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European equity market integration and joint relationship of conditional Volatility and Correlations

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Abstract

We analyse the integration patterns of seven leading European stock markets from 1990 to 2013 using daily data and mismatched monthly macroeconomic data. To study the mismatch of data frequencies we use the DCC-MIDAS (Dynamic Conditional Correlation - Mixed Data Sampling) technique developed by Colacito, Engle and Ghysels (Journal of Econometrics, 2011). We benchmark European integration patterns against the German stock market. The reported integration patterns show a clear divide between large and (relatively) small equity markets' short run and long run return correlations: the small markets display higher short run European convergences than the large markets and vice versa. The across-the-board divergence from Greek risk, during the crisis period, is the most unambiguous conclusion of our study. During this period, cross-country joint relationships of conditional variances and return correlations – a 'convergence of risks' resulting in global/regional contagious spillovers – are typically positive. Only exceptions are the German stock market's joint relationships.

Keywords: Correlation, DCC-MIDAS, GARCH, Volatility.

JEL: C32, C58, F36 and G15.

1. Introduction

The financial markets have become ever more interlinked and recent literature identifies different channels in driving these inter-linkages. These inter-linkages, across financial markets, could be driven by similarity in industrial structure (Roll (1992)), monetary integration (Wälti (2011)), bilateral trade (Forbes and Chinn (2004)) and geographical proximity (Flavin et al. (2002)). Pretorius (2002) shows that no universal economic determinant drives financial market integration across countries; however countries in close geographical proximity are more correlated than countries in other regions. Liu (2013) reports that dissimilar mechanisms are at work to drive financial market integration across developed and developing markets.

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Savva et al. (2009) reports that after the introduction of the Euro, the return correlations among developed markets as well as the European economic and monetary union (EMU) stocks markets have increased considerably. Savva (2009) reports these (higher) interdependences among EMU markets have stablised in the post-Euro period. Connor and Suurlaht (2013) reports an increasing trend in the dynamic cross-country correlations for the Eurozone (EMU) countries after the introduction of the Euro.

In this study, we aim to explore the market interdependences for seven leading European stock markets of which four stock markets share common currency and monetary policy decisions. The selection of European equity markets includes France, Germany, Greece, Italy, Spain, Switzerland and the UK. These subjective choices are driven to uncover relative importance of geography and monetary integration in establishing financial market interdependences[1]. We study the integration patterns through a novel approach: the joint relationship of dynamic pairwise correlation[2] predictions with the conditional predictions for equity market variance (belonging to one of the pair country) has been analysed. This analysis follows Cappiello et al. (2006) which reported the average joint relationship at country level.

Greece, Italy and Spain belong to the group of commonly referred PIIGS countries[3]. The turbulent economic conditions in these countries during the ongoing European debt crisis (EDC) will allow us to unfold relationship among EMU markets over periods of growth and turmoil. Greece has remained at the very centre of political events during the greater part of year 2014 and 2015. Policy makers, politicians and financial markets had operated in a sense of detachment from the threat of possible Greek exit (GREXIT) from EMU[4]. Therefore, to keep the impact of political side of events isolated from the motivation of our study we exclude the data for the year 2014 and onwards (earlier part of the year 2015) from our main estimations. Nonetheless, the

[1]These stock markets approximately make up more than 90 percent of the European continent equity market capitalization.

[2]Dynamic correlations are a widely used measure to report the financial market integration across countries (see Savva et al. (2009) and Engle et al. (2013) among others)

[3]These countries include Portugal, Ireland, Italy, Greece and Spain and they have experienced far greater volatility during the recent financial crisis of 2008-2009 and the volatility lumbered for these markets even after the 2009 for the unstainable levels of government debts and fiscal deficits as percentage of their GDP levels. Market turbulences in these markets, especially Greece, shaped the European debt crisis from 2009 onwards, this is more commonly referred as Greek sovereign debt crisis. Greece witnessed sovereign debt default in 2012 and on June 30 2015 Greece became the first developed country to fail on IMF loan repayment besides the grand initiation of quantitative easing (QE) programme by the European central Bank in March 2015. This scheme, following similar programmes by the US, Japanese, and British central banks, targets buying government bonds amounting to e60bn each month across Eurozone economies. This programme may be extended beyond the planned end date of September 2016 and may effectively inflate the planned bond buying of 1.1tr Euros if the target inflation of 2 percent in the Eurozone countries i s not achieved as proclaimed by the European Central Bank President Mario Draghi.

[4]For details, see at http://blogs.ft.com/gavyndavies/2015/06/19/greece-and-the-insouciance-of-global-markets/

introduction of European QE in March 2015, which is formally known as Public Sector Purchase Programme (PSPP) has planned to run until growth returns to Euro area. Initially this asset purchase was planned to run until September 2016. This illustrates that the EDC, which started in the earlier part of 2009 is still not over. In this regards the latter part of the sample period i.e. December 2007 onwards will let us interrogate the degree of stability in EU integration levels during calamitous market conditions.

Moreover, this analytic design allows us to investigate variations in EMU and European equity market integration patterns across changing economic conditions. Whereas earlier evidence has shown that, (i) the correlation across markets tends to increase during bearish economic conditions and (ii) after the introduction of Euro, EMU countries' synchronicity has increased.

The methodological design of our study makes use of, the novel technique of mixed data sampling and volatility modelling, the GARCH-MIDAS framework[5]. This study follows Colacito et al. (2011) in employing Dynamic Conditional Correlation (DCC) and MIDAS framework (hereafter DCC-MIDAS) to retrieve dynamic predictions, both for short run and the long run, for the paired country correlations. The impact of macroeconomic information on the volatility and correlations will report the effect of broader macroeconomic conditions in driving financial market integration. Furthermore, to the best of our knowledge, this is the first study which distinguishes between the independent impact of sharing a common monetary policy (EMU effect) and changes in the business cycle conditions in shaping EU as well as EMU stock market integration. Otherwise, earlier studies have either focused on impact of monetary integration or business cycle conditions in reporting the financial market interdependencies (Wälti (2011); Engle et al. (2013); Asgharian et al. (2013) among others).

A clear manifestation of determinants shaping stock market variances and cross-country return correlations and the joint relationship between these two processes is important for investors, practitioners and policy makers. This makes our study valuable on a number of fronts. First, we will report the patterns in the financial market integration

[5]In the last two and half decades the research on volatility modelling has grown exponentially, however it has been limited to predicting volatility based on time series information. Historically, the modelling of time-varying volatility has utilized high-frequency intraday data or has used as low as daily/ weekly data frequencies. This has limited the incorporation of long run information, coming from the non-synchronized macroeconomic environment, in the evolution of long memory volatility processes (Engle et al. (2013). There has been a dearth of models which could link the state of the economy and aggregated volatility. Earlier attempts to establish these links have turn out to be weak and only make a small fraction of measured volatility. The availability of MIDAS (mixed data sampling) regression by [13] has paved the way to include information coming from macroeconomic data available at different time frequencies in the volatility modelling literature. Colacito et al. (2011) propose the GARCH-MIDAS model in which volatility is evolved in a two component processes comprising of long-term and short-term components. Thus, the GARCH-MIDAS model allows linking asset volatility at high or daily frequency with macroeconomic and financial variables, sampled at lower frequencies, to examine the direct impact of the long run components of risk on the asset volatility.

across varying economic conditions. This will also show the differences between the EMU equity market co-movements and broader EU level integration patterns across states of the world. Reportedly conditional bivariate equity market correlations have been much higher, on average, in the post-Euro period than the pre-Euro period among European markets (Cappiello et al. (2006); Savva (2009), among others). However, we benchmark all results against German stock market to draw both i.e. EMU and EU level integration simplifications, and for above noted joint relationship as well. Second, by virtue of studying equity markets bunched in a region, we will be able to uncover the relative importance of unified monetary policy for EMU countries and/or overall European geographical closeness in driving cross-country co-movements[6]. Third, the availability of two distinctive macroeconomic information channels (monetary policy and business cycle information based variables) will shed light on the relative strength of these two processes on the evolution of conditional volatility and paired-correlation predictions across countries. These response differences, if any, will provide new insights in financial market integration literature regardless of the fact whether equity markets belong to EMU or are from non-EMU region.

Fourth, knowledge of the joint relationship of market volatility and cross-country correlation patterns is imperative for portfolio managers, risk strategists and insurers. A higher association between the volatility of country X and the bivariate correlation of country X with country Y will stipulate simultaneous discounting of profits under poor market conditions and the exacerbated need to manage the integrated risk or to insure against this spiral risk. Studying this relationship is important given literature has identified that asset allocation strategies which time/benchmark dynamic volatility (Fleming et al. (2001) or dynamic correlations (Kalotychou et al. (2014)) could yield economically higher profits. Kalotychou et al. (2014) reports that risk-averse investor could pay substantially higher fees to reap greater economic benefits of a richer correlation specification such as the DCC model. Our analysis will make portfolio managers and investors aware of the flip side of this investing: in tandem movement of the two processes (volatility and correlations) can result in increased investing fragilities. This implies that asset allocation strategies which time either asset volatility or underlying asset correlation patterns will face an incensed depreciation in the value of invested capital under adverse market conditions.

Our results show that total variance evolution is significantly influenced by long run variance factor components and foremost by realised variance (RV). The results for GARCH-MIDAS and DCC-MIDAS specifications (hereafter GARCH/DCC-MIDAS) show RV is an efficient proxy for long run variance. We notice business cycle vari-

[6]The United Kingdom has not introduced Euro despite being a member of EMU, which is being administered by an opt-out clause for not moving into the third stage of EMU. The United Kingdom is still in the second stage of EMU which does not require introduction of a common currency – a requirement for the signing countries which are the third stage of EMU. This also allows the UK to shape their independent monetary policy decisions with no interferences form the European Central Bank (ECB).

ations and monetary policy latent variables affect the total variance evolution across equity markets differently. We note a clear division between large markets and small markets in the EU region instead of EMU vs non-EMU divide. This segregation is manifested by, (i) the commonality of responses to certain macroeconomic latent risks and (ii) higher (lower) long (short) run convergences in the large markets than the relatively smaller stock markets. Nonetheless, conditional predictions for baseline-variance or pairwise correlations are not substantially different whether we add macroeconomic linked latent variables or only have RV in the tested specifications. This non-difference is especially noted for short run pairwise correlation predictions; which, with few exceptions apart, are also applicable to long run correlation predictions. This establishes the candidature of realised variance to proxy for long run variance in the modelling of dynamic total variance.

The reported European market integration patterns, benchmarked against the German stock market, are inline to the available evidence base. Our findings show that, approaching the launch of the Euro currency, the EU markets' dynamic return correlations surged to new heights. Furthermore, increased convergence is observed in the post-Euro period across all country pairs. These convergences also become stable, especially noted if we exclude the global and EDC crisis period from the post-Euro sample. The crisis period results show that the European convergence levels are greater than the respective pre-crisis counterparts. However, sharp divergences in conditional pairwise correlations are also observed during the EDC period. Overall, these interdependencies show the usual pattern of higher converging patterns across markets during bearish/crisis periods. The only exception is Greek market's crisis period EU divergence. This divergence is to the extent that Greek-German pair correlation almost halved, towards the end of year 2013, from the heights of 80 percent achieved at the beginning of the crisis period. This detachment demonstrates the gradual insouciance of the European financial markets towards Greek risk or towards an ex-ante dismal possibility of the so called Grexit.

Furthermore, the joint relationship between unconditional RV and realised correlations (RC) display substantial overstatement of relatedness than their dynamic counterparts. This overstatement may amplify the diversification benefits or losses and may result in mispriced derivative options and insurance plans. The joint relationship between the conditional predictions for volatility and pairwise correlations show dynamic variance and correlation predictions, both in the long run and at the short run, have higher correlations during the crisis period. This manifests aggravation of overall risk during crisis period to create investment depreciating spirals.

The organisation of our study is as follows: sections two and three provide, respectively, literature review and data descriptions. Section four details the methodological setup and results are discussed in section five. The conclusions are in section six.

2. Literature Review

The importance of volatility and correlations in studying financial integration and portfolio and risk diversification related financial decisions cannot be overstated. The degree of financial integration can be measured in a number of ways and various studies, employing different methodologies, have examined this phenomenon (see, Kearney and Lucey (2004) and references therein). However, one common aspect of the earlier studies has been their reliance on the static cross-country correlations. Those cross-country linkages tend to rise during bearish market conditions or when markets are under greater uncertainty (Erb et al. (1994); Longin and Solnik (2001) and Connor and Suurlaht (2013), among others). This greater co-movement under poor market conditions is a sign of time varying correlations and reduced diversification benefits when they are most required.

Therefore, while studying financial integration and given the time varying nature of crosscountry correlations, the assumption of constant correlations may not be a suitable approach and may prove misleading. Specifying dynamic correlations among equity markets is the first step in understanding the wider notion of market integration. Without it the end results may depict an erroneous reality and misleading implications for investors and practitioners. This stipulates the need to develop dynamic methods that allow frequent updating of risk estimates to depict changing economic conditions. Generally, autoregressive conditional heteroskedasticity (ARCH) class of models have been the most popular to get volatility (and correlations) predictions, for the latent nature of these risk phenomenon.

A number of GARCH modifications have been proposed to better capture the volatility and correlation dynamics. The flexibility of dynamic conditional correlation (DCC) model specification by Engle (2002) has been argued to provide better cross-country relationships among other competing specifications (Savva (2009)). Primarily, these contributions aim to develop methods which can model the time variation of the volatility and correlation processes and focus on stable out-of-sample volatility/correlation predictions. This has enabled the predictability of these processes over relatively short horizons, ranging from one day ahead to more than a few weeks (Engle et al. (2013)). Despite the sophisticated developments in modelling time varying volatility and correlation processes; linking the time series returns' volatility to the broadbased multiscaled macroeconomic volatility remained an unfulfilled aspect of these developments. However, the availability of GARCH/DCC-MIDAS approaches has filled this important gap. This combination of models allows the incorporation of long run risk components existing at mismatched data frequencies in the total volatility/correlation evolution (see Colacito et al. (2011) and Engle et al. (2013) for details), along with conventional short run risk components.

"Please insert Table 1 about here"

Given the wealth of evidence reporting that the capital markets share common trends

and stock volatility changes in the long run (Kasa (1992); Schwert (1989)), this methodology specifies the evolution of volatility/correlation process to not to miss the changes in the risk coming from real and macroeconomic activity. Furthermore, the shocks to monetary policy, as modelled by exchange rate volatility or as variations to target future interest rates, influence stock returns during recessions (Basistha and Kurov (2008)) and affect negatively the future excess stock returns. Nonetheless, Hausman and Wongswan (2011) reports volatility responses to changes to the target exchange rate and shocks to target rate may vary across countries. Therefore, linking equity market volatility and cross-correlations with information coming from different channels of macroeconomic activity would be helpful in making better predictions.

Asgharian et al. (2013) shows that addition of a business cycle proxy in the GARCH-MIDAS specification improves the model's forecasting ability compared to the conventional GARCH modifications. Engle et al. (2013) reports that the inclusion of a business cycle latent variable affects both the volatility components, i.e. long run and the short run variance components. Taken together, the inclusion of macroeconomic variables can depict the underlying cross-country correlation dynamics more accurately.

Numerous studies analyse the financial integration after the introduction of the Euro, and they adopt different dynamic approaches, Cappiello et al. (2006) finds significant evidence of structural breaks in the correlations of EMU countries. Savva (2009) shows, using the same framework, the correlations, among major international stock markets, are affected by business cycle variations. Savva et al. (2009) reports that the dynamic correlations in the post-Euro period have been on the increase among France, Germany, the UK and the US stock markets and the correlations between EMU stock markets were the highest. This shows increased integration between EMU countries, although Liu (2013) has reported the correlation among EMU countries reached its peak by 2002 and afterwards no increase has been observed among them. Connor and Suurlaht (2013) finds a significant relationship between business cycle variables and DCC predicted correlations for Eurozone equity markets.

"Please insert Table 2 about here"

3. Data

We use time consistent daily closing prices, available at 1730 Central European time (CET), of all stock market indices for France, Germany, Greece, Italy, Spain, Switzerland and the UK. All the downloaded price series are in USD. A number of macroeconomic variables are downloaded, to capture business cycle and monetary policy changes, such as consumer price index (CPI), industrial production, Brent oil prices, yields on ten year government bond and overnight inter-banking lending rates e.g. LIBOR and EURIBOR, exchange rates (against USD) and measures for broad money (M3) and narrow money (M1). All the macroeconomic data is at monthly frequency

and where appropriate is seasonally adjusted e.g. consumer price index (CPI) and industrial production. The chosen macro variables, for simplicity, are divided into two categories: 1) business cycle variables and 2) monetary policy variables. The business cycle category consists of consumer price index, industrial production, oil prices and interest rate of term structures, whereas the monetary policy variables are changes to exchange rate and measures for broad money (M3) and narrow money (M1).

The growth in the CPI, industrial production, oil prices and exchange rates is calculated as the logarithmic difference of the original series. The term structure of interest rates is calculated as the simple difference of yields on 10 year government bond and overnight lending rates for LIBOR, EURIBOR (proxy for risk free interest rates). Furthermore, we take log of the M1 and M3 money supply series for data scaling. The monetary policy variables for EMU countries are downloaded from Eurostat data portal while Swiss and the UK monetary data is available from OECD data portal. All the remaining data series are collected from DataStream.

The motivation to include separate macroeconomic channels is twofold. First, changes to business cycle and exchange rate are reported to affect stock returns for EMU countries (Virk (2012); Apergis et al. (2011)) and stock volatility and correlations have been reported to be influenced by business cycle variations (Engle et al. (2013) and Connor and Suurlaht (2013)). Second, we intend to isolate the independent impact of two macroeconomic channels on the volatility (and correlation) dynamics of the European markets. Finally we also want to document any cross-country response differences of the two above mentioned macroeconomic latent variables in the baseline variance process.

The availability of numerous macro variables, and their interdependence is a well reported issue. Taking multiple predictors can cause estimation problems such as biased and unstable regression estimates. We employ principal component analysis which clears the empirical analysis of over-parametrization issues and effectively removes noise from signal. Before taking the macro variables to the dynamic factor analysis, we apply adequate transformation to make them stationary. Finally, these transformed stationary series are standardised to have normal distribution with zero mean and unit variance. This technique helps us in summarizing information in a compact manner. First, two principal components (PC) are taken to the main estimations which collectively explain 70 to 90 percent of the variability in the total factor variance across the European countries[7]. More importantly the two principal components have stronger correlations with the variables in one category than the other, leading to a naming routine as PC_{BC} and PC_{MP}, where BC and MP are the abbreviations for business cycle and monetary policy. This will help us isolate the importance of each channel in affecting the variance dynamics for the selected stock markets.

[7]We run the principal component analysis across all countries and for EMU countries where country specific data is not available we resort to EMU level data for consistency.

Table 1 reports the summary statistics for the seven equity markets. All the markets have positive returns with Greece having the smallest annualized return and largest volatility among all. All return series are asymmetrically distributed for negative skewness and have positive excess kurtosis. Furthermore, the first four serial-correlation estimates for all the return series demonstrate low persistence and only Greece has a serial correlation of 10 percent at the first lag; illustration of the relative stale pricing of the daily index. The squared returns show greater persistence across all the markets and it is high at all four lags. Swiss equity market's squared returns have the highest persistence, on average 30 percent on all four lags. The average serial correlation is 20-25 percent for all the markets except Germany for which squared returns show autocorrelation, averaged across four lags, of approximately 15 percent. Table 2 reports the bivariate correlation for the full period, period after the introduction of euro[8] and the global/European crisis period[9].

Static bivariate correlations, against the German benchmark, demonstrate an overall EU convergence in the whole sample. After the introduction of the Euro, this convergence increases to an even higher level and is observed for all the equity markets, whether EMU or non-EMU. This convergence witnesses a further hike during the crisis period.

Greece has the lowest bivariate correlations among all the countries. This connectedness is even weaker than the association of non-EMU markets with the German benchmark and also with the remaining EMU stock markets. For example the Swiss market bivariate correlations during the crisis period with France, Germany and Italy are 89, 83 and 85 percent points respectively and in the same period these correlations for Greece are 67, 62 and 67 percent points. Nonetheless, the reported unconditional correlations, across the markets, are higher during the crisis period than the association

[8]The reported post-Euro correlations are for the period from January 1999 to November 2007. This is to ensure that variations in the correlations during the crisis period would have no influence on the postEuro correlation patterns and interdependencies between country pairs for these two states could be analysed distinctively.

[9]The crisis period in this study starts from December 2007 till the end of sample period, i.e. December 2013. The beginning of the crisis period is matched with the beginning of the global recession emanating from the US and subprime mortgage crisis and lasted till the end of 2009. Around which Europe, or more specifically the Eurozone region, entered into recession – a crisis more often known as European sovereign debt crisis and getting early impetus from housing and banking market collapse (Cipollini et al. (2015)). The severity of this crisis has required four Eurozone countries (namely Cyprus, Greece, Ireland and Portugal) to be salvaged by state-level bailout programs provided by the International Monetary Fund, European Commission and the ECB. Although Spain has not been the signatory of a government bailout, however propping up of its flailing banking sector drew €41bn of EU funds. Italy and Spain also experienced grave aversion from global investors, for the increasing possibilities to be part of a bailout program, which lead the soaring debt yields on the sovereign bonds from these countries as well. This ongoing crisis has disastrous economic effects on the EMU growth and has forced ECB to launch a quantitative easing program (January 2014) to stimulate growth in the Euro region.

levels achieved in the total and post-Euro periods. The bivariate correlations of the UK stock market with German stock market are even higher than the Swiss-German correlations across all periods.

4. Methodology

The construction of the DCC-MIDAS model is based on the GARCH-MIDAS process proposed by Engle et al. (2013). The reason of utilizing this model for our analysis is motivated by the fact that it allows us to incorporate multiscaled macroeconomic information within the dynamic correlation structure. Using this specification, we can study the behaviour of dynamic correlation effected by the variation in business cycle. In order to estimate the dynamic conditional correlation through the DCC-MIDAS model, we follow the two-step procedure of Engle (2002). In the first step, we estimate the parameters of univariate conditional volatility models. The standardised residuals from the estimated models are then used to estimate the correlation structure. We employ a GARCH-MIDAS model for this purpose. In this way, we are able to incorporate the macroeconomic factors into the variance equation. It has been showed in Asgharian et al. (2013) that this specification better cleans the residuals for volatility forecasting. The DCC-MIDAS parameters are estimated, using the estimated standardised residuals, in the second step.

Below we briefly describe the statistical structure of both the univariate and the DCC setup along with the two-step estimation algorithm.

4.1. Preliminaries - Univariate setup

The standardised residuals for the dynamic correlation estimation are estimated from a GARCH-MIDAS process. This new class of component GARCH models is based on the MIDAS regression scheme of Ghysels et al. (2004). MIDAS regression allows for analysis of the parameterised regression using data sampled at different frequencies. The MIDAS weighting scheme helps us extract the slowly moving secular component around which daily volatility moves.

Assume the returns on day i and month t are generated by the following process

$$r_{i,t} = \mu + \sqrt{\tau_t \cdot g_{i,t}}\xi_{i,t}, \quad \forall i = 1, \ldots, N_t. \tag{1}$$

$$\xi_{i,t}|\Phi_{i-1,t} \sim N(0,1)$$

where N_t is the number of trading days in month t. The conditional variance dynamics $g_{i,t}$ is assumed to follow a daily GARCH$(1,1)$ process,

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}. \tag{2}$$

where α and β are fixed (non-random) parameters and τ_t is constant for all days i in the month t. The process is defined as a combination of smoothed realised volatility and macroeconomic variables in the spirit of MIDAS regression

$$\tau_t = m + \theta_1 \sum_{k=1}^{K} \phi_k(w_1, w_2) RV_{t-k} + \theta_2 \sum_{k=1}^{K} \phi_k(w_1, w_2) X^l_{t-k} + \theta_3 \sum_{k=1}^{K} \phi_k(w_1, w_2) X^s_{t-k}. \quad (3)$$

$$RV_t = \textstyle\sum_{i=1}^{N_t} r^2_{i,j}.$$

where K is the number of periods over which we smooth the volatility, and X^l_{t-k} and X^s_{t-k} are the level and shocks of a macroeconomic variable respectively. The component τ_t does not change within a fixed time span (e.g. a month).

Finally, the total conditional variance can be explained as

$$\sigma^2_{i,t} = \tau_t \cdot g_{i,t}.$$

The weighting scheme used in equation (3) is described by a beta polynomial with weights w_1 and w_2 as

$$\phi_k(w_1, w_2) = \frac{\left(\frac{k}{K}\right)^{w_1-1} \left(1 - \frac{k}{K}\right)^{w_2-1}}{\sum_{j=1}^{K} \left(\frac{j}{K}\right)^{w_1-1} \left(1 - \frac{j}{K}\right)^{w_2-1}}. \quad (4)$$

4.2. **The DCC setup**

Having obtained the estimates of the standardised residuals, we can obtain the correlation structure using the DCC-MIDAS model. The DCC-MIDAS model stems from the idea of DCC model Engle (2002) and from the GARCH-MIDAS model. A key feature of the DCC-MIDAS model is that it decomposes the correlation into a low (e.g., monthly) and a high (e.g., daily) frequency component. Short-lived effects on correlations are captured by the autoregressive dynamic structure of DCC, where the intercept of the latter is a slowly moving process that reflects the fundamental or secular causes of time variation in the correlation. Distinguishing between components may not only help us measure correlation accurately, it will allow us differentiate between instruments, such as business cycle indicators, monetary policy changes etc. that are expected to predominantly affect the low frequency component.

Consider a set of n assets and let the vector of returns $r_t = [r_{1,t}, r_{2,t}, \dots r_{n,t}]$ be denoted as

$$r_t \sim N(\mu, H_t), \quad (5)$$

$$H_t \equiv D_t R_t D_t.$$

where μ is the vector of unconditional means, H_t is the variance covariance matrix and D_t is a diagonal matrix with standard deviations on the diagonal. R_t is the time-varying correlation matrix, defined as

$$R_t = E_{t-1}[\xi_t \xi_t'], \quad (6)$$

$$\xi_t = D_t^{-1}(r_t - \mu).$$

Therefore, $r_t = \mu + H_t^{\frac{1}{2}}\xi_t$ with $\xi_t \sim_{i.i.d.} N(0, I_n)$. The time-varying standard deviations, which can be seen as diagonal elements of D_t, are decomposed into a low and a high frequency component as

$$D_{i,t} = \sqrt{\tau_t \cdot g_{i,t}}.$$

where τ_t and $g_{i,t}$ have been defined in the previous section.

Using the standardised residuals, ξ_t obtained from the GARCH-MIDAS model, the component of the correlation matrix of the standardised residuals Q_t can easily be estimated. The short-term correlation between assets i and j is calculated as

$$q_{i,j,t} = \bar{\rho}_{i,j,t}(1 - a - b) + a\xi_{i,t-1}\xi_{j,t-1} + bq_{i,j,t-1}. \tag{7}$$

The long-term correlation component $\bar{\rho}_{i,j,t}$ is specified as

$$\bar{\rho}_{i,j,t} = \sum_{l=1}^{K_c^{i,j}} \phi_k(w_1, w_2)c_{i,j,t-1}, \tag{8}$$

where $K_c^{i,j}$ is the span length of historical correlations and

$$c_{i,j,t} = \frac{\sum_{k=l-N_c^{i,j}}^{l} \xi_{i,k}\xi_{j,k}}{\sqrt{\sum_{k=l-N_c^{i,j}}^{l} \xi_{i,k}^2}\sqrt{\sum_{k=l-N_c^{i,j}}^{l} \xi_{j,k}^2}}.$$

The polynomial function $\phi_k(w_1, w_2)$ is that in equation (4).

4.3. **Estimation strategy**

In order to estimate the parameters for the system of equations (1) to (8), we follow the two-step procedure of Engle (2002) described above. By maximizing the following quasi-likelihood function, QL, we can thus estimate the parameters.

$$QL(\Psi, \Xi) = QL_1(\Xi) + QL_2(\Psi, \Xi),$$

with

$$QL_1(\Psi) = -\sum_{t=1}^{T}(\mathrm{n}\log(2\pi) + 2\log|D_t| + r_t' D_t^{-2} r_t),$$

and

$$QL_2(\Psi, \Xi) = \sum_{t=1}^{T}(\log|R_t| + \xi_t' R_t^{-1}\xi_t + \xi_t'\xi_t).$$

where, $\Psi \equiv [(\alpha, \beta, w_2, m, \theta_1, \theta_2, \theta_3)]$ is the vector of all the parameters in the univariate volatility model for each series and $\Xi \equiv (a, b, w_2)$ is a vector of parameters of the conditional correlation model. In the first step, we estimate the parameters driving the dynamics of volatility for each asset in equations (1) to (4) and collect them in a vector Ψ (yielding $\hat{\Psi}$). The second step consists of an estimation of the standardised residuals,

$\hat{\xi}_t = \hat{D}_t^{-1}(r_t - \mu)$ in equation (7) using $QL_2(\hat{\Psi}, \Xi)$.

To facilitate the estimation of the chosen model, we first need to decide on the choice of polynomial characteristics K and N_t in equation (3) and $K_c^{i,j}$ and $N_c^{i,j}$ in equation (8). In the former case, K determines the total number of lags needed to optimize the log-likelihood function. In the univariate case, these lags can be equivalent to a month, a quarter, or a half year. This lag value will then be used in the MIDAS polynomial specification for τ_t in equation (3). As stated in Engle et al. (2013), this amounts to model selection with fixed parameter space and is therefore achieved by profiling the likelihood function for various combinations of K and N_t. We use the lag number $K = 12$, which is equivalent to a so called one MIDAS year period and $N_t = 22$, the number of trading days in each month. In order to determine the long-term conditional correlation , we proceed in exactly the same way, namely by selecting the number of lags $K_c^{i,j} = 504$ (which is equivalent to two years of daily values with the exception for France-Greece pair, where K=756 is used to achieve the convergence) for historical correlations and the time span over which to compute the historical correlations $N_c^{i,j} = 22$ in equation (8).

To set the weights, w_1 and w_2, in the beta polynomial given in equation (4), we follow the specification from Engle et al. (2013) where we fix the weight w_1 to one, which makes the weights decrease monotonically over the lags. Since there are no prior preferences for weight w_2, we let the model optimally estimate w_2 for each asset. The details about the behaviour of weights as the function of the number of lags can be found in Asgharian et al. (2013).

5. Empirical results

5.1. Preliminary estimations

Table 3 and 4 report the results of the preliminary univariate GARCH-MIDAS specification to later calibrate dynamic correlations. Table 3 only uses the 1-year rolled squared market returns to proxy for realised volatility, at monthly frequency, as an input series to carry out the MIDAS estimation. This provides us predictions for the long run component of the conditional/baseline variance. The short run variance component ($g_{i,t}$) is estimated using equation (2) and the long run component (τ_t) is retrieved from equation (3). The estimate for the baseline/total variance is the product of these two components as stipulated in equation (4)[10]. Results in table 3 show that the short run volatility (or GARCH effect) is persistent across all the markets: the sum of GARCH estimates ($\alpha + \beta$) are close to integration for all the considered country indices. Moreover, we notice that different weight structures are required for all the stock markets

[10]The unreported results (available upon request) display the superiority of GARCH-MIDAS specification over the conventional GARCH (1, 1) specification. The better volatility forecasting ability of the GARCH-MIDAS specification is consistent with Engle et al. (2013) and Asgharian et al. (2013). We employ the root mean squared errors (RMSE), as decision criterion in measuring the better fit of the tested model specifications.

for the convergence of the estimated specifications. For example, a comparatively lower weight (w) is required for the German stock market to achieve the univariate GARCH-MIDAS model convergence.

"Please insert Table 3 about here"

For Switzerland and the UK, the long run volatility component decays because of the negative estimate for the level (m). However θ_1 is positive and significant across all markets. Whereas the long run volatility component is mean reverting: $m + \theta_1$ is sufficiently less than 0.5 for all stock markets. Importantly, the level of long run volatility component is higher for Greece, Italy and Spain than France and Germany manifesting higher long run risk fault lines of the former markets.

Engle et al. (2013) notes that if there are several components to volatility then estimates for realised volatility may not be a suitable proxy for the underlying process. This makes inclusion of macroeconomic variables pertinent. Therefore the independent factors capturing business cycle conditions and monetary policy namely PC_{BC} and PC_{MP} are added to the estimated specifications reported in Table 3. We decompose each PC into two parts i.e. level and shock (the $AR(1)$ component to the level of PC). This will help in describing if the baseline variance, across markets, is sensitive towards aggregate expectations for these variables or to the shocks to them. This could also be interpreted as a test to analyse the candidature of realised volatility to proxy long run volatility component when we take independent factors capturing the macroeconomic environment. Beta polynomial is used to smooth the long-term components of volatility and correlations. Outputs from these regressions are reported in Table 4.

"Please insert Table 4 about here"

Table 4 shows that the level of long run volatility is negative (insignificantly) for all markets except for the UK market. However the GARCH component remains its persistence. The baseline variance is significantly exposed to RV for EMU markets only: Greece has the largest exposure to realised volatility with an estimate of 0.01 for θ_1. The size of exposure to RV for France, Italy and Spain is also sufficiently higher than the exposure for Germany.

The results for PC_{BC} and PC_{MP} factors are mixed at best: shocks to monetary policy variables are positive and significant for large European markets i.e. France, Germany and the UK. The baseline variance for the Swiss market is significantly affected by variability in the level of PC_{MP}. Italian and Spanish total variance evolution are responsive to the shock and the level of business cycle principal component respectively. Whereas Greece baseline variance dynamics respond neither to level nor to the shocks in the latent macroeconomic factors. Because of the fragile economic state of the Greek economy, this implies its equity market baseline variance is exposed to a broader measure of uncertainty than a specific response to changes in a particular macroeconomic state

variable. Overall, the variability in the significance of macroeconomic based PCs can be positioned parallel to the evidence in Liu (2013) i.e. dissimilar mechanisms are at work in shaping integration processes across markets.

The mixed results for the sensitivity of total variance towards macroeconomic risks and the frequent significance of θ_1 reflects the greater importance of RV in capturing long run variance component than the decomposed PCs, especially for EMU equity markets. Moreover, the differences could effectively be representative of relative risk levels in accordance to their market capitalisations. Effectively as we move through large markets to small equity markets baseline variance displays sensitivity to broader measure of uncertainty. This is seen by total variance's exposure to shocks to PC_{MP} for large markets vs sensitivity to changes in business cycle conditions or RV for PIIGS equity markets. For example, Greece is smallest equity market amongst all the markets and therefore its total variance shows sensitivity to a liberal measure of risk such as RV than specific macroeconomic risks. Accordingly large stock markets' variance may be a hedge for aggregate monetary policy but not for the shocks to the monetary policy.

The exposure of baseline variance process to RV for EMU stock markets could be an effect of their higher interdependence because of sharing monetary policy. This makes realised volatility to be a effective information container of the long run variance component for Eurozone markets: baseline variance only responds to new information content coming from a particular dimension of macroeconomic risks. This is displayed through the significant exposure of baseline variance to shocks to PC_{MP} for France and Germany, whereas Italy's variance exposure to PC_{BC}. The only exception is Spain whose variance is sensitive to fluctuations in the level of aggregate business cycle component.

5.2. European market short run integration patterns

Following Colacito et al. (2011) the standardised residuals return volatility from univariate GARCHMIDAS models, estimated in Table 3 and 4, are taken to the DCC-MIDAS specification. The DCC-MIDAS estimates the dynamic correlation between the pair markets. By virtue of the MIDAS weight filter, the total correlation structure is decomposed into a slowly moving long run component around which daily correlations move, see equations (7) and (8). The DCC-MIDAS results, reported in Table 5, are divided into two vertical panels. In panel I , the pairwise DCC-MIDAS specification is estimated using standardised residuals from GARCH-MIDAS specification with RV as proxy for long run variance component. The second panel uses standardised unexplained returns from the specification which also includes the level and shock to the two PCs and is notated as $RV + Econ$. The tested DCCMIDAS specifications converged for all pair-countries: w is significant at 5% confidence interval although with varying weights across pair countries. The short-lived effects i.e. $(a + b)$, reported in the first panel, show high persistence across the European market. This persistence in daily correlations is in line with the widely reported evidence studying European market integration using non-MIDAS based techniques (Savva et al. (2009); Connor and Suurlaht (2013) among other).

"Please insert Table 5 about here"

The persistence of our proxy EU short run pair correlations does not show an EMU vs non-EMU divide, instead it shows segregation between the large and small markets. To highlight this categorisation, we note that Greek, Italian, Spanish and Swiss equity markets' short run pair correlations with the German benchmark are far more persistent, a sign of higher EU convergence than the respective persistence exhibited by Franco-German and German-UK daily correlations.

This relatively lower short run persistence manifests another important aspect in the overall integration patterns: large stock markets show sizeable secular longrun correlations on the total correlation dynamics. For example, France-Germany and Germany-UK pairs depicting France and UK markets' EU integration patterns, short run correlations have a persistence of 83 percent and 88 percent respectively. This illustrates how much daily correlations are pegged to slow moving fundamental MIDAS correlations i.e. 17 percent and 12 percent respectively. Even higher persistence in the short run is observed for Greece, Italy, Spain and Switzerland pair correlations if we replace the EU proxy with France or the UK stock market. These persistence levels are in a range of 95-98 percent. Greece-UK pair is the only exception to these highly persistent bi-variate correlations. The results in panel II are not substantially different from DCC-MIDAS specification in panel I.

Overall, point estimates show that short run pairwise correlations have high convergences during the full sample period. Whereas the EU wide long run interdependences, against the German benchmark, are relatively higher for large economies[11] than the remaining equity markets. These patterns within the EU region show integration exist at different levels for large stock markets than the smaller equity markets independent of monetary policy integration. The implied convergence patterns from the DCC-MIDAS point estimates may overlook variability in the correlation patterns over time and across key events. Therefore, we plot the retrieved DCC-MIDAS short run and fundamental correlation series which are shown in figures 1 and 2 respectively.

"Please insert Figure 1 about here"

The dynamic pairwise correlations in figures 1 contain a number of time patterns across EU markets. First, pairwise correlations among EU equity markets tend to increase as they approach January 1999 i.e. the month in which common Euro currency was launched. This rise is sharper and achieved new heights which are stronger than the pre-Euro (period prior to introduction of Euro) levels for most of the stock markets.

[11]The German economy is the largest in size among the EU economies followed by the UK and France. These stock markets also make the three biggest stock markets in the region - not necessarily in the same order. They are followed by Swiss, Spanish, Italian and Greek stock markets with respect to their market capitalisations.

The importance of this event is evidenced by the six to ten times inflating of EU-wide short run interdependences compared to the levels observed at the beginning of the sample period. The exception is Swiss equity market: it had strong association with the German stock market at the beginning of the sample period in this study so had not as steep EU convergence than witnessed for the remaining equity markets. This co-movement in the EU stock markets is observed at a broader level: increases are reported for all the cross-country correlation pairs.

Second, the short run correlation predictions from the two DCC-MIDAS specifications are not drastically different. Third, these convergence levels become stable in the post-Euro period when pre-Euro cross-country return correlations are observing surging level shifts. After the introduction of the Euro, the EU convergence weakened for Greece and Switzerland in the following two year period only to become stable from thereafter. During the post-Euro period, the interdependence between the Swiss market and the proxy EU benchmark has been the most volatile amongst all the markets but nonetheless it maintained the same upward trend which others displayed. The short run pair convergences are also pan European in the post-Euro period.

To delve deeper into the pan European integration patterns, we induce a cut-off line at the beginning of the global crisis period of 2007-08 and refer to the period from December 2007 to December 2013 as the crisis period in this study. The short run integration patterns during this period have even higher correlations and are more stable than the achieved stability during the post-Euro period (January 1999 to November 2007 from hereon). The increased convergence levels are consistent with earlier reported empirical evidence (Erb et al. (1994); Connor and Suurlaht (2013), among others) that equity markets tend to co-move during crisis or bearish market conditions.

There are few pertinent temporal exceptions to the above noted generalisation of higher and more stable convergence. In the lead up to global financial crisis of 2007-08 all the stock markets showed smoothed increase in pairwise correlations against the German benchmark. However, EMU markets responded to the EDC specific, for that matter regional, shocks in a far more dramatic fashion.

This is inferred from the diverging correlations between the Franco-German pair in the buildup of the European debt crisis i.e. for the period from the end of 2008 to the beginning of the year 2009. From there on, France's convergence with the EU proxy was reinstated and evolved to heights of convergence not observed in the whole sample. This may describe the initial absence of confidence between the two largest EMU markets given the severity of the EDC crisis. Furthermore, French banks are the largest debt holders of the PIIGS countries. They owned more than 700 billion USD of the Greek (51 billion USD), Italian (412 billion USD) and Spanish (150 billion USD) debt as per the Bank of International Settlements (BIS) 2009 report. For that reason, during the crisis period, French stock market correlations with Italy and Spain are tumultuous at best. Nonetheless, maintained an upward converging trend. The most drastic are the French-Greek pair correlations that transpired into an overall divergence during the

course of crisis period. A deterioration which is a generality for Greek stock market pair correlations with all the remaining stock markets during the crisis period. We will discuss this anomaly in greater detail later.

"Please insert Figure 2 about here"

Put simply the initial divergence in the EU integration levels for French market was because of the French banking sectors' exposure to PIIGS economies. The later increase could be conjectured to be the outcome of European Union debt bailout programs for PIIGS countries[12].

The remaining equity markets show more than one instance of divergence against the German benchmark. Italian DCC dynamics with the EU benchmark deteriorated through the year 2008. This divergence reappears in 2012. The variabilities in the Spanish markets' EU integration is displayed by the greater number of co-movement wide diverging responses - at least four - between the German-Spanish short run pair correlations. The UK also decoupled from the high convergence level with the German benchmark during the year 2009 and 2010. In line when the PIIGS driven European debt crisis evaporated confidence from global financial market functioning and witnessed historical increases in the yields of the sovereign bonds from Greece, Italy and Spain among others (Cipollini et al. (2015)).

The German-Swiss short run return correlations exhibit ever-fluctuating integration patterns in the crisis period as well. Swiss market's EU integration displayed reduced co-movements during the global financial crisis of 2007-08 – a period when all other countries showed higher EU convergence. In addition to this, during the EDC period, Swiss market's EU convergence levels observed substantial episodic divergences. Overall, the Swiss market displayed high EU level converging pattern. The UK equity market also displayed severe divergences to the otherwise surging correlations, in the wake of 2008 and 2010 EDC shocks.

The most drastic exception among the ever converging patterns among the EU markets is the divergence between the German-Greek equity market correlations. The German-Greek short run correlations show that the convergence levels, which achieved its epitome in 2007-08 period, fizzled out quickly during the crisis period. This divergence is not observed for any of the remaining equity markets' EU integration patterns. This demonstrates detachment from Greek risk by all the equity markets during the crisis period. This EU wide insulation from Greek risk could also be a manifestation of the mistrust between the Greek and the European policy makers in the implementation of austerity plans by Greece - in response to the offered bail out packages. This

[12]These bailouts were managed by the European Financial Stability Facility mechanism (EFSF) initially as a temporary initiative in June 2010. From October 2012 European Stability Mechanism (ESM) started its work to provide financial assistance to new requests from Eurozone countries on permanent basis.

detachment from the Greek risk also explains the prevailing unconcern demonstrated by policy makers and financial markets in 2014 and 2015 for the ex-ante 'Greek default' or GREXIT.

The insulation of the EU markets from the Greek stock market has neutralised the earlier achieved high convergence levels. This neutralisation is to such an extent that Greek short run return correlations, which were around or above 70 percent before the crisis period, have dropped to 30 percent in most cases. The decreasing DCC effects between Greek and the remaining EU countries during the crisis period are in sharp contrast to the unconditional correlations reported in Table 2. This shows the importance of modelling equity returns dynamically when the static correlations may portray misleading patterns (Kalotychou et al. (2014)). It has been shown in Colacito et al. (2011) that the efficiency improvements in the estimation of dynamic correlations are even higher when specification allows estimation of slow moving long run component.

The long-term integration dynamics also reinforce the reported divergent pattern between the Greek and the remaining EU equity markets. This manifests that European markets have, over the crisis period, systematically decoupled themselves from the shocks emanating from the Greek stock market. Although the aggregate debt levels of the Italy and Spain are much higher than the Greek debt. Potentially, the political fallout between Greece and European Commission (EC) has resulted in different integration structures [13]. Overall, integration levels among EU markets follows previously reported patterns but the Greek market's crisis period EU divergence is new.

5.3. **European market long run integration patterns**

Furthermore, the two DCC- MIDAS specifications demonstrate almost similar trends in the evolution of long run correlations. Most of the exceptions are witnessed for Swiss market correlations with EMU markets among others, see plots in Figures 2. These patterns across sample periods are in line with to the patterns in Figures 1. However, the long run integration patterns, retrieved from the two DCC-MIDAS specifications show different evolutions. This variability in evolution of the fundamental component is evident from the more smoothed and lagged predictions from the $RV + Econ$ specification compared to the long run correlations predictions retrieved from RV specification. For example see the plots between Germany-UK, Italy-UK and Spain-Switzerland, among others.

Furthermore, there are also cross-country differences in the shaping of long run paired interdependencies. For example, the long run convergence between correlations of Greece and Spain with the German benchmark kept an upward trend till the beginning of global crisis of 2007-08. However, long run correlation patterns for France and

[13] Greece was offered two bailout packages in 2010 and 2012 and in return was required to take series of austerity measures and structural reforms. This fall out has its roots in the quid pro quo implementation of agreed reforms by the Greek government and earlier mistrust for manipulative reporting of Debt to GDP ratios to EC for several years by Greek governments.

Italy with the German benchmark rose at a stable rate during the same period. Swiss market long run correlation kept an upward trend across all the sample periods but displayed substantial fluctuations. The UK market's fundamental co-movements displayed a smoothed increase over the whole sample length. Other consistent simplification, in line with the evidence reported in the previous section, includes the EU wide decoupling of stock markets from the Greek risk during the crisis period.

The long run correlations converged to higher levels for French and British equity markets with the German benchmark as the latter part of the crisis period approaches. This is consistent with the higher persistence of the secular component for large stock markets in the EU region.

5.4. **Joint relationship of volatilities and correlations**

The increases in the correlations when volatility is also rising can inflate the overall portfolio risk, whether the portfolios are constructed using basic assets or are composed of derivative securities. This co-movement makes the comprehension of the joint relationship between the two processes, important for active or passive investment decisions, constructing insurance plans and devising hedging risk strategies. Since we have estimated the short run and long-term components of dynamic volatilities and correlations through the GARCH-MIDAS and DCC-MIDAS specifications respectively, we estimate the joint relationship for both components following Cappiello et al. (2006)[14].

The joint relationships of dynamically retrieved series are compared with the joint relationships of unconditional counterparts. Cappiello et al. (2006) reported the average of the correlations between the variance of a country and associated pairwise correlations of that country. In reporting these joint relationships we delve deeper than them: we document joint relationships for and against each country, and also report the cross-country averages as in Cappiello et al. (2006). The interrelations between the two year rolling RC computed from daily data and the rolling RV are reported in Table 6.

"Please insert Table 6 about here"

We define the correlation of each asset's variance with all its associated pairwise correlations as:

$$\phi_i = \frac{\sum_{t=1}^{T}(h_{i,t} - \bar{h}_i)(\rho_{i,j,t} - \bar{\rho}_{i,j})}{\sqrt{\sum_{t=1}^{T}(h_{i,t} - \bar{h}_i)\sum_{t=1}^{T}(\rho_{i,j,t} - \bar{\rho}_{i,j})}} \tag{9}$$

[14]We only report results for joint relationships of the short run variances and short run pairwise correlations from GARCH/DCC-MIDAS specifications, respectively, using RV in the approximation of long run variance component. The results for joint relationships for the GARCH/DCC-MIDAS specification using $RV + Econ$ are available upon request. However, as noted in Figures 1 and 2 implications are not particularly different from the ones reported using only realised volatility.

The static joint relationships[15] show that European integration levels have moved in tandem with the German stock market volatility over the full period in this study. However, increases in German volatility, during the post-Euro and during the crisis period, are negatively related to its associated pairwise correlations. The strength across these periods is almost identical i.e. on average it is 50 percent, however it is negative in the latter periods. The latter period joint relationships, especially during the crisis period, entail an important implication for portfolio diversification: portfolio strategies timing German market's volatility and/or its pairwise correlations are safe hedges for spillover risks coming from either market's volatility risk. To elucidate, German market pairwise correlations tend to decrease if German volatility is on the rise and the same is also true when volatility increases are witnessed for the pair country. For example, the crisis period Franco-German joint relationship, for increases in French stock volatility, is [-0.61] and it is [-0.60] for the German market volatility increases

With the exception of the Greek market's joint relationship during the crisis period, similar diversification/ hedging benefits are not witnessed for investing strategies in the remaining equity markets. For example, the French-UK joint relationship between the French-UK RC and the French market's RV is [0.61]. This joint relationship is even higher for the increases in the UK market volatility i.e. [0.77]. However, across all the markets static joint relationships are negative in the post-Euro period.

The unconditional joint relationships for the Greek, Italian and Spanish (PIIGS countries) market volatilities display the largest opposite movement to the associated pairwise correlations during the post-Euro period. The joint association of PIIGS market volatilities with their respective linked correlation pairs, with the exception of Greek stock market volatility, show a positive relationship during the crisis period. This signifies a higher integrated riskiness of these markets during the crisis period.

Numerous studies report issues in the modelling of static correlations such as their ability to capture true dynamics, their dismal performance when used in constructing portfolios or developing strategies to cover portfolio risk. Therefore, the veracity of these unconditional patterns needs to be confirmed with the dynamic counterparts.

"Please insert Table 7 about here"

Table 7 reports the short run joint dynamics between the GARCH component and dynamic return correlations from the GARCH/DCC-MIDAS specification using RV only. The only consistency between ϕ_i's, in the full period, using dynamic series versus rolling series is the positive relatedness. Otherwise, on average the dynamic joint correlations are far weaker than the ones reported in Table 6. This decline in the joint relationship

[15]From here on ϕ_i or average joint relationship will be used interchangeably. The relationship using rolling series will be noted as static joint relationships and correlations between dynamic series from GARCH/DCC-MIDAS will be noted as dynamic relationships for matter of convenience. Because the reported ϕ_i's using rolling or dynamic correlations are unconditional for the matter of fact.

is to the extent that for Greece and Italy dynamic equity market variance increases are almost uncorrelated with their respective dynamic pairwise correlations: for the whole sample period the average joint relationship is only 0.04 and 0.09 respectively. The full sample average joint relationship for Germany is also small, i.e. 0.16 which using the static series was substantially higher, i.e., approximately 50 percent.

The overstatement of static correlations, in either direction, is also established by analysing the post-Euro and crisis period joint relationships. The highly negative static ϕ_i during the post-Euro period using dynamic counterparts are only weakly correlated. For EMU markets this establishes a case of uncorrelated relationship between dynamic series in the short run. Only for Greece, the average joint relationship is negative i.e. (-0.13) which is at least 6 times lower than its unconditional counterpart. The highest positive ϕ_i is reported for the non-EMU equity market, i.e. Switzerland and the UK.

The crisis period joint relationships are weakly positive across markets except for the German stock market: the highest ϕ_i is for UK at 0.27. German market volatility has negative association with EU-wide pair correlations. This displays the marginal diversification benefits, for making portfolio strategies which time German volatility against the increases in dynamic correlations during the crisis period. The only exception is Germany joint relationship with Greece: German-Greek DCC correlation increases, during the crisis period, in response to the increases in the GARCH component of German market baseline variance.

"Please insert Table 8 about here"

"Please insert Table 9 about here"

The joint relationships between the GARCH-MIDAS long run variance component and the DCC-MIDAS long run correlation component, reported in Table 8, demonstrates more suEUtantial differences across the sample periods compared to the short run relationships. The full period pairwise correlations tend to increase more in response to increases in the equity variances than reported at daily frequency. Whereas the postEuro relationships, on average, invert the uncorrelated pattern reported for short run joint dynamics. The crisis period long run equity variance rises are enjoined with increases in associated pairwise correlations as well. These long run dependencies are greater for EMU countries except for Germany. The rises in the fundamental component of the German total variance attracts mixed association with its pairwise dynamic correlations -manifesting once again large market vs small market pattern segregation. The average joint relationship between Germany long run variance and associated long run pairwise correlations is a meagre 0.07. This positive, yet minuscule, relatedness is more a vindication of the skewed impact of increases in the German-Greek and German-Spanish long run correlations when German long run volatility is also increasing.

Excluding joint dynamics of the Greece and Spain with Germany, the average of the German joint relationships are negative during the crisis period. Aggregating these

joint relationships, the rises in the benchmark German equity variance are negatively related to large EU markets during the crisis period i.e. France and the UK. This relationship is observed whether scrutinised through dynamically retrieved series or from a static version of them and is also reported consistently for the long run and the short run joint relationships. Analysing how the EU integration patterns respond to the variance shocks emanating from the rest of the EU markets show that variance increases in the EU markets tend to decrease their proxy EU integration patterns. This shows that Germany is a stable market and its return correlations does not increase, rather decrease when volatility shocks are emanating from paired market(s). This is not the case for the other two larger equity markets i.e. France and the UK. This provides credibility to German stock market's benchmarking as an EU proxy in our study.

Taken together these results establish two important corollaries. First, joint relationships from RV and RC series tend to overstate the magnitude of directedness. This overstatement is considerably higher than the joint relationships reported for the dynamic series extracted from GARCH-MIDAS and DCC-MIDAS specifications, respectively. This overstatement amplifies resultant benefits or risks to develop diversification strategies and possibly results in mispriced insurance plans. For example, increases in the Greek market static variance are inversely related to its pairwise correlations during the post-Euro period. The employment of these patterns could have resulted in unfavourable investment outcomes than the ones based on relationships from dynamic variance and correlation series. Second, except for Germany, the average short run joint relationships show that increases in dynamic equity variance accompany increases in cross-country dynamic return correlations during the crisis period when compared to the growth (post-Euro) period. This is much severer indication of the integration of risks during periods of turmoil which could build up contagious market states. This pattern is also observed for the average long run joint relationships across all markets excluding Germany, as discussed earlier and is shown in Table 8. Table 9 reports joint relationships using dynamic predictions using GARCH/DCC-MIDAS $RV + Econ$ specifications. Results are qualitatively similar to the ones reported in Table 8.

6. Conclusion

We employed state-of-the-art GARCH/DCC-MIDAS technique to estimate conditional return volatilities and dynamic pairwise correlations. European financial markets have been reported to have increased integration levels among themselves after the introduction of the Euro. The witnessed surging co-movement at European level is broadbased and is not only limited to EMU markets. European markets also experienced increased levels of convergences in the post-Euro period. We document differences in cross-country market responses to monetary policy and business cycle linked latent variables depending upon the relative size of the stock market. We show large stock markets may anticipate exchange rate fluctuations but not shocks to the monetary policy variabilities. In addition relatively small equity markets such as Greece, Italy and Spain show sensitivity towards variations to business cycle latent variable or RV. Most importantly, we find no particular improvements in volatility predictions between spec-

ifications using RV as a proxy for long run variance or specification augmented with latent factors to proxy different macroeconomic risks. This is consistent with the results reported by Lieven et al. (2010) who showed a variance based measure is critical for explaining stock volatility. This, combined with our results, stipulates realised variance is an efficient proxy for the long run variance component and this holds, in our sample, especially for short run volatility and integration patterns.

The short run and slow moving fundamental component from DCC-MIDAS specification shows results convergent with the extant European integration literature: EU markets have converged more substantially in the post-Euro period than the pre-Euro period. European equity market integration patterns, benchmarked against German stock market, display that the dynamic pairwise correlation are stable in the post-Euro period but achieved even greater heights during the crisis period, although at higher variability. Furthermore, our results show that European convergence patterns could be divided into large markets vs small markets in the EU region instead of EMU vs non-EMU integration patterns. This is shown by the lower (higher) persistence of the short-lived DCC effects for large (relatively small) stock markets and resultantly higher (lower) persistence in the fundamental MIDAS component. The only exception to the EU converging integration patterns has been the EU wide Greek equity market's divergence in the crisis period. This highlights the mitigation of Greek risk at the European level. The observed mitigation of Greek risk at the EU level provides credence to DCC-MIDAS' ability to capture effectively underlying market co-movements.

Analysing static joint relationships, using rolling variance and rolling correlations, tend to over project co-movements. These over statement of the magnitude of relationships could result in adverse diversification strategies and mispriced insurance plans when compared against their more reliable dynamic counterpart joint relationships. The joint relationship between the dynamic volatility and pairwise dynamic correlation predictions highlights important cross-country patterns. Our results show the stability of German market's proxy status for EU region: during the crisis period all markets displayed increased positive movements between volatility and their associated pairwise correlations except for the German stock market. This shows that the German equity market is a safe bet when volatility shocks emanate from the pair equity market(s). Nonetheless, the increased co-movement between different dimensions of risks results in higher aggregate risk - reducing diversification benefits during bullish market states and results in investment discounting spirals during during crisis periods. This type of 'convergence of risks' increases uncertainty and results in calamitous states – the severity of which may otherwise be ignored if analysed only from cross-country correlation patterns.

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Appendix

Tables

Table 1: The table below summarizes the descriptive statistics of each return series. The mean and standard deviations are annualized. The * shows significance of autocorrelations at 5% level.

Description	France	Germany	Greece	Italy	Spain	Swistzerland	UK
Annualized mean return	0.06	0.06	0.007	0.03	0.07	0.09	0.05
Annualized mean volatility	0.22	0.21	0.29	0.24	0.23	0.18	0.20
Skewness	-0.08	0.05	-0.01	-0.10	-0.05	-0.12	-0.19
Kurtosis	8.92	10.9	6.81	7.68	8.51	7.62	12.27
Autocorrelations of	0.02	0.03*	0.09*	0.02	0.05*	0.03*	0.00
daily returns	-0.03*	-0.01	-0.01	-0.02	-0.03*	-0.03*	-0.03*
	-0.05*	-0.03*	0.00	-0.03*	-0.03*	-0.04*	-0.07*
	0.03*	0.02	0.00	0.05*	0.01	0.03*	0.04*
Autocorrelations of	0.17*	0.13*	0.14*	0.16*	0.17*	0.23*	0.19*
daily squared	0.23*	0.17*	0.16*	0.21*	0.17*	0.26*	0.26*
returns	0.24*	0.15*	0.21*	0.22*	0.20*	0.24*	0.27*
	0.22*	0.15*	0.18*	0.23*	0.26*	0.22*	0.27*

Table 2: Unconditional pairwise correlations of the European equity markets. The static correlations for the full sample period (March 1993-December 2013) are shown in **bold** case, those from the introduction of the Euro until the beginning of global financial crisis (January 1998-November 2007) are in *italics* and while those from the start of crisis until the end (December 2007-December 2013) are shown in [].

Description	France	Germany	Greece	Italy	Spain	Switzerland	UK
France	**-**	**0.80**	**0.44**	**0.75**	**0.79**	**0.75**	**0.77**
	-	*(0.88)*	*(0.53)*	*(0.89)*	*(0.88)*	*(0.82)*	*(0.84)*
	-	[0.91]	[0.67]	[0.95]	[0.93]	[0.89]	[0.92]
Germany	**0.80**	**-**	**0.44**	**0.69**	**0.73**	**0.75**	**0.69**
	(0.88)	-	*(0.55)*	*(0.83)*	*(0.82)*	*(0.78)*	*(0.77)*
	[0.91]	-	[0.62]	[0.87]	[0.84]	[0.83]	[0.85]
Greece	**0.44**	**0.44**	**-**	**0.39**	**0.42**	**0.45**	**0.39**
	(0.53)	*(0.51)*	-	*(0.52)*	*(0.53)*	*(0.50)*	*(0.47)*
	[0.67]	[0.62]	-	[0.67]	[0.66]	[0.62]	[0.62]
Italy	**0.75**	**0.69**	**0.39**	**-**	**0.73**	**0.65**	**0.66**
	(0.89)	*(0.83)*	*(0.52)*	-	*(0.87)*	*(0.79)*	*(0.79)*
	[0.95]	[0.87]	[0.67]	-	[0.93]	[0.85]	[0.88]
Spain	**0.79**	**0.73**	**0.42**	**0.73**	**-**	**0.69**	**0.69**
	(0.88)	*(0.82)*	*(0.53)*	*(0.87)*	-	*(0.77)*	*(0.77)*
	[0.93]	[0.84]	[0.66]	[0.93]	-	[0.82]	[0.85]
Switzerland	**0.75**	**0.75**	**0.45**	**0.65**	**0.68**	**-**	**0.69**
	(0.82)	*(0.78)*	*(0.50)*	*(0.79)*	*(0.77)*	-	*(0.76)*
	[0.89]	[0.83]	[0.62]	[0.85]	[0.82]	-	[0.84]
UK	**0.77**	**0.69**	**0.39**	**0.66**	**0.69**	**0.69**	**-**
	(0.84)	*(0.77)*	*(0.47)*	*(0.79)*	*(0.77)*	*(0.76)*	-
	[0.92]	[0.85]	[0.62]	[0.88]	[0.85]	[0.84]	-

Table 3: Result for the univariate part of estimation for GARCH-MIDAS (RV). The * implies the significance at 5% level.

Countries	μ	α	β	m	θ_1	w
France	0.06*	0.08*	0.89*	0.06	0.009*	1.31*
Germany	0.06*	0.09*	0.88*	0.03	0.01*	1.00*
Greece	0.05*	0.11*	0.84*	0.23*	0.01*	1.21*
Italy	0.05*	0.09*	0.88*	0.30*	0.01*	1.08*
Spain	0.06*	0.08*	0.89*	0.16	0.01*	1.17*
Switzerland	0.06*	0.08*	0.88*	-0.19	0.01*	1.30*
UK	0.05*	0.08*	0.90*	-0.09	0.008*	1.00*

Notes: The considered model for long run component is $\tau_t = m + \theta_1 \sum_{k=1}^{K} \phi_k(1, w) RV_{t-k}$.

Table 4: Results for the univariate part of estimation for GARCH-MIDAS (RV+Econ). The * implies the significance at 5% level.

Countries	μ	α	β	m	θ_1	θ_2	θ_3	θ_4	θ_5	w
France	0.06*	0.08*	0.89*	-0.14	0.006*	0.33	0.60	-0.17	0.11*	1.36*
Germany	0.06*	0.08*	0.89*	-0.08	0.001*	1.07	-1.59	-0.21	0.19*	1.58*
Greece	0.06*	0.11*	0.84*	0.21	0.01*	-0.22	1.24	0.02	-0.02	1.12*
Italy	0.05*	0.10*	0.87*	-0.14	0.007*	-0.93	6.52*	-0.11	0.03	1.22*
Spain	0.06*	0.08*	0.88*	-0.08	0.007*	0.19*	2.88	-0.16	0.07	1.53*
Switzerland	0.06*	0.08*	0.89*	-0.05	0.002	0.20	0.79	-0.79*	0.02	1.73*
UK	0.05*	0.08*	0.89*	-0.36*	0.005	-0.89	3.22	-0.49	0.06*	1.26*

Notes: The considered model for long run component is $\tau_t = m + \theta_1 \sum_{k=1}^{K} \phi_k(1, w) RV_{t-k} + \theta_2 \sum_{k=1}^{K} \phi_k(1, w) PC^l_{BC} + \theta_3 \sum_{k=1}^{K} \phi_k(1, w) PC^s_{BC} + \theta_4 \sum_{k=1}^{K} \phi_k(1, w) PC^l_{MP} + \theta_5 \sum_{k=1}^{K} \phi_k(1, w) PC^s_{MP}$.

Table 5: Results for the estimation of DCC-MIDAS. The * implies the significance at 5% level.

	RV			RV+Econ		
Countries	a	b	w	a	b	w
France - Germany	0.07*	0.76*	6.23*	0.06*	0.76*	6.58*
France - Greece	0.03*	0.95*	5.49*	0.02*	0.95*	5.04*
France - Italy	0.05*	0.93*	3.58*	0.05*	0.93*	2.82*
France - Spain	0.04*	0.93*	2.96*	0.04*	0.93*	2.91*
France - Switzerland	0.06*	0.91*	3.47*	0.05*	0.93*	1.00*
France - UK	0.05*	0.92*	1.54*	0.05*	0.92*	1.34*
Germany - Greece	0.03*	0.91*	4.29*	0.03*	0.91*	4.22*
Germany - Italy	0.06*	0.85*	5.89*	0.06*	0.85*	5.72*
Germany - Spain	0.06*	0.88*	2.50*	0.05*	0.88*	2.50*
Germany - Switzerland	0.05*	0.86*	5.69*	0.05*	0.89*	4.22*
Germany - UK	0.05*	0.83*	3.26*	0.05*	0.87*	1.00*
Greece - Italy	0.04*	0.58*	6.87*	0.04*	0.53*	6.22*
Greece - Spain	0.02*	0.96*	5.09*	0.02*	0.97*	2.76*
Greece - Switzerland	0.02*	0.97*	3.42*	0.02*	0.97*	3.47*
Greece - UK	0.05*	0.83*	4.33*	0.04*	0.85*	4.01*
Italy - Spain	0.05*	0.89*	5.47*	0.05*	0.89*	5.27*
Italy - Switzerland	0.05*	0.92*	3.54*	0.05*	0.92*	2.82*
Italy - UK	0.05*	0.93*	2.96*	0.05*	0.93*	2.05*
Spain - Switzerland	0.05*	0.92*	2.95*	0.04*	0.93*	1.00*
Spain - UK	0.05*	0.93*	1.71*	0.05*	0.93*	1.51*
Switzerland - UK	0.05*	0.93*	1.00*	0.05*	0.93*	1.00*

Table 6: Unconditional joint correlations between two year rolling realised variance (RV) and corresponding two year pairwise realised correlations (RC). Rows define individual volatility while columns define paired correlations. The joint correlation values for the full sample period (March 1993-December 2013) are shown in **bold** case, those from the introduction of the Euro until the beginning of global financial crisis (January 1998-November 2007) are in *italics* and while those from the start of crisis until the end (December 2007-December 2013) are shown in [].

Countries	France	Germany	Greece	Italy	Spain	Switzerland	UK	Average
France	**-**	**- 0.47**	**0.61**	**0.58**	**0.60**	**0.61**	**0.65**	**0.59**
	-	*(-0.20)*	*(-0.65)*	*(-0.20)*	*(-0.36)*	*(-0.28)*	*(-0.06)*	*(-0.29)*
	-	[-0.61]	[0.33]	[0.62]	[0.59]	[0.69]	[0.61]	[0.37]
Germany	**0.47**	**-**	**0.51**	**0.51**	**0.47**	**0.43**	**0.55**	**0.49**
	(-0.47)	-	*(-0.72)*	*(-0.43)*	*(-0.66)*	*(-0.56)*	*(-0.43)*	*(-0.54)*
	[-0.60]	-	[0.04]	[-0.60]	[-0.57]	[-0.59]	[-0.55]	[-0.48]
Greece	**0.26**	**0.17**	**-**	**0.33**	**0.30**	**0.10**	**0.22**	**0.23**
	(-0.76)	*(-0.81)*	-	*(-0.72)*	*(-0.71)*	*(-0.80)*	*(-0.78)*	*(-0.76)*
	[-0.41]	[-0.56]	-	[-0.38]	[-0.31]	[-0.43]	[-0.41]	[-0.42]
Italy	**0.24**	**0.17**	**0.35**	**-**	**0.27**	**0.27**	**0.32**	**0.27**
	(-0.76)	*(-0.73)*	*(-0.78)*	-	*(-0.78)*	*(-0.62)*	*(-0.67)*	*(-0.72)*
	[0.50]	[-0.42]	[0.07]	-	[0.68]	[0.36]	[0.27]	[0.24]
Spain	**0.52**	**0.40**	**0.56**	**0.53**	**-**	**0.51**	**0.55**	**0.51**
	(-0.71)	*(-0.75)*	*(-0.82)*	*(-0.73)*	-	*(-0.73)*	*(-0.69)*	*(-0.74)*
	[0.32]	[-0.49]	[0.09]	[0.70]	-	[0.19]	[0.13]	[0.16]
Switzerland	**0.56**	**0.32**	**0.47**	**0.55**	**0.56**	**-**	**0.58**	**0.50**
	(-0.17)	*(-0.33)*	*(-0.60)*	*(-0.26)*	*(-0.42)*	-	*(-0.12)*	*(-0.32)*
	[0.79]	[-0.78]	[0.57]	[0.76]	[0.75]	-	[0.66]	[0.46]
UK	**0.60**	**0.47**	**0.68**	**0.58**	**0.63**	**0.61**	**-**	**0.60**
	(0.03)	*(-0.09)*	*(-0.51)*	*(-0.11)*	*(-0.22)*	*(-0.04)*	-	*(-0.16)*
	[0.77]	[-0.82]	[0.70]	[0.75]	[0.75]	[0.65]	-	[0.47]

Table 7: Correlations between short-term equity variance and the corresponding pair-wise equity correlations. The aim is to evaluate the pairwise correlation from DCC and the idiosyncratic volatility of one of the pair country. The joint relationship will highlight idiosyncratic volatility correlation with pair-wise correlations obtained from DCC. Rows define individual volatility while columns define paired correlations. The joint correlation values for the full sample period (March 1993-December 2013) are shown in **bold** case, those from the introduction of the Euro until the beginning of global financial crisis (January 1998-November 2007) are in *italics* and while those from the start of crisis until the end (December 2007-December 2013) are shown in []

Countries	France	Germany	Greece	Italy	Spain	Switzerland	UK	Average
France	**-**	**0.18**	**0.27**	**0.26**	**0.28**	**0.27**	**0.28**	**0.26**
	-	*(0.08)*	*(-0.10)*	*(0.17)*	*(0.13)*	*(0.09)*	*(0.12)*	*(0.08)*
	-	[-0.31]	[0.33]	[0.30]	[0.31]	[0.26]	[0.38]	[0.21]
Germany	**0.13**	**-**	**0.19**	**0.16**	**0.16**	**0.14**	**0.17**	**0.16**
	(0.03)	-	*(-0.06)*	*(0.07)*	*(0.04)*	*(0.09)*	*(0.05)*	*(0.04)*
	[-0.42]	-	[0.22]	[-0.18]	[-0.06]	[-0.12]	[-0.16]	[-0.12]
Greece	**0.09**	**0.04**	**-**	**0.02**	**0.02**	**0.03**	**0.05**	**0.04**
	(-0.16)	*(-0.12)*	-	*(-0.15)*	*(-0.15)*	*(-0.14)*	*(0.07)*	*(-0.13)*
	[0.19]	[0.13]	-	[0.16]	[0.17]	[0.15]	[0.21]	[0.17]
Italy	**0.09**	**0.03**	**0.10**	**-**	**0.09**	**0.12**	**0.13**	**0.09**
	(0.13)	*(0.05)*	*(-0.19)*	-	*(0.02)*	*(0.05)*	*(0.06)*	*(0.02)*
	[0.27]	[-0.08]	[0.25]	-	[0.26]	[0.26]	[0.33]	[0.22]
Spain	**0.23**	**0.17**	**0.24**	**0.22**	**-**	**0.25**	**0.25**	**0.23**
	(0.13)	*(0.07)*	*(-0.07)*	*(0.08)*	-	*(0.06)*	*(0.07)*	*(0.06)*
	[0.23]	[0.00]	[0.28]	[0.21]	-	[0.29]	[0.29]	[0.22]
Switzerland	**0.28**	**0.20**	**0.20**	**0.25**	**0.28**	**-**	**0.31**	**0.25**
	(0.20)	*(0.19))*	*(-0.06))*	*(0.19)*	*(0.20)*	-	*(0.28)*	*(0.17)*
	[0.24]	[-0.02]	[0.29]	[0.28]	[0.31]	-	[0.31]	[0.24]
UK	**0.32**	**0.25**	**0.33**	**0.32**	**0.33**	**0.35**	**-**	**0.32**
	(0.22)	*(0.17)*	*(0.04)*	*(0.20)*	*(0.22)*	*(0.30)*	-	*(0.19)*
	[0.36]	[-0.14]	[0.37]	[0.34]	[0.36]	[0.30]	-	[0.27]

Table 8: Correlations between long-term (RV) equity variance and the corresponding pairwise equity correlations. Rows define individual volatility while columns define paired correlations. The joint correlation values for the full sample period (March 1993-December 2013) are shown in **bold** case, those from the introduction of the Euro until the beginning of global financial crisis (January 1998-November 2007) are in *italics* and while those from the start of crisis until the end (December 2007-December 2013) are shown in [].

Countries	France	Germany	Greece	Italy	Spain	Switzerland	UK	Average
France	**-**	**0.32**	**0.48**	**0.36**	**0.40**	**0.37**	**0.42**	**0.39**
	-	*(-0.16)*	*(-0.42)*	*(-0.06)*	*(-0.20)*	*(-0.26)*	*(-0.21)*	*(-0.22)*
	-	[-0.31]	[0.48]	[0.24]	[0.49]	[0.12]	[0.41]	[0.24]
Germany	**0.33**	**-**	**0.43**	**0.34**	**0.35**	**0.33**	**0.37**	**0.36**
	(-0.57)	-	*(-0.31)*	*(-0.35)*	*(-0.52)*	*(-0.53)*	*(-0.47)*	*(-0.46)*
	[-0.15]	-	[0.36]	[0.14]	[0.23]	[0.09]	[-0.25]	[0.07]
Greece	**0.34**	**0.29**	**-**	**0.33**	**0.30**	**0.37**	**0.39**	**0.34**
	(-0.67)	*(-0.60)*	-	*(-0.56)*	*(-0.53)*	*(-0.70)*	*(-0.72)*	*(-0.63)*
	[0.09]	[0.07]	-	[0.08]	[0.16]	[0.18]	[0.15]	[0.12]
Italy	**0.24**	**0.22**	**0.35**	**-**	**0.25**	**0.26**	**0.30**	**0.27**
	(-0.38)	*(-0.45)*	*(-0.43)*	-	*(-0.35)*	*(-0.42)*	*(-0.54)*	*(-0.43)*
	[0.29]	[0.14]	[0.35]	-	[0.39]	[0.33]	[0.31]	[0.30]
Spain	**0.43**	**0.38**	**0.50**	**0.41**	**-**	**0.40**	**0.49**	**0.44**
	(-0.48)	*(-0.55)*	*(-0.35)*	*(-0.31)*	-	*(-0.57)*	*(-0.60)*	*(-0.48)*
	[0.46]	[0.20]	[0.44]	[0.42]	-	[0.34]	[0.37]	[0.37]
Switzerland	**0.34**	**0.27**	**0.42**	**0.35**	**0.36**	**-**	**0.31**	**0.34**
	(-0.14)	*(-0.26)*	*(-0.33)*	*(-0.15)*	*(-0.27)*	-	*(-0.31)*	*(-0.24)*
	[0.11]	[-0.06]	[0.61]	[0.30]	[0.36]	-	[-0.29]	[0.17]
UK	**0.38**	**0.32**	**0.49**	**0.35**	**0.41**	**0.33**	**-**	**0.38**
	(-0.15)	*(-0.20)*	*(-0.29)*	*(-0.20)*	*(-0.27)*	*(-0.28)*	-	*(-0.23)*
	[0.45]	[-0.42]	[0.62]	[0.29]	[0.50]	[-0.26]	-	[0.20]

Table 9: Correlations between long-term (RV+Econ) equity variance and the corresponding pairwise equity correlations. Rows define individual volatility while columns define paired correlations. The joint correlation values for the full sample period (March 1993-December 2013) are shown in **bold** case, those from the introduction of the Euro until the beginning of global financial crisis (January 1998-November 2007) are in *italics* and while those from the start of crisis until the end (December 2007-December 2013) are shown in []

Countries	France	Germany	Greece	Italy	Spain	Switzerland	UK	Average
France	**-**	**0.24**	**0.40**	**0.26**	**0.29**	**0.27**	**0.30**	**0.29**
	-	*(-0.67)*	*(-0.76)*	*(-0.79)*	*(-0.80)*	*(-0.78)*	*(-0.87)*	*(-0.78)*
	-	[-0.12]	[0.47]	[0.19]	[0.46]	[-0.06]	[0.40]	[0.22]
Germany	**0.18**	**-**	**0.27**	**0.20**	**0.21**	**0.10**	**0.18**	**0.19**
	(-0.61)	-	*(-0.55)*	*(-0.62)*	*(-0.68)*	*(-0.59)*	*(-0.78)*	*(-0.64)*
	[-0.22]	-	[0.41]	[0.05]	[0.19]	[-0.17]	[-0.38]	[-0.02]
Greece	**0.31**	**0.26**	**-**	**0.32**	**0.29**	**0.41**	**0.38**	**0.33]**
	(-0.69)	*(-0.62)*	-	*(-0.58)*	*(-0.58)*	*(-0.71)*	*(-0.73)*	*(-0.65)*
	[-0.07]	[-0.07]	-	[-0.09]	[0.01]	[0.00]	[-0.04]	[-0.04]
Italy	**0.15**	**0.14**	**0.22**	**-**	**0.17**	**0.14**	**0.22**	**0.17**
	(-0.74)	*(-0.64)*	*(-0.68)*	-	*(-0.60)*	*(-0.75)*	*(-0.81)*	*(-0.70)*
	[0.36]	[0.29]	[0.17]	-	[0.59]	[0.18]	[0.14]	[0.29]
Spain	**0.33**	**0.30**	**0.43**	**0.31**	**-**	**0.33**	**0.39**	**0.35**
	(-0.84)	*(-0.84)*	*(-0.69)*	*(-0.68)*	-	*(-0.66)*	*(-0.83)*	*(-0.76)*
	[0.48]	[0.28]	[0.45]	[0.50]	-	[0.18]	[0.33]	[0.37]
Switzerland	**0.30**	**0.24**	**0.46**	**0.34**	**0.29**	**-**	**0.30**	**0.32**
	(-0.16)	*(0.09)*	*(0.04)*	*(0.04)*	*(-0.36)*	-	*(0.21)*	*(-0.02)*
	[-0.38]	[-0.31]	[0.50]	[0.11]	[0.12]	-	[-0.32]	[-0.05]
UK	**0.29**	**0.26**	**0.39**	**0.27**	**0.32**	**0.25**	**-**	**0.30**
	(-0.16)	*(-0.15)*	*(-0.31)*	*(-0.24)*	*(-0.26)*	*(-0.26)*	-	*(-0.23)*
	[0.42]	[-0.56]	[0.59]	[0.18]	[0.42]	[-0.26]	-	[0.13]

Figures:

Figure 1: The figures below show the short-term pairwise correlation structure

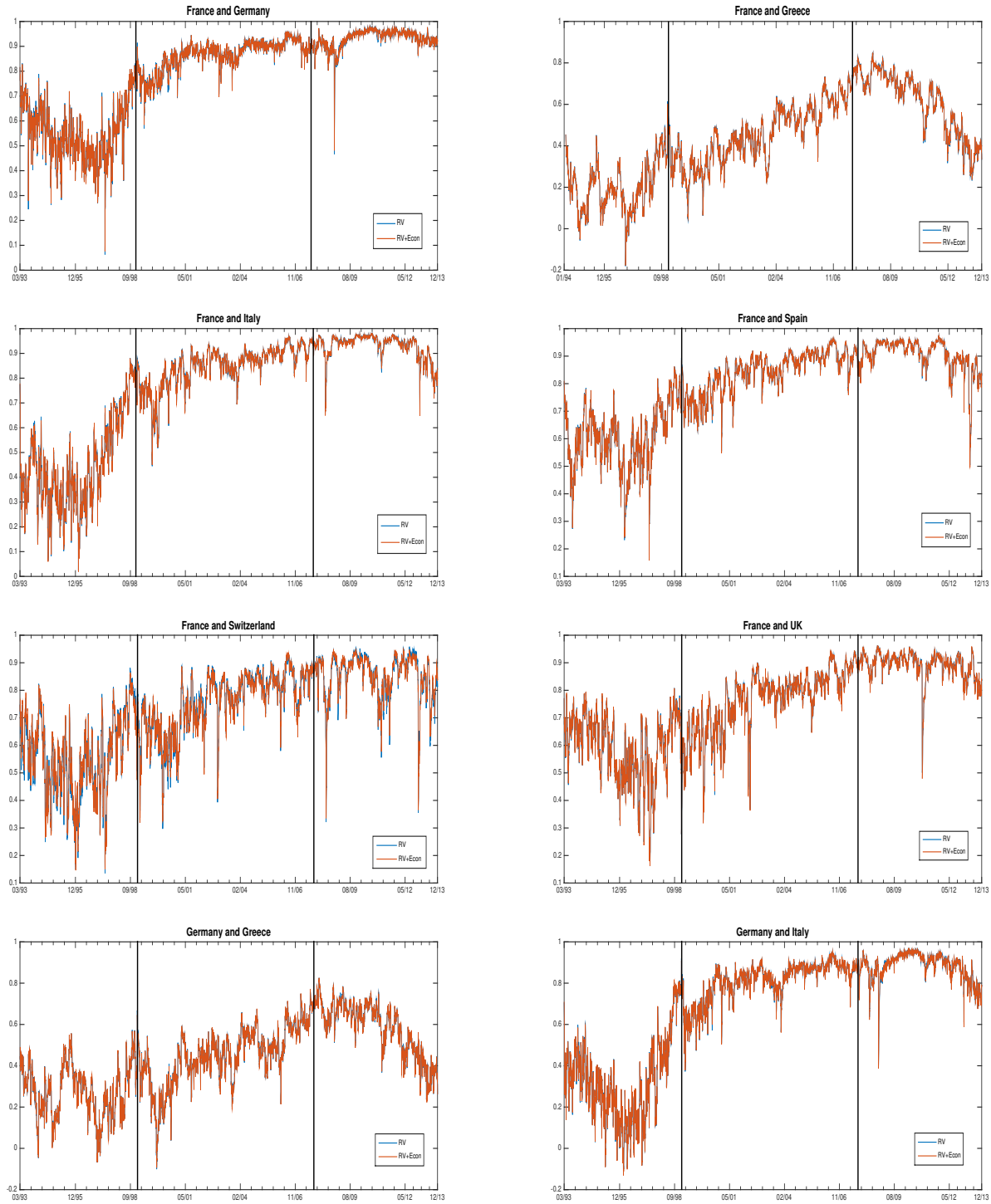
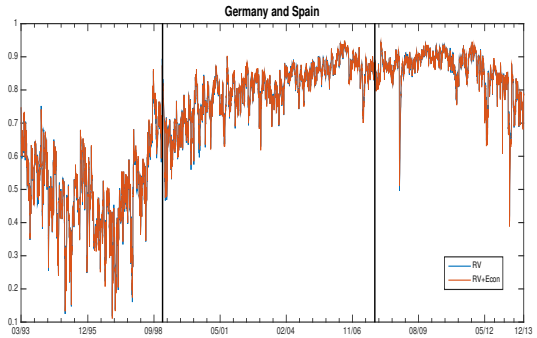


Figure 1: The short-term pairwise correlations.


Germany and Spain
RV
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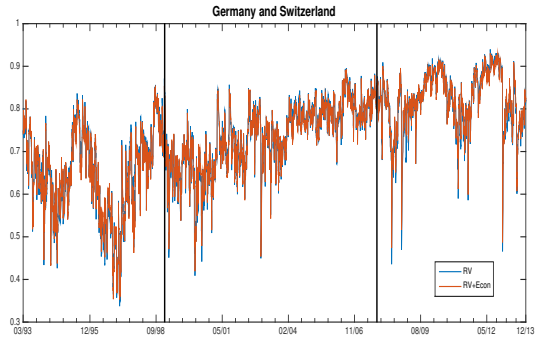
Germany and Switzerland
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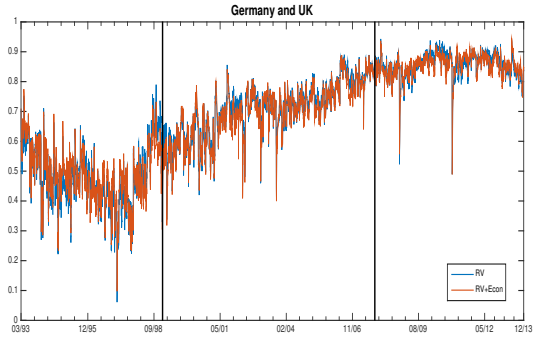
Germany and UK
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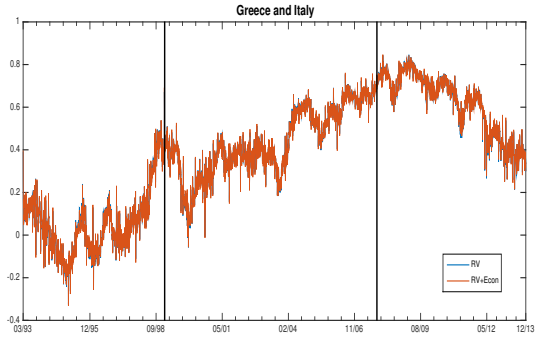
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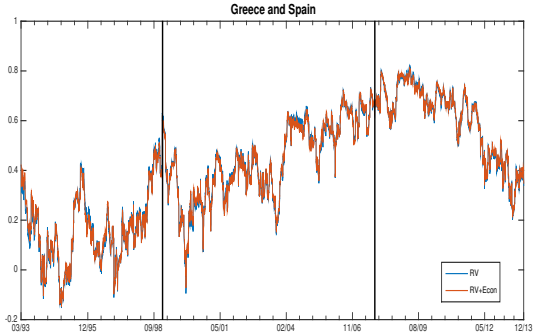
Greece and Spain
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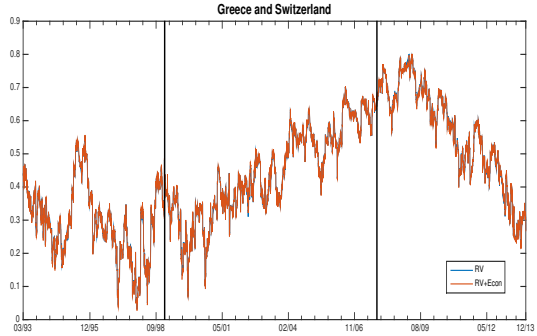
Greece and Switzerland
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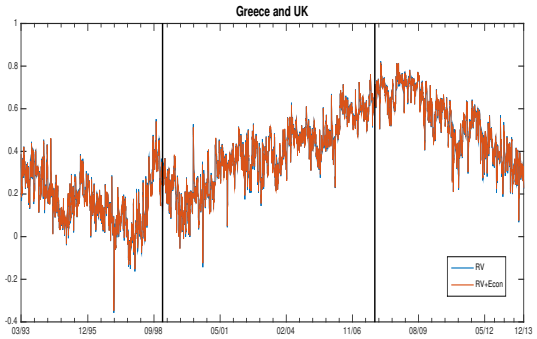
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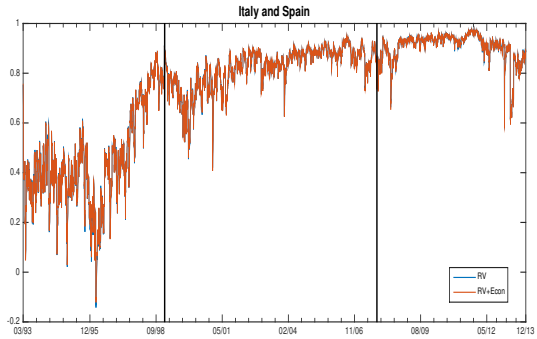
Italy and Spain
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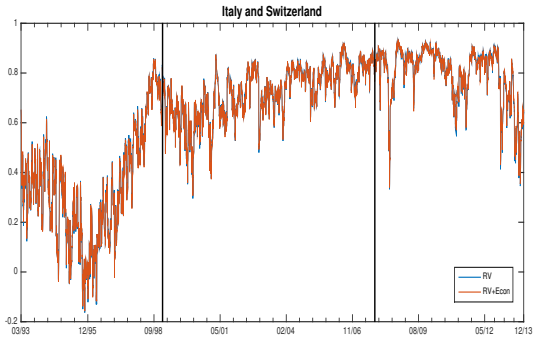
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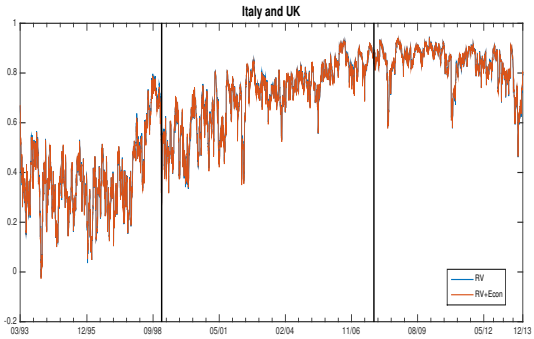
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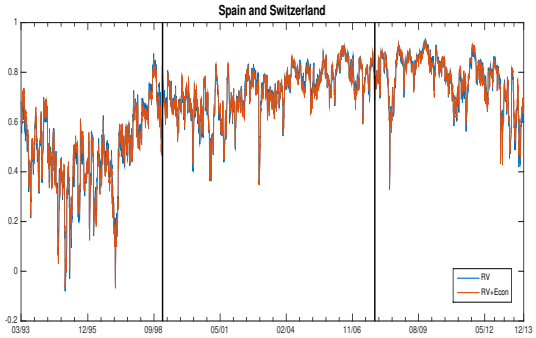
Spain and Switzerland
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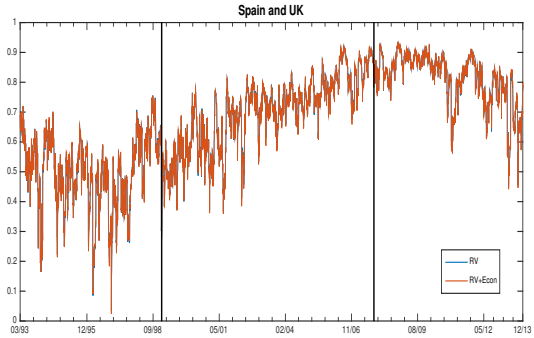
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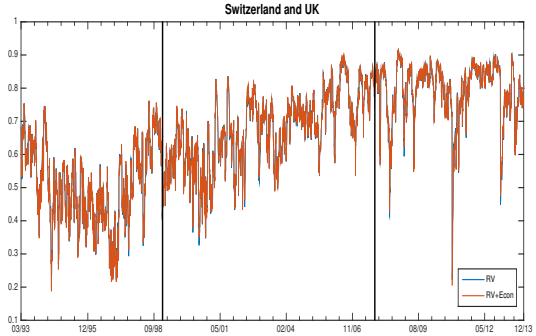
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Figure 2: The figures below show the long-term pairwise correlation structure

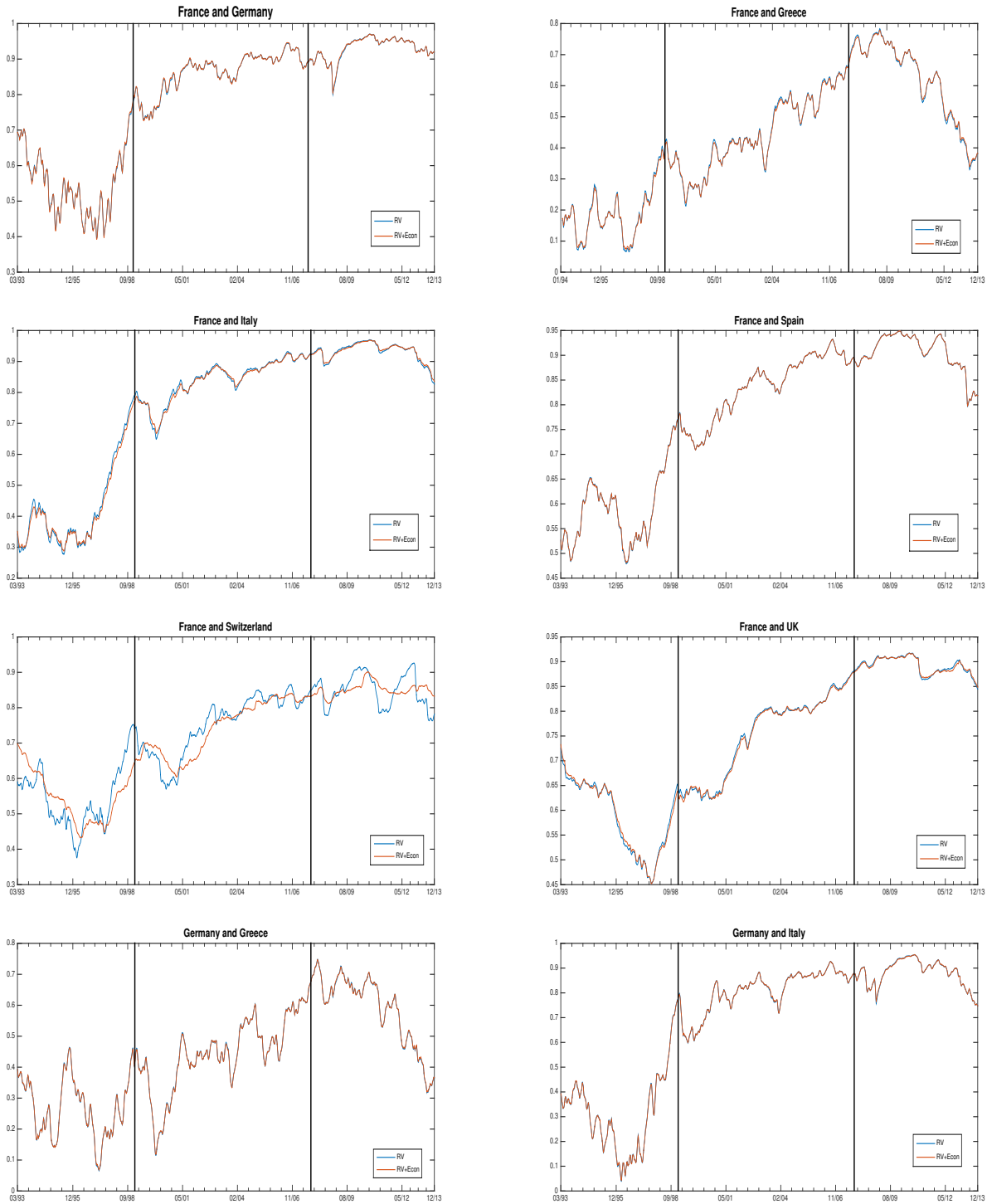
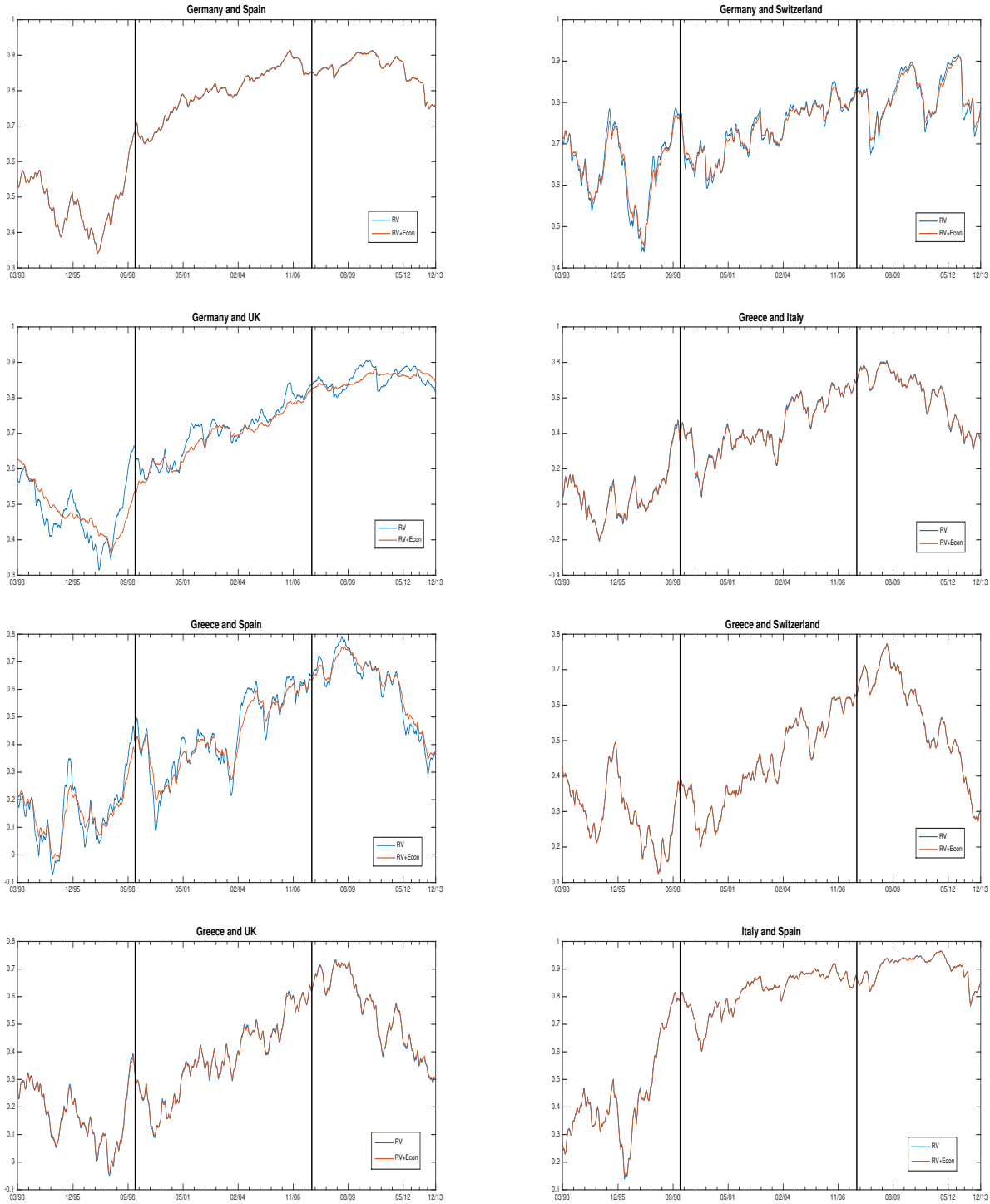


Figure 2: The long-term pairwise correlations.


Germany and Spain
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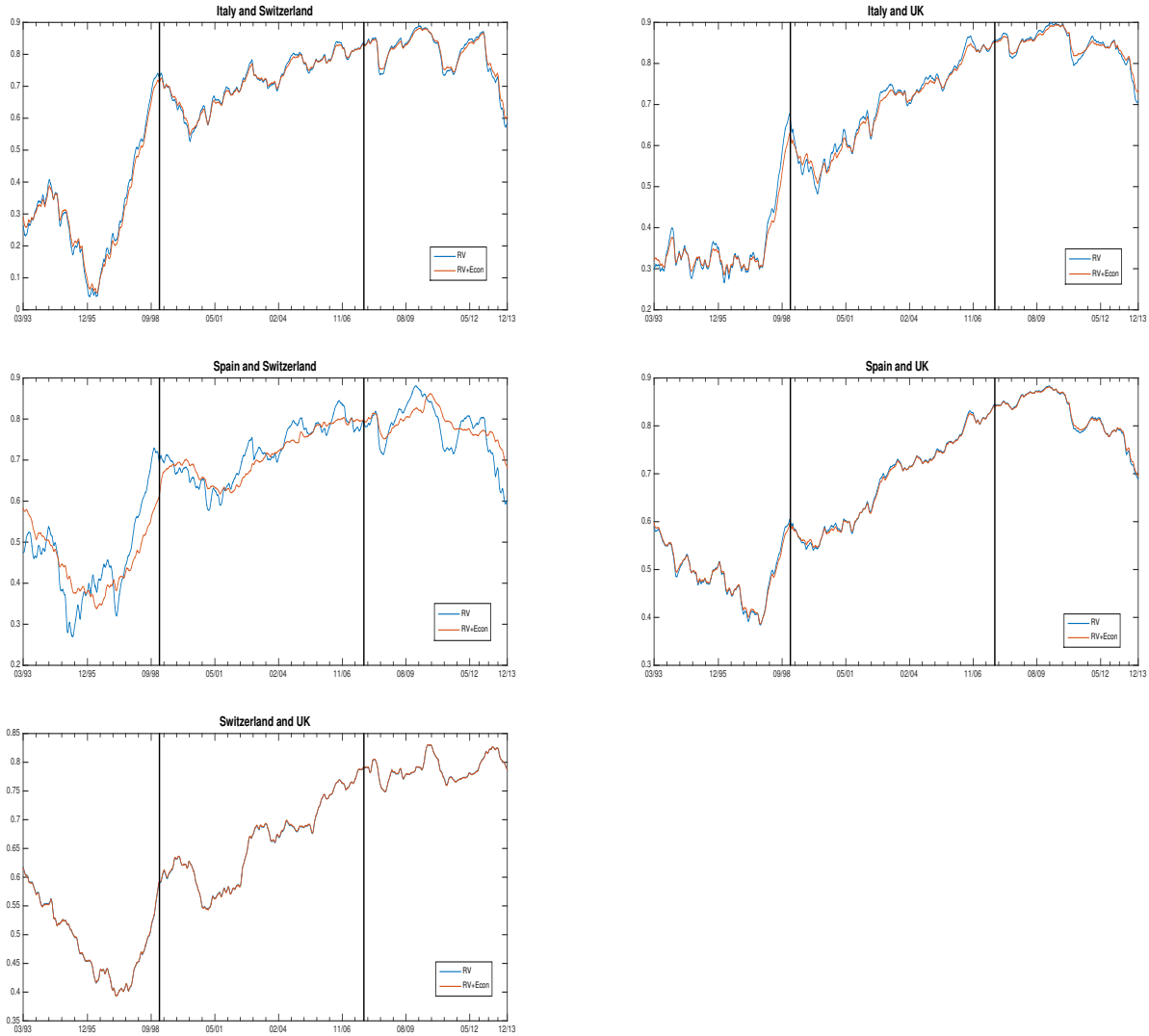
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