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Comovements in European government bond spreads: jumps, cojumps, macrofactors and correlations

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Chapter 1

Introduction

In many respect, Europe is more integrated nowadays than ever. For instance, the per-capita wealth has converged significantly relative to early post-war levels and as of 2004, intra-EU trade has risen to approximately two-thirds of total trade and one-third of total EU GDP. The current economic and financial crisis has slowed down if not stopped the convergence process highlighting imbalances within the Euro area which had been undervalued/overlooked during the years of economic growth and stability. It was as if the sovereign debt markets had underestimated the possibility that governments might default.

The financial crisis was triggered by the US-subprime crisis and then by the Lehman & Brothers default in September 2008. The main message that this event delivered to markets was that no institution is risk-free, that policy makers and monetary authorities are not always willing to prevent them from defaulting, and this holds true for governments too. As consequence, countries with high debt levels began to face more stress on their debt servicing capabilities and, hence, were penalized more.

With the rescue of Greece and Ireland in 2010, and of Portugal and Greece again in 2011, it became clear that the origin of the sovereign debt crisis in Europe was beyond the imbalances in public finances. For instance the interconnection between the private and public debt is important as, while the ratio of public debt in the euro area dropped from 66% in 2003 to 63% in 2007, household debt increased from 41% to 56% of GDP during the same period and financial institutions increased their debt levels from 126% of GDP to around 200%. The main causes of the debt crises in Europe vary from country to country. The origin of the debt crisis in Greece, Portugal and Italy was the structural deficit in the government sector. Greece and Italy's large fiscal deficit and huge public debt are the cumulative result of chronic macroeconomic imbalances. However, the case of Portugal illustrates the importance of foreign debt; Portugal's debt-to-GDP ratio (63% at the end of December 2010) was much lower than Belgium's (123%), but whilst the latter is a net creditor towards the rest of the world, the markets are worried about Portuguese high external debt, specifically, that of its private sector namely banks and enterprises. In Ireland as well the crisis was mainly caused by imbalances in the private sector, particularly a domestic housing boom which was financed by foreign borrowers who did not require a risk premium related to the probability of default (Lane, 2011). In Spain, since absorption exceeded production, the external debt grew and the real exchange rate appreciated, implying a loss of competitiveness for the economy. Unlike previous expansions, the resort to financing was not led by the public sector but by private households and firms. The average value of the debt-to-GDP ratio during the period 2007-2010 in Spain was over 80% in the public sector and was close to 90% in the private. Government exposure to weakness in the financial sector may have also become a factor in explaining sovereign spreads in the euro area. In this respect, some countries have committed large resources to guarantee financial institutions, thereby establishing a potentially important link between financial sector distress and public sector bailouts.

Concerns about the solvency of the national financial sectors have risen in almost every Euro country, particularly in Austria, Finland, Greece, and Portugal while for some other countries, such as Belgium, Ireland, and Italy, worries are more focused on domestic fiscal sustainability.

Europe is under stress and integration among European countries seems more fragile than during the first years of Euro-era. It is important to understand how dependent countries belonging to a common monetary area are from each other. The strongest measures of financial integration are those based on the law of one price. Insofar, as government bonds are sufficiently homogeneous across the various Euro area markets, one can directly test the law of one price by comparing the yields on local government bonds across countries. If we assume that the degree of systematic risk is identical across countries, then risk premia should also be identical in perfectly integrated markets, and hence yields on government bonds with the same maturity should be identical as well. It is important that the bonds from which these yields are calculated are as homogeneous as possible: ideally, the bonds will all be on-the-run with the same maturity, liquidity, coupon schedule, issuance date, and embedded options. Among the possible government bonds, 10-year are usually considered as their markets are much more active than other maturities.

In Figure 1.1, 10 years government yields of eleven countries belonging to the Euro are reported.

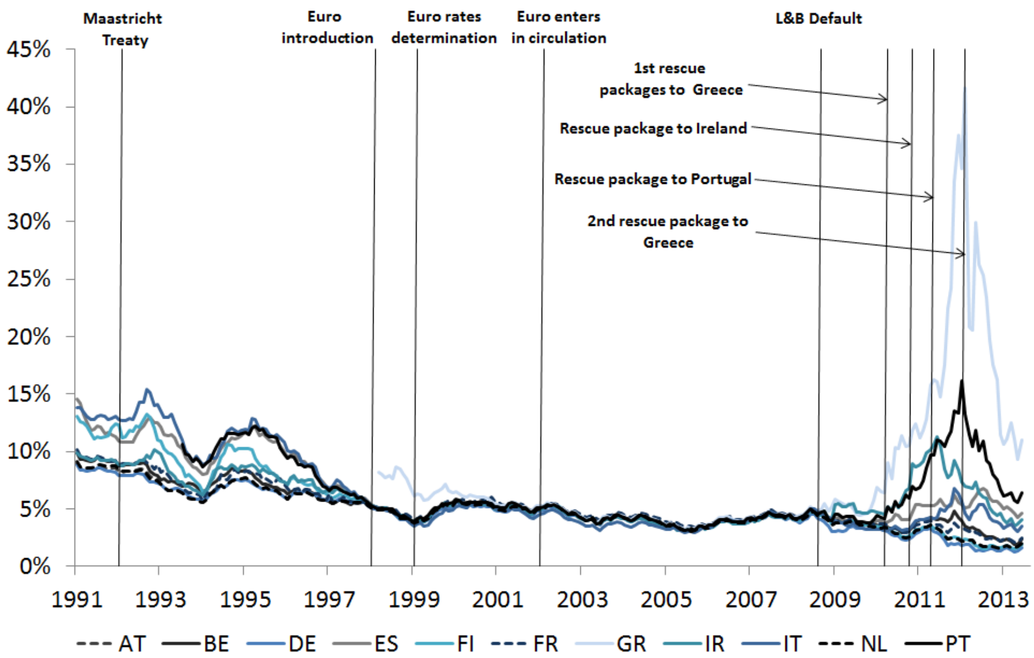

Figure 1.1: **10-year yields**

In Figure 1.1 we report benchmark 10-year government yields for Euro denominated bonds for the years 1991-2013.

From picks in excess of 300 basis points in the pre-EMU period, 10-year yield converged significantly in correspondence to the monetary union creation: one year after the introduction of the Euro the maximum spread was 30 basis points. Specifically, after the introduction of the Euro in January 1999 and until the subprime crisis in global financial markets in August 2007, spreads on bonds of Eurozone members moved in a narrow range with only slight differentiations across countries. The stability and convergence of spreads was considered a hallmark of successful financial integration inside the Euro area. The subprime crisis in 2007 set a turning point and yield spreads of Euro area issues with respect to Germany spiraled in parallel with the rise in global financial instability. In 2008 and 2009, interest rate differentials became sizeable but it was in 2010 and 2011 that they went back to the levels (or even higher) than those of the pre-euro era: in only four years the EMU bond markets went from a situation of stability and tranquility to their current situation of turmoil.

As the crisis unfolded, several factors might have affected the valuation of sovereign bonds. First, the global market price for risk went up, as investors sought higher compensation for risk. Deleveraging and balance sheet-constrained investors developed a systemically stronger preference for a few selected assets vis-à-vis riskier instruments, the so called *flight-to-quality*. This behavior not only benefited sovereign securities as an asset class at the expense of corporate bonds and other riskier assets, but also introduced a higher degree of differentiation within the sovereign spectrum itself. Second, as the crisis spread to the public sector and policy authorities stepped in to support troubled financial institutions, probabilities of distress went up across sovereigns.

Typically spreads between government bonds reflect three types of risks:

- *Exchange rate risk*, which refers to the risk for investors of an adverse exchange rate movement (which in turn could be linked to inflation differentials, credibility of monetary policies, as well as sustainability of fiscal positions);

- *Liquidity risk*, which relates to the size and depth of the government's bond market. In particular this is the risk of selling less liquid assets at worse market conditions (higher transaction costs, greater price impact) than more liquid ones;

- *Credit or default risk*, which refers to the country's creditworthiness as reflected by its macroeconomic and fiscal position and to its sustainability.

In addition, other technical factors such as differences in taxation, or in the issuance clearing and settlement procedures, may contribute to generate positive spreads together with international risk aversion, i.e. investor sentiment towards this asset class for each country. Finally, the effect of announcements, for example macroeconomic news/surprises or fiscal policy events (e.g. government plans) might also play a role in the development of sovereign bond spreads.

With the introduction of the single currency, the exchange rate risk obviously vanished as well as the liquidity risk. Moreover, due to the centralization of the monetary policy, credit risk was no longer perceived different for each European country and this lead to reduce the financing costs for the less virtuous Member States. Anyway, at least from a theoretical point of view, we would have expected bonds to be more accurately priced due to higher financial integration as this represents a necessary condition for market discipline: the more developed and integrated the financial markets are, the higher the degree of market efficiency and the more accurate prices are. Market-imposed discipline of this kind is especially relevant in large federal states, such as Canada or the US, and in monetary unions, such as the European Economic and Monetary Union (EMU), where governments of the member states can issue debt in their own right but are more restricted in their ability to respond to financial difficulties since they do not control their own monetary policies. Faced with a fiscal crisis, such governments are likely to turn to other governments or the common central bank and ask for a bail-out.

The resulting remarkable compression of sovereign risk premium differentials, experienced in the first years of the Euro era, has raised doubts about financial markets' ability to provide fiscal discipline across Euro area members, to discriminate between the qualities of fiscal policies and to be coherent with economic rationality. Starting from the sovereign debt crisis, this ability was by far regained by markets which became more careful in monitoring the fiscal performance of member states and restarted to exert disciplinary pressure on their governments. Anyway, while before the main concern was that government spreads were too low and too close, now the question is whether these high spreads reflect the fundamentals of a country or whether they also reflect a regime shift in the market pricing of government credit risk: during crisis periods, market penalization of fiscal imbalances can be higher than during normal times.

Understanding what has prompted recent developments in sovereign risk is particularly relevant for policymaking in particular for the macroeconomic consequences that their movements can have. Persistently higher spreads could, in fact, have a major impact on many euro area governments' marginal funding costs, possibly undoing the beneficial effects of declining risk-free interest rates. Most importantly, any loss of market confidence is deemed to lead to increase in long-term real interest rates and debt-service costs, partly offsetting the stimulus effects of measures taken to deal with the crisis both to consumption and investment and further adding to financing pressures. Rollover risk can increase too, as debt might have to be refinanced at unusually high cost or, in extreme cases, cannot be rolled over at all. Apart from the importance that government spreads levels have per se, comovements are probably even more important. This distress dependence among sovereigns might be due to several factors. For instance, trade linkages might play an important role in an environment of slowing global demand. Capital flow linkages represent another possibility as financial institutions tend to engage in important cross-border activities, and can therefore be another channel of contagion. In fact, several of these sovereigns were required, almost simultaneously, to provide support to the banks and other systemic financial institutions operating on their domestic markets.

According to Schuknecht (2010), bond yield spreads can still largely be explained on the basis of economic principles during the crisis. Once the crisis started and through to the rescue of Bear Stearns, the movement in spreads reflected global factors, in particular a flight to quality and global financial sector instability. After the Bear Stearns rescue, the global factors became less relevant and the prospects of the domestic financial sector acquired a more prominent role in explaining changes in sovereign spreads. The sensitivity of countries to their domestic vulnerabilities appears to be conditioned by their loss of competitiveness over the upswing of the previous economic cycle. The countries with the largest decline in competitiveness display a particularly strong link between the prospects of the financial sector and sovereign spreads with impacts on governments debt levels as well. A relationship also exists for the other countries, but its economic strength is more moderate. The inference is that as external competitiveness has weakened, domestic vulnerabilities have acquired greater salience. In addition to that, Manganelli and

Wolswijk (2007) show that spreads in Euro area countries are systematically related to credit ratings.

1.1 This dissertation and why

The European Monetary Union (EMU) brought to life an integrated market for fixed income government securities in the Euro-area. Common euro denomination made bonds issued by Euro-area Member States close, but not perfect, substitutes. European sovereign bonds achieved only partial integration even before the recent financial turbulence implying that monetary unification is a necessary but not sufficient condition for financial integration in the Euro area. Additionally, sovereign bond spreads are found to reflect macroeconomic expectations, as well as risk aversion, while the degree to which the spreads are affected by either macroeconomic or risk perceptions varies both across sovereigns and through time.

The overall aim of this dissertation is to assess the impact of macroeconomics on government bond spreads, through both macroannouncements and proper macroeconomic fundamentals.

In particular, in Chapter 2 we draw our attention to jumps in European government bond markets trying to assess whether a relationship exists between jumps in the different countries analyzed and public releases such as macroannouncements, government bond auctions and rating actions. The purpose is to evaluate whether jumps react to country specific releases, meaning that countries risk is idiosyncratic, or whether there exists some systemic pattern arising from releases. To provide a global view of countries sensitivity to jumps, we will go further taking into account even cojumps, that are contemporaneous jumps in more than one market. The contribution made by Chapter 2 is both empirical as well as methodological. In fact, not only we evaluate a great amount of macroannouncements referring to US, Euro area and individual countries while literature on this topic generally limit the attention to US ones, but we firstly propose to assess the impact of government bond auctions too. To complete the picture, we consider even rating actions. From a methodological point of view, we propose a unified framework for jointly modelling the impact of all the public events taken into consideration allowing to disentangle even between a pre from a post announcement effect.

In Chapter 3, we focus on comovements with the purpose of investigating the existence and the nature of the relationship between market volatility and correlation and macroeconomic fundamentals. The idea is to estimate correlations using two different time-scales, 15-minute and monthly data, in order to evaluate whether and how correlations estimated using low frequency macroeconomic data impact on comovements at the intraday level and therefore to assess whether a country's credithowthiness has some impacts on trading activity. The answer to this point requires the involvement of data measures at both high as well as low frequency, issue that we address by MIxed DAta Sampling. Examination and research on different types of comovements and correlations in time is of a great importance. In fact, in addition to the time dimension of the market dynamics, there are different types of investors who influence such dynamics. Starting with noise traders with an investment horizon of several minutes or hours, the spectrum of investors ranges through technicians with the horizon of several days to fundamentalists with the horizon of several weeks or months to pension funds with the investment horizon of several years. Thus, apart from the time domain, there is a frequency domain approach, which represents various investment horizons. Again the contribution to the current literature of Chapter 3 is twofold; from the methodological point of view we extend a previous work recognizing the existence of two time domains, high and low frequency, but where both were modeled by a pure time series approach while we propose to model the low frequency component of both volatilities and correlations by slowly-varying macroeconomic fundamentals. In addition to that, to the best of our knowledge, this is the first work combining two so different frequencies, namely 15-minute and monthly. From an empirical point of view, we provide evidence of the role that macroeconomic factors had in driving both volatilities and correlations of European government spreads even during the sovereign crisis although financial markets resulted more integrated than what we would have expected relying on pure macroeconomic fundamentals.

Finally, Chapter 4 is more on the technical side as it is aimed at evaluating alternative correlation matrix estimators relying on high frequency data recently proposed in literature. There is even an empirical motivation behind that analysis. In fact, as in Chapter 3 we identify peculiar patterns in correlations, we decide to adopt alternative estimators to assess whether that pattern was model specific rather than a true characteristic of our data. Estimating correlations using high frequency data require to deal with two important features, such the asynchronicity of trading activity and microstructure noise preventing from observing the true efficient market prices. To deal with these two issues, a number of synchronization methods and integrated covariance estimators were introduced, although there is no clear picture about which one provides the best estimates of the true integrated covariance matrix. Therefore we propose a comprehensive Monte Carlo simulation exercise aimed at comparing the alternative integrated covariance estimators combined with the possible synchronization schemes together with an empirical risk management exercise based on backtesting both Value-at-Risk and tail risk measures of a portfolio obtained combining the benchmark government bonds. Both applications concur in identifying a couple of estimators and a synchronization method which work particularly well in all the cases evaluated.

A final point is about that this dissertation focused on spreads based on yields reported in the secondary market trades of government bonds rather than on credit default swaps (CDS), as CDS are an insurance premium on a notional outstanding amount and therefore they offer another prospective on the market's perception of default risk. Moreover, CDS markets are thinner than conventional government bonds ones.

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Chapter 2

Macroannouncements, Bond Auctions and Rating Actions in the European Government Bond Spreads

Abstract

This Chapter investigates the impact of macroannouncements, government bond auctions and rating actions on the 10-year government bond spreads for Belgium, France, Italy, the Netherlands, Spain with respect to Germany. Using a unique tick-by-tick dataset over 1/02/2009-05/31/2012, we identify the impact of the three drivers via jump and cojump detection procedures. Disentangling the pre- from the post-announcement effects, real economy and forward looking news releases from US and Euro area, country specific Spanish and German macroannouncements, and auctions hold in distressed countries such as Italy and Spain have a statistically and economically significant effect. No role is played by rating actions.

Keywords: Jumps, Cojumps, Government Bond Spreads, Macroannouncements, Government Bond Auctions, Rating Actions.

J.E.L. Classification Numbers: C58, C12, H63, G24.

2.1 Introduction

Europe is under stress and integration among European countries seems more fragile than ever. Starting from the subprime crisis in 2007, markets are more aware of the differences between European countries, and this sentiment is reflected, amongst others, in increasing differentials of government bond yields. In 2008 and 2009, government bond spreads become sizeable but it was in 2010 and 2011 that spreads substantially increase, getting higher than the levels experienced in the pre-Euro era. In only four years, the European bond markets went from a situation of stability and tranquility to the current turmoil. The most recent European sovereign debt crisis involving Cyprus is just the last of a series of systemic events whose market depth and persistence have questioned the much celebrated markets' self-regulatory power as well as the ability of policy makers and regulators to adopt overall stability measures and stimulate economic growth. Thus, understanding which factors drive sovereign risk is particularly timely also for the macroeconomic consequences of the comovements associated to these factors. For instance, higher spreads deteriorate borrowing capabilities and market confidence which simultaneously impact on consumption and investment. The way to ameliorate the effects of the crisis on the real economy is a current political debate but the recipes to put in place still to be fully understood.

In this Chapter-, we identify the role that market movers like macroeconomic announcements, government bond auctions and rating actions have in driving government bond markets, and whether the occurrence of specific events in a country affects other European countries. To this aim, we make use of a unique dataset of high frequency data on 10-year European government bond spreads. Moreover, we analyze the impact of the three drivers on both conditional mean and variance specifications, disentangling the pre- from the post-announcement effect. The econometric analysis is conducted using recent developments in the financial econometrics literature on jump and cojump detection procedures.

In the literature, the relationship between macroannouncements and returns is widely studied while the sensitivity of jumps is analyzed in a handful of papers such as Dungey et al. (2008), Lahaye et al. (2011) and Jiang et al. (2011). In particular, Lahaye et al. (2011) estimate jumps and cojumps at intradaily frequency mapping jumps and cojumps to macro news to find that bond markets are the most sensitive to news releases and that macroannouncement surprises are associated with cojumps even more consistently than jumps. Lahaye et al. (2011) point out the advantage of using very high frequency data to study the impact of such events. On the other hand, Jiang et al. (2011) conclude that although a majority of jumps occurs at prescheduled news announcement times, surprises related to macroannouncements have limited power in explaining bond price jumps. Moreover, authors show that liquidity shocks play a key role in explaining jumps and that usually, during the preannouncement period, it is possible to observe a drop in market depth. Jiang et al. (2011) explain this result as that, as also discussed in Fleming and Piazzesi (2006), dealers tend to withdraw orders and place them further out to avoid being picked off in the upcoming information event. Thus, Authors conclude that jumps observed in correspondence to macroannouncement releases are not only determined by news, but also by the drop in liquidity that is a market mover per se.

As far as government bond auctions are concerned, we refer to Fleming and Remolona (1997) where the impact of US treasury auctions on returns is assessed. Fleming and Remolona (1997) compute the "surprise" effect as the difference between the yield in the when-issued market with the actual ex-post yield without relevant findings.

Finally, although rating actions are expected to be an important determinant of spreads, as the creditworthiness represents the long-term sustainability of countries' debt, the role and reliability of credit rating agencies (CRA) has been under investigation. In addition to concerns on CRAs effective capability to give accurate risk assessments, there is a sustained debate about the timing of recent downgrades of European sovereigns claimed to promote uncertainty in financial markets: see for instance Akdemir and Karsli (2012), Alsakka and Gwilym (2012, 2013), He et al. (2012) and Opp et al. (2013). In terms of the impact of rating actions, Afonso et al. (2012) reports that ratings are systematically related to daily movements in sovereign bond spreads, to budgetary developments, and that rating actions are not anticipated at 1-2 months horizon; in addition, Authors show the existence of spillover effects, especially from lower rated countries to higher rated countries, as well as of persistent effects for recently downgraded countries. In our analysis, we consider S&P, Moody's and Fitch separately to measure the distinct impact of the three rating agencies motivated by the results reported in Hill and Faff (2010) where it is shown that S&P is more active and provides higher flow of news information than Moody's and Fitch during crisis periods.

This Chapter makes an important contribution to the literature on the empirical determinants of government bonds spreads. Using a unique tick-by-tick 10-year government bonds spreads resampled at 5-minute frequency, we map jumps and cojumps to the three main drivers of spreads. We show that jumps and cojumps are very sensitive to macroannouncements from US and Euro area but also to individual countries releases in particular to those related to Germany and Spain. As per the category of macroannouncements, a very relevant role is played by real economy indicators, in particular US non-farm payroll, and forward looking indicators, such as consumer confidence and purchase manager index. In addition, significant is the role of the ECB Introductory Statement, bringing to the market the key information concerning decisions on ECB rates. We show the importance of taking into account the pre-announcement effect which explain a great amount of jumps. Pre- and post-announcements convey different kind of information, where the pre-announcements provide an indication about traders' perception of future news relevance and the post-announcements, captured by surprises, are able to lead traders to revise their positions according to the actual releases. As far as government bond auctions are concerned, they explain a great deal of jumps and cojumps, especially for auctions hold in Italy and Spain. On the contrary, rating actions play no role as determinants of spreads' movements. Finally, we observe an increasing number of jumps and cojumps during the preannouncement periods for both macroannouncements and auctions.

The remainder of the Chapter- is organized as follows. In Section 2.2, we describe the dataset while in Section 2.3 we introduce the testing procedures adopted to detect jumps and cojumps and the summary statistics of identified jumps and cojumps events and related market activities (Section 2.3.1), we map jumps to macroannouncements, auctions and rating actions and we introduce the mean and variance models we propose (Section 2.3.2). The empirical results are reported and discussed in Section 2.4. Section 2.5 concludes.

2.2 Data and Methodology

2.2.1 Data Description

2.2.1.1 Spreads

We use data for the benchmark 10-year government bonds of Belgium, France, Germany, Italy, the Netherlands and Spain over the period 2nd January 2009 - 31st May 2012. We consider bid, rather than mid, data as more representative of the spreads during crisis periods because of very large bid-ask spreads. The 10-year bond benchmarks are identified according to maturity and liquidity criteria. Morningstar provided us with this unique tick-by-tick data sample that we resampled at 5-minute frequency using calendar time, excluding time intervals with missing values for at least one country. The 5-minute frequency is robust to microstructure noise and offers sufficiently high frequency to properly evaluate the impact of specific events. Moreover, this frequency is consistent with previous seminal contributions such as Fleming and Remolona (1997) and Balduzzi et al. (2001).

The trading period considered is 8 a.m. - 3:30 p.m. coordinated universal time (UTC). We detect and remove holidays and outliers applying a filter which is a modification of the procedure to remove outliers proposed in Brownlees and Gallo (2006) that we implement following the steps suggested by Barndorff-Nielsen et al. (2011, p. 156), that we summarize below.

Let $p_{t,i}$ be a tick-by-tick time series of prices, where t denotes day and i the time interval of day t, then an observation is removed if:

$$\left|p_{t,i}-\overline{p}_{t,i}\left(k^{L}\right)\right|>\max\left\{4MD_{t,i}(k),n\gamma\right\}\quad\wedge\quad\left|p_{t,i}-\overline{p}_{t,i}\left(k^{R}\right)\right|>\max\left\{4MD_{t,i}(k),n\gamma\right\} \tag{2.1}$$

where k the bandwidth; $\overline{p}_{t,i}\left(k^{L}\right)$ and $\overline{p}_{t,i}\left(k^{R}\right)$ sample medians of the $k/2$ observations respectively before (L for left) and after (R for right) (t,i); $MD_{t,i}(k)$ mean absolute deviation from the median of the whole neighborhood of length k; $\wedge$ the intersection operator; γ mean of the k absolute returns; n is $\gamma-$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 five-minute intervals. Data selecting procedure is summarized in Table 2.1.

Table 2.1: **Government bond yields and spreads: data selection and summary statistics**

	DE	IT	FR	ES	BE	NL
PANEL A						
No. ticks	2,980,063	917,630	1,035,631	903,233	799,610	605,155
Limiting trading time	2,294,951	704,701	794,602	796,529	682,408	512,789
Outliers: No. (%)	2,528 (0.11)	1,247 (0.18)	1,468 (0.18)	1,372 (0.17)	1,313 (0.19)	772 (0.15)
No. trades per day: Mean (SD)	2,629 (1,197)	805 (316)	908 (358)	910 (356)	780 (326)	586 (290)
Trade duration: Mean (SD) [s]	10.17 (27.01)	33.09 (62.97)	29.38 (58.16)	28.49 (57.85)	34.15 (69.05)	45.42 (82.33)
5-minute intervals	79,534	79,534	79,534	79,534	79,534	79,534
Exclude 1st daily obs	78,660	78,660	78,660	78,660	78,660	78,660
Bid YTM						
Mean (SD) [%]	2.76 (0.58)	4.67 (0.80)	3.29 (0.37)	4.67 (0.75)	3.82 (0.42)	3.11 (0.57)
Median (1st - 99th pct) [%]	3.00 (1.44 - 3.57)	4.49 (3.75 - 7.05)	3.39 (2.49 - 3.97)	4.39 (3.75 - 6.49)	3.82 (2.94 - 4.87)	3.29 (1.93 - 4.04)
Bid-Ask Spread of YTM						
Mean (SD) [bps]	0.63 (0.05)	0.65 (0.05)	0.80 (0.07)	0.76 (0.05)	0.97 (0.04)	0.70 (0.03)
Median (1st - 99th pct) [bps]	0.60 (0.55 - 0.76)	0.64 (0.59 - 0.81)	0.82 (0.68 - 0.94)	0.76 (0.70 - 0.90)	0.97 (0.89 - 1.08)	0.70 (0.64 - 0.77)
Bid Spread						
Mean (SD) [bps]	-	191 (124)	54 (34)	192 (117)	106 (63)	35 (16)
Median (1st - 99th pct) [bps]	-	148 (60 - 513)	38 (20 - 154)	184 (50 - 481)	90 (34 - 295)	30 (15 - 81)
Bid-Ask Spread of Spread						
Mean (SD) [bps]	-	0.03 (0.05)	0.18 (0.06)	0.13 (0.07)	0.35 (0.07)	0.07 (0.06)
Median (1st - 99th pct) [bps]	-	0.03 (-0.08 - 0.14)	0.17 (0.10 - 0.30)	0.13 (0.00 - 0.24)	0.35 (0.19 - 0.48)	0.10 (-0.04 - 0.19)
PANEL B						
Around macroannouncements						
No. trades per hour: Mean (SD)	298 (211)	86 (54)	96 (61)	96 (62)	83 (54)	63 (44)
Trade duration: Mean (SD) [s]	9.56 (25.05)	33.10 (63.87)	29.65 (60.45)	28.61 (58.68)	34.34 (71.29)	44.91 (82.37)
Other						
No. trades per hour: Mean (SD)	314 (178)	100 (46)	114 (53)	110 (54)	98 (48)	73 (41)
Trade duration: Mean (SD) [s]	10.65 (23.40)	32.96 (59.28)	29.09 (51.98)	28.31 (51.78)	33.83 (63.00)	45.49 (77.65)
Around auctions						
No. trades per hour: Mean (SD)	257 (199)	80 (53)	89 (60)	92 (62)	75 (52)	56 (43)
Trade duration: Mean (SD) [s]	10.26 (30.86)	33.81 (72.50)	30.03 (64.25)	28.86 (63.25)	35.74 (77.55)	47.45 (92.91)
Other						
No. trades per hour: Mean (SD)	334 (190)	103 (47)	116 (54)	110 (56)	100 (49)	75 (42)
Trade duration: Mean (SD) [s]	10.12 (21.62)	32.69 (58.43)	28.99 (52.21)	28.20 (51.43)	33.37 (63.17)	44.40 (76.38)
Around rating actions						
No. trades per hour: Mean (SD)	263 (205)	74 (52)	82 (58)	83 (59)	70 (51)	59 (44)
Trade duration: Mean (SD) [s]	8.87 (24.40)	31.65 (51.31)	28.66 (49.94)	27.36 (50.68)	33.30 (58.21)	39.47 (59.91)
Other						
No. trades per hour: Mean (SD)	355 (184)	109 (44)	123 (50)	119 (53)	105 (46)	79 (41)
Trade duration: Mean (SD) [s]	10.17 (22.22)	33.06 (60.62)	29.31 (53.97)	28.44 (53.36)	34.07 (65.63)	45.44 (79.33)

PANEL A of Table 2.1 reports the data procedure selection 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 (2.1) in the text. Tick-by-tick data are resampled using calendar time (see details in the body of the chapter). The 1st observation of each day is removed as it presents excess volatility. In square brackets is the unit of measurement. **PANEL B** of Table 2.1 offers an analysis of trading activity around the three categories of events analyzed: macroannouncements, government bond auctions and rating actions. The window around the event ranges from 1 hour before the release up to 1 hour after.

In Panel A, 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. We also remove outliers following the description in (2.1) which lead us to detect percentage of outliers ranging from 0.11% for Germany to the 0.19% 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; both statistics indicate that the most liquid market is the German one with a daily average number of trades of 2,629 and a trade duration of 10.2 seconds, followed by Spain (910 trades, 28.5 seconds), France (908 trades, 29.4 seconds), Italy (805 trades, 33.1 seconds), Belgium (780 trades, 34.1 seconds) and the

Netherlands (586 trades, 45.4 seconds). After resampling at the 5-minute frequency and removing the 8 a.m. time interval for each day, we end up with 78,660 returns, covering 874 days corresponding to 90 observations per day. In Table 2.1, we also report descriptive statistics about yields and spreads with respect to German Bund: Italy and Spain have the highest average yields, both corresponding to 4.67%, while Germany has the lowest equal to 2.76% denoting its safe heaven status; the average bid spread on Germany is equal to 192 bps for Spain, 191 for Italy, 106 for Belgium, 54 for France and 35 for the Netherlands. Of course, the information that the average indicator offers is limited in the light that government bond spreads vary a lot throughout our sample period as can be seen from Figure 2.1.

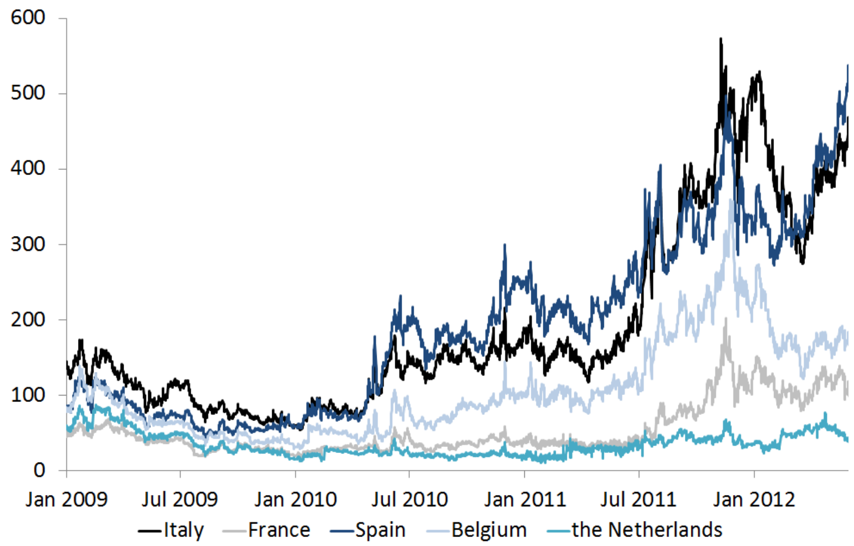


Figure 2.1: **10-year government bond spreads**

Figure 2.1 reports the 10-year government bond spreads (in bps) with respect to Germany for Italy, France, Spain, Belgium and the Netherlands over the period 2nd January 2009 - 31st May 2012. Spreads are computed on bid yields at 5-minute sampling frequency.

Government bond spreads were moving very closely until May 2010, when markets start to pay more attention to sovereign debt risk in correspondence to the burst of the Greek crisis. In May 2010, Greek government deficit was revised and estimated to be 13.6% of GDP with a correspondent decrease in international confidence in Greece's ability to repay its sovereign debt. As consequence, despite the first rescue package approved by Eurozone countries and the IMF, concerns about Euro countries solvability began to raise together with spreads.

In Panel B of Table 2.1, we report the analysis of the trading activity around the public events we are taking into consideration namely macroannouncements, government bond auctions and rating actions. The time window analyzed ranges from 1 hour before up to 1 hour after the release of each event. We compare both the number of trades per hour as well as the time elapsed between two consecutive trades with respect to trading hours with no particular events. Results in Table 2.1 show that there is no great evidence of a different trading activity around the events analyzed.

2.2.1.2 Macroannouncements

Macroannouncements are a wide range of news, coming from a number of countries, which constitute one of the most important source of information driving trading activity. The reason why bond markets are generally found to be more influenced by macroannouncement releases is hilighted by the Fisher equation stating that the Yield-To-Maturity (YTM) of a bond can be decomposed into two parts: the real interest rate component (y_t^r), which is closely linked to expectations about economic activity, and the average inflation expected to prevail over the maturity of the bond (π_t). Consequently, the nominal yield y_t^n may be expressed as:

$$y_t^n = E\left(y_t^r|\Omega_t\right) + E\left(\pi_t|\Omega_t\right) \tag{2.2}$$

From this decomposition it is clear that every change in y_t^n is determined by the information set Ω at time t. Unlike stocks or corporate bonds, government bonds returns are hardly affected by any asset-specific or private information; therefore we can claim that Ω is to a great extent formed by public information in the form of regularly scheduled announcements, macroeconomic or not, which constitute the main source of volatility for this asset class at the intraday level.

We consider news releases related to the US, the Euro area, Belgium, France, Germany, Greece, Italy, the Netherlands, Portugal and Spain. In some cases, we are unable to use all available macroannouncements as they are released when some markets are still closed. This is for instance the case of France, with releases occurring between 6:30 and 7:45 a.m. UTC. Finally, in case of Spain, although macroannouncements are released at 8:00 a.m. UTC, we keep these indicators shifting them to 8:05 a.m. in order to match with spreads data. Data related to macroannouncements are median expected value by survey panelists (E), forecasts standard deviation (σ) and actual value of the release (A) and they were collected from Bloomberg. Surveys are conducted on a number of forecasters by the Money Market Service (MMS) and these data are generally found to possess reasonable properties as expectations series as they are unbiased, pass simple forecast rationality tests and outperform naive time series forecasts (see, for instance, Balduzzi et al. (2001)).

In our application, we adopt the standard surprise measure defined as $S = (A - E)/\sigma$. A complete list of the macroannouncements analyzed is presented in Table 2.2.

Table 2.2: **Macroannouncements with prescheduled releases**

Country	**Macroannouncement**	**Frequency**	**Release time** (UTC)	**No.**	**Category**	**Surprise Mean (SD)**
US	Business inventories	M	15:00	41	RE	-0.55 (2.08)
	Chicago PMI	M	14:45	39	FL	0.87 (2.54)
	Consumer confidence	M	15:00	39	FL	-0.29 (3.40)
	CPI	M	13:30	41	P	0.01 (1.03)
	Durable goods	M	13:30	40	FL	-0.59 (2.70)
	Factory orders	M	15:00	40	FL	0.16 (1.11)
	GDP advance	Q	12:30 / 13:30	14	RE	-0.13 (1.00)
	GDP preliminary	Q	12:30 / 13:30	14	RE	-0.53 (1.45)
	GDP final	Q	12:30 / 13:30	13	RE	0.00 (2.28)
	Industrial production	M	14:15	41	RE	-0.29 (1.82)
	Initial jobless claim	W	13:30	175	RE	0.00 (0.00)
	Nonfarm payroll	M	13:30	39	RE	-0.09 (2.23)
	Philadelphia FED Index	M	15:00	41	FL	-0.10 (3.69)
	PPI	M	13:30	41	P	0.06 (1.75)
	Retail sales	M	13:30	41	RE	0.05 (1.81)
	University of Michigan	M	14:55	39	FL	1.12 (1.49)
EA	Business climate	M	09:00	42	FL	0.17 (2.05)
	Consumer confidence	M	10:00	42	FL	0.14 (2.00)
	Flash HICP	M	10:00	42	P	0.07 (1.40)
	HICP	M	10:00	41	P	0.00 (0.00)
	Industrial production	M	10:00	41	RE	-0.29 (1.82)
	Introductory Statement	M	13:30	40	RE	-
	M3	M	09:00	41	P	-0.44 (2.66)
	Monthly Bulletin	M	10:00	41	RE	-
	PMI flash	M	09:00	41	FL	0.18 (2.51)
	PMI final	M	09:00	41	FL	0.79 (2.87)
	PPI	M	10:00	41	P	-0.05 (0.86)
	Retail sales	M	10:00	41	RE	-0.79 (1.66)
	Unemployment	M	10:00	41	RE	0.41 (1.67)
DE	CPI preliminary	M	13:00	37	P	0.00 (1.32)
	IFO: business confidence	M	09:00	41	FL	1.24 (2.55)
	Industrial production	M	11:00	41	RE	-0.15 (2.58)
	Unemployment	M	08:55	42	RE	-0.63 (2.54)
	ZEW	M	10:00	41	FL	0.73 (2.53)
IT	Business confidence	M	08:30 / 09:00	41	FL	0.26 (2.85)
	CPI preliminary	M	10:00	42	P	0.35 (2.49)
	CPI final	M	09:00 / 10:00	41	P	-0.98 (3.00)
	GDP preliminary	Q	09:00 / 10:00	13	RE	-1.33 (2.78)
	GDP final	Q	09:00 / 10:00	12	RE	-0.25 (0.87)
	Industrial production	M	09:00	41	RE	-0.04 (2.44)
FR	Industrial production	M	07:45 / 08:45	2	RE	6.67 (25.93)
ES	CPI	M	08:00	41	P	0.06 (0.75)

Table 2.2: **Macroannouncements with prescheduled releases**

Country	**Macroannouncement**	**Frequency**	**Release time (UTC)**	**No.**	**Category**	**Surprise Mean (SD)**
	GDP preliminary	Q	08:00	14	RE	0.14 (2.03)
	GDP final	Q	08:00	14	RE	-0.29 (0.73)
	Industrial production	M	08:00	40	RE	-0.38 (2.69)
	Unemployment	Q	08:00	14	RE	0.75 (1.42)
PT	CPI	M	10:00	40	P	-0.84 (2.79)
	GDP preliminary	Q	10:00	14	RE	6.43 (10.70)
	GDP final	Q	11:00	12	RE	-3.00 (2.38)
NL	CPI	M	08:30	39	P	0.02 (1.18)
	Industrial production	M	08:30	39	RE	-0.65 (3.74)
	Unemployment	M	08:30	41	RE	-0.37 (2.14)
BE	Business confidence	M	14:00	41	P	0.10 (2.19)
GR	CPI	M	10:00	40	P	-0.84 (3.49)
	GDP preliminary	Q	08:30 / 10:00	8	RE	-0.19 (1.03)
	GDP final	Q	08:30 / 10:00	7	RE	-3.00 (2.38)
	Unemployment	M	10:00	38	RE	-0.02 (2.61)

Table 2.2 reports a description of macroeconomic announcements released in the period 2nd January 2009 - 31st May 2012. In some cases the release time changes according to the summertime. FL stands for Forward Looking, P for price and RE for Real Economy macroannouncement categories. Surprise is computed as (Actual Release -Median Forecasts)/SD Forecasts.

The size of the surprises related to US and Euro area macroannouncements are smaller than those concerning individual countries, implying a more accurate forecast by surveyors in the first two cases, though it is fair to mention that the number of surveyors interviewed for US and Euro area releases is higher than for individual countries. Finally, we drop the France industrial production given that in only two cases macroannouncements were released after 8 a.m. UTC, and the Portugal preliminary GDP because of its very high dispersion (standard deviation equals 10.7) due to both poor forecasts and low number of surveyors for this specific news. For the Euro area HICP we did not dispose about forecasts. The distribution of macroannouncement surprises is represented in Figures 2.2-2.5:

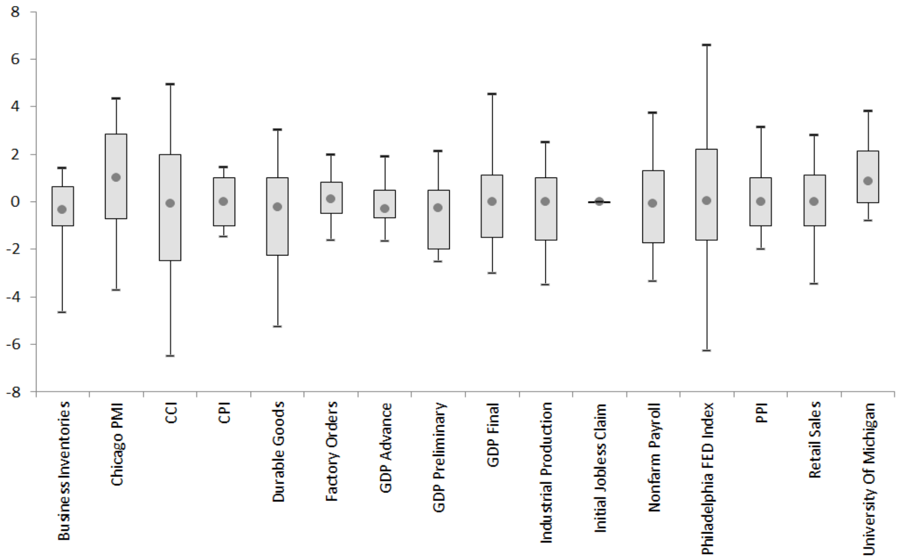


Figure 2.2: **US macroannouncement surprises**

Figure 2.2 presents the distribution of surprises related to US macroeconomic announcements released in the period 2nd January 2009 - 31st May 2012.

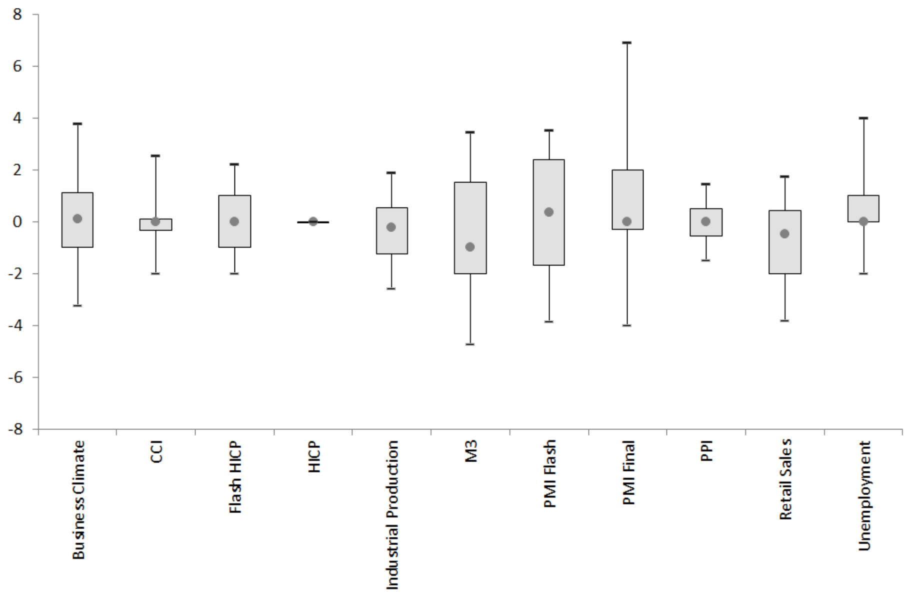


Figure 2.3: **EA macroannouncement surprises**

Figure 2.3 presents the distribution of surprises related to Euroa area macroeconomic announcements released in the period 2nd January 2009 - 31st May 2012.

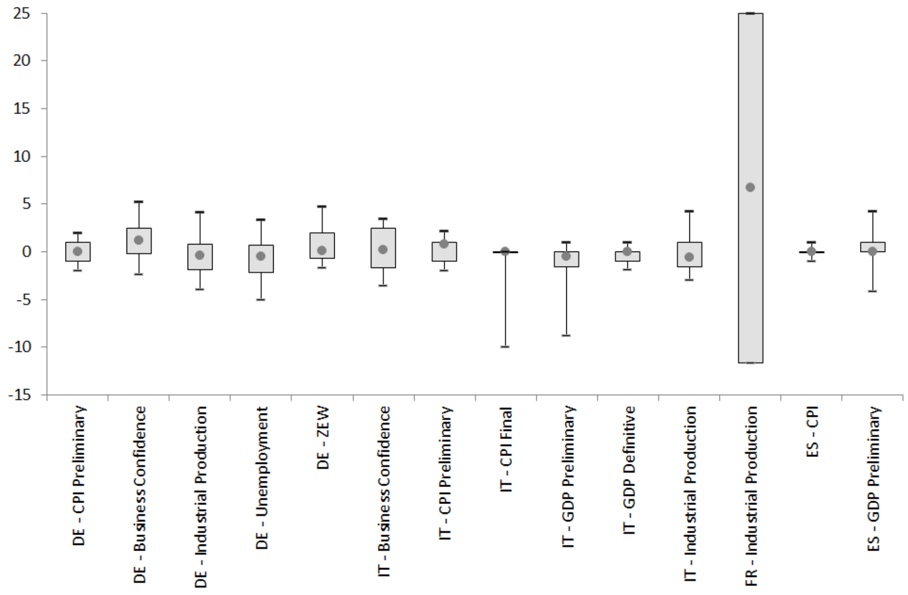


Figure 2.4: **National countries macroannouncement surprises (1)**

Figure 2.4 presents the distribution of surprises related to German, French, Italian and Spanish macroeconomic announcements released in the period 2nd January 2009 - 31st May 2012.

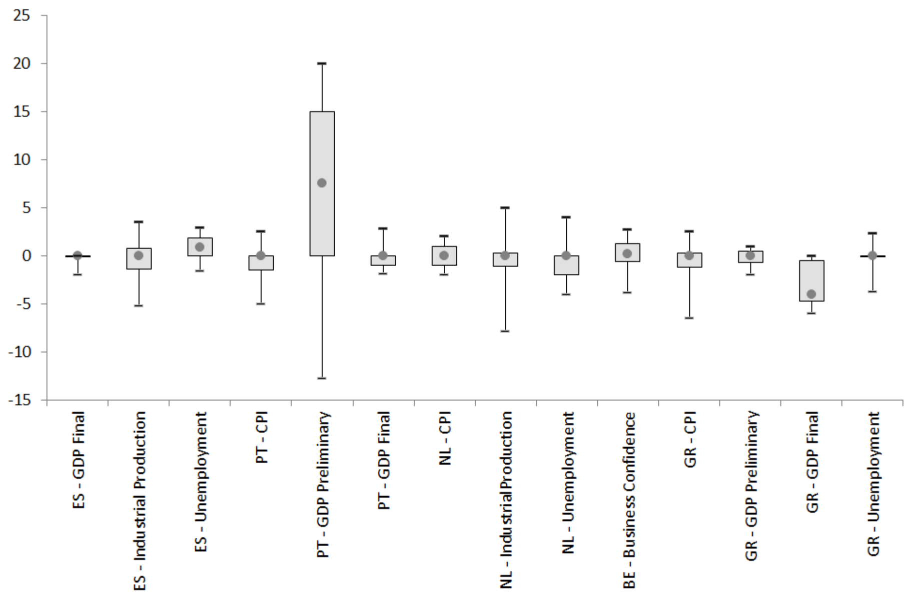


Figure 2.5: **National countries macroannouncement surprises (2)**

Figure 2.5 presents the distribution of surprises related to Spanish, Portuguese, Belgian, Greek and Dutch macroeconomic announcements released in the period 2nd January 2009 - 31st May 2012.

2.2.1.3 Bond Auctions

We take into consideration auctions of European countries issuing Euro-denominated bonds: Austria, Belgium, Finland, France, Germany, Greece, Italy, Portugal, Spain and the Netherlands. Most auctions take place between 8 and 10 a.m. UTC. To capture the performance of an auction, we use two main variables: the average yield at which the government sells the bonds and the bid-to-cover, that is how many bids the Government received with respect to the total offer. These two data were collected just for auctions relative to 10-year bonds as they not only correspond to the maturity of the spreads analyzed but they even represent the most relevant ones.

In Table 2.3, we report the total number of auctions per country together with the detail of 10-year bond auctions for which we provide details on mean and standard deviation of the average yield and the bid-to-cover.

Table 2.3: **Government bond auctions**

	No. of auctions	**No. of 10-year bond auctions**	**Average yield [%] Mean (SD)**	**Bid-to-cover Mean (SD)**
Austria	34	15	3.64 (0.68)	2.16 (0.44)
Belgium	113	25	3.98 (0.55)	2.07 (0.56)
Finland	8	4	2.75 (0.46)	na
France	271	38	3.61 (0.59)	2.34 (0.75)
Germany	220	35	3.04 (0.84)	1.53 (0.29)
Greece	53	0	-	-
Italy	193	46	4.76 (0.75)	1.42 (0.17)
Portugal	104	16	5.01 (0.79)	2.05 (0.76)
Spain	163	25	4.85 (0.81)	1.94 (0.40)
the Netherlands	142	18	3.42 (0.74)	na

Table 2.3 reports a description on government bond auctions hold in the period 2nd Janaury 2009 - 31st May 2012. Average yield: yield at which the government allocated the bonds issued in an auction. Bid-to-cover: ratio between the number of bids the Government received and the amount of bonds offered. Average yield and bid-to-cover are collected just for auctions concerning 10-year bonds.

Bid-to-covers are very similar for all the countries analyzed ranging from a minimum of 1.42 for Italian auctions to a maximum of 2.34 for French ones, while average yields reflect countries different sovereign risk: safer countries such as Finland and Germany succeed in selling bonds at higher prices and lower returns, with an average yield of 2.75% and 3.04% respectively, while riskier countries such as Italy, Spain and Portugal allocate their bonds at an average yield of 4.76%, 4.85% and 5.01%, respectively.

The distributions of bid-to-cover and average yield per country are reported in Figures 2.6 and 2.7 respectively:

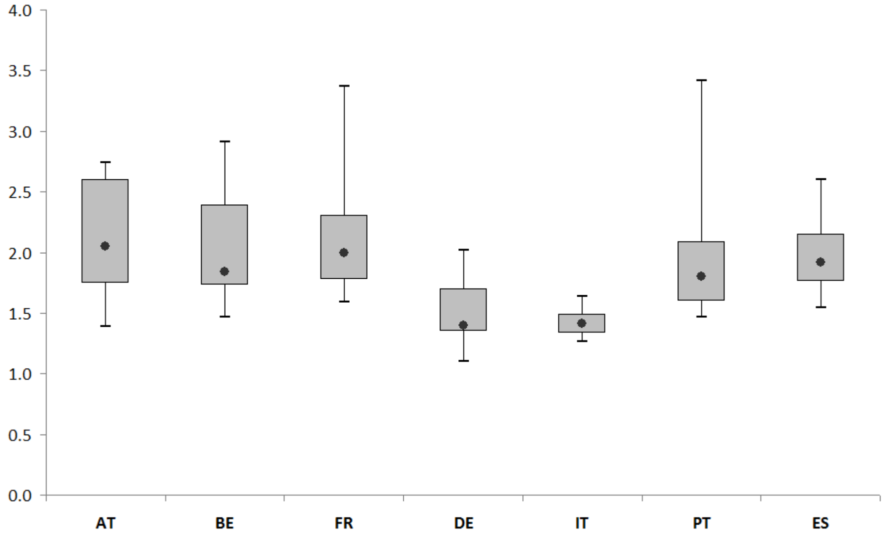


Figure 2.6: **Bid-to-cover**

Figure 2.6 presents the distribution of bid-to-cover for 10-year government bond auctions hold in the period 2nd January 2009 - 31st May 2012. Bid-to-cover offer information about the number of bids the Government received with respect to the total offer.

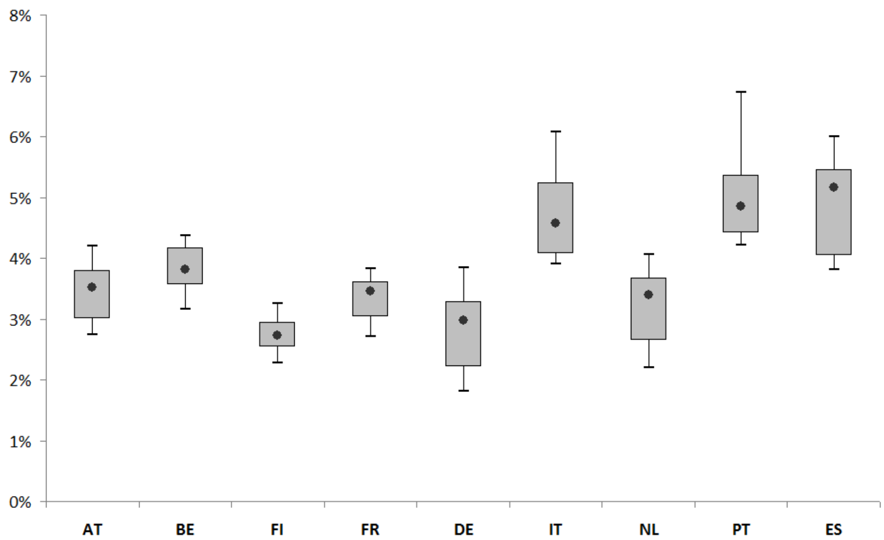


Figure 2.7: **Average Yield**

Figure 2.7 presents the distribution of average yields for 10-year government bond auctions hold in the period 2nd January 2009 - 31st May 2012. Average yields are the yield at wihich the Government succeded in selling its bonds.

2.2.1.4 Rating Actions

We collect data concerning rating actions from the three main rating agencies: Standard & Poor's, Moody's and Fitch. The aim is not only to assess whether downgradings have an impact on government bond spreads but also to investigate whether some agencies have bigger and/or more lagged impacts in comparison to the others. Note that in our sample we deal mainly with downgrading actions as only two upgrading actions occurred during the period considered, namely on 22nd February 2011 and 13th March 2012 for Greece. Downgrading actions were undertaken against Austria, Belgium, France, Greece, Ireland, Italy, Portugal and Spain as reported in Table 2.4.

Table 2.4: **Rating actions**

	S&P's	**Moody's**	**Fitch**
Austria	13-Jan-12	-	-
Belgium	25-Nov-11	16-Dec-11	27-Jan-12
France	13-Jan-12	-	-
Greece	14-Jan-09	22-Dec-09	22-Oct-09
	16-Dec-09	22-Apr-10	08-Dec-09
	27-Apr-10	14-Jun-10	09-Apr-10
	29-Mar-11	07-Mar-11	14-Jan-11
	09-May-11	01-Jun-11	20-May-11
	13-Jun-11	25-Jul-11	13-Jul-11
	27-Jul-11	02-Mar-12	22-Feb-11 (•)
	27-Feb-12		09-Mar-12
	02-May-12		13-Mar-12 (•)
			17-May-12
Ireland	30-Mar-09	02-Jul-09	08-Apr-09
	08-Jun-09	19-Jul-10	04-Nov-09
	24-Aug-10	17-Dec-10	06-Oct-10
	23-Nov-10	15-Apr-11	09-Dec-10
	02-Feb-11	12-Jul-11	
	01-Apr-11		
Italy	19-Sep-11	05-Oct-11	07-Oct-11
	13-Jan-12	13-Feb-12	27-Jan-12
Portugal	21-Jan-09	13-Jul-10	24-Mar-10
	27-Apr-10	16-Mar-11	23-Dec-10
	24-Mar-11	05-Apr-11	24-Mar-11
	29-Mar-11	06-Jul-11	01-Apr-11
	24-Nov-11		24-Nov-11
	13-Jan-12		
Spain	19-Jan-09	30-Sep-10	28-May-10
	28-Apr-10	10-Mar-11	07-Jul-11
	13-Oct-11	18-Oct-11	27-Jan-12
	13-Jan-12	13-Feb-12	07-Jun-12
	26-Apr-12		

Table 2.4 reports the rating actions undertaken by S&P's, Moody's and Fitch during the period 2nd Janaury 2009 - 31st May 2012. All the rating actions presented in Table 2.4 are downgradings, the only exceptions are the two upgradings (•) which took place on 22nd February 2011 and 13th March 2012 for Greece by Fitch.

2.3 Econometric Identification and Modelling of Jumps and Cojumps

2.3.1 Identifying jumps and cojumps

We briefly describe the testing procedures implemented to correctly identify jumps and cojumps.

2.3.1.1 Detecting jumps

There exist a vast range of jump detecting procedures proposed in literature and Dumitru and Urga (2012) report a comprehensive comparison among the available tests. As we are interested in identifying the exact time of occurrence of jumps, the Andersen, Bollerslev and Dobrev (2007, ABD henceforth) and the Lee and Mykland (2008, LM) jump detecting procedures are the only two suitable tests to this purpose.

ABD and LM both assume a continuous time jump-diffusion data generating process in the following log price process:

$$dp_{t,i} = \mu_{t,i} d(t,i) + \sigma_{t,i} dW(t,i) + \kappa_{t,i} dq(t,i) \qquad t = 1, ..., T,\ i = 1, ...N \tag{2.3}$$

where $p_{t,i}$ log asset price for the i-th subinterval belonging to day t; N number of equally spaced subintervals belonging to day t with the interval time length being equal to Δ; $\mu_{t,i}$ locally bounded variation process; $\sigma_{t,i}$ volatility process, strictly positive and càdlàg; $W(t,i)$ Wiener process; $dq(t,i)$ counting process, possibly a non-homogenous Poisson process; $\kappa_{t,i} = p_{t,i} - p_{t,i-}$ jump size. The Brownian motion $W(t,i)$, the jump sizes $\kappa_{t,i}$ and the counting process $q(t,i)$, are independent of each other. Moreover, in the absence of jumps, the drift $\mu_{t,i}$ and the instantaneous volatility $\sigma_{t,i}$ are such that the underlying data generating process is an Itô process with continuous sample paths.

The ABD test can be summarized as follows. The first step consists in choosing the size α of the jump test at the daily frequency and defining $\beta = 1-(1-\alpha)^{\Delta}$ the level of the corresponding $(1-\beta)$ confidence interval for a randomly drawn intraday diffusive return approximately distributed as a normal with zero mean and variance $N \times BV_t$, where BV_t is the bipower variation for day t. The bipower variation is defined in Appendix 2.A.

In mathematical terms, the ABD test statistics is defined as:

$$k_{t,i}(\Delta) = r_{t,i} I \left[\frac{|r_{t,i}|}{\sqrt{BV_t(N)}} > \Phi(1-\beta/2) \right] \tag{2.4}$$

where $|r_{t,i}|$ is the absolute value of return on day t and time-interval i defined as $p_{t,i} - p_{t,i-1}$; $\Phi(1-\beta/2)$ refers to the corresponding critical value from the standard normal distribution. Anyway, this procedure will tend to over-reject the diffusive null hypothesis whenever there is substantial intraday variation in volatility; therefore Andersen et al. (2007) suggest to set α to a conservatory level $10e^{-5}$ in order to achieve satisfactory practical performance in terms of effective power and size.

The LM test differs from the ABD just for the number of observations the BV is computed on $(K < N)$ and for the choice of the critical value, here not coming from the normal but from the Gumbel distribution. The jump test statistic $L_{t,i}$ is defined as follows:

$$L_{t,i} = \frac{|r_{t,i}|}{\sqrt{BV_t(K)\,\frac{1}{K-2}}} \tag{2.5}$$

The window size K should be large enough so that the effect of jumps on the estimation of the instantaneous volatility disappears but at the same time it should be smaller than the total number of observations per day, N. The condition $K = O_p(\Delta^\alpha)$ with $-1 < \alpha < -0.5$ satisfies the requirements. Therefore there exists a relationship between the choice of the sampling frequency Δ and the window length K. In general for N, number of observations per day, we have that $\sqrt{252 \times N} \leq K \leq 252 \times N$. Moreover, results in Lee and Mykland (2008) show that when K is within the range, increasing K only elevates the computational burden without marginal contribution and therefore the optimal choice seems to be the smallest integer satisfying the necessary condition, $\sqrt{252 \times N}$. Lee and Mykland (2008) specific recommendation of optimal window sizes for one-week, one-day, one-hour, 30-minute, 15-minute and 5-minute data are 7, 16, 78,110, 156 and 270 respectively for a 24-hour trading day.

As stated, the LM test does not use critical values from the normal distribution rather from the maximum of the test statistics. Under some assumptions, it is possible to show that:

$$\frac{\max(L_{t,i}) - C_{(T\times N)}}{S_{(T\times N)}} \to \xi \tag{2.6}$$

where ξ has a Gumbel *cdf*: $P(\xi \leq x) = \exp(-e^{-x})$, $T\times N$ represents the total number of observations, $C_{T\times N} = (2\log(T\times N))^{1/2} - \frac{\log\pi + \log(\log(T\times N))}{2(2\log(T\times N))^{1/2}}$ and $S_{(T\times N)} = \frac{1}{(2\log(T\times N))^{1/2}}$.

Therefore, the null hypothesis of no jump is rejected in case:

$$\frac{L_{t,i} - C_{(T\times N)}}{S_{(T\times N)}} > \beta^* \tag{2.7}$$

where $P(\xi \leq \beta^*) = \exp\left(-e^{-\beta^*}\right) = 1 - \alpha$.

The main drawback of ABD and LM tests is that they assume that spot volatility measured by BV is approximately constant over the local window, hence one day for the ABD or roughly the 90% of the observations in a day for LM. In fact, although the volatility is time varying through a day, ABD and LM tests are both based on an estimate of the average volatility of the returns in the local window. In order to deal with this problem, Andersen et al. (2007) introduce the filtered J test (FJ) statistic based on the standardization of returns even by a periodicity estimate $s_{t,i}$ which has the function of making the volatility time-varying through the local window:

$$FJ_{t,i} = \frac{|r_{t,i}|}{\widehat{BV}_t \widehat{s}_{t,i}} \tag{2.8}$$

To obtain an estimate of the periodicity component $\widehat{s}_{t,i}$, we implement the Boudt et al. (2010) robust estimation technique based on the Truncated Maximum Likelihood (TML) estimator. Boudt et al. (2010) show that the filtered jump test statistics increases the accuracy of intraday jump detection methods. Finally, to control for the intraday periodicity, we adopt the Andersen and Bollerslev (1998) formulation modified with the inclusion of government bond auctions and rating actions as follows:

$$\widehat{s}_{t,i} = \frac{\exp f\left(\hat{\theta}_{TML}; x_{t,i}\right)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\exp f\left(\hat{\theta}_{TML}; x_{t,i}\right)\right)^2}} \quad \forall t = 1, ..., T \tag{2.9}$$

$$\begin{aligned} f\left(\hat{\theta}_{TML}; x_{t,i}\right) \quad = \quad & \delta_0 + \delta_{0,1}\frac{i}{N_1} + \delta_{0,2}\frac{i^2}{N_2} + \sum_{j=1}^{J}\lambda_j S_{t,i}^j + \\ & \sum_{b=1}^{B}\phi_b R_{t,i}^b + \sum_{j=1}^{4}\vartheta_j Weekdays_j + \\ & \sum_{p=1}^{P}\left(\delta_{c,p}\cos\left(\frac{2\pi p}{N}i\right) + \delta_{s,p}\sin\left(\frac{2\pi p}{N}i\right)\right) + \varepsilon_{t,i} \end{aligned} \tag{2.10}$$

where N number of intraday intervals i belonging to day t; $N_1 = (N+1)/2$ and $N_2 = (N+1)(N+2)/6$ normalizing constants; $S_{t,i}^j$ surprise for macroannouncements and government bond auctions (for the last ones, surprise is computed as the difference in bid-to-cover between current and previous 10-year auction); J the sum of macroannouncements and auctions considered; $R_{t,i}^b$ dummy variable for rating action undertaken by rating agency b; B is the number of rating agencies; λ_j and ϕ_b event specific loading coefficients; P tuning parameter determining the order of the expansion of the sinusoids; $\hat{\theta}_{TML}$ full parameter vector to be estimated.

Moreover, the loading coefficients λ_j and ϕ_b are modeled applying the Andersen and Bollerslev (1998) decay-structure which allows the specific event to impact over a time window but with decaying weights. Macroannouncement surprises are allowed to impact starting from 30 minutes before the release up to one hour and 30 minutes after, as in Andersen and Bollerslev (1998). As far as government bond auctions are concerned, we use a wider window, ranging from two hours before the auction ends, up to one hour after it as we want to take into account the uncertainty in the markets during the auction period. Finally, as the timing of rating actions is not foreseeable, we set the start of the window in correspondence of the rating action up to two hours after it.

2.3.1.2 Detecting Cojumps

In order to evaluate whether and how markets are dependent from each other, we assess whether markets share a simultaneous jump, that is whether there is evidence of a cojump. To do that we firstly need to characterize co-jumps.

Let consider the multivariate version of (2.3) so that the log-prices of M assets can be written as $X_{t,i} = \left(p^1_{t,i}, ..., p^M_{t,i}\right)'$ for $(t,i) \geq 0$. Assuming the log-price vector of $X_{t,i}$ is a semimartingale on some filtered probability space $\left(\Omega, \mathcal{F}_{(t,i)\geq 0}, P\right)$, the continuously compounded log-return can be written as:

$$d\log X_{t,i} = u_{t,i}d(t,i) + s_{t,i}dW\left(t,i\right) + C_{t,i}dJ\left(t,i\right) \qquad t = 1,...,T,\ i = 1,...N \tag{2.11}$$

where $u_{t,i}$ M-vector drift rate, $\mathcal{F}_{(t,i)}$ adapted càdlàg process; $s_{t,i}$ $(M \times M)$ matrix, $\mathcal{F}_{(t,i)}$ adapted càdlàg process; $W\left(t,i\right)$ M-vector of independent standard Brownian motions; $J\left(t,i\right)$ M-vector of counting process independent of $W\left(t,i\right)$; $C_{t,i}$ $(M \times M)$ matrix of jump sizes, independent of each other and identically distributed. $C_{t,i}$ is assumed to be independent from $W\left(t,i\right)$ and $J\left(t,i\right)$.

The most naïve method to test for the presence of co-jumps is to apply the univariate test simultaneously on each asset and then to evaluate whether they occur simultaneously; for example some early literature detected co-jumps by applying standard Barndorff-Nielsen and Shephard (2004) test. Let consider to deal with M assets for which we want to test the presence of co-jumps at α confidence level. In case we don't care about the correlation among the assets, the confidence level for each test should be set at α/M. Anyway, as the assets are usually correlated, the total significant level is lower than α and therefore we might loose some power or significance in the inference. In light of that, before conducting the tests, returns are usually standardized by a robust estimation of the instantaneous covariance matrix accounting for the local covariation of the returns from the continuous part of the process.

Following developments in testing procedures for cojumps are introduced by Gobbi and Mancini (2007) and Jacod and Todorov (2009) who specifically propose strategies to test for co-jumps between a particular pair of asset returns. Instead Bollerslev et al. (2008) introduce a panel based test statistic explicitly based on the covariance structure in order to deal with idiosyncratic noise in individual returns.

In the empirical part of this Chapter, we adopt the definition proposed in Lahaye et al. (2011), recently extended by Maini and Urga (2012). Given C assets, the contemporaneous cojump is defined as:

$$CoJump_{t,i} = \prod_{c=1}^{C} I\left(\left|FJ^c_{t,i}\right|\right) \tag{2.12}$$

where $I(.)$ indicator function taking value 1 in case on day t at the interval i there was a significant jump $FJ_{t,i}$ as per (2.8). In order to identify a sufficient number of cojumps for further analysis, we define a cojump if two or more jumps occur within a 15 minutes time window.

2.3.2 Modelling jumps and cojumps

2.3.2.1 Mapping Jumps

We now turn to assess the linkage between jumps and their possible determinants, namely macroannouncements, government bond auctions and rating actions. To this purpose, we compare the number of jumps around a pre-specified event with respect to other periods as it is discussed later in the Chapter. However, this simple comparison does not take into account neither other variables which could cause the observed difference going beyond the impact of the single event nor the concurrence with other news. Moreover, it is widely documented (see for instance Balduzzi et al. (2001); Lu and Wu (2009); Rangel (2011)) that it is not the release per se which explains jumps as the surprise related to a particular event; in case of government bond auctions we define the surprise as the difference in the bid-to-cover and the average yield with the previous auction of bond of the same maturity. When the release is within market expectation, there is no reason for market to jump after the announcement. Moreover, when two releases occur simultaneously, the only way to impute the impact to the correct release is to use surprise.

The econometric model we propose is able to map jumps to macroannouncements, government bond auctions and rating actions in both the process governing the conditional mean and the conditional variance of government bond spreads. With respect to the conditional mean, we extend the Tobit-GARCH model in Lahaye et al. (2011):

$$|FJ_{t,i}| = \begin{cases} \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \varepsilon_{t,i} & \text{if} >0 \\ 0 & \text{otherwise} \end{cases} \tag{2.13}$$

where $|FJ_{t,i}|$ absolute size of significant detected jumps; $\eta_{t,i}$ linear combination of day-of-the-week dummies; $\mu_{t,i}$ standardized US news surprises $\sum_{j=1}^{J} \lambda_j \left|S_{t,i}^j\right|$; $\xi_{t,i}$ intraday periodic component and N number of intraday periods within a day. Lahaye et al. (2011) allow for a potential delayed response to news by testing for lagged news; moreover they correct for heteroskedasticity estimating the Tobit-GARCH model of Calzolari and Fiorentini (1998) as proposed in Andersen et al. (2011).

With respect to the model for the conditional variance, rather than a simple GARCH model as in Lahaye et al. (2011), we use a GARCH formulation driven by macroannouncements as in de Goeij and Marquering (2006):

$$h_{t,i} = \omega_1 + \omega_2 D_{t,i-1} + \beta h_{t,i-1} + \left(\alpha_1 + \alpha_2 D^{*}_{t,i-1}\right) \varepsilon^2_{t,i-1} + \left(\nu_1 + \nu_2 D^{*}_{t,i-1}\right) \left(\varepsilon^{-}_{t,i-1}\right)^2 \tag{2.14}$$

where macroannouncements impact in three alternative ways. First, ω_2 allows for the unconditional volatility level to differ from ω_1 when an announcement $D_{t,i-1}$ is scheduled in the near future. This is the so-called preannouncement effect and, when it is found to be positive, it implies a higher unconditional volatility level in the period preceding the releases. Second, the coefficient α_2 captures the difference in persistency of macroannouncements with respect to other kind of news. In particular, $D^*_{t,i-1}$ are dummy variables taking value 1 in case the absolute size of the surprise is greater than its standard deviation and zero otherwise. If the parameters α_2 are found to be negative/positive and statistically significant, this means that macroannouncements are less/more persistent with respect to regular shocks. Finally, ν_2 accounts for a different leverage effect in correspondence to macroannouncements and, if it is found to be positive/negative, it implies that negative surprises have higher/lower impact than positive ones and that the leverage effect is more/less pronounced for macroannouncements with respect to other kind of news.

2.3.2.2 Modelling Jumps

The jump model we estimate is a Tobit-GARCH where both the mean and variance processes are driven by macroannouncements, government bond auctions and rating actions. In particular, we allow for a pre-announcement effect that takes into account of future releases of macroannouncements and government bond auctions for a pre-specified number of time intervals, while rating actions are excluded as they are not prescheduled. As per post-announcement, in our model we capture news announcement effect directly via surprise effects related to macroannouncements and auctions rather than via dummy variables, the only exception being the rating actions which indeed enter the model by dummy variables taking value 1 after the rating action is public. Finally, another novelty in our model is that we allow the surprise effect to impact for a pre-specified time window after the release by modelling the coefficients loading the surprises by the polynomial decay structure proposed in Andersen and Bollerslev (1998). Andersson et al. (2006) as well as Lahaye et al. (2011) account for delayed response of the dependent variable after an announcement but entering the model with lags of the surprise each loaded by its own coefficient making the estimation procedure extremely complex. In our model, the response pattern for each macroannouncement and auction is 12 periods long corresponding to one hour after the release. The model for the mean equation is formalized as follows:

$$\begin{aligned}
|FJ_{t,i}| &= \mu + \sum_{j=1}^{J} \gamma_{1,j} D_\tau^j I\left[\tau \in \left(\left(t,i\right),\left(t,i+\Delta\right)\right)\right] + \\
&\sum_{j=1}^{J} \gamma_{2,j} \left|S_\tau^j\right| I\left[\tau \in \left(\left(t,i-\Delta\right),\left(t,i\right)\right)\right] + \\
&\sum_{b=1}^{B} \gamma_{2,J+b} R_\tau^b I\left[\tau \in \left(\left(t,i-\Delta\right),\left(t,i\right)\right)\right] + \xi_{t,i} + \varepsilon_{t,i}
\end{aligned} \tag{2.15}$$

where $|FJ_{t,i}|$ absolute size of significant detected jumps at $\alpha = 0.05$ by the LM test filtered by the intraday periodicity estimated by (2.9) and (2.10); D_τ^j dummy variable taking value 1 if macroannouncements or government bond auctions are prescheduled in the next Δ periods after (t,i); $\left|S_\tau^j\right|$ absolute surprise for macroannouncements and government bond auctions released up to Δ periods before (t,i); J sum of the number of macroannouncements and auctions; R_τ^b dummy variable taking value 1 if a rating action was undertaken up to Δ periods before (t,i); $\xi_{t,i} = \delta_1 \frac{i}{N_1} + \delta_2 \frac{i^2}{N_2} + \sum_{p=1}^{5}\left(\delta_{2+p}\cos\frac{2\pi p}{N} i + \delta_{7+p}\sin\frac{2\pi p}{N} i\right)$ intraday periodicity as per Lahaye et al. (2011); $\varepsilon_{t,i}|\digamma_{t,i-1} \sim N\left(0,h_{t,i}\right)$, $\digamma_{t,i-1}$ being the information set available up to $(t,i-1)$.

The conditional volatility $h_{t,i}$ is specified as follows:

$$\begin{aligned}
h_{t,i} &= \omega_1 + \sum_{j=1}^{J} \omega_{2,j} D_\tau^j I\left[\tau \in \ \left(\left(t,i\right),\left(t,i+\Delta\right)\right)\right] + \beta h_{t,i-1} + \\
&\left(\alpha_1 + \sum_{j=1}^{J} \alpha_{2,j} D_\tau^{*\,j} I\left[\tau \in \left(\left(t,i-\Delta-1\right),\left(t,i-1\right)\right)\right] + \right. \\
&\left. \sum_{b=1}^{B} \alpha_{2,J+b} R_\tau^b I\left[\tau \in \left(\left(t,i-\Delta-1\right),\left(t,i\right)\right)\right]\right) \varepsilon_{t,i-1}^2 + \\
&\left(\nu_1 + \sum_{j=1}^{J} \nu_{2,j} D_\tau^{*\,j} I\left[\tau \in \left(\left(t,i-\Delta-1\right),\left(t,i-1\right)\right)\right]\right) + \\
&\left.\sum_{b=1}^{B} \nu_{2,J+b} R_\tau^b I\left[\tau \in \left(\left(t,i-\Delta\right),\left(t,i\right)\right)\right]\right) \left(\varepsilon_{t,i-1}^{-}\right)^2
\end{aligned} \tag{2.16}$$

where D_τ^j denotes the dummy variable taking value 1 if a macroannouncement or an auction is scheduled to take place in the next Δ periods after (t,i); $D_\tau^{*\,j}$ denotes the dummy variable taking value 1 for large macroannouncement surprises or big changes in bid-to-cover or average-yield occurred in the previous Δ periods; R_τ^b denotes the dummy variable taking value 1 if in the previous Δ periods a rating action occurred.

Unlike de Goeij and Marquering (2006), we define large surprises if the absolute surprise is higher than one half of the standard deviation of this measure for all the macroannouncement of the same kind in order to set a unique rule for macroannouncements and bond auctions as, for auctions, we do not dispose of standard deviation of forecasts.

The Tobit-GARCH approximate log-likelihood is given by (2.17):

$$\begin{aligned}\log L &= \sum_{t=1}^{T}\sum_{i=1}^{N}\log\left(1-\Phi\left(\vartheta\right)\right) I\left(\left|FJ_{t,i}\right|=0\right)\\ &-\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N}\left(\log\left(\widetilde{h}_{t,i}\right)+\frac{\varepsilon_{t,i}^{2}}{\widetilde{h}_{t,i}}\right) I\left(\left|FJ_{t,i}\right|>0\right)\end{aligned} \tag{2.17}$$

where $\vartheta = \frac{\widehat{FJ}_{t,i}-Threshold_{t,i}}{\widetilde{h}_{t,i}^{1/2}}$ with $Threshold_{t,i}$ the threshold adopted to identify jumps in (2.8); Φ normal *cdf* function; $\widetilde{h}_{t,i}$ defined as in (2.16) where, instead of $\varepsilon_{t,i}$ we substitute $\widetilde{u}_{t,i-1}$ which is obtained as:

$$\widetilde{u}_{t,i-1} = \begin{cases} \varepsilon_{t,i}^{2} & \text{if } \left|FJ_{t,i}\right|>0 \\ -\frac{\widehat{h}_{t,i-1}^{1/2}\phi(\vartheta)}{1-\Phi(\vartheta)} & \text{if } \left|FJ_{t,i}\right|=0 \end{cases}$$

with ϕ normal *pdf* function.

2.3.2.3 Modelling Cojumps

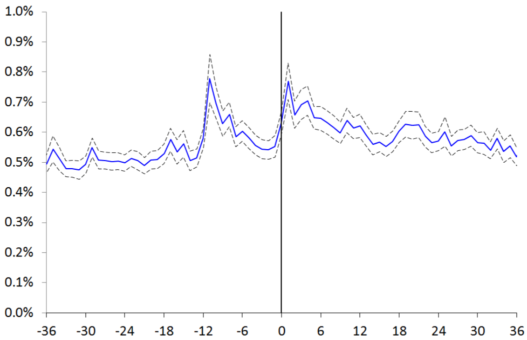
In order to determine the probability of a cojump occurrence we adopt a simple logit model. We consider even the opportunity to estimate a multinomial model allowing to distinguish between 2, 3, 4 or 5 cojumps occurrence probability but this model could not be implemented because only very few observations are available for each class of cojumps. Therefore we collapse cojump in a simple dummy variable: occurrence vs. non occurrence. The model has the same specification adopted for jump mean in (2.15) except for the estimation of the response pattern as here we load macroannouncement surprises and delta in average yield and bid-to-cover for 10 years government bond auctions with unitary weights throughout the time window considered. We model the cojumps identified by the LM test filtered by the parametric estimate of intraday periodicity discussed in Section 2.3.1.1. Considering that although we are modeling the simple event, cojump vs no-cojump, the identified cojumps are usually very few and that logit model requires at least 20% of events to get robust estimates (see for instance Tomz et al. (2003)), we proceed with an oversampling by creating an artificial sample of size M with all the identified cojumps representing 20% of M while the other observations are chosen randomly. The procedure provides consistent and efficient estimates provided appropriate statistical corrections are implemented. To this purpose, a prior correction approach can be implemented consisting in computing the usual logistic regression estimators corrected using prior information about the fraction of ones in the population, τ, and the observed fraction of ones in the sample, $\overline{y}$. For the logit model, the MLE $\widehat{\beta}_i$ estimator for the covariate in the subsample is a statistically consistent estimate of β_i while the corrected estimate for the intercept β_0 is:

$$\widehat{\beta}_0 - \ln\left[\left(\frac{1-\tau}{\tau}\right)\left(\frac{\overline{y}}{1-\overline{y}}\right)\right]. \tag{2.18}$$

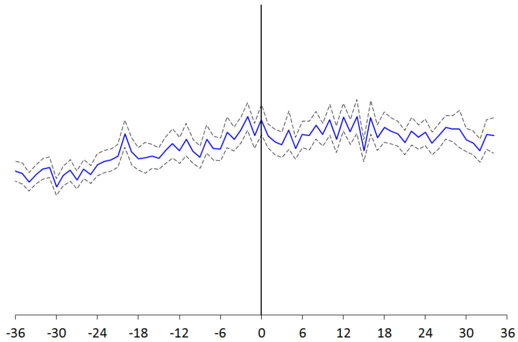
2.4 Empirical Findings

2.4.1 Preliminary Analysis

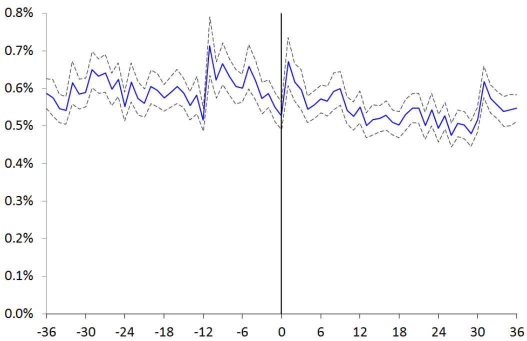
Though, as already mentioned, we may identify jumps by applying the ABD and LM testing procedures, we only report the LM tests adjusted for the intraday periodicity estimated by TML as this is the procedure allowing to reduce spurious jumps detection (see for instance Boudt et al. (2010)). As first step in assessing the relationship between jumps and macroannouncements, bond auctions and rating actions, we compare jumps occurrence around a specific event with respect to other periods. We set the time window for the macroannouncement releases and government bond auctions ranging from 1 hour before up to 1 hour after while for rating actions, given that these events are not prescheduled as the other two cases, we set the window equal to two hours after the release. For the selection of the time windows, we refer to Pearce and Roley (1983, 1985) and Jain (1988) who find that the stock price response essentially completes in the trading day and, more precisely, within one hour after the announcements. Wongswan (2006) shows that announcement surprises induce large but short-lived increases in volatility within thirty minutes of the announcements. Balduzzi et al.(2001), Gurkaynak et al. (2005) and Andersen et al. (2007) confirm that reaction times to news are very short. Moreover, in order to properly set response time windows, we analyze the empirical behaviour of the absolute returns around the event specified. In Figures 2.8-2.9, we report the mean absolute returns around macroannouncements, government bond auctions and rating actions together with the 95% confidence level, on the left, and the same statistics but for days with no event although around the typical hour of release on the right. We distinguish between US and Euro Area macroannouncements as the usual release time is between 13:30 and 15:00 UTC and between 8:00 and 10:00 UTC respectively. On the x-axis we report the number of 5-minute intervals preceding/following the time of release.



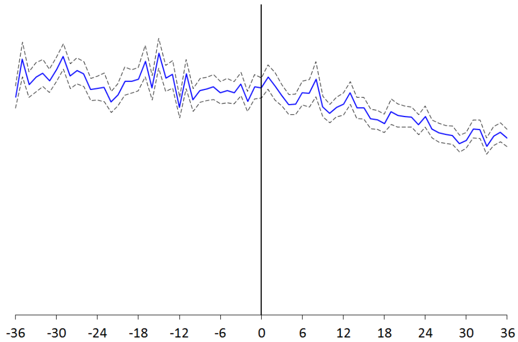
US macroannouncements



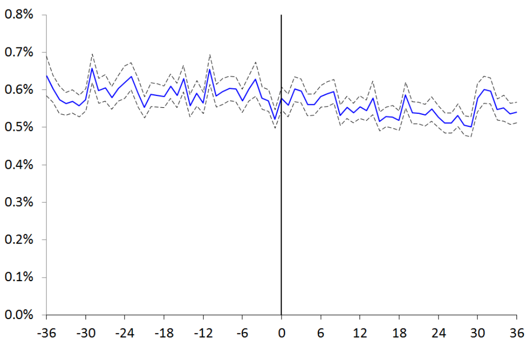
Not US macroannouncements



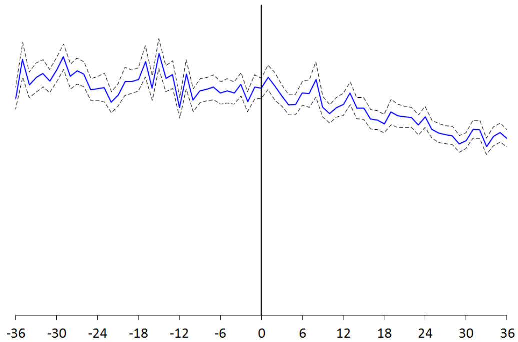
Euro area macroannouncements



Not Euro area macroannouncements



Individual countries macroannouncements



Not individual countries macroann.

Figure 2.8: **Market activities around events: US, Euro area and individual countries macroannouncements**

The left-hand column of Figure 2.8 plots the mean absolute returns together with the 95% confidence interval around the release of the US, Euro area and individual countries macroannouncements. The right-hand column of Figure 2.8 plots the mean absolute returns around the typical average release time of the news: 14:15 UTC for US macroannouncements, 9:00 UTC for Euro area and individual countries macroannouncements. On the x-axis, we report the number of 5-minute intervals preceding/following the time of the release.

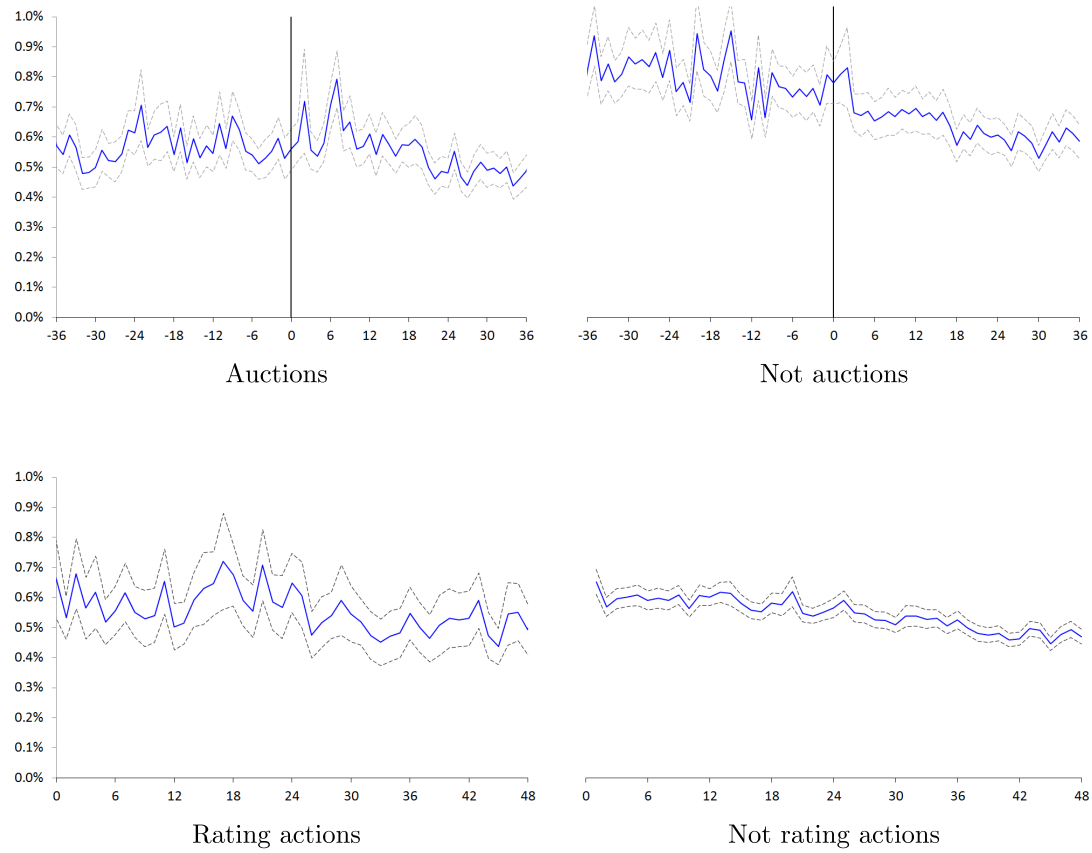


Figure 2.9: **Market activities around events: government bond auctions and rating actions**

The left-hand column of Figure 2.9 reports the plots of the mean absolute returns with the 95% confidence interval around the government bond auctions and rating actions. The right-hand column of Figure 2.9 plots the mean absolute returns around the typical average release time of the news: 9:00 UTC for government bond auctions and 8:00 UTC for rating actions. On the x-axis, we report the number of 5-minute intervals preceding/following the time of the release.

In Table 2.5, we report the jumps detected for each country and a comparison of jump occurrences during news with respect to no-news periods. Estimates for the intraday periodicity in (2.10) are reported in Appendix I.

Table 2.5: **Jumps: summary statistics**

	All	**IT**	**FR**	**ES**	**BE**	**NL**
PANEL A						
No.	4,255	1,134	486	1,313	961	361
P(Jump)	1.10	1.46	0.63	1.69	1.24	0.47
Mean abs. size [%]	1.73	1.56	1.77	1.50	2.40	1.32
	z-test	**z-test**	**z-test**	**z-test**	**z-test**	**z-test**
PANEL B: Macroannouncements						
All	**3.69** ***	**2.56** ***	**2.02** **	**2.30** **	**3.73** ***	**3.35** ***
US	**5.16** ***	**3.53** ***	**3.55** ***	**2.51** ***	**4.99** ***	**4.17** ***
Euro area	**2.02** **	**2.06** **	0.35	**1.93** **	1.12	0.02
Individual countries	-0.40	-0.25	-0.35	0.25	0.23	1.14
US - Real economy	**4.82** ***	**2.98** ***	**3.34** ***	**2.02** **	**5.38** ***	**4.47** ***
US - Forward looking	**1.86** **	**2.07** **	0.34	1.06	1.00	**1.54** *
US - Price	1.28	0.05	**2.32** **	0.79	0.81	-0.09
Euro area - Real economy	-0.72	0.46	-1.40	-0.83	-0.03	-0.62
Euro area - Forward looking	**3.03** ***	**1.91** **	**1.42** *	**2.93** ***	**2.15** **	**1.81** **
Euro area - Price	1.11	**1.34** *	0.39	1.22	0.27	-2.01
Individual countries - Real economy	-1.46	-0.83	-1.42	-0.84	-1.60	-0.34
Individual countries - Forward looking	**2.37** ***	**1.34** *	0.87	**2.08** **	**2.42** ***	**3.22** ***
Individual countries - Price	-1.31	-0.86	-0.85	-0.64	-0.49	-0.39
PANEL C: Bond auctions						
All	**1.90** **	0.01	0.28	**2.72** ***	0.13	0.02
France	-1.99	-2.30	0.02	-1.29	-1.40	-0.50
Germany	0.55	-0.57	1.11	**2.60** ***	-0.36	1.23
Greece	**3.35** ***	0.61	**2.00** **	1.20	**2.41** ***	**2.38** ***
Italy	**3.65** ***	**2.42** ***	1.09	**3.62** ***	**1.65** **	0.78
Spain	**2.95** ***	**3.01** ***	**1.94** **	0.88	-0.21	0.96
PANEL D: Rating actions						
All	**2.15** ***	**2.04** ***	-0.22	0.96	1.07	-0.34
S&P	**1.99** **	**1.57** *	0.01	**1.63** *	0.77	-1.14
Moody's	1.16	-0.24	-0.16	1.06	**1.78** **	0.36
Fitch	0.25	**1.95** **	-0.32	-1.21	-0.80	0.20
Belgium	**5.22** ***	**1.83** **	**2.24** **	**2.45** ***	**6.34** ***	-0.59
Greece	-0.23	0.82	-1.53	-0.91	-1.09	0.57
Ireland	-0.03	-1.27	-0.02	1.08	-0.01	-1.23
Italy	**2.73** ***	**6.00** ***	-0.97	0.93	0.11	0.36
Portugal	0.19	0.84	0.55	0.03	-0.65	0.29
Spain	**1.94** **	**1.74** **	0.09	0.86	1.20	-0.34

Panel A of Table 2.5 reports the number of 5-minute returns identified as jumps by applying the Lee and Mykland (2008) test adjusted by the intraday periodicty of volatility according to Boudt et al. (2010), defined in (2.8), at the 5% significance level as well as the average absolute size of jumps. **Panels B-D** provide a preliminary analysis of the degree of association between jumps and macroannouncements, government bond auctions and rating actions by applying the z-test to compare the frequency of jumps occurrence around the event in analysis with respect to no-event situation. The null hypothesis is that the two percentages are equal. As per macroannouncements, we just show the analysis according to the classification in real economy, forward looking and price releases as reported in Table 2.2 while for government bond auctions, we report only relevant countries. ***, **, * denote 1%, 5% and 10% significance level, respectively.

Overall, macroannouncements play an important role in explaining jumps in all countries. In particular, the biggest impact is due to US and Euro area releases while news concerning individual countries do not seem to determine jumps. As far as the economic category of macroannouncements is concerned, news regarding the US real economy, such as production and employment indicators with the non-farm payroll (the so called "king of macroannouncements") are the most important together with Euro area forward looking indicators, such as confidence indicators and purchase manager index, and some national forward looking indicators.

As far as **government bond auctions** are concerned, their impact on jumps is particularly important when we focus on countries with very high public debt, such as Italy and Greece, when we see that around auctions, government bond spreads of almost all countries jump substantially. Note that in 2011, Italy public debt was 120% of GDP and in Greece 160%, while it was 106% for Portugal, 98% for Belgium, 86% for France, 81% for Germany 72% for Austria, 68% for Spain, 66% for the Netherlands and 48% for Finland. In particular, around the Greek auctions, there is evidence of jumps in France, Belgium and the Netherlands, while around the Italian auctions, the Italian, Spanish and Belgian spreads jump significantly. Some evidence of presence of jumps is also found when Spanish auctions take place, affecting in particular Italy and France. We interpret this result as a sign of raising concern about Spanish government's solvability.

Turning to **rating actions**, there is evidence that downgradings cause jumps when considering all rating actions in all markets but the three rating agencies do not seem to have a different impact. However, a crucial role is played by the country which was the object of the rating action. In particular, actions taken against countries such as Belgium, Italy and Spain cause jumps on government bond spreads while actions against smaller and more fragile countries such as Greece, Ireland and Portugal do not seem to have any significant effect. This result contradicts those reported in other studies. Alsakka and Gwilym (2012) find that Moody's decision to downgrade Greece to Caa1 from B1 on 1st June 2011 determined an increase by 12 basis point in Greek 10-year government bond yields and a decline of bond prices for Ireland, Spain and Portugal. On 13 June 2011, S&P downgraded Greece from B to CCC (with negative outlook), causing Greek, Portuguese and Irish 10-year bond yields to jump of 16.79%, 10.66% and 11.34% respectively. See also Alsakka and Gwilym (2013)

Cojumps. To detect a large number of cojumps, we define cojumps whether two or more jumps occur in a 15-minute time window rather than 5-minute window. When we define a cojump considering a 5-minute time window we come up with just 475 cojumps while, when expanding the time window to 15 minutes, we can detect up to 2,392 cojumps. However, whenever possible, we conduce our analysis on both 5-minute and 15-minute window with substantially unchanged results.

In Table 2.6, we report the analysis for cojumps identified applying (2.12).

Table 2.6: **Cojumps: summary statistics**

	≥ 2	**2**	**3**	**4**	**5**
PANEL A					
No.	1,196	828	271	62	35
P(Cojump)	1.54	1.07	0.35	0.08	0.05
P(Cojump|Jump)	33.15	22.95	7.51	1.72	0.97
	z-test	**z-test**	**z-test**	**z-test**	**z-test**
PANEL B: Macroannouncements					
All	**1.87 *****	0.23	1.10	3.15	**2.51 *****
US	**2.00 ****	0.06	1.24	**2.98 *****	**3.88 *****
EA	**4.22 *****	**3.74 *****	0.90	1.13	**2.41 *****
Individual countries	-0.55	-0.31	-0.55	1.02	na
US - Real economy	**3.07 *****	0.97	**1.77 ****	**3.00 *****	**4.25 *****
US - Forward looking	-1.71	-2.11	-0.67	na	na
US - Price	-0.11	0.68	na	na	na
EA - Real economy	0.33	0.32	-0.57	na	**3.30 *****
EA - Forward looking	**4.92 *****	**4.25 *****	**1.86 ****	na	na
EA - Price	0.69	0.51	0.00	na	na
Individual countries - Real economy	0.06	0.63	-0.04	na	na
Individual countries - Forward looking	**1.29 ***	0.05	**2.91 *****	-0.16	-0.64
Individual countries - Price	-2.64	-1.17	-4.03	1.16	na
PANEL C: Bond auctions					
All	**1.57 ***	0.96	0.54	**1.52 ***	0.94
France	-0.97	-1.01	0.17	na	na
Germany	1.02	-0.76	1.24	0.84	**5.03 *****
Greece	**3.06 *****	**3.20 *****	1.12	na	na
Italy	**4.30 *****	**2.68 *****	**1.80 ****	**3.76 *****	na
Spain	**1.86 ****	**2.59 *****	-0.88	na	na

Panel A of Table 2.6 reports the number of contemporaneous cojumps identified by applying (2.12) on jumps identified by applying the Lee and Mykland (2008) test adjusted by the intraday periodicty of volatility according to Boudt et al. (2010), defined in (2.8), at the 5% significance level. Moreover, in order to identify a sufficient number of cojumps for further analysis, we define a cojump if two or more jumps occured in a 15-minute time window. P(Cojump|Jump) denotes the probability of a cojump given that at least one of the country had a jump. **Panels B-C** provide a preliminary analysis of the degree of association between cojumps and macroannouncements and government bond auctions by applying the z-test to compare the frequency of cojumps occurrence around the event in analysis with respect to no-event. The null hypothesis is that the two percentages are equal. We did not report tests for rating actions as we observe a very low number of cojumps around rating actions which did not allow us to carry out the tests. In case one of the two categories has less than 10 observations, the test statistic is not reported (na). As per macroannouncements, we just show the analysis according to the classification in real economy, forward looking and price releases as reported in Table 2.2 while for government bond auctions, we report only relevant countries. ***, **, * denote 1%, 5% and 10% significance level, respectively.

The results confirm what already reported for the jumps analysis. In particular, US and Euro area macroannouncements are the most important drivers of cojumps, with particular relevance of those concerning real economy and those related to forward looking measures. As per auctions, those impacting the most are again those hold in Italy, Greece and Spain while we did not report the analysis for rating actions as we did not dispose of sufficient information to carry out a meaningful comparison. It is worth noting that the largest impact of macroannouncements and auctions is found when considering cojumps in 4 or 5 countries simultaneously with respect to fewer series. For instance, in 6 out of 8 events (75%) for which we can compare the occurrence of cojumps in 5 series, cojumps take place more often in correspondence to macroannouncements and auctions; when considering 4 time series instead, we find cojumps in 4 out of 10 events (40%), while when 3 time series are considered we have 4 out of 18 (22%), and for 2 time series 5 out of 19 (26%). These findings are in support of the presence of systemic factors affecting all the markets simultaneously.

2.4.2 Results for the Jump Model

The first step to estimate the model for the absolute jump size in (2.15) is the estimation of the response pattern of jumps on macroannouncements and government bond auctions. In Figure 2.10 we report some examples of response patterns.

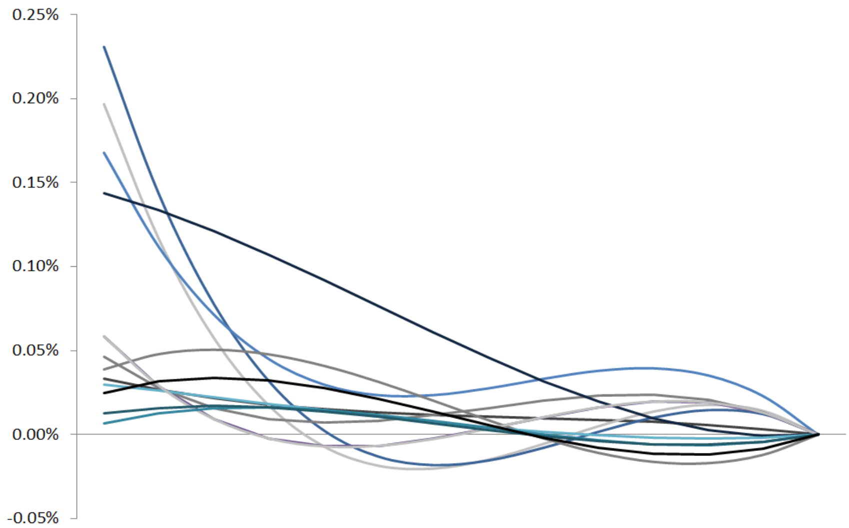


Figure 2.10: **Jump responses patterns**

In Figure 2.10 we report some examples of jump responses patterns. These patterns capture the possible delayed response of jumps to macroannouncements and government auctions surprises in a one hour time window. The underlying assumption is that jumps responses vanish as time passes and therefore the polynomial decay structure by Andersen and Bollerslev (1998) is adopted.

Once jumps response patterns are estimated, we pre-select, for the mean equation, statistically significant variables at $\alpha = 0.30$ using a simple Tobit regression. After this pre-selection, we estimate jointly the mean and the variance equations (2.15) and (2.16), respectively, following Calzolari and Fiorentini (1998).

2.4.2.1 Mean Equation.

Table 2.7 reports the results of mean equation in (2.15). When interpreting Tobit coefficients remember that they measure the impact of a change in the corresponding independent variable on the latent dependent variable weighted by the probability of being above the threshold that in our case corresponds to the probability of observing a jump.

Table 2.7: **Jumps: mean model**

	IT	**FR**	**ES**	**BE**	**NL**
constant	**-1.2294 *****	**-1.6069 *****	**-1.2543 *****	**-1.2023 *****	**-2.3056 *****
Macroannouncements - pre-release					
$\gamma_{1,2}$ (US - Chicago PMI)	**0.1146 *****	**0.2635 *****		-0.0932	
$\gamma_{1,5}$ (US - Durable goods)			**0.0625 *****		
$\gamma_{1,7}$ (US - GDP advance)	**-1.0008 *****		**-1.1920 *****		
$\gamma_{1,8}$ (US - GDP preliminary)			**-1.6089 *****		
$\gamma_{1,10}$ (US - Industrial production)		**0.0526 *****	**0.0361 *****		
$\gamma_{1,12}$ (US - Nonfarm payroll)	**0.1906 *****	**0.0175 *****	**0.2522 *****	**-0.0936 *****	**0.3491 *****
$\gamma_{1,13}$ (US - Philadelphia FED index)	**-0.2954 *****				
$\gamma_{1,14}$ (US - PPI)		**-0.9893 *****	**-0.1098 *****		**-0.9936 *****
$\gamma_{1,18}$ (EA - Consumer confidence)	**0.1010 *****		**0.1099 *****		
$\gamma_{1,21}$ (EA - Industrial production)	**0.0563 *****	**-0.0673 *****		**0.1215 *****	0.0824
$\gamma_{1,22}$ (EA - Introductory Statement)	**0.0921 *****	**-0.2162 *****	**0.0378 *****	**0.0683 *****	**-0.1960 *****
$\gamma_{1,23}$ (EA - M3)		**-0.1935 *****			
$\gamma_{1,24}$ (EA - Monthly Bulletin)	**-0.0871 *****		**0.0471 *****		
$\gamma_{1,25}$ (EA - PMI Flash)			**0.0082 ****		
$\gamma_{1,26}$ (EA - PMI Final)		**0.0705 *****	**0.0468 ****	**-0.1487 *****	
$\gamma_{1,27}$ (EA - PPI)		**0.1948 *****			
$\gamma_{1,28}$ (EA - Retail sales)	**-0.1257 *****				
$\gamma_{1,34}$ (DE - ZEW)	**-0.0131 *****	**0.1393 *****			**0.0095 *****
$\gamma_{1,30}$ (DE - CPI preliminary)			**-0.0937 *****		**-1.0607 *****
$\gamma_{1,31}$ (DE - IFO Business confidence)			**0.0662 *****	**0.1883 *****	
$\gamma_{1,32}$ (DE - Industrial production)	**-0.1276 *****		**-0.0364 *****	**-0.182 *****	
$\gamma_{1,33}$ (DE - Unemployment)		**0.0779 *****			
$\gamma_{1,37}$ (IT - GDP final)					**0.2157 *****
$\gamma_{1,40}$ (IT - Industrial production)	**-0.1329 *****				
$\gamma_{1,42}$ (ES - CPI)	**-0.1138 *****		**-0.1662 *****		
$\gamma_{1,47}$ (PT - CPI)	**-0.0899 *****			**-0.1786 *****	**-1.1927 *****
$\gamma_{1,50}$ (NL - CPI)	**-0.1031 *****		**-0.3226 *****		
$\gamma_{1,52}$ (NL - Unemployment)	**0.0663 *****		**0.0905 *****		-0.0625
$\gamma_{1,53}$ (BE - Business confidence)			**-0.0337 *****		
$\gamma_{1,54}$ (GR - CPI)		**0.2102 *****	**0.1006 *****	**-0.1495 *****	
$\gamma_{1,55}$ (GR - GDP preliminary)			**-0.9971 *****		

Table 2.7: **Jumps: mean model**

	IT	FR	ES	BE	NL
Macroannouncements - post-release					
$\gamma_{2,2}$ (US - Chicago PMI)		-0.8424 ***			
$\gamma_{2,4}$ (US - CPI)			0.7151 ***		
$\gamma_{2,7}$ (US - GDP advance)					1.0035 ***
$\gamma_{2,8}$ (US - GDP preliminary)	-0.1218 ***		0.5839 ***		-0.0951 ***
$\gamma_{2,10}$ (US - Industrial production)	-0.6848 ***				
$\gamma_{2,11}$ (US - Initial jobless claim)			0.9997 ***		-1.0000 ***
$\gamma_{2,12}$ (US - Nonfarm payroll)	0.3075 ***	0.0671 ***	0.5770 ***	0.5992 ***	1.4448 ***
$\gamma_{2,13}$ (US - Philadelphia FED index)		-0.1163 ***			
$\gamma_{2,15}$ (US - Retail sales)	-0.2377 ***		0.2867 ***	0.3586 ***	
$\gamma_{2,16}$ (US - University of Michigan)					0.8618 ***
$\gamma_{2,17}$ (EA - Business climate)	-0.8374 ***			0.0321 ***	
$\gamma_{2,18}$ (EA - Consumer confidence)			0.1723 ***		
$\gamma_{2,19}$ (EA - Flash HICP)	-0.0134 ***				
$\gamma_{2,22}$ (EA - Introductory Statement)	0.0866 ***	0.0905 ***		0.2380 ***	-0.0957
$\gamma_{2,23}$ (EA - M3)	-0.5505 ***				
$\gamma_{2,24}$ (EA - Monthly Bulletin)	-0.1758 ***			-1.4494 ***	
$\gamma_{2,25}$ (EA - PMI flash)			0.0439 ***		0.0045
$\gamma_{2,26}$ (EA - PMI final)	-0.0631 ***		0.4480 ***	-0.3419 ***	
$\gamma_{2,30}$ (DE - CPI preliminary)			-0.9986 ***		
$\gamma_{2,33}$ (DE - Unemployment)	-0.8114 ***		-0.4523 ***		
$\gamma_{2,42}$ (ES - CPI)	0.2379 ***				-0.6807
$\gamma_{2,44}$ (ES - GDP final)		-1.0042 ***	-0.9992 ***	2.0739 ***	0.8127 ***
$\gamma_{2,45}$ (ES - Industrial production)	-0.1800 ***	-0.7106 ***	0.2289 ***		
$\gamma_{2,46}$ (ES - Unemployment)	-0.1959 ***			0.9603 ***	-0.5733 ***
$\gamma_{2,54}$ (GR - CPI)	0.2096 ***		0.2496 ***		
$\gamma_{2,55}$ (GR - GDP preliminary)	-0.1251 ***				
$\gamma_{2,56}$ (GR - GDP final)					1.2908 ***
$\gamma_{2,57}$ (GR - Unemployment)	-0.1795 ***				
Auctions - pre-release					
$\gamma_{1,58}$ (Austria)	-0.0534 ***				
$\gamma_{1,59}$ (Belgium)	0.0361 ***	0.0259 ***	0.0438 ***	0.0678 ***	0.3233 ***
$\gamma_{1,60}$ (Finland)	0.1539 ***		0.1032 ***	0.1309 ***	
$\gamma_{1,61}$ (France)	-0.0756 ***	-0.1313 ***		-0.0218	-0.0163
$\gamma_{1,62}$ (Germany)			0.0145 ***		
$\gamma_{1,63}$ (Greece)			-0.1215 ***		-0.2130 ***
$\gamma_{1,64}$ (Italy)	-0.0212 **				
$\gamma_{1,65}$ (the Netherlands)		0.1484 ***		-0.0137	0.1097
Auctions - post-release (bid-to-cover)					
$\gamma_{2,58}$ (Austria)	1.0154 ***		1.0107 ***		
$\gamma_{2,59}$ (Belgium)			-1.0029 ***		

Table 2.7: **Jumps: mean model**

	IT	FR	ES	BE	NL
$\gamma_{2,61}$ (France)	**-0.7427 *****			**1.0022 *****	
$\gamma_{2,62}$ (Germany)				**-1.0011 *****	1.0041
Auctions - post-release (average yield)					
$\gamma_{2,71}$ (France)	**1.0058 *****				
$\gamma_{2,72}$ (Germany)	**1.0039 *****	**1.0015 *****	**1.0013 *****	**1.0007 *****	1.0052
$\gamma_{2,74}$ (Italy)	**-0.8344 *****	**0.7390 ****	**0.9945 *****	**1.0035 *****	
$\gamma_{2,75}$ (the Netherlands)		**1.0016 *****		**-0.9904 *****	
$\gamma_{2,76}$ (Portugal)			**1.0094 *****		
$\gamma_{2,77}$ (Spain)	**-0.6236 *****		**1.0260 *****		
Rating actions					
$\gamma_{2,78}$ (S&P)			**-0.0351 *****		

Table 2.7 reports the estimates for the mean equation of the Tobit-GARCH model in (2.15). The dependent variable is the absolute size of jumps identified by applying the Lee and Mykland (2008) test corrected by the intraday periodicity of the volatility as proposed by Boudt et al. (2010) and defined in (2.8). **Macroannouncements and auctions pre-release** are dummy variables taking value equal to 1 for time intervals preceding the release up to 1 hour before. **Macroannouncements and auctions post-release** effect is captured by the absolute size of surprise associated to the specific release. For bond auctions we define surprise as the difference in average yield and bid-to-cover with respect to the previous auction. These "surprises" are available just for 10-year bond auctions. Surprises are loaded by specifc polynomial which have a decay structure as proposed by Andersen and Bollerslev (1998) up to 1 hour after the release. **Rating actions** are dummy variables taking value 1 for time intervals following the action up to 2 hours after the release, zero otherwise.
We report just variables which are significant at 10% level for at least one country. In some cases estimates are missing because the correspondent dependent variable was not selected in the pre-selection procedure described in Section 2.4.2. Estimates for the periodic component ξ are not reported. ***, **, * denote 1%, 5% and 10% significance level, respectively.

It is evident the relevance that macroannouncements and government bond auctions have in explaining jumps in government bond spreads and in particular both effects, pre- and post-announcement, turned out to be statistically significant. Moreover, releases concerning individual countries are often important in explaining government bond spreads of other countries. This result constitutes an additional evidence in favour of the strong linkages existing among European countries. No role is found for rating actions. Note that the strong relevance of macroannouncements and government bond auctions in determining jumps we find can also be interpreted along the Veronesi (1999) equilibrium model showing that stock prices overreact to bad news in good times and underact to good news in bad times.

Macroannouncements. The results in Table 2.7 suggest that the pure knowledge about a forthcoming announcement in the following hour is statistically important in explaining jumps. 8 out of 16 US, 9 out of 13 Euro area and 15 out of 26 individual countries future macroannouncement releases significantly determine jumps. US non-farm payroll together with the Introductory Statement are the most important factors of jumps in the five series considered with a coefficient ranging from a -0.0936 for Belgium to 0.3491 for the Netherlands in the case of US Nonfarm payroll and from -0.2162 for France to 0.0683 for Belgium as far as the ECB Introductory Statement. Besides these two announcements, the other main drivers of jumps during the pre-announcement period are US PPI on France, Spain and the Netherlands, Euro area industrial production on Italy, France and Belgium and Euro area purchase manager index final on France, Spain and Belgium, German ZEW on Italy, France and the Netherlands and German industrial production on Italy, Spain and Belgium. Turning now to the post-announcement effects, 10 out of 16 from US, 8 out of 13 from Euro area and 11 out of 26 from individual countries surprises are statistically significant. In particular, the most important releases are non-farm payroll, explaining large absolute jump sizes for all the five spread series considered with coefficient ranging from 0.3075 for Italy to 1.4448 for the Netherlands, the Introductory Statement determining sizeable jumps in Italy (0.0866), France (0.0905) and Belgium (0.2380), and the Spanish GDP release explaining jumps for France (-1.0042), Spain (-0.9992), Belgium (2.0739) and the Netherlands (0.8127). Among other macroannouncements, we notice the statistical significance of US GDP preliminary on Italy, Spain and the Netherlands, US retail sales on Italy, France and Belgium, Euro area purchase manager index final on Italy, Spain and Belgium and other Spanish releases such as industrial production on Italy, France and Spain and unemployment on Italy, Belgium and the Netherlands.

The most important finding of our analysis so far is the high sensitivity of government bond spreads to US and Euro area macroannouncements together with a low sensitivity to individual countries, the only exception being Spain and Germany. The worsening of the Spanish macroeconomic fundamentals represents an important news for the markets and particularly important is the role of unemployment (at present the highest in Europe) and the industrial production, that is falling more than any other European country. Moreover, while Greece and Portugal are small economies, Spain is the fourth largest economy in the Euro area and this makes the deterioration of its macro fundamentals extremely relevant to the markets. As far as Germany is concerned, the largest economy in Europe, markets pay attention to signals coming from Germany's economic indicators as they serve as leading indicators for the entire Euro area.

As per the category of macroannouncements, there is a confirmation of what already reported in the preliminary analysis that is the important role played by economic indicators such as employment level and industrial production, and forward looking variables, with Euro area purchase manager index and German ZEW, as opposite to those related to the consumer prices/inflation indicator.

It is interesting to compare and contrast the results of our analysis with those reported in the literature. For instance, we find a very high sensitivity of European government bond spreads to US releases. This result confirms the findings in Ehrmann and Fratzscher (2003), who investigate US, Germany and the Euro area money markets reaction to monetary policy announcements by the Federal Reserve, the Bundesbank and the ECB respectively. Authors show that linkage between money markets has increased over time as movements in interest rate and volatility in either the US or the Euro area are mirrored in the other market; in particular German and Euro area react to Federal Reserve decision but no evidence supports the other way round. The important role played by the non-farm payroll and GDP is also documented in Lahaye et al. (2011), Jiang et al. (2011) and Miao et al. (2012). This variable indeed plays a fundamental role given it represents an important leading indicator of economy's strength as, among US real economy, it is released before durable goods, factory orders, retails sales and production index. This result is consistent also with what reported in Andersen et al. (2007) where it is showed that announcements released earlier impact much more than those released later in time. Focusing now on Andersson et al. (2006), the only paper analyzing the impact of a broad range of US, Euro area and individual countries macroannouncements, namely Germany, France and Italy, Authors report that US are the most important macroannouncements in explaining returns of German bond market while our analysis shows that, in addition to the US ones, also a wide range of Euro area as well as individual countries measures have explanatory power for jumps. Note that this result in Andersson et al. (2006), confirming the evidence also in Andersen et al. (2007), stress the importance of the timing of the news releases, and so macroannouncements related to Euro area, released earlier than the US ones, already discount news coming from the US market and therefore have a lower impact. Andersson et al. (2006) findings include the assessment of the importance of non-farm payroll, Euro area industrial production and consumer confidence, German and French industrial production together with forward looking measures such as IFO, ZEW and French, Italian business confidence and Introductory Statement in driving the volatility equation. These findings are quite in line with what reported in our analysis.

There are some novel and interesting results from our analysis that the existing literature does not document. First of all, we find evidence of the important role played by the ECB Introductory Statement bringing to the market the key information concerning decisions on ECB rates. Moreover, our results show the sensitivity of European government bond spreads not only towards US and Euro area releases but also to individual countries, with particular reference to those related to Germany and Spain. Finally, we showed the importance of taking into account the pre-announcement effects which are found to explain a great amount of jumps. Pre- and post-announcement convey different kind of information with the first providing an indication about traders' perception of future news relevance while the second one, captured by surprises, leading traders to revise their positions according to the actual releases.

Government bond auctions. Focusing on government bond auctions, the difference in bid-to-cover with respect to the previous 10-year auction of 4 out of 7 countries (Austria, Belgium, France and Germany) significantly explains government bond spread in at least one case although the average yield of 10-year bond auctions has a greater impact. In particular the German and Italian auctions are relevant for Italy (coefficients: 1.0039 and -0.8344), France (1.0015 and 0.7390), Spain (1.0013 and 0.9945) and Belgium (1.0007 and 1.0035), while Spanish are for Italy (-0.6236) and Spain (1.0260). In addition, we distinguish the post from the pre-release effect finding evidence of sizeable jumps even before the publication of auctions results hold in 8 out of 10 countries namely Austria, Belgium, Finland, France, Germany, Greece, Italy and the Netherlands. It is worth noticing that we consider dummies for future auctions regardless of the maturity of bonds while when turning to bid-to-cover and average yield we just analyze 10-year bond auctions.

When analyzing the pre-publication period, no clear pattern is found in that almost all auctions, regardless of the country where they are hold, determine jumps, including countries such as Finland and the Netherlands, while when focusing on average yield we find strong impact of auctions hold in distressed countries, namely Italy and Spain, together with those hold in Germany, representing a benchmark in the Euro area. This result is not surprising as average yields to which bonds are allocated provide a better signal of the performance of an auction and allow to discriminate more between safer and riskier countries.

Rating actions. Turning now to the rating actions, this factor is statistically irrelevant and there is no difference among the rating agencies. Our results contrast with findings in the literature assessing the impact of rating actions on returns or jumps. Kiff et al. (2012) discuss that the most of the incremental information value is transmitted through negative credit warnings (i.e., “outlooks,” “reviews,” and “watches,”), rather than actual rating changes. The same conclusion is also reported in Pukthuanthong-Le et al. (2007), Hooper et al. (2008) and Hill and Faff (2010). Our analysis instead confirms a "reputation issue" attached to rating agencies: market participants do not rely on rating agencies assessment in default risks in government bonds in the current European sovereign debt crisis in the light that they were unable to correctly quantify risk in the structured products on US mortgage loans.

2.4.2.2 Variance Equation.

Table 2.8 reports the results of variance equation (2.16).

Table 2.8: **Jumps: variance model**

	IT	**FR**	**ES**	**BE**	**NL**
ω_1	0.0038	**0.1916 *****	**0.0283 *****	**0.0539 *****	**0.2122 *****
Macroannouncements - pre-release					
$\omega_{2,2}$ (US - Chicago PMI)	-0.0003	**-0.0391 *****	-0.0007	**0.0043 ***	**-0.0184 *****
$\omega_{2,4}$ (US - CPI)	0.0021	**0.0295 *****	-0.0015	0.0011	-0.2051
$\omega_{2,5}$ (US - Durable goods)	-0.0003	-0.0067	0.0012	**-0.0190 *****	**-0.0423 *****
$\omega_{2,7}$ (US - GDP advance)	0.0028	-0.0465	**0.0227 *****	-0.0023	**0.0232 *****
$\omega_{2,8}$ (US - GDP preliminary)	0.0022	0.0041	**0.0371 *****	-0.0050	**0.0281 *****
$\omega_{2,9}$ (US - GDP final)	0.0030	-0.1457	0.0030	**-0.0388 *****	-0.2047
$\omega_{2,10}$ (US - Industrial production)	-0.0013	0.0236	0.0052	-0.0013	**0.0159 ****
$\omega_{2,12}$ (US - Nonfarm payroll)	0.0018	**0.1141 *****	**-0.0091 ****	**0.0243 *****	0.0157
$\omega_{2,15}$ (US - Retail sales)	0.0007	**0.0264 *****	**0.0077 ****	**0.0099 *****	0.0307
$\omega_{2,16}$ (US - University of Michigan)	0.0011	**-0.0335 *****	0.0043	-0.0033	-0.0140
$\omega_{2,17}$ (EA - Business climate)	-0.0015	**-0.0466 *****	-0.0034	**-0.0075 *****	-0.0186
$\omega_{2,22}$ (EA - Introductory Statement)	0.0009	0.0580	-0.0003	**0.0103 *****	**0.1089 *****
$\omega_{2,23}$ (EA - M3)	-0.0004	**0.1089 *****	0.0024	**0.0050 ***	0.0227
$\omega_{2,25}$ (EA - PMI flash)	0.0006	**0.0229 *****	0.0041	**0.0107 *****	**0.0220 ***
$\omega_{2,29}$ (EA - Unemployment)	0.0010	**-0.0588 *****	-0.0054	0.0041	**-0.1049 *****
$\omega_{2,37}$ (IT - GDP final)	0.0001	**0.0629 *****	0.0053	**0.0216 *****	0.0239
$\omega_{2,40}$ (IT - Industrial production)	-0.0012	**0.0280 *****	0.0014	**-0.0099 *****	-0.0748
$\omega_{2,52}$ (NL - Unemployment)	0.0013	**-0.0409 *****	-0.0074	-0.0015	0.0114
$\omega_{2,53}$ (BE - Business confidence)	0.0026	**0.0381 *****	0.0062	-0.0036	**0.0624 *****
$\omega_{2,54}$ (GR - CPI)	0.0001	-0.0240	-0.0064	**0.0110 *****	**-0.0182 ****
$\omega_{2,56}$ (GR - GDP final)	-0.0005	**-0.1160 *****	-0.0070	**0.0152 *****	0.0557
$\omega_{2,57}$ (GR - Unemployment)	-0.0001	**0.0365 *****	0.0041	**0.0050 ***	0.0270
Auctions - pre-release					
$\omega_{2,62}$ (Germany)	-0.0004	**0.0126 *****	0.0018	-0.0041	-0.0108
$\omega_{2,63}$ (Greece)	0.0004	0.0026	0.0066	**0.0032 ****	**0.1048 *****
$\omega_{2,66}$ (Portugal)	-0.0001	**-0.0153 *****	-0.0017	0.0002	-0.0090
$\omega_{2,67}$ (Spain)	0.0008	0.0049	0.0001	**0.0142 *****	**-0.0113 ***
β	**0.9548 ***	**0.0548 *****	**0.7337 *****	**0.6268 *****	**0.2269 *****
α_1	0.0191	**0.0760 *****	0.00427	**0.0471 *****	**0.0840 *****
Macroannouncements - post-release					
$\alpha_{2,2}$ (US - Chicago PMI)	-0.0006	-0.0699	0.0352	**-0.0138 *****	**-0.0834 *****
$\alpha_{2,3}$ (US - Consumer confidence)	0.0018	**0.1864 *****	0.0054	0.0024	**0.1161 *****
$\alpha_{2,4}$ (US - CPI)	-0.0030	**-0.0618 ****	-0.0079	0.0016	-0.0479
$\alpha_{2,5}$ (US - Durable goods)	0.0039	**-0.0431 *****	-0.0316	**-0.0227 *****	0.0207
$\alpha_{2,7}$ (US - GDP advance)	0.0085	-0.0016	-0.0399	**0.0986 *****	**0.0876 *****
$\alpha_{2,8}$ (US - GDP preliminary)	-0.0189	-0.0730	**-0.0317 *****	0.0003	-0.0066
$\alpha_{2,9}$ (US - GDP final)	-0.0165	**-0.0745 *****	-0.0050	**-0.0319 *****	-0.0842
$\alpha_{2,12}$ (US - Nonfarm payroll)	-0.0039	**0.1442 *****	0.0436	**0.0305 *****	0.0916
$\alpha_{2,16}$ (US - University of Michigan)	0.0027	-0.0052	0.0068	**-0.0189 *****	**0.0831 ****

Table 2.8: **Jumps: variance model**

	IT	**FR**	**ES**	**BE**	**NL**
$\alpha_{2,21}$ (EA - Industrial production)	-0.0005	-0.0162	**0.0497 ***	-0.0055	-0.0470
$\alpha_{2,22}$ (EA - Introductory Statement)	-0.0074	**0.1162 *****	**0.0296 *****	0.0062	**0.0742 *****
$\alpha_{2,26}$ (EA - PMI final)	-0.0122	-0.0353	**0.0249 *****	**-0.0299 *****	-0.0072
$\alpha_{2,33}$ (DE - Unemployment)	0.0023	**0.1261 *****	-0.0175	0.0052	-0.0789
$\alpha_{2,37}$ (IT - GDP final)	-0.0179	-0.0718	-0.0265	**-0.0325 *****	**-0.0840 ****
$\alpha_{2,45}$ (ES - Industrial production)	0.0050	-0.0479	0.0208	**0.0384 *****	**0.2065 *****
$\alpha_{2,47}$ (PT - CPI)	0.0031	**-0.0335 ****	-0.0238	**0.0245 *****	0.0857
$\alpha_{2,52}$ (NL - Unemployment)	0.0056	0.0161	0.0210	**0.0261 *****	**0.1948 *****
$\alpha_{2,53}$ (BE - Business confidence)	-0.0124	**-0.0320 ***	-0.0017	**0.0206 *****	-0.0366
Auctions - post-release (bid-to-cover)					
$\alpha_{2,61}$ (France)	0.0012	0.0122	**-0.0228 *****	**0.0456 *****	-0.0028
Auctions - post-release (average yield)					
$\alpha_{2,75}$ (the Netherlands)	0.0058	**0.1715 ***	-0.0277	**0.0084 ****	-0.0027
$\alpha_{2,76}$ (Portugal)	0.0289	0.0490	**0.1135 ****	**0.0993 *****	0.2423
ν_1	0.0056	**0.3343 *****	**0.1516 *****	**0.1002 *****	0.2692
Macroannouncements - post-release - Asymmetric effect					
$\nu_{2,1}$ (US - Business Inventories)	0.0113	**-0.0351 *****	**-0.0282 *****	**-0.0071 ****	-0.0105
$\nu_{2,2}$ (US - Chicago PMI)	-0.0002	**-0.0410 *****	**-0.0591 *****	-0.0002	0.0331
$\nu_{2,3}$ (US - Consumer confidence)	**-0.0070 ***	**-0.2700 *****	**-0.0416 *****	**-0.0883 *****	**-0.2885 *****
$\nu_{2,4}$ (US - CPI)	0.0046	**-0.0834 *****	**-0.0089 ****	**-0.0266 *****	**-0.0633**
$\nu_{2,5}$ (US - Durable goods)	-0.0036	0.0017	**0.0288 *****	**-0.0085 ****	-0.0009
$\nu_{2,6}$ (US - Factory orders)	**0.0134 *****	**-0.0750 *****	**-0.0061 ***	-0.0017	**-0.0129 *****
$\nu_{2,7}$ (US - GDP advance)	**-0.0065 ***	**-0.0983 *****	**0.0061 ***	**-0.0936 *****	**-0.2295 *****
$\nu_{2,8}$ (US - GDP preliminary)	**0.0227 *****	0.0007	0.0053	**-0.0071 ****	0.0000
$\nu_{2,9}$ (US - GDP final)	**0.0194 *****	**-0.0561 *****	**0.0555 *****	**-0.0153 *****	**-0.0092 ****
$\nu_{2,10}$ (US - Industrial production)	0.0015	**-0.0381 *****	0.0042	-0.2667	0.0018
$\nu_{2,11}$ (US - Initial jobless claim)	0.0031	**-0.0721 *****	**-0.0080 ****	0.0011	**-0.0983 *****
$\nu_{2,12}$ (US - Nonfarm payroll)	-0.0010	**-0.3404 *****	**-0.0508 *****	**-0.0466 *****	**-0.1100 *****
$\nu_{2,13}$ (US - Philadelphia FED Index)	**0.0097 *****	**-0.2049 *****	0.0037	**-0.0482 *****	-0.0005
$\nu_{2,14}$ (US - PPI)	**-0.0076 ****	0.0048	-0.0028	-0.6172	0.0034
$\nu_{2,16}$ (US - University of Michigan)	**-0.0060 ***	**-0.0825 *****	**-0.0074 ****	-0.0044	**-0.0983 *****
$\nu_{2,17}$ (EA - Business confidence)	**0.0069 ***	-0.0003	**-0.0157 *****	0.0052	**-0.0079 ****
$\nu_{2,18}$ (EA - Consumer confidence)	**0.0182 *****	0.0031	0.0154	**-0.0117 *****	**-0.0134 *****
$\nu_{2,19}$ (EA - Flash HICP)	0.0030	**-0.0398 *****	**0.0178 *****	0.0052	0.0045
$\nu_{2,21}$ (EA - Industrial production)	**-0.0076 ****	0.0004	**-0.0545 *****	0.0015	**0.0266 *****
$\nu_{2,22}$ (EA - Introductory Statement)	**0.0078 ****	**-0.1282 *****	**-0.1326 *****	**-0.0668 *****	**-0.0961 *****
$\nu_{2,23}$ (EA - M3)	**0.0104 *****	**-0.0358 *****	**0.0073 ****	**-0.0253 *****	**-0.0140 *****
$\nu_{2,24}$ (EA - Monthly Bulletin)	**0.0086 ****	0.0058	**-0.0866 *****	**0.0091 ****	0.0000
$\nu_{2,25}$ (EA - PMI flash)	0.0038	-0.0002	0.0038	**-0.0186 *****	**-0.0891 *****
$\nu_{2,26}$ (EA - PMI final)	**0.0161 *****	0.0002	**-0.0383 *****	0.0036	0.0010
$\nu_{2,27}$ (EA - PPI)	**-0.0123 *****	**0.0071 ****	**-0.0480 *****	**-0.0289 *****	**0.0148 *****

Table 2.8: **Jumps: variance model**

	IT	**FR**	**ES**	**BE**	**NL**
$\nu_{2,28}$ (EA - Retail sale)	-0.0048	0.0030	**-0.0361 *****	**-0.0178 *****	0.0007
$\nu_{2,29}$ (EA - Unemployment)	**0.0129 *****	-0.0026	0.0036	0.0026	0.0000
$\nu_{2,30}$ (DE - CPI preliminary)	0.0055	**-0.1306 *****	**-0.0087 ****	**-0.0178 *****	0.0000
$\nu_{2,31}$ (DE - IFO: business confidence)	0.0043	-0.0038	**0.0094 *****	**-0.0178 *****	0.0044
$\nu_{2,32}$ (DE - Industrial production)	**0.0143 *****	**-0.0390 *****	**-0.0823 *****	0.0031	**-0.0478 *****
$\nu_{2,33}$ (DE - Unemployment)	-0.0031	**-0.0736 *****	0.0053	**-0.0322 *****	**0.0133 *****
$\nu_{2,34}$ (DE - ZEW)	**-0.0064 ***	-0.0023	**-0.1083 *****	-0.0033	**-0.0868 *****
$\nu_{2,35}$ (IT - Business confidence)	**0.0126 *****	-0.0006	**0.0200 *****	**-0.0164 *****	**-0.0346 *****
$\nu_{2,36}$ (IT - CPI preliminary)	**-0.0283 *****	**-0.0066 ***	**-0.0834 *****	0.0035	0.0000
$\nu_{2,37}$ (IT - CPI final)	**-0.0134 *****	**-0.0261 *****	**0.0249 *****	**-0.0307 *****	-0.0020
$\nu_{2,38}$ (IT - GDP preliminary)	**-0.0115 *****	**0.0099 *****	0.0021	0.0028	0.0049
$\nu_{2,39}$ (IT - GDP final)	**0.0211 *****	0.0016	**0.0147 *****	**0.0061 ***	**0.0109 *****
$\nu_{2,40}$ (IT - Industrial production)	0.0019	0.0009	**-0.0182 *****	**-0.0307 *****	0.0019
$\nu_{2,42}$ (ES - CPI)	-0.0047	**-0.1374 *****	**-0.1202 *****	**-0.0631 *****	**-0.3038 *****
$\nu_{2,43}$ (ES - GDP Preliminary)	**0.0169 *****	0.0001	**0.0066 ***	0.0000	0.0000
$\nu_{2,44}$ (ES - GDP Final)	0.0037	**-0.0981 *****	**-0.0660 *****	**-0.0269 *****	**-0.0408 *****
$\nu_{2,45}$ (ES - Industrial Production)	-0.0049	**-0.0315 *****	**-0.1322 *****	**-0.0249 *****	**-0.1096 *****
$\nu_{2,46}$ (ES - Unemployment)	**0.0190 *****	0.0010	0.0009	-0.0024	**-0.0192 *****
$\nu_{2,47}$ (PT - CPI)	0.0001	0.0016	**0.0208 *****	-0.0046	**-0.0105 *****
$\nu_{2,49}$ (PT - GDP final)	0.0051	0.0000	**-0.0401 *****	**-0.0068 ***	**-0.0703 *****
$\nu_{2,50}$ (NL - CPI)	**0.0105 *****	0.0105	**-0.0162 *****	0.0000	0.0000
$\nu_{2,51}$ (NL - Industrial production)	**0.0149 *****	-0.0052	**-0.0724 *****	**-0.0109 *****	**-0.0458 *****
$\nu_{2,52}$ (NL - Unemployment)	**-0.0098 *****	**-0.0138 *****	**-0.0849 *****	**-0.0547 *****	**-0.2027 *****
$\nu_{2,53}$ (BE - Business confidence)	**0.0142 *****	**-0.0925 *****	**-0.1295 *****	**-0.0622 *****	-0.0002
$\nu_{2,54}$ (GR - CPI)	**0.0171 *****	0.0000	**-0.0093 *****	**-0.0086 ****	-0.0164
$\nu_{2,55}$ (GR - GDP preliminary)	**-0.0088 ****	0.0000	**0.0271 *****	0.0011	0.0003
$\nu_{2,56}$ (GR - GDP final)	**-0.0067 ***	-0.0010	**0.0139 *****	-0.0054	**-0.0895 *****
$\nu_{2,57}$ (GR - Unemployment)	0.0032	0.0015	**0.0085 ****	**0.0111 *****	**0.0060 ***
Auctions - post-release (bid-to-cover) - Asymmetric effect					
$\nu_{2,58}$ (Austria)	**0.0094 *****	0.0000	0.0003	0.0022	**-0.0402 *****
$\nu_{2,59}$ (Belgium)	**0.0175 *****	**-0.0132 *****	**0.0088 ****	**-0.0645 *****	0.0007
$\nu_{2,61}$ (France)	-0.0034	0.0007	**-0.0124 *****	**-0.0675 *****	0.0029
$\nu_{2,62}$ (Germany)	**0.0075 ****	**-0.0310 *****	**-0.0173 *****	0.0019	0.0008
$\nu_{2,64}$ (Italy)	**-0.0104 *****	**-0.0553 *****	**0.0294 *****	**-0.015 *****	**-0.1558 *****
$\nu_{2,66}$ (Portugal)	**0.0248 *****	-0.0012	**-0.0273 *****	**-0.0426 *****	**0.0279 *****
$\nu_{2,67}$ (Spain)	**0.0087 ****	0.0049	**0.0270 *****	**-0.0094 ****	**-0.0390 *****
Auctions - post-release (average yield) - Asymmetric effect					
$\nu_{2,68}$ (Austria)	**0.0119 *****	0.0000	**0.0181 *****	0.0004	0.0000
$\nu_{2,69}$ (Belgium)	**-0.0229 *****	**-0.0744 *****	**0.0180**	**-0.0404 *****	**-0.0769 *****
$\nu_{2,71}$ (France)	**0.0098 *****	**-0.0110 *****	**-0.0184 *****	**-0.0108 *****	**-0.0067 ***
$\nu_{2,72}$ (Germany)	**-0.0075 ****	**-0.2470 *****	**-0.1325 *****	**-0.0339 *****	**-0.1292 *****

Table 2.8: **Jumps: variance model**

	IT	**FR**	**ES**	**BE**	**NL**
$\nu_{2,74}$ (Italy)	**-0.0066 ***	**-0.0154 *****	**-0.1812 *****	**-0.0793 *****	**-0.0084 ****
$\nu_{2,75}$ (the Netherlands)	**-0.0126 *****	**-0.0979 *****	**0.0161 *****	**-0.0353 *****	0.0000
$\nu_{2,76}$ (Portugal)	**-0.0369 *****	**-0.0096 *****	**-0.1983 *****	**-0.0644 *****	-0.2994
$\nu_{2,77}$ (Spain)	**-0.0251 *****	**-0.0097 *****	**-0.0852 *****	**-0.0242 *****	**-0.0140 *****
Rating actions - Asymmetric effect					
$\nu_{2,78}$ (S&P)	-0.0004	0.0034	0.0028	0.0088	**0.0070 ***

Table 2.8 reports the estimates for the variance equation of the Tobit-GARCH model in (2.16). The dependent variable is the absolute size of jumps identified by applying the Lee and Mykland (2008) test corrected by the intraday periodicity of the volatility as proposed by Boudt et al. (2010) and defined in (2.8). **Macroannouncements and auctions pre-release** are dummy variables taking value equal to 1 for time intervals preceding the release up to 1 hour before the release. **Macroannouncements and auctions post-release** effect is captured by dummy variables equal to 1 for large surprise. Large surprises are defined as: $|\text{Surprise}| \geq 0.5$ SD(Surprise). For bond auctions we define surprise as the difference in average yield and bid-to-cover with respect to the previous auction. These "surprises" are available just for 10-year bond auctions. Surprises are evaluated up to 1 hour after the release. **Rating actions** are dummy variables taking value 1 for time intervals following the action up to 2 hours after the release, zero otherwise. **Macroannouncements and auctions post-release - Asymmetric** and **Rating actions - Asymmetric** are defined as for Macroannouncements and auctions post-release. We report just variables which are statistically significant at 10% level for at least one country. ***, **, * denote 1%, 5% and 10% significance level, respectively.

The coefficients $\omega_{2,j}$, $j = 1, ..., J$ account for a different level of unconditional volatility in correspondence to the future macroannouncements or government bond auctions releases with respect to time intervals not preceding any news. The coefficients are positive and statistically significant, meaning that in the hour preceding one of the events in our analysis, the level of volatility raises above the level ω_1. In particular, 22 macroannouncements out of 55 are significant with higher relevance of those concerning US, among which non-farm payroll for France (coefficient: 0.1141), Spain (-0.0091) and Belgium (0.0243), retail sales for France (0.0264), Spain (0.0077) and Belgium (0.0099) and Chicago PMI for France (-0.0391), Belgium (0.0043) and the Netherlands (-0.0184) and Euro area with the PMI flash for France (0.0229), Belgium (0.0107) and the Netherlands (0.0220). Moreover we found that the level of volatility raises in correspondence to Italian and Greek releases. In particular, Italian GDP final and industrial production future releases impact on France (coefficients: 0.0629 and 0.0280) and Belgium (0.0216 and -0.0099) while Greek GDP final and unemployment significantly explain jump sizes for France (coefficients: -0.1160 and 0.0365) and Belgium (0.0152 and 0.0050) and Greek CPI determines jumps in Belgium (0.0110) and the Netherlands (-0.0182). Turning now the attention to auctions, we found little evidence of a raise in volatility in correspondence of prescheduled auctions with limited impact of those which will be held in Greece and Spain both on Belgium and the Netherlands.

All variables used so far capture the pre-announcement effect. Once information is released, traders process information and adjust the price according. Parameters $\alpha_{2,j}$, $j = 1, ..., J + B$ account for persistency of announcement news while parameters $\nu_{2,j}$ allow for the different leverage effect in correspondence to negative surprise lead by macroannouncements with respect to standard negative news.

As far as the persistency parameters are concerned, starting from macroannouncements there is no particular pattern in the significance as overall 19 parameters are positive while 14 are negative. This finding implies that macroannouncements do not persist differently from other news. The same holds true for auctions. The only release deserving attention is the ECB Introductory Statement whose release increases persistency in volatility in France (coefficient: 0.1162), Spain (0.0296) and the Netherlands (0.0742). As already reported earlier in the Chapter, the ECB Introductory Statement conveys a lot of information which can take some time to be completely processed by the market. Moreover, the reading of the Introductory Statement per se together with the time devoted to questions and answers may take some time to be carried out.

The asymmetric effect is the most relevant part in the variance equation. In particular, as far as both macroannouncements and auctions are concerned, quite a few coefficients are negative and statistically significant implying that the leverage effect associated to these events is less pronounced than other news. We like to interpret this finding as follows: the availability of forecasts together with the scheduling of macroannouncement releases decrease the uncertainty associated to these news. In contrast, other negative shocks to the market, for instance political downturns or some banks failures, are completely unforeseeable and thus have higher impact on government bond spreads. The evidence of the lower leverage effect associated to macroannouncements with respect to other kind of news contrasts the finding in de Goeij and Marquering (2006) where it is found evidence of positive estimates for the leverage effect associated to macroannouncements. In our analysis, we are using 5-minute data while de Goeij and Marquering (2006) paper is based on daily data, thus our results should be more precise in assessing the different impact of macroannouncements with respect to standard news.

Turning now to the analysis of the leverage effect associated to auctions, we still observe a less pronounced effect than other news; this result too can be supported by better quality in terms of information content and by that auctions are prescheduled events.

2.4.3 Results for the Cojump Model

In this final section, we report the results from model estimation for cojumps.

First, in order to get robust estimates, we remove all the dummy variables which had less than 15 observations for all the possible combinations with dependent variable in a 2x2 contingency table; on the remaining variables we then estimate the logit model and adjust the estimates according to prior correction. In Table 2.9, we report only statistically significant variables explaining cojumps.

Table 2.9: **Cojumps: logit model**

	Constant	-5.1789
Macroannouncements - pre-release		
	$\gamma_{1,12}$ (US - Nonfarm payroll)	2.1708 ***
	$\gamma_{1,22}$ (EA - Introductory Statement)	1.1798 ***
	$\gamma_{1,25}$ (EA - PMI flash)	1.1897 ***
	$\gamma_{1,26}$ (EA - PMI final)	1.5830 ***
	$\gamma_{1,27}$ (EA - PPI)	0.6163 *
Macroannouncements - post-release		
	$\gamma_{2,7}$ (US - GDP advance)	3.0476 ***
	$\gamma_{2,12}$ (US - Nonfarm payroll)	0.6829 ***
	$\gamma_{2,15}$ (US - Retail sales)	0.5907 ***
	$\gamma_{2,26}$ (EA - PMI final)	0.2946 ***
	$\gamma_{2,24}$ (EA - Monthly Bulletin)	-1.4181 *
	$\gamma_{2,45}$ (ES - Industrial production)	0.1866 **
	$\gamma_{2,56}$ (GR - GDP final)	0.7799 **
Auctions - pre-release		
	$\gamma_{1,59}$ (Belgium)	0.3908 *
	$\gamma_{1,64}$ (Italy)	0.4389 **
	$\gamma_{1,66}$ (Portugal)	-0.6717 **
Auctions - post-release (average yield)		
	$\gamma_{2,61}$ (France)	4.1493 **
	$\gamma_{2,64}$ (Italy)	2.4961 ***
Test statistics		
LogL		-4,888.52
LR test		346.38 ***
Area under ROC curve		0.61

Table 2.9 reports the estimates for the logit model on cojumps. The dependent variable is the contemporaneous cojump defined in (2.12) based on jumps identified according to Lee and Mykland (2008) test corrected by the intraday periodicity of the volatility as proposed by Boudt et al. (2010) and defined in (2.8). The interecept of the logit model is corrected by (2.18) as suggested by the prior correction approach. **Macroannouncements and auctions pre-release** are dummy variables taking value equal to 1 for time intervals preceding the release up to 1 hour before the release. **Macroannouncements and auctions post-release** effect is captured by the absolute size of surprise associated to the specific release. For bond auctions we define surprise as the difference in average yield and bid-to-cover with respect to the previous auction. These "surprises" are available just for 10-year bond auctions. Surprise effects are taken into consideration up to 1 hour after the release. We report just variables which are statistically significant at 10% level. ROC curve: receiver operating characteristic curve. ***, **, * denote significance at 1%, 5% and 10%, respectively.

Although the area under the ROC (receiver operating characteristic) curve indicates that we are not able to model in a satisfactory way cojump being equal to 0.61 (a completely random classifier model has an area under the ROC curve equal to 0.5 while in the case of a perfect discriminating model this value is equal to 1), the results we get are robust enough to suggest interesting findings. The most important variables in explaining cojumps are those related to the US real economy, among which a prominent role is played as usual by non-farm payroll (0.6829) but even by GDP advance (3.0476) and retail sales (0.5907), together with forward looking measures concerning Euro area such as PMI flash (1.1897) and PMI final (1.5830). Moreover, the importance of the Introductory Statement is confirmed with a statistically significant coefficient of 0.1866. The relevance of US non-farm payroll and retail sales in explaining cojumps is also stated in Lahaye et al. (2011), while as far as auctions are concerned, we can see that Italian auctions are crucially entering the model with the change in average yield with a coefficient of 2.4961 as well as with the pre-release effect (0.4389). Even for this model, the impact of rating actions is statistically insignificant.

2.5 Conclusions

In this Chapter, we jointly modelled the impact of macroannouncements, government bond auctions and rating actions on the 10-year government bond spreads for the benchmarks of Belgium, France, Italy, the Netherlands and Spain with respect to the German Bund, over the period 2nd January 2009 - 31st May 2012. We measured the impact of three drivers on both mean and variance specifications, disentangling the pre- from the post-announcement effect, via the identification and mapping of jumps and cojumps. We considered a wide range of macroannouncements covering US, Euro area and individual countries together with government bond auctions and rating actions about largest European countries.

Our results show the high sensitivity of jumps and cojumps to US and Euro area macroannouncements plus specific Spanish and German macroannouncements. With respect to macroannouncements categories, very important is the role played by the variables concerning real economy, such as US non-farm payroll, retail sales and GDP, together with the forward looking indicators among all consumer confidence indicators and purchase manager indexes playing a key role; monetary news are found to be irrelevant. Moreover, the ECB Introductory Statement turned out to be a significant determinant of both jumps and cojumps. Finally, macroannouncements are important drivers for both the mean and variance of spreads entering significantly at both pre and post-announcement levels.

Government bond auctions hold in countries experiencing deep economic downturn, such as Italy and Spain, significantly explain jumps and cojumps. Finally, rating actions do not produce sizeable jumps in the markets.

To the best of our knowledge this is the first paper assessing in a comprehensive way the drivers of jumps and cojumps associated to government bond spreads. Our framework allows to consider simultaneously a relevant number of variables which is crucial in order to properly measure the impact of these events; this is important also because macroannouncements in the Euro area and government bond auctions take place at almost the same time. Finally, the evaluation of the impact of auctions on spreads is relevant also to practitioners who focus even on government bond auctions in setting their trading strategies.

There are important policy implications from our analysis. We showed that movements in government bond spreads are significantly determined by macroannouncements and government bond auctions, and thus in the current sovereign crisis intraday movements were driven by changes in macroeconomic fundamentals and not, or at least not only, by speculative actions. In addition, the fact that events taking place in some individual country, such as Germany and Spain for macroannouncements and Italy and Spain for auctions, have a significant impact in other countries, shows the great level of interdependence between countries. This conclusion is supported also by that the higher number of cojumps for all the government bond spreads in the analysis are significantly associated to macroannouncements and government bond auctions.

The findings in this Chapter suggest interesting additional developments. Our analysis is very comprehensive about the possible determinants of jumps and cojumps, however we envisage that at least two other possible drivers may play an important role in an uncertain and volatile environment. In this Chapter, we analyzed the impact of the downgrading actions once the decision of the rating agency becomes public: it will be interesting to study whether warnings and outlook changes announced by rating agencies could have some impacts on government bond spreads. The second issue deals with the analysis of market's reactions to political uncertainty. For instance, the inconclusive results of Italian elections of the 25th February 2012 brought on the market a high level of uncertainty which determined a substantial increase in Italian government bond spread of 51 bps in just one day and which affected even Spanish spread with an increase of 30 bps. Finally, following Beechey and Wright (2009) who look at announcement effects in the real and nominal US Treasury market using real yields, nominal yields, and the spread between the two, we may also look at yields on the German Bund, yields on the other bonds, and the spreads between them. This is part of an ongoing research agenda.

2.A Appendix I - Realized Measures

Consider a scalar log-price X_t evolving in continuous time as:

$$dX_t = \mu_t dt + \sigma_t dW_t + dJ_t \tag{2.19}$$

where μ_t drift, σ_t volatility, W_t Brownian motion, J_t pure Lévy process with increments $J_t - J_s = \sum_{\tau=s}^{t} k(\tau)$ with $k(\tau)$ jump size.

The overall volatility of (2.19) is the *Quadratic Variartion* (QV) which is defined as:

$$QV_t = \int_{t-1}^{t} \sigma_s^2 ds + \sum_{\tau=1}^{M_t} k(\tau)^2 \tag{2.20}$$

where M_t number of jumps in day t.

QV in (2.20) can be decomposed into two components, the *Integrated Variance* (IV):

$$IV_t = \int_{t-1}^{t} \sigma_s^2 ds \tag{2.21}$$

and the *Jump Variance* (JV):

$$JV_t = \sum_{\tau=1}^{M_t} k(\tau)^2 \tag{2.22}$$

A consistent estimator of QV is the *Realized Volatility* (RV) by Barndorff-Nielsen and Shephard (2004):

$$RV_t = \sum_{\tau=1}^{N} r(\tau)^2 \xrightarrow{p} QV_t \tag{2.23}$$

with N number of intraday transactions belonging to day t.

In absence of any jumps, the limiting distribution of the RV estimator is $\sqrt{N}\left(RV_t - IV_t\right) \to N\left(0, 2IQ_t\right)$ with IQ the *Integrated Quarticity* defined as:

$$IQ_t = \int_{t-1}^{t} \sigma_s^4 ds \tag{2.24}$$

A consistent estimator of the IV is the *Bipower Variation* (BV) by Barndorff-Nielsen and Shephard (2004) defined as:

$$BV_t = \mu_1^{-2}\left(\frac{N}{N-1}\right)\sum_{\tau=2}^{N} |r_{\tau-1}|\,|r_\tau| = \frac{\pi}{2}\left(\frac{N}{N-1}\right)\sum_{\tau=2}^{N} |r_{\tau-1}|\,|r_\tau| \tag{2.25}$$

The BV is robust to the presence of jumps in previous periods as it measures only the integrated variance attributable to the diffusive component.

2.B Appendix II - Intraday Deterministic Component

2.B.1 Methodology

The combination of recurring cycles at the daily frequency and a slow decay in the average autocorrelations may be explained by the joint presence of the pronounced intraday periodicity coupled with the strong daily conditional heteroskedasticity. Andersen and Bollerslev (1998) formalize the relationship between intradaily and daily returns as follows:

$$r_{t,i} - \overline{r}_{t,i} = \sigma_t s_{t,i} z_{t,i} \quad t = 1, ..., T \quad i = 1, ..., N \tag{2.26}$$

where T number of days in the sample; N number of intraday intervals belonging at each t; $r_{t,i}$ observed return on day t and interval i; $\overline{r}_{t,i}$ expected return; σ_t daily conditional volatility; $s_{t,i}$ deterministic intraday periodic component; $z_{t,i}$ *i.i.d.* mean zero and unit variance term. All the return components σ_t, $s_{t,i}$ and $z_{t,i}$ are assumed to be independent. In the absence of intraday periodicity ($s_{t,i} = 1$), the intradaily returns may be represented in the form $r_{t,i} = \sigma_t z_{t,i}$. Thus, (2.26) extends the standard volatility model for daily returns to an intraday setting with independent return innovations and deterministic volatility pattern.

Without additional restrictions, the components of (2.26) are not separately identifiable. The estimation of (2.26) can be carried out by squaring and taking the logs so that the deterministic intraday periodic component $s_{t,i}$ can be isolated as the sole explanatory variables:

$$2\log\left[\left|r_{t,i} - \overline{r}_{t,i}\right|\right] - 2\log\left|\sigma_t\right| = 2\log\left|s_{t,i}\right| + 2\log\left|z_{t,i}\right| \tag{2.27}$$

and setting $2\log\left|z_{t,i}\right| = u_{t,i} + c$ with $c = E\left[2\log z_{t,i}\right]$, (2.27) becomes:

$$2\log\left[\left|r_{t,i} - \overline{r}_{t,i}\right|\right] - 2\log\left|\sigma_t\right| = 2\log\left|s_{t,i}\right| + c + u_{t,i}$$

Andersen and Bollerslev (1998) model the intraday periodicity using a parametric approach and by replacing $2\log\left|s_{t,i}\right|$ with $f(\theta; x_{t,i})$ ending up with:

$$2\log\left[\left|r_{t,i} - \overline{r}_{t,i}\right|\right] - 2\log\left|\widehat{\sigma}_t\right| = f(\theta; x_{t,i}) + c + \widehat{u}_{t,i} \tag{2.28}$$

where $\widehat{u}_{t,i}$ i.i.d. distributed with zero mean and density function corresponding to that of the centered absolute value of the log of a standard normal random variable as in (2.29):

$$g(z) = \sqrt{\frac{2}{\pi}} \exp\left[z + c - 0.5\exp\left(2\left(z + c\right)\right)\right] \tag{2.29}$$

with $c = -0.65318$, that is the mean of the log of the absolute value of a standard normal random variable.

In modelling the intraday periodicity component, Andersen and Bollerslev (1998) assume that the volatility process is driven by simultaneous interaction of numerous components, some associated with economic news releases, some with predominantly predictable calendar effects, and some with persistent, unobserved (latent) factor.

The baseline assumption is that the log-volatility response, conditional on the type of the macroannouncement, the time of the release and other relevant calendar information, has a well-defined expected value, $E[\log s_{t,i}]$. This average impact is then governed by purely deterministic regressors. Of course, the innovations, $\log s_{t,i} - E[\log s_{t,i}]$, will typically be highly correlated for the immediate period following a new release. This will induce serial correlation and heteroskedasticity in the error terms of the regression proposed below. The term $\log|\sigma|_t$ is assumed to be strictly stationary and with finite unconditional mean, $E[\log|\sigma_t|]$.

The presence of the intraday periodic component reduces the overall level of the intradaily return autocorrelations without affecting the autocorrelation pattern. The intraday periodic component $s_{t,i}$ can be modeled using two alternative approaches, both based on the approximation through polynomial terms and trigonometric functions which are parametrizations particularly useful in case of regularly recurring patterns. The first approach is based on the Fourier Flexible Functional (FFF) form proposed by Gallant (1981) and popularized by Andersen and Bollerslev (1998). The second one was introduced by Dacoronga (1993) relying on the sum of three polynomials corresponding to the three distinct geographical locations of the markets; this approach does not apply to our data as we are investigating just the Euro area market. We now present the FFF approach as in Andersen and Bollerslev (1998).

In the first step, the mean process $\overline{r}_{t,i}$ is modeled given a reasonable estimator for $\widehat{\sigma}_t^2$. In particular, the daily volatility σ_t can be estimated according to a GARCH process, even on a longer data sample, in order to capture the daily volatility clustering. The intradaily volatility estimate is obtained using the following transformation:

$$\widehat{\sigma}_{t,i} = \widehat{\sigma}_t / N^{1/2} \tag{2.30}$$

where N is the number of observations for day t. At this point, the observable regressand and regressors in (2.28) are provided.

In the second step, a parametric representation of the regressor $E[\log f(\theta; t, i)]$ of the form $f(\theta; x_{t,i})$ is imposed. In detail Andersen and Bollerslev (1998) propose the following form:

$$\begin{aligned} f(\theta; x_{t,i}) &= \delta_0 + \delta_{0,1}\frac{i}{N_1} + \delta_{0,2}\frac{i^2}{N_2} + \sum_{j=1}^{J} \lambda_j S_{t,i}^j + \\ &\sum_{p=1}^{P}\left(\delta_{c,p}\cos\left(\frac{2\pi p}{N}i\right) + \delta_{s,p}\sin\left(\frac{2\pi p}{N}i\right)\right) + \varepsilon_{t,i} \end{aligned} \tag{2.31}$$

where $N_1 = (N+1)/2$ and $N_2 = (N+1)(N+2)/6$ normalizing constants; $S^j_{t,i}$ surprise effect of macroannouncement j during interval i on day t; λ_j event specific loading coefficient; P tuning parameter determining the order of the expansion of the sinusoids; θ full parameter vector to be estimated. The role of λ_j is to capture the response of returns to macroeconomic announcements. The idea under study is that the event j impacts volatility over N_j intervals. In Andersen and Bollerslev (1998) this is achieved imposing a decay-structure on the volatility response pattern and estimating the degree to which events load onto this pattern by:

$$\lambda(j,i) = \lambda_j \gamma(i) \qquad i = 0, 1, ..., N_j \tag{2.32}$$

where $\gamma(i)$ dictates the response at lag $i = 0, 1, ..., N_j$ modeled by a third-order polynomial:

$$\gamma(i) = \alpha \left[1 - (i/(N_j+1))^3\right] + \beta \left[1 - (i/(N_j+1))^2\right] i + \phi \left[1 - (i/(N_j+1))\right] i^2 \tag{2.33}$$

Equation (2.33) is obtained starting from:

$$p(\tau) = c_0 + c_1\tau + ... + c_p\tau^p \tag{2.34}$$

to which two bounds are imposed, $p(0) = 0$, so that the impact reflects a gradual movement away from the standard pattern, $c_0 = 0$, and $p(\overline{N}) = 0$ so that the macroannouncement effect slowly fades. The next step is to substitute $\tau = N$ in (2.34), solving for c_p and inserting the resulting expression for c_p back into (2.34). In this way, a restricted polynomial with one less parameter is obtained:

$$p(\tau) = c_0 \left[1 - \left(\tau/\overline{N}\right)^p\right] + c_1 \left[1 - \left(\tau/\overline{N}\right)^{p-1}\right] \tau^1 + ... + c_{p-1} \left[1 - \left(\tau/\overline{N}\right)\right] \tau^{p-1} \tag{2.35}$$

The common response structure is finally obtained:

$$p_j(\tau) = \lambda_j p_0(\tau) \tag{2.36}$$

The cumulative response measure over the entire event window is expressed as a multiplicative factor scaled in units of average volatility per interval over the period and takes the following form:

$$M(j) = \sum_{i=0}^{N_j} \left[\exp\left(\frac{\widehat{\lambda}_j \gamma(i)}{2}\right) - 1\right] \tag{2.37}$$

Through translation of the resulting estimates for λ_j from (2.32), the immediate response in the j absolute returns is then given by $\exp\left(\widehat{\lambda}_j \gamma(0)/2\right) - 1$, while the response at the $i-$th lag equals $\exp\left(\widehat{\lambda}_j \gamma(i)/2\right) - 1$. At lag $i = N_j$ the impact is forced to be 0.

Once (2.32) is estimated, the intraday periodic component for interval i belonging to day t is given by:

$$\widehat{s}_{t,i} = \frac{T \exp\left(f\left(\widehat{\theta}; x_{t,i}\right)/2\right)}{\sum_{t=1}^{T}\sum_{i=1}^{N}\exp\left(f\left(\widehat{\theta}; x_{t,i}\right)/2\right)} \tag{2.38}$$

Although the two-step method is not fully efficient as the error terms are not normally distributed, given correct specification of the first-step FFF regressor, the estimated parameters are consistent. The logarithmic transformation introduced in (2.27) is particular useful for eliminating the extreme outliers in the 5-minute return series and let the regression be more robust. Anyway, price jumps may cause a large bias in the periodicity estimator proposed by Andersen and Bollerslev (1998). Therefore Boudt et al. (2010) introduce a robust alternative to intraday periodicity estimation.

To introduce Boudt et al. (2010) estimation technique, we first have to introduce the non-parametric estimation of the intraday periodicity factor. The non-parametric periodicity estimator is based on a scale estimate of the returns standardized by an estimate of volatility, $\widetilde{r}_{1,m}, \ldots, \widetilde{r}_{\widetilde{T},m}$ $m = 1, ..., M = N \times 5$, 5 being the days in a week, sharing the same periodicity factor $\widetilde{r}_m$ and $M = N \times 5$ be the total number of local windows. Assuming that the periodicity factor depends only on the time of the day and day of the week m at which $r_{t,i}$ is observed, we have that $\widetilde{r}_{1,i}, \ldots, \widetilde{r}_{\widetilde{T},i}$ are the $\widetilde{T}$ (T/M) returns observed on the same time of the day and day of the week m. The non-parametric periodicity factor estimators are generally defined as the square root of the expected value of the ratio between the spot variance and the mean variance over a local window:

$$s_m^2 = E\left[\frac{\sigma_m^2}{\frac{1}{M}\int_{(l-1)M}^{lM}\sigma_m^2 dm}\right] \tag{2.39}$$

The alternative non-parametric estimators differ for the the measure of the volatility used. The denominator in (2.39) ensures that the standardization condition that the squared periodicity factor has mean one over the local window is met:

$$\frac{1}{M}\sum_{m=1}^{M} s_m^2 = 1 \tag{2.40}$$

The first non-parametric periodicity estimator was proposed by Taylor and Xu (1997) and was based on the standard deviation of all standardized returns belonging to the same local window. Anyway in presence of jumps, the SD estimator is strongly biased. Therefore, Boudt et al. (2010) suggest to use a robust scale estimator, the Shortest Half Scale proposed by Rousseeuw and Leroy (1998). To define the Shortest Half (ShortH henceforth) scale estimator, we need to introduce the corresponding order statistics $\widetilde{r}_{(1),m}, \ldots,$ $\widetilde{r}_{(\widetilde{T}),m}$ where $m = 1, ..., M$ such that $\widetilde{r}_{(1),m} \leq \widetilde{r}_{(2),m} \leq ... \leq \widetilde{r}_{(\widetilde{T}),m}$. The shortest half scale is the smallest length of all halves consisting of $h_m = \left[\widetilde{T}/2\right] + 1$ contiguous order statistics:

$$ShortH_m = 0.741 \min \left\{ \widetilde{r}_{(h_m),m} - \widetilde{r}_{(1),m}, ..., \widetilde{r}_{(\widetilde{T}),m} - \widetilde{r}_{(\widetilde{T}-h_m+1),m} \right\} \tag{2.41}$$

The ShortH estimator for the periodicity factor equals:

$$\widehat{s}_m^{ShortH} = \frac{ShortH_m}{\sqrt{\frac{1}{\widetilde{T}} \sum\limits_{m=1}^{\widetilde{T}} ShortH_m^2}} \tag{2.42}$$

The ShortH is highly robust to jumps, but it has only a 37% efficiency under normality of the $\overline{r}_{t,m}s$ (Rousseeuw and Leroy, 1988). A more efficient estimator than the ShortH, being robust to jumps as well, is obtained using the Weighted Standard Deviation (WSD henceforth), where the weights depend on the value of the standardized returns divided by the ShortH periodicity estimate:

$$\widehat{s}_m^{WSD} = \frac{WSD_m}{\sqrt{\frac{1}{\widetilde{T}} \sum\limits_{t=1}^{\widetilde{T}} WSD_{t,m}^2}} \tag{2.43}$$

where:

$$WSD_m = \sqrt{1.081 \frac{\sum_{t=1}^{\widetilde{T}} w_{t,m} \widetilde{r}_{t,m}^2}{\sum_{t=1}^{\widetilde{T}} w_{t,m}}} \tag{2.44}$$

The weights are given by $w_{t,m} = w\left(\widetilde{r}_{t,m}/\widehat{s}_m^{ShortH}\right)$ where we use as a weight function $w(z) = 1$ if $z^2 \leq 6.635$ and 0 otherwise. The threshold 6.635 equals the 99% quantile of the χ^2 distribution with one degree of freedom. If there are no price jumps, the WSD gives a zero weight to on average 1% of the returns. If there are jumps, more observations are downweighted. The WSD in (2.44) has a 69% efficiency under normality of the $\overline{r}_t$s, as opposed to the 37% efficiency of the ShortH (see Boudt et al. (2010) for further details).

The main drawback of non-parametric estimators for the intraday periodic component is that they only use the subset of the data for which the returns have the same periodicity factor. Andersen and Bollerslev (1998) show that more efficient estimates can be obtained if the whole time series dimension of the data is used for the estimation of the periodicity process as it is done when parametric estimation is carried out. Anyway, we were stating that OLS is not efficient because of non-normality of the error term. Therefore, the maximum likelihood estimator should be preferred. Denote $\rho^{OLS}(z) = z^2$ and, recalling (2.29), let $\rho^{ML}(z)$ be the negative log likelihood function:

$$\rho^{ML}(z) = -0.5 \log(2/\pi) - z - c + 0.5 \exp(2(z + c)) \tag{2.45}$$

The OLS and ML estimators for (2.28) are given by:

$$\widehat{\theta}^{OLS} = \arg\min_{\theta} \frac{1}{\widetilde{T}M} \sum_{t=1}^{\widetilde{T}} \sum_{m=1}^{M} \rho^{OLS}(u_{\theta;t,m}) \tag{2.46}$$

$$\widehat{\theta}^{ML} = \arg\min_{\theta} \frac{1}{\widetilde{T}M} \sum_{t=1}^{\widetilde{T}} \sum_{m=1}^{M} \rho^{ML}(u_{\theta;t,m}) \tag{2.47}$$

These ρ-functions are called loss functions. The non-robustness of the OLS and ML estimators to jumps is due to the unbounded effect an observation can have on their loss function. Martens et al. (2002) mention that the effect of jumps on the OLS estimator is attenuated because the regression is based on the log of the standardized returns, but solely a log-transformation is not sufficient to attain robustness to jumps.

As an alternative to the OLS and ML estimators, Boudt et al. (2010) propose to use the Truncated Maximum Likelihood (TML) estimator introduced by Marazzi and Yohai (2004). This estimator gives a zero weight to observations that are outliers according to the value of the ML loss function. Therefore, in a first step residuals are computed using the robust non-parametric estimator $\widehat{f}_{WSD}$ in (2.43). Recalling again (2.28), let

$$u_{t,i}^{WSD} = \log\left[\frac{|r_{t,i} - \overline{r}_{t,i}|}{\widehat{\sigma}_{t,i}}\right] - c - \log \widehat{f}(x_{t,i})^{WSD} \tag{2.48}$$

Observations for which $\rho^{ML}(u_{t,i}^{WSD})$ is large have a low likelihood and are therefore likely to be outliers. Denote q an extreme upper quantile of the distribution of $u_{t,i}$. The TML estimator is defined as:

$$\widehat{\theta}^{TML} = \arg\min_{\theta} \frac{1}{\sum_{t=1}^{T}\sum_{i=1}^{N} w_{t,i}} \sum_{t=1}^{T}\sum_{i=1}^{N} w_{t,i}\rho^{ML}(u_{\theta;t,i}) \tag{2.49}$$

with $w_{t,i} = 1$ if $\rho^{ML}(u_{t,i}^{WSD}) \leq \rho^{ML}(q)$ and 0 otherwise. Henceforth, we take q as the 99.5% quantile such that all observations with $\rho^{ML}(u_{t,i}^{WSD}) > 3.36$ receive a zero weight in the objective function of the TML estimator. Like for the WSD, the choice of these thresholds implies that, if there are no price jumps, the TML gives a zero weight to on average 1% of the returns. If there are jumps, more observations are downweighted.

Like for the non-parametric periodicity estimators, we impose that the squared periodicity factor has mean one in the local window. The parametric estimate for the periodicity factor thus equals:

$$\widehat{s}_{t,i}^{TML} = \frac{\exp f\left(\hat{\theta}_{TML}; x_{t,i}\right)}{\sqrt{\frac{1}{N_i}\sum\limits_{i=1}^{N_i}\left(\exp f\left(\hat{\theta}_{TML}; x_{t,i}\right)\right)^2}} \qquad \forall t = 1, ..., T \tag{2.50}$$

where $x_{t,i}$ set of covariates used to model the intraday periodicity as in (2.31).

In a recent paper, Hecq et al. (2012) test for the presence of commonalities in the intraday periodic components in a set of 30 US asset returns concluding that only three factors are driving the intraday periodicity in volatility. The first one can be attributed to the typical U-shaped pattern observed in return volatility over the trading day while the other two capture more erratic fluctuations: the second factor shows a slowly decreasing intraday trend while the third factor has a sinusoidal behaviour.

2.B.2 Empirical Results

Focusing on data used in this Chapter, we estimated both non-parametric, ShortH and WSD, and parametric versions of the intraday periodicity. The parametric specification is in (2.10). As far as non-parametric estimation is concerned, we consider as local window a day of the week so that we effectively estimate the intraweekly periodicity. In Table 2.B.1 we report the estimates obtained through the parametric approach combined with the Truncated Maximum Likelihood technique.

Table 2.B.1: **Intraday periodicty estimates**

	IT	**FR**	**ES**	**BE**	**NL**
Constant	0.0000	0.0000	0.0000	0.0000	0.0000
AR(1)	0.1436	0.4944	0.1332	0.2513	0.5330
MA(1)	-0.2728	-0.7641	-0.3039	-0.4431	-0.8121
δ_0	0.7755	0.0736	-0.8062	0.1983	-0.2417
$\delta_{0,1}$	-1.8378	-0.1945	2.9184	-0.2654	0.7914
$\delta_{0,2}$	0.6314	0.0792	-0.9748	0.1064	-0.2684
Macroannouncement Surprises					
λ_1 - US - Business Inventories	0.0046	0.0010	0.0010	-0.0039	0.0030
λ_2 - US - Chicago PMI	0.0026	0.0017	0.0017	0.0006	-0.0001
λ_3 - US - Consumer Confidence	0.0007	0.0019	0.0038	0.0023	0.0017
λ_4 - US - CPI	0.0018	0.0092	0.0046	0.0002	0.0084
λ_5 - US - Durable Goods	-0.0009	-0.0010	-0.0022	-0.0025	-0.0030
λ_6 - US - Factory Orders	0.0058	0.0073	-0.0030	-0.0049	0.0049
λ_7 - US - GDP Advance	-0.0033	-0.0010	-0.0057	-0.0106	-0.0063
λ_8 - US - GDP Preliminary	-0.0020	-0.0003	-0.0049	-0.0049	0.0005
λ_9 - US - GDP Final	0.0017	0.0041	-0.0019	0.0048	-0.0064
λ_{10} - US - Industrial Production	-0.0008	-0.0013	-0.0022	-0.0011	0.0022
λ_{11} - US - Initial Jobless Claim	1.7785	-0.3580	0.7952	1.2892	-2.5060
λ_{12} - US - Nonfarm Payroll	-0.0003	0.0014	0.0035	-0.0002	0.0012
λ_{13} - US - Philadelphia FED	0.0012	-0.0014	0.0005	-0.0013	0.0021
λ_{14} - US - PPI	0.0053	-0.0014	-0.0016	-0.0027	-0.0036
λ_{15} - US - Retail Sales	-0.0019	0.0009	0.0020	-0.0009	-0.0013
λ_{16} - US - University Of Michigan	-0.0028	0.0003	0.0026	-0.0102	-0.0040

Table 2.B.1: **Intraday periodicty estimates**

	IT	**FR**	**ES**	**BE**	**NL**
λ_{17} - EA - Business Climate	0.0008	-0.0013	-0.0017	0.0004	-0.0019
λ_{18} - EA - Consumer Confidence	0.0013	0.0011	-0.0047	-0.0025	-0.0045
λ_{19} - EA - Flash HICP	0.0023	0.0010	0.0003	0.0033	0.0078
λ_{21} - EA - Industrial Production	0.0003	0.0009	0.0053	0.0065	-0.0027
λ_{22} - EA - Introductory Statement	0.0063	0.0137	0.0113	0.0194	0.0241
λ_{23} - EA - M3	-0.0018	-0.0019	-0.0019	0.0005	-0.0007
λ_{24} - EA - Monthly Bulletin	0.0014	-0.0052	0.0116	0.0031	-0.0020
λ_{25} - EA - PMI Flash	-0.0010	0.0003	-0.0017	-0.0015	0.0013
λ_{26} - EA - PMI Final	0.0036	0.0021	0.0041	0.0011	0.0027
λ_{27} - EA - Purchase Price	-0.0005	-0.0092	-0.0104	-0.0001	-0.0024
λ_{28} - EA - Retail Sales	0.0062	-0.0003	0.0135	0.0089	0.0067
λ_{29} - EA - Unemployment	0.0005	0.0002	-0.0009	-0.0006	-0.0038
λ_{30} - DE - CPI	0.0000	-0.0042	0.0027	-0.0039	0.0014
λ_{31} - DE - IFO:Business Confidence	0.0012	0.0014	0.0026	0.0015	0.0021
λ_{32} - DE - Industrial Production	0.0005	-0.0047	-0.0007	-0.0022	-0.0047
λ_{33} - DE - Unemployment	0.0038	0.0043	0.0030	0.0013	-0.0007
λ_{34} - DE - ZEW	0.0019	0.0023	0.0038	0.0035	0.0047
λ_{35} - IT - Business Confidence	0.0010	-0.0001	-0.0017	-0.0015	-0.0007
λ_{36} - IT - CPI Preliminary	-0.0003	0.0016	-0.0006	-0.0012	-0.0014
λ_{37} - IT - CPI Final	0.0027	0.0000	0.0028	0.0011	0.0035
λ_{38} - IT - GDP Preliminary	-0.0037	-0.0005	-0.0033	-0.0016	0.0054
λ_{39} - IT - GDP Final	0.0211	0.0094	0.0116	0.0251	0.0139
λ_{40} - IT - Industrial Production	0.0022	0.0021	-0.0016	0.0020	0.0011
λ_{41} - FR - Industrial Production	-0.0033	-0.0046	-0.0032	-0.0020	-0.0050
λ_{42} - SP - CPI	0.0049	0.0007	0.0032	0.0079	0.0110
λ_{43} - SP - GDP Preliminary	-0.0030	0.0050	-0.0029	0.0027	-0.0011
λ_{44} - SP - GDP Final	-0.0008	-0.0160	-0.0054	-0.0093	-0.0007
λ_{45} - SP - Industrial Production	-0.0021	-0.0009	0.0016	-0.0006	0.0029
λ_{46} - SP - Unemployment	-0.0024	-0.0087	-0.0013	-0.0017	-0.0074
λ_{47} - PT - CPI	0.0015	-0.0034	-0.0001	-0.0006	0.0020
λ_{48} - PT - GDP Preliminary	0.0004	-0.0001	0.0002	0.0005	-0.0006
λ_{49} - PT - GDP Final	0.0045	0.0041	0.0129	0.0035	-0.0079
λ_{50} - NL - CPI	-0.0002	0.0016	0.0058	0.0083	-0.0036
λ_{51} - NL - IndustrialProduction	0.0003	0.0005	-0.0017	0.0005	-0.0009
λ_{52} - NL - Unemployment	0.0041	-0.0004	0.0057	0.0007	0.0010
λ_{53} - BE - Business Confidence	-0.0057	-0.0042	-0.0037	-0.0060	-0.0020
λ_{54} - GR - CPI	-0.0014	-0.0011	-0.0012	-0.0003	0.0021
λ_{55} - GR - GDP Preliminary	0.0034	0.0044	0.0105	0.0018	0.0171
λ_{56} - GR - GDP Final	-0.0029	-0.0003	-0.0015	-0.0020	-0.0047
λ_{57} - GR - Unemployment	-0.0034	-0.0003	-0.0002	-0.0019	-0.0011

Table 2.B.1: **Intraday periodicty estimates**

	IT	FR	ES	BE	NL
Bid-to-cover 10yrs Auctions					
λ_{58} - Austria	0.0034	-0.0004	0.0031	-0.0018	0.0026
λ_{59} - Belgium	-0.0084	-0.0047	-0.0095	-0.0014	-0.0028
λ_{61} - France	0.0037	0.0061	0.0004	0.0036	-0.0004
λ_{62} - Germany	0.0021	0.0189	0.0009	-0.0124	-0.0162
λ_{64} - Italy	0.0112	0.0391	0.0186	0.0328	0.0391
λ_{66} - Portugal	-0.0039	0.0052	0.0013	0.0013	0.0035
λ_{67} - Spain	-0.0084	-0.0023	0.0050	-0.0128	0.0052
Rating					
ϕ_1 - S&P	0.0028	-0.0001	0.0010	-0.0017	-0.0072
ϕ_2 - Moody's	-0.0053	-0.0055	-0.0004	0.0127	-0.0028
ϕ_3 - Fitch	0.0063	0.0020	0.0081	-0.0002	0.0034
Day of the Week					
θ_1 - Tuesday	0.0101	0.0086	-0.0268	-0.0099	0.0015
θ_2 - Wednesday	0.0007	0.0081	-0.0170	-0.0004	0.0137
θ_3 - Thursday	0.0097	0.0092	-0.0239	-0.0060	0.0054
θ_4 - Friday	0.0376	0.0225	-0.0059	0.0249	0.0151
Periodic Component					
$\delta_{c,1}$	-0.2600	0.0555	0.6921	0.0242	0.2420
$\delta_{c,2}$	-0.1312	-0.0303	0.1245	-0.0282	0.0094
$\delta_{c,3}$	-0.0425	0.0041	0.0687	0.0057	0.0314
$\delta_{c,4}$	-0.0302	-0.0075	0.0388	0.0063	0.0138
$\delta_{c,5}$	-0.0156	0.0222	0.0389	0.0166	0.0444
$\delta_{s,1}$	0.0365	0.0164	0.0599	0.0394	-0.0221
$\delta_{s,2}$	0.0514	0.0459	0.0467	0.0359	0.0293
$\delta_{s,3}$	0.0256	-0.0027	0.0096	0.0031	0.0052
$\delta_{s,4}$	0.0245	0.0313	0.0096	0.0117	0.0156
$\delta_{s,5}$	0.0071	0.0108	-0.0189	-0.0082	0.0046

Table 2.B.1 reports the estimates for the parametric intraday periodicity following (2.10) and estimated by TML.

Figure 2.11 depicts a comparison among the three alternative estimates for the intraweekly periodicity: ShortH in grey, WSD in black and the parametric one in blue.

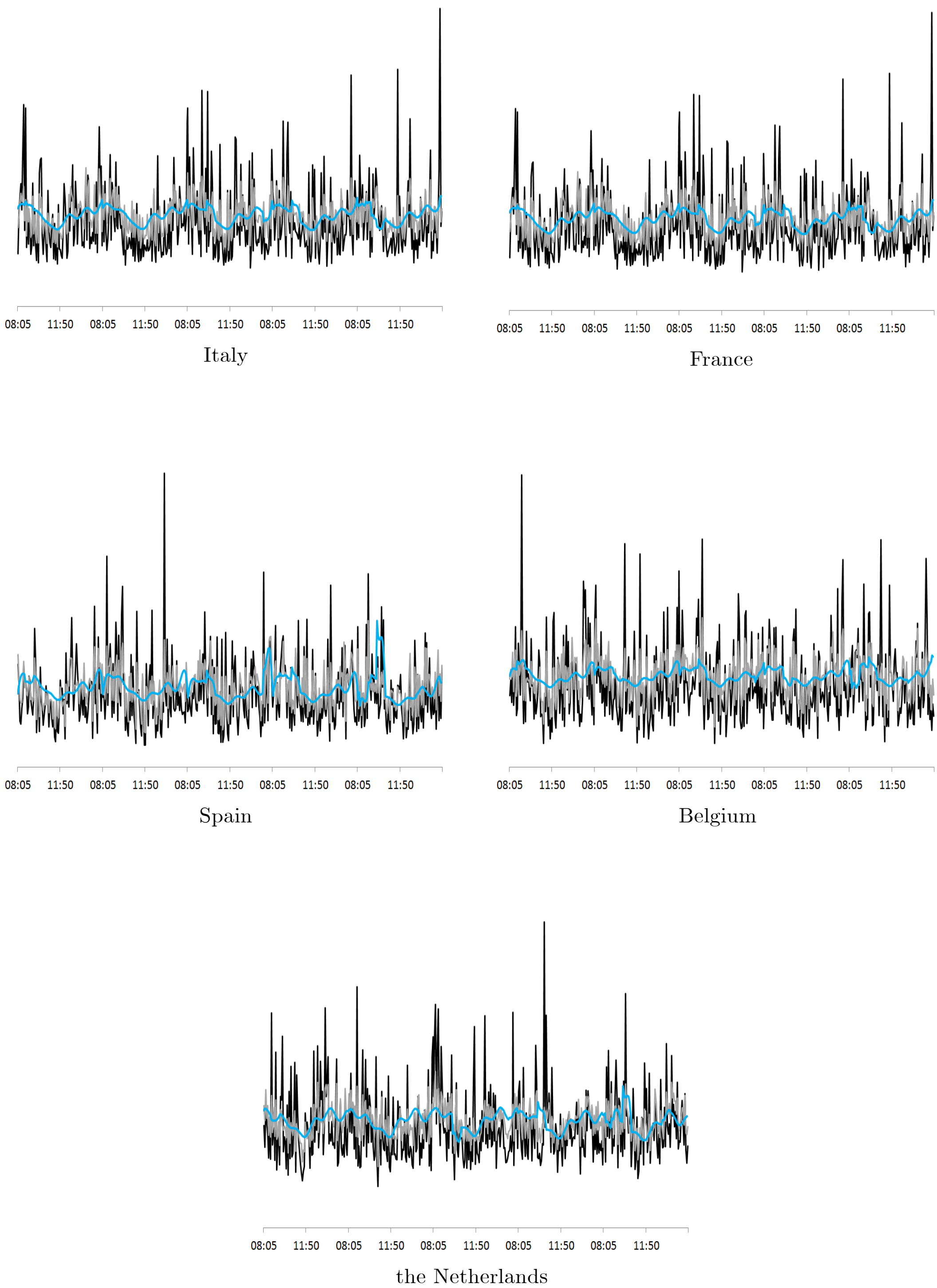


Figure 2.11: **Intraweekly Periodicity Estimates**

In Figure 2.11 we represent the three intraday periodicity components estimated by ShortH (grey), WSD (black) and parametric-TML (blue).

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Chapter 3

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

Abstract

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

We provide evidence of strong linkages between European government bond spreads volatility and worsening macroeconomic fundamentals with respect to Germany. Moreover, our results show that as two countries get similar in terms of their macroeconomic fundamentals, relative spreads tend to get more correlated, though the increasing correlation in spreads during the worst phase of the sovereign crisis could not be completely ascribed to macroeconomic factors. These results highlight the presence of increasing financial integration and systemic risk during that period.

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

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

3.1 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 exist 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 institutions 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 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 with respect to 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 in the higher general risk aversion, measured by corporate credit spreads, 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. (2013) where the importance of industrial production in explaining returns for both bonds and foreign exchange is assessed. 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).

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 analysis, 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 Chapter also offers a methodological contribution. In order to jointly model high- 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. [See also recent developments in regression models as Andreou et al. (2010) and VAR models as in Ghysels (2012), in modelling and testing for Granger causality as in Ghysels et al. (2013), and predictive ability of financial variables as in Andreou et al. (2013) and Galvao (2013)]. This Chapter 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 Chapter is organized as follows. In Section 3.2, we discuss the dataset and the macroeconomic variables. Section 3.3 presents the high frequency MIDAS regression models and discusses some data preparation procedures. In Section 3.4, we report the results for both univariate and multivariate GARCH-MIDAS models. Section 3.5 concludes.

3.2 Data Description

3.2.1 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 dataset 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) that we implement 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 log-prices, where $t = 1, ..., T$ denotes day and $i = 1, ..., N$ the time interval of day t, then an observation is removed iff:

$$\left|p_{t,i} - \overline{p}_{t,i}\left(k^L\right)\right| > \max\left\{4MD_{t,i}(k), n\gamma\right\} \quad \wedge \quad \left|p_{t,i} - \overline{p}_{t,i}\left(k^R\right)\right| > \max\left\{4MD_{t,i}(k), n\gamma\right\} \tag{3.1}$$

where k the bandwidth; $\overline{p}_{t,i}\left(k^L\right)$ and $\overline{p}_{t,i}\left(k^R\right)$ sample medians of the $k/2$ observations respectively before (L for left) and after (R for right) (t, i); $MD_{t,i}(k)$ mean absolute deviation from the median of the whole neighborhood of length k; $\wedge$ intersection operator; γ mean of the k absolute returns; 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 intervals. The data selection procedure is summarized in Table 3.2.1.

Table 3.2.1: **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)	1.00 (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)	1.00 (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)

Table 3.2.1 reports the data procedure selection 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 (3.1) in the text. Tick-by-tick data are resampled using calendar time (see details in the body of the chapter). The 1st observation of each day is removed as it presents excess volatility. In square brackets is the unit of measurement. Pct stands for percentile.

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 (3.1) 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 3.2.1,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 3.1:

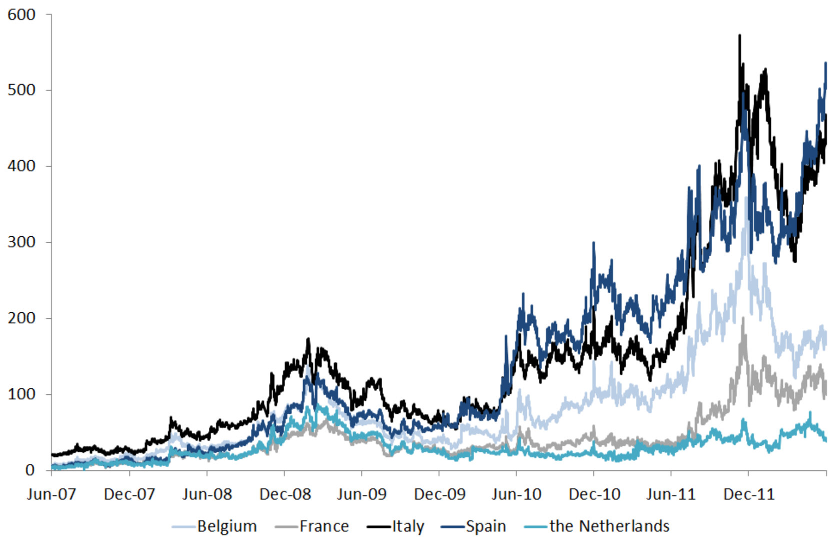


Figure 3.1: **10-year Government Bond Spreads (bps)**

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.

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.

3.2.2 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 3.2-3.4, are expressed in terms of difference between each country and

Germany macrovariables.

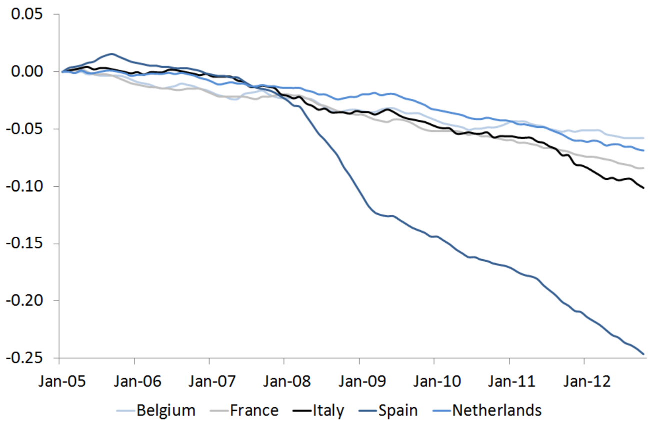


Figure 3.2: **Employment - Level**

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.

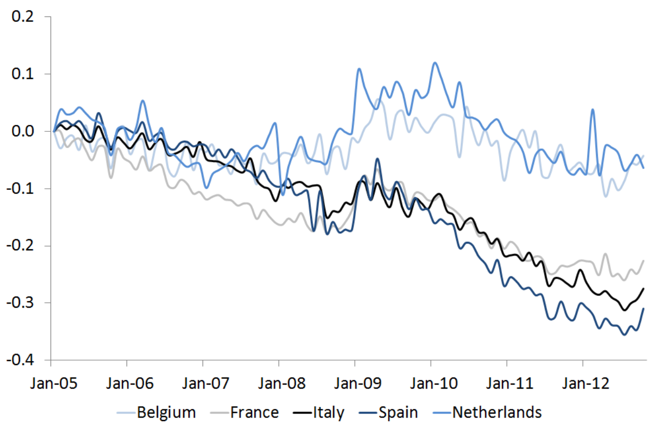


Figure 3.3: **Industrial Production - Level**

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.

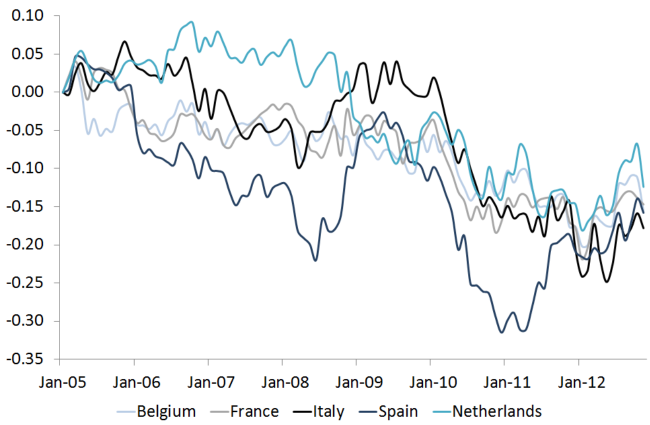


Figure 3.4: **Economic Sentiment - Level**

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.

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 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^j_τ corresponding to the aggregation period of interest U (e.g. months, quarters, years):

$$Y_\tau = \sum_{j=1}^{U} \alpha_j D^j_\tau + \sum_{i=1}^{U} \beta_i Y_{\tau-i} + \varepsilon_\tau \tag{3.2}$$

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

3.3 Modelling Mixed Frequency Times Series

The idea of combining two kind of models and two sampling frequencies with the aim of incorporating in a same model macroeconomic effects and time series dynamics has already had some developments in literature. The underlying idea of these kind of models is that the same news may have a different effect on high frequency returns depending on the state of the economy which is measured at a lower frequency.

One of the most promising approach to deal with two sampling frequencies is the so-called MIxed Data Sampling (MIDAS) introduced by Ghysels, Santa-Clara and Valkanov (2004, 2005, 2006) and Ghysels, Sinko, and Valkanov (2007). MIDAS represents a simple, parsimonious and flexible class of time series models that allow the left-hand and right-hand variables of time series regressions to be sampled at different frequencies. The MIDAS framework allows to use the raw data avoiding any apriori prefiltering. The literature on MIDAS deals with the high-frequency component measured at daily frequency while the data at low frequency are usually sampled monthly or quarterly.

To introduce MIDAS, let Y_t be sampled at some fixed sampling frequency and call this the interval of reference and $X^{(m)}$ be sampled m times faster. The MIDAS regression can be written as $Y_t = \beta_0 + \beta_1 \sum_{j=0}^{J} B(j) X^{(m)}_{t-j/m} + \varepsilon_t$ where the dependent variable Y_t is projected onto a history of previous J lagged observations of $X^{(m)}_{t/m}$. In order to keep the number of parameters low, each lagged variable $X^{(m)}$ is not loaded by a specific coefficient rather by a weighting function $B(j;\theta)$ of a few parameters summarized in vector θ while the overall impact of lagged $X^{(m)}_t$ on Y_t is captured by β_1. There exist alternative weight function which can be adopted among which the exponential Almon lag as specified in (3.3):

$$B(j;\theta) = \frac{e^{\theta_1 j + \ldots + \theta_Q j^Q}}{\sum_{j=1}^{J} e^{\theta_1 j + \ldots + \theta_Q j^Q}} \tag{3.3}$$

Note that the rate of weights decline determines how many lags are included in the MIDAS regression so that the lag data selection is purely data driven. Ghysels et al. (2005) use the function form in (3.3) with two parameters θ_1 and θ_2; in that case a declining weight is guaranteed as long as $\theta_2 \leq 0$.

Alternatively, weights parametrization can be based on Beta function in (3.4):

$$B(j;\theta_1,\theta_2)=\frac{f(\frac{j}{J};\theta_1,\theta_2)}{\sum_{j=1}^{J} f(\frac{j}{J};\theta_1,\theta_2)} \tag{3.4}$$

where $f(\frac{j}{J};\theta_1,\theta_2)$ is the Beta function which allows a greater flexibility with respect to the exponential Almon. In particular, setting $\theta_1=1$ and $\theta_2>1$ implies weights to be slowly declining while as θ_2 increases, weights decrease faster. Finally, when $\theta_1>1$ weights are allowed to assume a hump-shaped pattern. Both Almon polynomial and Beta lag specification provide some very useful features. First of all, as they give positive weights, the estimated volatility is guaranteed to be positive; moreover weights sum up to unity and the lag data selection is purely data driven.

Ghysels et al. (2004) show that the common practice of aggregating all the data to the common least frequently sampled process will always be less efficient than a MIDAS regression that exploits the availability of the higher sampled time series $X^{(m)}$. Alternative MIDAS specifications exist which can take into account nonlinearities, unequally spaced observations and multiple equations. Some applications of MIDAS framework to GARCH models have been recently proposed in the literature too by Engle and Rangel (2008) and Engle et al. (2013).

The literature available up to now on MIDAS deals with data measured at daily frequency together with data sampled at lower frequencies such as months and quarters. In this Chapter, we 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. In particular, we extend the MIDAS approach 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 robust to both asynchronicity and microstructure noise although sufficiently thick to provide a flavour of intraday movements. 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).

3.3.1 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 $(M \times 1)$ 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:

$$r_{\tau,i} = \mu + \sqrt{\psi_\tau g_{\tau,i}}\varepsilon_{\tau,i} \tag{3.5}$$

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:

$$g_{\tau,i} = (1-\alpha-\beta) + \alpha\frac{\varepsilon^2_{\tau,i-1}}{\psi_\tau} + \beta g_{\tau,i-1} \tag{3.6}$$

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 computed on a fixed span window as described in (3.7) below:

$$\log\psi_\tau = m + \vartheta\sum_{u=1}^{U}\varphi_u(\omega)\,RV_{\tau-u} \tag{3.7}$$

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

$$\varphi_u(\omega) = \begin{cases} \frac{(u/U)^{\omega_1-1}(1-u/U)^{\omega_2-1}}{\sum_{j=1}^{U}(j/U)^{\omega_1-1}(1-j/U)^{\omega_2-1}} & \textit{Beta} \\ \omega^u/\left(\sum_{j=1}^{U}\omega^j\right) & \textit{Exponential} \end{cases} \tag{3.8}$$

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. In our empirical applications, we adopt the specification as described in (3.9) below:

$$\log\psi_\tau = m + \sum_{s=1}^{S}\vartheta^{s,l}\sum_{u=1}^{U}\varphi_u^{s,l}(\omega)\,X_{\tau-u}^{s,l} + \sum_{s=1}^{S}\vartheta^{s,v}\sum_{u=1}^{U}\varphi_u^{s,v}(\omega)\,X_{\tau-u}^{s,v} \tag{3.9}$$

where $X_{\tau-u}^{s,l}$ is defined as $abs\left(\frac{Y_{\tau-u}^{s,l}}{Y_{\tau0}^{s,l}} - \frac{Y_{\tau-u}^{s,l,DE}}{Y_{\tau0}^{s,l,DE}}\right)$, $Y_\tau^{s,l}$ indicates the level (l) of the macroeconomic variable s at month τ so that $Y_{\tau0}^{s,l}$ is the first available value, $Y_\tau^{s,l,DE}$ refers to the same macrovariable s for Germany (DE) 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 trend between the two time series. $X^{s,v}_{\tau-u}$ is specified as $abs\left(Y^{s,v}_{\tau-u} - Y^{s,v,DE}_{\tau-u}\right)$ where $Y^{s,v}_{\tau}$ volatility (v) of macrovariable s defined as in (3.2). $Y^{s,v,DE}_{\tau}$ refers to the volatility of the same macrovariable s for Germany. $\varphi_u(\omega)$ are beta weights as in (3.8) 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 (3.7), 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:

$$\frac{Var\left(\log\left(\psi_\tau\right)\right)}{Var\left(\log\left(g_{\tau,i}\psi_\tau\right)\right)} \tag{3.10}$$

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 $\rho^{kj}_{\tau,i}$ of the conditional correlation matrix $R_{\tau,i}$ for month τ and subinterval i, with $k, j = 1, ..., M$, are computed as:

$$\rho^{kj}_{\tau,i} = \frac{q^{kj}_{\tau,i}}{\sqrt{q^{kk}_{\tau,i}}\sqrt{q^{jj}_{\tau,i}}} \tag{3.11}$$

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

$$q^{kj}_{\tau,i} = \overline{\rho}^{kj}_{\tau}(1-a-b) + a\xi^{k}_{\tau,i-1}\xi^{j}_{\tau,i-1} + bq^{kj}_{\tau,i-1} \tag{3.12}$$

where the intercept is time dependent and it is specified as a smooth weighted average of the most recent U^{kj} correlation matrices of standardized residuals $\xi_{\tau,i} = D^{-1}_{\tau,i}\left(r_{\tau,i} - \mu\right)$ as in (3.13):

$$\overline{\rho}^{kj}_{\tau} = \sum_{u=1}^{U^{kj}} \varphi_u\left(\omega^{kj}\right) c^{kj}_{\tau,i-u} \tag{3.13}$$

$$c^{kj}_{\tau,i-u} = \frac{\sum\limits_{l=\tau,i-U^{kj}}^{\tau,i} \xi^{k}_{l}\xi^{j}_{l}}{\sqrt{\sum\limits_{l=\tau,i-U^{kj}}^{\tau,i}\left(\xi^{k}_{l}\right)^2}\sqrt{\sum\limits_{l=\tau,i-U^{kj}}^{\tau,i}\left(\xi^{j}_{l}\right)^2}} \tag{3.14}$$

where $\varphi_u\left(\omega^{kj}\right)$ is the beta weighting function in (3.8).

The model proposed in Colacito et al. (2011) is a pure time series approach as the long run correlation is allowed to be time dependent. In our analysis, we propose to link the long run correlation $\overline{\rho}_\tau^{kj}$ 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:

$$\begin{aligned}\gamma_\tau^{kj} &= m^{kj} + \sum_{s=1}^{S} \vartheta^{s,l} \sum_{u=1}^{U} \varphi_u^{s,l}(\omega) \left| \Delta Y_{\tau-u}^{k;s,l} - \Delta Y_{\tau-u}^{j;s,l} \right| + \\ & \sum_{s=1}^{S} \vartheta^{s,v} \sum_{u=1}^{U} \varphi_u^{s,v}(\omega) \left| \Delta Y_{\tau-u}^{k;s,v} - \Delta Y_{\tau-u}^{j;s,v} \right| \end{aligned} \tag{3.15}$$

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 $\Delta Y_\tau^{k;s,l} = 100 \times \left[\ln\left(Y_\tau^{k;s,l}\right) - \ln\left(Y_{\tau-1}^{k;s,l}\right)\right]$ 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:

$$\overline{\rho}_\tau^{kj} = \frac{\exp\left(2\gamma_\tau^{kj}\right) - 1}{\exp\left(2\gamma_\tau^{kj}\right) + 1} \tag{3.16}$$

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:

$$\widetilde{R}_{\tau,i} = (1-\lambda) R_{\tau,i} + \lambda I \tag{3.17}$$

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.

The approach described here to model the correlation matrix allows to get consistent estimates of the long run volatility obtained at the first step. Note that Chirac and Voev (2011) propose to estimate the variance covariance matrix by decomposing correlation matrix time series into Cholesky factors, guaranteeing the matrix to be positive semidefinite, and modelling them with a suitable time series model. Afterwards, the matrix is reconstruct. In our case, this approach is not suitable as it implies the estimation of the entire covariance matrix and this would imply a re-estimation of variances which have already been modeled in the first step. Instead, in our framework, we estimate variances in the first step and, in the second step, we just model the correlation matrix.

3.3.2 Data Preparation

For both model specifications, first 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):

$$FJ_{t,i} = \frac{|r_{t,i}|}{\widehat{\sigma}_t \widehat{s}_{t,i}} \tag{3.18}$$

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:

$$\left(S_T \beta^* + C_T\right)\left(\widehat{\sigma}_t \widehat{s}_{t,i}\right) sgn(r_{t,i}) \tag{3.19}$$

where $S_T = 1/\left(2\log\left(T \times N\right)\right)^{1/2}$; $(T \times N)$ time series length; $\beta^* = -\ln(-\ln\left(1-\alpha\right))$; α the significance level of the test; $C_T = \left(2\log\left(T \times N\right)\right)^{1/2} - \log\pi + \left(\log\left(\log\left(T \times N\right)\right)\right)/\left(2\left(2\log\left(T \times N\right)\right)^{1/2}\right)$; sgn the sign function.

As far as the periodicity component $\widehat{s}_{t,i}$, following Chapter 2 we adopt a parametric formulation which is estimated by the Truncated Maximum Likelihood (TML) approach by Boudt et al. (2010) described respectively in (3.20) and (3.21):

$$\widehat{s}_{t,i} = \frac{\exp f\left(\hat{\theta}_{TML}; x_{t,i}\right)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\exp f\left(\hat{\theta}_{TML}; x_{t,i}\right)\right)^2}} \quad \forall t = 1, ..., T \tag{3.20}$$

$$f\left(\hat{\theta}_{TML}; x_{t,i}\right) = \delta_0 + \delta_{0,1}\frac{i}{N_1} + \delta_{0,2}\frac{i^2}{N_2} + \sum_{j=1}^{J}\lambda_j S_{t,i}^{j} + \sum_{b=1}^{B}\phi_b R_{t,i}^{b} + \sum_{j=1}^{4}\vartheta_j Weekdays_j + \sum_{p=1}^{P}\left(\delta_{c,p}\cos\left(\frac{2\pi p}{N}i\right) + \delta_{s,p}\sin\left(\frac{2\pi p}{N}i\right)\right) + \varepsilon_{t,i} \tag{3.21}$$

where N the number of intraday intervals i belonging to day t; $N_1 = (N+1)/2$; $N_2 = (N+1)(N+2)/6$ normalizing constants; $S_{t,i}^{j}$ the surprise for macroannouncements and government bond auctions (for the last ones, surprise is computed as the difference in bid-to-cover between current and previous 10-year auction); J the sum of macroannouncements and auctions considered; $R_{t,i}^{b}$ dummy variable for rating actions undertaken by rating agency b; B number of rating agencies; λ_j and ϕ_b event specific loading coefficients; P tuning parameter determining the order of the expansion of the sinusoids; $\hat{\theta}_{TML}$ full parameter vector to be estimated. For a description of macroannouncements, government bond auctions and rating actions we refer to Chapter 2, Tables 2.2-2.4.

Moreover, the loading coefficients λ_j and ϕ_b are modeled applying the Andersen and Bollerslev (1998) decay-structure which allows the specific event to impact over a time window but with decaying weights. Macroannouncement surprises are allowed to impact starting from 30 minutes before the release up to one hour and 30 minutes after, as in Andersen and Bollerslev (1998). As far as government bond auctions are concerned, we use a wider window, ranging from two hours before the auction ends up to one hour after it as we want to take into account the uncertainty in the markets during the auction period. Finally, as the timing of rating actions is not foreseeable, we set the start of the window in correspondence of the rating action up to two hours after it. The estimates of the intraday periodicity is reported in Appendix 3.A. while a skinny description of detected jumps is shown in Table 3.3.1.

Table 3.3.1: **Jumps description**

	IT	**FR**	**ES**	**BE**	**NL**
No	404	261	483	462	213
%	1.14	0.74	1.37	1.31	0.60
Mean abs size [%]	6.28	4.63	5.80	4.46	3.70

Table 3.3.1 reports the number of jumps and their absolute mean size detected by the Lee and Mykland (2008) test corrected for the intraday periodicity as described in (3.18)-(3.21).

We identify a variable percentage of jumps: 1.31% for Belgium, 0.74% for France, 1.14% for Italy, 1.37% for Spain 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.

Once jumps have been censored, returns are standardized by the intraday periodicty $\widehat{s}_{t,i}$ in (3.20)-(3.21) in order to control for the U-shape. Finally, on the standardized and jump-free returns, we fit an ARMA(1,1) model whose estimates are reported in Table 3.3.2.

Table 3.3.2: **Parameter estimates for ARMA**

	IT	FR	ES	BE	NL
μ	**0.0000 *****	**0.0000 *****	**0.0002 *****	0.0000	**0.0000 *****
θ	**0.7784 *****	**0.0757 *****	**-0.4425 *****	**-0.1098 *****	**0.2157 *****
ϕ	**-0.7509 *****	**-0.2774 *****	**0.4078 *****	**-0.0015 ****	**-0.5906 *****

Table 3.3.2 reports the ARMA parameters estimated on jump-free returns standardized by the intraday periodicty as described in the text. ***,** and * denote statistically significance at 1%, 5% and 10% signficance level respectively.

3.4 Empirical Results

3.4.1 Univariate Models

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 (3.7). In Table 3.4.1, 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 (3.8) 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.

Table 3.4.1: **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

Table 3.4.1 reports estimates for the TS GARCH-MIDAS model where the long run component is a smooth weighted average of previous six monthly realized volatilities. Realized volatilities are estimated on a fix monthly 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. ***, **, * denote 1%, 5% and 10% significance level, respectively.

Almost all coefficients in Table 3.4.1 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 3.4.1 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 3.5, we report the estimated volatility, at high-frequency (blue line) and at low-frequency (black line) components obtained from the estimates reported in Table 3.4.1.

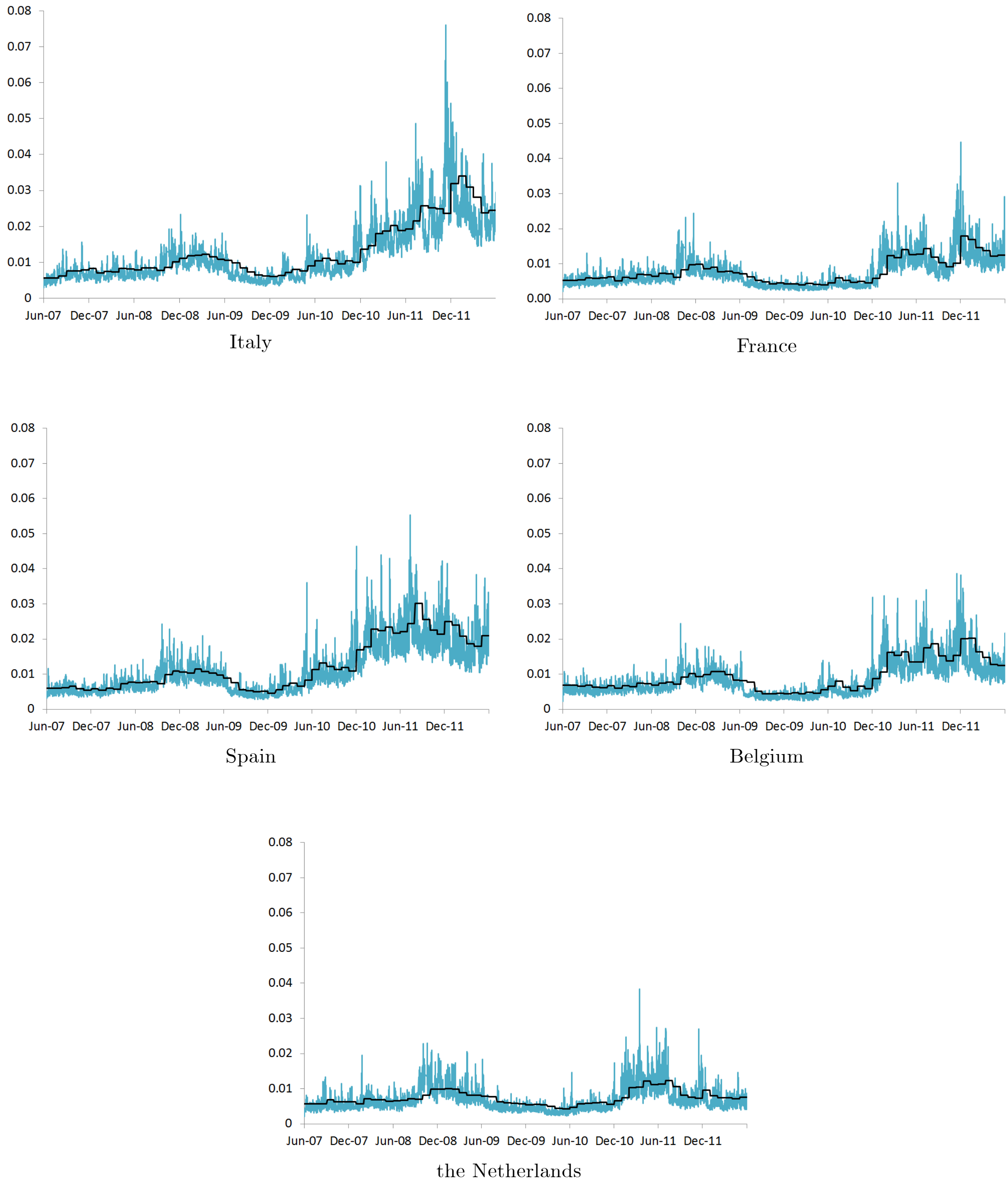


Figure 3.5: **TS GARCH-MIDAS Models**

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 TS GARCH-MIDAS model where the long run component is a smooth weighted average of previous six monthly realized volatilities. Estimates are reported in Table 3.4.1. The blue line is the high-frequency (15-minute) component while the black line is the low-frequency (monthly) component.

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.

3.4.1.1 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 (3.9). 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 3.4.1, we fix the MIDAS lag equal to 6 months and in the beta lag function in (3.8) 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 3.4.2.

Table 3.4.2: **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

Table 3.4.2 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 (3.9). 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.

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 spread and a decrease in Dutch spread. This finding is supported also by Ludvigson and Ng (2009) and Lustig et al. (2013). 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, we can say 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 3.4.2 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 3.6, we depict the low and the high-frequency components of volatility obtained from the estimates reported in Table 3.4.2.

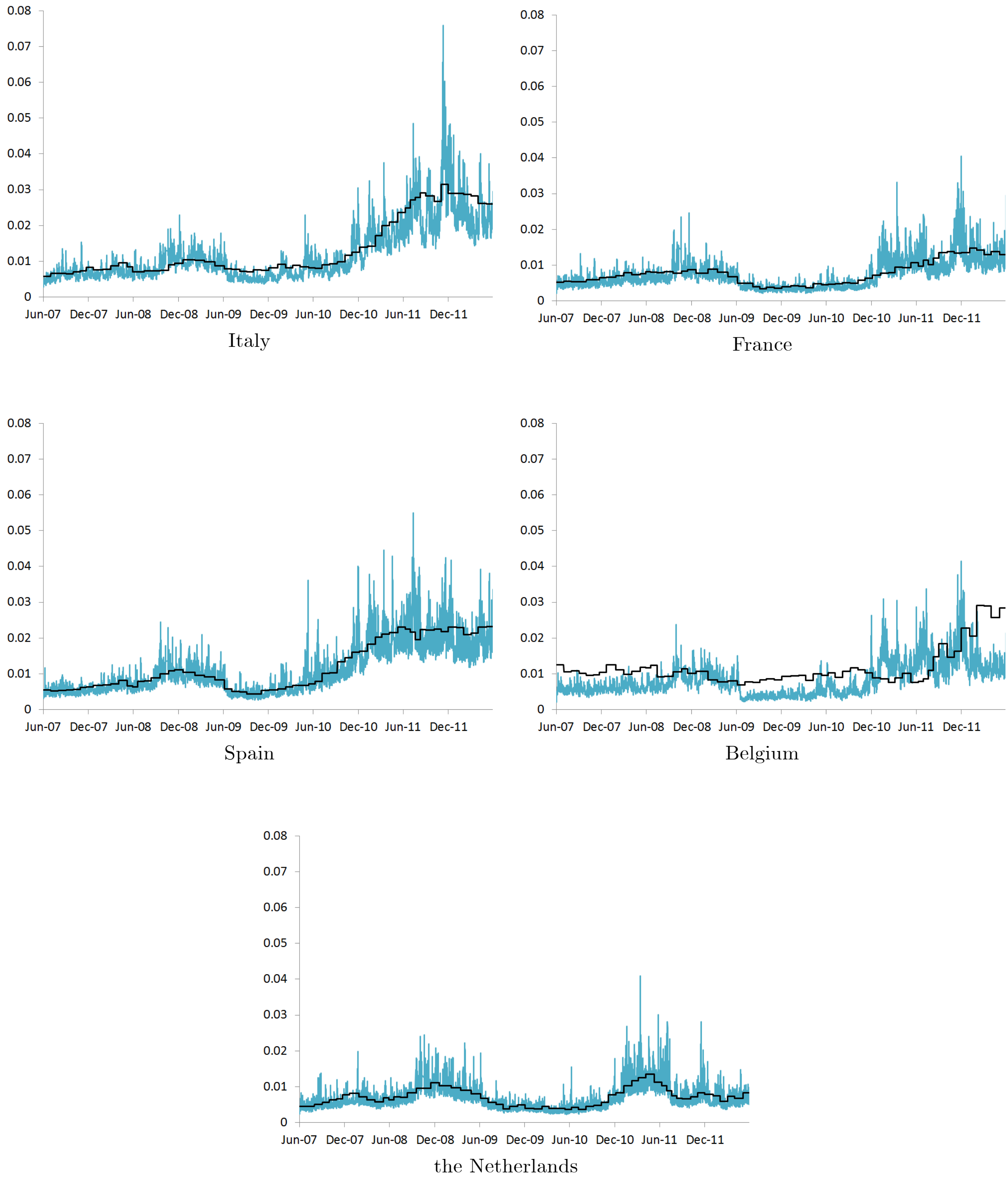


Figure 3.6: **MV GARCH-MIDAS Models**

Figure 3.6 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 MV 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 (3.9). Both levels and volatilities of macroeconomic fundamentals concur in determining the long run component of volatilities. Estimates are reported in Table 3.4.2. The blue line is the high-frequency (15-minute) component while the black line is the low-frequency (monthly) component.

3.4.1.2 Comparison Between the TS GARCH-MIDAS and MV GARCH-MIDAS Specifications.

We now compare the two alternative GARCH-MIDAS specifications with a standard GARCH whose estimates are reported in Table **??**:

In Table 3.4.3, we report the results of the comparison between TS GARCH-MIDAS and MV GARCH-MIDAS specifications as well as with standard GARCH models.

Table 3.4.3: **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**

Table 3.4.3 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 3.4.1. 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 3.4.2. 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=35,286. Variance ratio, defined in (3.10), indicates the overall amount of volatility explained by the long run component. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

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 3.5-3.6 that report a strong break in the volatility pattern from 2010 onwards.

When comparing the two GARCH-MIDAS model, Akaike information criteria selects the MV GARCH-MIDAS specification for all the countries but Belgium while, when considering Schwarz information criteria, the best model is always the TS GARCH-MIDAS exception made for the Netherlands. This result is justified by the preference for lower parametrized models accorded by Schwarz criteria and by the fact that in Table 3.4.2 some parameters which are not statistically significant are left in the equations. This fact determines a blow up of the number of parameters used for inference, raising up the Schwarz criteria and penalizing the MV GARCH-MIDAS.

Focusing now on the variance ratio, providing an indication of 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 (0.67 vs. 0.37). Instead the TS GARCH-MIDAS is selected for France (0.65 vs. 0.63) and Belgium (0.70 vs. 0.42).

The existence of a countercyclicality relationship between macroeconomic environment and market volatility was already assessed by Schwert (1989) where he showed that, as the macroeconomic fundamentals deteriorate, market volatility increases and viceversa. Engle et al. (2013) analyze this relationship more deeply carrying out a forecasting comparison among the alternative GARCH-MIDAS specifications for volatility showing that, when the long term component is driven by inflation and industrial production growth, they obtain the same out-of-sample predictability for horizons of one quarter while, at longer horizons, this model outperforms the pure time series statistical models. Instead, according to variance ratio TS GARCH-MIDAS outperforms MV GARCH-MIDAS.

The other only paper dealing with GARCH-MIDAS is Conrad et al. (2012) where authors study the long and high volatility components of oil and stock. In particular, the low frequency component is a function of some macroeconomic variables among which the term spreads, housing starts, corporate profits and unemployment rate are the most relevant. In particular they show that, in general, survey-based ex-ante measures of economic uncertainty are more informative with respect to standard economic measures. In addition, Conrad et al. (2012) compare their model with a GARCH-MIDAS where the long-run component is a smoothed average of past realized volatility showing that when macroeconomic factors are used instead, the goodness of fit improves, which is the same evidence we find. Baele et al. (2010) too show the relevance of macroeconomic variables in explaining long-term bond volatility. In their paper they consider both stock and bond volatility and they show that macroeconomic variables have actually a harder time in fitting stock market volatility than they do with bond volatility, where the short term interest rate is strongly relevant. Instead, non-macroeconomic variables, such as cash-flow growth or liquidity measures, significantly explain stock market volatility while they do not impact on bond volatility.

Paye (2012) explores the relationship between S&P volatility and macroeconomic fundamentals taking into account a number of variables such as current and expected GDP growth, the investement-capital ratio for US economy, volatility of growth in industrial production, net payout, volatility of inflation growth and the term spread. In a forecasting exercise, the Author shows that variables capturing the level of future uncertainty Granger cause volatility although the Giacomini and White test for superior predictive ability rarely indicates a better performance of the model including macroeconomic variables. Finally, Paye (2012) provides evidence that macroeconomic variables become more significant during recession periods with a prominent role of the investment per capital ratio.

Another paper dealing with this topic is Christiansen et al. (2012) where macroeconomic and financial variables impact on return volatility is assessed. In their paper Authors take into account a broad range of asset classes, including stocks, bonds, foreign exchange and commodities, and they model assets realized volatilities as autoregressive processes augmented with some macroeconomic variables as well as with market and funding liquidity measures and credit and counterparty risk. They show that the most important drivers of stock volatility are associated with the effects of leverage while money market stress and funding liquidity measures are relevant for all the asset classes considered. The TED spread, defined as the difference between the interest rates on interbank loans and on US Treasury-bills, providing a measure of both funding market liquidity and counterparty credit risk is found to have overall a strong impact. As per specific bond volatility drivers, credit spread, term spread and the S&P 500 turnover, which is commonly viewed as a proxy for difference in opinion, turn out to be statistically significant. Finally, focusing on proper macroeconomic variables, Christiansen et al. (2012) evaluate inflation and industrial production but these variables were always found to be statistically not significant.

3.4.2 Multivariate Models

Correlation matrices 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 3.4.1, 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 (3.13) and (3.14). 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 3.4.2, while as per correlation matrix, the long run component is inferred from macroeconomic fundamentals of the countries in analysis as described in (3.15).

3.4.2.1 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 matrices of standardized residuals in (3.13) 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 (3.13) and therefore we test some alternative specifications, ranging from 2 to 12 months, and compare models in terms of log-likelihood. Results are reported in Table 3.4.4.

Table 3.4.4: **DCC-MIDAS lag selection**

MIDAS Lag	LogLikelihood
2 months	630,029
3 months	630,019
4 months	630,003
5 months	629,974
6 months	629,956
9 months	629,893
12 months	629,975

Table 3.4.4 reports the log-likelihood for alternative TS DCC-MIDAS models obtained by varying the MIDAS lag U^{kj} in (3.13).

According to the log-likelihood, we should choose a MIDAS lag of 2 months which presents the highest value but, when that MIDAS lag is selected, ω_2 in the beta weight function takes value equal to 150 which could be sign of numerical instability. Therefore we decide to set the MIDAS lag equal to 3 months in which case the loglikelihood is 630,019 against 630,029 when MIDAS lag is set to 2 months. Moreover, although we could have selected alternatives U^{kj} for all the 10 covariances to be modeled, we set it equal for all of them.

In Table 3.4.5, we report the estimates of the TS DCC-MIDAS model (3.13):

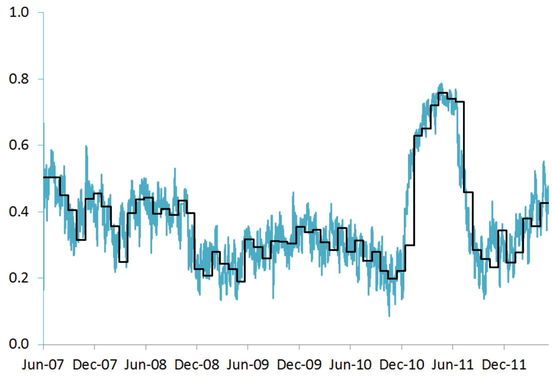
Table 3.4.5: **Parameters Estimates for the TS DCC-MIDAS Model**

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

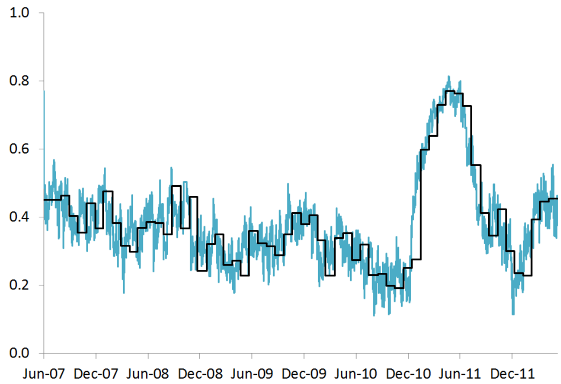
Table 3.4.5 reports estimates for the TS DCC-MIDAS model where the long run component of correlation is a smooth weighted average of previous three monthly correlation matrixes of standardized residuals. The long run component is kept fixed throughout the month while the high frequency component is evaluated on a 15-minute time window. Weights are computed according to the beta function where the first parameter ω_1 is set to 1. Univariate volatilities are obtained by the TS GARCH-MIDAS model where the long run component is a smooth weighted average of RVs reported in Table 3.4.1. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

The parameter governing the weight function is greater than 1 and, as ω_1 is set to 1, this implies that weights are decaying with time: higher weights are attributed to most recent correlation matrices of standardized residuals.

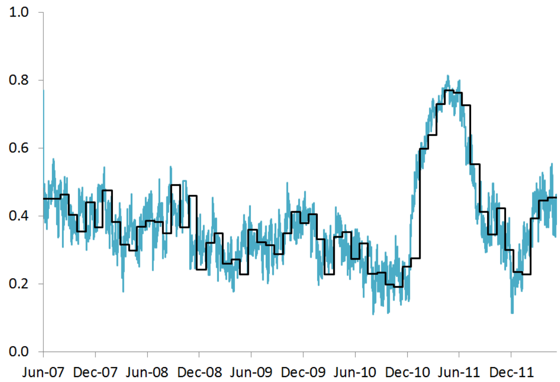
In Figures 3.7-3.8, we report the pattern of the high- and low-frequency correlations estimated using the pure time series approach.



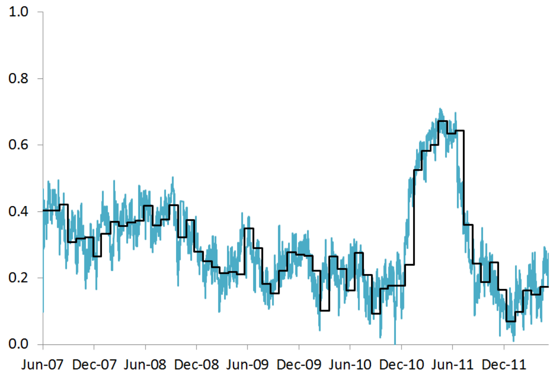
Italy vs France



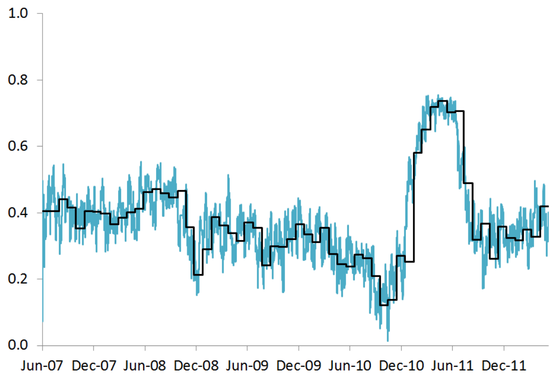
Italy vs Spain



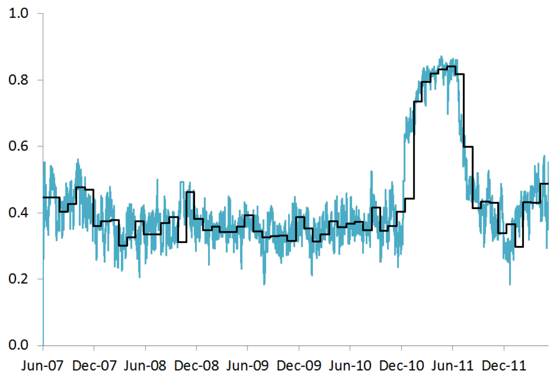
Italy vs Belgium



Italy vs the Netherlands



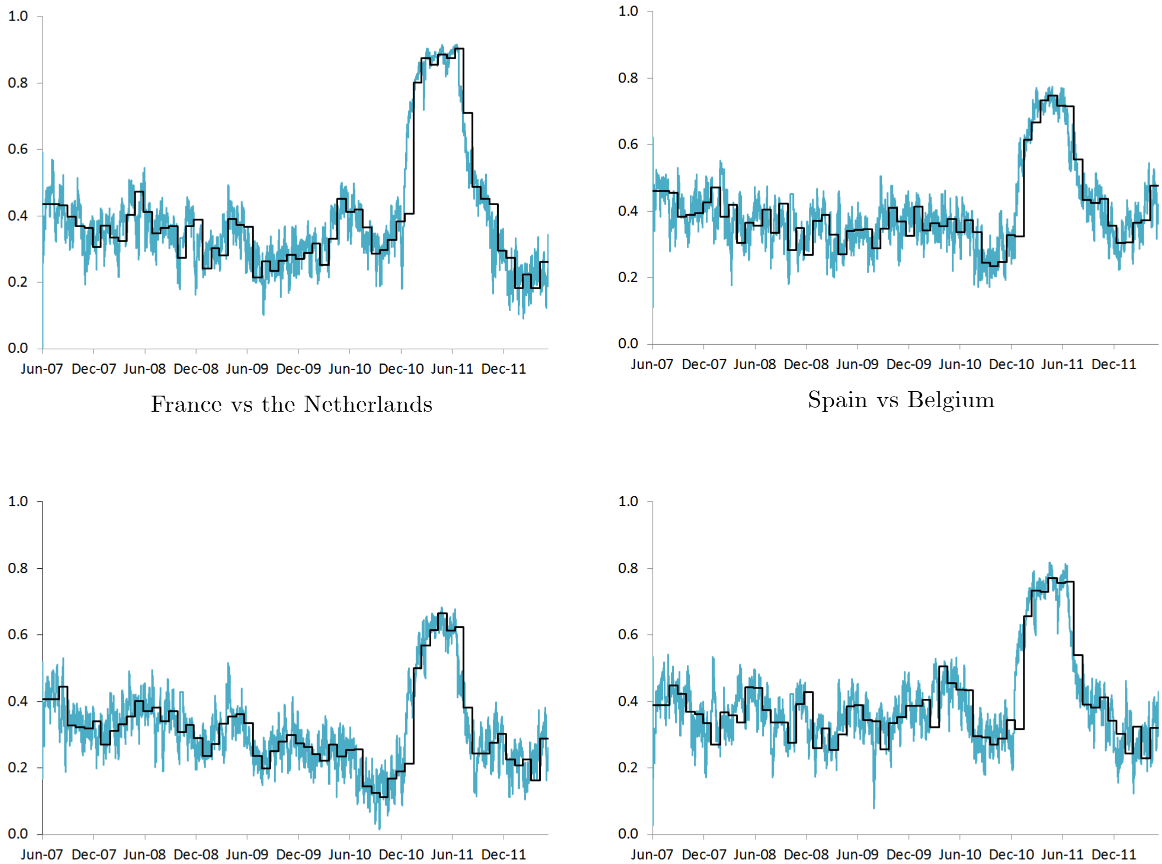
France vs Spain



France vs Belgium

Figure 3.7: **TS DCC-MIDAS Model**

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 matrices of standardized residuals. Univariate volatilities are obtained from the TS GARCH-MIDAS reported in Table 3.4.1. DCC-MIDAS estimates are reported in Table 3.4.5. 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 3.8: **TS DCC-MIDAS Model**

See notes to Figure 3.7.

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 determined a sensible increase in risk aversion, with the consequence that market movements got heavily news-driven and traders started to operate in a synchronized way across the different markets. In Chapter 4, we estimate correlations using alternative techniques robust to both microstructure noise and asynchronous trading, e.g. inter alia Aït-Sahalia et al. (2010) and Barndorff-Nielsen et al. (2011), finding the same pattern inferred here during the period December 2010 - July 2011. In Chapter 4 we will argue that the pattern of the estimated correlations over that period can be explained by a negative correlations between Germany and the other European countries, as the result of completely different/opposite trading activity in German bond with respect to bonds of other countries.

3.4.2.2 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 (3.15). In particular, we assume that the correlation between country A and country B depends just on countries A and B fundamentals. As discussed in Section 3.3, macroeconomic variables enter the model via a measure of the absolute distance between the rate of changes of macroeconomic drivers of countries A and B. We expect that, as the fundamentals of the two countries get closer, and therefore their absolute difference goes to zero, the government bond spreads of the two countries become more correlated and viceversa. As per the univariate analysis, we take into consideration employment, industrial production and economic sentiment. In order to keep comparability with results in Table 3.4.5, we fix the MIDAS lag equal to 3 months and adopt the beta lag specification, always fixing ω_1 equal to 1. We report estimates in Table 3.4.6.

Table 3.4.6: **Parameters Estimates for the MV DCC-MIDAS Model**

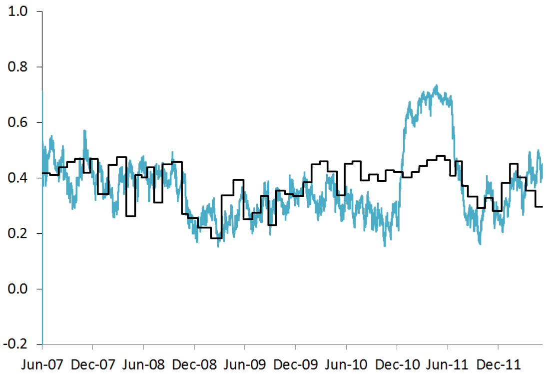
	IT vs FR	**IT vs ES**	**IT vs BE**	**IT vs NL**	**FR vs ES**	**FR vs BE**	**FR vs NL**	**ES vs BE**	**ES vs NL**	**BE vs NL**
m	0.55	**0.73 ****	0.49	0.31	**0.44 ****	0.30	**0.92 ****	0.58	0.32	0.36
$\theta_{1,l}$ (Employment)	**-0.46 *****	**-0.55 ****	-0.60	**-0.39 ****	**-0.36 ****	**0.17 ***	**-0.16 *****	**-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									

Table 3.4.6 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 as reported in Table 3.4.2. Differences were rescaled. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

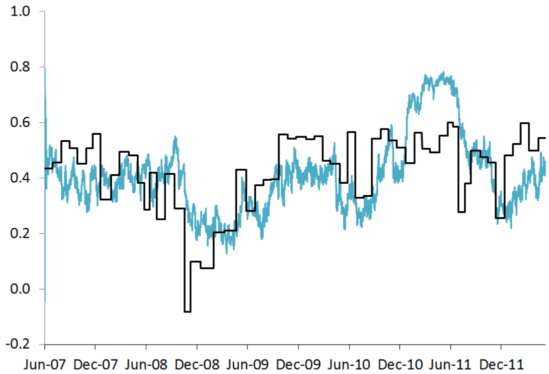
Overall, the macroeconomic variables turned out to be statistically significant drivers of correlations between each pair of countries. Starting from the level of macroeconomic variables, an increase in the absolute differences in the rate of change of employment determines a statistically significant decrease in correlations in 6 out of 10 pairs of countries while a positive relationship is detected just for Belgium and France. Focusing on 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 increase 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, their government bond spreads get even more correlated.

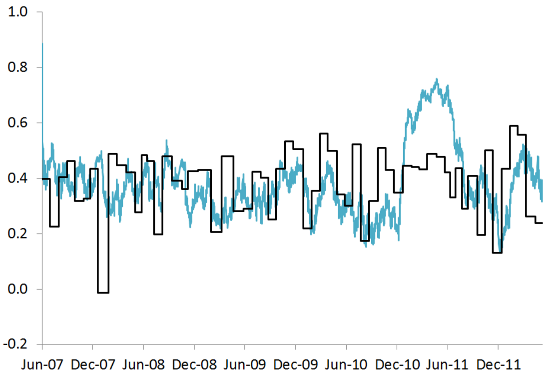
In Figures 3.9-3.10, we depict the pattern of correlations according to estimates reported in Table 3.4.6:



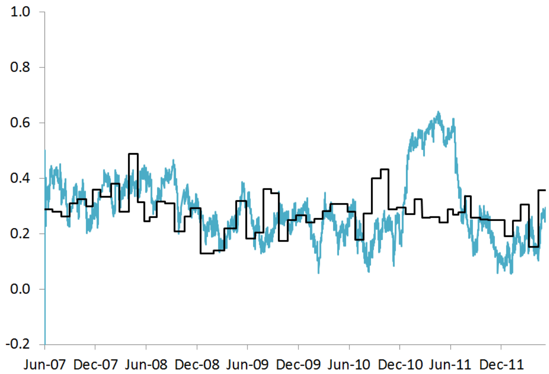
Italy vs France



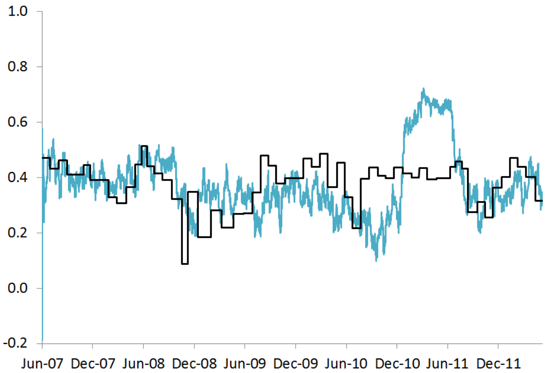
Italy vs Spain



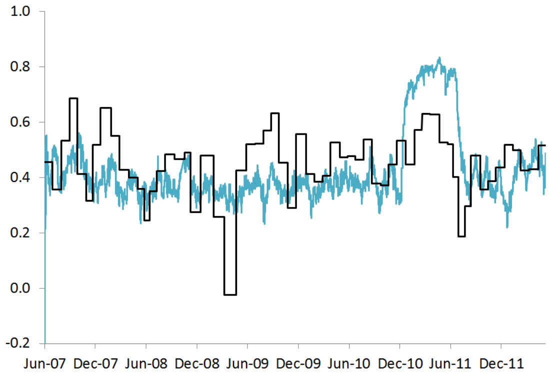
Italy vs Belgium



Italy vs the Netherlands



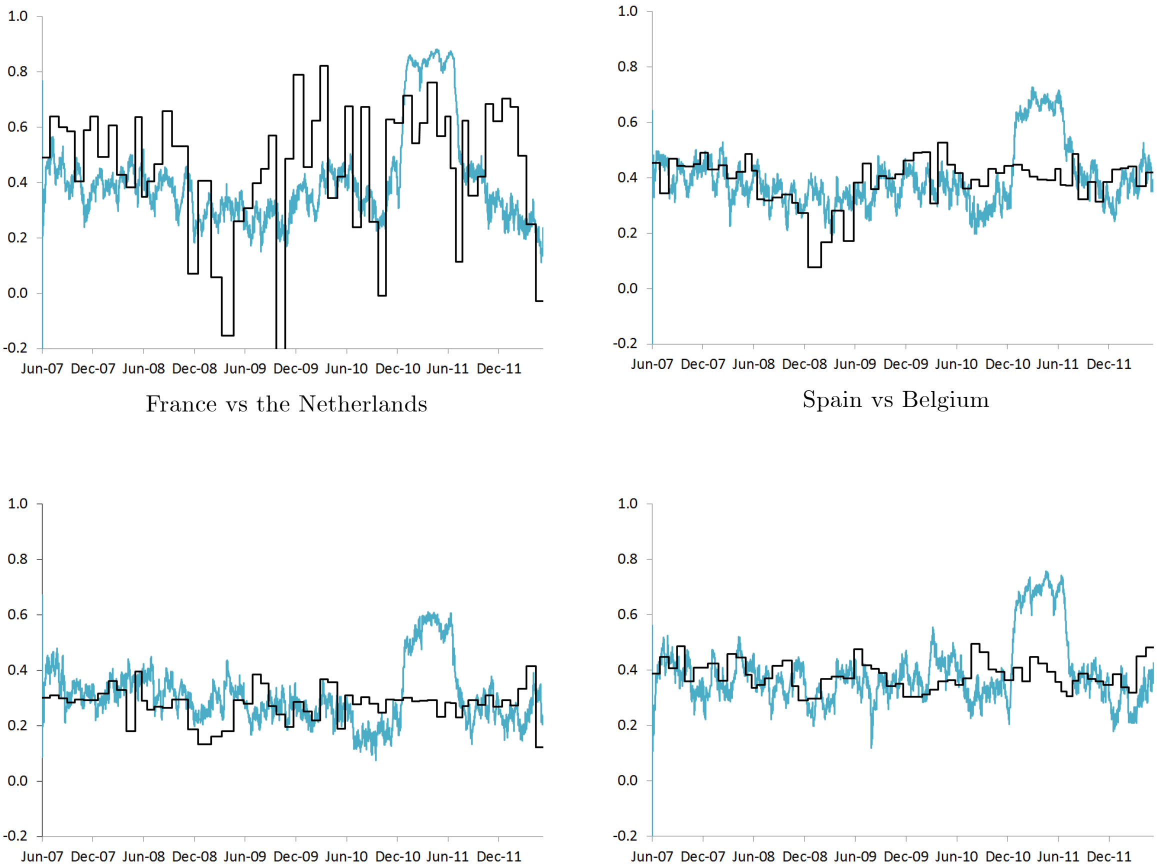
France vs Spain



France vs Belgium

Figure 3.9: **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 (3.15). Both levels and volatilities of macrovariables concur in determining the long run component of correlations. Estimates are reported in Table 3.4.6. 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 3.10: **MV DCC-MIDAS Model**

See notes to Figure 3.9.

From Figures 3.9-3.10, we evidence a failure of the model in describing 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 capture what happened at high-frequency level in the markets during that very distressed period.

In Table 3.4.8 we compare the two DCC-MIDAS reported in Table 3.4.5 and 3.4.6 together with the classical DCC model by Engle (2002) whose parameters are reported in Table 3.4.7. Note that as the two DCC-MIDAS models are not nested, we apply the likelihood ratio test just to compare the two DCC-MIDAS with the standard DCC.

Table 3.4.7: **DCC**

	a	**b**
	0.0045 ***	**0.9953 *****
LogL	629,410	

*** denotes significance at 0.01. ω_1 is set to 1.

Table 3.4.8: **DCC-MIDAS Models: A Comparison**

	LogL	**LR test vs DCC**	**AIC**	**BIC**
DCC	629,410		-35.6747	-35.6742
TS DCC-MIDAS	630,019	**1,218 *****	**-35.7091**	**-35.7084**
MV DCC-MIDAS	630,054	**1,288 *****	-35.7038	-35.6721

Table 3.4.8 reports a comparison of alternative DCC models. DCC is the classical DCC(1,1) model by Engle (2002) whose parameters are reported in Table 3.4.7. In TS DCC-MIDAS model, the low frequency component is a smooth weighted average of previous three correlation matrices of standardized residuals and reported in Table 3.4.5. In the TS DCC-MIDAS univariate volatilities are obtained by the TS GARCH-MIDAS reported in Table 3.4.1. 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 3.4.6. In this case univariate volatilities are obtained by the TS GARCH-MIDAS reported in Table 3.4.2. 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=35,286. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

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 3.7-3.8 and 3.9-3.10, which show a strong break in the pattern of correlations during the period December 2010 - July 2011. 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 -35.7091 to -35.7038 and Schwarz criterion from -35.7084 to -35.6721. This finding confirms what reported earlier in the Chapter in commenting Figures 3.9-3.10: 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 underlying the increasing systemic risk: 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 3.9-3.10 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 asset classes in terms of systemic risk. There are alternative views in literature according to the causes behind change in systemic risk. Our results are in line with Ang and Longstaff (2011) where a stronger linkage among CDS spreads of Eurozone countries with respect to the US is assessed. This result provides evidence that systemic risk is not directly caused by macroeconomic integration but it has its roots in financial markets. A similar evidence is reported in other papers such as Kodres and Pritsker (2002), Brunnermeier and Pedersen (2009) and Allen et al. (2009) where it is shown that systemic risk is created through channels such as capital flows, funding availability, risk premia and liquidity shocks rather than macroeconomic shocks. Another study supporting our results is Baele et al. (2010) where the factors explaining the dynamics of the correlation between stock and bond returns are investigated. Their main result is that macroeconomic fundamentals, such as output gap and inflation, do not explain significantly stock and bond returns correlations while other variables, such as liquidity proxies and risk aversion, have a prominent role. Karloyi and Stulz (1996) study whether there exists a relationship between US macroeconomic announcements and covariances. They come out with a negative answer providing evidence that instead, what determines higher covariances are large contemporaneous return shocks in the national markets. Therefore these findings may be used to support our results about the presence of large and simultaneous shocks in European government bond spreads behind the sharp increase in correlations.

3.4.2.3 DCC-MIDAS MVRA, macroeconomic and risk aversion approach

In order to assess whether the change in the correlation structure evidenced in previous Section reflects an increasing risk adverse environment, we augment (3.15) with some variables usually adopted to describe risk aversion such as TED, VIX and the price of gold. The TED is defined as the difference between the interest rates on interbank loans and on short-term US government debt and it is a measure of credit risk; in practice it is usually computed as the difference between the 3 months LIBOR and the 3 months yield-to-maturity of US T-bill. The VIX is a measure of the implied volatility of S&P

500 index option and therefore it gives an idea of market perceived volatility. Finally we consider even the price of gold as it usually works as the safe heaven investment; therefore an increase in its price should reflect a higher demand in consequence of raising risk aversion. In Figure 3.11 we report the time series for the period of interest for the three variables.

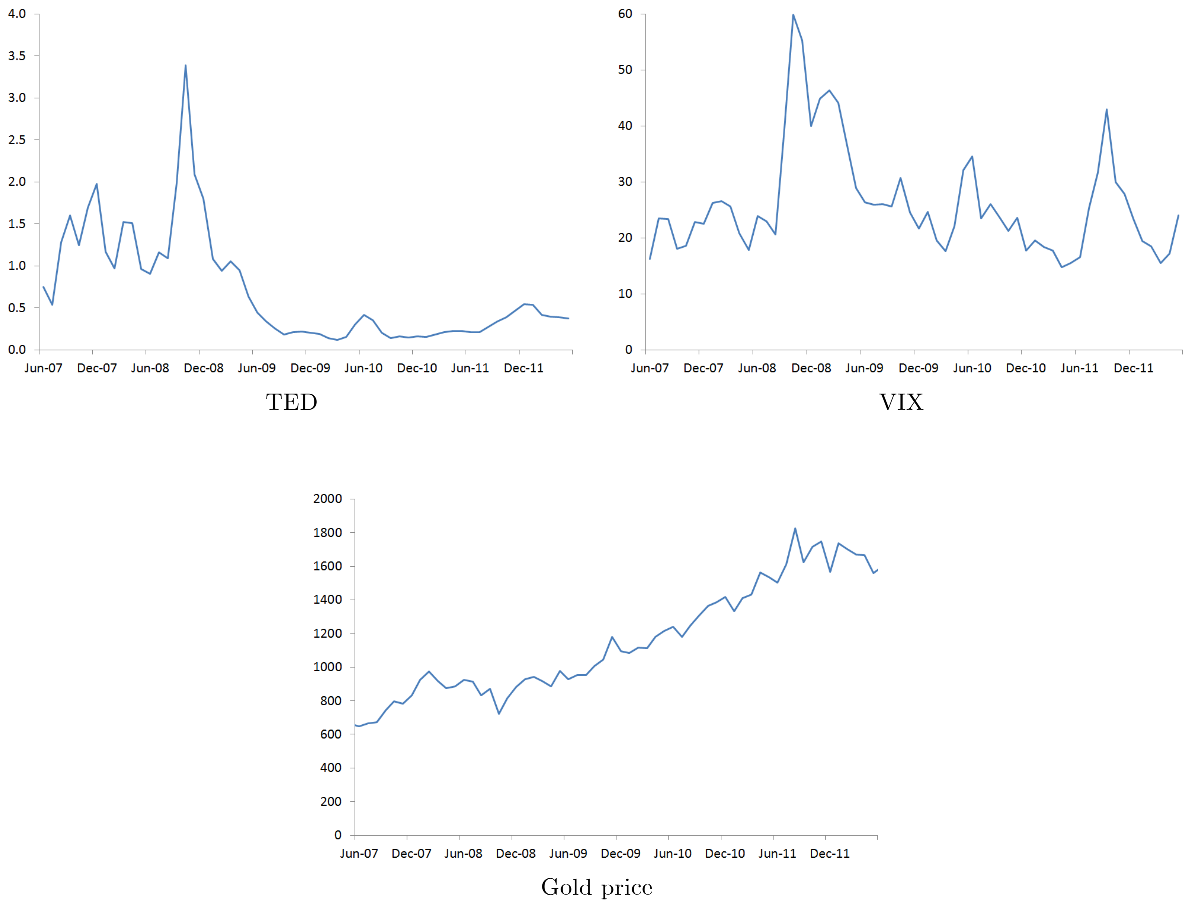


Figure 3.11: **Risk aversion variables**

Figure 3.11 reports the pattern of TED, VIX and gold price during the period June 2007 - May 2012.

From a simple graphical analysis, we can see that neither VIX nor TED show an increase during the period December 2010 - July 2011 corresponding to the break in correlations for all the pairs of European government bond spreads observed in Figures 3.7-3.8 and 3.9-3.10. Anyway we try to add all the three variables in (3.15) and estimate a model for the conditional correlations based on countries macroeconomic fundamentals and risk aversion measures. Results are reported in Table 3.4.9.

Table 3.4.9: **Parameters Estimates for the MV DCC-MIDAS Model**

	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	**0.80 ****	0.91	**0.78 ****	**0.52 *****	0.67	**0.60 *****	**1.02 *****	**0.75 *****	0.47	**0.57 ***
$\theta_{1,l}$ (Employment)	**-3.10 ***	**-0.59 *****	-1.69	-0.28	**-0.09 ****	**12.37 ***	-11.2	**-0.93 ***	-0.10	0.30
$\theta_{2,l}$ (Industrial Production)	**-1.77 *****	0.06	0.71	**1.88 *****	**0.60 *****	**2.53 ****	-2.61	**-0.86 ****	**0.78 ***	**2.30 *****
$\theta_{3,l}$ (Economic Sentiment)	1.15	1.45	**3.38 *****	-0.71	**0.90 *****	**-3.34 *****	**-13.77 *****	**-1.54 ****	**0.87 ***	**1.28 ***
$\omega_{2,1,l}$ (Employment)	**1.12 *****	**8.37 ****	**9.54 *****	**5.87 ***	1.38	**0.98 *****	8.91	4.62	13.91	2.08
$\omega_{2,2,l}$ (Industrial Production)	**8.85 *****	1.34	**1.13 *****	0.56	12.29	1.15	1.25	4.50	**1.12 ***	**0.99 *****
$\omega_{2,3,l}$ (Economic Sentiment)	1.05	1.17	**0.67 ***	5.05	7.64	6.80	7.87	0.73	0.69	4.90
$\theta_{1,v}$ (Employment)	**0.45 *****	**-4.07 *****	-13.40	-0.06	6.74	-5.43	3.04	2.46	-2.03	-1.18
$\theta_{2,v}$ (Industrial Production)	13.92	0.31	**1.59 ****	0.39	**4.00 ****	-4.29	-2.24	**1.89 ****	-1.65	-0.63
$\theta_{3,v}$ (Economic Sentiment)	**-1.04 *****	**-2.13 *****	**-2.83 ****	-1.49	**-3.31 ****	**4.09 *****	1.40	-1.66	**-1.37 ***	-1.34
$\omega_{2,1,v}$ (Unemployment)	0.58	**2.07 ****	5.06	**0.14 *****	1.13	3.73	6.72	1.14	6.94	1.58
$\omega_{2,2,v}$ (Industrial Production)	1.35	**0.05 *****	11.17	11.47	5.46	1.15	**0.11 *****	1.35	0.9	**0.57 ***
$\omega_{2,3,v}$ (Economic Sentiment)	1.06	11.56	1.27	3.66	7.46	2.69	0.47	0.52	3.66	0.28
$\theta_{4,l}$ (TED)	-0.09	-0.17	-0.06	0.02	-0.03	-0.19	**-0.31 *****	-0.05	0.04	**-0.09 ***
$\theta_{5,l}$ (VIX)	-0.13	**-0.11 *****	**-0.12 ***	**-0.10 ***	**-0.11 ***	**-0.05 *****	**0.05 ***	-0.07	**-0.08 *****	**-0.06 ****
$\theta_{6,l}$ (Gold)	1.06	**-0.54 *****	-0.97	-0.06	0.18	**-1.28 *****	**1.39 ****	-0.99	-0.13	**-1.18 ***
$\omega_{2,4,l}$ (TED)	**0.98 ****	**8.02 ****	5.31	1.40	**7.04 *****	**2.68 ***	1.41	5.64	3.57	**1.14 *****
$\omega_{2,5,l}$ (VIX)	**7.81 ****	1.11	**4.54 *****	1.25	**7.28 ****	**1.01 *****	**5.79 *****	6.29	**7.55 *****	**1.46 ***
$\omega_{2,6,l}$ (Gold)	**0.96 *****	**3.13 *****	**1.24 ****	2.60	1.36	**1.10 ****	9.31	1.10	**0.25 *****	**8.90 ****
DCC										
a	0.0037									
b	**0.9953 *****									
LogL	630,107									

Table 3.4.9 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 as reported in Table 3.4.2. Differences were rescaled. ***, **, and * denote 1%, 5% and 10% significance level, respectively.

Results in Table 3.4.9 show that there exists a negative relationship between the risk aversion measures and correlations for some of the countries analyzed contradicting our initial hypothesis about the existence of a positive relationship. The log-likelihood of the model improves, moving from 630,054 to 630,107 and the Likelihood ratio test is 106.18 with a p-value of 0.0002 which allows not to reject the hypothesis of a better fitting of the model including the risk measures. Anyway, the increase in correlation during the period December 2010 - July 2011 still remains unexplained (we do not report Figures here).

3.4.3 A Useful Eigensystem Decomposition of the Correlation Matrix

According to the analysis carried out up to now, we have obtained two correlation patterns: the first, measured at 15-minute frequency, capturing financial markets behaviour; the second one, inferenced from countries macroeconomic fundamentals, is assessed at monthly frequency. In this final section, we evaluate the presence of time-varying (ongoing) integration between European countries. This is an interesting exercise for the implications in terms of the presence of contagion and /or systemic risk during the sovereign crisis.

Applying the classical definition of contagion by Forbes and Rigobon (2002), that is a significant increase in crossmarket linkages after a shock to one country or to a group of countries, we can therefore conclude with strong evidence of contagion according to high frequency data while this evidence does not seem so clear using macroeconomic data. Anyway, in this context we feel that contagion analysis is not appropriate. In fact, although Greece could be identified as the source country from which contagion propagated to the rest of Europe, we do not think that the bursting of European sovereign crisis could be attributed entirely to Greece as for example occurred during the subprime crisis where the crisis originated completely in the US. In fact, Greece is a very small Economy in Europe and therefore its bailout could not be the unique reason for the increase in European government bond spreads. From our point of view, Europe in itself experienced and is experiencing an harder situation in which a number of countries among which Ireland, Italy, Portugal and Spain saw their fundamentals to deteriorate and their GDP to decline. We could even speak about contagion but in a broader sense in which each country became more sensitive to each other countries, a phenomenon that we could call European Systemic risk. Therefore we think it is more appropriate to analyze the degree of integration of European countries rather than testing for contagion from Greece.

From a theoretic point of view, two markets are said to be integrated when two identical assets traded on two alternative markets have identical prices at a time. Baele et al. (2004) test for integration among government bond markets through a simple regression:

$$\Delta R_t^j = \alpha_t^j + \beta_t^j \Delta R_t^k + \varepsilon_t^j \tag{3.22}$$

where ΔR_t^j change in the yield on an asset in country j at time t and ΔR_t^k yield change on a comparable asset in benchmark country k. In the framework of (3.22) two markets are said to be integrated when the intercept α_t^j converges to zero and β_t^j tends to 1 implying that changes in the benchmark country k are perfectly reflected in country j.

Recently, Muller et al. (2005) proposed a conceptually simple and yet powerful tool for detecting and characterizing time dependent phase-shape correlations in multivariate datasets based on the eigenvalue decomposition of the correlation matrix. This decomposition was applied by Rak et al. (2006) with the purpose of assessing the evolution of the components of the WIG20. Muller et al. (2005) showed 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 and that information on the channels involved and the type of their interactions can be obtained from the corresponding eigenvectors. This kind of analysis is part of the random matrix theory; random matrix theory is based on the comparison of the results obtained for the eigenvalues of the correlation matrix of a real system with eigenvalues of the correlation matrix of a pure random system. We just recall some results drawn from that theory.

Proposition 1 *Let $L \times N$ be a matrix with random numbers built on a Gaussian distribution with mean zero and standard deviation σ such that its limit $Q = L/N$ for $L \to \infty$ and $N \to \infty$ remains finite and greater than 1. The eigenvalues λ of such a matrix will have the following Marenko-Pastur probability density function:*

$$\rho(\lambda) = \frac{Q}{2\pi\sigma^2} \frac{\sqrt{(\lambda_+ - \lambda)(\lambda - \lambda_-)}}{\lambda} \tag{3.23}$$

where

$$\lambda_- = \sigma^2 \left(1 + \frac{1}{Q} - 2\sqrt{\frac{1}{Q}}\right) \quad \text{and} \quad \lambda_+ = \sigma^2 \left(1 + \frac{1}{Q} + 2\sqrt{\frac{1}{Q}}\right) \tag{3.24}$$

Muller et al. (2005) show that in general the lower part of the spectrum of eigenvalues and eigenvectors is not dominated by noise and/or random correlations, but also contains essential information about the correlation dynamics of the system. In particular, they present evidence supporting the concept that there exist situations for which the lower part of the spectrum contains statistically more relevant information than the largest eigenvalues and their corresponding eigenvectors. Muller et al. (2005) show how the analysis of the largest and smallest eigenvalues and their corresponding eigenvectors can be combined to extract details of changes in the correlation pattern.

Proposition 2 *Let C be a correlation matrix of variables X; the sum of the eigenvalues of C is time independent and equal to the dimension of the multivariate data set M. Hence, the change of any of the eigenvalues has to be compensated by a corresponding change of at least one of the others.*

Proposition 3 *Let X be variables which are not correlated. The values of the nondiagonal elements of their correlation matrix C tend to zero if the time window Δt tends to infinity* ($\lim_{\Delta t \to \infty} C_{jk} = 0 \ \forall j \neq k$)*. In that case the spectrum of C is completely degenerate and $\lambda_j = 1 \ \forall j$. For any finite value of Δt, however, the values of C_{jk}, with $j \neq k$, remain finite, which leads to a lifting of the degeneracy. In this case the eigenvalues are distributed around 1, reflecting the presence of random correlations within the finite window Δt.*

In order to assess which components contribute the most to the time structure of correlation matrices, Muller et al. (2005) introduce the *participation ratio* or number of principal component. Let a_{jm} be the expansion coefficient of eigenvector v_j, the number of principal components contributing to the dynamic of the system is defined as:

$$N_j^p = \frac{1}{M \sum_{m=1}^{M} |a_{jm}|^4} \tag{3.25}$$

In case all the basis states m contribute equally to the expansion of the eigenvector j, N_j^p will take values close to 1 while, when the eigenvector v_j is driven by few components, N_j^p will take values close to $1/M$.

Moreover, Muller et al. (2005) propose the *symmetry parameter* which allows to discriminate between positive and negative correlations defined as:

$$S_j = \left| \sum_{m=1}^{M} sgn\left(a_{jm}\right) |a_{jm}|^2 \right| \tag{3.26}$$

We now apply Muller et al. (2005) framework to the time varying correlation matrices, at high and low frequency level, estimated by the MV DCC-MIDAS reported in Table 3.4.6. This procedure will allow us to assess integration in financial markets, at high frequency level, and in countries fundamentals, measured at monthly frequency. Our purpose is, in both cases, to evaluate whether the European countries analyzed, Belgium, France, Italy, Spain and the Netherlands, experienced an increase in integration through the time period analyzed. Moreover, by computing the participation ratio in (3.25), we will be able even to understand whether a specific country played a more active role in the changing integration pattern or whether all the countries contributed almost in the same manner to that process.

Figure 3.12 reports the contribution of each eigenvector to the evolving structure of high-frequency correlation matrix.

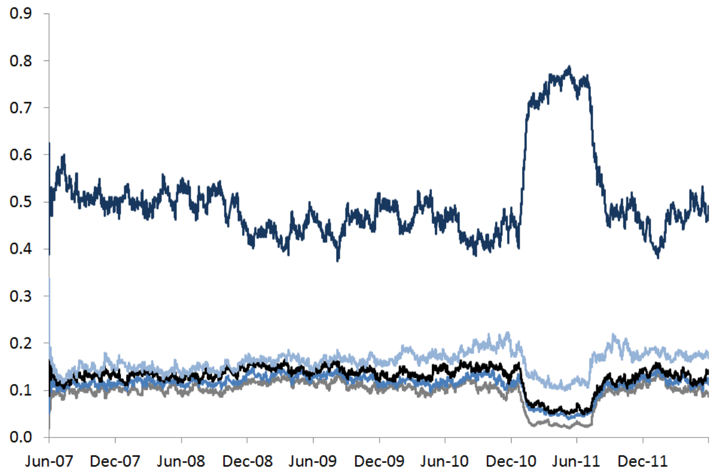


Figure 3.12: **Eigenvectors contribution to the time pattern of high frequency correlation matrix**

Figure 3.12 reports the contribution of the eigenvectors extracted from the high frequency correlation matrix and its time dynamics.

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 3.9-3.10, 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 3.13, we report the participation ratio as defined in (3.25).

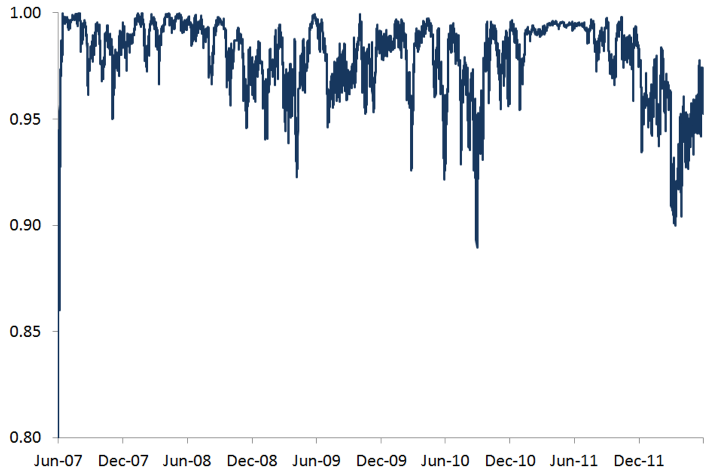


Figure 3.13: **Participation Ratio Based on the High-Frequency Correlation Matrix**

The figure reports the participation ratio for the 15-minute correlation matrix computed applying (3.25).

From Figure 3.13 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 the 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). The component of the eigenvectors are all positive making the computation of the symmetry parameter in (3.26) meaningless.

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 3.14 reports the percentage of variability of the low-frequency correlation matrix explained by its eigenvectors.

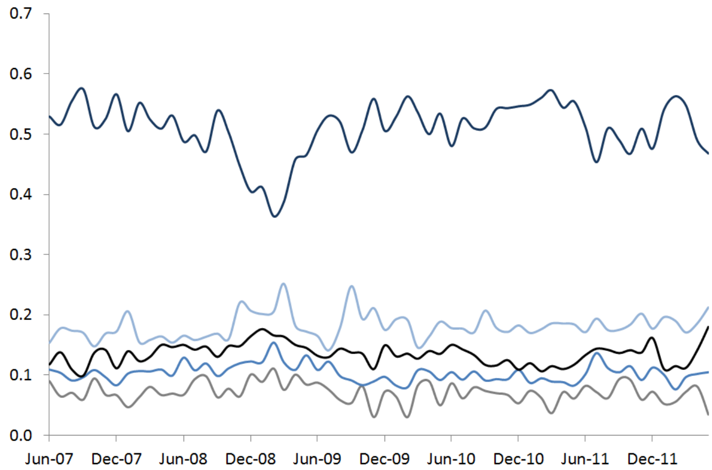


Figure 3.14: **Eigenvectors contribution to the time pattern of Low Frequency Correlation Matrix**

Figure 3.14 reports the contribution of the eigenvectors extracted from the low frequency correlation matrix and its time dynamics.

Figure 3.14 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 60%. 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 3.15, we report the participation ratio computed on the time varying long-term correlation matrix.

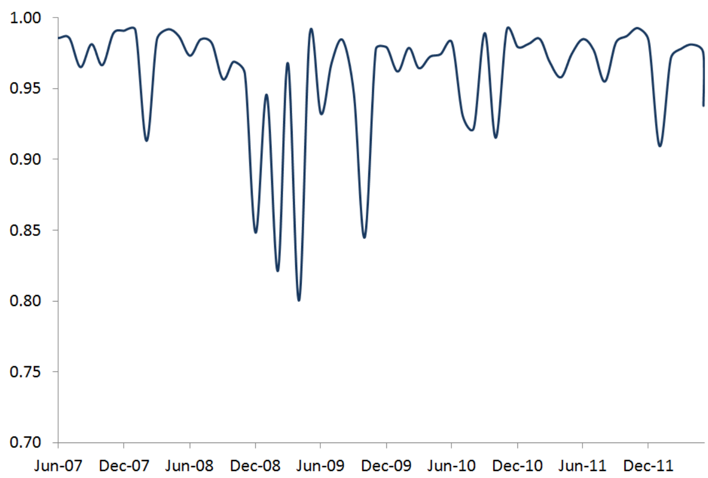


Figure 3.15: **Participation Ratio Based on the Low-Frequency Correlation Matrix**

The figure reports the participation ratio for the monthly correlation matrix computed by (3.25).

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 October 2009. These results can be interpreted jointly with what reported in Figures 3.2-3.4: 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.

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.

Some research on market integration has already been carried out. See for instance

Matheson (2013) who, by investigating the growth-pattern of 185 countries, shows that the crisis led to a widespread synchronization/integration across countries, though in the early part of the recovery, the integration decreased because of differences in countries macroeconomic conditions and in fiscal and monetary policy responses to the crisis itself. Moreover, while during the crisis period a global factor seems to have driven country's growth, during the post-crisis period the global factor looses its explanatory power, indicating that the country specific characteristics explain the different growth patterns. In addition to that, Schulz and Wolff (2008) show that the homogenization of trading platforms, through technical innovations promoting price transparency and competition, increases integration in the ultra-high frequency European sovereign bond yields. These findings are also supported by von Hagen et al. (2011).

3.5 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 Chapter, 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, Spain and the Netherlands 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-aversion 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 Chapter 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's 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, rising 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.

3.A Appendix I - Intraday Periodicity

Table 3.A.1: **Intraday periodicity estimates**

	IT	**FR**	**ES**	**BE**	**NL**
Constant	0.0000	0.0000	0.0002	0.0001	0.0000
AR(1)	0.6350	0.1246	-0.4570	-0.0756	0.2171
MA(1)	-0.6068	-0.2990	0.4327	-0.0023	-0.5625
δ_0	4.6638	3.0354	4.9300	7.0209	5.1410
$\delta_{0,1}$	-13.3151	-9.0558	-14.0015	-20.1177	-15.5761
$\delta_{0,2}$	4.6828	3.2026	4.8788	6.9948	5.5255
Macroannouncement Surprises					
λ_1 - US - Factory Orders	-0.0035	0.0016	0.0011	-0.0006	0.0056
λ_2 - US - Durable Goods	0.0000	0.0016	0.0016	0.0012	0.0009
λ_3 - US - CCI	-0.0036	0.0002	0.0012	0.0000	-0.0018
λ_4 - US - Chicago PMI	-0.0049	-0.0006	-0.0035	-0.0010	-0.0051
λ_5 - US - CPI	-0.0002	0.0025	0.0084	0.0050	-0.0003
λ_6 - US - GDP Advance	-0.0024	0.0003	0.0021	0.0013	-0.0031
λ_7 - US - GDP Preliminary	-0.0065	-0.0066	-0.0085	-0.0057	0.0055
λ_8 - US - GDP Final	0.0062	0.0004	0.0023	0.0037	-0.0065
λ_9 - US - Business Inventories	-0.0001	0.0025	-0.0036	-0.0047	0.0038
λ_{10} - US - NonFarm Payroll	-0.0037	0.0021	0.0028	-0.0019	-0.0011
λ_{11} - US - Initial Jobless Claim	-0.0018	0.0011	-0.0023	-0.0009	0.0009
λ_{12} - US - University Of Michigan	0.0010	0.0047	-0.0103	-0.0013	0.0177
λ_{13} - US - Retail Sales	-0.0040	-0.0024	0.0058	-0.0011	0.0018
λ_{14} - US - Philadelphia FED Index	0.0002	0.0011	0.0004	-0.0029	0.0024
λ_{15} - US - PPI	0.0039	-0.0016	-0.0023	-0.0069	-0.0033
λ_{16} - US - Production Index	0.0019	-0.0012	-0.0003	-0.0068	0.0032
λ_{17} - EA - HICP Flash Estimate	-0.0029	-0.0092	-0.0070	-0.0106	0.0024
λ_{18} - EA - Business Confidence Indicator	0.0007	-0.0001	0.0007	-0.0011	0.0006
λ_{19} - EA - Consumer Confidence Indicator	-0.0021	0.0039	0.0006	-0.0001	-0.0011
λ_{20} - EA - Industrial Production	-0.0037	0.0060	0.0053	-0.0017	-0.0011
λ_{21} - EA - M3	-0.0057	-0.0014	-0.0004	0.0005	0.0002
λ_{22} - EA - Retail Sales	0.0069	0.0001	0.0188	0.0081	0.0054
λ_{23} - EA - Unemployment	0.0060	0.0023	0.0001	0.0012	-0.0045
λ_{24} - EA - PPI	-0.0116	-0.0144	-0.0049	0.0006	-0.0049
λ_{25} - EA - PMI Flash	0.0032	0.0002	-0.0035	-0.0053	-0.0018
λ_{26} - EA - PMI Final	0.0042	0.0025	0.0080	0.0027	-0.0028
λ_{27} - EA - Introductory Statement	0.0020	0.0054	0.0042	0.0107	0.0147
λ_{28} - EA - Monthly Bulletin	0.0012	-0.0070	0.0047	-0.0126	-0.0064
λ_{29} - DE - ZEW	0.0007	0.0019	0.0010	0.0039	0.0025
λ_{30} - DE - Business Confidence	0.0048	-0.0011	0.0034	0.0004	0.0030
λ_{31} - DE - CPI Preliminary	0.0077	-0.0136	0.0043	-0.0033	0.0003
λ_{32} - DE - Unemployment	0.0000	0.0000	0.0000	0.0000	0.0000
λ_{33} - DE - Industrial Production	-0.0051	-0.0050	-0.0002	-0.0031	-0.0029
λ_{34} - IT - GDP Preliminary	-0.0010	-0.0011	-0.0006	-0.0027	0.0010
λ_{35} - IT - GDP Definitive	0.0229	0.0037	0.0135	0.0124	0.0073
λ_{36} - IT - Business Confidence	0.0028	0.0005	0.0003	0.0022	-0.0007

Table 3.A.1: **Intraday periodicity estimates**

	IT	**FR**	**ES**	**BE**	**NL**
λ_{37} - IT - CPI Preliminary	-0.0041	-0.0021	0.0002	-0.0031	-0.0018
λ_{38} - IT - CPI Final	0.0002	0.0003	0.0013	-0.0007	0.0008
λ_{39} - IT - Industrial Production	0.0055	0.0037	-0.0055	-0.0006	0.0006
λ_{40} - FR - Business Confidence	0.0000	0.0000	0.0000	0.0000	0.0000
λ_{41} - FR - Industrial Production	0.0003	-0.0010	0.0010	0.0010	-0.0005
λ_{42} - PT - CPI	0.0029	-0.0015	-0.0012	0.0005	0.0015
λ_{43} - PT - GDP Preliminary	0.0012	-0.0002	-0.0002	-0.0010	0.0000
λ_{44} - PT - GDP Final	0.0006	-0.0024	-0.0031	0.0013	-0.0042
λ_{45} - BE - Business Confidence	-0.0021	-0.0018	-0.0011	-0.0027	0.0007
λ_{46} - GR - GDP Final	-0.0027	-0.0043	-0.0013	-0.0028	-0.0027
λ_{47} - GR - GDP Preliminary	-0.0016	0.0139	0.0297	-0.0094	0.0083
λ_{48} - GR - CPI	-0.0023	-0.0003	-0.0039	-0.0005	0.0029
λ_{49} - GR - Unemployment	-0.0035	-0.0001	0.0013	-0.0016	0.0038
λ_{50} - NL - Unemployment	-0.0017	0.0002	-0.0002	0.0030	0.0013
λ_{51} - NL - CPI	0.0074	0.0028	0.0145	0.0074	-0.0018
λ_{52} - NL - IndustrialProduction	0.0005	0.0005	-0.0008	-0.0006	-0.0003
Bid-to-cover 10yrs Auctions					
γ_1 - Austria	0.0079	0.0025	-0.0041	0.0021	-0.0005
γ_2 - Belgium	-0.0112	-0.0031	-0.0128	0.0054	-0.0028
γ_3 - France	-0.0052	0.0026	0.0007	-0.0038	-0.0017
γ_4 - Germany	0.0019	-0.0126	-0.0006	-0.0071	-0.0183
γ_5 - Greece	-0.0389	0.0484	0.0073	0.0463	-0.0354
γ_6 - Italy	-0.0517	0.0229	-0.0430	0.0101	0.0462
γ_7 - Portugal	-0.0204	-0.0043	0.0067	-0.0077	0.0018
γ_8 - Spain	0.0619	0.0310	-0.0092	0.0164	0.0086
Rating					
ϕ_1 - S&P	0.3409	0.1578	0.2421	0.0417	-0.0275
ϕ_2 - Moody's	-0.4756	0.0130	0.1431	0.1366	0.0390
ϕ_3 - Fitch	0.1720	-0.0674	0.1768	0.1043	-0.0213
Day of the week					
θ_1 - Tuesday	-0.1005	-0.0051	-0.0557	-0.1004	-0.0185
θ_2 - Wednesday	-0.1373	-0.0268	-0.0134	-0.1040	-0.0486
θ_3 - Thursday	-0.0729	0.0143	-0.0039	-0.0582	-0.0331
θ_4 - Friday	-0.0939	-0.0170	-0.0330	-0.0805	-0.0502
Periodic Component					
$\delta_{c,1}$	-2.3539	-1.5858	-2.4144	-3.6652	-2.8998
$\delta_{c,2}$	-0.5068	-0.3516	-0.5133	-0.8455	-0.6802
$\delta_{c,3}$	-0.1871	-0.0966	-0.1485	-0.3263	-0.2563
$\delta_{c,4}$	-0.0217	-0.0006	-0.0163	-0.1293	-0.0880
$\delta_{c,5}$	-0.0243	0.0151	-0.0068	-0.0530	-0.0441
$\delta_{s,1}$	-0.1065	-0.0673	-0.1849	-0.2861	-0.0712
$\delta_{s,2}$	-0.0180	0.0147	-0.0655	-0.1128	0.0220
$\delta_{s,3}$	0.0168	0.0078	-0.0476	-0.0756	0.0049
$\delta_{s,4}$	0.0006	0.0287	-0.0249	-0.0349	0.0037
$\delta_{s,5}$	0.0236	0.0150	-0.0258	-0.0156	0.0207

3.B Appendix II - Daily Data

In this Appendix we report a similar exercise to the one presented in Section 3.4 where the high frequency component is evaluated at daily frequency rather than at 15-minute.

Table 3.B.1: **Parameter Estimates for the TS GARCH-MIDAS Models - Daily Data**

	IT	**FR**	**ES**	**BE**	**NL**
α	**0.2247 *****	**0.2007 *****	**0.2563 *****	**0.1757 *****	**0.2261 *****
β	**0.6497 *****	**0.5884 *****	**0.6623 *****	**0.7512 *****	**0.6817 *****
m	**-3.0419 *****	**-3.5617 *****	**-2.7556 *****	**-2.6074 *****	**-4.0034 *****
θ	**0.8203 *****	**0.8166 *****	**0.8584 *****	**0.8741 *****	**0.6594 *****
ω_2	**4.49 ****	28.48	**3.83 ****	**0.97 *****	**3.30 *****
LogL	1,995	2,929	2,001	2,410	3,082
Variance ratio	0.77	0.83	0.78	0.69	0.37

Table 3.B.1 reports estimates for the TS GARCH-MIDAS model where the long run component is a smooth weighted average of previous six monthly realized volatilities. Realized volatilities are estimated on a fix monthly span while the high frequency component is measured at daily frequency. Weights are computed according to the beta function where the first parameter ω_1 is set to 1. ***, **, * denote 1%, 5% and 10% significance level, respectively.

Table 3.B.2: **Parameter estimates for the MV-GARCH-MIDAS models - Daily Data**

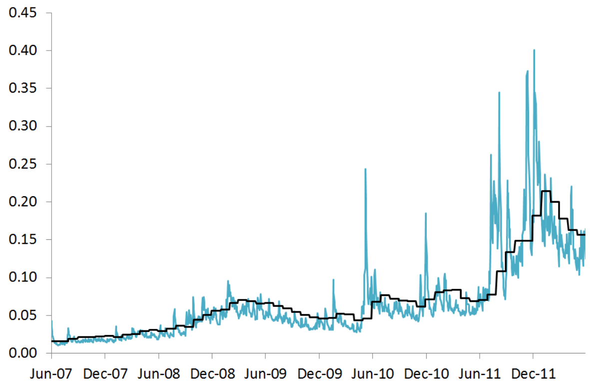
	IT	FR	ES	BE	NL
α	**0.2176 *****	**0.1489 ****	**0.2509 *****	**0.1677 *****	**0.1607 *****
β	**0.5852 ****	**0.6725 *****	**0.6003 *****	**0.7309 *****	**0.7764 *****
m	-8.68	**-11.49 *****	**-8.71 *****	**-9.15 *****	**-7.38 *****
$\theta_{1,l}$ (Employment)	-15.24	**43.23 *****	3.3	21.96	3.95
$\theta_{2,l}$ (Industrial Production)	29.06	**22.8 *****	10.91 **	-7.69	**-14.28 *****
$\theta_{3,l}$ (Economic Sentiment)	-3.07	**-5.78 ***	9.25 ***	28.28	**6.86 ***
$\omega_{2,1,l}$ (Employment)	152.5	**0.88 *****	28.27	**0.97 *****	151.02
$\omega_{2,2,l}$ (Industrial Production)	1.32	**1.38 *****	4.04	155.36	108.75
$\omega_{2,3,l}$ (Economic Sentiment)	0.6	98.08	131.94	**1 *****	137.02
$\theta_{1,v}$ (Unemployment)	31.96	23.06	-6.79	**-8.14 *****	**-67.66 ****
$\theta_{2,v}$ (Industrial Production)	-280.05	**-49.18 ****	**188.62 ****	41.92	**104.99 *****
$\theta_{2,v}$ (Economic Sentiment)	-52.8	**-58.62 *****	**-235.5 *****	26.53 *	9.56
$\omega_{2,1,v}$ (Employment)	**0.98 *****	**1.07 *****	**0.95 *****	145.83	**0.98 *****
$\omega_{2,2,v}$ (Industrial Production)	**2.05 ***	248.29	**1 *****	**8.36 ****	**1.86 *****
$\omega_{2,3,v}$ (Economic Sentiment)	5.4	109.96	**1.36 *****	149.18	13.06
LogL	2,016	2,952	2,017	2,423	3,101
Variance ratio	0.89	0.89	0.86	0.86	0.55

Table 3.B.2 reports estimates for the MV-GARCH-MIDAS model where the long run component is a function of the absolute difference in macroeconomic fundamentals (employment, industrial production and economic sentiment) observed over the last six month for each country with respect to Germany as specified in (3.9). Both levels and volatilities of macrovariables are considered. The low frequency component is updated monthly, in correspondence to new macroeconomic data, while the high frequency component is evaluated on a daily basis. The absolute difference in volatilities were rescaled: employment volatility by 1e4 while industrial production and economic sentiment volatility by 1e2. Weights are computed according to the beta function where the first parameter ω_1 is set to 1. ***, **, * denote 1%, 5% and 10% significance level, respectively.

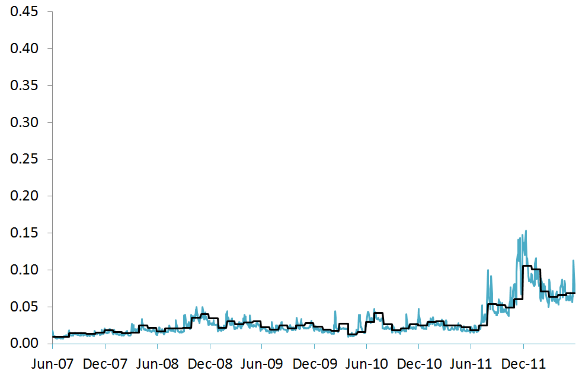
Table 3.B.3: **GARCH MIDAS Models: A Comparison - Daily Data**

	IT	**FR**	**ES**	**BE**	**NL**
Log Likelihood					
GARCH	1,973	2,908	1,975	2,376	3,072
TS GARCH-MIDAS	1,995	2,929	2,001	2,410	3,082
LR test (vs GARCH)	**43.84 *****	**42.98 *****	**52.94 *****	**70.44 *****	**20.37 *****
MV GARCH-MIDAS	2,016	2,952	2,017	2,423	3,101
LR test (vs GARCH)	**85.67 *****	**88.93 *****	**84.73 *****	**96.34 *****	**59.23 ****
AIC					
GARCH	-3.0842	-4.5473	-3.0871	-3.7138	-4.8038
TS GARCH-MIDAS	-3.1139	-4.5762	-3.1238	-3.7642	-4.8150
MV GARCH-MIDAS	**-3.1309**	**-4.5965**	**-3.1330**	**-3.7688**	**-4.8298**
BIC					
GARCH	-3.0762	-4.5392	-3.0790	-3.7057	**-4.7957**
TS GARCH-MIDAS	**-3.0937**	**-4.5561**	**-3.1036**	**-3.7440**	-4.7949
MV GARCH-MIDAS	-3.0705	-4.5360	-3.0725	-3.7083	-4.7693
Variance Ratio					
TS GARCH-MIDAS	0.77	0.83	0.78	0.69	**0.37**
MV GARCH-MIDAS	**0.89**	**0.89**	**0.87**	**0.86**	**0.55**

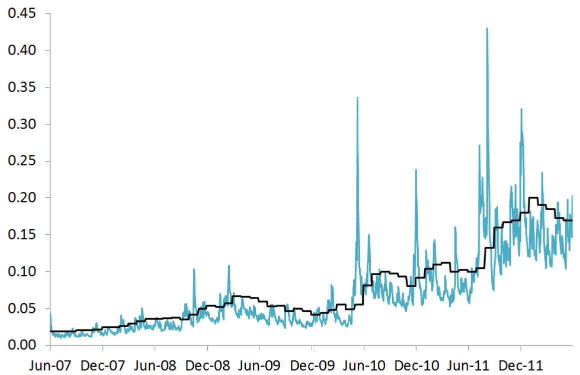
Table 3.B.3 reports a comparison of alternative volatilites estimates. GARCH is the classical GARCH(1,1) model by Bollerslev (1986) (estimates are not reported here). In the TS GARCH-MIDAS, the low frequency component is a smooth weighted average of previous six monthly realized volatilities and reported in Table 3.B.1. In the MV GARCH-MIDAS the low frequency component is a function of the absolute difference in macroeconomic fundamentals, namely employment, industrial production and economic sentiment, for each country with respect to Germany and reported in Table 3.B.2. LR test is provided just with respect to classical GARCH as the two GARCH-MIDAS specifications are not nested. AIC and BIC are Akaike and Schwarz information respectively, whose values are divided by T=1,279. Variance ratio, defined in (3.10), indicates the overall amount volatility explained by the long run component. ***, **, * denote 1%, 5% and 10% significance level, respectively.



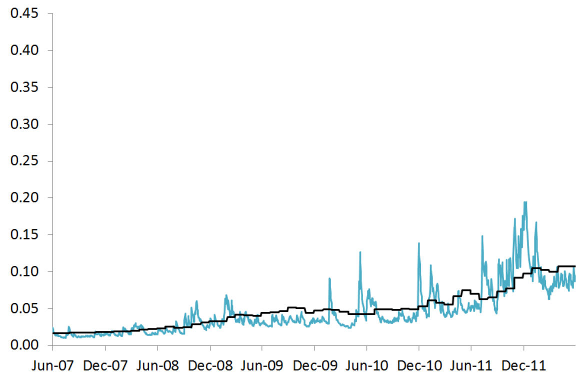
Italy



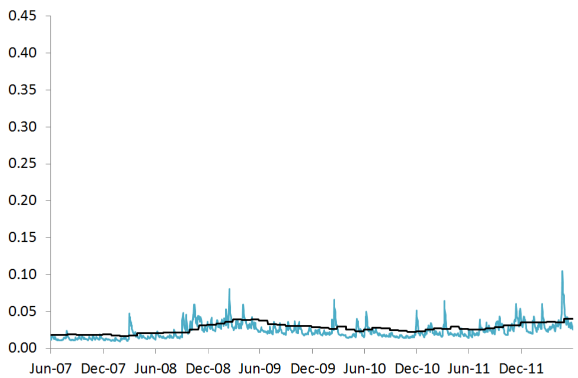
France



Spain



Belgium



the Netherlands

Figure 3.B.1: **MV GARCH-MIDAS Models - Daily Data**

Figure 3.B.1 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 (3.9). Both levels and volatilities of macrovariables are considered. Estimates are reported in Table 3.B.2. The black line is the low frequency (monthly) component while the blue one is the daily component.

Table 3.B.4: **Parameter estimates for the TS DCC-MIDAS Model - Daily Data**

	a	**b**	ω_2
	0.0048 ***	**0.9942 *****	1.3009
LogL	14,120		

Table 3.B.4 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 matrices of standardized residuals. The long run component is kept fixed throughout the month while the high frequency component is evaluated on a daily basis. Weights are computed according to the beta function where the first parameter ω_1 is set to 1. Univariate volatilities are obtained by the TS GARCH-MIDAS model where the long run component is a smooth weighted average of RVs reported in Table 3.B.1. ***, **, * denote 1%, 5% and 10% significance level, respectively.

Table 3.B.5: **Parameter estimates for the MV DCC-MIDAS model - Daily Data**

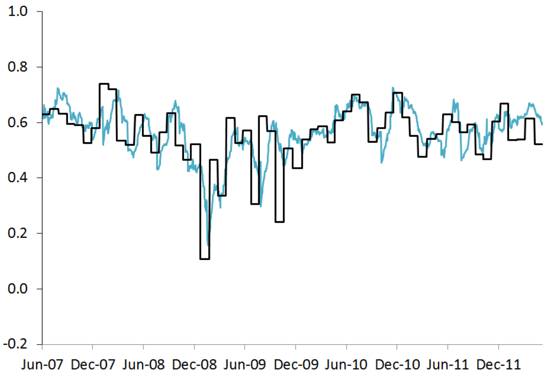
	IT-FR	**IT-ES**	**IT-BE**	**IT-NL**	**FR-ES**	**FR-BE**	**FR-NL**	**ES-BE**	**ES-NL**	**BE-NL**
m	**0.64 *****	**0.97 *****	**0.85 *****	**0.50 *****	**0.70 *****	**1.15 *****	**1.07 *****	**0.85 *****	**0.57 *****	**0.83 *****
$\theta_{1,l}$ (level Employment)	**4.50 *****	**-9.29 *****	-4.83	**-8.25 *****	2.14	**1.93 *****	**-26.51 *****	2.19	-0.80	**-3.81 *****
$\theta_{2,l}$ (level Industrial Production)	**-3.80 *****	-14.96	**7.82 *****	-0.83	5.11	**-2.58 *****	**-5.54 ***	**4.31 *****	**0.95 *****	**4.27 *****
$\theta_{3,l}$ (level Economic Sentiment)	**-0.52 *****	**23.97 *****	4.77	3.64	-1.97	**-4.43 *****	-3.44	**-6.70 ****	**-5.42 *****	**-11.42 *****
$\omega_{2,1,l}$ (Employment)	**1.15 *****	14.17	1.30	10.30	5.47	13.22	14.99	**1.06 *****	0.54	**1.30 ****
$\omega_{2,2,l}$ (Industrial Production)	0.52	1.15	12.39	3.18	13.45	11.43	14.99	1.12	13.49	2.94
$\omega_{2,3,l}$ (Economic Sentiment)	7.89	1.02	**13.02 *****	12.65	1.02	1.30	**14.11 ****	**1.10 *****	12.01	12.82
$\theta_{1,v}$ (volatility Employment)	**2.03 *****	-0.07	-1.21	2.93	**-0.93 *****	**-7.70 *****	4.28	1.93	2.10	2.38
$\theta_{2,v}$ (volatility Industrial Production)	**-8.72 *****	-11.08	-8.44	-2.46	3.51	**-3.14 ***	14.62	**-10.57 *****	-8.71	**-9.67 *****
$\theta_{3,v}$ (volatility Economic Sentiment)	**-9.08 *****	**1.58 *****	-17.37	**3.82 *****	-19.85	-10.87	**21.99 *****	-12.80	**24.96 ****	**7.85 *****
$\omega_{2,1,v}$ (Employment)	1.13	4.62	1.63	**11.89 ***	1.20	0.98	2.07	**8.58 *****	1.05	8.90
$\omega_{2,2,v}$ (Industrial Production)	**1.17 *****	1.15	9.52	**0.98 ****	3.08	4.02	**0.84 *****	**5.36 *****	10.09	**5.94 *****
$\omega_{2,3,v}$ (Economic Sentiment)	**0.74 *****	1.62	1.15	**8.32 *****	1.26	2.51	11.45	**0.97 *****	**9.25 *****	6.88
DCC										
a	**0.0185 ***									
b	**0.9392 *****									
LogL	14,367									

Table 3.B.5 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 GARCH-MIDAS model where the long run component is a function of macrovariables reported in Table 3.B.2. Differences were rescaled: ***, **, * denote 1%, 5% and 10% significance level, respectively.

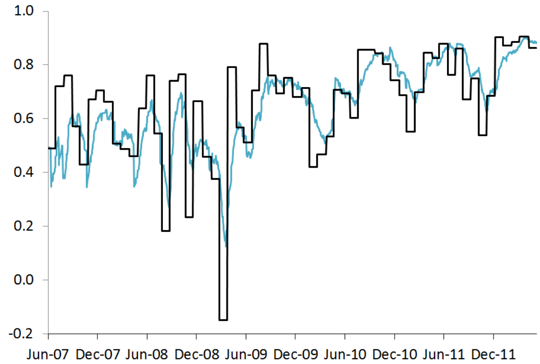
Table 3.B.6: **DCC-MIDAS Models: A Comparison - Daily Data**

	LogL	**LR test vs DCC**	**AIC**	**BIC**
DCC	14,069		-22.00	-21.99
TS DCC-MIDAS	14,120	**101.82 *****	-22.07	**-22.05**
MV DCC-MIDAS	14,367	**596.47 *****	**-22.25**	-21.73

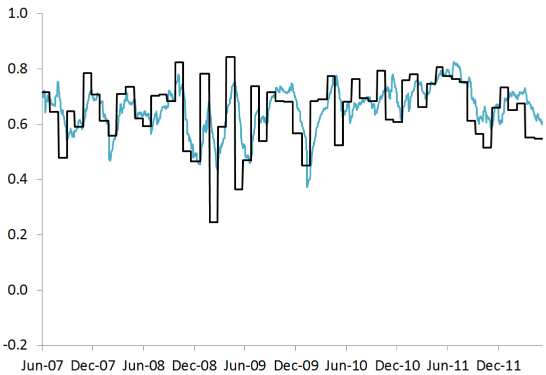
Table 3.B.6 reports a comparison of alternative DCC models. DCC is the classical DCC(1,1) model by Engle (2002) whose parameters are not reported here. The TS DCC-MIDAS estimates are reported in Table 3.B.4 and MV DCC-MIDAS in Table 3.B.5. LR test is provided just with respect to classical DCC as the two DCC-MIDAS specifications are not nested. AIC and BIC are Akaike and Schwarz information respectively, whose values are divided by T=1,279. ***, **, * denote 1%, 5% and 10% significance level, respectively.



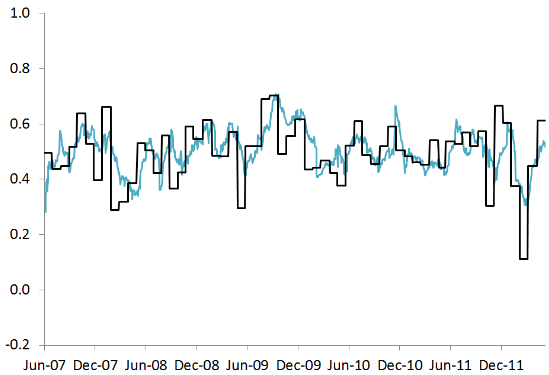
Italy vs France



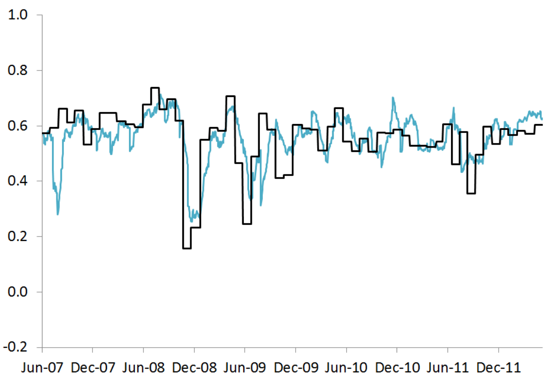
Italy vs Spain



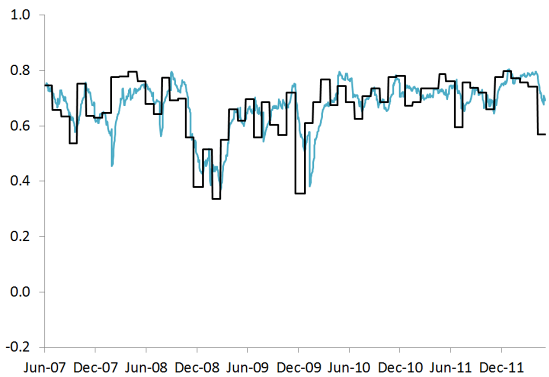
Italy vs Belgium



Italy vs the Netherlands



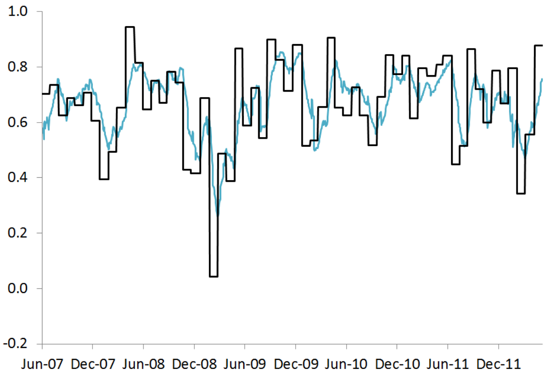
France vs Spain



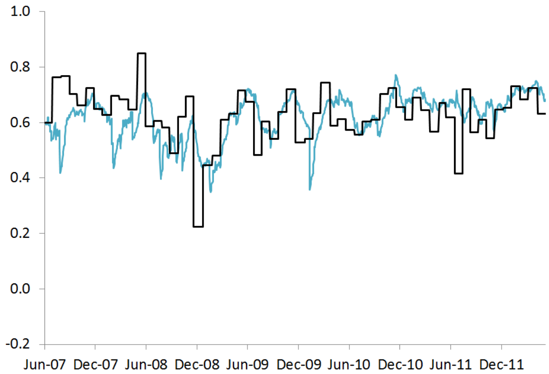
France vs Belgium

Figure 3.B.2: **MV DCC-MIDAS Model - Daily Data**

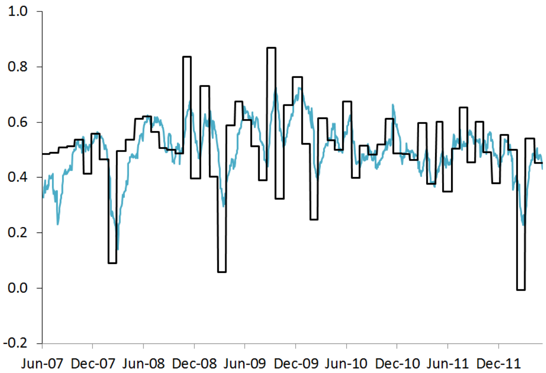
Figure 3.B.2 plots the correlation estimates of 10-year government bond spreads with respect to the German Bund for Belgium, France, Italy, Spain and the Netherlands during the period June 2007 - May 2012. Correlations are obtained from the MV DCC-MIDAS model where the long run component is a function 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 (3.9). Both levels and volatilities of macrovariables concur in determining the long run component of correlations. Estimates are reported in Table 3.B.5. The black line is the low frequency (monthly) component while the blue one is the high frequency (15-minute) component.



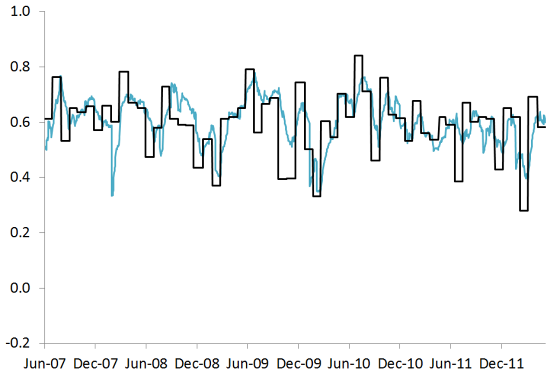
France vs the Netherlands



Spain vs Belgium



Belgium vs the Netherlands



Belgium vs the Netherlands

Figure 3.B.3: **DCC-MIDAS MV Model - Daily Data**

See notes to Figure 3.B.2

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Chapter 4

Comparing alternative integrated covariance estimators

Abstract

In this Chapter, we carry out a comprehensive Monte Carlo simulation exercise aimed at comparing the alternative integrated covariance estimators and synchronization methods that have been recently proposed in the literature. The Monte Carlo comparison evidences as the two best estimators are those introduced by Aït-Sahalia, Fan and Xiu (2010) and by Shephard and Xiu (2012). The best performance of Aït-Sahalia, Fan and Xiu (2010) estimator is achieved in combination with the refresh time synchronization procedure while the Shephard and Xiu (2012), directly applied on non-synchronized data, suffers from upward bias which is anyway averaged out when evaluating correlations. We even propose a backtesting risk management exercise based on a portfolio of European government bonds confirming Monte Carlo results.

Keywords: Integrated Covariance, Asynchronicity, Microstructure Noise, Monte Carlo, Risk management, Backtesting.

J.E.L. Classification Numbers: C01, C14, C58, D53, D81.

4.1 Introduction

The proper estimation of correlation matrix is fundamental in a lot of finance fields such as portfolio optimization and risk management (e.g. Schafer et al. (2009)). The availability of high frequency data has opened the route to the development of a new set of covariance matrix estimators based on such data, the integrated covariance estimators.

The first estimator of integrated covariance relying on high frequency data was originally introduced by Barndorff-Nielsen and Shephard (2004). This estimator was successively shown to be strongly biased when applied to tick-by-tick data given that it does not take into account neither market microstructure noise nor non-synchronous trading.

Asynchronicity deals with the fact that transaction data are recorded at random times so that prices are available at irregularly spaced times. Unfortunately, classical econometrics techniques cannot be applied to asynchronous data as a general underlying assumption is that data are recorded at the same time. Therefore, in order to be able to deal with asynchronous data, specific synchronization tools were developed, so that classical econometrics can still be applied even to non-synchronous recorded data, together with new estimators explicitly designed to deal with such kind of data.

The simplest procedure to synchronize data is carried out by selecting a common interval length h and interpolating the missing observations in some way. This procedure presents two main pitfalls: firstly it is heavily dependent on the choice of h; in a second place interpolation could be another bias source (see for instance Barucci and Renò (2002)). Moreover, Münnix et al. (2010) show that each term of the Pearson correlation coefficient can be divided into two parts, one contributing to the correlation, deriving from the overlapping of returns, and the other which is uncorrelated, not overlapping, just causing the correlation coefficient to decrease and being the origin of the so called Epps effect.

The Epps effect has a long history and different are the reasons ascribed to it. A first empirical assessment of the existence of a negative relationship between sampling frequency and correlation can be found in Niederhoffer and Osborne (1966). In their paper they argue that the negative correlation in tick-by-tick price changes is due to the presence of queues of limit orders acting as temporary barriers between which market price moves back and forth as each order in a flow of randomly arranged market orders to buy or sell (at the best available price) transacts with one of the limit orders. Epps (1979) explains the existence of a negative relationship between successive price changes in the same stock with the persistence for short periods of a similar effect that exists among changes in price from one transaction to the next. A successive work by Lundin et al. (1990) provides evidence of a significant inverse relationship between correlation and activity: the more an asset is traded, the less evident the Epps effect is. In addition to that, they claim that the reason why we do not recover the same correlation at different time scales is that different actors play different roles at different frequencies. Renò (2003) shows, through an extensive Monte Carlo simulation, that when two assets are traded synchronously, and if there is no lead-lag relationship, no frequency effects should be observed in the correlation measurements. This finding would suggest that the most relevant determinant of the Epps effect is asynchronicity. Finally Münnix et al. (2010) identify another cause of the Epps effect in the discretization of the price process. A more intuitive reason justifying the Epps effect is that, as the sampling frequency increases, there are more and more zero-returns in the presence of non-synchronous trading causing the estimated correlation being biased towards zero.

Together with synchronicity, a general assumption underlying classical financial econometrics techniques is that observed prices are the true efficient prices. Anyway, especially when moving to very high frequencies, we hardly observe the true prices due to the presence of the microstructure noise. Microstructure noise is commonly claimed to be determined by discreteness and bid-ask spread bounce and its main detrimental effect is inducing autocorrelation in high frequency returns. Moreover noise is often pointed out to be one of the causes of the Epps effect as, while the magnitude of the noise relative to the price signal increases, so does the realized variance estimator (Griffin and Oomen (2008)).

Starting from Barndorff-Nielsen and Shephard (2004), numerous researchers tried to identify a good integrated covariance estimator robust to both asynchronicity and microstructure noise, but there is no clear view about which one is the best. For instance the Cumulative Covariance by Hayashi and Yoshida (2005) does not deal with microstructure noise; the Multivariate Realized Kernel by Barndorff-Nielsen et al. (2011) and the Modulated Realized Covariance by Christensen et al. (2010) do not converge at the optimal rate while the Two Scale Realized Covariance by Zhang (2011) and the QMLE by Aït-Sahalia et al. (2010) are not guaranteed to be positive semidefinite.

In order to shed some light on this stream of literature, we carry out an extensive Monte Carlo simulation evaluating the alternative integrated covariance estimators behavior in presence of alternative degrees of microstructure noise and liquidity; the estimators are even compared with respect to alternative synchronization schemes. Moreover, we accompany the Monte Carlo simulation with an empirical risk management exercise where the alternative estimators are evaluated in a comprehensive backtesting appraisal with respect to a number of possible tests involving both Value-at-Risk as well as Tail risk measures.

The remainder of the Chapter is organized as follows. In Section 4.2 we review the alternative estimators proposed together with the possible synchronization schemes; in Section 4.3 we describe our Monte Carlo experiment while the risk management empirical exercise is reported in Section 4.4. Section 4.5 concludes.

4.2 Synchronization and Integrated Covariance Estimators

Consider a matrix $((T \times N) \times M)$ of log-prices $X = (X_{(t,i)})_{(t,i)\geq 0}$ defined on a probability space $(\Omega^0, \mathcal{F}^0, P^0)$ with an information filtration $\left(F^0_{(t,i)}\right)_{(t,i)\geq 0}$, T being the number of days included in the sample, N the number of tick data recorded for each day and M the number of assets under consideration. Efficient prices are supposed to be Brownian semimartingales:

$$X_{(t,i)} = X_{(t,0)} + \int_0^t a_u du + \int_0^t \sigma_u dW_u \qquad (t,i) \geq 0 \tag{4.1}$$

with $a = (a_{(t,i)})_{(t,i)\geq 0}$ M-dimensional predictable locally bounded drift vector, $\sigma = (\sigma_{(t,i)})_{(t,i)\geq 0}$ adapted càdlàg $M \times M$ covolatility matrix and $W = (W_{(t,i)})_{(t,i)\geq 0}$ M-dimensional Brownian motion.

The quadratic covariation process of X for day t is defined as:

$$[X_t] = \lim_{N\to\infty} \sum_{i=1}^{N} \left(X_{(t,i)} - X_{(t,i-1)}\right)\left(X_{(t,i)} - X_{(t,i-1)}\right)' = \int_0^1 \Sigma(u)du \qquad \Sigma = \sigma\sigma' \tag{4.2}$$

for any sequence of deterministic partitions $0 = (t,0) < (t,1) < ... < (t,N) = 1$ with $\sup_i \{(t,i) - (t,i-1)\} \to 0$ for $N \to \infty$.

Anyway, due to microstructure noise, we hardly observe the efficient price X rather we usually deal with its noisy version $Y = (Y_{(t,i)})_{(t,i)\geq 0}$, recorded at discrete time points:

$$Y = X + \varepsilon \tag{4.3}$$

where $\varepsilon = (\varepsilon_{(t,i)})_{(t,i)\geq 0}$ i.i.d. process accounting for the microstructure noise and independent from X.

In the remainder of this Section we will first discuss how to synchronize data to move afterwards to the alternative integrated covariance estimators proposed in the literature.

4.2.1 Synchronization

Synchronization is the process of transforming two or more time series recorded at different frequencies in two or more processes with concurrently trading times, which can be regularly or irregularly spaced.

The general idea about synchronization is to resample original tick-by-tick data with respect to a pre-specified grid with the alternative methods differentiating in the way the initial grid is set. To simplify the exposure we will consider just one trading day t. Let

$\widetilde{N}$ be the number of sampling points constituting the resampling grid $V_{\widetilde{N}}$: $[0,1]$. Each element of $V_{\widetilde{N}}$ can be indicated as $v_{(t,z)}$ with $z = 0, ..., \widetilde{N}$ where $v_{(t,0)} = 0$ and $v_{(t,\widetilde{N})} = 1$. The simplest case is to consider $V_{\widetilde{N}}$ a regular grid where the sampling points are equally spaced so that $v_{(t,z)} - v_{(t,z-1)} = \Delta$ for $\forall z = 1, ..., \widetilde{N}$. An alternative is to let the $v_{(t,z)}$'s depend on the observation times (e.g. refresh time) so that the resampling time points belonging to the grid won't be equally spaced: $v_{(t,z)} - v_{(t,z-1)} = \Delta^{(t,z)}$ for $z = 1, ..., \widetilde{N}$ with $\Delta^{(t,z)}$ denoting the time length between sampling points $v_{(t,z-1)}$ and $v_{(t,z)}$.

Unfortunately synchronization does not come at any costs. In fact, as new information gets built into prices at varying intensities according to their different trading times, synchronization causes spurious cross-autocorrelation among assets. Moreover, any synchronization method implies a discard of a number of prices with consequences on the efficiency of the estimators.

In the remainder of this Section we will discuss the alternative synchronization methods proposed in the literature.

4.2.1.1 Previous Tick

The first synchronization tool we introduce, the *Previous Tick* (PT henceforth), is may be even the simplest one as it is based on an equally-spaced grid. To each grid time point, the price immediately preceding the pre-specified sampling point is imputed. To formalize, let Y^1 be recorded on L_{T^1} time scale and Y^2 on S_{T^2}, the previous ticks $l_{(t,z)}$ and $s_{(t,z)}$ are identified as follows:

$$\begin{aligned} l_{(t,z)} &= \max\left\{\phi \in L_{T^1} : \phi \leq v_{(t,z)}\right\} \\ s_{(t,z)} &= \max\left\{\theta \in S_{T^2} : \theta \leq v_{(t,z)}\right\} \end{aligned} \tag{4.4}$$

where $v_{(t,z)}$ elements belonging to $V_{\widetilde{N}} : 0 = v_{(t,0)} < v_{(t,1)} < ... < v_{\left(t,\widetilde{N}\right)} = 1$ and $\Delta = 1/\widetilde{N}$ resampling frequency. We will indicate the resampled times for day t with $z = 1, ..., \widetilde{N}$.

A specific drawback of Previous Tick synchronization scheme is that it is highly dependent on the regular sampling frequency Δ selected.

4.2.1.2 Refresh time

A more advanced synchronization scheme not based on an equally spaced grid is the *Refresh Time* (RT henceforth) proposed by Barndorff-Nielsen et al. (2011).

Let $Y = \left(Y^1, Y^2, ..., Y^M\right)'$ be a M-dimensional log-price process where prices are observed irregularly and non-synchronously over the interval $[0,1]$. Observation times for the m-th asset are indicated as $(t,1)^m, (t,2)^m, ..., (t,N^m)^m$ where N^m is the overall number of tick-by-tick data recorded for the m-th asset.

Definition 4 *The first refresh time on* $[0,1]$ *is defined as* $(t,z(1)) = \max\left((t,1)^1, ..., (t,1)^M\right)$ *while the subsequent* z*-th refresh times are identified as* $(t,z+1) = \max\left(\left(t, N^1_{t,z}+1\right)^1, ...,\right.$

$\left.\left(t, N^M_{t,z}+1\right)^M\right)$.

Refresh time can be interpreted as the $(z+1)$-th time that all the prices have been refreshed. In particular $(t,z(1))$ is the time that it has taken for all the M assets to trade for the first time. The refresh times' sample size $\widetilde{N}$ is determined by the degree of non-synchronicity and by the sample size of the M-assets $T^1, T^2, ..., T^M$. The main drawback of the Refresh Time is that it is highly dependent on the relatively illiquid assets. This could lead some bias in the estimation as refresh time points are determined by the occurrence of the relatively more illiquid assets letting the selected observations of the other assets always ahead of the corresponding illiquid asset.

4.2.1.3 Generalized synchronization scheme

The *Generalized Synchronization* scheme was proposed by Aït-Sahalia et al. (2010); this is a class of synchronization methods which subsumes both previous tick and refresh time schemes.

Definition 5 *A sequence of time points* $\left\{(t,0), (t,1), ..., \left(t, \widetilde{N}\right)\right\}$ *is said to be the Generalized Sampling Time for a collection of* M *assets if:*

1. $0 = (t,0) < (t,1) < ... < \left(t, \widetilde{N}\right) = 1$*;*
2. *there exists at least one observation for each asset between consecutive* (t,z)*'s;*
3. *the time intervals* $\left\{\Delta^z = (t,z) - (t,z-1), \quad z = 1, ..., \widetilde{N}\right\}$*, satisfy* $\sup_z \Delta^z \xrightarrow{p} 0$.

The Generalized Synchronization scheme consists in choosing an arbitrary observation $Y^m_{t,i}$ for the $m-$th asset between the time interval $((t,z-1), (t,z)]$. The synchronized data sets can be indicated as $\left\{Y^m_{(t,z)} \text{ with } z = 1, ..., \widetilde{N} \text{ and } m = 1, ..., M\right\}$. In particular, to overcome the limit of Refresh Time arising when assets with different degree of liquidity are taken into consideration, Aït-Sahalia et al. (2010) propose to design a synchronization scheme requiring each asset to lead in turn: for example, requiring the first asset to lead, they set $(t,z(1)) = \left(t, N^2((t,1)^1)+1\right)^2$ and for $z \geq 2$ $(t,z) = \left(t, N^2\left(\left(t, N^1(t,z-1)+1\right)^1\right)+1\right)^2$. In both Monte Carlo simulation and empirical application, we are going to adopt this scheme; we will refer to it as Modified Refresh Time (MRT henceforth).

As the Generalized Synchronization scheme has no requirements on tick selection, the estimator of integrated covariance based on it is robust to data misplacement error, as long as these misplaced data points are within the same sampling intervals.

The Previous Tick approach is recalled requiring (t, z) to be equally spaced on $[0, 1]$ and by selecting for each grid time point the price immediately preceding the grid point while the Refresh Time is obtained choosing (t, z) recursively as $(t, z+1) = \max_{1 \leq m \leq M} \left\{ \left(t, N^m_{t,z+1}\right)^m \right\}$ where $(t, z(1)) = \max \left\{ (t, 1)^1, (t, 1)^2, ..., (t, 1)^M \right\}$ with $N^m(.)$ being the number of observations for asset m before time t and selecting those ticks that occur right before or at (t, z)'s.

4.2.1.4 Hayashi and Yoshida (2005)

To deal with asynchronicity, Hayashi and Yoshida (2005) suggest working on common trading intervals of two assets. We will refer to this approach as *Intersection*. The greatest advantage of this method is that it makes use of all the possible data. Anyway Aït-Sahalia et al. (2010) state that the synchronization approach embedded in Hayashi and Yoshida (2005) method effectively deletes some data. For example, if three consecutive ticks of the first asset form two intervals which share the same corresponding interval of the second asset, then the middle observation of the first asset will not be used either.

To illustrate the idea about common trading interval, consider again two assets Y^1 and Y^2 respectively recorded on L_{N^1} and S_{N^2} time scales both partitioning the interval of interest $[0, 1]$. Hayashi and Yoshida (2005) estimator, called *Cumulative Covariance*, is defined as:

$$HY = \sum_{l=0}^{L_{N^1}} \sum_{s=0}^{S_{N^2}} y^1_l \left(L_{N^1}\right) y^2_s \left(S_{N^2}\right)_{\left\{L_{N^1} \cap S_{N^2} \neq \varnothing\right\}} \tag{4.5}$$

Hayashi and Yoshida (2005) show that (4.5) is a consistent estimator of integrated covariance matrix. The most serious drawback of (4.5) is that it does not deal with noise. In successive works, Voev and Lunde (2007) provide a bias correction to the original Hayashi and Yoshida (2005) estimator, although this new estimator does not achieve consistency. Even Christensen et al. (2010) work on a microstructure noise robust version of (4.5) based on pre-averaging.

From (4.5) it is clear that the embedded synchronization method consists in taking into consideration just prices belonging to overlapping intervals of L_{N^1} and S_{N^2} so that even information concerning transaction times in the form of the indicator function enter the estimation of covariance matrix.

4.2.2 Robust estimators

4.2.2.1 Realized Covariance

Barndorff-Nielsen and Shephard (2004) introduce the first generation of estimators of integrated covariance, namely the *Realized Covariance* (RC henceforth).

Barndorff-Nielsen and Shephard (2004) state that empirical covariance matrix does not apply to high frequency data as, while the number of observations $\widetilde{N}$ on which it is computed goes to infinity, the covariance matrix converges in probability to a matrix of zeros. In a more formal way, under the assumption of synchronized data:

$$\frac{1}{\widetilde{N}}\sum_{z=0}^{\widetilde{N}} y_{t,z}y_{t,z}^{'} - \left(\frac{1}{\widetilde{N}}\sum_{z=0}^{\widetilde{N}} y_{t,z}\right)\left(\frac{1}{\widetilde{N}}\sum_{z=0}^{\widetilde{N}} y_{t,z}\right)^{'} = \frac{1}{\widetilde{N}}\sum_{z=0}^{\widetilde{N}} y_{t,z}y_{t,z}^{'} - \frac{1}{\widetilde{N}^2}y_{t,z}y_{t,z}^{'} \tag{4.6}$$

where $y_{t,z}$ $(M \times \widetilde{N} - 1)$ matrix of observed log-returns.

Therefore Barndorff-Nielsen and Shephard (2004) introduce the realized covariance which is a generalization of the idea underlying realized variance to the multivariate case as it is based on the aggregation of $\widetilde{N} \rightarrow \infty$ synchronized and equally spaced prices belonging to a non-stochastic time window $[0, 1]$. Realized covariance is defined as:

$$RC = \sum_{z=0}^{\widetilde{N}} y_{t,z}y_{t,z}^{'} \tag{4.7}$$

Andersen et al. (2003) show that, as long as returns are linearly independent, the realized covariance matrix in (4.7) will be positive definite. The choice of the resampling frequency influences the properties of the realized covariance estimator as it both affects the number of returns on which (4.7) is computed as well as the level of noise. In addition to that, Hayashi and Yoshida (2005) state that realized covariance estimators can be severally biased when the regular resampling frequency h is small relative to the frequency of actual trades.

As stated in the introduction, the two main problems affecting realized covariance are asynchronicity and microstructure noise. Martens (2004) proposes to solve the problem of non-synchronicity by adding lead and lag terms in (4.7) along the lines of the Scholes and Williams (1977) beta correction technique. This is obtained as:

$$SW_{q,(t,i)} = RC_{t,i} + \sum_{z=1}^{q}\sum_{w=1}^{N-z}\left(y_{t,i+(w+z)}y_{t,i+w}^{'} + y_{t,i+w}^{'}y_{t,i+(w+z)}\right) \tag{4.8}$$

A drawback of the estimator in (4.8) is that it is not guaranteed to be positive definite.

Hayashi and Yoshida (2005) state that the downward bias of the realized covariance matrix estimator derives from the fact that covariance increases just when and only when both prices jump together during the interval of length h while all other cases, when just one series jumps alone, are ignored. Such occasions of zero increments will become dominant if h becomes finer while, when h gets too large, too many data are discarded with the consequence that rapid movements of the return process are ignored.

4.2.2.2 Two Scales Realized Covariance

The first estimator of integrated covariance robust to both asynchronous data and microstructure noise is the *Two Scales Realized Covariance* (TSCV henceforth) which was proposed by Zhang (2011).

Having defined the average lag S covariance for two time series of synchronized log-prices Y^1 and Y^2 as:

$$[Y^1, Y^2]_{\widetilde{N}}^S = \frac{1}{S} \sum_{z=S}^{\widetilde{N}} \left(Y_{t,z}^1 - Y_{t,z-s}^1\right)\left(Y_{t,z}^2 - Y_{t,z-s}^2\right) \tag{4.9}$$

the TSCV estimator is given by:

$$TSCV[Y^1, Y^2] = c_{\widetilde{N}} \left([Y^1, Y^2]_{\widetilde{N}}^K - \frac{n_k}{n_j} [Y^1, Y^2]_{\widetilde{N}}^J \right) \tag{4.10}$$

where $1 \leq J << K = O\left(\widetilde{N}^{2/3}\right)$ with J which can be fixed or go to infinity with $\widetilde{N}$ (in the classical two scales setting $J = 1$); $n_s = \left(\widetilde{N} - S + 1\right)/S$ with $S = K, J$; $c_{\widetilde{N}} = 1 + o_p\left(\widetilde{N}^{-1/6}\right)$ constant taking into account small sample precision.

The TSCV estimator presents two important limits. The first one is that, as it is defined just for the bivariate case, when dealing with a number of assets greater than two it is not guaranteed to be positive definite. In fact, when three or more assets are considered, it is necessary to estimate the covariance for each pair of assets independently and, relying on these results, build up the overall matrix. The second limit is that the estimator is not efficient.

4.2.2.3 Modulated Realized Covariance

Christensen, Kinnerbrock and Podolskij (2010) introduce the so called *Modulated Realized Covariance* (MRC henceforth) which basically consists in revisiting the realized covariance estimator in (4.7) exploiting pre-averaging to deal with microstructure noise. Pre-averaging, introduced by Podolskij and Vetter (2009) and Jacod et al. (2009) finds a number of possible applications in finance, and it depends on a bandwidth parameter that grows with the sample and dictates the amount of averaging to be carried out. The choice of this tuning parameter controls the influence of microstructure noise. The MRC for synchronized observed prices Y is given by (4.11):

$$MRC[Y]_{\widetilde{N}} = \frac{\widetilde{N}}{\widetilde{N} - k_{\widetilde{N}} + 2} \frac{1}{\psi_2 k_{\widetilde{N}}} \sum_{z=0}^{\widetilde{N} - k_{\widetilde{N}} + 1} \bar{Y}_{t,z}^{\widetilde{N}} \left(\bar{Y}_{t,z}^{\widetilde{N}}\right)' \tag{4.11}$$

where $\bar{Y}_{t,z}^{\widetilde{N}} = \frac{1}{k_{\widetilde{N}}} \left(\sum_{s=k_{\widetilde{N}}/2}^{k_{\widetilde{N}}-1} Y_{\frac{t,z+s}{\widetilde{N}}} - \sum_{s=0}^{k_{\widetilde{N}}/2-1} Y_{\frac{t,z+s}{\widetilde{N}}} \right)$ the pre-averaged returns; $k_{\widetilde{N}}$ pre-averaging window s.t. $\frac{k_{\widetilde{N}}}{\sqrt{\widetilde{N}}} = \theta + o\left(\widetilde{N}^{-1/4}\right)$ depending on the tuning parameter θ; ψ_2

parameter depending on the weight function chosen for computing pre-averaged values that, in this case, corresponds to $g(x) = \min(x, 1-x)$ and consequently $\psi_2 = 1/12$. See Christensen et al. (2010) for further details.

There is no general rule for selecting θ and therefore in the following Monte Carlo and empirical exercise we follow Christensen et al. (2010 - 2010b) and set $\theta = 1$. The reason for that choice is that in general it is preferable to choose a high value for $k_{\widetilde{N}}$ as it helps to reduce the effect of price discreteness.

Unfortunately MRC is a biased estimator of the integrated covariance as it can be seen in (4.12):

$$MRC[Y]_{\widetilde{N}} \xrightarrow{p} \int_0^1 \Sigma_s ds + \frac{\psi_1}{\theta^2 \psi_2} \psi \tag{4.12}$$

and therefore (4.11) needs to be corrected for the bias. The bias term depends from ψ_1 and ψ_2, equal to 1 and 1/12 respectively given the choice for $g(x)$, while ψ is unknown but can be approximated as:

$$\widehat{\psi}_{\widetilde{N}} = \frac{1}{2\widetilde{N}} \sum_{z=0}^{\widetilde{N}} \Delta_{t,z}^{\widetilde{N}} Y \left(\Delta_{t,z}^{\widetilde{N}} Y \right)' \tag{4.13}$$

where $\Delta_{t,z}^{\widetilde{N}}$ time elapsed between two consecutive resampled prices.

Anyway, when accounting for bias, we loose the property of positive definiteness especially when working with small samples. Therefore, a positive-definite version of MRC (MRC-Psd henceforth) is proposed which basically relies on increasing the bandwidth parameter $k_{\widetilde{N}}$ in (4.11) as per:

$$\frac{k_{\widetilde{N}}}{\widetilde{N}^{1/2+\delta}} = \theta + o\left(\widetilde{N}^{-1/4+\delta/2} \right) \tag{4.14}$$

The MRC-Psd estimator is robust to bias without need of any correction; anyway MRC-Psd converges at a lower rate to the true integrated covariance with respect to (4.11), with the rate of convergence depending on δ. The optimal choice for δ is shown to be 0.1 resulting in a rate of convergence of $\widetilde{N}^{-1/5}$.

4.2.2.4 Multivariate Realized Kernel

Barndorff-Nielsen et al. (2011) introduce an estimator for the integrated covariance based on synchronized data obtained applying the refresh time scheme described in Section 4.2.1. This estimator is called the *Multivariate Realized Kernel* (MRK henceforth). In addition to synchronization, they propose to apply jittering-end conditions consisting in averaging ω prices at the beginning and at the end of the day. This procedure is needed in order to assure consistency. Jittering-end conditions can be defined as follows.

Definition 6 *Let $\psi, \omega \in \mathbb{N}$ such that $\psi - 1 + 2\omega = \widetilde{N}$ and set the vector of observations $Y_0, Y_1, ..., Y_\psi$ as $Y_{t,z} = Y_{t,z+\omega}$ with $z = 1, 2, ..., \psi - 1$ with $Y_0 = \frac{1}{\omega}\sum_{z=1}^{\omega} Y_{t,z}$ and $Y_\psi = \frac{1}{\omega}\sum_{i=1}^{\omega} Y_{\tau,\widetilde{N}-\omega+i}$, (t, z) being refresh times.*

In Definition 6, ω should be quite large although if small with respect to $\widetilde{N}$ in order to average out the error.

Having defined the vector of synchronized high frequency log-returns as $y_{\tau,z} = Y_{\tau,z} - Y_{\tau,z-1}$ with $z = 1, 2, ..., \widetilde{N}$, the class of positive semi-definite multivariate realized kernels is defined as:

$$K(Y) = \sum_{h=-\widetilde{N}}^{\widetilde{N}} k\left(\frac{h}{H+1}\right)\Gamma_h \tag{4.15}$$

where $\Gamma_h = \sum_{z=h+1}^{\widetilde{N}} y_{t,z}y'_{t,z-h}$ with $h \geq 0$, the h-th realized autocovariance such that $\Gamma_h = \Gamma'_{-h}$ for $h < 0$; k a non-stochastic weight (kernel) function; H the bandwidth parameter controlling for the number of leads and lags used for all the series which needs to increase with $\widetilde{N}$ quite quickly to remove the influence on the estimator of the noise. Barndorff-Nielsen et al. (2011) define the bandwidth as $H = c_0\widetilde{N}^{3/5}$. In the univariate context, the minimum mean square error of the $H = c_0\widetilde{N}^{3/5}$ estimator is achieved by setting for the m-th component $c_0 = c^*\xi_m^{4/5}\widetilde{N}^{3/5}$ with c^* and ξ be defined as:

$$c^* = \left\{\frac{k''(0)^2}{k^{0,0}}\right\}^{1/5} \qquad \xi_m^2 = \frac{\Omega_{mm}}{\sqrt{IQ_{mm}}} \tag{4.16}$$

where $k^{0,0} = \int_0^\infty k(x)^2 dx$; Ω long run variance estimated by one of the possible high frequency estimator (e.g. realized variance); IQ integrated quarticity defined in a multivariate context as $\int_0^1 \{\Sigma(u)\Sigma(u)\} \frac{\varkappa_2(u)}{\varkappa_1(u)} dx$ and usually approximated by $\int_0^1 \Sigma(u) du$ and estimated by a low frequency estimator (in their paper Barndorff-Nielsen et al. (2011) use the debiased version of realized volatility by Bandi and Russel (2008) corrected by the noise estimate as per Barndorff-Nielsen et al. (2008)).

As per the selection of the weighting function $k(.)$, many kernels can be chosen such as the Quadratic Spectral, the Parzen and the Fejér. In order to apply the most efficient realized kernel, Barndorff-Nielsen et al. (2011) compare them in terms of the constant $\left|k''(0)(k^{0,0})^2\right|^{1/5}$; that analysis suggests to use the Parzen kernel which is defined as follows:

$$k(x) = \begin{cases} 1 - 6x^2 + 6x^3 & 0 \leq x \leq 1/2 \\ 2(1-x)^3 & 1/2 < x \leq 1 \\ 0 & x < 0 \text{ or } x > 1 \end{cases} \tag{4.17}$$

In case of Parzen kernel $\left|k''(0)\right|$ is equal to 12 and $k^{0,0}$ to 0.269 so that c^* is 3.51.

Turning now to the $M-$multivariate specification, Barndorff-Nielsen et al. (2011) define the global bandwidth H starting from the bandwidth for the m-th asset H^m and then using some possible alternatives such as $H_{\min} = \min(H^1, ..., H^M)$, $H_{\max} = \max(H^1, ..., H^M)$ or $\overline{H} = \frac{1}{M}\sum_{m=1}^{M} H^m$. In their paper, Barndorff-Nielsen et al. (2011) use $\overline{H}$ and therefore in both Monte Carlo and empirical application we proceed in the same way.

The MRK is positive definite, consistent and robust to endogeneity, serial dependence and semi-staleness of prices. The main drawback of that estimator is that it converges at a relatively low rate $\widetilde{N}^{3/5}$; moreover the bandwidth H selection is not that straightforward in empirical applications.

4.2.2.5 QMLE Covariance

Aït-Sahalia et al. (2010) propose a consistent and efficient estimator for the integrated covariance which is robust to market microstructure noise although still relying on synchronized data.

To introduce their estimator, we recall the QMLE for univariate volatility proposed in Xiu (2010). Let's move from (4.3) and assume that the microstructure noise ε_t has mean 0 and variance a^2 and that the volatility σ_u of the true price X in (4.1) is time invariant. Under these two assumptions, log-returns of synchronized log-prices $y_{t,z} = Y_{t,z} - Y_{t,z-1}$ with $z = 1, 2, ..., \widetilde{N}$ follow a MA(1) process so that the log-likelihood function takes the form:

$$\log L\left(y|a^2, \sigma^2\right) = -\frac{1}{2}\log\det\left(\Omega\right) - \frac{\widetilde{N}}{2}\log\left(2\pi\right) - \frac{1}{2}y'\Omega^{-1}y \tag{4.18}$$

with $\Omega = \begin{pmatrix} \sigma^2\Delta + 2a^2 & -a^2 & 0 & ... & 0 \\ -a^2 & \sigma^2\Delta + 2a^2 & -a^2 & ... & ... \\ 0 & -a^2 & \sigma^2\Delta + 2a^2 & ... & 0 \\ ... & ... & ... & ... & -a^2 \\ 0 & ... & 0 & -a^2 & \sigma^2\Delta + 2a^2 \end{pmatrix}$

According to Xiu (2010), the QMLE of a^2 and σ^2 are consistent even when volatility is stochastic, so that the assumption about its time-invariance is not too strict, and they converge at optimal rate.

Under this setup, Aït-Sahalia et al. (2010) develop a covariance estimator which is limited to the bivariate case. Starting from (4.3), they assume that $E\left(dW_t^1 dW_t^2\right) = \rho_t dt$ and that the noise ε_t in (4.3) is an i.i.d. 2-dimension vector with mean 0, diagonal variance-covariance matrix and finite fourth moment. The variance covariance estimator is then given by:

$$Cov\left(Y^1, Y^2\right) = \frac{1}{4}\left(Var\left(Y^1 + Y^2\right) - Var\left(Y^1 - Y^2\right)\right) \tag{4.19}$$

where $Var\,(.)$ denotes the QMLE of the quadratic variation that is obtained from (4.18).

The QMLE converges at a higher rate in comparison to both TSCV and MRK and it has the advantage of not requiring to set any tuning parameters as it happens for both the MRC and the MRK estimators. The main drawback of the QMLE estimator is that it is not guaranteed to be positive definite. To enforce it, it is possible to project the resulting symmetric matrix onto the space of positive semi-definite matrices, as already suggested by Hayashi and Yoshida (2005), for instance applying the transformation $\varphi(\rho) = (\rho \wedge 1) \vee (-1)$. In Hayashi and Yoshida (2005) it is stated that although this transformation can induce an extra bias, due to the continuing mapping theorem, the transformed correlation matrix is expected to properly estimate the true one on quite large samples.

4.2.2.6 Shephard and Xiu (2012)

Shephard and Xiu (2012) (SX henceforth) introduce an estimator for the covariance matrix which is positive definite and deals explicitly with both market microstructure noise and non-synchronicity. This estimator distinguishes itself from the previous ones as it does not require any data pre-synchronization. We will refer to it as SX.

To introduce Shephard and Xiu (2012) estimator, let's firstly define the ordered union of the all distinct times of trades as (t, i) with $i = 0, 1, ..., N$ and a $Z_{(t,i)}$ matrix of dimension $M_{(t,i)} \times M$, $0 \leq M_{(t,i)} \leq M$, associated with each time (t, i) accounting for the M assets traded at time (t, i). Moreover, the error term $\varepsilon_{(t,i)}$ in (4.3) is assumed to follow a normal distribution with zero mean and diagonal covariance matrix Λ.

Under this framework, Shephard and Xiu (2012) develop an estimator for the integrated covariance based on the maximization of a quasi-likelihood computed using a Kalman filter and a disturbance smoother. The optimization is carried out by iterating the EM algorithm until convergence.

Starting from (4.3) and indicating with $X_{(t,0):(t,N)} = \left(X_{(t,0)}, ..., X_{(t,N)}\right)'$ the vector of true efficient prices not contaminated by microstructure noise, the complete log-likelihood is defined as follows:

$$\begin{aligned}
&\log f\left(Y_{(t,0):(t,N)} | X_{(t,0):(t,N)}; \Lambda_t\right) + \log f\left(X_{(t,0):(t,N)}; \Sigma_t\right) = \\
&c - \frac{1}{2}\sum_{i=0}^{N} \log\left|Z_{(t,i)}\Lambda_t Z'_{(t,i)}\right| - \frac{1}{2}\sum_{i=0}^{N} \varepsilon'_{(t,i)}\left(Z_{(t,i)}\Lambda_t Z_{(t,i)}\right) \\
&-\frac{1}{2}(N-1)\log|\Sigma_t| - \frac{1}{2}\sum_{i=1}^{N} \frac{1}{\Delta^N_{(t,i)}} Y'_{(t,i)}\Sigma_t^{-1} Y_{(t,i)}
\end{aligned} \tag{4.20}$$

where $\Delta^N_{(t,i)}$ distance between two consecutive time ticks.

From the log-likelihood function (4.20), the two EM updates for the covariance matrix of prices Σ and noises Λ are obtained as:

$$\widehat{\Sigma_t} = \frac{1}{N-1}\sum_{i=0}^{N}\frac{1}{\Delta^N_{(t,i)}}\left\{\widehat{u}_{(t,i)|(t,N)}\widehat{u}'_{(t,i)|(t,N)} + U_{(t,i)|(t,N)}\right\} \tag{4.21}$$

$$diag\left(\widehat{\Lambda_t}\right) = \left(\sum_{i=0}^{N} Z'_{(t,i)}Z_{(t,i)}\right)^{-1} diag\left(\sum_{i=0}^{T} Z'_{(t,i)}\left\{\widehat{\varepsilon}_{(t,i)|(t,N)}\widehat{\varepsilon}'_{(t,i)|(t,N)} + D_{(t,i)|(t,N)}\right\}Z_{(t,i)}\right) \tag{4.22}$$

where quantities $\widehat{y}_{(t,i)|(t,N)}$, $U_{(t,i)|(t,N)}$, $\widehat{\varepsilon}_{(t,i)|(t,N)}$ and $D_{(t,i)|(t,N)}$ are obtained from the Kalman filter and the disturbance smoother that we briefly summarize. In the first step the Kalman filter is run forward in time taking the form:

$$\begin{aligned}
\varepsilon_{(t,i)} &= y_{(t,i)} - Z_{(t,i)}\widehat{x}_{(t,i)} \\
F_{(t,i)} &= Z_{(t,i)}\left(P_{(t,i)} + \Lambda_t\right)Z'_{(t,i)} \\
K_{(t,i)} &= P_{(t,i)}Z'_{(t,i)}F^{-1}_{(t,i)} \\
L_{(t,i)} &= I - K_{(t,i)}Z_{(t,i)} \\
\widehat{x}_{(t,i+1)} &= \widehat{x}_{(t,i)} + K_{(t,i)}\varepsilon_{(t,i)} \\
P_{(t,i+1)} &= P_{(t,i)}L'_{(t,i)} + \Delta^T_{(t,i+1)}\Sigma_t
\end{aligned}$$

The disturbance smoother (Durbin and Koopman (2001)) is then run backward through the data and it is specified as follows:

$$\begin{aligned}
H_{(t,i)} &= Z_{(t,i)}\Lambda_t Z'_{(t,i)} \\
\widehat{\varepsilon}_{(t,i)|(t,N)} &= H_{(t,i)}\left(F^{-1}_{(t,i)}\varepsilon_{(t,i)} - K'_{(t,i)}r_{(t,i)}\right) \\
D_{(t,i)|(t,N)} &= H_{(t,i)} - H_{(t,i)}\left(F^{-1}_{(t,i)} + K'_{(t,i)}R_{(t,i)}K_{(t,i)}\right)H_{(t,i)} \\
\widehat{u}_{(t,i)|(t,N)} &= \Delta^N_{(t,i)}\Sigma_t r_{(t,i-1)} \\
U_{(t,i)|(t,N)} &= \Delta^N_{(t,i)}\Sigma_t - \left(\Delta^N_{(t,i)}\right)^2\Sigma_t R_{(t,i-1)}\Sigma_t \\
r_{(t,i-1)} &= Z'_{(t,i)}F^{-1}_{(t,i)}v_{(t,i)} + L'_{(t,i)}r_{(t,i)} \\
R_{(t,i-1)} &= Z'_{(t,i)}F^{-1}_{(t,i)}Z_{(t,i)} + L'_{(t,i)}R_{(t,i)}L_{(t,i)}
\end{aligned}$$

Shephard and Xiu (2012) show that according to their methodology, synchronization is not needed as the distortion due to non-synchronicity is less important than the presence of noise, a result which is stated even in the univariate work by Aït-Sahalia et al. (2005) and Aït-Sahalia and Mykland (2003). Moreover, in their Monte Carlo experiment they show that besides being robust to microstructure noise and asynchronicity, their estimator works well in presence of assets with different degrees of liquidity.

4.3 Monte Carlo simulation

4.3.1 Simulation design

Following Barndorff-Nielsen et al. (2011) and Christensen et al. (2010), we consider the following bivariate factor stochastic volatility model:

$$dX^m_{(t,i)} = \mu^m d\,(t,i) + \rho^m \sigma^m_{(t,i)} dB^m_{(t,i)} + \sqrt{1-(\rho^m)^2}\sigma^m_{(t,i)} dW_{(t,i)} \quad m = 1,2 \tag{4.23}$$

where $E\left(dW_{(t,i)}dB^m_{(t,i)}\right) = 0$; $\rho^m \sigma^m_{(t,i)} dB^m_{(t,i)}$ the idiosyncratic component; $\sqrt{1-(\rho^m)^2}\sigma^m_{(t,i)} dW_{(t,i)}$ the common factor whose strength is determined by ρ^m. The spot volatility is modeled as $\sigma^m_{(t,i)} = \exp\left(\beta^m_0 + \beta^m_1 \varrho^m_{(t,i)}\right)$ with $d\varrho^m_{(t,i)} = \alpha^m \varrho^m_{(t,i)} d\,(t,i) + dB^m_{(t,i)}$ being an Ornstein-Uhlenbeck process. This implies that there is perfect correlation between the innovations $\rho^m \sigma^m_{(t,i)} dB^m_{(t,i)}$ and $\sigma^m_{(t,i)}$while the correlation between $dX^m_{(t,i)}$ and $d\varrho^m_{(t,i)}$ is given by ρ^m. The magnitude of correlation between the two underlying process $X^1_{(t,i)}$ and $X^2_{(t,i)}$ is $\sqrt{1-[\rho^1]^2}\sqrt{1-[\rho^2]^2}$.

The simulations are based on the following parameters $\mu^m = 0.03$, $\beta^m_0 = -5/16$, $\beta^m_1 = 1/8$, $\alpha^m = -1/40$, $\rho^m = -0.3$ for $m = 1,2$ and are the same as in Barndorff-Nielsen et al. (2011) and Christensen et al. (2010). According to these parameters it follows that $E\left(\int_0^1 [\sigma^m_s]^2 \, ds\right) = 1$.

We generate 1,000 possible daily paths for $X^m_{(t,i)}$, $m = 1,2$, using a standard Euler scheme, each simulation being started at $\varrho^m_0 \sim N(0,(-2\alpha^m)^{-1})$. Moreover, in order to avoid discretization errors, we employed the exact discretization for the Ornstein-Uhlenbeck (see for instance Glasserman 2004 p. 110). For simulation purposes, we consider a trading day of 7.5 hours, in line with the dataset used in the empirical exercise, and simulate prices at second frequency leading to 27,000 observations per day.

Once efficient prices were generated, we add microstructure noise simulated as:

$$U^m_{(t,i)}\left(\sigma^m_{(t,i)}, X^m_{(t,i)}\right) \sim N(0,\omega_2) \text{ with } \omega_2 = \xi^2 \sqrt{N^{-1}\sum_{i=0}^{N} \sigma^4_{(t,i)}(i/N)} \quad m = 1,2 \tag{4.24}$$

where ξ the signal-to-noise ratio accounting for the amount of microstructure noise. Eq. (4.24) implies that the variance of the noise process increases with the level of volatility of $X^m_{(t,i)}$ as documented in Bandi and Russel (2006).

The time series of synchronized prices generated up to now can be affected by noise simply adding $U^m_{(t,i)}$ in (4.24) to $X^m_{(t,i)}$ in (4.23). Finally, to introduce asynchronicity, we rely on two independent Poisson process sampling schemes with intensity λ_1 and λ_2, determining the average time elapsed between two consecutive prices.

4.3.2 Results

In our Monte Carlo experiment we are interested in comparing the performance of the alternative estimators presented in Section 4.2.2 combined with the synchronization schemes described in Section 4.2.1. Moreover we want to carry out this comparison we respect to alternative data generation assumptions, considering pairs of assets affected by a different degree of microstructure noise and with different degrees of liquidity.

With this purpose, our Monte Carlo exercise is organized as follows. We evaluate the behavior of the alternative integrated covariance estimators considering three different levels of microstructure noise: no noise, low noise and high noise obtained by setting ξ^2 in (4.24) to 0, 0.001 and 0.01 respectively . For all of these levels of signal-to-noise ratio, we carry out a full Monte Carlo comparison respectively reported in Tables 4.3.1 ($\xi^2 = 0$, no noise), 4.3.2 ($\xi^2 = 0.001$, low noise) and 4.3.3 ($\xi^2 = 0.1$, high noise). We evaluate the estimates obtained for the variance of X^1 and X^2, σ_{11}^2 and σ_{22}^2, their covariance, σ_{12}, and their correlation, ρ_{12}, under the assumption of different degrees of liquidity which are obtained by varying the values for the parameters λ_1 and λ_2 of the Poisson process sampling schemes. In particular we firstly evaluate the case of two assets with the same degree of liquidity by setting both λ_1 and λ_2 to 120, 10 and 3 implying one transaction every 120, 10 and 3 seconds respectively. In addition to that, we compare the behavior of the alternative estimators in presence of assets with different degrees of liquidity considering all the possible combinations of λ_1 and λ_2 obtaining (120,10), (120,3) and (10,3). For all the quantities of interest, σ_{11}^2, σ_{22}^2, σ_{12} and ρ_{12} and all the possible degrees of liquidity, we consider the synchronization schemes discussed in Section 4.2.1, namely Previous Tick, Refresh Time, Modified Refresh Time and Intersection, combined with the integrated covariance estimators presented in Section 4.2.2, namely RC, TSCV, MRC, MRK and QMLE. Apart we evaluate the SX estimator as it does not require data to be pre-synchronized. We avoid reporting the MRC-Psd as it roughly behaves like MRC. In all the Tables, the estimator with the lowest RMSE is highlighted in grey.

Table 4.3.1: **Monte Carlo simulation - No noise**

			Previous Tick					Refresh time					Modified refresh time					Intersection					
			RC	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**SX**
σ^2_{11}	(λ_1=120, λ_2=120)	Bias	-0.008	-0.146	-0.054	-0.010	-0.059	-0.007	-0.020	0.045	0.004	-0.059	-0.009	-0.020	0.045	0.003	-0.060	-0.008	-0.018	0.135	0.006	-0.057	-0.207
		RMSE	0.293	0.459	1.105	0.416	0.299	0.248	0.414	1.061	0.395	0.297	**0.244**	0.414	1.060	0.391	0.294	1.709	1.805	2.214	1.807	1.635	0.439
	(λ_1=10, λ_2=10)	Bias	-0.001	-0.049	0.098	0.005	-0.018	-0.001	-0.087	0.125	0.003	-0.018	-0.001	0.004	0.128	0.004	-0.018	0.000	-0.030	0.166	0.002	-0.014	-0.149
		RMSE	0.094	0.258	0.845	0.258	0.104	0.080	0.279	0.766	0.263	0.093	**0.078**	0.258	0.753	0.260	0.092	1.719	1.684	1.739	2.141	1.699	0.281
	(λ_1=3, λ_2=3)	Bias	0.000	-0.042	0.116	0.002	-0.011	0.000	-0.037	0.136	0.001	-0.009	0.000	-0.065	0.144	0.001	-0.008	0.000	-0.041	0.168	0.001	-0.008	0.169
		RMSE	0.054	0.243	0.660	0.237	0.072	0.049	0.241	0.623	0.236	0.056	**0.046**	0.251	0.612	0.230	0.054	1.718	1.652	2.139	1.728	1.703	0.304
	(λ_1=120, λ_2=10)	Bias	-0.020	-0.138	-0.052	0.000	-0.067	-0.012	-0.129	0.169	-0.004	-0.055	-0.012	-0.129	0.169	-0.004	-0.055	-0.017	-0.126	0.163	-0.005	-0.059	-0.165
		RMSE	0.324	0.420	1.103	0.391	0.349	**0.275**	0.386	1.093	0.343	0.307	**0.275**	0.386	1.093	0.343	0.307	1.672	1.566	2.285	1.774	1.618	0.333
	(λ_1=120, λ_2=3)	Bias	-0.014	-0.142	-0.051	-0.005	-0.066	0.001	-0.133	0.160	0.010	-0.044	0.001	-0.133	0.160	0.010	-0.044	-0.004	-0.130	0.155	0.006	-0.048	-0.127
		RMSE	0.268	0.457	1.098	0.433	0.314	**0.238**	0.395	1.007	0.387	0.269	**0.238**	0.395	1.007	0.387	0.269	1.723	1.590	2.220	1.833	1.646	0.250
	(λ_1=10, λ_2=3)	Bias	0.003	-0.049	0.097	0.005	-0.018	0.002	-0.061	0.167	0.004	-0.013	0.002	-0.100	0.169	0.005	-0.013	0.002	-0.054	0.175	0.005	-0.013	-0.039
		RMSE	0.076	0.258	0.843	0.258	0.104	**0.063**	0.265	0.674	0.258	0.081	**0.063**	0.292	0.668	0.258	0.077	1.731	1.639	2.161	1.743	1.700	0.080
σ^2_{22}	(λ_1=120, λ_2=120)	Bias	-0.040	-0.183	-0.093	-0.040	-0.098	-0.027	-0.049	0.019	-0.025	-0.083	-0.025	-0.049	0.018	-0.025	-0.083	1.585	7.057	8.812	6.791	1.599	-0.230
		RMSE	0.674	0.703	1.764	0.607	0.694	0.618	0.556	1.628	0.607	0.672	0.617	**0.555**	1.625	0.607	0.684	6.579	22.611	25.069	21.108	6.613	0.848
	(λ_1=10, λ_2=10)	Bias	-0.004	-0.075	0.110	-0.014	-0.024	-0.004	-0.114	0.142	-0.013	-0.023	-0.003	-0.015	0.143	-0.013	-0.023	2.003	11.205	13.407	11.478	2.006	-0.164
		RMSE	0.102	0.709	1.035	0.569	0.120	0.086	0.659	0.988	0.448	0.108	**0.080**	0.519	0.977	0.445	0.108	8.172	29.172	31.810	30.160	8.175	0.468
	(λ_1=3, λ_2=3)	Bias	-0.001	-0.064	0.130	-0.014	-0.012	0.000	-0.058	0.138	-0.014	-0.009	0.000	-0.088	0.141	-0.014	-0.010	1.574	7.580	9.447	7.997	1.575	0.192
		RMSE	0.051	0.514	0.905	0.406	0.065	0.048	0.466	0.821	0.374	0.055	**0.041**	0.508	0.788	0.367	0.052	7.070	22.076	29.049	23.125	7.071	0.522
	(λ_1=120, λ_2=10)	Bias	-0.023	-0.181	-0.095	-0.036	-0.104	-0.005	-0.163	0.193	-0.028	-0.064	-0.008	-0.163	0.193	-0.028	-0.065	0.146	0.270	0.769	0.468	0.148	-0.233
		RMSE	0.383	0.733	1.771	0.650	0.763	0.286	0.716	1.269	0.622	0.333	**0.275**	0.722	1.270	0.626	0.328	3.299	3.558	5.405	3.907	3.299	0.677
	(λ_1=120, λ_2=3)	Bias	-0.028	-0.180	-0.095	-0.036	-0.102	-0.017	-0.174	0.184	-0.019	-0.078	-0.017	-0.174	0.185	-0.019	-0.079	0.018	-0.067	0.330	0.097	-0.008	-0.173
		RMSE	0.539	0.732	1.767	0.657	0.706	0.329	0.671	1.248	0.586	0.693	**0.328**	0.673	1.248	0.589	0.683	2.690	2.597	3.864	2.860	2.535	0.476
	(λ_1=10, λ_2=3)	Bias	-0.005	-0.076	0.110	-0.015	-0.027	0.001	-0.089	0.177	-0.016	-0.018	-0.001	-0.133	0.176	-0.016	-0.020	0.529	1.722	2.381	1.893	0.528	-0.084
		RMSE	0.111	0.736	1.032	0.598	0.150	**0.070**	0.639	0.926	0.481	0.114	0.120	0.717	0.902	0.489	0.144	4.221	6.498	9.005	6.965	4.221	0.247
σ_{12}	(λ_1=120, λ_2=120)	Bias	-0.278	-0.126	-0.034	-0.045	-0.159	-0.192	-0.032	0.031	-0.018	-0.109	-0.196	-0.032	0.031	-0.018	-0.110	-0.003	0.840	1.144	0.826	0.021	-0.149
		RMSE	0.411	0.285	0.700	0.252	0.268	0.299	0.263	0.678	0.246	**0.201**	0.302	0.263	0.678	0.245	0.203	0.903	2.220	3.070	2.154	0.934	0.241
	(λ_1=10, λ_2=10)	Bias	-0.276	-0.040	0.068	-0.003	-0.151	-0.198	-0.065	0.084	-0.003	-0.100	-0.227	-0.004	0.085	-0.003	-0.114	-0.002	1.145	1.535	1.193	0.014	-0.106
		RMSE	0.385	0.160	0.540	0.149	0.214	0.279	0.170	0.481	0.147	**0.148**	0.319	0.152	0.472	0.147	0.165	0.901	2.484	3.418	2.543	0.923	0.156
	(λ_1=3, λ_2=3)	Bias	-0.279	-0.033	0.076	-0.002	-0.150	-0.162	-0.029	0.087	-0.002	-0.081	-0.254	-0.048	0.091	-0.003	-0.127	0.001	0.874	1.211	0.946	0.019	0.134
		RMSE	0.388	0.135	0.428	0.126	0.210	0.228	0.129	0.396	0.121	**0.117**	0.355	0.138	0.386	0.119	0.179	0.906	2.108	2.789	2.206	0.930	0.186
	(λ_1=120, λ_2=10)	Bias	-0.272	-0.123	-0.033	-0.040	-0.162	-0.050	-0.096	0.117	-0.010	-0.051	-0.055	-0.096	0.117	-0.010	-0.054	-0.010	-0.011	0.221	0.083	-0.008	-0.137
		RMSE	0.405	0.281	0.704	0.251	0.276	0.275	0.386	1.093	0.343	0.307	0.155	0.241	0.709	0.214	**0.154**	0.884	0.945	1.614	1.060	0.889	0.204
	(λ_1=120, λ_2=3)	Bias	-0.266	-0.121	-0.032	-0.037	-0.152	-0.015	-0.100	0.112	-0.002	-0.040	-0.020	-0.100	0.112	-0.002	-0.042	-0.005	-0.076	0.138	0.021	-0.025	-0.103
		RMSE	0.390	0.283	0.706	0.259	0.253	**0.120**	0.251	0.655	0.227	0.150	0.122	0.251	0.654	0.227	0.150	0.897	0.855	1.352	0.980	0.865	0.150
	(λ_1=10, λ_2=3)	Bias	-0.241	-0.039	0.067	-0.002	-0.129	-0.114	-0.047	0.108	-0.002	-0.057	-0.159	-0.074	0.109	-0.002	-0.080	0.000	0.257	0.480	0.315	0.013	-0.036
		RMSE	0.336	0.160	0.540	0.148	0.183	0.162	0.153	0.426	0.138	0.086	0.223	0.171	0.420	0.138	0.116	0.904	1.256	1.717	1.334	0.923	**0.056**
ρ_{12}	(λ_1=120, λ_2=120)	Bias	-0.384	-0.039	-0.029	-0.049	-0.159	-0.267	-0.017	-0.019	-0.023	-0.095	-0.271	-0.017	-0.019	-0.023	-0.097	-0.336	-0.150	-0.169	-0.156	-0.297	-0.014
		RMSE	0.392	0.066	0.141	0.069	0.185	0.274	0.047	0.106	0.045	0.121	0.278	0.047	0.106	0.045	0.122	0.340	0.172	0.249	0.170	0.306	**0.032**
	(λ_1=10, λ_2=10)	Bias	-0.383	-0.004	-0.010	-0.005	-0.193	-0.273	-0.002	-0.007	-0.002	-0.121	-0.313	-0.002	-0.007	-0.002	-0.141	-0.373	-0.161	-0.168	-0.162	-0.356	-0.007
		RMSE	0.384	0.022	0.066	0.021	0.197	0.273	0.020	0.055	0.019	0.125	0.314	0.021	0.054	0.019	0.144	0.374	0.167	0.199	0.167	0.359	**0.011**
	(λ_1=3, λ_2=3)	Bias	-0.389	-0.002	-0.006	-0.001	0.126	-0.225	-0.001	-0.005	-0.001	-0.104	-0.354	-0.001	-0.005	-0.001	-0.170	-0.330	-0.142	-0.147	-0.143	-0.311	0.022
		RMSE	0.389	0.016	0.050	0.015	0.202	0.225	0.015	0.045	**0.014**	0.106	0.354	0.015	0.043	0.014	0.171	0.330	0.146	0.171	0.146	0.315	0.022
	(λ_1=120, λ_2=10)	Bias	-0.368	-0.040	-0.030	-0.048	-0.152	-0.062	-0.006	-0.012	-0.006	-0.020	-0.068	-0.006	-0.012	-0.006	-0.022	-0.062	-0.055	-0.067	-0.055	-0.037	-0.015
		RMSE	0.375	0.065	0.142	0.067	0.179	0.067	0.038	0.078	0.033	0.037	0.073	0.038	0.078	0.033	0.038	0.067	0.078	0.130	0.073	0.054	**0.022**
	(λ_1=120, λ_2=3)	Bias	-0.364	-0.035	-0.028	-0.043	-0.142	-0.018	-0.004	-0.013	-0.004	-0.008	-0.025	-0.004	-0.013	-0.004	-0.011	-0.017	-0.019	-0.028	-0.018	-0.014	-0.011
		RMSE	0.371	0.062	0.140	0.063	0.168	0.025	0.036	0.079	0.031	0.025	0.031	0.036	0.079	0.031	0.026	0.025	0.045	0.089	0.040	0.031	**0.015**
	(λ_1=10, λ_2=3)	Bias	-0.334	-0.004	-0.010	-0.004	-0.163	0.000	0.000	0.000	0.000	0.000	-0.222	-0.001	-0.005	-0.001	-0.099	-0.165	-0.106	-0.114	-0.106	-0.142	0.006
		RMSE	0.335	0.022	0.066	0.020	0.167	1.251	0.218	0.476	0.201	0.665	0.222	0.019	0.044	0.018	0.103	0.165	0.112	0.143	0.111	0.147	**0.008**

Table 4.3.2: **Monte Carlo simulation - Low noise**

			Previous Tick					Refresh time					Modified refresh time					Intersection					
			RC	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**SX**
σ_{11}^2	(λ_1=120, λ_2=120)	Bias	0.135	-0.132	-0.049	0.006	-0.018	0.228	-0.127	0.068	0.014	-0.019	0.227	-0.127	0.068	0.013	-0.022	0.335	-0.168	0.158	0.019	-0.011	-0.188
		RMSE	0.756	0.419	1.114	0.405	0.417	1.246	0.384	1.051	0.383	**0.295**	1.254	0.384	1.049	0.386	0.300	3.304	1.527	2.217	1.873	1.752	0.386
	(λ_1=10, λ_2=10)	Bias	1.745	-0.039	0.100	0.021	0.088	2.571	-0.072	0.126	0.014	-0.005	2.656	-0.114	0.129	0.015	-0.004	3.790	0.002	0.164	0.018	-0.002	-0.098
		RMSE	8.604	0.252	0.842	0.268	0.299	12.731	0.254	0.774	0.256	0.207	13.156	0.283	0.765	0.250	**0.195**	20.1	1.762	2.145	1.796	1.705	0.208
	(λ_1=3, λ_2=3)	Bias	5.802	-0.021	0.120	0.018	0.167	8.061	-0.036	0.132	0.014	0.003	8.671	0.012	0.142	0.014	0.004	11.284	-0.013	0.166	0.013	0.002	-0.038
		RMSE	28.623	0.230	0.662	0.247	0.456	39.271	0.224	0.614	0.238	0.170	42.090	0.242	0.605	0.238	0.157	56.479	1.748	2.137	1.779	1.726	**0.088**
	(λ_1=120, λ_2=10)	Bias	0.143	-0.135	-0.053	0.010	-0.014	0.336	-0.225	0.166	0.007	-0.010	0.336	-0.225	0.166	0.007	-0.010	0.326	-0.228	0.160	0.003	-0.019	-0.123
		RMSE	0.802	0.427	1.114	0.425	0.405	1.607	0.481	0.999	0.396	0.347	1.607	0.481	0.999	0.396	0.347	3.162	1.410	2.261	1.849	1.770	**0.279**
	(λ_1=120, λ_2=3)	Bias	13.854	0.926	0.033	1.690	0.366	33.486	0.828	0.128	1.574	0.038	33.486	0.828	0.128	1.574	0.038	33.5	0.829	0.123	1.573	0.035	0.626
		RMSE	62.219	4.728	1.539	7.553	2.323	167.4	4.540	1.191	7.717	**0.691**	167.4	4.540	1.191	7.717	**0.691**	168.7	6.013	2.248	9.163	1.964	1.467
	(λ_1=10, λ_2=3)	Bias	177	1.852	0.254	1.658	0.361	369	1.695	0.144	1.231	0.007	378	1.801	0.164	1.199	0.007	393	1.738	0.159	1.220	0.009	0.153
		RMSE	898	9.453	1.190	8.171	1.144	1863	8.571	0.873	5.825	0.414	1905	8.777	0.874	5.678	**0.391**	1981	10.122	2.077	7.458	1.765	0.568
σ_{22}^2	(λ_1=120, λ_2=120)	Bias	0.347	-0.155	-0.099	-0.001	0.001	0.663	-0.144	0.045	0.027	-0.011	0.663	-0.144	0.045	0.027	-0.011	2.934	7.641	11.6	10.459	2.953	-0.176
		RMSE	5.119	0.545	1.862	0.660	0.591	11.741	0.531	1.450	0.595	0.700	11.741	0.531	1.450	0.595	0.700	23.437	38.025	43.840	51.731	23.541	**0.442**
	(λ_1=10, λ_2=10)	Bias	4.456	-0.046	0.113	0.025	0.100	6.650	-0.086	0.152	0.014	-0.027	7.005	-0.133	0.153	0.017	-0.026	11.928	29.9	39.7	29.9	11.9	-0.114
		RMSE	72.780	0.412	1.025	0.360	0.368	109.2	0.441	1.044	**0.323**	0.429	116.9	0.489	1.025	0.343	0.400	173.7	352.8	514.4	349.0	173.7	0.331
	(λ_1=3, λ_2=3)	Bias	15.746	-0.019	0.133	0.017	0.166	21.643	-0.032	0.135	0.011	-0.018	23.231	0.017	0.138	0.009	-0.022	32.481	43.582	45.150	44.996	32.495	-0.050
		RMSE	263	0.401	0.917	0.291	0.462	360	0.439	0.811	0.280	0.359	385	0.422	0.770	0.255	0.450	533	627	514	646	533	**0.190**
	(λ_1=120, λ_2=10)	Bias	0.452	-0.158	-0.091	0.003	-0.043	0.870	-0.271	0.135	-0.016	-0.043	0.869	-0.270	0.134	-0.012	-0.042	1.067	0.857	1.975	1.467	1.076	-0.136
		RMSE	7.913	0.565	1.743	0.674	0.534	13.993	0.876	1.326	0.490	0.879	13.940	0.847	1.359	0.465	0.804	17.3	15.5	23.7	20.8	17.4	**0.388**
	(λ_1=120, λ_2=3)	Bias	46.563	1.828	-0.233	3.102	0.016	87.99	2.418	0.278	4.419	-0.040	88.2	2.178	0.298	4.164	-0.036	90	65	76	77	75	0.246
		RMSE	850	28	5.871	47	1.623	1487	48	6.183	84	**1.613**	1499	39	6.800	73	2.173	1568	1284	1338	1507	1427	2.823
	(λ_1=10, λ_2=3)	Bias	528.6	4.998	0.232	3.914	0.007	1019	4.845	0.225	3.398	0.045	1023	4.899	0.092	3.168	0.029	1068	958	981	1002	1068	0.157
		RMSE	8603	87.6	4.054	69.070	0.920	17493	84.874	1.820	57.8	1.033	17430	82.647	2.227	51.433	**0.879**	18188	17341	14581	18039	18195	1.224
σ_{12}	(λ_1=120, λ_2=120)	Bias	-0.241	-0.121	-0.033	-0.044	-0.102	-0.223	-0.109	0.045	-0.018	-0.065	-0.229	-0.109	0.045	-0.019	-0.067	0.000	0.703	1.394	1.034	0.071	-0.138
		RMSE	0.370	0.277	0.702	0.247	0.195	0.348	0.256	0.676	0.239	**0.175**	0.355	0.257	0.675	0.239	0.179	0.919	2.049	3.520	2.508	1.058	0.218
	(λ_1=10, λ_2=10)	Bias	-0.282	-0.039	0.067	-0.003	0.005	-0.192	-0.059	0.087	-0.003	-0.007	-0.224	-0.088	0.088	-0.003	-0.007	-0.006	1.146	1.470	1.159	0.194	-0.074
		RMSE	0.395	0.162	0.534	0.150	0.095	0.289	0.165	0.505	0.143	0.080	0.337	0.184	0.498	0.141	**0.077**	0.874	2.471	3.143	2.483	1.288	0.103
	(λ_1=3, λ_2=3)	Bias	-0.274	-0.033	0.076	-0.003	0.060	-0.168	-0.041	0.085	-0.003	-0.001	-0.263	-0.009	0.090	-0.003	-0.001	-0.003	0.859	1.153	0.913	0.291	-0.032
		RMSE	0.395	0.136	0.428	0.126	0.137	0.265	0.138	0.390	0.124	0.062	0.387	0.125	0.382	0.122	0.060	0.924	2.096	2.942	2.169	1.482	**0.054**
	(λ_1=120, λ_2=10)	Bias	-0.238	-0.123	-0.033	-0.038	-0.106	-0.060	-0.168	0.105	-0.018	-0.025	-0.063	-0.168	0.105	-0.018	-0.025	-0.017	-0.087	0.243	0.086	0.013	-0.095
		RMSE	0.351	0.290	0.710	0.269	0.190	1.607	0.481	0.999	0.396	0.347	0.162	0.288	0.595	0.209	0.165	0.883	0.841	1.593	1.073	0.941	**0.134**
	(λ_1=120, λ_2=3)	Bias	-0.291	-0.116	-0.035	-0.027	0.084	0.032	-0.088	0.098	0.003	0.012	-0.086	-0.081	0.103	0.012	0.025	-0.012	-0.122	0.078	-0.045	0.005	0.204
		RMSE	2.218	0.466	0.701	0.550	0.786	2.328	0.360	0.658	0.451	0.372	4.977	**0.325**	0.730	0.357	0.359	1.958	0.990	2.643	1.104	1.605	0.352
	(λ_1=10, λ_2=3)	Bias	0.040	-0.040	0.066	-0.005	0.091	0.065	-0.054	0.111	-0.003	0.001	-0.016	0.000	0.110	-0.005	-0.001	0.127	0.168	0.378	0.182	0.044	0.049
		RMSE	10.077	0.229	0.519	0.213	0.303	8.039	0.184	0.444	0.252	0.170	11.325	0.173	0.412	0.216	0.165	5.432	2.817	6.288	3.431	4.428	**0.145**
ρ_{12}	(λ_1=120, λ_2=120)	Bias	-0.352	-0.036	-0.029	-0.048	-0.117	-0.348	-0.022	-0.017	-0.030	-0.079	-0.355	-0.023	-0.017	-0.030	-0.082	-0.404	-0.134	-0.136	-0.150	-0.329	-0.021
		RMSE	0.360	0.064	0.143	0.070	0.148	0.355	0.050	0.101	0.050	0.112	0.362	0.050	0.101	0.050	0.114	0.408	0.153	0.205	0.165	0.348	**0.037**
	(λ_1=10, λ_2=10)	Bias	-0.544	-0.008	-0.011	-0.010	-0.071	-0.500	-0.005	-0.007	-0.006	-0.007	-0.531	-0.005	-0.007	-0.006	-0.009	-0.558	-0.217	-0.220	-0.218	-0.338	-0.008
		RMSE	0.550	0.024	0.066	0.024	0.089	0.512	0.022	0.055	0.021	0.030	0.541	0.022	0.054	0.021	0.034	0.565	0.232	0.262	0.233	0.397	**0.013**
	(λ_1=3, λ_2=3)	Bias	-0.663	-0.008	-0.007	-0.006	-0.035	-0.637	-0.007	-0.005	-0.004	0.000	-0.696	-0.007	-0.005	-0.004	0.000	-0.666	-0.267	-0.277	-0.266	-0.335	-0.002
		RMSE	0.670	0.020	0.050	0.018	0.046	0.647	0.019	0.045	0.016	0.016	0.702	0.019	0.042	0.016	0.017	0.674	0.288	0.319	0.287	0.424	**0.006**
	(λ_1=120, λ_2=10)	Bias	-0.357	-0.040	-0.029	-0.048	-0.115	-0.152	-0.009	-0.011	-0.011	-0.012	-0.157	-0.009	-0.011	-0.011	-0.013	-0.145	-0.087	-0.098	-0.087	-0.070	-0.016
		RMSE	0.364	0.066	0.142	0.068	0.145	0.170	0.038	0.072	0.034	0.043	0.174	0.038	0.072	0.034	0.044	0.161	0.114	0.161	0.110	0.106	**0.024**
	(λ_1=120, λ_2=3)	Bias	-0.759	-0.242	-0.042	-0.288	-0.038	-0.762	-0.201	-0.005	-0.253	-0.012	-0.760	-0.199	0.017	-0.250	-0.007	-0.760	-0.551	-0.522	-0.562	-0.493	-0.005
		RMSE	0.770	0.290	0.177	0.332	0.131	0.771	0.246	0.087	0.296	0.094	0.770	0.243	0.717	0.293	0.089	0.769	0.593	0.628	0.598	0.551	**0.039**
	(λ_1=10, λ_2=3)	Bias	-0.886	-0.288	-0.029	-0.245	-0.019	0.000	0.000	0.000	0.000	0.000	-0.895	-0.273	-0.003	-0.213	-0.002	-0.892	-0.748	-0.720	-0.741	-0.729	-0.001
		RMSE	0.887	0.326	0.085	0.284	0.088	6.692	3.602	0.610	2.866	0.649	0.895	0.310	0.030	0.251	0.056	0.892	0.758	0.761	0.752	0.748	**0.014**

Table 4.3.3: **Monte Carlo simulation - High noise**

			Previous Tick					Refresh time					Modified refresh time					Intersection					
			RC	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**RC**	**MRC**	**TSCV**	**MRK**	**QMLE**	**SX**
σ^2_{11}	(λ_1=120, λ_2=120)	Bias	15.008	0.974	-0.003	1.770	0.222	22.130	0.954	-0.014	1.523	0.009	22.3	0.943	-0.020	1.564	0.005	34.345	0.741	0.150	1.679	0.010	-0.018
		RMSE	73.397	5.401	1.192	9.475	1.684	105.7	4.711	1.045	7.470	0.807	106	4.723	1.014	7.806	0.816	165.6	5.701	2.245	9.812	1.843	**0.505**
	(λ_1=10, λ_2=10)	Bias	175.7	1.820	0.246	1.619	0.315	263	1.792	0.128	1.242	0.003	272	1.724	0.130	1.213	0.001	391	1.710	0.173	1.192	0.014	0.116
		RMSE	866.5	8.861	1.263	7.603	0.897	1284	8.777	0.874	6.113	**0.454**	1336	8.568	0.873	5.791	0.473	1902	10.016	2.168	7.296	1.789	0.474
	(λ_1=3, λ_2=3)	Bias	579	1.886	0.360	1.467	0.419	809	1.726	0.134	1.067	0.013	870	1.779	0.149	1.026	0.011	1132	1.732	0.162	0.991	0.006	0.116
		RMSE	2823	9.528	1.543	7.355	0.977	3988	8.559	0.683	4.993	**0.271**	4260	8.639	0.653	4.811	0.275	5571	9.852	2.117	6.185	1.744	0.414
	(λ_1=120, λ_2=10)	Bias	14.599	0.945	0.004	1.675	0.314	34.2	0.753	0.187	1.603	0.039	34.2	0.753	0.187	1.603	0.039	34.1	0.757	0.180	1.605	0.033	0.051
		RMSE	77.0	5.531	1.291	8.606	1.830	170	4.759	1.161	8.255	0.787	170.1	4.759	1.161	8.255	0.787	171	6.143	2.376	9.821	1.973	**0.536**
	(λ_1=120, λ_2=3))	Bias	13.869	1.602	0.002	1.558	0.250	32.0	1.575	0.124	1.554	0.012	32.0	1.575	0.124	1.554	0.012	31.8	1.578	0.119	1.561	0.011	0.142
		RMSE	66.8	8.703	1.204	8.483	1.332	155	8.644	1.004	8.123	0.804	155	8.644	1.004	8.123	0.804	155	10.025	2.166	9.597	2.041	**0.718**
	(λ_1=10, λ_2=3)	Bias	176	1.814	0.241	1.701	0.335	365	1.687	0.151	1.236	0.004	376	1.781	0.140	1.213	0.004	391	1.710	0.160	1.212	0.003	0.149
		RMSE	864.7	9.102	1.131	8.675	0.800	1776	8.453	0.721	5.964	**0.369**	1834	8.672	0.810	5.870	0.376	1913	9.999	2.120	7.317	1.734	0.571
σ^2_{22}	(λ_1=120, λ_2=120)	Bias	36.6	3.687	0.134	5.763	0.172	57.925	3.054	0.128	5.092	-0.044	59.2	3.167	0.149	5.161	-0.047	84.4	128.8	171.4	170.1	84.761	0.013
		RMSE	579	84	3.734	123	2.650	966	61	3.373	100	2.337	1001	65	4.026	102	2.321	1274	1464	1735	1959	1279	**1.154**
	(λ_1=10, λ_2=10)	Bias	459.1	5.147	0.519	4.854	0.505	707.9	4.747	0.212	3.331	-0.006	726.5	4.559	0.220	3.196	-0.002	1062	1874	1987	2045	1063	0.202
		RMSE	7583	85.7	6.558	79.9	2.052	11711	77.513	2.873	54.513	0.540	11967	73.5	3.454	50.8	**0.532**	17643	31654	29238	34176	17649	1.789
	(λ_1=3, λ_2=3)	Bias	1586	5.024	0.745	3.782	0.467	2214	4.646	0.039	2.806	0.006	2378	4.669	0.000	2.682	0.003	3086	3589	4024	3710	3086	0.176
		RMSE	26770	84.735	10.334	60.145	2.210	37473	78.767	2.819	46.704	0.584	40209	76.867	4.399	43.341	**0.416**	52152	62521	68175	64599	52170	1.476
	(λ_1=120, λ_2=10)	Bias	46.8	2.756	-0.219	4.418	0.001	94.6	2.291	0.223	4.395	-0.038	94.3	2.375	0.297	4.239	-0.034	91.4	70.2	137.9	86.2	89.5	0.017
		RMSE	819	57	3.947	85	2.479	1631	45	2.577	79	1.941	1638	47	3.894	75	2.233	1517	1134	2814	1350	1471	**0.591**
	(λ_1=120, λ_2=3)	Bias	44.2	4.151	0.078	3.357	-0.003	80.3	3.997	0.189	3.868	-0.042	85.5	4.121	0.231	3.832	-0.036	83.0	52.7	73.4	60.8	64.8	0.187
		RMSE	753	69.495	4.226	54.4	**1.347**	1191	61.0	1.924	61.5	2.313	1392	65.3	1.853	57.6	2.288	1303	811	1089	943	1086	1.670
	(λ_1=10, λ_2=3)	Bias	543	4.615	0.057	3.391	0.002	963.9	4.702	0.217	3.224	0.017	994	4.725	0.160	3.145	0.005	1032	934	1296	980	1032	0.156
		RMSE	9089	76.9	1.916	54.9	0.665	15837	82.1	2.210	55.5	0.850	16261	79.5	0.943	54.0	**0.514**	16875	15725	23009	16311	16882	1.090
σ_{12}	(λ_1=120, λ_2=120)	Bias	-0.283	-0.131	-0.031	-0.057	0.110	-0.184	-0.040	0.005	-0.016	0.006	-0.192	-0.046	0.003	-0.012	0.006	-0.087	0.732	1.756	0.998	0.290	-0.029
		RMSE	1.339	0.385	0.820	0.494	0.965	1.983	0.341	0.605	0.476	0.403	1.765	0.337	0.607	0.483	0.421	1.413	2.479	6.835	2.835	2.046	**0.276**
	(λ_1=10, λ_2=10)	Bias	-0.177	-0.036	0.065	-0.003	0.217	-0.175	0.002	0.086	0.001	0.001	-0.199	-0.031	0.087	0.002	0.002	0.048	1.161	1.854	1.275	0.415	0.044
		RMSE	7.936	0.209	0.540	0.293	0.490	10.324	0.196	0.487	0.204	0.197	7.970	0.184	0.465	0.204	0.193	7.256	4.090	10.884	4.349	4.411	**0.176**
	(λ_1=3, λ_2=3)	Bias	-0.182	-0.036	0.073	-0.001	0.248	-0.246	-0.046	0.086	-0.001	-0.004	-0.760	-0.012	0.090	0.000	-0.001	-0.042	0.804	1.190	0.858	0.227	0.044
		RMSE	7.655	0.171	0.389	0.217	0.397	9.430	0.184	0.378	0.175	0.133	19.111	0.155	0.396	0.171	**0.128**	8.505	3.830	10.220	3.886	8.176	0.147
	(λ_1=120, λ_2=10)	Bias	-0.217	-0.128	-0.041	-0.045	0.060	-0.110	-0.127	0.114	-0.012	0.012	-0.149	-0.124	0.115	-0.007	0.015	-0.039	-0.040	0.164	0.100	0.090	-0.003
		RMSE	1.831	0.390	0.767	0.430	0.671	170	4.759	1.161	8.255	0.787	3.083	0.303	0.652	0.359	0.375	1.853	1.858	4.779	2.148	1.782	**0.180**
	(λ_1=120, λ_2=3)	Bias	-0.205	-0.102	-0.034	-0.046	0.046	-0.121	-0.108	0.089	-0.026	0.002	-0.149	-0.103	0.092	-0.018	0.012	-0.158	-0.096	0.130	-0.005	0.037	0.059
		RMSE	1.522	0.335	0.643	0.373	0.441	2.180	0.365	0.579	0.443	0.375	2.646	0.390	0.623	0.485	0.399	2.172	1.039	2.608	1.182	1.463	**0.192**
	(λ_1=10, λ_2=3)	Bias	-0.293	-0.037	0.066	-0.001	0.093	0.099	-0.062	0.102	-0.016	-0.006	0.153	-0.013	0.106	-0.016	-0.006	0.146	0.246	0.340	0.280	0.472	0.047
		RMSE	5.567	0.193	0.529	0.261	0.287	6.756	0.179	0.415	0.218	0.168	5.767	0.160	0.409	0.222	0.168	4.935	2.297	4.722	2.565	6.100	**0.146**
ρ_{12}	(λ_1=120, λ_2=120)	Bias	-0.783	-0.255	-0.049	-0.305	-0.049	-0.771	-0.210	-0.013	-0.269	-0.016	-0.774	-0.211	-0.013	-0.270	-0.015	-0.789	-0.488	-0.428	-0.516	-0.452	-0.010
		RMSE	0.791	0.302	0.176	0.349	0.138	0.781	0.259	0.081	0.315	0.104	0.783	0.260	0.145	0.316	0.100	0.794	0.522	0.521	0.545	0.553	**0.056**
	(λ_1=10, λ_2=10)	Bias	-0.888	-0.296	-0.054	-0.267	-0.023	-0.893	-0.276	-0.005	-0.221	-0.004	-0.895	-0.282	-0.005	-0.218	-0.003	-0.894	-0.708	-0.674	-0.699	-0.686	-0.003
		RMSE	0.888	0.333	0.103	0.306	0.082	0.893	0.313	0.064	0.259	0.060	0.895	0.319	0.064	0.256	0.061	0.894	0.720	0.715	0.712	0.727	**0.020**
	(λ_1=3, λ_2=3)	Bias	0.904	0.329	0.105	0.281	0.061	-0.903	-0.282	-0.005	-0.198	-0.002	-0.905	-0.276	-0.005	-0.193	-0.001	-0.904	-0.779	-0.759	-0.770	-0.776	-0.001
		RMSE	8667	28.130	8.375	23.404	9.555	0.903	0.319	0.044	0.235	0.048	0.905	0.312	0.050	0.230	0.047	0.904	0.785	0.787	0.777	0.796	**0.012**
	(λ_1=120, λ_2=10)	Bias	-0.759	-0.245	-0.040	-0.291	-0.047	-0.773	-0.208	-0.009	-0.260	-0.011	-0.774	-0.208	-0.010	-0.260	-0.010	-0.766	-0.568	-0.530	-0.583	-0.505	-0.004
		RMSE	0.770	0.290	0.165	0.334	0.131	0.782	0.253	0.100	0.305	0.094	0.783	0.252	0.095	0.304	0.089	0.774	0.604	0.624	0.613	0.561	**0.032**
	(λ_1=120, λ_2=3)	Bias	-0.758	-0.331	-0.035	-0.287	-0.035	-0.765	-0.301	-0.004	-0.257	-0.009	-0.768	-0.300	-0.006	-0.255	-0.008	-0.762	-0.563	-0.488	-0.553	-0.476	-0.001
		RMSE	0.768	0.369	0.165	0.330	0.122	0.775	0.343	0.174	0.303	0.092	0.777	0.341	0.179	0.300	0.090	0.772	0.595	0.587	0.585	0.526	**0.013**
	(λ_1=10, λ_2=3)	Bias	-0.888	-0.290	-0.030	-0.248	-0.021	0.000	0.000	0.000	0.000	0.000	-0.895	-0.275	-0.001	-0.216	-0.001	-0.892	-0.752	-0.735	-0.743	-0.729	-0.002
		RMSE	0.889	0.327	0.093	0.288	0.087	6.690	3.645	0.577	3.002	0.649	0.896	0.313	0.067	0.256	0.056	0.892	0.761	0.770	0.753	0.748	**0.014**

Starting from Table 4.3.1, we provide evidence that, in absence of microstructure noise, the best estimator for the two variances σ_{11}^2 and σ_{22}^2 is the RC by Barndorff-Nielsen and Shephard (2004) combined with the Modified Refresh Time synchronization scheme for all the alternative degrees of liquidity taken into consideration. When moving to the covariance σ_{12}, the RC is no longer the best estimator as the QMLE presents now the lowest RMSE for almost all the alternative degrees of liquidity evaluated, exception made for the case of ($\lambda_1 = 120$, $\lambda_2 = 3$) and ($\lambda_1 = 10, \lambda_2 = 3$) when the RC and the SX estimator are the best ones respectively. Even for the case of covariance, the best synchronization schemes are the two versions of Refresh Time. Finally, focusing on the correlation coefficient ρ_{12}, the SX estimator is the one with the lowest RMSE for all the possible values of λ_1 and λ_2 exception made for the case of two assets with the same average elapsed time between two transactions equal to 3 seconds. It is interesting to note that, when considering the two variances, the SX estimator has a relative large RMSE due to a negative bias while, when evaluating the correlation coefficient, this estimator becomes the preferred one as the bias is averaged out. In addition to that, we want to highlight the fact that neither the Previous Tick nor the Intersection resampling schemes are ever selected by the RMSE criteria.

Moving now to Table 4.3.2, we evaluate the behavior of the alternative estimators and resampling schemes when some degree of noise is introduced by setting ξ^2 to 0.001. The first result to be highlighted is that when some noise is added, the RC is no longer the best estimator, neither for the two variances. This result was almost expected as we know that RC is not robust to microstructure noise. Instead, the two best estimators turned out to be the QMLE and the SX. In particular, focusing on variances σ_{11}^2 and σ_{22}^2, we see that the SX estimator performs particularly well in presence of two assets with the same high degree of liquidity ($\lambda_1 = 3$, $\lambda_2 = 3$) and when two assets have a different degree of liquidity equal to ($\lambda_1 = 120$, $\lambda_2 = 10$). In all the other cases the QMLE presents the smallest RMSE. Similarly to Table 4.3.1, we can see that the main drawback of the SX estimator is that it is downward bias in most cases while the bias becomes positive for ($\lambda_1 = 120$, $\lambda_2 = 10$) and ($\lambda_1 = 10$, $\lambda_2 = 3$). Moving to the covariance σ_{12}, we identify a clearer pattern in favour of the SX estimator as more data become available, although it remains biased; in fact this estimator presents the lowest RMSE for ($\lambda_1 = 3$, $\lambda_2 = 3$), ($\lambda_1 = 120$, $\lambda_2 = 10$) and ($\lambda_1 = 10$, $\lambda_2 = 3$) while for ($\lambda_1 = 120$, $\lambda_2 = 120$) and ($\lambda_1 = 10$, $\lambda_2 = 10$) the best estimator turned out to be the QMLE one and for ($\lambda_1 = 120$, $\lambda_2 = 3$) the MRK. Finally, when considering the correlation coefficient ρ_{12}, the SX estimator is always the best one regardless from the degree of liquidity of the assets. Note that here the bias becomes extremely low confirming the idea that when computing ρ_{12} the bias affecting variances and covariance is averaged out. As per the synchronization schemes, even in Table 4.3.2 we never find support to the Previous Tick nor to the Intersection scheme.

Finally, in Table 4.3.3 we analyze the case of high noise obtained by setting $\xi^2 = 0.1$. The Monte Carlo simulations show results which are very close to those already discussed in Table 4.3.2. In fact, the two estimators presenting the lowest RMSE are still the QMLE and the SX. In particular, the two estimators are almost equivalent when focusing on variances as, for the six alternative degrees of liquidity, they alternate themselves as the best estimator with the SX still showing some bias problems. Anyway, when moving to covariance, the SX dominates the QMLE when the two assets are either very liquid ($\lambda_1 = 3, \lambda_2 = 3$) or when they show a high degree of asynchronicity ($\lambda_1 = 120, \lambda_2 = 10$), ($\lambda_1 = 120, \lambda_2 = 3$) and ($\lambda_1 = 10, \lambda_2 = 3$). Finally, as already seen in the case of no and low noise, when turning to the correlation coefficient the SX estimator is by far the best one. Again, neither the Previous Tick nor the Intersection synchronization schemes are ever selected.

The overall Monte Carlo exercise gives us some very useful insights about the alternative synchronization schemes and integrated covariance estimators. Firstly, Refresh Time schemes dominate by far both the Previous Tick as well as the Intersection schemes indicating that when adopting one of the integrated covariance estimator requiring synchronized data, the Refresh Time schemes should be adopted. In addition to that, we provide evidence that regardless from the degree of microstructure noise affecting asset prices and the different degrees of liquidity, the SX estimator is the one providing the best estimate for the correlation coefficient. Anyway, when focusing on variances and covariances, the SX estimator is found to be biased, result which was shown even in Shephard and Xiu (2012) where it is claimed that a more sophisticated model of market microstructure noise is needed. In the cases when the SX fails, two other estimators turned out to be the best ones in terms of the lowest RMSE that are the Realized Covariance, in the case of absence of noise, and the QMLE in case of low and high noise. The other three integrated covariance estimators, namely the MRC, the TSCV and the MRK are clearly dominated by the RC, the QMLE and the SX, each one in the cases just described.

4.4 Empirical application

In order to compare the alternative integrated covariance estimators, we now propose an application aimed at assessing their performance in a comprehensive risk management exercise.

With this purpose, the first step is to compute the profit and loss distribution. Given that we are evaluating 10-year benchmark government bonds rather than specific bonds for each country, we cannot use the price time series as we would face the issues connected to the change in the benchmark bond during the time-span analyzed. Therefore we use a "zero-coupon bond approximation" consisting in treating the set of coupon bonds as if they were zero-coupon bonds and get prices through the standard yield-to-price formula:

$$100 = Y_t^m \left(1 + YTM_t^m\right)^{10} \tag{4.25}$$

where YTM_t is the closing yield to (constant) maturity at day t for country m.

Given the time series of daily price Y_t, we consider a portfolio constituted by one bond for each country so that the portfolio value at each time t is given by:

$$Y_t^* = \sum_{m=1}^{M} Y_t^m \tag{4.26}$$

and the profit and loss distribution can be obtained as the simple difference between the daily values of the portfolio.

To compute the Value at Risk (VaR) of Y_t^*, we have to compute the VaR of each bond position m that is given by:

$$VaR_t^m\left(\alpha\right) = Y_t^m MD_t^m \sigma_t^m \Phi^{-1}(1-\alpha) \tag{4.27}$$

where MD_t^m is the modified duration of the benchmark bond in country m at day t; σ_t^m is the standard deviation obtained from one of the possible integrated covariance estimator taken into consideration; $\Phi^{-1}(1-\alpha)$ denotes the $(1-\alpha)$-th percentile of the normal distribution. Given the value-at-risk for the position in the m-th bond, VaR^m, the VaR^* portfolio can be computed as

$$VaR_t^*\left(\alpha\right) = VaR_t\left(\alpha\right) \Sigma_t VaR_t^{'}\left(\alpha\right) \tag{4.28}$$

where Σ_t is the correlation matrix obtained from one of the possible integrated correlation estimators.

4.4.1 Backtesting procedures

4.4.1.1 Unilevel VaR tests

We start by recalling the most famous backtesting procedures for the Value-at-Risk, namely the unconditional coverage (uc), the independence (ind), the conditional coverage (cc) and the Weibull duration tests introduced by Christoffersen (1998) and Christoffersen and Pelletier (2004).

The uc, ind, and cc tests. Given the vector of log-returns $y_t = Y_t - Y_{t-1}$, the hit sequence of VaR violations defined as

$$I_t = \begin{cases} 1 & \text{if } y_t < -VaR_t(\alpha) \\ 0 & \text{otherwise} \end{cases} \tag{4.29}$$

In the *uc* test, the null hypothesis under investigation is that the sequence I_t is i.i.d. Bernoulli with parameter $(1-\alpha)$ against the alternative that Bernoulli parameter is $\widehat{\pi}_1$, where $\widehat{\pi}_1$ is the empirical ratio of violations $T1/T$ where $T1$ number of days with violations. If the VaR method is correct, then the empirical failure rate $\widehat{\pi}$ must be equal to $(1-\alpha)$. As the likelihood function of a Bernoulli variable z with parameter p is given by:

$$L(z;p) = (1-p)^{T-T1}p^{T1} \tag{4.30}$$

the likelihood ratio test of the *uc* test is then defined as:

$$LR_{uc} = 2\left(\ln L(z;\widehat{\pi}_1) - \ln L(z;p)\right) \sim \chi^2_1. \tag{4.31}$$

The *ind* test explicitly evaluates the assumption of independence of the hit sequence I_t:

$$H_{0,ind} : \pi_{01} = \pi_{11} \tag{4.32}$$

where π_{rs} is the probability of a r at day $t-1$ being followed by a s at day t.

The alternative hypothesis here is that the hit sequence I_t follows a first-order Markov sequence with switching probability matrix:

$$\Pi = \begin{bmatrix} 1-\pi_{01} & \pi_{01} \\ 1-\pi_{11} & \pi_{11} \end{bmatrix}.$$

The test statistic is then defined as:

$$LR_{ind} = 2\left(\ln L(z;\widehat{\pi}_{01},\widehat{\pi}_{11}) - \ln L(z;\widehat{\pi}_1)\right) \sim \chi^2_1 \tag{4.33}$$

where

$$L(z;\pi_{01},\pi_{11}) = (1-\pi_{01})^{T0-T01}\pi_{01}^{T01}(1-\pi_{11})^{T1-T11}\pi_{11}^{T11} \tag{4.34}$$

with T_{rs} number of observations with a r followed by a s; $\widehat{\pi}_{01} = T01/T0$; $\widehat{\pi}_{11} = T11/T1$.

Neither the *uc* test nor the *ind* tests are complete on their own, the first one evaluating whether on average the coverage rate α of the VaR model is correct, while the second focusing just on the clustering effect on the failures sequence. The *cc* test combines both assumptions testing the null hypothesis:

$$H_{0,cc} : \pi_{01} = \pi_{11} = \alpha. \tag{4.35}$$

The likelihood ratio test for the conditional coverage test is given by

$$LR_{cc} = 2\left(\ln L(z;\widehat{\pi}_{01},\widehat{\pi}_{11}) - \ln L(z;p)\right) \sim \chi^2_2 \tag{4.36}$$

Christoffersen and Pelletier (2004) propose a generalization of the *ind* test considering a broader alternative with respect to the Markov first-order. Therefore, to apply this test we should firstly define the duration between two VaR violations (i.e., the no-hit duration) as:

$$D_s = t(I_s) - t(I_{s-1}) \tag{4.37}$$

where $t(I_s)$ denotes the time interval of the s-th violation.

Under the null hypothesis that the risk model is correctly specified, the no-hit duration should have no memory and a mean duration of $1/p$ time intervals; the distribution satisfying the memoryless property is the exponential distribution:

$$f_{\exp}(D; p) = p \exp(-pD) \tag{4.38}$$

while the Weibull distribution is selected as alternative distribution as it both allows for duration dependence as well as being a generalization of the exponential:

$$f_{Weibull}(D; p) = a^b b D^{b-1} \exp\left(-(aD)^b\right). \tag{4.39}$$

We will refer to this test as the $DurW$. The hypothesis we want to test is therefore:

$$H_{0,DurW} : b = 1 \tag{4.40}$$

While the large-sample distribution of the LR tests described above is the chi-squared, the dearth of violations of 1% VaR make the effective sample size rather small, even when the nominal size is large. To overcome this problem and to obtain p-values robust to finite sample scenarios, we employed the Monte Carlo tests of Dufour (2006) as in Christoffersen and Pelletier (2004). This procedure consists in generating S independent realizations, 1,000 in our case, for each one of the four test statistics: $LR_{s,type}$, $s = 1, ..., S$, $type = uc, ind, cc, DurW$. The cases $LR_{0,type}$ corresponds to the calculated test statistic. The Monte Carlo p-value $\widehat{p}_S(LR_0)$ is given by:

$$\widehat{p}_S(LR_0) = \frac{\widehat{G}_S(LR_0) + 1}{S + 1} \tag{4.41}$$

where

$$\widehat{G}_S(LR_0) = S - \sum_{s=1}^{S} \mathbf{I}(LR_s < LR_0) + \sum_{s=1}^{S} \mathbf{I}(LR_s = LR_0)\mathbf{I}(U_s \geq U_0) \tag{4.42}$$

where $\mathbf{I}(\cdot)$ indicator function and $U_s, s = 0, ..., S$ are independent realizations of a Uniform distribution on the [0,1] interval.

4.4.1.2 Expected shortfall and Tail Risk tests

Berkowitz and O'Brien (2002) test for Expected Shortfall (ES). To introduce this test, let first define the following truncated distribution:

$$y_t^* = \begin{cases} VaR_t(\alpha) & \text{if } I_t = 1 \\ y_t & \text{if } I_t = 0 \end{cases} \tag{4.43}$$

Log-returns are assumed to be normally distributed with parameters μ and σ^2. Therefore the MLE estimators of μ and σ^2 can be obtained maximizing the log-likelihood of y_t^* which, being a truncated normal distribution, can be written as:

$$\begin{aligned} L\left(\mu,\sigma|y_t^*\right) &= \sum_{y_t^*<VaR_t(\alpha)} \left(-\frac{1}{2}\ln\left(2\pi\sigma^2\right) - \frac{1}{2\sigma^2}\left(y_t^*-\mu\right)^2\right) + \\ & \sum_{y_t^*=VaR_t(\alpha)} \ln\left(1-\Phi\left(\frac{VaR_t(\alpha)-\mu}{\sigma}\right)\right) \end{aligned} \tag{4.44}$$

This likelihood function can be used to construct a LR test for the null hypothesis that $\mu = 0$ and $\sigma^2 = 1$:

$$LR_{tail} = 2\left[L\left(\hat{\mu},\hat{\sigma}^2\right) - L\left(0,1\right)\right] \sim \chi_2^2 \tag{4.45}$$

Wong (2010) test for Tail Risk (TR). The tail risk (TR) statistic is defined as the sum of the sizes of all exceptions in excess of VaR divided by the sample size. The TR measure at α-level is defined as:

$$\widehat{TR}_\alpha = -\frac{1}{T}\sum_{i=1}^{T}\left(y_t - VaR_t(\alpha)\right) I\left(y_t - VaR_t(\alpha)\right) \tag{4.46}$$

The reason why we use TR in addition to ES is that the latter assumes the expected loss as being in the tail interval, whereas the former measures the unconditional expected loss. The implication for backtesting is that a risk model that passes the ES test can be rejected by TR because of inaccurate $T1$. Although $T1/T$ is approximately $(1-\alpha)$ for large T, under the null hypothesis $T1$ can be too small or too large when the VaR forecasts are inaccurate. For further details see Wong (2010). The test is based on the saddlepoint technique which is adopted to approximate the distribution of the sample mean of y_t; the null hypothesis is:

$$H_0: TR = TR_0 \quad vs \quad H_1: TR > TR_0 \tag{4.47}$$

4.4.1.3 Multilevel VaR tests

The tests discussed up to now are defined unilevel as they are based on a single coverage probability α. Berkowitz et al. (2011) show that these tests have small power which can be overcome by multilevel procedures.

Given a coverage probability α, the $VaR\left(\alpha\right)$ for day $t+1$, given the information set up to time t, satisfies:

$$P\left(y_t \leq -VaR_{t+1|t}(\alpha)|F_t\right) = \alpha$$

Consider K different critical levels $\alpha_1 > \alpha_2 > ... > \alpha_K$ with associated VaRs in opposite monotonic order:

$$VaR_{t+1|t}(\alpha_1) < VaR_{t+1|t}(\alpha_2) < ... < VaR_{t+1|t}(\alpha_K).$$

For each VaR measure, an indicator variable is constructed as follows:

$$J_{t+1} \begin{cases} 1 & \text{if } -VaR_{t+1|t}\left(\alpha_{k+1}\right) < y_{t+1} \leq -VaR_{t+1|t}(\alpha_k) \\ 0 & \text{otherwise} \end{cases} \tag{4.48}$$

where $\{J_{k,t+1}\}_{k=1}^{K}$ are Bernoulli distributed with probability $\theta_k = \alpha_k - \alpha_{k+1}$ under the null hypothesis that the VaR model is unconditionally accurate. J can be expressed as:

$$J_{k,t+1} = I_{k,t+1} - I_{k+1,t+1} \quad k = 1, ..., K$$

where $I_{k,t}$ indicator function taking value 1 when there was a violation of coverage rate k at time t and 0 otherwise, as already defined in (4.29).

Perignon and Smith test. The Perignon and Smith test (2008) is basically a multivariate version of the unconditional coverage test for the null hypothesis that the empirical failure rates $\pi = (\pi_0, \pi_1, ..., \pi_K)$ significantly deviate from the theoric $\theta = (\theta_0, \theta_1, ..., \theta_K)$. The test statistic is:

$$PSLR_{uc} = 2\left(\sum_{k=0}^{K} \ln\left(\frac{\widehat{\pi}_k}{\theta_k}\right)^{T_k}\right) \sim \chi^2_K \tag{4.49}$$

with $\widehat{\pi}_k = \frac{T_k}{T}$ maximum likelihood estimator of the $k-$th component of π.

Hurlin and Tokpavi test. Hurlin and Tokpavi (2006) jointly test the absence of autocorrelation and cross-correlation in the vector of hit sequences for K various coverage rates. Their null hypothesis is:

$$H_0 : E\left[\left(I_{r,t} - \alpha_h\right)\left(I_{s,t-z} - \alpha_k\right)\right] = 0 \quad \forall z = 1, ..., m \quad \forall r, s = 1, ..., K$$

The Authors propose using the multivariate portmanteau statistic of Li and McLeod (1981), which is a multivariate extension of the Box and Pierce test. The elements of the hits covariance matrix at the lag z can be estimated by

$$\widehat{\gamma}_z^{r,s} = \frac{1}{T-z}\sum_{t=z+1}^{T}\left(I_{r,t} - \alpha_r\right)\left(I_{s,t-z} - \alpha_s\right) \tag{4.50}$$

The test statistic is:

$$Q_k(m) = T(T+2)\sum_{z=1}^{m}\frac{1}{T-z}vec\left(R_z\right)'\left(R_0^{-1} \otimes R_0^{-1}\right)vec\left(R_z\right)$$

where R_z is the cross-correlation matrix whose element at position (r, s) is defined as:

$$R_z^{r,s} = \frac{\widehat{\gamma}_z^{r,s}}{\sqrt{\widehat{\gamma}_0^{r,r}\widehat{\gamma}_0^{s,s}}} \quad \text{for } r, s = 1, ..., K$$

Markov tests. In Leccadito et al. (2013) two Markov tests are proposed, one being a generalization of the independence test to the multilevel case the other being a generalization of the unilevel coverage test. Both the two Markov tests specify the transition matrix as:

$$\Pi = [\pi_{r,s}]_{r,s=0,...,K} \tag{4.51}$$

where $\pi_{r,s} = P\left(J_{r,t+1} = 1 | J_{s,t+1} = 1\right)$.

The null hypothesis for the conditional coverage test can be formulated as:

$$H_{0,cc} : \pi_{0,s} = \pi_{1,s} = ... = \pi_{K,s} = \theta_s \quad \text{for } s = 0, ..., K-1.$$

where $\theta_k = (\theta_0, ..., \theta_K)$. The test statistic is a likelihood ratio test taking the following form:

$$MLR_{cc} = 2\left(\sum_{r=0}^{K}\sum_{s=0}^{K} T_{r,s}\ln\left(\widehat{\pi}_{r,s}\right) - \sum_{k=0}^{K} T_k \ln\left(\theta_k\right)\right) \sim \chi^2_{K^2} \tag{4.52}$$

where $T_{r,s}$ number of observations in the sample of T with s following an r; $\widehat{\pi}_{r,s} = \frac{T_{r,s}}{T_r}$ maximum likelihood estimator of the (r, s)-th element of matrix Π.

Pearson's χ^2 tests. The Markov test just described is powerful only against the first-order Markov alternative. Therefore in Leccadito et al. (2013) the Pearson's χ^2 test is introduced. Consider the bivariate distribution:

$$p_{N_t,N_{t-z}}(x, y) = P\left(N_t = x, N_{t-z} = y\right)$$

where $N_{t+1} = \sum_{k=1}^{K} I_{k,t+1}$. Under the null of the conditional coverage test, it holds that:

$$p_{N_t,N_{t-z}}(x, y) = P\left(N_t = x\right)P(N_{t-z} = y) = \theta_x\theta_y \quad \forall x, y$$

The test statistic for a sample of T observations can be defined as:

$$X_m = \sum_{z=1}^{m} X^z \tag{4.53}$$

where $X^z = \sum_{x,y} \frac{\left(T_{x,y}^{(z)} - (T-z)\theta_x\theta_y\right)^2}{(T-z)\theta_x\theta_y}$. The distribution of (4.53) is not standard and therefore critical values are computed via simulation.

4.4.2 Data description

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 dataset. The trading period considered is 8 a.m. - 3:30 p.m. coordinated universal time (UTC). We detect and remove outliers by applying a filter which is a modification of the procedure to remove outliers proposed in Brownlees and Gallo (2006) that we implement following the steps suggested by Barndorff-Nielsen et al. (2011, p. 156), that we summarize below.

Let $p_{(t,i)}$ be a tick-by-tick time series of prices, where t denotes day and i the time interval of day t, then an observation is removed if:

$$\left|p_{(t,i)} - \overline{p}_{(t,i)}\left(k^L\right)\right| > \max\left\{4MD_{(t,i)}(k), n\gamma\right\} \wedge \left|p_{(t,i)} - \overline{p}_{(t,i)}\left(k^R\right)\right| > \max\left\{4MD_{(t,i)}(k), n\gamma\right\} \tag{4.54}$$

where k the bandwidth; $\overline{p}_{(t,i)}\left(k^L\right)$ and $\overline{p}_{(t,i)}\left(k^R\right)$ sample medians of the $k/2$ observations respectively before (L for left) and after (R for right) (t,i); $MAD_{(t,i)}(k)$ mean absolute deviation from the median of the whole neighborhood; $\wedge$ intersection operator; γ mean of the k absolute returns; n $\gamma-$multiplier. The advantage of this rule lies in the separate comparison of the $(t,i)-$th trade against the left and right neighbors 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.

Data selecting procedure is summarized in Table 4.4.1:

Table 4.4.1: **Data selection and descriptive statistics on government bond yields**

	DE	**IT**	**FR**	**ES**	**BE**	**NL**
No. ticks	3,077,442	978,261	1,096,247	978,357	841,854	657,249
Limiting trading time	2,928,107	917,455	1,027,268	969,129	831,094	645,773
No. trades per day: Mean (SD)	2,345 (1,889)	736 (526)	828 (596)	764 (512)	659 (481)	513 (378)
Trade duration: Mean (SD) [s]	14.2 (44.4)	42.9 (97.1)	38.0 (88.6)	38.1 (90.3)	47 (115.7)	60.4 (123.4)
Bid YTM						
Mean (SD) [%]	3.2 (0.8)	4.7 (0.7)	3.6 (0.6)	4.6 (0.7)	4.0 (0.5)	3.5 (0.8)
Median (1st - 99th pct) [%]	3.2 (1.5 - 4.6)	4.6 (3.8 - 7.0)	3.6 (2.5 - 4.8)	4.4 (3.8 - 6.4)	4.1 (3.0 - 5.0)	3.5 (2.0 - 4.8)
Bid-Ask Spread of YTM						
Mean (SD) [bps]	0.6 (0.1)	0.6 (0.1)	0.8 (0.1)	0.8 (0.1)	1.0 (0.1)	0.7 (0.1)
Median (1st - 99th pct) [bps]	0.6 (0.6 - 0.8)	0.6 (0.5 - 0.8)	0.8 (0.7 - 0.9)	0.8 (0.7 - 0.9)	1.0 (0.9 - 1.1)	0.7 (0.7 - 0.9)

Table 4.4.1 reports the data procedure selection on government bond yields together with some descriptive 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 (4.54) in the text. In square brackets is the unit of measurement. Pct stands for percentile.

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. We remove outliers following the description in (4.54) which lead us to detect 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; 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 14.2 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). In Table 4.4.1, we also report descriptive statistics about yields: Italy has the highest average yield equal to 4.7%, while Germany has the lowest equal to 3.2%. Of course, the information that the average indicator offers is limited in the light that government bond yields vary a lot throughout our sample period as can be seen from Figure 4.4.1.

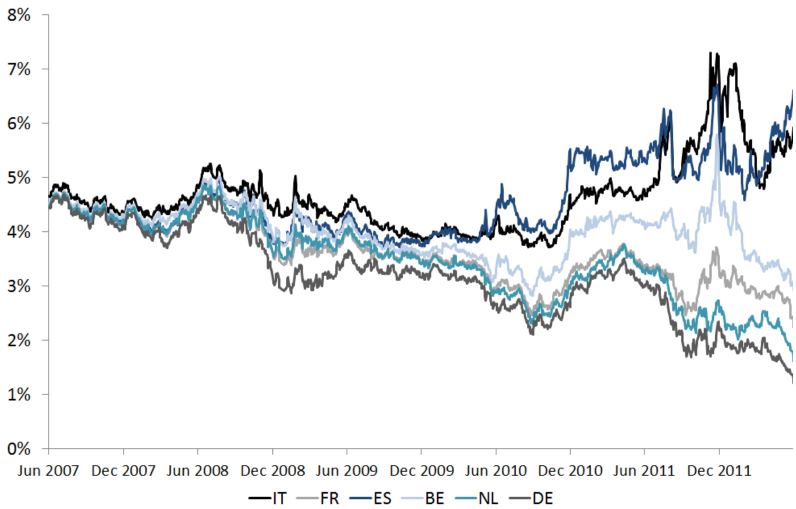


Figure 4.4.1: **10-year government bond yields**

Figure 4.4.1 reports the benchmark 10-year government bond yields for Italy, France, Spain, Belgium, the Netherlands and Germany over the period 1st July 2007 - 31st May 2012.

Government bond yields move very closely until May 2010, when markets start to pay more attention to sovereign debt risk in correspondence with the burst of Greek crisis. In May 2010, Greek government deficit was revised and estimated to be 13.6% of GDP with a correspondent decrease in international confidence in Greece's ability to repay its sovereign debt. As consequence, despite the first rescue package approved by Eurozone countries and the IMF, concerns about Euro countries solvability began to raise together with the difference in yields of the most distressed countries, as Italy, Spain and Belgium, with respect to the safest ones as France, the Netherlands and Germany.

4.4.3 Results

4.4.3.1 Preliminary insights

In Figure 4.4.2 we compare the alternative synchronization schemes. With this purpose, we selected a couple of countries, Italy and France, and report their pairwise daily correlation for all the alternative integrated covariance estimators namely MRC, QMLE, RC, MRC, MRC-Psd and TSCV, computed on synchronized data obtained under the four synchronization schemes presented in Section 4.2.1, namely Previous Tick (black diamond), Refresh Time (grey square), the Modified Refresh Time (blue cross) and the Intersection approach (pale blue diamond).

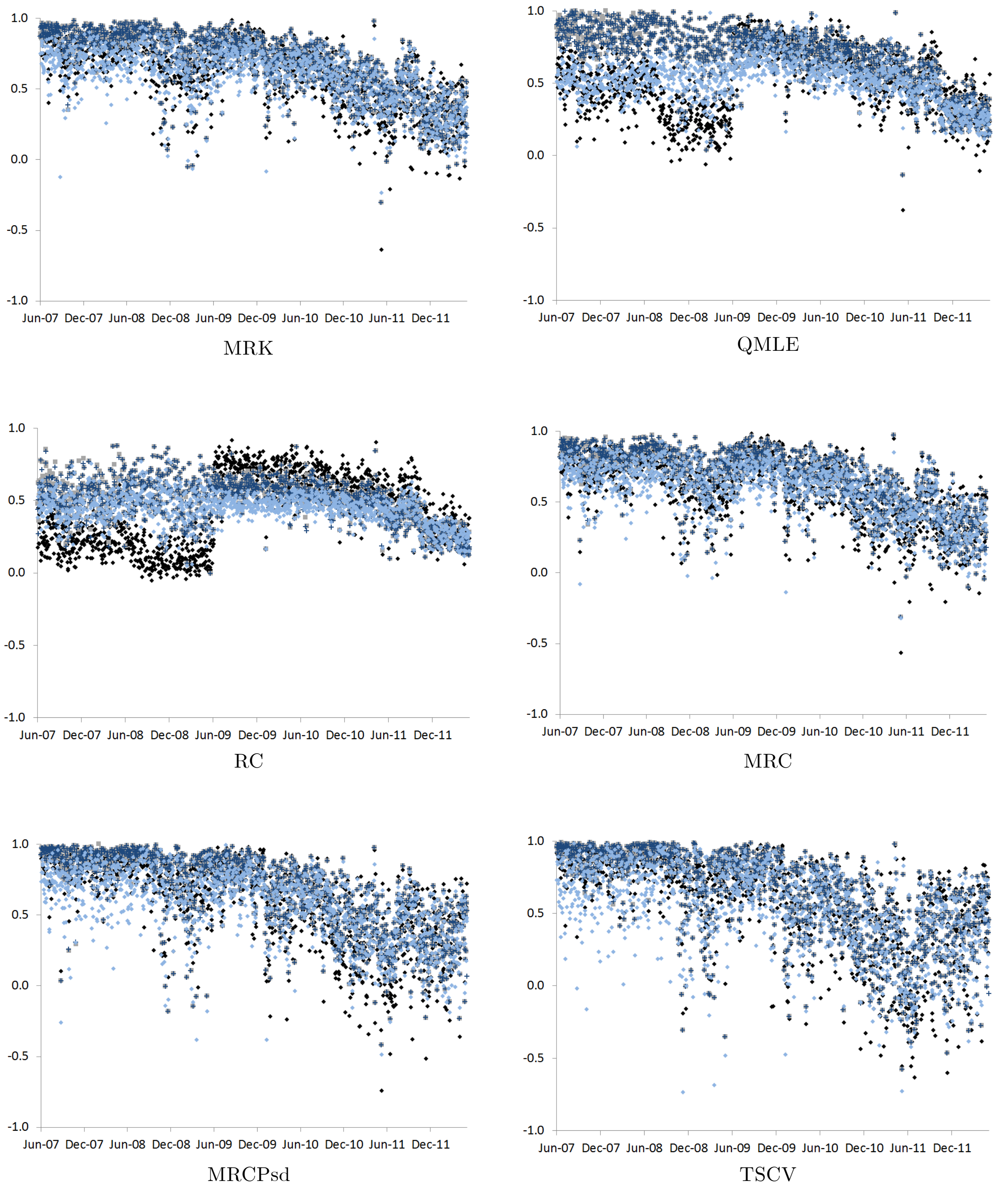


Figure 4.4.2: **IT-FR synchronization schemes**

Figure 4.4.2 plots Italy-France correlations for the alternative integrated covariance estimators computed on synchronized data obtained under Previous Tick (black diamond), Refresh Time (grey square), Modified Refresh Time (blue cross) and Intersection approach (pale blue diamond) synchronization schemes.

From Figure 4.4.2 we can get some preliminary insights about the alternative synchronization schemes and integrated correlation estimators. Firstly, the synchronization scheme which deviates the most from the others is the previous tick one. This evidence is particular relevant when the QMLE and the RC estimators are taken into consideration and it can be justified by the fact that previous tick is notoriously known to discard a higher number of observations with respect to the other synchronization schemes. In addition to that, the two versions of the refresh time scheme do not deliver very different results, regardless from the integrated correlation estimator used, while the intersection scheme deviates quite noticeably from refresh time and this is quite evident for the QMLE estimator. Turning now to the estimators, we can see that the identified pattern is similar for all the six estimators evaluated as in all the cases the correlation between Italy and France is decreasing through the time span considered. Anyway, it is interesting to note that in case of RC, the evolution of correlation seems to remain quite flat while for the positive definite version of the MRC and for the TSCV, the correlations are more widespread.

To get some more clear ideas about the behavior of the alternative integrated covariance estimators, we selected a synchronization scheme, the modified refresh time, and report in Figure 4.4.3 the correlation patterns for the same couple of countries, Italy and France.

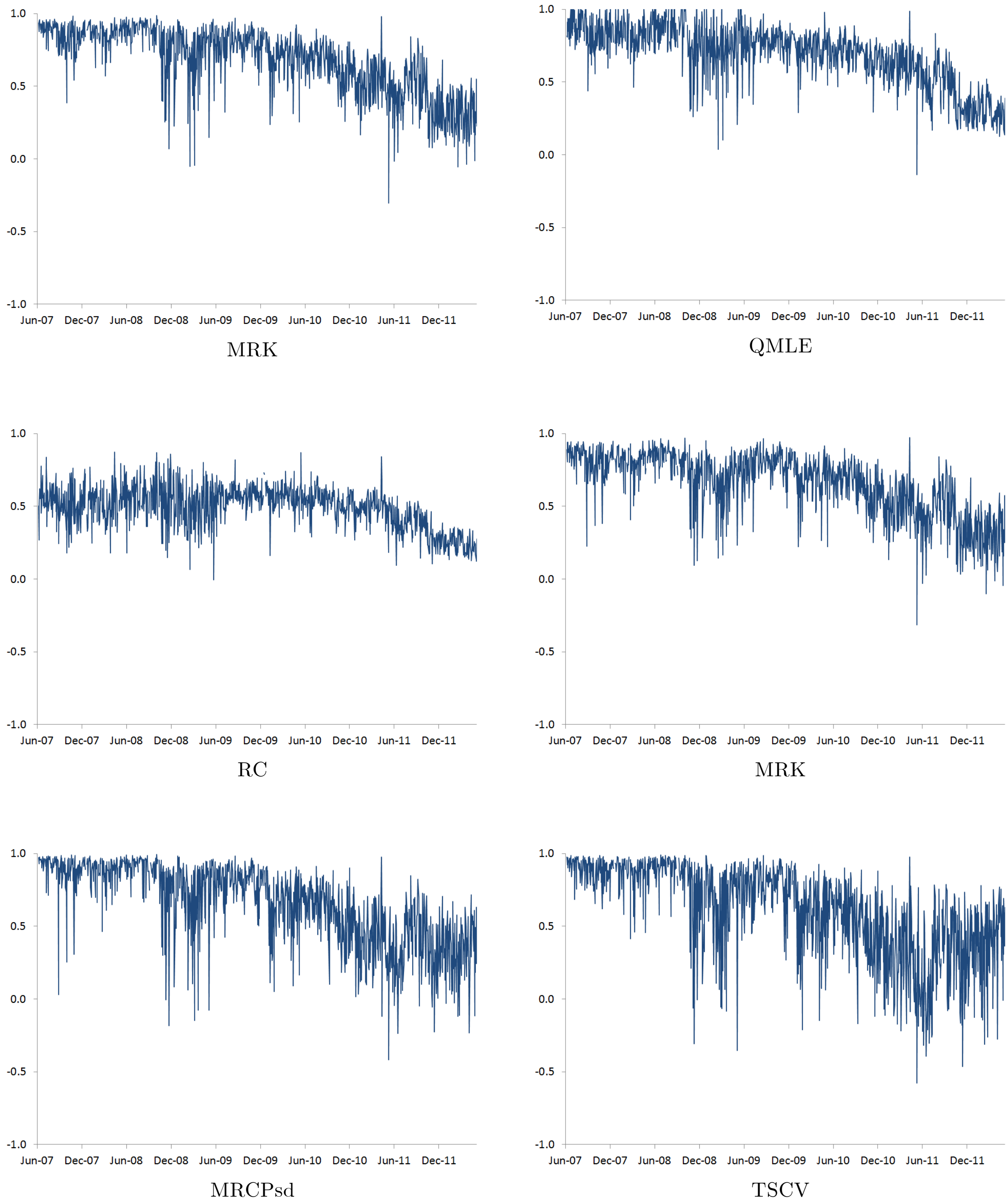
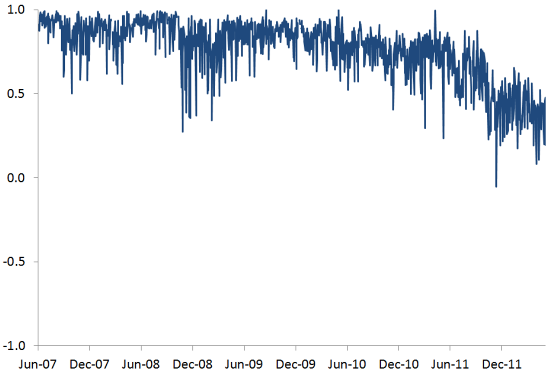


Figure 4.4.3: **IT-FR integrated covariance estimators**

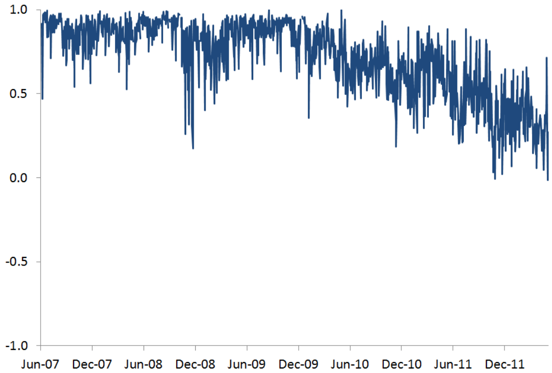
Figure 4.4.3 plots Italy-France correlations for the alternative integrated covariance estimators computed on synchronized data obtained under the Modified Refresh Time.

From Figure 4.4.3 we can almost draw the same conclusions as from Figure 4.4.2. In fact, the correlation between Italy and France started to decrease in correspondence to the beginning of the sovereign crisis which is a result somehow deviating from classical contagion literature in which it is stated that during turmoil periods, assets tend to behave in a more similar manner (see for instance Bekaert et al. (2005)) with respect to stable periods. This result is anyway supported from the fact that during the burst of the sovereign crisis, local investors decided to buy their own country's debt in order to support their country; this behavior determined correlations among European countries to decrease. In addition to that, sovereign crisis is a systemic event which involved, although if at different extents, all the European countries decreasing the benefits of portfolio diversification. This fact prevented investors to diversify their portfolio leading in turn to decrease bond correlations.

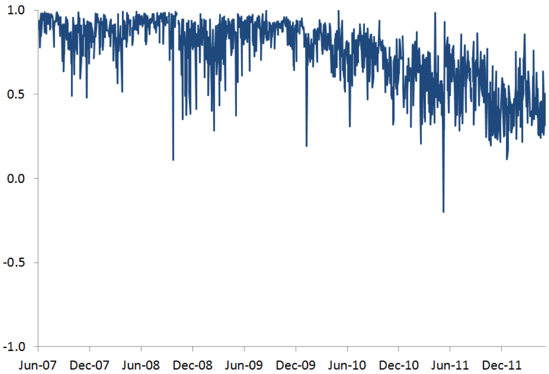
In order to get an insight about the correlation patterns between all the pairs of countries taken into consideration, we depict in Figures 4.4.4-4.4.6 the pairwise correlations obtained applying the Shephard and Xiu (2012) estimator that we remind is synchronization-free and which resulted to provide the most precise estimates for correlation in our Monte Carlo analysis.



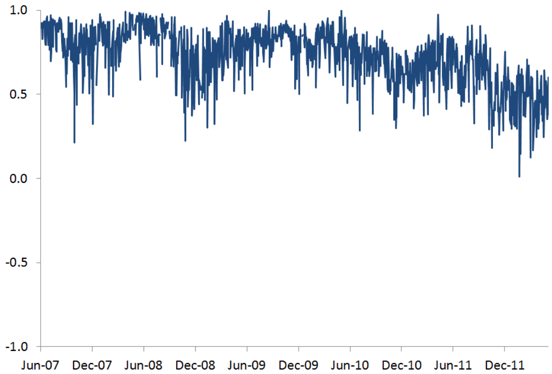
Italy vs France



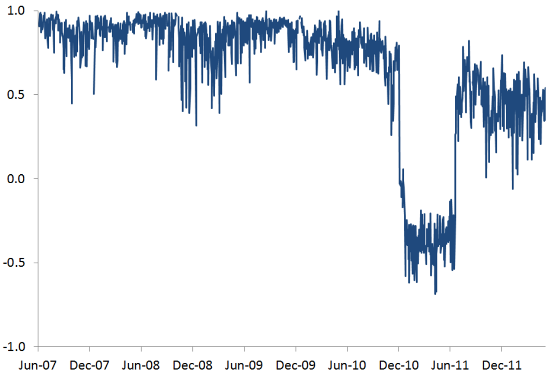
Italy vs Spain



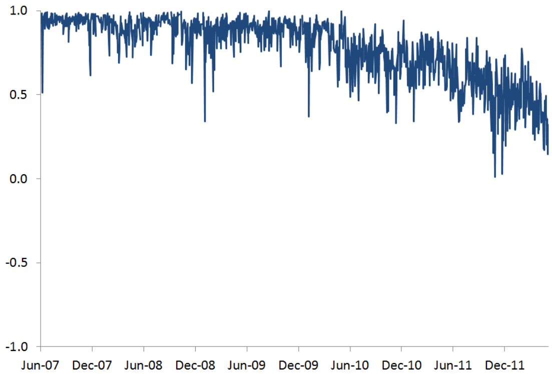
Italy vs Belgium



Italy vs the Netherlands



Italy vs Germany



France vs Spain

Figure 4.4.4: **Countries pairwise correlations**

Figure 4.4.4 plots pairwise correlations obtained by the Shephard and Xiu (2012) estimator.

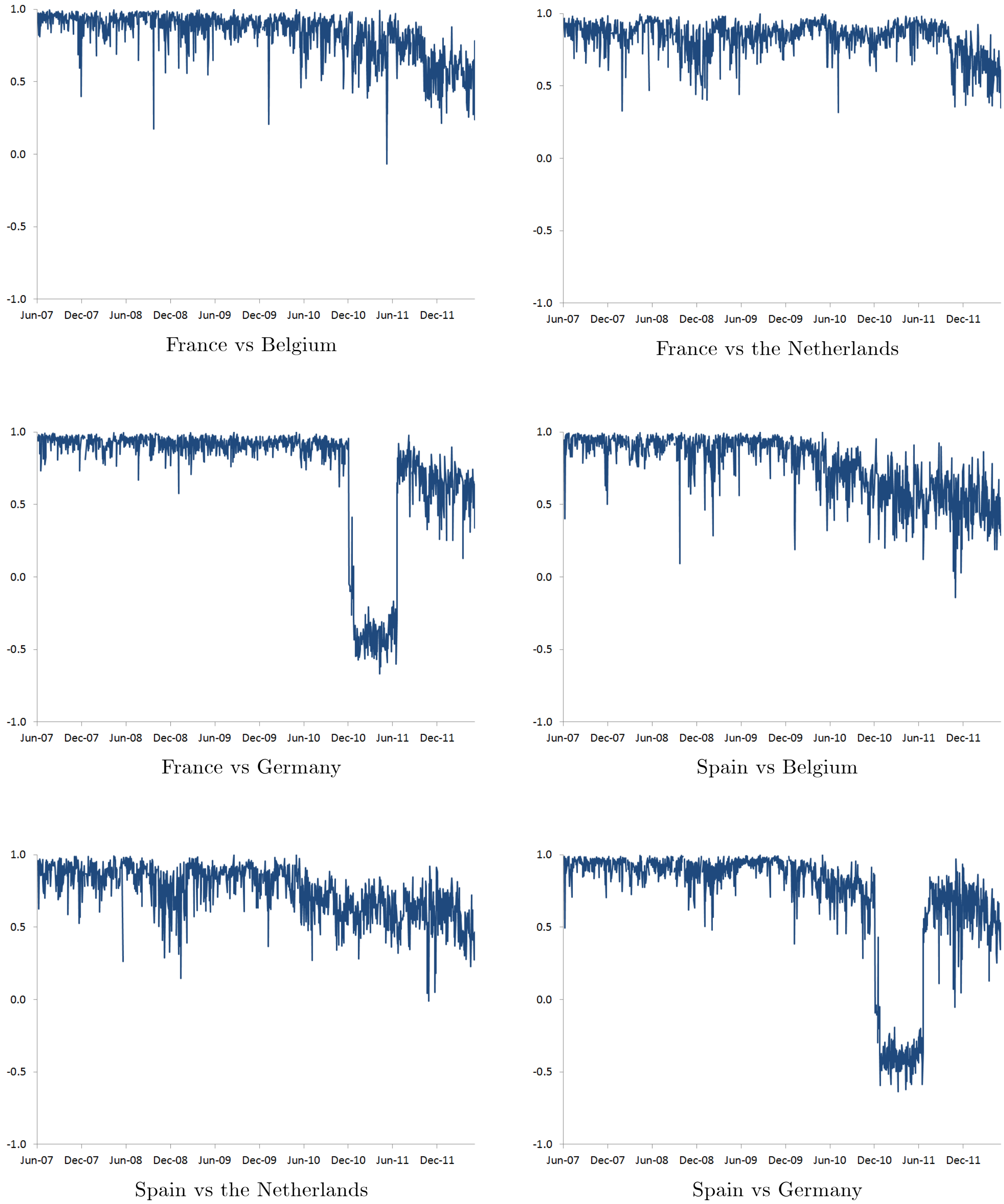
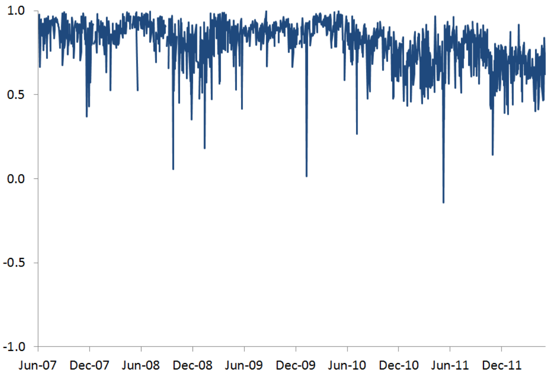
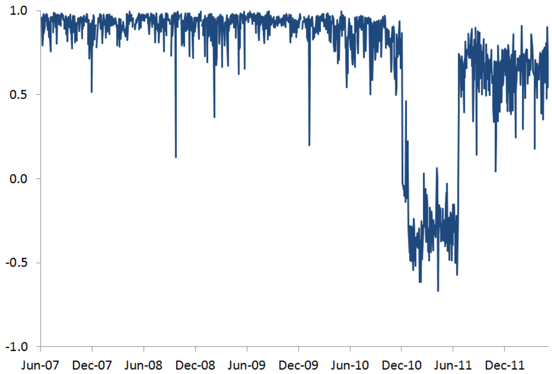


Figure 4.4.5: **Countries pairwise correlations**

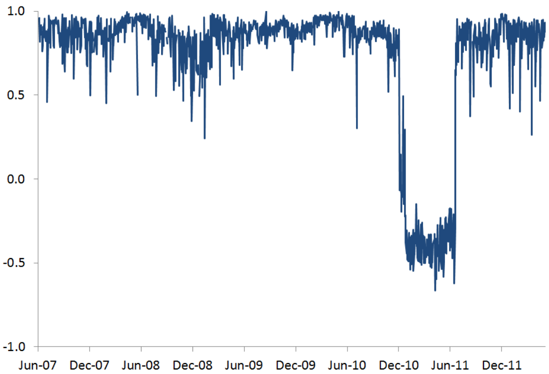
Figure 4.4.5 plots pairwise correlations obtained by the Shephard and Xiu (2012) estimator.



Belgium vs the Netherlands



Belgium vs Germany



the Netherlands vs Germany

Figure 4.4.6: **Countries pairwise correlations**

Figure 4.4.6 plots pairwise correlations obtained by the Shephard and Xiu (2012) estimator.

Figures 4.4.4-4.4.6 support results already discussed when focusing on Italy and France as all the possible pairs of countries almost experienced a decrease in pairwise correlations during the sovereign crisis. In addition to that, we identify a sharp drop in correlations for all the countries analyzed with Germany during the period December 2010 - July 2011, corresponding to the worst period of the sovereign crisis. Firstly we would like to point out that this evidence is exactly specular to the increase in spreads correlations identified in Chapter 3. Anyway, Figures 4.4.4-4.4.6 are more informative as they allow us to understand what was behind the change in correlations. In fact we guess that the sharp drop in correlations among all the countries and Germany is dictated by the safe heaven status gained by Germany during the sovereign crisis which lead investors to undertake different positions on German and ex-German bonds. The trading activity during that period was very much sentiment driven and for instance, in correspondence to negative macroeconomic releases such as those discussed in Chapter 2, investors sold ex-German bonds and bought German bonds. This trading behavior was very likely the reason behind the sharp drop in correlations between Italy, France, Spain, Belgium and the Netherlands with respect to Germany. An additional analysis, not reported here, shows that this change in the correlation patterns between all countries and Germany is not present when using daily data indicating that the movements in government bond yields at high frequency scale were very much dictated by a sentiment driven trading activity.

4.4.3.2 Risk management results

After having described the correlation patterns which characterized European government bonds, we now turn to the proper risk management exercise aimed at identifying empirically the best integrated covariance estimator. In Table 4.4.2 we report the unilevel backtesting procedures described in Section 4.4.1.1 for the alternative estimators presented in Section 4.2.2 combined with the synchronization schemes described in Section 4.2.1 following the Monte Carlo exercise. In grey are highlighted all the cases when the tests allow not to reject the null hypothesis that the model is correctly specified. Starting from the unconditional coverage test, we see that the MRK, the QMLE and the SX estimator provide the best performance. In particular, coherently with the findings about the upward bias of the SX estimator in the Monte Carlo simulation, we show that this estimator succeeds just at the 99% confidence level. A similar pattern is evident for the most important unilevel test, the conditional coverage, while for the independence test we see that all the estimators perform quite well. Finally, as per the Duration test based on the Weibull distribution ($DurW$), we detect a dominance of the MRK and the QMLE associated with one of the refresh time resampling schemes.

In all the unilevel tests, the RC estimator does not allow not to reject the null hypothesis that the model is correctly specified as, as it is expected, our data are affected by some microstructure noise. In addition to that, we can see that the MRK based on synchronized data obtained by both previous tick and the intersection approach perform quite well while, in Monte Carlo comparison, we never find evidence in favour of previous tick nor intersection.

A clearer pattern is evident when the tail risk measures are analyzed in Table 4.4.3. In fact the SX estimator is the only one allowing not to reject the null hypothesis that the model is correctly specified for both tail risk and Berkowitz test, at both 95% and 99% confidence level. This finding is particularly relevant and coherent with results obtained for the unilevel test procedures as it denotes the ability of SX estimator to capture extreme events.

Finally, in Table 4.4.4 we report the backtesting exercise involving multilevel procedures. Starting from the most comprehensive one, the Pearson χ^2 test, we find that the best estimators are the MRK and the QMLE based on synchronized data obtained from refresh time resampling schemes. The dominance of these two estimators is supported even by the Perignon and Smith test and by the Markov test while when focusing on the Hurlin and Topkavi test, a less clear figure emerges. In fact, according to this last test, almost all the estimators perform equally well exception made for the TSCV and the SX which do not allow not to reject the null hypothesis that the models are correctly specified. Note that the SX estimator never succeeds as the multilevel tests are based on two confidence levels, 95% and 99%, and in Table 4.4.2 we show that this estimator performs well at the 99% confidence level but not at the 95%.

Table 4.4.2: **Unilevel VaR backtesting**

			Previous Tick					Refresh time					Modified refresh time					Intersection					
			RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	SX
UC	0.95	Test	18.42	12.21	603.39	0.01	17.46	4.85	4.33	573.36	0.09	0.36	5.39	4.33	569.65	0.09	0.52	7.82	16.53	641.67	2.54	21.41	45.61
		p-value	0.001	0.001	0.001	**0.925**	0.001	0.027	0.038	0.001	**0.782**	**0.547**	0.019	0.035	0.001	**0.789**	**0.455**	0.009	0.001	0.001	**0.094**	0.001	0.001
	0.99	Test	62.14	21.56	952.75	8.47	41.20	9.85	16.11	903.27	2.18	3.88	9.85	16.11	903.27	2.18	4.89	17.86	27.60	996.61	8.47	34.16	2.18
		p-value	0.001	0.001	0.001	0.009	0.001	0.005	0.002	0.001	**0.140**	**0.066**	0.005	0.002	0.001	**0.138**	0.029	0.002	0.001	0.001	0.006	0.001	**0.153**
Ind	0.95	Test	5.72	2.48	3.37	2.06	0.13	0.24	4.79	2.02	1.65	0.73	0.31	4.79	2.24	1.65	0.83	0.53	1.82	1.81	1.66	0.00	0.47
		p-value	0.029	**0.132**	**0.094**	**0.166**	**0.759**	**0.678**	**0.054**	**0.176**	**0.215**	**0.433**	**0.636**	**0.053**	**0.149**	**0.215**	**0.395**	**0.500**	**0.195**	**0.195**	**0.214**	**0.965**	**0.546**
	0.99	Test	0.50	0.04	0.69	0.94	0.07	0.49	1.38	1.66	0.53	0.65	0.49	1.38	1.66	0.53	0.72	0.14	0.00	0.44	0.94	0.01	0.47
		p-value	**0.181**	**0.993**	**0.130**	**0.118**	**0.956**	**0.181**	**0.098**	**0.092**	**0.180**	**0.130**	**0.181**	**0.098**	**0.092**	**0.180**	**0.128**	**0.774**	**1.000**	**0.203**	**0.117**	**1.000**	**0.203**
CC	0.95	Test	22.25	13.13	63.14	2.07	14.87	4.58	8.17	79.28	1.84	0.85	5.15	8.17	81.73	1.84	1.05	7.08	16.56	40.48	3.48	19.40	48.70
		p-value	0.002	0.002	0.002	**0.377**	0.002	**0.125**	0.022	0.002	**0.471**	**0.686**	**0.103**	0.020	0.002	**0.471**	**0.607**	0.036	0.002	0.002	**0.175**	0.002	0.002
	0.99	Test	59.87	21.60	291.02	9.42	38.87	8.97	17.49	316.38	2.71	4.53	8.97	17.49	316.38	2.71	5.61	16.26	27.60	272.93	9.42	31.92	1.96
		p-value	0.002	0.002	0.002	0.009	0.002	0.009	0.003	0.002	**0.176**	**0.058**	0.009	0.003	0.002	**0.184**	0.041	0.004	0.002	0.002	0.008	0.002	**0.277**
DurW	0.95	Test	30.27	14.01	563.04	0.36	19.25	7.13	5.86	533.39	0.17	0.90	7.74	5.86	529.93	0.17	1.15	9.37	18.45	596.18	3.99	23.32	43.76
		p-value	0.002	0.003	0.002	**0.837**	0.002	**0.055**	**0.093**	0.002	**0.906**	**0.656**	0.038	**0.093**	0.002	**0.906**	**0.606**	0.019	0.002	0.002	**0.202**	0.002	0.002
	0.99	Test	90.73	30.95	930.58	15.75	53.01	20.41	23.84	884.73	6.23	9.18	20.41	23.84	884.73	6.23	10.21	28.50	36.63	965.84	14.86	41.27	12.96
		p-value	0.002	0.002	0.002	0.002	0.002	0.002	0.002	0.002	**0.063**	0.014	0.002	0.002	0.002	**0.063**	0.011	0.002	0.002	0.002	0.003	0.002	0.004

Table 4.4.2 reports the unilevel VaR backtesting procedures presented in Section 4.4.1.1. that are the unconditional coverage (UC), the indepence (Ind), the conditional coverage (CC) and the independence test based on the Weibull distribution (DurW). All the tests are presented for all the four sychronization schemes combined with the six integrated covariance estimators introduced in Sections 4.2.1 and 4.2.2 respectively, The integrated covariance estimator are: Realized Covariance (RC), Two Scales Realized Covariance (TSRC), Modulated Realized Covariance (MRC), Multivariate Realized Kernel (MRK), QMLE by Ait-Sahalia et al. (2010) and Shephard and Xiu (SX). Two confidence levels are taken into consideration, 95% and 99%. In grey are highlighted the cases when the tests allow not to reject the null hypothesis that the models are correctly specified at the 5% significance level.

Table 4.4.3: **Tail Risk backtesting**

			Previous Tick					**Refresh time**					**Modified Refresh time**					**Intersection**					
			RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	SX
Tail Risk	0.95	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	**0.207**
	0.99	p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.000	**0.137**
Berkowitz	0.95	test	203.85	101.76	3940.55	44.92	100.52	25.70	75.65	3970.74	25.28	21.98	26.44	77.26	3976.64	25.47	22.02	25.76	38.49	3604.35	9.60	49.82	2.17
		p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.008	0.000	**0.339**
	0.99	test	201.28	89.52	3898.75	43.78	97.72	24.94	70.76	3902.55	28.23	24.00	25.57	72.27	3910.95	28.36	22.90	26.09	36.35	3543.50	9.20	48.72	2.15
		p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.010	0.000	**0.342**

Table 4.4.3 reports the tail risk and the Berkowitz expected shortfall backtesting procedures presented in Section 4.4.1.2. All the tests are presented for all the four sychronization schemes combined with the six integrated covariance estimators introduced in Sections 4.2.1 and 4.2.2 respectively. The integrated covariance estimator are: Realized Covariance (RC), Two Scales Realized Covariance (TSRC), Modulated Realized Covariance (MRC), Multivariate Realized Kernel (MRK), QMLE by Ait-Sahalia et al. (2010) and Shephard and Xiu (SX). Two confidence levels are taken into consideration, 95% and 99%.. In grey are highlighted the cases when the tests allow to not to reject the null hypothesis that the models are correctly specified at the 5% significance level.

Table 4.4.4: **Multilevel VaR backtesting**

		Previous Tick					**Refresh time**					**Modified refresh time**					**Intersection**					
		RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	RC	MRC	TSCV	MRK	QMLE	SX
X1	Test	239.89	76.01	18044	29.45	145.82	34.60	51.36	14785	10.04	11.83	35.16	51.36	14783	10.04	14.63	56.96	99.30	20166	25.46	126.14	110.64
	p-value	0.000	0.000	0.000	0.014	0.000	0.006	0.001	0.000	**0.260**	**0.187**	0.006	0.001	0.000	**0.260**	**0.112**	0.001	0.000	0.000	0.022	0.000	0.000
X5	Test	1597.56	397.13	99501	148.10	790.02	161.33	248.21	88991.77	45.15	67.01	163.45	248.21	88872	45.15	79.81	287.99	500.58	113431	135.29	642.10	553.72
	p-value	0.000	0.000	0.000	0.005	0.000	0.003	0.000	0.000	**0.303**	**0.115**	0.003	0.000	0.000	**0.303**	0.067	0.000	0.000	0.000	0.008	0.000	0.000
X10	Test	3005.94	799.39	202890	313.40	1573.98	319.83	520.66	181118.05	93.30	133.37	325.24	520.66	180841	93.30	159.27	630.88	1013.77	229168	261.15	1303.59	1106.64
	p-value	0.000	0.000	0.000	0.003	0.000	0.003	0.000	0.000	**0.274**	**0.111**	0.002	0.000	0.000	**0.274**	**0.064**	0.000	0.000	0.000	0.009	0.000	0.000
PS	Test	62.15	23.53	1002.05	10.93	42.29	10.49	16.13	951.72	3.47	4.02	10.73	16.13	950.02	3.47	5.03	18.56	30.46	1051.97	8.53	38.08	103.55
	p-value	0.000	0.000	0.000	0.004	0.000	0.006	0.000	0.000	**0.181**	**0.134**	0.005	0.000	0.000	**0.181**	**0.083**	0.000	0.000	0.000	0.015	0.000	0.000
Markov	Test	72.36	28.35	1009.51	14.18	45.87	13.59	22.44	959.33	6.53	4.88	13.88	22.44	958.27	6.53	6.01	19.72	35.76	1056.00	10.46	42.85	102.11
	p-value	0.000	0.000	0.000	0.013	0.000	0.016	0.000	0.000	**0.203**	**0.335**	0.014	0.000	0.000	**0.203**	**0.239**	0.001	0.000	0.000	**0.055**	0.000	0.000
Q1	Test	17.36	3.15	61.84	2.50	3.70	2.94	3.92	52.73	2.59	1.54	2.91	3.92	53.37	2.59	1.58	1.75	2.97	60.41	1.99	4.66	1245.27
	p-value	0.019	**0.386**	0.000	**0.471**	**0.322**	**0.412**	**0.302**	0.001	**0.459**	**0.715**	**0.416**	**0.302**	0.001	**0.459**	**0.701**	**0.641**	**0.409**	0.000	**0.572**	**0.247**	0.000
Q5	Test	74.12	26.74	267.89	19.62	32.92	14.96	17.72	254.37	10.23	16.74	14.27	17.72	252.61	10.23	16.36	16.82	26.05	290.97	20.53	28.39	6208.46
	p-value	0.002	**0.182**	0.000	**0.406**	**0.088**	**0.638**	**0.493**	0.000	**0.875**	**0.542**	**0.675**	**0.493**	0.000	**0.875**	**0.562**	**0.538**	**0.197**	0.000	**0.368**	**0.150**	0.000
Q10	Test	131.60	56.50	544.03	43.06	69.33	31.49	47.26	523.78	22.09	30.24	30.84	47.26	516.37	22.09	29.86	51.32	57.09	587.25	33.51	60.86	12369.17
	p-value	0.001	0.106	0.000	0.324	0.034	0.688	0.231	0.000	0.940	0.731	0.710	0.231	0.000	0.940	0.743	0.164	0.100	0.000	0.619	0.072	0.000

Table 4.4.4 reports the multilevel VaR backtesting procedures presented in Section 4.4.1.3. that are the Pearson χ^2 (X) with m equal to 1, 5 and 10, the Perignon and Smith (PS), the Markov test and the Hurlin and Topkavi test (Q) with k equal to 1, 5 and 10. All the tests are presented for all the four sychronization schemes combined with the six integrated covariance estimators introduced in Sections 4.2.1 and 4.2.2 respectively, The integrated covariance estimator are: Realized Covariance (RC), Two Scales Realized Covariance (TSRC), Modulated Realized Covariance (MRC), Multivariate Realized Kernel (MRK), QMLE by Ait-Sahalia et al. (2010) and Shephard and Xiu (SX). The multilevel tests are based on two confidence levels, 95% and 99%. In grey are highlighted the cases when the tests allow to not to reject the null hypothesis that the models are correctly specified at the 5% significance level.

Overall, results shown in Tables 4.4.2-4.4.4 allow us to draw a very clear picture indicating that the best integrated covariance estimators are the MRK and the QMLE based on synchronized data obtained from the refresh time schemes. By the way, when focusing on tail risk or on just extreme percentiles, the SX estimator dominate all the other competitors. This result is coherent with the finding from the Monte Carlo comparison about the upward bias affecting the SX (in presence of high noise) estimator and indicates that although it is very promising, it still needs some improvements.

4.5 Conclusions

In this Chapter we carried out a very comprehensive comparison among the integrated covariance estimators and the synchronization schemes proposed in the literature. Both the Monte Carlo exercise and the empirical application allow us to draw a clear picture about the topic of properly estimating the integrated covariance matrix in a framework characterized by two very big issues that are microstructure noise and asynchronicity. In fact we provide evidence that both the Two Scales Realized Covariance by Zhang (2011) and the Modulated Realized Covariance by Christensen et al. (2010) lead behind other estimators. Instead, the QMLE by Aït-Sahalia et al. (2010) shows a good performance in both Monte Carlo and empirical exercise. In addition, the most promising estimator, the Shephard and Xiu (2012), by far dominates all the other ones when focusing on correlation estimates and in the backtesting exercises involving extreme events, namely VaR at 99% confidence level and tail risk measures. Anyway it suffers from some upward bias resulting in a non optimal estimation of variances and covariances in the Monte Carlo exercise and in VaR estimation at the standard 95% confidence level. The estimator proposed by Shephard and Xiu (2012) is the most appealing one even from a theoretical point of view as it does not suffer from any drawbacks such as non-positive definiteness, as the QMLE by Aït-Sahalia et al. (2010) does, nor by non-optimal convergence, as it is the case for the MRK by Barndorff-Nielsen at al. (2011). Therefore we think that, as suggested in a final part of their paper, some job should be carried out aimed at generalizing the noise model underlying their framework in order to deal with the bias. Finally, although the Multivariate Realized Kernel by Barndorff-Nielsen at al. (2011) does not perform particularly well in the Monte Carlo exercise, the same cannot be said in the empirical application where it shows a similar performance with respect to the QMLE. In addition to that, as per the synchronization schemes, we show that the previous tick as well as the intersection approach embedded in the Hayashi and Yoshida (2005) are clearly dominated by the refresh time resampling schemes.

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Chapter 5

Conclusions and further works

The recent sovereign crisis led to a sharp increase in European government bond yields determined by a renewed ability of markets to exercise a discipline through the price of risk embedded in alternative assets. The question is whether the price of risk is accurate in terms of properly reflecting countries fundamentals or whether, especially for peripheral bonds, high yields are the sign of an increasing risk aversion. In addition to that, during sovereign crisis concerns about evidences of contagion and increasing systemic risk, especially in the Euro area, have risen. In fact, in a very integrated market as the European one is, shocks to one country are very likely going to affect other countries.

To this purpose, we evaluated the impact of macroannouncements and time varying macroeconomic fundamentals on European government spreads of Italy, France, Spain, Belgium and the Netherlands with respect to Germany. The overall findings confirm the high sensitivity of government bond markets to macroeconomics, both in terms of macroannouncements as well as countries fundamentals. In particular, in Chapter 2, we provided evidence of the high sensitivity of spreads to US and European macroannouncements releases, with strong relevance of those concerning real economy, together with the ECB Introductory Statement and with news regarding Germany and Spain. In addition to that, we evaluated the impact of government bond auctions and rating actions too, reporting evidences supporting the high sensitivity of spreads to auctions held in two of the most distressed and biggest countries in our sample, Italy and Spain, while we did not find any evidence for rating actions. We interpret that result in light of the loss in reliability that rating agencies suffered after the subprime crisis together with the high predictability of their actions which therefore did not bring to markets any surprise.

As per macroeconomic fundamentals, we showed the existence of a strong linkage between spreads volatility and the difference of industrial production with respect to the German one, as well as with economic sentiment and unemployment. Anyway, when considering correlations, there is evidence of a sharp increase in all pairwise spread correlations during the period December 2010-July 2011 as a signal of the increasing systemic risk inside Europe rather than linked to macroeconomic fundamentals.

In order to estimate consistently correlations, we made advantage of recent developments in financial econometrics, in particular to the techniques introduced alternative estimators robust to both microstructure noise and asynchronous trading. In Chapter 4, we carried out an extensive Monte Carlo simulation exercise to compare the performance of the available estimators jointly with the alternative synchronization methods. The numerical analysis undertaken in Chapter 4 allowed us to identify two estimators, the Shephard and Xiu (2012) and the Aït-Sahalia et al. (2010) combined with refresh time synchronization method, as the optimal for correct inference. In addition, we also report a variety of risk-management applications implementing the alternative estimators on European yields. Very importantly, the empirical application helped us to identify the reason underlying the sharp increase in correlations of government bond spreads identified in Chapter 3. Estimating correlations on yields, we identified a similar but reverse pattern in pairwise correlations between all the countries and Germany and this evidence can be interpreted as result of nervousness in the markets during the burst of the sovereign crisis which led Germany to gain the safe heaven status and traders to undertake completely opposite positions on German and ex-German bonds.

There are a number of interesting developments that the findings in this dissertation open the route to. First, it will be important to understand why spreads of some countries are higher with respect to other countries, despite better fundamentals of the former country. A possible explanation may be related to the political stability together with government ability to set up proper and credible measures to introduce reforms and stimulate economic growth. This is for instance the case of Italy characterized by persistent political instability. On the other hand, this is the case of Portugal and Spain for instance, there are some countries whose private debt has sharply grown during recent years, probably contributing in boosting government bond spreads. Second, from a trading mechanisms and policy point of view, it would be interesting to understand what kind of measures governments and monetary authorities could undertake to prevent that trading mechanisms that could led government bond yields to increase so sharply with the effect of contributing to put countries, already experiencing financial difficulties, in an even more dangerous and unstable situation. In fact, increasing government bond yields directly impact on public debt, rising the amount of interests payment a country has to face; in addition, when yields are rising, coupons of newly issued bonds will rise too implying that a current pressure on bonds will last for a long span in the future. The main issue the European union has to face in this sense is, as already broadly discussed, a fiscal union besides a monetary union.

Though this dissertation mainly focused on insightful empirical issues on the European government bond market, it also offers some methodological contributions. In particular, in Chapter 3, we extended the MIDAS approach to the case of high-frequency data by introduced a model able to estimate correlations in presence of data sampled at different frequencies, where the low frequency component captures the macroeconomic fundamentals of countries. Further, Chapter 4 is devoted to evaluate and sort existing estimators for integrated covariance matrix. Follow up of these two methodological developments have already been explored and the main findings are summarized in the following three papers.

5.1 A Frequency-Specific Factorization to Identify Commonalities with an Application to the European Bond Markets

This paper, joint with Jan Novotný and Giovanni Urga, introduces a new framework for modelling mixed-frequency multivariate time series with respect to the MIDAS approach described in Chapter 3. The proposed methodology is specifically built to treat commonality of rare events identified at high-frequency, namely price jump arrivals, across a large portfolio of time series and link them to macroeconomic fundamentals measured at a lower frequency. In particular, the link between cojumps in financial markets and the real economy is established through the evaluation of the dependence of co-arrival and cojump based measures on the real economy indicators, namely unemployment, industrial production and economic sentiment, observed at monthly frequency, and the aggregate monthly surprise carried by macro-announcements and government bond auctions. The notions of co-arrivals and cojumps are based on the cofeatures introduced by Engle and Granger (1987) and Engle and Kozicki (1993). Full details can be found in Novotný and Urga (2013).

The dataset is the same used throughout the previous chapters although here we focus our attention on 10-year government bond yields, rather than spreads, of Belgium, France, Germany, Italy, the Netherlands and Spain from 1st June 2007 to 31st May 2012 sampled at 5-minute frequency. As per macroannouncements and government bond auctions, we analyzed the same indicators as in Chapter 2 while the macroeconomic indicators are those adopted in Chapter 3.

The most relevant result is the assessment of statistically significant difference between idiosyncratic and common jump arrivals, with idiosyncratic arrivals being more sensitive to financial distress. In particular, we provide evidence of strong statistical evidence that the commonality feature of the jump arrivals are explained by news announcements from the US, the European Monthly Bulletin, the Spanish GDP and unemployment, and the

Greek unemployment. In both the subprime crisis of 2008/2009 and the European debt crisis in 2011, 10-year European yields show a low level of commonality as well as a low level of correlation in jump arrivals. This finding contrasts the evidence from asset returns (see, e.g., Bekaert (2005)), of a persistently higher correlation during distressed periods with respect to the tranquil ones. In particular, the measure of commonality, bounded between 0 and 1, during the financial crisis of 2008/2009 is about 0.3 while jumped to 0.6 in the aftermath of the crisis. This means that the probability to observe a common jump during the crisis was half the probability immediately afterwards. Another measure introduced in the paper indicated that during the 2008 crisis if jump occurred then up to two countries were affected by the same jump, while in the aftermath of the 2008 crisis, if jump occurred more than three countries were affected. In correspondence to the European debt crisis, both measures decreases to the levels around the 2008/2009 crisis.

During the subprime crisis of 2008, the overall number of jump arrivals increased which was not observed during the European debt crisis. Further, for the European debt crisis, we observed a significant change in the structure of common jumps in yields providing clear evidence that Euro area was hit by country specific risks. Finally, from October 2010 to July 2011, the behaviour of German yields showed a completely different pattern compared to the rest of the countries. In this period, we observed a significant change in correlation between German yields and yields from any other country in the sample. We like to interpret this finding as a supportive evidence for the increase of the risk-awareness of investors, who favoured the German bonds serving as a safe heaven.

The paper has been submitted for possible publication.

5.2 Co-arrivals and Information Flow in the European Debt Market

This paper, joint with Jan Novotný and Giovanni Urga, extends the univariate framework of Lee (2012) to a multivariate setup. In Lee (2012), the dynamics and predictability of jumps is investigated by introducing a two-stage semi-parametric jump predictor test aimed at identifying covariates that determine jump occurrences. In the first stage, jumps are detected by applying the Lee and Mykland (2010) test while in the second step, the estimation based on the maximum partial likelihood inference is carried out. The second step allows to identify the covariates that impact more on jump arrivals through a logit parametrization. In our paper, we generalize the parametrization in Lee (2012) by proposing a Probit specification, which allows for more versatile multivariate approach. This new framework is empirically illustrated using the 10-year European government bond benchmarks in order to identify the most relevant drivers of jumps and cojumps. In particular, we estimate a number of alternative specifications, considering first all the available jumps to focus later on pure idiosyncratic jumps and on common jumps (co-jumps). Finally, we also propose several empirically relevant extensions of the theoretical likelihood framework, which aims to estimate the financial phenomena like market pressure and systemic drops.

The paper has been submitted for possible publication.

5.3 Evaluating the Accuracy of Value-at-Risk Forecasts: New Multilevel Tests

The paper, joint with Arturo Leccadito and Giovanni Urga, proposes independence and conditional coverage tests aimed at evaluating the accuracy of Value-at-Risk (VaR) forecasts from the same model at different confidence levels. The proposed procedures are therefore named multilevel tests and were used in the empirical section of Chapter 4 to compare alternative estimator of the correlation matrix for a portfolio of government bonds. The multilevel setup presents two big advantages with respect to standard unilevel testing procedures. First it is able to overcome the reduced power of the unilevel tests in presence of small samples; second they make the best use of the limited amount of information regarding the return distribution made available by banks or financial institutions in general to assess their risk exposure. In addition to that, as econometricians usually estimate quantiles for two or more different probability levels, multilevel tests are intuitively more efficient, and statistically more powerful, than to use separate unilevel tests.

The first test introduced in this paper, the Markov test, is a generalization of the Christoffersen (1998) independence and conditional coverage test to the multilevel case which anyway is powerful only against the first-order Markov independence alternative hypothesis. Therefore a more general test is introduced, the Pearson's χ^2 test, which is designed to detect whether the average number of violations at different confidence levels is correct and to check for independence in number of violations at different confidence levels with respect to its lags up to a specific lag m.

In a comprehensive Monte Carlo exercise, where returns were generated under alternative GARCH models with skewed and leptokurtic innovations, and where VaR were estimated using models commonly used in practice (i.e. Normal, HS, Hybrid HS and RM), the new multilevel tests showed higher power than both the multilevel unconditional test of Perignon and Smith (2008) and the multilevel conditional tests of Hurlin and Tokpavi (2006). The superiority of the new introduced tests is particularly strong when small samples, that are even the most common in practice, are considered. Via an empirical application using daily returns on 15 MSCI world indices, we implemented the available multilevel tests and we showed that in some cases different tests deliver different conclusions.

The paper is forthcoming in the *International Journal of Forecasting*.

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