth noticing that the literature on the topic (see for instance Barrios et al. 2009, and Gros 2011), often consider as potential macroeconomic drivers measures of fiscal sustainability such as debt-to-GDP. First, there is the case that Spain was experiencing a very high spread despite it had a debt-to-GDP ratio (69.3% in 2011 and 84.2% in 2012, defined as consolidated general government gross debt to GDP) below or approximately equal to the German one (80.4% and 81.9%), on the contrary Belgium showed a low spread despite a debt-to-GDP (97.8% and 99.6%) higher than the Spanish one (Note that it was 85.8% and 90.2% for France, 120.8% and 127.0% for Italy, 106.4% and 117.6% for Ireland, 65.5% and 71.2% for the Netherlands). This suggests that debt-to-GDP may not be an appropriate economic indicator to influence government bond spreads. In addition, the debt dynamics is determined by economic growth perspectives which are better captured by the macroeconomic variables considered in our analysis. Finally, deb-to-GDP is available at quarterly frequency while all the other macroeconomic indicators are available at monthly frequency. For all these reasons, especially last one, we do not consider this indicator in our analysis.

In addition to the level of macroeconomic fundamentals, we are going to investigate also the impact of their volatilities on government bond spreads: ceteris paribus, a country with more volatile fundamentals is more likely to experience a severe weakening of its macroeconomic conditions which may force it into default. Volatility of macroeconomic fundamentals is estimated, following Schwert (1989), by fitting an autoregressive model for each macrovariable Y_τ augmented by some dummy variables D_τ^j corresponding to the aggregation period of interest U (e.g. months, quarters, years):

$$Y_\tau = \sum_{j=1}^{U} \alpha_j D_\tau^j + \sum_{i=1}^{U} \beta_i Y_{\tau-i} + \varepsilon_\tau \tag{2}$$

The squared residuals $\widehat{\varepsilon}_\tau^2$ provide an estimate of macroeconomic volatility whose frequency corresponds to the frequency at which macrovariables are sampled.

3 Modelling Mixed-Frequency Times Series

MIDAS represents a simple, parsimonious and flexible class of time series models that allow the left- and right-hand variables of time series regressions to be sampled at different frequencies. The MIDAS framework allows using the raw data avoiding any apriori prefiltering. The literature on MIDAS deals with high-frequency data measured at daily frequency while the data at low-frequency are sampled monthly and quarterly.

In this paper, we extend the MIDAS approach into intraday frequency domain and propose to evaluate the impact of the slowly moving component measured at monthly frequency on high-frequency returns sampled using a 15-minute time window. This intraday frequency is fast enough to capture intraday movements and it is robust to both asynchronicity and microstructure noise. In particular, we compare models estimated using a pure *time series approach*, where both high- and low-frequency components are obtained from asset returns, with the case where the slowly moving component, in both volatility and correlation, is driven by *macroeconomic variables* measured at monthly frequency. For this purpose, we extend the GARCH-MIDAS model of Engle et al. (2013) and the DCC-MIDAS model proposed by Colacito et al. (2011).

3.1 High-Frequency MIDAS Regression Models

Let us consider an $(M \times 1)$ vector of returns for the i-th subinterval belonging to month τ $r_{\tau,i} = \left[r^1_{\tau,i}, ..., r^M_{\tau,i}\right]'$ distributed as a multivariate normal variable with mean vector μ and variance covariance matrix $H_{\tau,i}$ of order $(M \times M)$. Following the classical DCC model of Engle (2002), the variance-covariance matrix $H_{\tau,i}$ can be decomposed as $D_{\tau,i}R_{\tau,i}D_{\tau,i}$ with $D_{\tau,i}$ diagonal matrix of volatilities and $R_{\tau,i}$ conditional correlation matrix. By applying the GARCH-MIDAS by Engle et al. (2013), where the overall volatility can be decomposed into two parts, one pertaining to short term fluctuations, $g_{\tau,i}$ and the other to a long-run secular component, ψ_τ, the univariate volatilities can be modeled as:

$$r_{\tau,i} = \mu + \sqrt{\psi_\tau g_{\tau,i}}\varepsilon_{\tau,i} \tag{3}$$

where $\varepsilon_{\tau,i}|\Phi_{\tau,i-1} \sim N(0,1)$ with $\Phi_{\tau,i-1}$ the information set available up to $(\tau, i-1)$.

The volatility dynamics of the high-frequency component $g_{\tau,i}$ is modeled as a GARCH(1,1) process:

$$g_{\tau,i} = (1 - \alpha - \beta) + \alpha \frac{\varepsilon^2_{\tau,i-1}}{\psi_\tau} + \beta g_{\tau,i-1} \tag{4}$$

while the low-frequency component can be modeled using a pure time series approach with ψ_τ being a smooth average of the most recent U monthly realized volatilities RV_τ on a fixed span window as described in:

$$\log \psi_\tau = m + \vartheta \sum_{u=1}^{U} \varphi_u(\omega) RV_{\tau-u} \tag{5}$$

with $\varphi_u(\omega)$ being the weighting scheme which can be based on either a beta or an exponential function:

$$\varphi_u(\omega) = \begin{cases} \frac{(u/U)^{\omega_1-1}(1-u/U)^{\omega_2-1}}{\sum_{j=1}^{U}(j/U)^{\omega_1-1}(1-j/U)^{\omega_2-1}} & \text{Beta} \\ \omega^u / \left(\sum_{j=1}^{U} \omega^j\right) & \text{Exponential} \end{cases} \tag{6}$$

In our empirical applications, in the light that the two weighting functions are equivalent in terms of goodness of fit (see Engle et al. 2013), we use the beta exponential function where the parameter ω_1 is set to 1 in order to assure that weights are slowly decaying. We call this the Time Series GARCH-MIDAS (TS GARCH-MIDAS) model.

The second specification for the low-frequency component ψ_τ depends on macroeconomic variables. We adopt the following specification:

$$\log \psi_\tau = m + \sum_{s=1}^{S} \vartheta^{s,l} \sum_{u=1}^{U} \varphi_u^{s,l}(\omega) X_{\tau-u}^{s,l} + \sum_{s=1}^{S} \vartheta^{s,v} \sum_{u=1}^{U} \varphi_u^{s,v}(\omega) X_{\tau-u}^{s,v} \tag{7}$$

where $X_{\tau-u}^{s,l}$ is defined as $\text{abs}\left(\frac{Y_{\tau-u}^{s,l}}{Y_{\tau 0}^{s,l}} - \frac{Y_{\tau-u}^{s,l,DE}}{Y_{\tau 0}^{s,l,DE}}\right)$, $Y_\tau^{s,l}$ indicates the level (l) of the macroeconomic variable s at month τ so that $Y_{\tau_0}^{s,l}$ is the first available value, $Y_\tau^{s,l,DE}$ refers to the same macrovariable s for Germany which serves as benchmark country. During the time window analyzed both government bond spreads volatility and the absolute difference between macroeconomic fundamentals of each country and Germany increased substantially and therefore it is mandatory to maintain the common pattern between the two time series. $X_{\tau-u}^{s,v}$ is specified as $abs\left(Y_{\tau-u}^{s,v} - Y_{\tau-u}^{s,v,DE}\right)$ where $Y_{\tau}^{s,v}$ volatility (v) of macrovariable s defined as in (2). $Y_{\tau}^{s,v,DE}$ refers to the volatility of the same macrovariable s for Germany. $\varphi_u(\omega)$ are beta weights as in (6) and U is the maximum lag for macrovariable s, with $s = 1, ..., S$ with S representing the total number of macroeconomic variables. We refer to this model as the GARCH-MIDAS with Macroeconomic Variables (MV GARCH-MIDAS) model.

Similarly to the TS GARCH-MIDAS in (5), the long run component is a smooth average of the most recent U values of each macrovariable s, for which we consider both level and volatility. Unlike Engle et al. (2013), we allow each macrovariable s, in both level and volatility components, to enter the model with a specific coefficient $\vartheta^{s,l/v}$. In this way, the model is more flexible and it also allows to measure the role played by each macroeconomic variable in explaining the long run volatility.

Engle et al. (2013) propose a measure of the amount of volatility explained by the long-term component on the overall volatility, the so-called *variance ratio* specified as:

$$\frac{Var\left(\log\left(\psi_{\tau}\right)\right)}{Var\left(\log\left(g_{\tau,i}\psi_{\tau}\right)\right)} \tag{8}$$

Once univariate volatilities are estimated, the main focus is on the correlation dynamics. Colacito et al. (2011) show that the high-frequency correlations obey a standard DCC scheme but here the intercept is a slowly moving process that reflects the fundamental or long-run causes of time variation in correlations.

Based on the DCC framework by Engle (2002), the elements $\rho_{\tau,i}^{kj}$ of the conditional correlation matrix $R_{\tau,i}$ for month τ and subinterval i, with $k, j = 1, ..., M$, are computed as:

$$\rho_{\tau,i}^{kj} = \frac{q_{\tau,i}^{kj}}{\sqrt{q_{\tau,i}^{kk}}\sqrt{q_{\tau,i}^{jj}}} \tag{9}$$

whose elements $q^{kj}_{\tau,i}$ are modeled by:

$$q^{kj}_{\tau,i} = \overline{\rho}^{kj}_{\tau}(1 - a - b) + a\xi^{k}_{\tau,i-1}\xi^{j}_{\tau,i-1} + bq^{kj}_{\tau,i-1} \tag{10}$$

where the intercept is time dependent and it is specified as a smooth weighted average of the most recent U^{kj} correlation matrixes of standardized residuals $\xi_{\tau,i} = D^{-1}_{\tau,i}\left(r_{\tau,i} - \mu\right)$ as in (11):

$$\overline{\rho}^{kj}_{\tau} = \sum_{u=1}^{U^{kj}} \varphi_u\left(\omega^{kj}\right) c^{kj}_{\tau,i-u} \tag{11}$$

$$c^{kj}_{\tau,i-u} = \frac{\sum\limits_{l=\tau,i-U^{kj}}^{\tau,i} \xi^{k}_{l}\xi^{j}_{l}}{\sqrt{\sum\limits_{l=\tau,i-U^{kj}}^{\tau,i} \left(\xi^{k}_{l}\right)^{2}}\sqrt{\sum\limits_{l=\tau,i-U^{kj}}^{\tau,i} \left(\xi^{j}_{l}\right)^{2}}} \tag{12}$$

where $\varphi_u\left(\omega^{kj}\right)$ is the beta weighting function in (6).

The model proposed in Colacito et al. (2011) is a pure time series approach where the long run correlation is allowed to be time dependent. In this paper, we propose to link the long run correlation $\overline{\rho}^{kj}_{\tau}$ to relevant macroeconomic indicators/variables. The intuition is that the long-term correlation component should be interpreted as the predicted or the expected correlation given a certain state of the economy, while deviations of the short-run correlations from the long-run should be influenced by other factors related to trading activity.

Thus, we propose the following specification:

$$\begin{aligned}\gamma^{kj}_{\tau} \;\; = \;\; & m^{kj} + \sum_{s=1}^{S} \vartheta^{s,l} \sum_{u=1}^{U} \varphi^{s,l}_{u}\left(\omega\right)\left|\Delta Y^{k;s,l}_{\tau-u} - \Delta Y^{j;s,l}_{\tau-u}\right| + \\ & \sum_{s=1}^{S} \vartheta^{s,v} \sum_{u=1}^{U} \varphi^{s,v}_{u}\left(\omega\right)\left|\Delta Y^{k;s,v}_{\tau-u} - \Delta Y^{j;s,v}_{\tau-u}\right|\end{aligned} \tag{13}$$

Given that correlations follow stationary processes, we consider the rate of changes of the macroeconomic variable levels (l) with respect to the previous period defined as $\Delta Y^{k;s,l}_{\tau} =$

$100 \times \left[\ln\left(Y_{\tau}^{k;s,l}\right) - \ln\left(Y_{\tau-1}^{k;s,l}\right)\right]$ for the macroeconomic fundamental s of country k between months τ and $\tau - 1$. Moreover, we expect that the correlation between country k and country j increases when the absolute difference in fundamentals of the two countries vanishes and to decrease when the fundamentals diverge. Therefore, we enter the model with a measure of the absolute difference in the rate of change for macrovariable s during the period $(\tau, \tau - 1)$ between two countries k and j defined as $\left|\Delta Y_{\tau}^{k;s,l} - \Delta Y_{\tau}^{j;s,l}\right|$. For the volatility component, we compute the volatility of changes for macroeconomic fundamental s occurred during the period $(\tau, \tau - 1)$ for country k defined as $\Delta Y_{\tau}^{k;s,v}$. As for the level, we consider the absolute difference between the volatility of changes for macrovariable s for the two countries k and j which takes the form $\left|\Delta Y_{\tau}^{k;s,v} - \Delta Y_{\tau}^{j;s,v}\right|$. Again the assumption is that as the absolute difference of fundamentals volatility between two countries tends to zero, countries should move in a more similar way and vice versa.

To guarantee that γ_{τ}^{kj} lies between -1 and +1, following Christodoulakis and Satchell (2002), we adopt the Fisher-z transformation (Fisher 1915) of the correlation matrix:

$$\overline{\rho}_{\tau}^{kj} = \frac{\exp\left(2\gamma_{\tau}^{kj}\right) - 1}{\exp\left(2\gamma_{\tau}^{kj}\right) + 1} \tag{14}$$

and we apply the shrinkage technique as proposed in Kwan (2008) and implemented in Golosnoy and Herwartz (2012), consisting in identifying the minimum $\lambda \in [0, 1)$ such that the matrix $\widetilde{R}_{\tau,i}$, defined as:

$$\widetilde{R}_{\tau,i} = (1 - \lambda)R_{\tau,i} + \lambda I \tag{15}$$

is positive semidefinite, where I is $(M \times M)$ identity matrix and λ determines the proportion to which the eigenvalues of the matrix $R_{\tau,i}$ shrunk to unity.

3.2 Data Preparation

For both model specifications, we identify jumps for all the returns series so that variance estimates obtained from GARCH models are not influenced by large jump deviations. For the identified jumps, we substitute the value of the threshold used to test for the presence of jumps. For instance, we identify jumps using the robust Lee and Mykland (2008) test filtered for the intraday periodicity $\widehat{s}_{t,i}$ as proposed by Boudt et al. (2010):

$$FJ_{t,i} = \frac{|r_{t,i}|}{\widehat{\sigma}_t \widehat{s}_{t,i}} \tag{16}$$

where $|r_{t,i}|$ is the absolute value of log-return on day t and time-interval i and $\widehat{\sigma}_t$ is the bipower volatility of day t. Having adopted the Lee and Mykland (2008) test, the threshold is given by:

$$\left(S_T\beta^* + C_T\right)\left(\widehat{\sigma}_t \widehat{s}_{t,i}\right) sgn(r_{t,i}) \tag{17}$$

where $S_T = 1/\left(2\log\left(T \times N\right)\right)^{1/2}$, $(T \times N)$ time series length, $\beta^* = -\ln(-\ln(1-\alpha))$ with α the significance level of the test, and

$$C_T = \left(2\log\left(T \times N\right)\right)^{1/2} - \log\pi + \left(\log\left(\log\left(T \times N\right)\right)\right) / \left(2\left(2\log\left(T \times N\right)\right)^{1/2}\right)$$

where sgn indicates the sign function.

We identify a variable percentage of jumps: 1.37% for Spain, 1.31% for Belgium, 1.14% for Italy, 0.74% for France, and 0.60% for the Netherlands. The mean absolute size of jumps ranges from a minimum of 3.70% for the Netherlands to a maximum of 6.28% for Italy.

As far as the periodicity component $\widehat{s}_{t,i}$, we adopt a non-parametric formulation, namely the Weighted Standard Deviation (WSD). Let $\widetilde{r}_{(1),m}, \ldots, \widetilde{r}_{(\widetilde{T}),m}$ be the order statistics of standardized returns (by the bipower volatility) such that $\widetilde{r}_{(1),m} \leq \widetilde{r}_{(2),m} \leq \ldots \leq \widetilde{r}_{(\widetilde{T}),m}$ sharing the same periodicity factor $\widetilde{r}_m$. Assume that the periodicty factor depends only on the time of the day and day of the week shared by $\widetilde{T}$ observations. The WSD periodicity factor is defined as:

$$\widehat{s}_m^{WSD} = \frac{WSD_m}{\sqrt{\frac{1}{\widetilde{T}} \sum_{j=1}^{\widetilde{T}} WSD_{j,m}^2}} \tag{18}$$

where:

$$WSD_m = \sqrt{1.081 \frac{\sum_{j=1}^{\widetilde{T}} w_{j,m} \widetilde{r}_{j,m}^2}{\sum_{j=1}^{\widetilde{T}} w_{j,m}}} \tag{19}$$

The weights in (19) are given by $w_{j,m} = w\left(\widetilde{r}_{j,m}/\widehat{s}_m^{ShortH}\right)$ where the weight function is defined as $w(z) = 1$ if $z^2 \leq 6.635$ and 0 otherwise and $\widehat{s}_m^{ShortH}$ is an alternative less efficient non-parametric estimator for the periodicity (see Boudt et al. 2010, for more details).

Once jumps have been filtered out, returns are standardized by the intraday periodicty $\widehat{s}_{t,i}$, in order to control for the U-shape. Finally, on the standardized and jump-free returns, we fit an ARMA(1,1) model.

4 Empirical Results

4.1 Univariate Models

4.1.1 Time Series GARCH-MIDAS Models (TS GARCH-MIDAS)

The first model we estimate is the GARCH-MIDAS where the long run component is a smooth weighted average of monthly realized volatilities (RV) computed on a fixed span window as described in (5). In Table 2, we report estimates for the TS GARCH-MIDAS. The monthly frequency is adopted as this is the shortest frequency at which the macroeconomic variables are available. Following Engle et al. (2013), in estimating the GARCH-MIDAS model we put special care in selecting the lag structure in each MIDAS polynomial specification for ψ_τ (U in our notation). To this purpose, we estimate three alternative specifications corresponding to 3, 6 and 12 months and comparing the log-likelihoods we choose the MIDAS lag equal to 6 months. As per the weight function, we select the beta lag function in (6) setting $\omega_1 = 1$ so that weights are monotonically decreasing over the lags, with the shape of weights governed by ω_2. Moreover, following Engle et al. (2013), in order to avoid numerical instability in the estimation procedure, we set an upper bound equal to 300 for ω_2.

[Insert Table 2 here]

Almost all coefficients in Table 2 are statistically significant, both those related to standard GARCH (α and β) and those related to the MIDAS model (m, θ, and ω_2). As expected, the sum of the parameters α and β is close to 1. Estimates of θ indicate that long run volatility at time (τ, i) depends positively on past realized volatilities. The beta weight parameters ω_2 assume values greater than 1 ranging from 3.37 to 6.84, implying that weights follow a decaying pattern with higher weights attributed to more recent RVs and lower weights to the past RVs.

Another important result in Table 2 is the high values of the variance ratios measuring the amount of the overall volatility explained by the long term component. There is evidence that the long run variance contributes substantially to explain the overall volatility, ranging from a maximum of 0.85 for Spain to a minimum of 0.37 for the Netherlands.

In Figure 5, we report the estimated volatility, at high-frequency (blue line) and at low-frequency (black line) components obtained from the estimates reported in Table 2.

[Insert Figure 5 here]

There is evidence that the volatility of government bond spreads increased substantially for all the countries, and this pattern is particularly pronounced for Italy and Spain and to a less extent for France, Belgium and the Netherlands.

4.1.2 GARCH-MIDAS Models with Macroeconomic Variables (MV GARCH-MIDAS)

In the second GARCH-MIDAS specification, the low-frequency component is driven by macroeconomic variables (employment, industrial production and economic sentiment) as described in (7). As macroeconomic variables are measured at monthly frequency, the long run component of volatility remains constant through each month. Finally, in order to be able to compare the results of this model with those reported in Table 2, we fix the MIDAS lag equal to 6 months and in the beta lag function in (6) we set $\omega_1 = 1$, estimating the parameter ω_2 with an upper bound for ω_2 equal to 300. We report the results of the estimated MV GARCH-MIDAS in Table 3.

[Insert Table 3 here]

Overall, the macroeconomic variables are statistically relevant in explaining the volatility of European sovereign spreads. In particular, the most important driver is the absolute difference between each country industrial production with respect to Germany: an increase of that difference determines a correspondent increase in volatility of Belgian, French, Italian and Spanish and Belgian spread and a decrease in Dutch spread. This finding is supported also by Ludvigson and Ng (2009) and Lustig et al. (2012). As far as the economic sentiment is concerned, an increase in the absolute difference with respect to Germany implies a higher spread volatility for Belgium, Italy and Spain while it is negative for the Netherlands. In line with findings in Aizenman (2013) and Veronesi (1999), this result suggests that volatility has a forward looking nature reflecting the uncertainty about future macroeconomic conditions: the higher the uncertainty, the lower the economic sentiment is and the higher the market volatility becomes. Finally, increasing absolute difference in employment level with respect to Germany determines an increase in spreads just for the Netherlands while it has a negative effect on all other countries. Considering now the differences between each country and German volatility fundamentals, it is possible to conclude that they are less important than the levels. Moreover, no clear pattern is identifiable as, in case of employment, an increase in volatility difference determines a lower volatility in France, Italy and Spain and a higher one for the Netherlands. Higher volatility difference for industrial production generates higher volatility for France while an increase in volatility difference of economic sentiment implies a lower spread volatility for France and the Netherlands. A final important result reported in Table 3 relates to the variance ratios, which appear quite high for each country, ranging from a minimum of 0.42 for Belgium to a maximum of 0.87 for Spain. This indicates that the long term component modeled by macroeconomic variables explains a great amount of total volatility. In Figure 6, we depict the low and the high-frequency components of volatility obtained from the estimates reported in Table 3.

[Insert Figure 6 here]

4.1.3 Comparison Between the TS GARCH-MIDAS and MV GARCH-MIDAS Specifications

In Table 4, we report the results of the comparison between TS GARCH-MIDAS and MV GARCH-MIDAS specifications as well as with standard GARCH models[3]. Both TS and MV GARCH-MIDAS specifications provide a better fit in terms of log-likelihood with respect to classical GARCH: the likelihood ratio tests (LR) reject the null hypothesis of model equivalence for all the countries. This result indicates that the assumption of constant long run volatility over time in GARCH models is restrictive, as it can also be seen from a visual inspection of Figures 5-6 that report a strong break in the volatility pattern from 2010 onwards.

[Insert Table 4 here]

When comparing the two GARCH-MIDAS model, the Akaike information criterion selects the MV GARCH-MIDAS specification for all the countries but Belgium while the Schwarz information criterion favours the TS GARCH-MIDAS, with the only exception being the Netherlands.

Focusing now on the variance ratio, which tells us the amount of total variability explained by the long run component, we find evidence supporting MV GARCH-MIDAS on TS GARCH-MIDAS for Italy (0.80 vs. 0.74), Spain (0.87 vs. 0.85) and the Netherlands

[3] The estimates of standard GARCH models are not reported in the paper but available upon request.

(0.67 vs. 0.37); on the contrary, the TS GARCH-MIDAS is selected for Belgium (0.70 vs 0.42) and France (0.65 vs 0.63).

4.2 Multivariate Models

Correlation matrixes are estimated using the following two approaches. In the first specification, the TS DCC-MIDAS model, univariate volatilities are obtained from the TS GARCH-MIDAS, where the long run component is a weighted average of past RVs presented in Table 2, and the long-run component is a weighted average of correlation matrices of past standardized residuals as in Colacito et al. (2011) model described in (11) and (12). In the second specification, the MV DCC-MIDAS, the univariate volatilities are obtained from the MV GARCH-MIDAS, where the slowly varying component is modeled through macroeconomic variables as presented in Table 3, while as per correlation matrix, the long run component is inferred from macroeconomic fundamentals of the countries in analysis as described in (13).

4.2.1 The TS DCC-MIDAS Model

Starting from the TS DCC-MIDAS model, we estimate the long-run correlation matrix using a fixed step rather than a rolling window and therefore the long run correlation matrix is computed on the first day of each month on previous month standardized residuals and then it is kept fixed through the current month. This choice is motivated to assure the comparison between the TS DCC-MIDAS model with the MV DCC-MIDAS as macroeconomic fundamentals are observed monthly and therefore the long run component of correlation is fixed through the month. As already done for the univariate GARCH-MIDAS, we impose a beta lag structure for weights loading the past correlation matrixes of standardized residuals in (11) and, as in Colacito et al. (2011), we set ω_1 to 1 in the beta function. In the multivariate framework, we deal with the MIDAS lag selection corresponding to U^{kj} in (11) and therefore we test some alternative specifications, ranging from 2 to 12 months. Based on the log-likelihoods, we choose the MIDAS with lag equal to 3 months. The same lag structure is set for all the 10 covariances.

In Table 5, we report the estimates of the TS DCC-MIDAS model (10):

[Insert Table 5 here]

The parameter governing the weight function ω_2 is greater than 1 implying that weights are decaying with time: higher weights are attributed to most recent correlation matrixes of standardized residuals.

In Figures 7-8, we report the pattern of the high- and low-frequency correlations estimated using the pure time series approach.

[Insert Figures 7-8 here]

A very interesting feature is the jump in the high-frequency correlations that emerge for all the pairs of countries between December 2010 and July 2011, when a series of important events occur including the second Greek bailout and the Portuguese bailout. Note that at the beginning of December 2010, the ECB announces the purchasing of government bonds in large scale and Ireland asked for financial help. All these events determine a sensible increase in risk aversion, with the consequence that market movements are heavily news-driven and traders operate in a synchronized way across the different markets[4].

4.2.2 The MV DCC-MIDAS Model

We now turn to the MV DCC-MIDAS specification where the long run component is modeled by macroeconomic fundamentals as described in (13). We assume that the correlation between country A and country B depends just on countries A and B fundamentals. As discussed in Section 3, macroeconomic variables enter the model via a measure of the absolute

[4] We also estimate correlations using alternative techniques robust to both microstructure noise and asynchronous trading, e.g. inter alia Ait-Sahalia et al. (2010) and Barndorff-Nielsen et al. (2011), finding the same pattern during the period December 2010 - July 2011. The pattern of the estimated correlations over that period can be explained by negative correlations between Germany and the other European countries, as the result of completely different/opposite trading activity of German Bund with respect to bonds of other countries.

distance between the rate of change of macroeconomic drivers of countries A and B. We expect that, as the fundamentals of the two countries get closer, and therefore the absolute difference tends to zero, the government bond spreads of the two countries become more correlated and vice versa. For the univariate analysis, we take into consideration employment, industrial production and economic sentiment. In order to keep comparability with results in Table 5, we fix the MIDAS lag equal to 3 months and we adopt the beta lag specification, always fixing ω_1 equal to 1. We report estimates in Table 6.

[**Insert Table 6 here**]

Overall, the macroeconomic variables turned out to be statistically significant drivers of correlations between each pair of countries. Starting from the level of macroeconomic variables, an increase in the absolute differences in the rate of change of employment determines a statistically significant decrease in correlations in 6 out of 10 pairs of countries while a positive relationship is detected just for Belgium and France. As per the industrial production, as the rate of changes of two countries diverge, the government bond spreads with respect to Germany get more dissimilar in 4 out of 10 cases while a positive relationship is found just for the correlation between France and the Netherlands. Finally, as far as the economic sentiment is concerned, for 7 out of 10 pairs of countries we observe a negative sign indicating that as the two countries become more dissimilar in terms of the forward looking measure, they move in a less correlated way. Therefore, there is a confirmation of our assumption about a negative dependence between the correlation of two countries and the absolute difference between their macroeconomic fundamentals: as two countries get more similar in terms of their macroeconomic fundamentals, the respective government bond spreads start to move more closely.

Focusing now on the absolute difference in volatility of the rate of change of fundamentals, our results support the empirical evidence highlighted for the level of macroeconomic variables. A divergence in employment volatility determines a decrease in correlations in 4 out of 5 pairs of countries for which the estimates are statistically significant, in 6 out of 6 when taking into account industrial production and in 5 out of 6 when focusing on economic sentiment volatility. Therefore, not only convergence in rates of change of macroeconomic variables determines an increasing in correlation but the volatility of the rate of change too explains correlations in the same direction: as two countries get more similar in terms of volatilities of their fundamentals, they government bond spreads get even more correlated.

In Figures 9-10, we report the pattern of correlations according to estimates reported in Table 6:

[**Insert Figures 9-10 here**]

First, we note the failure of the model in picking-up the break in correlations occurred during the period December 2010 - July 2011. This can be explained by that macroeconomic variables used in this study are not able to capturing what happened at high-frequency level in the markets during that very distressed period.

In order to assess whether the change in the correlation structure was more sentiment-driven rather than imputable to macroeconomic factors, to the long run component of MV DCC-MIDAS in (13) we add variables capturing risk aversion such as TED, VIX and the price of gold. Although the model improves in terms of log-likelihood increasing to 630,107 from 630,054 of the MV DCC-MIDAS model reported in Table 6, the risk aversion variables appear statistically insignificant thus unable to capture the sharp increase in correlations between December 2010 and July 2011.

We now compare the two DCC-MIDAS reported in Tables 5 and 6 with the classical DCC model by Engle (2002). The results are reported in Table 7. Given that the two DCC-MIDAS models are not nested, we apply the likelihood ratio test just to compare the two (TS and MV) DCC-MIDAS models with the standard DCC model.

[**Insert Table 7 here**]

Both the likelihood ratio tests and the information criteria indicate that the two DCC-MIDAS specifications outperform the classical DCC model by Engle (2002). This finding is relevant given that, as already discussed for the volatilities, the classical assumption that the unconditional or long run correlation is fixed over time is rejected by the data. Allowing the long run correlation to be time varying, independently of which DCC-MIDAS specification we adopt, improves substantially the explanatory power of the model. This conclusion is also evident from a visual inspection of Figures 7-8 and 9-10, which show a strong break in the pattern of correlations during the period December 2010 - July 201. In terms of which DCC-MIDAS specification to use, the TS DCC-MIDAS outperforms the alternative MV DCC-MIDAS model with Akaike criterion increasing from -7.1418 to -7.1408 and Schwarz criterion from -7.1417 to -7.1344. This finding confirms what reported earlier in the paper in commenting Figures 9-10: the macroeconomic variables are unable to explain what happened in the financial markets during the recent distressed period. This result sheds light in identifying the possible sources of the increasing systemic risk experienced: the substantial break in correlations in government bond spreads, despite no change in correlations between countries fundamentals, shows that the increase in risk originated from financial markets rather than from shocks coming from the real economy. The sharp increase in correlations is most likely due to a change in market sentiment, and markets during crisis periods becoming more volatile and investment activities myopic. In particular, during the recent sovereign crisis, markets penalized more peripheral European countries in favour of Germany considered a "safe heaven".

Figures 9-10 highlight interesting linkages of our findings to the concept of contagion (Forbes and Rigobon 2002, Bekaert et al. 2005, 2012), as increasing correlations not entirely explained by macroeconomic fundamentals, and are also in line with the evidence reported for other classes of assets in terms of systemic risk. Ang and Longstaff (2011) highlight that the stronger linkage among CDS spreads of Eurozone countries with respect to the US is evidence that systemic risk is not directly caused by macroeconomic integration but it has its roots in financial markets. Kodres and Pritsker (2002), Brunnermeier and Pedersen (2009) and Allen et al. (2009) show that systemic risk is created through channels such as capital flows, funding availability, risk premia and liquidity shocks rather than macroeconomic shocks. Baele et al. (2010) report liquidity proxies and risk aversion have a more prominent role in explaining the dynamics of the correlation between stock and bond returns. Karloyi and Stulz (1996) show that large contemporaneous return shocks in national markets determine higher covariances. All this is in support of our findings about the presence of large and simultaneous shocks in European government bond spreads behind the sharp increase in correlations, although we cannot exclude that possible causes originating these shocks were macroeconomic announcements.

4.2.3 A Useful Eigensystem Decomposition of the Correlation Matrix

In this final section, we implement a conceptually simple and yet powerful tool proposed by Muller et al. (2005) for detecting and characterizing time dependent phase-shape correlations in a multivariate framework. This final exercise allows to interpret the main findings reported earlier in the paper in terms of time-varying (ongoing) integration between the European countries considered in this paper, with implications in terms of the presence of contagion and/or systemic risk during the sovereign crisis.

Muller et al. (2005) show that changes in the degree of synchronization in all or a subset of signals are reflected in coordinated changes in the highest and lowest eigenvalues: if the highest eigenvalue decreases, the lowest eigenvalue increases, and vice versa. Thus, the information on the interaction between the European countries in this paper can be extracted from the temporal evolution of eigenvalues and eigenvectors of the correlation matrix. Based on the eigensystem decomposition of the correlation matrix, Muller et al. (2005) propose to calculate the *participation ratio* to assess which components contribute most to the time structure of the correlation matrix. More formally, let a_{ij} be the expansion coefficient of eigenvector v_i, the number of principal components contributing to the dynamic of the system is defined as:

$$N_i^p = \frac{1}{M \sum_{j=1}^{M} |a_{ij}|^4} \tag{20}$$

When all the basis states j contribute equally to the expansion of the eigenvector i, N_i^p takes values close to 1, while when the eigenvector v_i is driven by few components, N_i^p takes values close to $1/M$, where M represents the number of countries.

We apply the Muller et al. (2005) framework to the time varying correlation matrixes estimated via the MV DCC-MIDAS reported in Table 6 in order to get some insights about time varying integration in financial markets, evaluated on the basis of the high- frequency component, and in country macroeconomic fundamentals, on the basis of the low-frequency correlations. The TS DCC-MIDAS, as it does not rely on countries' macroeconomic fundamentals, would not allow us to analyze the two dynamics, in financial markets and in macroeconomics. The results are very insightful.

Figure 11 reports the contribution of each eigenvector to the evolving structure of high-frequency correlation matrix. The principal eigenvector explains on average a 50% of the total variability of the correlation matrix confirming the existence of a global risk factor through the period considered. Moreover, as already seen when analyzing the pairwise correlations in Figures 9-10, we find evidence of a substantial increase in the variability explained by the eigenvector associated to the largest eigenvalue during the deepest period of the crisis corresponding to December 2010 - July 2011. The other four eigenvectors explain a similar amount of variability of the evolution of correlation matrix with a drop in correspondence of the period December 2010 - July 2011 due to an increasing importance of the leading eigenvector. In Figure 12, we report the participation ratio as defined in (20). It is interesting to see that, although the participation ratio takes very high values throughout the entire period of our analysis, it is persistently close to 1 during the crisis period between December 2010 and July 2011, meaning that all countries in that period contributed equally to the expansion of the maximum eigenstate. This result supports the evidence that there was no leading country during the crisis period, no country determined contagion, but all European countries play a similar role in the development of the sovereign crisis. This suggests the presence of a dominant global market factor resulting from the interactions of all other/local markets (see also Belvisi et al. 2013).

[Insert here Figures 11 and 12]

The analysis carried out so far is based on the high-frequency correlations providing an indication of time-varying integration between European financial markets. We turn now to the analysis of the low-frequency correlations driven by macroeconomic variables to assess whether a similar pattern is present in the integration in the economies of European countries. Figure 13 reports the percentage of variability of the low-frequency correlation matrix explained by its eigenvectors. The figure shows that Belgium, France, Italy, Spain and the Netherlands correlations estimated via macroeconomic factors were mainly driven by a leading eigenvector explaining a percentage of variability between 30% and 50%. In addition, the amount of variability explained by the leading eigenvector shows a noticeable drop starting from the end of 2008 and lasting up to the end of 2009 in correspondence of the subprime crisis; we also note the existence of another drop starting from the beginning of 2012. On the contrary, no systematic pattern is found over the period December 2010 - July 2011. In Figure 14, we report the participation ratio computed on the time varying long-term correlation matrix. The figure shows a sharp drop during the period September 2008 - April 2009, corresponding to the burst of the subprime crisis with the default of Lehman Brothers, followed by another drop around September 2009. These results can be interpreted jointly with what reported in Figures 2-4: a sharp increase in the Spanish level of unemployment starting in the mid of 2008, when also the industrial production differential for Belgium and the Netherlands vs Germany decreases much less than for France, Italy and Spain; finally, no evidence of increase in participation ratio is found during the period December 2010 - July 2011.

[Insert here Figures 13 and 14]

To summarize, when considering 15-minute (high-) frequency component of correlations, reflecting financial market conditions, we note a sharp rising in integration during the period

December 2010 - July 2011 shown by both an increase in the overall amount of variability of the correlation matrix explained by the leading eigenvector and by the participation ratio being very close to one, with little or no variability indicating that all countries have a similar role in explaining the increase in integration. When we focus on macroeconomic factors, although there is evidence that European countries are very integrated, we do not find evidence of a change in the level of integration during the period December 2010 - July 2011. On the contrary, we find a low degree of integration in correspondence of the burst of the subprime crisis of 2008-2009. Thus, there is strong evidence of increasing systemic risk in European bond markets during the pick of the sovereign debt crisis mainly determined by sentiment driven trading activities across European financial markets which appear highly integrated.

5 Conclusions

Since the introduction in 1999 of the Euro with the single monetary policy under the authority of the ECB, the 10-year yields converged significantly from highs in excess of 300 basis points to a maximum of 30 basis points one year after the birth of the common currency. The resulting remarkable compression of sovereign risk premium differentials was considered a hallmark of successful financial integration in the Euro area but it also raised doubts about the ability of financial markets to impose fiscal discipline across union members and to discriminate between the qualities of fiscal policies coherently based on economic rationality. With the explosion of the sovereign debt crisis in 2011, financial markets became more careful in monitoring the fiscal performance of member states and restarted to exert disciplinary pressure on governments. The main question was whether the high spreads reflected the fundamentals of a country or rather they were determined by a regime shift in the market pricing of government credit risk as, during crisis periods, market penalization of fiscal imbalances can be higher than during normal times.

In this paper, we propose a DCC-MIDAS model for jointly estimating the high- and low-frequency components for both volatilities and correlations of European government bond spreads. We consider 10-year benchmarks for Belgium, France, Italy, the Netherlands and Spain with respect to Germany, over the period 1st June 2007 - 31st May 2012. The high-frequency component of volatilities and correlations, supposed to reflect financial markets conditions, is evaluated at 15-minute sampling while the low-frequency component, remaining fixed through a month, is expected to depend on country specific macroeconomic conditions.

We provide evidence of the strong linkage between increasing volatility of European government bond spreads and deteriorating countries macroeconomic fundamentals with respect to German ones. In particular, we show that the model augmented by macroeconomic fundamentals provides a better fit than the pure time series model, stressing the role of macroeconomic variables in driving government bond spreads even during the sovereign crisis. In addition, by estimating a DCC-MIDAS model where the long run component is driven by macroeconomic fundamentals, we show that as two countries get more similar in terms of their macroeconomic fundamentals, their bond spreads tend to move together. Moreover, unlike for volatilities, the pure time series model for correlations outperforms the specification including macroeconomic fundamentals. The different performance of the two DCC-MIDAS is particularly evident during the period December 2010 - July 2011, when a severe uprise in all the pairwise correlation patterns is identifiable. This finding supports the idea of increasing risk-awareness of investors who favoured the German bonds serving as a safe heaven. Finally, we analyze the time-varying degree of integration of European countries and we show that the increasing integration in financial markets during the period December 2010 - July 2011 is not supported by a similar increasing integration of countries in terms of their macroeconomic fundamentals.

The findings in this paper suggest further developments. We showed that among the factors which contribute the most to explain the pattern in European government bond spreads are country specific macro fundamentals together with the expectation about future economic outlook as captured by the economic sentiment. During the recent crisis, future expectations played a prominent role. In particular, government's ability to set up proper measures to face the crisis together with political uncertainty were priced in government bonds. In this respect, the case of Italy is very exemplary as the country experienced an abnormal increase in its government bond spread both in November 2011, in correspondence of Berlusconi government downturn, and in recent days (September 2013) when the Italian bond spread was above the Spanish one despite the better Italian macroeconomic fundamentals because of new political uncertainty. On the other side, the Irish case, with the spread moving from highs of 800 bps in June 2011 to the actual 220 bps, shows as government's ability to undertake proper reforms can lead investors to revise their judgment on a country creditworthiness.

For policymakers it is important to identify the factors driving markets as this step helps to estimate the probability that risk materializes and thus to take appropriate policy actions which become particularly important in the presence of a highly integrated financial system which rises the risk that shocks propagate across markets. Thus, it is also important to analyze whether other factors besides macroeconomic shocks, such as for instance political uncertainty and procyclical behaviour of policy authorities and major institutional investors, impact on government bond spreads. This is part of an ongoing research agenda.

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Figures and Tables

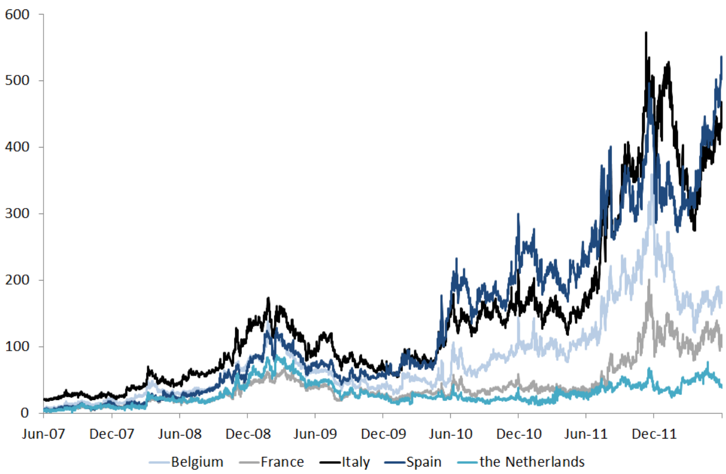


Figure 1: **10-year Government Bond Spreads (bps)**
The figure reports the 10-year government bond spreads with respect to Germany for Belgium, France, Italy, Spain and the Netherlands over the period 1st June 2007 - 31st May 2012. Spreads are computed on bid yields at 15-minute sampling frequency.

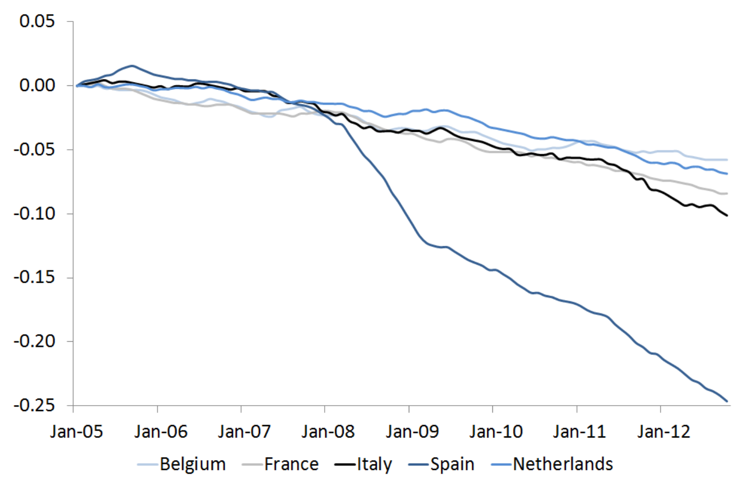


Figure 2: **Employment - Level**
The figure reports the difference in employment levels for Belgium, France, Italy, Spain and the Netherlands with respect to Germany over the period January 2005 - May 2012. Series are normalized by the initial value.

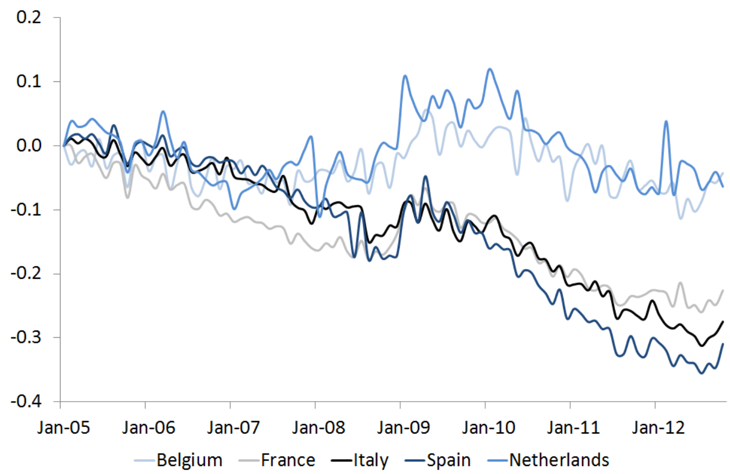


Figure 3: **Industrial Production - Level**
The figure reports the difference in industrial production levels for Belgium, France, Italy, Spain and the Netherlands with respect to Germany over the period January 2005 - May 2012. Series are normalized by the initial value.

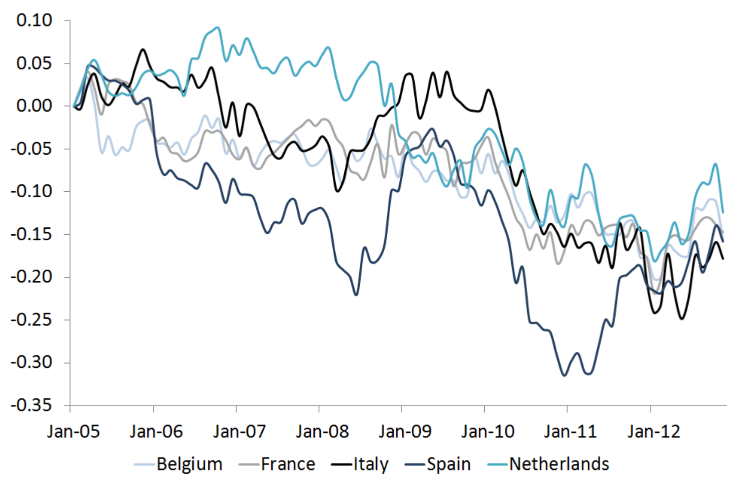


Figure 4: **Economic Sentiment - Level**
The figure reports the difference in economic sentiment levels for Belgium, France, Italy, Spain and the Netherlands with respect to Germany over the period January 2005 - May 2012. Series are normalized by the initial value.

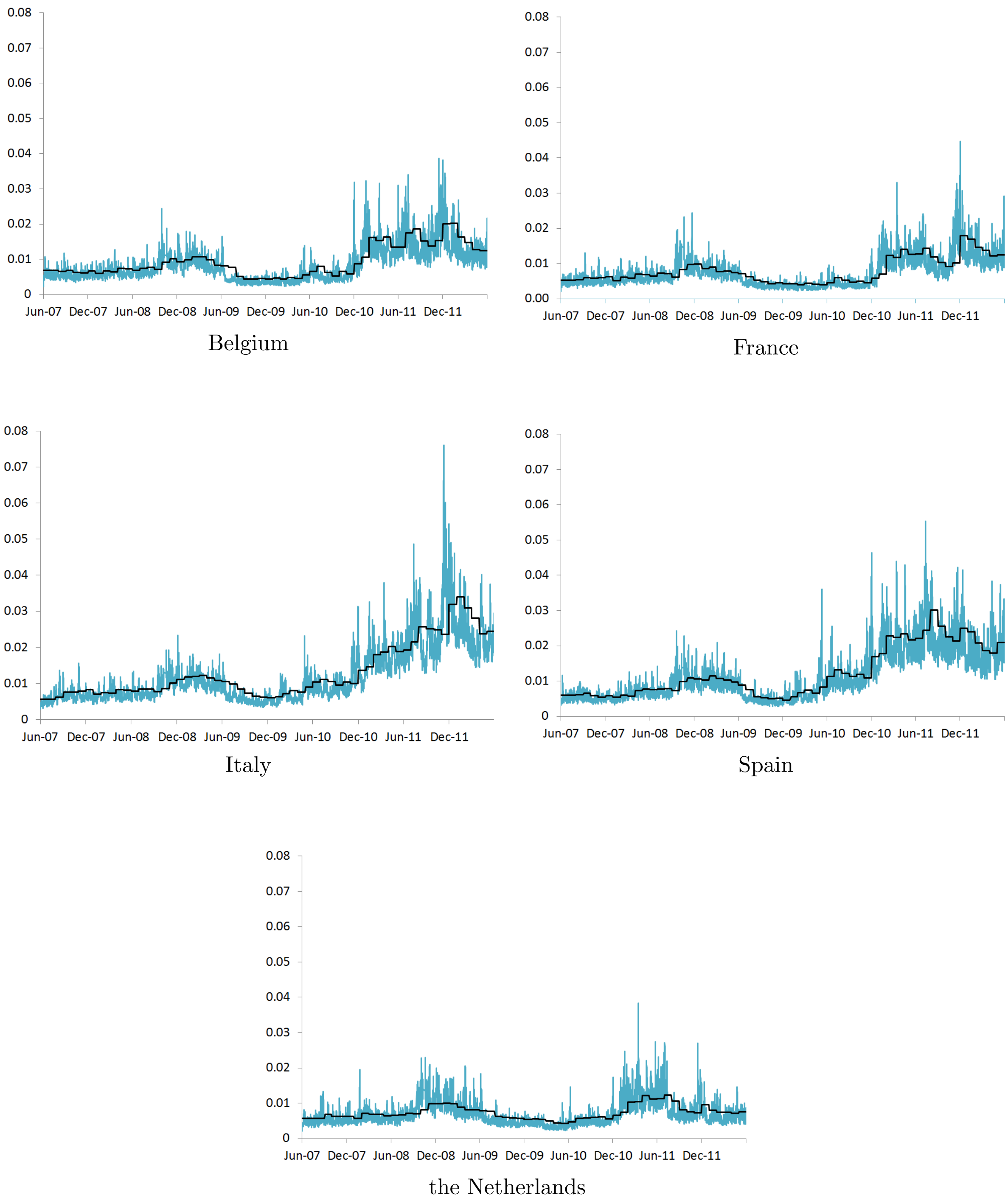
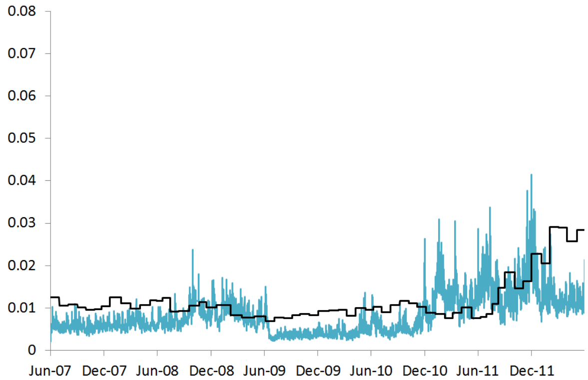
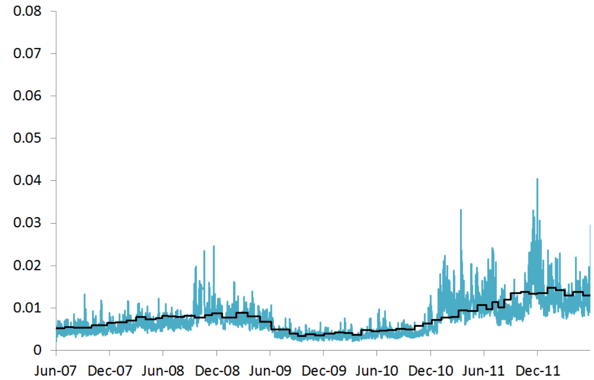


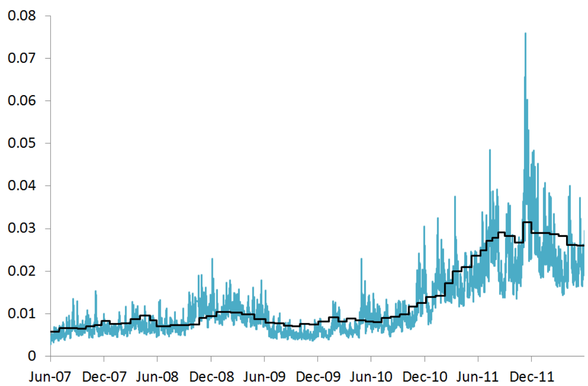
Figure 5: **TS GARCH-MIDAS Models**
The figure reports the volatility estimates of 10-year government bond spreads with respect to the German Bund for Belgium, France, Italy, Spain and the Netherlands during the period June 2007 - May 2012. Volatilities are obtained from the GARCH-MIDAS model where the long run component is a smooth weighted average of previous six monthly realized volatilities. Estimates are reported in Table 2. The blue line is the high-frequency (15-minute) component while the black line is the low-frequency (monthly) component.



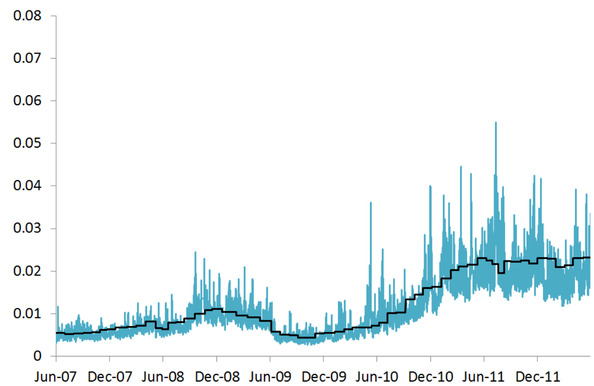
Belgium



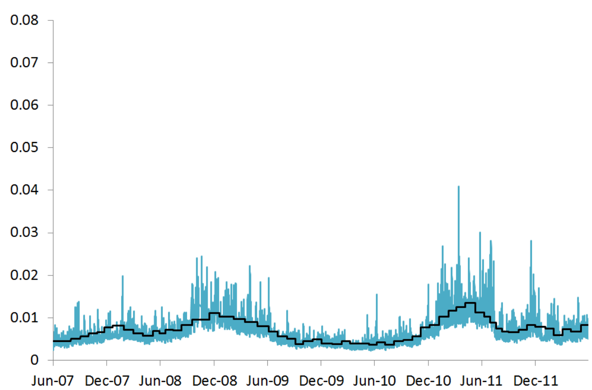
France



Italy

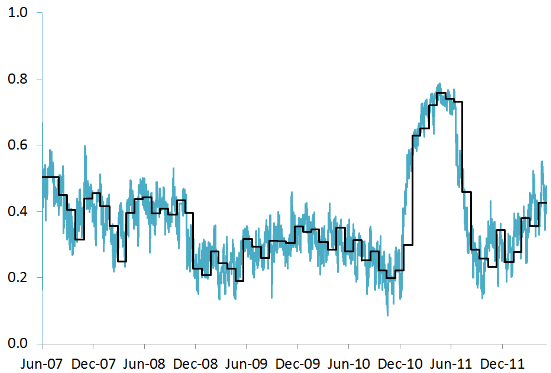


Spain

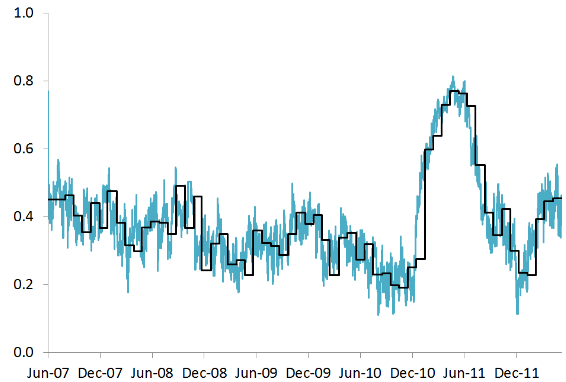


the Netherlands

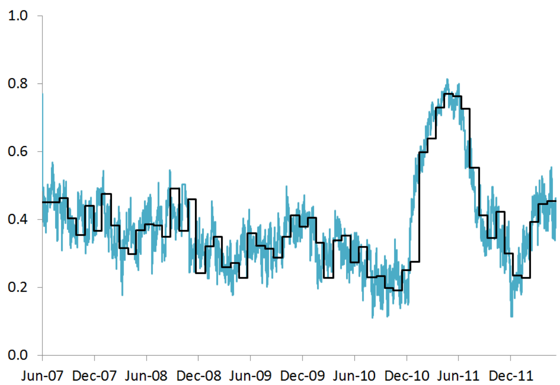
Figure 6: **MV GARCH-MIDAS Models**
Figure 6 plots the volatility estimates of 10-year government bond spreads with respect to the German Bund for Belgium, France, Italy, Spain and the Netherlands during the period June 2007 - May 2012. Volatilities are obtained by the GARCH-MIDAS model where the long run component is a function of the absolute difference in macroeconomic fundamentals, namely employment, industrial production and economic sentiment, observed over the last six months for each country with respect to Germany, as specified in (7). Both levels and volatilities of macroeconomic fundamentals concur in determining the long run component of volatilities. Estimates are reported in Table 3. The blue line is the high-frequency (15-minute) component while the black line is the low-frequency (monthly) component.



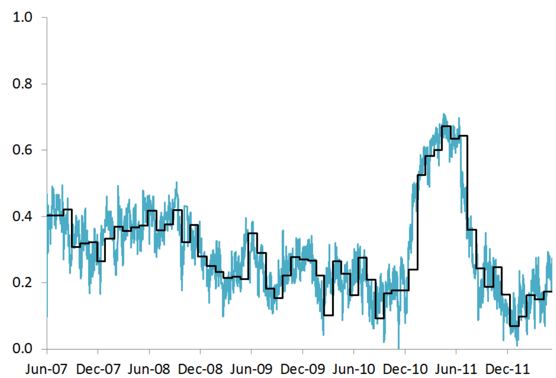
Italy vs France



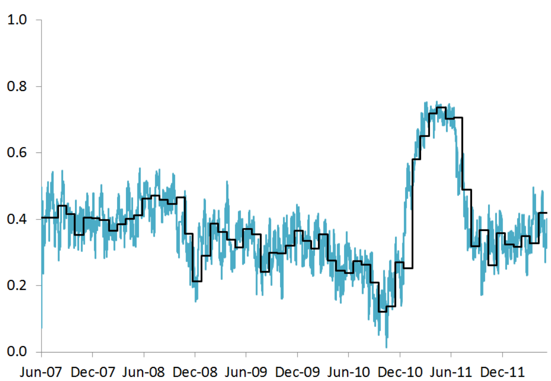
Italy vs Spain



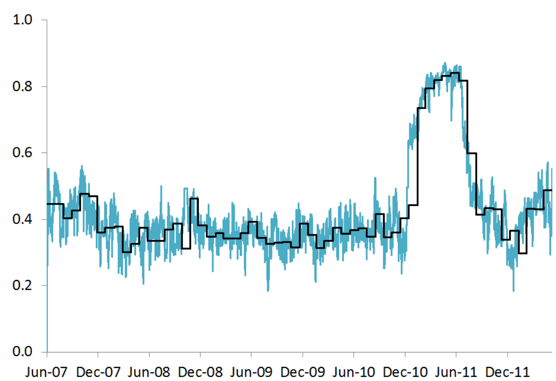
Italy vs Belgium



Italy vs the Netherlands

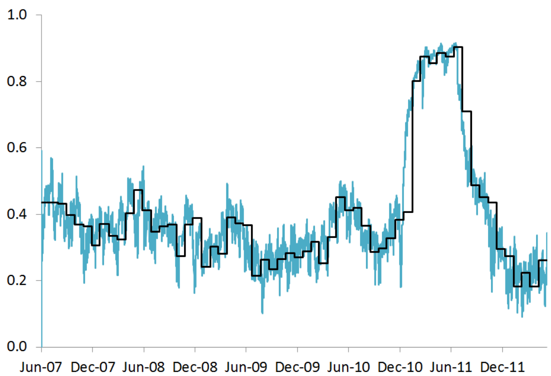


France vs Spain

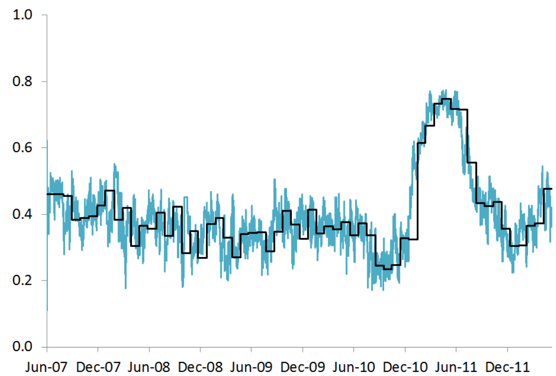


France vs Belgium

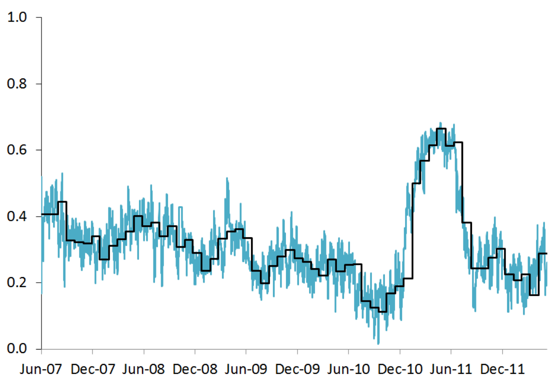
Figure 7: **TS DCC-MIDAS Models**
The figure reports the pairwise correlations estimates of 10-year government bond spreads with respect to the German Bund for Belgium, France, Italy, Spain and the Netherlands during the period June 2007 - May 2012. Correlations are obtained from the TS DCC-MIDAS model where the long run component is a smooth weighted average of previous three monthly correlation matrixes of standardized residuals. Univariate volatilities are obtained from the TS GARCH-MIDAS reported in Table 2. DCC-MIDAS estimates are reported in Table 5. The black line is the low-frequency (monthly) component while the blue line is the high-frequency (15-minute) component.



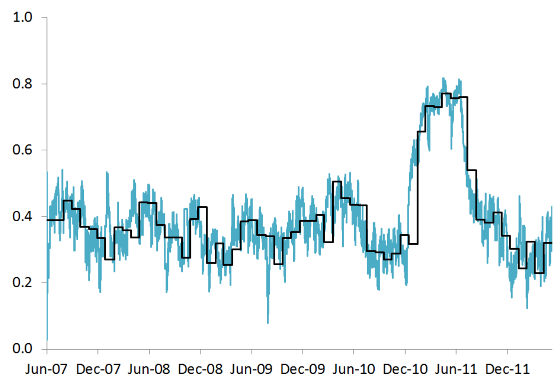
France vs the Netherlands



Spain vs Belgium

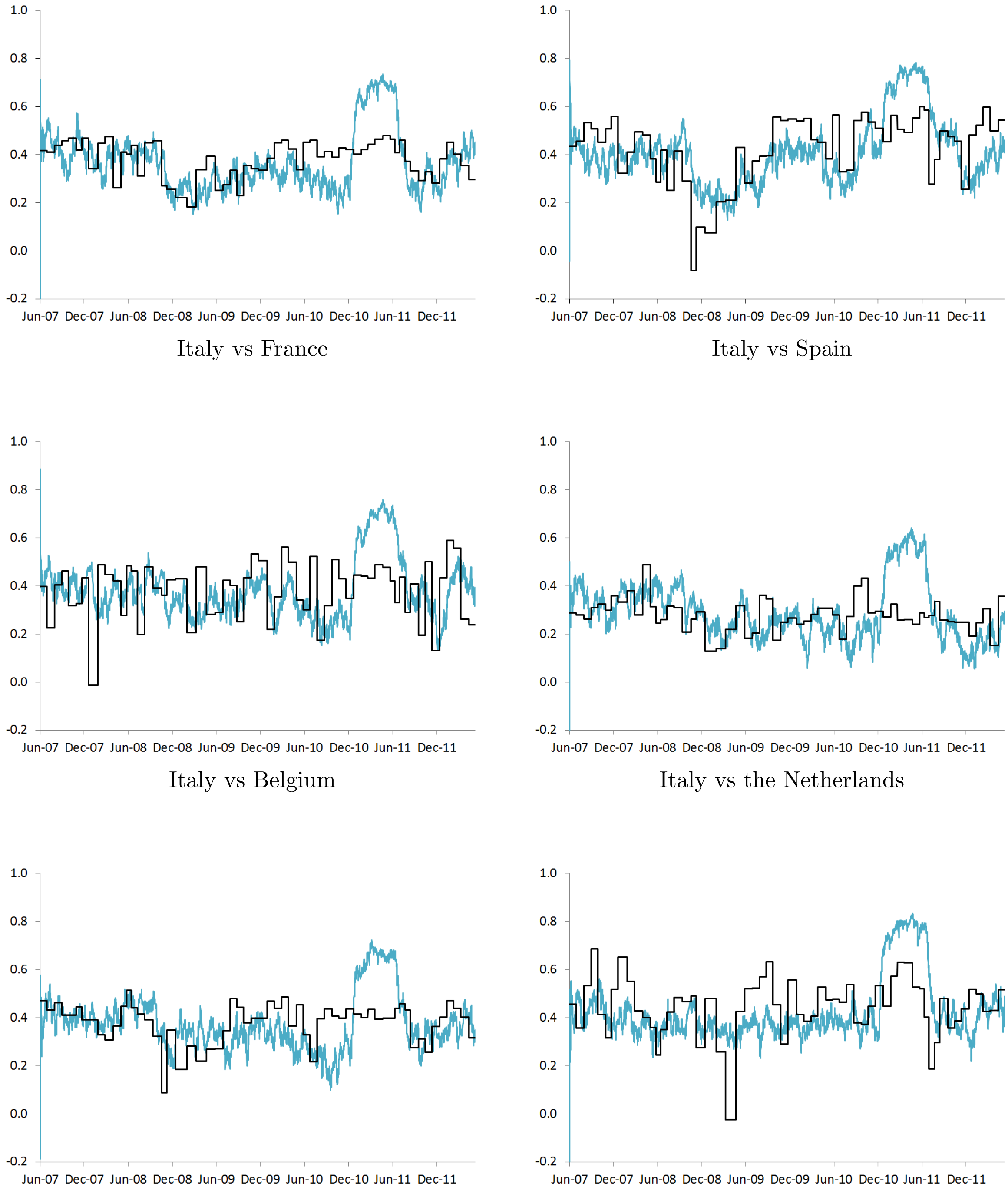


Spain vs the Netherlands



Belgium vs the Netherlands

Figure 8: **TS DCC-MIDAS Models**
See notes to Figure 7.



Italy vs France

Italy vs Spain

Italy vs Belgium

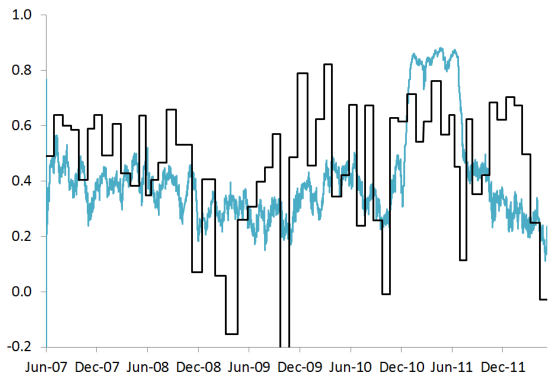
Italy vs the Netherlands

France vs Spain

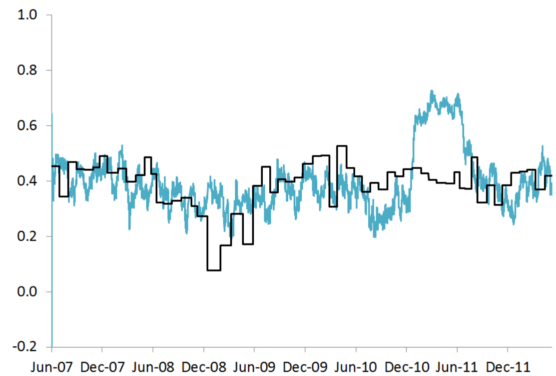
France vs Belgium

Figure 9: **MV DCC-MIDAS Models**

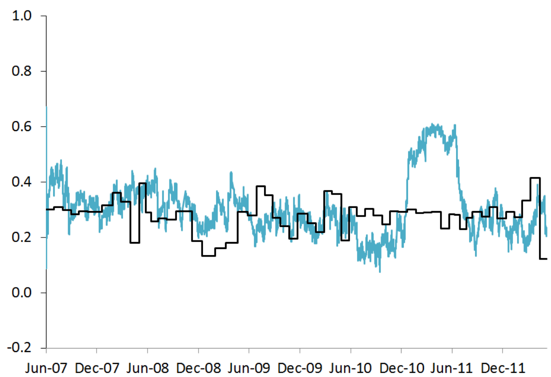
The Figure plots the pairwise correlations estimates of 10-year government bond spreads with respect to the German Bund for Belgium, France, Italy, Spain and the Netherlands during the period June 2007 - May 2012. Correlations are obtained from the MV DCC-MIDAS model where the long run component is a function of the absolute difference in macroeconomic fundamentals, namely employment, industrial production and economic sentiment, observed over the last three months for each pair of countries as specified in (13). Both levels and volatilities of macrovariables concur in determining the long run component of correlations. Estimates are reported in Table 6. The black line is the low-frequency (monthly) component while the blue one is the high-frequency (15-minute) component.



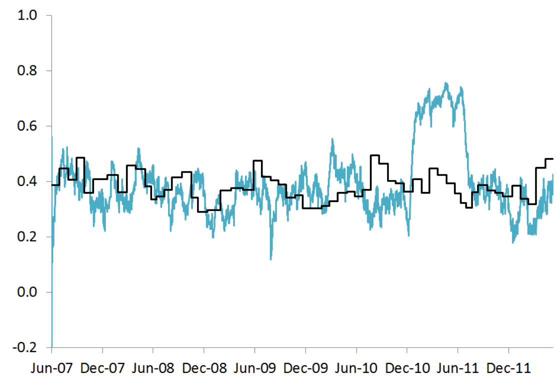
France vs the Netherlands



Spain vs Belgium



Spain vs the Netherlands



Belgium vs the Netherlands

Figure 10: **MV DCC-MIDAS Models**
See notes to Figure 9.

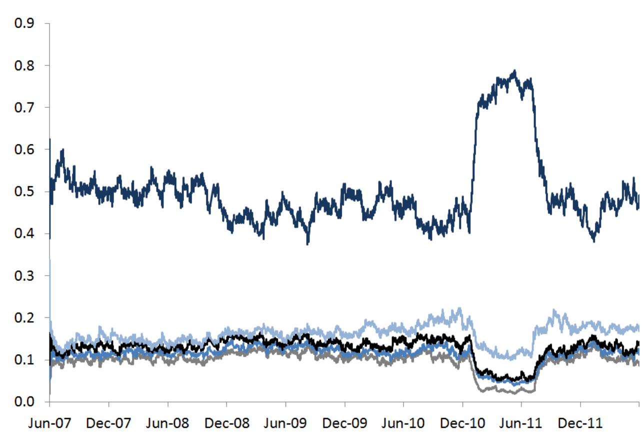


Figure 11: **Eigenvectors Contribution to the Time Pattern of the High-Frequency Correlation Matrix**

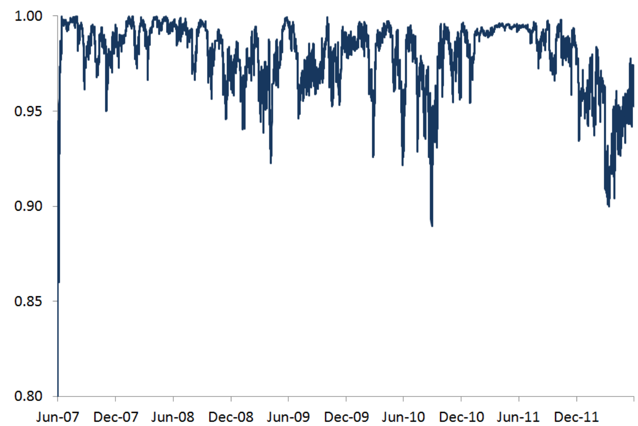


Figure 12: **Participation Ratio Based on the High-Frequency Correlation Matrix**
The figure reports the participation ratio for the 15-minute correlation matrix computed using (20).

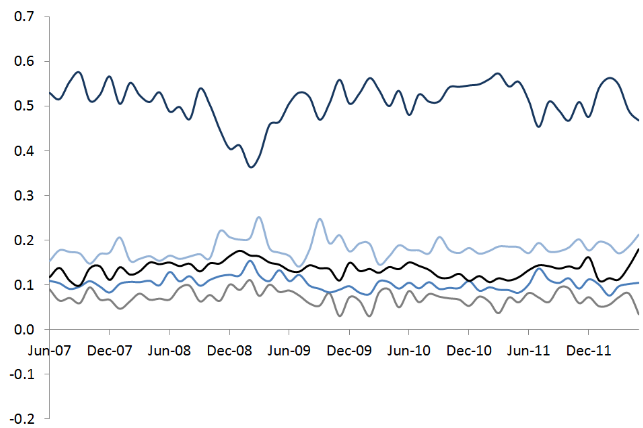


Figure 13: **Eigenvectors Contribution to the Time Pattern of the Low-Frequency Correlation Matrix**

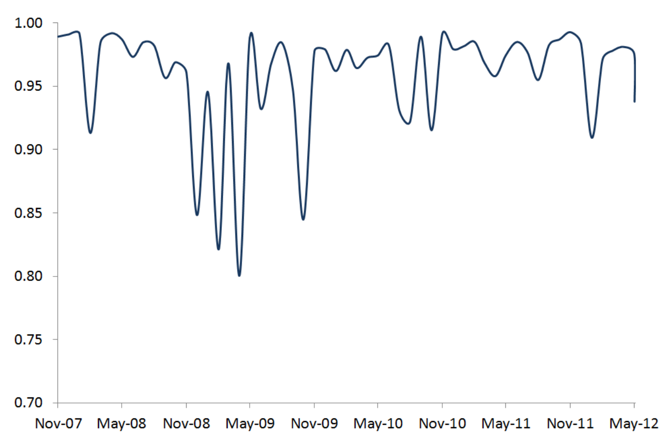


Figure 14: **Participation Ratio Based on the Low-Frequency Correlation Matrix**
The figure reports the participation ratio for the monthly correlation matrix computed using (20).

Table 1: **Government Bond Yields and Spreads: Data Selection and Descriptive Statistics**

	DE	BE	FR	IT	ES	NL
No. ticks	3,077,442	841,854	1,096,247	978,261	978,357	657,249
Limiting trading time	2,928,107	831,094	1,027,268	917,455	969,129	645,773
No. trades per day: Mean (SD)	2,345 (1,889)	659 (481)	828 (596)	736 (526)	764 (512)	513 (378)
Trade duration: Mean (SD) [s]	14.2 (44.4)	47.0 (115.7)	38.0 (88.6)	42.9 (97.1)	38.1 (90.3)	60.4 (123.4)
15-minute intervals	39,649	39,649	39,649	39,649	39,649	39,649
Exclude 1st daily obs	38,370	38,370	38,370	38,370	38,370	38,370
Bid YTM						
Mean (SD) [%]	3.18 (0.82)	4.01 (0.47)	3.61 (0.58)	4.66 (0.69)	4.58 (0.65)	3.48 (0.75)
Median (1st - 99th pct) [%]	3.20 (1.48 - 4.64)	4.08 (2.99 - 4.96)	3.56 (2.52 - 4.78)	4.57 (3.76 - 6.99)	4.41 (3.76 - 6.38)	3.54 (1.98 - 4.79)
Bid-Ask Spread of YTM						
Mean (SD) [bps]	0.63 (0.05)	1 (0.06)	0.78 (0.08)	0.64 (0.05)	0.75 (0.05)	0.72 (0.05)
Median (1st - 99th pct) [bps]	0.62 (0.56 - 0.76)	1 (0.89 - 1.11)	0.79 (0.66 - 0.94)	0.64 (0.51 - 0.8)	0.75 (0.67 - 0.89)	0.72 (0.65 - 0.85)
Bid Spread						
Mean (SD) [bps]	-	83 (64)	42 (33)	150 (125)	141 (124)	30 (17)
Median (1st - 99th pct [bps])	-	65 (7 - 272)	34 (5 - 147)	117 (27 - 505)	82 (5 - 472)	26 (4 - 81)
Bid-Ask Spread of Spread						
Mean (SD) [bps]	-	0.34 (0.20)	0.16 (0.07)	0.01 (0.06)	0.12 (0.07)	0.09 (0.08)
Median (1st - 99th pct) [bps]	-	0.39 (-0.62 - 0.48)	0.15 (-0.01 - 0.29)	0.03 (-0.12 - 0.13)	0.13 (0.00 - 0.24)	0.11 (-0.05 - 0.21)

The table reports data selection procedures on government bond yields and spreads together with some summary statistics. Limiting trading time means removing all holidays, weekend days and considering trades occurred between 8:00 and 15:30 UTC. Outliers are detected as described in (1) in the text. Tick-by-tick data are resampled using calendar time and 15-minute frequency. The 1st observation of each day is removed as it presents excess volatility. In square brackets is the measurement unit.

Table 2: **Parameter Estimates for the TS GARCH-MIDAS Models**

	BE	FR	IT	ES	NL
α	**0.0534 *****	**0.0590 *****	**0.0417 *****	**0.0558 *****	**0.0714 *****
β	**0.9370 *****	**0.9274 *****	**0.9507 *****	**0.9302 *****	**0.9139 *****
m	**-6.3869 *****	**-6.6277 *****	**-6.3461 *****	**-6.2041 *****	**-7.2470 *****
θ	**0.9080 *****	**0.8685 *****	**0.9042 *****	**0.9749 *****	**0.7047 *****
ω_2	**5.5888 *****	**6.8412 *****	3.3698	**6.8412 *****	**5.5588 *****
LogL	124,087	128,523	111,814	114,503	129,831
Variance ratio	0.70	0.65	0.74	0.85	0.37

The table reports estimates for the TS GARCH-MIDAS. Realized volatilities are estimated on a fix 6 months span while the high-frequency component is measured at 15-minute frequency. Weights are computed according to the beta function where the first parameter ω_1 is set to 1. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

Table 3: **Parameter Estimates for the MV GARCH-MIDAS Models**

	BE	**FR**	**IT**	**ES**	**NL**
α	**0.0447 *****	**0.0611 *****	**0.0398 *****	**0.0582 *****	**0.0921 *****
β	**0.9536 *****	**0.9234 *****	**0.9534 *****	**0.9209 *****	**0.8658 *****
m	**-10.71 *****	**-12.56 *****	**-11.19 *****	**-11.40 *****	**-8.92 *****
$\theta_{1,l}$ (Employment)	-19.14	**-9.39 *****	**-36.76 ***	-5.09	**24.64 *****
$\theta_{2,l}$ (Industrial production)	**26.99 ****	**20.21 *****	**27.52 *****	**13.56 *****	**-40.20 *****
$\theta_{3,l}$ (Economic sentiment)	**12.49 *****	-0.38	**1.70 ***	**3.33 *****	**-3.59 *****
$\omega_{2,1,l}$ (Employment)	0.62	**29.71 *****	**29.40 ***	**29.22 *****	56.09
$\omega_{2,2,l}$ (Industrial production)	**1.87 ****	**0.96 *****	**0.98 *****	1.36	**0.99 *****
$\omega_{2,3,l}$ (Economic sentiment)	**33.82 ****	**39.75 ****	**39.46 ***	**39.60 ****	3.23
$\theta_{1,v}$ (Employment)	-7.49 **	**-2.7 *****	**-3.27 *****	**-9.24 *****	**31.5 *****
$\theta_{2,v}$ (Industrial production)	-20.62	**33.17 ***	-6.19	23.91	14.00
$\theta_{3,v}$ (Economic sentiment)	13.88	**-1.44 *****	-1.28	3.48	**-5.69 *****
$\omega_{2,1,v}$ (Employment)	**0.98 *****	**1.08 *****	**0.97 *****	**1.02 *****	**1.03 *****
$\omega_{2,2,v}$ (Industrial production)	**5.28 *****	**2.12 *****	0.78	1.55	**0.96 *****
$\omega_{2,3,v}$ (Economic sentiment)	**1.00 *****	**0.69 *****	3.52	**1.09 *****	**1.40 *****
LogL	124,052	128,541	111,826	114,567	129,950
Variance ratio	0.42	0.63	0.80	0.87	0.67

The table reports estimates for the MV GARCH-MIDAS where the long run volatility is a function of the absolute difference in macroeconomic variables (employment, industrial production and economic sentiment) observed over the last six month for each country with respect to Germany as specified in (7). Both levels and volatilities of macroeconomic fundamentals concur in determining the long run component of volatilities. The low-frequency component is updated monthly, in correspondence to new macroeconomic data, while the high-frequency component is evaluated on a 15-minute time window. The absolute difference in volatilities were rescaled: employment volatility by 10e4 while industrial production and economic sentiment volatility by 10e2. Weights are computed according to the beta function where the first parameter ω_1 is set to 1. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

Table 4: **GARCH MIDAS Models: A Comparison**

	IT	**FR**	**ES**	**BE**	**NL**
Log Likelihood					
GARCH	111,739	128,403	114,335	123,992	129,751
TS GARCH-MIDAS	111,814	128,523	114,503	124,087	129,831
LR test (vs GARCH)	**149.45 *****	**239.25 *****	**336.32 *****	**190.74 *****	**160.29 *****
MV GARCH-MIDAS	111,826	128,541	114,567	124,052	129,950
LR test (vs GARCH)	**174.27 *****	**275.56 *****	**464.77 *****	**120.02 *****	**398.78 ****
AIC					
GARCH	-6.333	-7.278	-6.480	-7.028	-7.354
TS GARCH-MIDAS	-6.337	-7.284	-6.4901	**-7.033**	-7.358
MV GARCH-MIDAS	**-6.338**	**-7.285**	**-6.493**	-7.030	**-7.365**
BIC					
GARCH	-6.333	-7.277	-6.480	-7.027	-7.354
TS GARCH-MIDAS	**-6.336**	**-7.283**	**-6.489**	**-7.032**	-7.357
MV GARCH-MIDAS	-6.334	-7.281	**-6.489**	-7.026	**-7.361**
Variance Ratio					
TS GARCH-MIDAS	0.74	**0.65**	0.85	**0.70**	0.37
MV GARCH-MIDAS	**0.80**	0.63	**0.87**	0.42	**0.67**

The table reports a comparison of alternative volatilites estimates. GARCH is the classical GARCH(1,1) model by Bollerslev (1986). In the TS GARCH-MIDAS model, the low-frequency component is a smooth weighted average of previous six monthly realized volatilities and reported in Table 2. In the MV GARCH-MIDAS model, the low-frequency component is a function of the absolute difference in macroeconomic variables (employment, industrial production and economic sentiment) for each country with respect to Germany and reported in Table 3. LR test is provided only with respect to classical GARCH as the two GARCH-MIDAS specifications are not nested. AIC and BIC are Akaike and Schwarz information criterion respectively, whose values are divided by T=38,370. Variance ratio, defined in (8), indicates the overall amount of volatility explained by the long run component. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

Table 5: **Parameters Estimates for the TS DCC-MIDAS Models**

	a	**b**	ω_2
	0.0062 * **	**0.9893 *** **	**3.1333 ***
LogL	630,019		

The table reports estimates for the TS DCC-MIDAS model where the long run component of correlation is a smooth weighted average of previous three monthly correlation matrixes of standardized residuals. The long run component is kept fixed throughout the month while the high frequency component is evaluated on a 15-minute time window. Weights are computed according to the beta function where the parameter ω_1 is set to 1. Univariate volatilities are obtained by the TS GARCH-MIDAS reported in Table 2. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

Table 6: **Parameters Estimates for the MV DCC-MIDAS Models**

	IT vs FR	**IT vs ES**	**IT vs BE**	**IT vs NL**	**FR vs ES**	**FR vs BE**	**FR vs NL**	**ES vs BE**	**ES vs NL**	**BE vs NL**
m	0.55	**0.73 ****	0.49	0.31	**0.44 ****	0.30	**0.92 ****	0.58	0.32	0.36
$\theta_{1,l}$ (Employment)	**-0.46 *****	**-0.55 ****	-0.60	**-0.39 ****	**-0.36 ****	**0.17 ***	**-0.16 *****	**-0.24 ****	-0.64	1.73
$\theta_{2,l}$ (Industrial production)	**-0.24 ***	**-0.23 ****	0.10	2.36	0.90	**0.55 ****	**-0.23 *****	**-1.11 *****	1.53	2.31
$\theta_{3,l}$(Economic sentiment)	**-0.80 ***	**0.43 ***	3.73	**-0.23 *****	2.06	**-0.31 ****	**-0.14 *****	**-1.74 ****	**-1.92 *****	**-0.24 *****
$\omega_{2,1,l}$ (Employment)	**1.13 *****	9.49	9.87	**1.06 ****	0.97	1.00	10.21	6.58	13.93	**0.46 ****
$\omega_{2,2,l}$(Industrial production)	8.45	0.48	**2.45 *****	0.86	12.17	1.17	**1.18 *****	**4.94 ****	**1.25 ***	1.02
$\omega_{2,3,l}$(Economic sentiment)	3.52	**1.16 *****	0.66	4.14	9.00	**5.21 ****	10.12	**2.77 ****	1.16	0.98
$\theta_{1,v}$ (Employment)	**-0.72 ***	**-1.66 ***	**-0.22 ****	1.06	1.83	**-0.42 *****	2.09	**1.36 *****	0.47	1.09
$\theta_{2,v}$ (Industrial production)	**-0.14 *****	**-0.58 *****	-0.05	0.61	3.11	**-1.16 *****	**-0.46 ***	-0.52	**-1.80 *****	**-2.25 *****
$\theta_{3,v}$(Economic sentiment)	**-0.57 ****	**-0.64 ****	**-0.79 *****	-0.60	**-0.76 *****	-0.10	**1.69 *****	**-0.49 *****	0.13	-0.68
$\omega_{2,1,l}$ (Employment)	**2.75 ****	**2.13 ****	7.22	1.30	1.00	**2.06 *****	8.88	1.07	**6.02 *****	0.63
$\omega_{2,2,v}$ (Industrial production)	0.36	**1.17 ****	11.26	11.49	**5.65 ****	**1.12 *****	0.63	0.41	0.29	**3.02 *****
$\omega_{2,3,v}$ (Economic sentiment)	**1.04 ***	11.37	**1.90 *****	0.51	8.64	0.65	0.69	0.50	5.56	**0.17 ***
DCC										
a	**0.0037 *****									
b	**0.9956 *****									
LogL	630,054									

The table reports estimates for the MV DCC-MIDAS model where the long run component is a function of the absolute difference in macroeconomic fundamentals, namely employment, industrial production and economic sentiment observed over the last three months, for the pairs of countries. Both levels and volatilities of macroeconomic fundamentals concur in determining the long run component of correlations. The long run component is kept fixed throughout the month while the high frequency component is evaluated on a 15-minute time window. Weights are computed according to the beta function where the first parameter ω_1 is set to 1. Univariate volatilities are obtained by the MV GARCH-MIDAS model where the long run component is a function of macrovariables and reported in Table 3. Differences were rescaled. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

Table 7: **DCC-MIDAS Models: A Comparison**

	LogL	**LR test vs DCC**	**AIC**	**BIC**
DCC	629,410		-7.1349	-7.1348
TS DCC-MIDAS	630,019	**1,218** ***	**-7.1418**	**-7.1417**
MV DCC-MIDAS	630,054	**1,288** ***	-7.1408	-7.1344

The table reports a comparison of alternative DCC models. DCC is the classical DCC(1,1) model by Engle (2002) whose parameters are a 0.0045 and b 0.9953 both of them statistically significant at 1% level. In TS DCC-MIDAS model, the low frequency component is a smooth weighted average of previous three correlation matrixes of standardized residuals and reported in Table 5. In the TS DCC-MIDAS univariate volatilities are obtained by the TS GARCH-MIDAS reported in Table 2. In the MV DCC-MIDAS model, the low frequency component is a function of the absolute difference in macroeconomic fundamentals, namely employment, industrial production and economic sentiment, for each pairs of countries and reported in Table 6. In this case univariate volatilities are obtained by the TS GARCH-MIDAS reported in Table 3. LR test is provided just with respect to classical DCC as the two DCC-MIDAS specifications are not nested. AIC and BIC are Akaike and Schwarz information criterion respectively, whose values are divided by T=38,370. ***, **, and * denote 1%, 5% and 10% significance level, respectively.