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

Farrukh Javed[a], Nader Virk[b,*]

[a]*Assistant Professor in Statistics, Örebro University, Sweden.*
[b]*Lecturer in Finance, Plymouth Business School, England.*

Abstract

We analyse the integration patterns of seven leading European stock markets from 1990 to 2013 using daily data and mismatched monthly macroeconomic data. For the mismatch of data frequencies, we use the DCC-MIDAS (Dynamic Conditional Correlation - Mixed Data Sampling) technique developed by [1]. We benchmark European integration patterns against German stock market. The reported integration patterns show a clear divide of large equity markets vs small equity markets: the relative small markets display higher short run European convergences than large markets in the region and vice a 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 spill overs – are more often positive. Only exceptions are German stock market's joint relationships.

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

1. Introduction

The financial markets have become ever more interlinked and extant literature identifies different channels in driving these inter-linkages. These inter-linkages, across financial markets, could be driven by similarity in industrial structure ([2]), monetary integration ([3]), bilateral trade [4] and geographical proximity [5]. [6] shows there is no universal economic determinant in driving financial market integration across countries; however countries in close geographical proximity are more correlated than countries in other regions. [7] reports that dissimilar mechanisms are at work to drive financial market integration across developed and developing markets.

[8] reports, after the introduction of Euro, the return correlations among developed markets as well as the European economic and monetary union (EMU) stocks markets

---

*Corresponding author
Email addresses: `Farrukh.Javed@oru.se` (Farrukh Javed), `nader.virk@plymouth.ac.uk` (Nader Virk)

have increased considerably. [9] reports these (higher) interdependences among EMU markets have **stablised in the post-Euro period**. [10] reports an increasing trend in the dynamic cross-country correlations for the Eurozone(EMU) countries after the introduction of euro.

In this study, we aim to explore the market interdependences for seven leading Euro-pean 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 fi-nancial 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 coun-try) has been analysed. This analysis follows [12] 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. As reported by Gavyn Davies[4], policy makers, politicians and financial markets **had** operated in a sense of detachment **for the threat of** possible Greek exit (GREXIT) from EMU. 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 introduction of European QE in March 2015, which is formally known

---

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

[2]Dynamic correlations are widely used measure to report the financial market integration across countries (see [8] and [11] 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 June 30 2015 Greece already witnessed Greece's government 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 he US, Japanese, and British central banks, targets buying government bonds amounting €60bn 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 is 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/

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 manifests 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/EMU integration levels during calamitous market conditions.

Moreover, this analytic design allows us to investigate variations in EMU and European equity markets 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 make use of the novel technique of mixed data sampling and volatility modelling from GARCH-MIDAS framework[5]. This study follows [1] in employing Dynamic Conditional Correlation (DCC) and MIDAS frame-work (hereafter DCC-MIDAS) to retrieve dynamic predictions, both for short run and the long run, for the paired country correlations. The impact of macroeconomic infor-mation 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 independent impact of following common monetary policy (EMU effect) and changes in** business cycle conditions **in shaping EMU/EU stock market** integration. Otherwise, existing studies have either focused on impact of monetary integration or business cycle conditions in reporting the financial market interdependencies ([3]; [11]; [14] 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 im**portant**

---

[5]In the last two and half decades the research on volatility modelling has grown exponentially, however it has been limited to predict 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 ([11]. There has been dearth of models which could link state of economy and aggregated volatility. And the earlier attempts to establish these links have turn out to be weak and only make a small fraction of measured volatility. For that appear unreasonable. 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. [1] propose the GARCH-MIDAS model in which volatility is evolved in a two component processes comprising of long-term and short-term components. Thus, 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.

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 inte-gration 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 ([12]; [9], 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 close-ness 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 inte-gration literature regardless of the fact whether **equity markets** belong to EMU or **are from** non-EMU countries.

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 ([15] or dynamic correlations ([16]) could yield economically higher profits. [16] 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 tan-dem 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)

---

[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).

show RV is an efficient proxy for long run variance. We notice business cycle variations and monetary policy latent variables affect the total variance evolution across equity markets differently. We note a clear divide of large markets vs small markets in the EU region instead of EMU vs non-EMU divide. This segregation is manifested by the commonality of responses of macroeconomic latent risks in the baseline (total) variance evolution of these markets and also in the formation of conditional integration pat-terns as estimated by DCC-MIDAS specifications. 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, is also applicable to long run correlation predictions. This establishes candidature of realised variance to proxy for long run variance in the modelling of dynamic total variance and correlation patterns across countries.

European market integration patterns **as reported in our study**, **benchmarked a**gainst the German **stock market**, are inline to **extant** evidence **base**. Our findings show that, approaching the launch of Euro currency, the EU markets' dynamic return correlations surged to new heights. Furthermore, increased convergence is observed in the post Euro period across all coun-try 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 have become even higher than their pre-crisis levels. However, sharp divergences in conditional pairwise correlations are also observed during the EDC period. **Overall, t**hese interdependencies show the usual pattern of higher convergi**ng patterns across markets during bearish/crisis periods**. Greek market's **crisis period EMU/EU** divergence is the only exception. 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: section two and three provides literature review and data descriptions, respectively. Section four details methodological setup and section five discusses results. Last section provides conclusions.

2. Literature Review

The importance of volatility and correlations in studying financial integration and portfolio and risk diversification related financial decisions cannot be over stated. The degree of financial integration can be measured in a number of ways and various studies, employing different methodologies, have examined this phenomenon (see, [17] and references therein). However, the common aspect of the earlier studies has been their reliance on the static cross-country correlations. Whereas cross-country linkages tend to rise during bearish market conditions or when markets are under greater uncertainty ([18]; [19] and [10], 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, given time varying nature of cross-country correlations the assumption of constant correlations, while studying financial integration, may not be a suitable approach and may prove misleading. Thus, specifying dynamic correlations among equity markets is a sound first step towards understanding the wider notion of market integration. Without it the end results may depict erroneous reality and 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 [20] has been argued to provide better cross-country relationships among other competing specifications ([9]). 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 ([11]). 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 [1] and [11] 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 ([21]; [22]), 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 and variations to target interest rates, had been reported to have impact on stock returns during recessions ([23]) and affect negatively the future excess stock returns. Nonetheless, [24] 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.

[14] shows that addition of a business cycle proxy in the GARCH-MIDAS specification improves the model's forecasting ability than the conventional GARCH modifications. [11] reports that the inclusion of 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. Using asymmetric DCC methodology,[12] finds significant evidence of structural breaks in the correlations of EMU countries.[9] shows, using the same framework, the correlations, among major international stock markets, are affected by business cycle variations. [8] reports that the dynamic correlations in the post-Euro period have been on increase among France, Germany, the UK and the US stock markets, whereas the correlations between EMU stock markets were the highest. This shows increased integration between EMU countries, although [7] has reported the correlation among EMU countries reached its peak by 2002 and afterwards no increase has been observed among them. [10] finds 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 download 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, Brendt 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 changes to exchange rate and measures for broad money (M3) and narrow money (M1) fills the list for monetary policy variables.

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 logarithmic 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 are downloaded from Eurostat data portal for EMU countries and for Switzerland 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 ([25]; [26]) and stock volatility and correlations have been reported to be influenced by business cycle variations ([11] and [10]). Second, we intend to isolate the independent impact of two macroeconomic channels on the volatility and correlation dynamics of the European markets, and also the cross-country response differences towards them.

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 makes the empirical analysis clear of over-parametrization issues and effectively removes noise from signal. Before taking the macro variables to the dynamic factor analysis, we apply adequate trans-formation to make them stationary with most of them being integrated of order one. Finally, these transformed stationary series are standardised to have standard normal distribution (zero mean and variance of one). This technique allows 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_{BS} and PC_{MP}, where BS 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.

Table 1 reports the summary statistics for the six equity markets. All the markets have positive returns with Greece having the smallest annualized return and volatility

---

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

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 representation of the relative stale pricing of the daily index. Whereas the squared returns show greater persistence across all the markets and is high at all four lags highest for the Swiss equity market, 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 auto-correlation, 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].

Against the German benchmark, static bivariate correlations demonstrate an overall EU convergence in the whole sample. After, the introduction of Euro, this convergence increases to even higher level and is observed for all the equity markets, whether EMU or non-EMU, against the German benchmark have also amplified after the introduction of Euro. 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 whereas in the same period these correlations for Greece are only 67, 62 and 67 percent points only. Nonetheless, the reported unconditional correlations are higher during the crisis period than the association 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 periods.

---

[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 post Euro 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 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 ([27]). 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 monetary easing program (January 2014) to stimulate growth in the Euro region.

4. Methodology

The construction of the DCC-MIDAS model is based on the GARCH-MIDAS process proposed by [11]. 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 [20]. 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 [14] 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 (Mixed Data Sampling) regression scheme of [13]. MIDAS regression allows for analysis of the parameterized regression using data sampled at different frequencies. The MIDAS weighting scheme helps us extracting the slowly moving secular component around which daily volatility moves.

Assume the returns on day i and day 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,

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

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

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

$$RV_t = \sum_{i=1}^{N_t} r_{i,j}^2.$$

where K is the number of periods over which we smooth the volatility, and X_{t-k}^{l} and X_{t-k}^{s} are the level and variance 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

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

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 [20] 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 [20] 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

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

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 $QL_2(\hat{\Psi}, \Xi)$.

12

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 [11], 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 [11] where we fix the weight w_1 to one, which makes the weights monotonically decreasing 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 [14].

5. Empirical results

5.1. Preliminary estimations

Table 3 and 4 report the results of the preliminary univariate GARCH-MIDAS specification for the chosen European stock markets. Table 3 only uses the 1-year rolled squared market returns to proxy for realised volatility, at monthly frequency, as an in-put 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 for the convergence of the estimated specifications. For example, fairly lower weight (w) is required for the German stock market to achieve the univariate **GARCH-MIDAS model convergence**.

---

[10]The unreported results (available upon request) display the superiority of GARCH-MIDAS specification than the conventional GARCH (1, 1) specification. The better volatility forecasting ability of the GARCH-MIDAS specification is consistent with [11] and [14]. We employ the root mean squared errors (RMSE), as decision criterion, in measuring the better fit of the tested model specifications.

"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.

[11] notes that if there are several components to volatility, 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_{BS} 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 macroeconomic environment. Beta polynomial is used to smooth the long-term com-ponents 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_{BS} and PC_{MP} factors are mixed at best: shocks to monetary pol-icy variables are positive and significant for large European markets i.e. France, Ger-many and the UK. The baseline variance for Swiss market is significantly affected by variability in the level of PC_{MP}. Italian and Spanish total variance evolution is re-sponsive to the shock and the level of business cycle principal component respectively. Whereas, Greece baseline variance dynamics does not respond to fluctuations in the latent macroeconomic factors both to the level and shocks to them. This may suggest that because of the fragile economic state of Greek economy, its equity market baseline variance evolution is exposed to a broader measure of uncertainty than a specific re-sponse 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 [7] 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 more often significance of θ_1 reflects the 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, moving from 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 among all the markets and therefore its total variance shows sensitivity to a liberal measure of risk such as RV than specific macroeconomic risk[11]. Whereas, large stock markets' variance may anticipate expectations around monetary policy but not 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 wholesome information container of long run 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_{BS}. Spain is the only exception whose variance is sensitive to fluctuations in the level of aggregate business cycle component.

5.2. European market short run integration patterns

Following [1] the standardised residuals return volatility from univariate GARCH-MIDAS 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 MIDAS weight filter, total correlation structure is decomposed into a slowly moving long run component around which daily correlations move, see equations (7) and (8) respectively. The DCC-MIDAS results, reported in Table 5, are divided in two vertical panels. In panel I, 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 DCC-MIDAS 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 per-sistence across European market. This persistence in daily correlations is in line with

---

11

the widely reported evidence studying European market integration using non-MIDAS based techniques ([8]; [10] among other).

"Please insert Table 5 about here"

The **persistence** of **our proxy** EMU/EU short-run pair correlations displays a divide of large equity markets vs relatively small equity markets in the EU instead of EMU vs non-EMU divide. To highlight this divide, we note that Greece, Italy, Spain and Switzerland equity market short run pair correlations with the German benchmark are far more persistent, a sign of higher convergence at EMU/EU, than the respective persistence exhibited by French-German and German- UK daily correlations.

This relatively lower short-run persistence manifests another important aspect in the overall integration patterns: large stock markets also have sizeable impact of the secular longrun correlations on the total correlation dynamics. For example, France-German and German-UK pairs depicting France and UK markets' EMU/EU integration patterns, short run correlations **have a persistence of** 83 percent and 88 percent respectively. This displays 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 EMU/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 EU wide long run interdependences, with German benchmark, are relatively higher for large economies[12] than the remain-ing equity markets. These patterns, within the EU/EMU 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, by 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 and 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.

---

[12]German economy is the largest in size among the EU economies followed by the UK and France. Their 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 manifested by the six to ten times inflating of EU-wide short run interdependences than the levels observed at the beginning of the sample period except for the Swiss equity market. Swiss market's beginning of the sample period high association with the German stock market is the reason for the not as steep EU convergence level than **reported** for the remaining equity markets. The importance of the event is evident by the level shift in the convergence levels across 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 with similar intensity.

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** correlation**s are observing surging level shifts**. After the introduction of Euro, the EU convergence weakened for Greece and Switzerland in the following two year period, only to **get stable** from thereon. 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. Nonetheless, maintained an upward trend as displayed by others. The short run pair convergences are also pan European in the post-Euro period, inline to pre-Euro convergences.

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 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 observed stability achieved during the post-Euro period (January 1999 to Novem-ber 2007 from hereon). The increased convergence levels are consistent with earlier reported empirical evidence ([18]; [10], among others) that equity markets tend to co-move during crisis or bearish market conditions.

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

This is evident from diverging correlations between the French-German pair in the buildup of the European debt crisis i.e. for period from the end of 2008 to the beginning of year 2009. From there on French convergence with the EU proxy was reinstated and evolved to convergence heights not observed in the whole sample. This **may** describe **the initial** absence of confidence **even between the two largest EMU markets given** the severity of EDC crisis. Furthermore, French banks are the largest debt holders of the PIIGS countries borrowings. 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 statistic report. For that reason, during the crisis period French stock market correlations with Italy and Spain are tumultuous at best. Nonetheless, maintained an upward trend from the convergence

levels achieved in the pre-crisis period. 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 EMU/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[13].

Whereas remaining equity markets show more than one instance of divergence against the German benchmark. Italy DCC dynamics with the EU benchmark deteriorated through the year 2008. This divergence reappears in 2012. The **variabilities in the** Spanish **markets' EMU/EU integration** is displayed by the greater number of EMU/EU 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. A period when 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 ([27]).

German-Swiss short run **return** correlations exhibit their 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/EMU convergence. In **addition to this, during the EDC period, Swiss market's EU convergence levels observed substantial episodic divergences**. Overall, 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/EMU markets is the divergence between the German-Greek equity market correlations. The short run correlations between German benchmark and Greek stock market show that the convergence levels, which achieved its epitome just before the beginning of global financial crisis, fizzled out quickly during the crisis period. This divergence is not observed for any of the remaining equity markets' EMU/EU integration patterns. This

---

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

demonstrates detachment from Greek risk by all the equity markets during the crisis period. This EU wide insularity from Greek risk can also be a manifestation of the mistrust between the Greek and European policy makers in the implementation of austerity plans for Greece - in response to the offered bail out packages.

The insulation of EU markets with the Greek stock market has neutralised the earlier achieved high convergence levels. This neutralisation is to an extent that Greece's short run return correlations, which were around or above 70 percent before the crisis period, have dropped to 30 percent is most of the 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 ([16]). It has been shown in [1] 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 Greek and the remaining EU equity markets. This manifests that European markets have, over the crisis period, decoupled themselves from the shocks emanating from Greek stock market systematically. 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. [Footnote: 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 Greek government and earlier mistrust for manipulative reporting of Debt to GDP ratios to EC for several years by Greek governments.] Overall, integration levels between EU/EMU markets support earlier evidence but the detachment of the EU markets with Greek market displays a new pattern.

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 inline to the patterns in Figures 1. However, the long run integration patterns, retrieved from the two DCC-MIDAS specifications elicit different evolutions. This variability in evolution of the fundamental component is evident from the more smoothed and lagging predictions from the $RV + Econ$ specification than the long run correlations predictions retrieved from RV specification. For exam-ple see the plots between Germany-UK, Italy-UK and Spain-Switzerland, among others.

Nonetheless, long run interdependences across EMU/EU pair countries have shaped over time differently. 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. Whereas long run correlation patterns between France~ and Italy with German benchmark rose at a stable rate during the same period. Swiss mar-ket long run correlation kept an upward trend over periods but displayed substantial fluctuations.
The UK market's fundamental co-movements displayed smoothed increase over the whole sample length. Other consistent pattern, inline with the evidence reported

in 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 latter part of crisis period approaches. This is consistent with higher persistence of 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 scenario makes the comprehension of the joint relationship, between the two processes, important to make 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 [12][14].

The joint relationship of dynamically retrieved series are compared with the joint relationship of unconditional counterparts. [12] 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 [12]. 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:

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

The static joint relationships[15] show that European integration levels have moved in tandem to 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,

---

[14]We only results for joint relationships for the variances and pairwise country 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 realized volatility.

[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.

are negatively related to its associated pairwise correlations. The strength across these periods is almost identical i.e. on average is 50 percent however 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 Ger-man market's volatility and/or its pairwise correlations are safe hedges for spill over risks coming from either market's volatility risk. That is German market joint rela-tionships tend to decrease if German volatility is on the rise and so is also true when volatility increases are witnessed **for** the pair country. For example, the crisis period joint relationship between France-Germany RC and France volatility is [-0.61] and between France-Germany RC and German market volatility is [-0.60].

With the exception of 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, French-UK joint relationship between the French-UK RC and French **market's** RV is [0.61]. This joint relationship is even higher for UK volatility **increases** during the crisis period **i.e.** [0.77] . Although, across all the markets static joint relationships are negative in the post Euro period.

The unconditional joint relationships for Greek, Italian and Spain (PIIGS countries) market volatilities display the largest opposite movement to the associated pairwise cor-relations 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. A sign of higher inte-grated 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 need 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 cor-relations are far weaker than the ones reported in Table 6. This decline in the joint relationship is to the extent that for Greece and I taly dynamic equity market variance increases are almost uncorrelated with their respective dynamic pairwise correlations: for 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

21

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 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 di-versification benefits, for making portfolio strategies which time German volatility against the increases in dynamic correlations during the crisis period. Germany joint relationship with Greece is the only exception: 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 DCC-MIDAS long run correlation component, reported in Table 8, demonstrate substantial differences across the sample periods than 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 post Euro relationships, on average, are inverted than 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 Ger-man 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 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 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 static version of them. And

is also reported consistently for the long run and the short run joint relationships. Analysing how EMU/EU integration patterns respond to the variance shocks emanating from the rest of EMU/EU markets show that variance increases in the EMU/EU markets tend to decrease their proxy EMU/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 EMU/EU proxy in our study.

Taken together these results establish few important corollaries. First, joint relation-ships from RV and RC series tend to overstate the magnitude of directedness. This overstatement is considerably high relative to the joint relationships reported for the dynamic series extracted from GARCH-MIDAS and DCC-MIDAS specifications, re-spectively. This overstatement amplifies resultant benefits or risks to develop diver-sification strategies and possible resulting of mispriced insurance plans. For example, increases in the Greek market static variance are inversely related to its pairwise cor-relations 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 Germany, the average short run joint relationships show that dynamic equity variance increases accompany dynamic equity market co-movements during the crisis period than the growth (post-Euro) period. A much severer indication of 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 Tables 8. Table 9 reports joint relationships using dynamic predictions using GARCH/DCC-MIDAS $RV + Econ$ specifications. Results are qualitatively are 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 mar-kets has been reported to have increased integration levels among themselves after the introduction of Euro. The witnessed surging co-movement at European level is broad based 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 relative size of the stock market. We show large stock markets may anticipate exchange rate fluctuations but not shocks to the monetary policy variabilities. Whereas, 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 specifications us-ing RV as proxy for long run variance or specification augmented with latent factors to proxy different macroeconomic risks. This is consistent with the results reported by

[28] who showed variance based measure is critical in explaining stock volatility. This, combined with our results, stipulates realised variance is an efficient proxy for long run variance component and this holds especially for short run volatility and integration patterns in our sample.

The short run and slow moving fundamental component from DCC-MIDAS specification shows consistent evidence to the extant European integration literature: EU markets have converged 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 with 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. 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 mitigation of Greek risk at the EMU/EU level provides credence to DCC-MIDAS' ability to capture underlying market co-movements pretty well.

Analysing static joint relationships, using rolling variance and rolling correlations, tend to over project co-movements. These over statement of magnitude of relationship could result in adverse diversification strategies and mispriced insurance plans across states of the world 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 stability of German market's proxy status for EMU/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 German equity market is a safe bet when volatility shocks are emanating from other markets in the region. 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.

References

[1] R. Colacito, R. F. Engle, E. Ghysels, A component model for dynamic correlations, Journal of Econometrics 164 (1) (2011) 45–59.

[2] R. Roll, Industrial structure and the comparative behavior of international stock market indices, The Journal of Finance 47 (1) (1992) 3–41.

[3] S. Wälti, Stock market synchronization and monetary integration. Journal of International Money and Finance 30 (1) (2011) 96–110.

[4] K. Forbes, and M. Chinn, A decomposition of global linkages in financial markets over time. The Review of Economics and Statistics 86 (2004) 705–722.

[5] T.J. Flavin, M.J. Hurley, F. Rousseau, Explaining stock market correlation: A gravity model approach. The Manchester School Supplement (2002) 87–106.

[6] E. Pretorius, Economic determinants of emerging stock market interdependence, Emerging Markets Review 3 (1) (2002) 84–105.

[7] L. Liu, International stock market interdependence: Are developing markets the same as developed markets? Journal of International Financial Markets, Institutions and Money 26 (2013) 226–238.

[8] C. S. Savva, D. R. Osborn, L. Gill, Spillovers and correlations between US and major European stock markets: The Role of the Euro, Applied Financial Economics 19 (2009) 1595–1604.

[9] C. S. Savva, International stock markets interactions and conditional correlations, Journal of International Financial Markets, Institutions and Money 19 (4) (2009) 645–661.

[10] G. Connor, A. Suurlaht, Dynamic stock market covariances in the eurozone, Journal of International Money and Finance 37 (2013) 353–370.

[11] R. F. Engle, E. Ghysels, B. Sohn, Stock market volatility and macroeconomic fundamentals, The Review of Economics and Statistics 95 (3) (2013) 776–797.

[12] L. Cappiello, R. F. Engle, K. Sheppard, Asymmetric dynamics in the correlations of global equity and bond returns, Journal of Financial Econometrics 4 (4) (2006) 537–572.

[13] E. Ghysels, P. Santa-Clara, R. Valkanov, The midas touch: Mixed data sampling regression models, Discussion paper UNC and UCLA.

[14] H. Asgharian, A. Hou, F. Javed, The importance of the economic variables in predicting the long term volatility; a garch midas approach, Journal of Forecasting 32 (2013) 600–612.

[15] J. Fleming, C. Kirby, B. Ostdiek, The economic value of volatility timing, The Journal of Finance 56 (1) (2001) 329–352.

[16] E. Kalotychou, S. K. Staikourasa, G. Zhao, The role of correlation dynamics in sector allocation, Journal of Banking & Finance 48 (2014) 1–12.

[17] C. Kearney, B. M. Lucey, International equity market integration: Theory, evidence and implications, International Review of Financial Analysis 13 (5) (2004) 571–583.

[18] C. B. Erb, C. R. Harvey, T. E. Viskanta, Forecasting international equity correlations, Financial Analysts Journal 50 (6) (1994) 32–45.

[19] F. Longin, B. Solnik, Extreme correlation of international equity markets, Journal of Finance 56 (2) (2001) 649–676.

[20] R. Engle, Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models, Journal of Business & Economic Statistics 20 (3) (2002) 339–350.

[21] K. Kasa, Common stochastic trends in international stock markets, Journal of Monetary Economics 29 (1) (1992) 95–124.

[22] G. W. Schwert, Why Does Stock Market Volatility Change Over Time? The Journal of Finance 44 (1989) 1115–1153.

[23] A. Basistha, A. Kurov, Macroeconomic cycles and the stock market's reaction to monetary policy, Journal of Banking & Finance 32 (12) (2008) 2606–2616.

[24] J. Hausman, J. Wongswan, Global asset prices and fomc announcements, Journal of International Money and Finance 30 (3) (2011) 547–571.

[25] N. S. Virk, Stock returns and macro risks: Evidence from Finland, Research in International Business and Finance 26 (2012) 47–66.

[26] N. Apergis, P. Artikis, J. Sorros, On a mixture garch time-series model, Asset pricing and foreign exchange risk 25 (3) (2011) 308–328.

[27] A. Cipollini, J. Coakley, H. Lee, The european sovereign debt market: from integration to segmentation, The European Journal of Finance 21 (2) (2015) 111–128.

[28] B. Lieven, G. Bekaert, K. Inghelbrecht, The determinants of stock and bond return comovements, Review of Financial Studies 23 (6) (2010) 2374–2428.

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	Swiss	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 association estimates for the full sample period are shown in bold case, for the period since the Euro introduction until the beginning of global financial crisis (November 2007) (italic) and finally the period since the start of crisis until the end of chosen sample period are provided in [].

Description	France	Germany	Greece	Italy	Spain	Swiss	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]
Swiss	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)

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*
Swiss	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: Result for the univariate part of estimation for GARCH-MIDAS (RV+Econ).

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*
Swiss	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
$\tau_t = m + \theta_1 \sum_{k=1}^{K} \phi_k(1,w) RV_{t-k} + \theta_2 \sum_{k=1}^{K} \phi_k(1,w) PC_{BC}^{l} + \theta_3 \sum_{k=1}^{K} \phi_k(1,w) PC_{BC}^{s} + \theta_4 \sum_{k=1}^{K} \phi_k(1,w) PC_{MP}^{l} + \theta_5 \sum_{k=1}^{K} \phi_k(1,w) PC_{MP}^{s}$.

Table 5: Estimation of DCC-MIDAS

Countries	RV			RV+Econ		
	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 - Swiss	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 - Swiss	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 - Swiss	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 - Swiss	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 - Swiss	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*
Swiss - UK	0.05*	0.93*	1.00*	0.05*	0.93*	1.00*

Table 6: Unconditional joint correlation between two year rolling realised variance (RV) and corresponding two year realised pairwise equity correlations (RC). Row defines individual volatility while columns define paired correlations. The joint correlation values for the full sample period are shown in **bold** case, since the Euro introduction until the beginning of global financial crisis (November 2007) (*italic*) and finally the period since the start of crisis until the end of chosen sample period are shown in [].

Countries	France	Germany	Greece	Italy	Spain	Swiss	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]
Swiss	**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: Correlation between short-term equity variance and the corresponding pair-wise equity correlations. The whole idea is to evaluate pairwise correlation from DCC and the idiosyncratic volatility for a country. Then the joint relationship will highlight idiosyncratic volatility correlation with pairwise correlations obtained from DCC. Row defines individual volatility while columns define paired correlations. The joint correlation values for the full sample period are shown in **bold** case, since the Euro introduction until the beginning of global financial crisis (November 2007) (*italic*) and finally the period since the start of crisis until the end of chosen sample period are shown in [].

Countries	France	Germany	Greece	Italy	Spain	Swiss	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]
Swiss	**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: Correlation between long-term (RV) equity variance and the corresponding pairwise equity correlations. Row dfines individual volatility while columns define paired correlations. The joint correlation values for the full sample period are shown in **bold** case, since the Euro introduction until the beginning of global financial crisis (November 2007) (*italic*) and finally the period since the start of crisis until the end of chosen sample period are shown in [].

Countries	France	Germany	Greece	Italy	Spain	Swiss	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]
Swiss	**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: Correlation between long-term (RV+Econ) equity variance and the corresponding pairwise equity correlations. Row defines individual volatility while columns define paired correlations. The joint correlation values for the full sample period are shown in **bold** case, since the Euro introduction until the beginning of global financial crisis (November 2007) (*italic*) and finally the period since the start of crisis until the end of chosen sample period are shown in [].

Countries	France	Germany	Greece	Italy	Spain	Swiss	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]
Swiss	**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
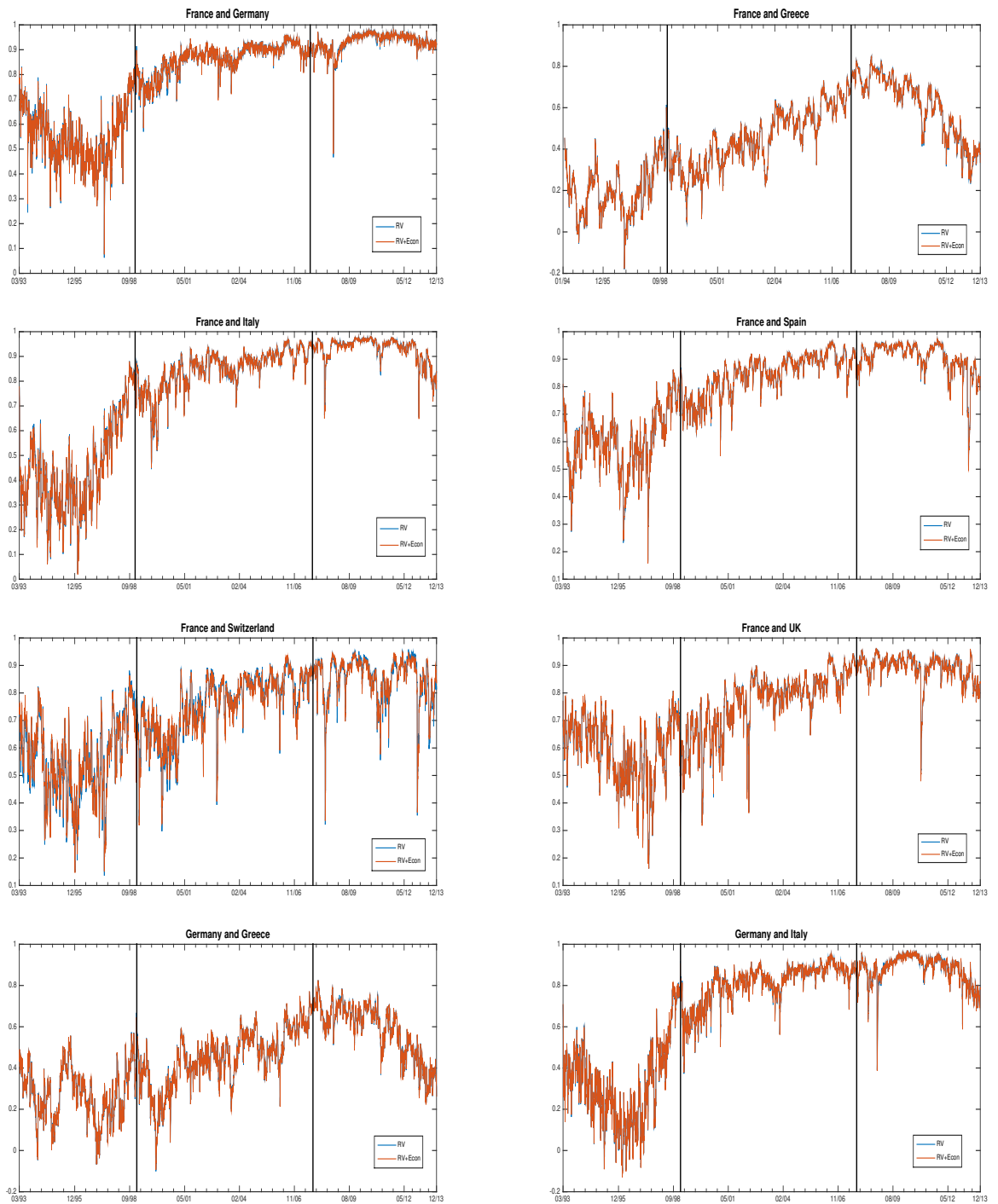
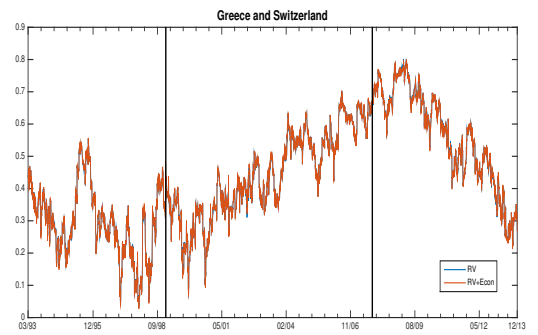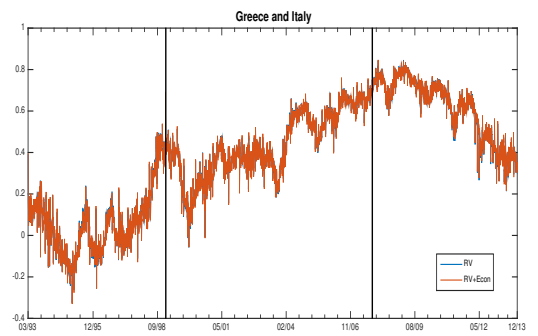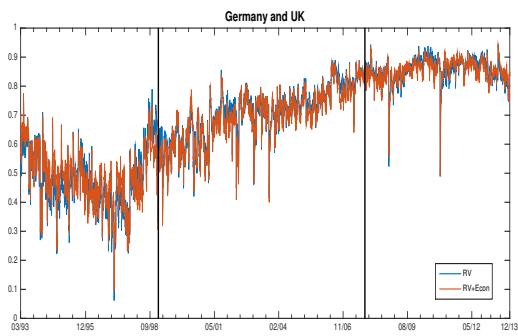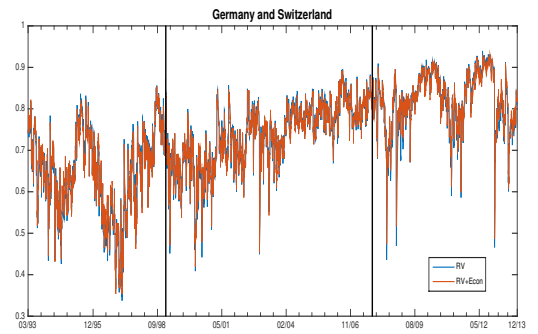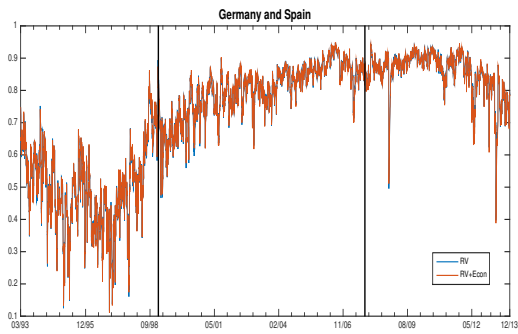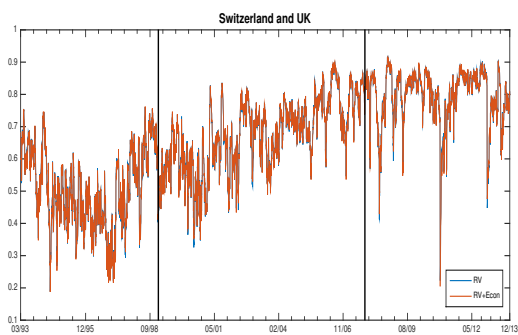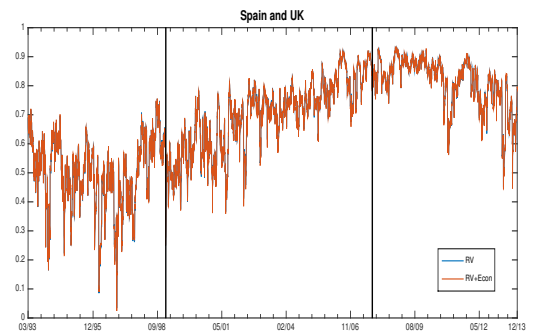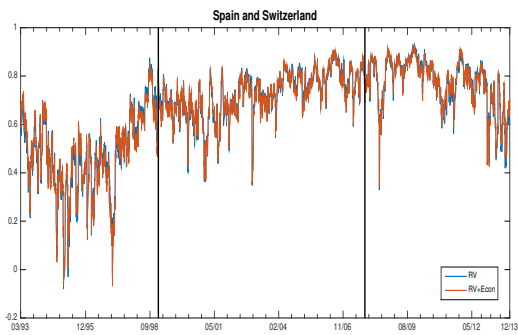Figure 1: The short-term pairwise correlations.

Germany and Spain

RV
RV+Econ

Germany and Switzerland

RV
RV+Econ

Germany and UK

RV
RV+Econ

Greece and Italy

RV
RV+Econ

Greece and Spain

RV
RV+Econ

Greece and Switzerland

RV
RV+Econ

Greece and UK

RV
RV+Econ

Italy and Spain

RV
RV+Econ

Italy and Switzerland

Italy and UK

Spain and Switzerland

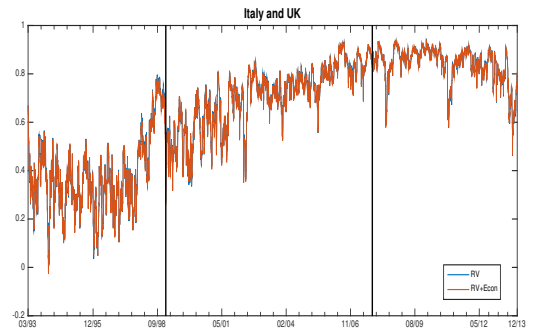Spain and UK

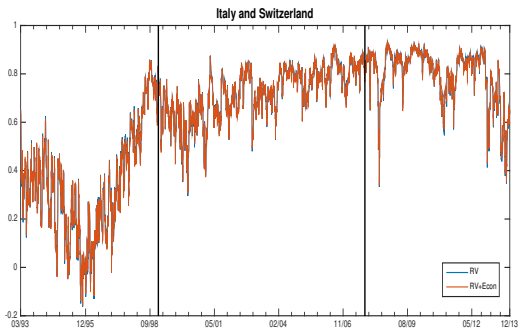
Switzerland and UK

37
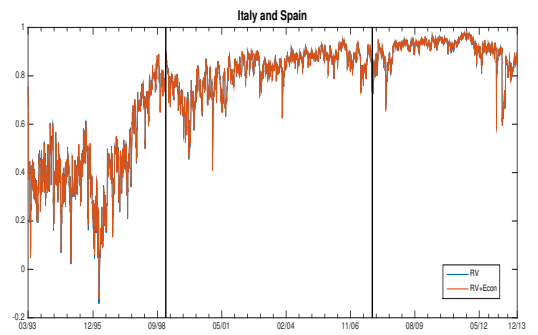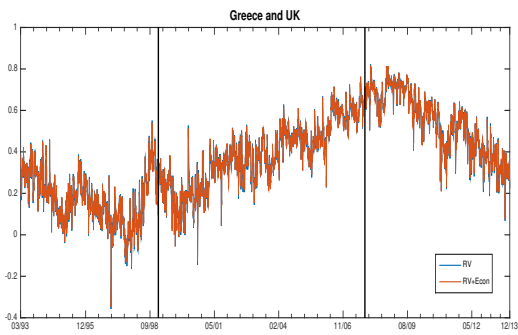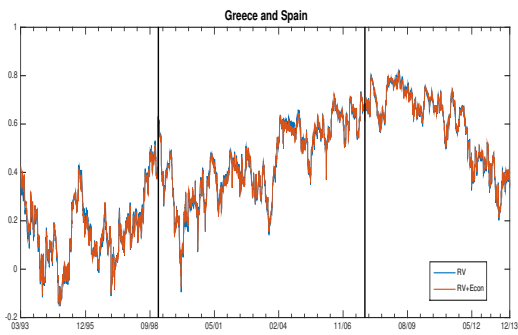
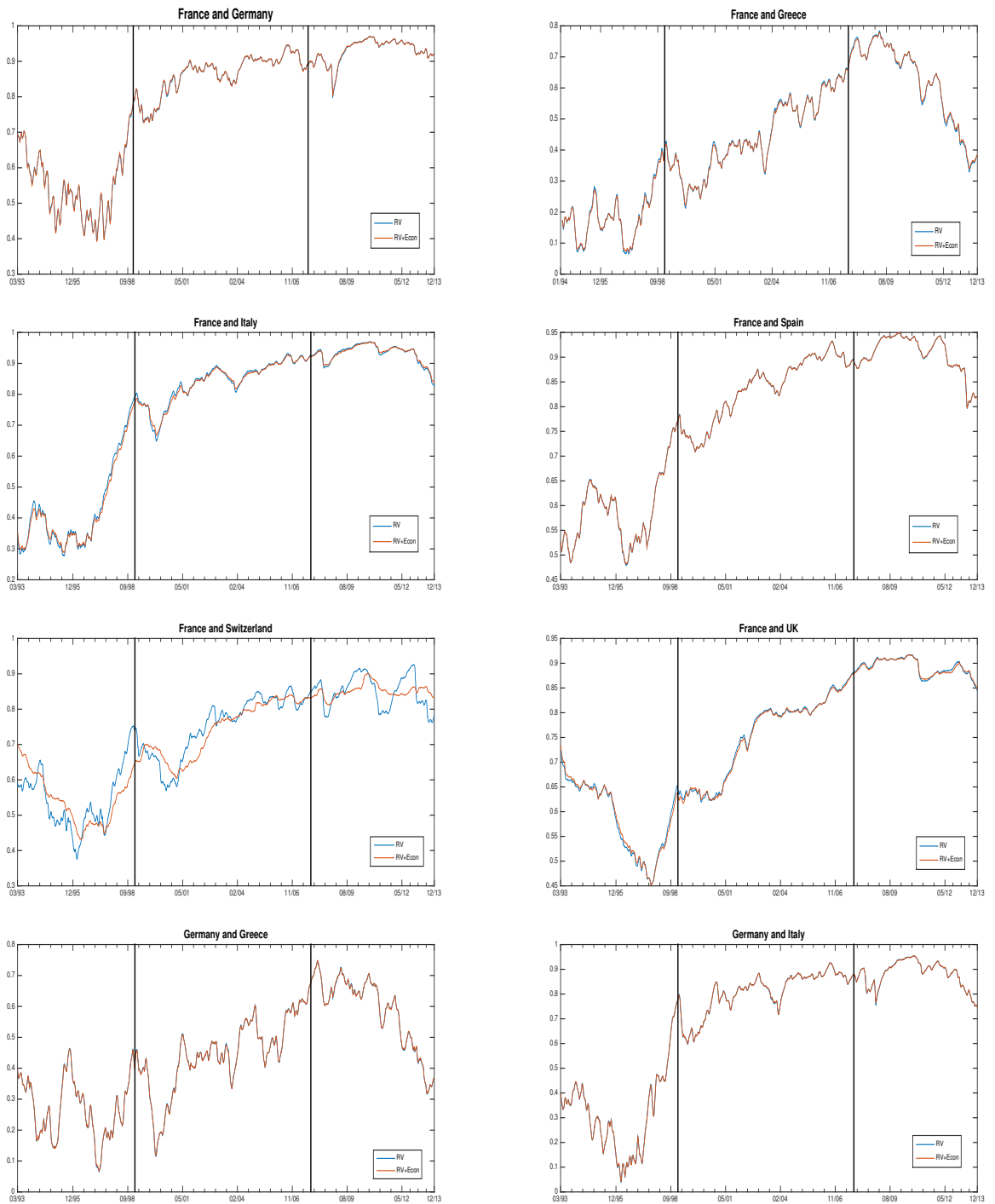**Figure 2: The figures below show the long-term pairwise correlation structure**

Figure 2: The long-term pairwise correlations.

Germany and Spain

Germany and Switzerland

Germany and UK

Greece and Italy

Greece and Spain

Greece and Switzerland

Greece and UK

Italy and Spain

Italy and Switzerland

Italy and UK

Spain and Switzerland

Spain and UK

Switzerland and UK

40