EUROPEAN EQUITY MARKET INTEGRATION AND JOINT RELATIONSHIP OF CONDITIONAL VOLATILITY AND CORRELATIONS

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Abstract

We analyse the financial market integration patterns of seven leading European stock markets for a period of 1990 to 2013 using time consistent daily data. To study the research problem we make use of novel mixed data sampling techniques combined with volatility/correlation predictions methods i.e. GARCH-MIDAS and DCC-MIDAS. Our results manifest DCC-MIDAS correlations portray altogether different market conditions when compared against unconditional correlations. Noticeable conclusions are macroeconomic denominated risks add information however this information more often has already been captured by realised variance. European equity markets have diverged from the Greek risk during the European debt crisis: such that cross-country dynamic correlations with Greece almost halved during this period. Importantly dynamic variance predictions and pairwise correlations tend to have positive relationship across markets. These co-movement could result in contagious market states during crisis period however Germanys joint relationships are exceptions to this investment discounting spirals.

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 (Roll, 1992), monetary integration (Wälti, 2011), bilateral trade (Forbes and Chinn) and geographical proximity (Flavin et al., 2002). Pretorius (2002) 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. Liu (2013) reports dissimilar mechanisms drive financial market integration across developed and developing markets.

Saava et al. (2009) report financial integration among developed markets and European economic and monetary union (EMU) stocks markets has increased considerably after the introduction of Euro. Saava (2009) reports these (higher) interdependences among EMU markets have also become more stable. Connor and Suurlaht (2013) report 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 European stock markets of which four stock markets share common currency and monetary policy decisions. We study the through a novel approach: the joint relationship of dynamic pairwise correlation[1] predictions with the conditional predictions for equity market variance (belonging to one of the pair country) is analysed. This analysis follows Capiello et al. (2006) which reported the average joint relationship at country level. The selection of European equity markets includes France, Germany, Greece, Italy, Spain, Switzerland and the UK, The monthly data spans from January 1990 till December 2013. These subjective choices are driven to uncover relative importance of geography and monetary integration in establishing financial market interdependences[2].

The availability of Greece, Italy and Spain form the group of commonly referred PIIGS countries in this study[3]. In this respect we will also try to unfold relationship among EMU markets during periods of growth and turmoil. Greece is the only developing equity market in the analysis among all the European markets. It has remained at the very centre of political events during the greater part of year 2014 and 2015: policy makers, politicians and practitioners parried the resolution of Greek debt settlement with an option 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 as Public Sector Purchase Programme (PSPP) is planned to run until September 2016, This manifests that the European debt crisis (EDC), which started in 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.

This analytic design allows us to investigate variations in EMU and European equity markets across changing economic conditions. Whereas earlier evidence has shown, (i) correlation across markets tends to increase during bearish economic conditions and (ii)

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

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

[3]These countries include Portugal, Ireland, Italy, Greece and Spain and they have experienced far greater volatility during the recent financial crisis of 2008-2009 and the volatility lumbered for these markets even after the 2009 for the unstainable levels of government debts and fiscal deficits as percentage of their GDP levels. Market turbulences in these markets especially Greece shaped the European debt crisis from 2009 onwards, this is more commonly referred as Greek sovereign debt crisis. This episode has already witnessed Greece's government sovereign debt default in 2012 and on 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 the Eurozone. 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.

after the introduction of euro EMU countries have become increasingly synchronised.

The methodological design of our study, in the retrieval of short run and the long run volatility processes, make use of the novel technique of mixed data sampling and volatility modelling from GARCH-MIDAS framework[4]. This study follows Colacito et al. 2011 in employing Dynamic Conditional Correlation (DCC) and MIDAS framework (hereafter DCC-MIDAS) to retrieve dynamic predictions, both for short run and the long run, for paired country correlation processes. The impact of macroeconomic information on the volatility and correlations, short run and long run components, will report the effect of business cycle conditions in driving financial market integration. Furthermore, ours is the first study (to the best of our knowledge) to segregate between EMU effect and impact of business cycle conditions while studying European financial market integration. We model the dynamic stocks market volatility and pairwise correlations by incorporating independent latent factors to proxy for monetary policy variations and business cycle conditions. Otherwise, studies have either focused on impact of monetary integration or business cycle conditions in reporting the financial market interdependencies (Wlti, 2011; Engle et al. 2013; Asgharian et al. 2013 among others)

A clear manifestation of the volatility and correlation dynamics, their joint relationships and the determinants shaping these processes is important for investors, practitioners and policy makers. This makes our study important on a number of fronts. First, we will report the patterns in the financial market integration with fluctuating economic conditions. This will allow us to comment on the differences between the EMU equity market integration and broader EU level integration patterns across states of the world. Reportedly conditional bi-variate equity market correlations have been much higher, on average, in the post Euro period than the pre Euro period among European markets (Capiello et al. 2006; Kim et al. 2006; Saava, 2009, among others). However, we will analyse the bi-variate correlations of the sample markets, benchmarked against Germany, to scrutinise EU/EMU integration patterns. Second, by taking only European markets, we are able to juxtapose two key characteristics pinned to the motivation of our study i.e. impact of unification of monetary policy (France, Germany, Greece, Italy

[4]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 (Engle and Rangel, 2008). 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 Ghysels et al. (2006) has paved the way to include information coming from macroeconomic data available at different time frequencies in the volatility modelling literature. Colacito et al. (2011) propose the GARCH-MIDAS model in which volatility is evolved in a two component processes comprising of long-term and short-term components. Thus, 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.

and Spain) and geographical closeness on the financial market integration[5]. Third, this study will highlight the relative importance of monetary and business cycle factors, on the dynamically retrieved volatility and pairwise correlation processes, for the monetary policy integrated markets and the non-monetary European equity markets (Switzerland and the UK). Therefore, differences in the conditional volatility/paired-correlation predictions, between these two groups prevailing together geographically, will provide new insights in financial market integration literature.

Fourth, analysing the degree of integration through the joint relationship of market volatility and the pairwise correlation between two countries is imperative for portfolio managers, risk strategists and insurers. The higher correlation between the volatility of country X with the bi-variate correlation of country X and Y will stipulate simultaneous discounting of profits under poor market conditions and the exacerbated need to manage the integrated risk. This relationship is important when we know that asset allocation strategies timing for dynamic volatility (Fleming et al. 2001) or dynamic correlations (Kalotychou et al. 2014) could yield economically higher profits. Kalotychou et al. 2014 report risk-averse investor could pay substantially higher fees to reap greater economic benefits of a richer correlation specification such as DCC model. Our analysis will make portfolio managers and investors aware of the flip side of this investing: when these processes (volatility and correlations) move in tandem to increase investing fragilities. Asset allocations under adverse market conditions timing one of these two processes will speedup depreciation in the value of invested capital.

Our results show that total variance evolution is significantly influenced by long run variance factors and foremost by realised variance (RV). The results for GARCH-MIDAS and DCC-MIDAS specifications (hereafter GARCH/DCC-MIDAS) show RV is an efficient proxy for long run variance. We notice business cycle variations and monetary policy latent variables affects the total variance evolution of the equity markets differently. However, conditional predictions for baseline variance or pairwise correlations are not substantially different whether we add macroeconomic linked latent variables or not given we already have RV in the tested specifications. This non-difference is especially noted for short run pairwise correlation predictions which, 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 against the German benchmark show consistent evidence to earlier studies: EU markets have converged to new heights in the run up to introduction of Euro and post Euro periods. The stability in the dynamic interdependencies is also reported in the post Euro period if we exclude the crisis period. During the crisis period the European convergence levels have increased further

[5] 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).

from their pre-crisis levels but also show sharp divergences in conditional correlations for shocks emanating from EDC. Whereas for the period falling under global financial crisis of 2007-08 these interdependencies tend to show the usual pattern of higher convergence in bearish market conditions. Only exception to this is the overall divergence of Greek market to the European integration. The Greek-German correlations have decreased to 40 percent towards the end of year 2013 from the heights of 80 percent around the beginning of crisis period i.e. the end of year 2007. This time series detachment also shows the gradual insouciance of the European financial markets towards Greek risk or towards an ex ante dismal possibility of so called Grexit.

Furthermore, the joint relationship between unconditional RV and realised correlations (RC) demonstrate 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 describes literature review data. 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 divarication related financial decisions cannot be over stated. The degree of financial integration can be measured in many ways and various studies, employing different methodologies, have examined this phenomenon (see, Kearney and Lucey, 2004 and Billio and Pelizzon, 2003, among others). 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 (Erb et al. 1994; Longin and Solnik, 1995 & 2001 and Connor and Suurlaht, 2013, among others) 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 market is the sound first step towards understanding a 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 changing economic conditions. Generally, autoregressive conditional heteroskedasticity (ARCH) class of models have been the most popular to get volatility (and correlation), for the latent nature of these risk phenomenon, predictions.

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

"Please insert Table 1 about here"

Given the wealth of evidence reporting that the capital markets share common trends and stock volatility changes in the long run (Kasa, 1992; Schwert, 1989), this methodology specifies the evolution of volatility/correlation process to not to miss on 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 (Basistha and Kurov, 2008) and affect negatively the future excess stock returns (Bredin et al. 2007). Nonetheless, Hausman and Wongswan, 2011 report volatility responses to changes to the target exchange rate and shocks to target rate may vary across countries. Therefore, linking equity market volatility and cross-correlations with information coming from different channels of macroeconomic activity would be helpful in making better predictions.

Asgharian et al. (2013) show that addition of a business cycle proxy in the GARCH-MIDAS specification improves the models forecasting ability than the conventional GARCH modifications. Engle et al. (2013) report the benefits of including business cycle information affects both of the volatility components, i.e. long run and the short run components. Taken together, the inclusion of macroeconomic variables can depict the underlying cross-country correlation dynamics more accurately. Knowing these patterns accurately are of considerable importance for investors and practitioners in constructing portfolios and developing diversification and hedging strategies. Numerous studies analyse the financial integration after the introduction of the Euro, and they adopt different dynamic approaches.

Using asymmetric DCC methodology, Cappiello et al. (2006) find significant evidence of structural breaks in the correlations of EMU countries. Saava (2009) shows, using the same framework, the correlations, among major international stock markets, are affected by business cycle variations. Saava et al. (2009) show 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 Liu (2013) has reported the correlation among EMU countries reached its peak by 2002 and afterwards no increases has been observed among them. Connor and Suurlaht (2013) find 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 DataStream market indices for France, Germany, Greece, Italy, 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 (Virk, 2012; Apergis et al, 2011) and stock volatility and correlations have been reported to influenced by business cycle variations (Engle et al. 2013 and Conner and Suurlaht, 2013). Second, we intend to isolate the independent impact of two macroeconomic channels on the volatility and correlation dynamics of the European markets, and also the cross-country response differences towards them, when few among the sampled countries belong to EMU.

The availability of numerous macro variables, depicting different aspects of the state of macro-economy, and their interdependence is a well reported issue. Taking multiple predictors can cause estimation problems such as biased and unstable regression estimates. Following Stock and Watson (2002), 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 transformation to make them stationary with most of them being integrated of order 1 (I1). Finally, these transformed stationary series are standardized 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[6]. 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 and bi-variate correlation dynamics, short-term and long term risk components, 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 among all. All return series are asymmetrically distributed for negative skewness and have positive excess kurtosis. Furthermore, the first four serial-correlation estimates for the all the return series demonstrate low persistence and only Greece has a serial-correlation of 10 percent at the first lag a 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 persistence is 20 percent for the remaining markets except Germany for which squared returns show persistence of approximately 15 percent across the four lags. Table 2 reports the bivariate correlation for the full period, period after the introduction of euro[7] and the global/European crisis period[8].

[6]We do 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.

[7]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.

[8]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 (Cipollini et al, 2013). 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

Against the German benchmark static bivariate correlations demonstrate on overall EU convergence such that not only for the correlations between EMU markets but for the correlations between EMU and non-EMU stock markets have also amplified after the introduction of euro. This convergence has witnessed a further hike during the crisis period. These correlations display the variability in the strength of these convergences among developed markets and their correlations with the developing Greek stock market.

Greece has the lowest bi-variate correlations among the European countries. This weak connectedness is to the extent that the non-EMU markets have more converging interrelations with the remaining EMU stock markets than what Greece has with the common currency countries. For example the Swiss market bi-variate correlations, in the crisis period, with France, Germany and Italy are 87, 72 and 81 percent points respectively whereas in the same period these correlations for Greece are only 49, 43 and 49 percent points respectively. Nonetheless, the unconditional correlations have increased during the crisis period than pre Euro and post Euro periods. The bi-varaite correlations of the UK with the developed EMU markets are even higher than the Swiss market.

4. **Methodology**

The construction of the DCC-MIDAS model is based on the GARCH-MIDAS process proposed by Engle et al. (2010). The reason of utilizing this model for our analysis is motivated by the fact that it allows us to incorporate macro economic information within the dynamic correlation structure. Using this specification, we can study the behaviour of dynamic correlation effected by the variation in business cycle. In order to estimate the dynamic conditional correlation through the DCC-MIDAS model, we follow the two-step procedure of Engle (2002). In the first step of this procedure, we estimate the parameters of univariate conditional volatility models. The standardized residuals from the estimated models will then be 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. Asgharian et al. (2012) shows that this specification better cleans the residuals for volatility forecasting. In the second step, the DCC-MIDAS parameters are estimated using the estimated standardized residuals.

In this section, 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 standardized 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 Ghysels et al. (2004, 2006a, b). MIDAS regression allows for analysis

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.

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. Consequently, the MIDAS methodology has gained considerable attention in recent years. Chen and Ghysels (2009) have extended the MIDAS setting to a multi-horizon semi-parametric framework and provided a comprehensive study to analyse the impact of news on volatility predictions. Kotze (2007) has used the MIDAS regression with high frequency data on asset prices and low frequency inflation forecasts. Alper et al. (2008) have compared the stock market volatility forecasts across emerging markets using MIDAS regression. Ghysels et al. (2009) have discussed the Granger causality with mixed frequency data. Below, we specify the models used in our analysis.

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

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

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

where $X^l_{i,t}$ is the level of the exogenous macroeconomic variable and 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,

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

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 realized volatility and macroeconomic variables in the spirit of MIDAS regression

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

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

where K is the number of periods over which we smooth the volatility, and X^l_{t-k} and X^v_{t-k} 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

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

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

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

4.2. **The DCC setup.** Having obtained the estimates of the standardized residuals, we can obtain the correlation structure using the DCC-MIDAS model. The DCC-MIDAS model stems from the idea of Engle's (2002) DCC model and from the GARCH-MIDAS model. A key feature of the DCC-MIDAS model is that it lets us decompose 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 also let us differentiate between instruments, such as business cycle indicators, 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

$$r_t \sim N(\mu, H_t), \qquad (5)$$
$$H_t \equiv D_t R_t D_t.$$

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

$$R_t = E_{t-1}[\xi_t \xi_t'], \qquad (6)$$
$$\xi_t = D_t^{-1}(r_t - \mu).$$

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

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

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

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

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

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

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

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

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

with

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

and

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

where, $\Psi \equiv [(\alpha, \beta, w_2, m, \theta_1, \theta_2, \theta_3)]$ is the vector of all the parameters in the univariate volatility model for each series and $\Xi \equiv (a, b, w_2)$ is a vector of parameters of the conditional correlation model. In the first step, we estimate the parameters driving the dynamics of volatility for each asset in equations (1) to (4) and collect them in a vector Ψ (yielding $\hat{\Psi}$). The second step consists of an estimation of the standardized residuals, $\hat{\xi}_t = \hat{D}_t^{-1}(r_t - \mu)$ in equation (7) using $QL_2(\hat{\Psi}, \Xi)$.

To facilitate the estimation of the chosen model, we first need to decide on the choice of polynomial characteristics K and N_t in equation (3) and $K_c^{i,j}$ and $N_c^{i,j}$ in equation (8). In the former case, K determines the total number of lags needed to optimize the log-likelihood function. In the univariate case, these lags can be equivalent to a month, a quarter, or a half year. This lag value will then be used in the MIDAS polynomial specification for τ_t in equation (3). As stated in Engle et al. (2010), 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. Following Asgharian et al. (2012), we use the lag number $K = 12$, which is equivalent to a so called three MIDAS years 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 $K_c^{i,j} = 504$ (two years of daily values) for historical correlations and the time span over which to compute the historical correlations $N_c^{i,j} = 22$ in equation (8).

To set the weights, w_1 and w_2, in the beta polynomial given in equation (4), we follow the specification from Engle et al. (2010) where they 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 the weighting function with respect to different weights can be found in Asgharian et al. (2012).

"Please insert Table 3 about here"

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 3-year rolled squared market returns to proxy for realized volatility, at monthly frequency, as an input series to carry out the mixed data sampling estimation. This provides us predictions for the long run component of the conditional/baseline variance. The short run variance component (g) is estimated using equation 2 and the long run component (τ) is retrieved from equation 3. The estimate for the baseline/conditional variance is the product of these two components as stipulated in equation 4[9]. Results in table 3 show that the short run volatility (or GARCH effect) is persistent across all the markets: the sum of GARCH estimates ($\alpha + \beta$) is $0.98, 0.99, 0.94, 0.97$, and 0.99 for France, Germany, Greece, Italy, Switzerland and the UK respectively. Moreover, we notice that different weight structures are required for all the stock markets for the convergence of the estimated specifications. For example, the convergence, of the univariate GARCH-MIDAS model, for the German stock market requires fairly lower weight (w) , although insignificantly estimated, assigned to the recent values of index returns than all the remaining stock markets.

Whereas, the long run volatility component is mean reverting: $m + \theta_1$is sufficiently less than 0.5 for EMU stock markets. The long run volatility component for Switzerland and the UK decays because of the negative estimate for the level (m) of the long run volatility however $\theta_1$is positive and significant across all 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.

"Please insert Table 4 about here"

Engle et al. (2013) 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. Beta polynomial is used to smooth the long-term components of volatility and correlations. Therefore, the independent factors capturing business cycle conditions and monetary policy namely PC_{BS} and PC_{MP}, both the level and shocks to them, are added in Table 3 regressions. Results are reported in Table 4. We decompose each PC into two parts i.e. level and variance. This will help in describing if the baseline variance, across markets, is sensitive towards aggregate expectations for these variables or to the shocks in 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.

Table 4 shows that the level of long run volatility is negative for all markets but insignificantly except for the UK however the GARCH component remains its persistence.

[9]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 Engle et al. (2013) and Asgharian et al. (2013). We employ the root mean squared errors (RMSE), as decision criterion, in measuring the better fit of the tested model specifications.

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.

"Please insert Table 5 about here"

The results for PC_{BS} and PC_{MP} factors are mixed at best: shocks to monetary policy variables are positive and significant for large European markets i.e. France, Germany and the UK. The baseline variance for Swiss market is significantly affected by variability in the level of PC_{MP}. Italian and Spanish total variance evolution is responsive to the shock and the level of business cycle principal component respectively. Whereas, Greece baseline variance dynamics does not respond to fluctuations both the latent macroeconomic variables both in the level and shocks. 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 response to changes in the aggregate business conditions or fluctuations in the exchanges rates etc.

The mixed results for the sensitivity of total variance towards macroeconomic risks and the more often significance of RV reflects the importance of RV in capturing long run variance component than the decomposedPCs, especially for EMU equity markets. Moreover the differences could effectively be representative of relative risk levels of these markets. This may result in baseline variances exposure to variations in business conditions and/or in monetary policy changes and more precisely by its sensitivity to the level of a particular PC or shock to it. Whereas for financial markets whose vulnerabilities are higher RV alone may explain long run evolution of variance component. For example Greece has been on the forefront of causing tremors in the ongoing European debt crisis thrice at least and therefore shows encompassing risk sensitivity to a measure of risk such as RV than specific changes to macroeconomic risks[10]. However large stock markets may anticipate exchange rate fluctuations but not shocks to the monetary policy variabilities.

Nonetheless, 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. Effectively 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 manifested by the significant exposure of baseline variance to shocks to PC_{MP} for France and Germany, whereas Italys variance evolution is sensitive shocks to PC_{BS}. Spain is 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 Colacito et al. (2011) the unexplained return volatility from univariate GARCH-MIDAS models, estimated in Table 3 and 4, is taken to the DCC-MIDAS specification. The DCC-MIDAS estimates the dynamic correlation which is decomposed into the short run and long run

[10]Three period of spreading risk across European and international markets: 2008, 2010, 2012.

dynamic correlation components see equations 7 and 8 respectively, between the pair markets. 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 to 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 short-run correlation estimates i.e.$(a + b)$, reported in the first panel, show high persistence across European market integration in line with evidence studying European market integration employing non-MIDAS techniques (Saava et al, 2009; Connor and Suurlaht, 2013 among other).

"Please insert Figure 1 about here"

The short run pair market correlations against the German benchmark demonstrate Greece, Italy, Spain and Switzerland equity markets are far more linked at EU/EMU level than the French and the UK equity markets. This manifests French and the UK stock markets integration levels are also responsive to long run correlations which are 0.17 and 0.12 respectively with the German stock market. With the exception of pairwise correlation of Greece with the UK stock market, the short run integration levels of the French and the UK stock market with the remaining stocks markets are in range of 0.95 percent to 0.98 percent. These correlations demonstrate the integration levels among these markets respond to short run market fluctuations far higher than the long run correlation component. Interestingly, Greece has the largest long run integration levels with Italian stock market: the short run pairwise correlation between the pair is the lowest, across all the reported correlations, at 0.62 percent.

The short run pairwise correlations in panel II are not substantially different than the ones reported in panel I. However, the European integration levels implied by the short run pairwise equity market correlations with German benchmark for the French and the UK equity markets have increased than the ones in panel I. The increase between EU benchmark and the UK increases by 4% when standardised residuals from the GARCH-MIDAS specification with RV+Econ specification are used. This increase is only 1% for the French-German pairwise short run co-movements. Other remarkable difference is the decrease in the short run correlation between Greece and Italy to 0.57 percent showing even higher long run pairwise movement between the two markets.

Overall, point estimates for the short run integration demonstrate that EU markets are highly integrated during the sample period. Long run interdependences are relatively higher for large economies[11] against German benchmark than the remaining countries in the study. The implied high integration may overlook variability in the correlation patterns over time and across key events. Therefore we plot the predicted dynamic short run and long run correlation series, retrieved from the DCC-MIDAS specifications, in figures 1 and 2 respectively.

The dynamic pairwise correlations in figures 1 contain a number of time patterns across

[11]German economy is the largest in size among the EU economies followed by the UK and France.

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 the achieved new integration level is stronger than the pre-euro levels for most of the markets. The importance of this event is manifested from the fact that short run interdependences against the German benchmark increased almost six to ten times than the levels in the period three prior to introduction of euro except for the Swiss equity market. The increase in the Germany-Switzerland interdependence is not as stark however the correlation between the two markets were already as high as 0.30 three year prior to the introduction of euro. Therefore the approximately three times increase between the Swiss markets EU integration translates into even higher interdependence than the few others such as Greece, Spain and the UK. Nonetheless, the importance of the event is evident from its ability to raise convergence levels even with the non-euro financial markets. These convergences among the EU stock markets are much broader such that correlations, in the same period, between other equity market pairs also increased with similar intensity.

Second, the short run correlation predictions from the two DCC-MIDAS specifications i.e. RV and $RV + Econ$ are not drastically different. This once again reinforces the sound candidature of RV to proxy for long run component of total variance evolution. Third, these convergence levels become stable in the post Euro period than pre Euro fluctuating correlation patterns. Furthermore, the short run correlations show an increasing trend in the pan European convergences in the later sub sample. The EU convergence weakened for Greece and Switzerland in the following two year period after the introduction or Euro and to be only stabilised from thereon. This could be seen as a period when rally in the German stock market boasted the integration levels further among the EMU and the UK equity indices. However the contrary movement in the Greek and Swiss stocks weakened the heightened correlations achieved during the adoption of common currency. The interdependence between the Swiss and the proxy EU benchmark has been the most volatile among all the markets but still kept an increasing trend. Besides the short run convergences not only increased between EMU stock markets, in the post euro period, but these increases are witnessed for non-euro equity markets as well.

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, as discussed earlier which overlapped with the European debt crisis (2009 to date), 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 are higher and more stable than the convergence stability achieved during the post euro period that ends at the beginning of the global financial crisis. The increased convergence levels are consistent with earlier reported empirical evidence (Erb et al, 1994; Connor and Suurleht, 2013, among others) that equity markets tend to co-move during crisis or bearish market conditions.

However, there are few pertinent exceptions to this lean observation. Pan European markets, which in the lead up to global financial crisis of 2007-08 achieved even higher convergence levels, responded to the EDC i.e. local shocks in far more dramatic fashion.

This is evident from substantial decrease in the French-German integration divergence for that matter in the build-up of the European debt crisis around the end of 2008 and the beginning of year 2009. From there on French convergence with the EU proxy was reinstated and converged to heights not observed in the whole sample. This construes because of the severity of EDC crisis the absence of confidence within the two largest equity markets in the euro region. Furthermore, French banks to date 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, French stock market correlations with Italy and Spain have numerous divergences during the crisis period while maintaining an upward trend than the pre-crisis convergence levels. Whereas the convergence between the French-Greek transpired into an overall divergence in the course of crisis period a deterioration which is widespread for the Greek stock market pairwise correlations with all remaining stock markets for this period. We will discuss this anomaly in greater detail later.

"Please insert Figure 2 about here"

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

Whereas remaining equity markets show more than one instance of divergence against the German benchmark. Italys earlier convergence with the EU benchmark showed sign of deterioration throughout the year 2008. The shock responsiveness once again diverge the short run correlations during the year 2012. Besides, the responses to European system wide shocks emanating from PIIGS economies debt frailties Italys convergence level tend to increase during the crisis period. The greater weakness of Spanish economy drew more responses and distinctively there are four divergences in its correlation pattern with the EU proxy. The UK also decoupled from the high convergence level with the German benchmark during the year 2009 ad 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 (Cipollini et al. 2014).

The EU benchmarked short run correlation patterns with the Switzerland are more tumultuous than the remaining. German-Swiss equity market integration observed reduced co-movements during the global financial crisis of 2007-08 a period when other countries showed higher EU convergence. Moreover, the integration levels in response to the shocks during the (ongoing) EDC period at times halved the otherwise high convergence levels. These repetitive divergences by the Swiss stock market display detachment of risk from Eurozone debt shocks during the crisis period. The UK equity

[12]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.

market also displayed severe divergences during this period, to the otherwise surging correlations, in the wake of 2008 and 2010 EDC shocks.

The most drastic exception among the integration levels of the EU/EMU markets is the divergence between the German-Greek equity market correlations. The short run correlation patterns between Greece and German benchmark show that the convergence levels which achieved its epitome just before the beginning of global financial crisis and fizzled out quickly during the crisis period. This divergence is not observed in the integration patterns for any of the remaining equity markets. This demonstrates where fault lines of the European debt crisis are and detachment from Greek risk by all the equity markets during the crisis period. This detachment may also display the state of being at political crossroads and mistrust between the Greek and European policy makers in the implementation of austerity plans in response to the offered bail out packages during this period.

As noted earlier, this divergent pattern is just not observed against German benchmark rather is present with all the remaining equity markets as well. This detachment of EU markets with the Greek stock market has neutralised the earlier achieved high convergence levels. This neutralisation is to the extent that the dynamic correlations, between Greek and the remaining EU stocks markets, which were around 0.70 or above just before the beginning of the global financial crisis have deteriorated and are around 0.30 and in most of the cases 0.20 or below. The decreasing dynamic correlations between Greek and the remaining EU countries during the crisis period are in sharp contrast to the unconditional correlations reported in Table 2 for the same period. This shows the importance of modelling equity returns dynamically when the static correlations may portray misleading patterns (Kalotychou et al. 2014).

The long term integration dynamics also reinforces these divergences 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 sovereign debt crisis systematically. Although, the aggregate debt levels of the Italy and Spain are much higher than the Greek debt but trust loss have resulted in different integration structures: 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 for Eurozone pair countries only, see plots in Figures 2. These patterns across the pre-Euro, post-Euro (before crisis) and the crisis periods are inline to the patterns in Figures 1. This highlight RV specification could be a good proxy for the long run volatility for markets which share common currency. More importantly, EMU markets integration has reached a level, in the modelling of total variance evolution and subsequent dynamic correlation projections, that the incorporation of PCs are not able to add new information.

Nonetheless, interdependences across EMU pair countries have shaped over time differently. For example the long run convergence between correlations of Greece and Spain, after the reported increases in the run to the introduction of euro, with the German benchmark kept an upward trend till the beginning of global crisis of 2007-08. The German-Greek long run convergence in the post Euro period (before crisis) showed frequent and substantial ebbs than all remaining equity markets. Overall this shaped a Greek convergence at EMU level. Whereas long run correlation patterns between France and Italy with German benchmark rose at a stable rate during the same period. Other consistent pattern also witnessed for the short run correlations includes that all the EU markets decoupled themselves from the Greek risk during the crisis period.

The long run correlations converged to higher levels for French and British equity markets with the German benchmark as the approach the later part of crisis period in this study. Although long run correlation around the tail end of the sample period in this study i.e. 2012-13 tend to diverge between Italian, Spanish and Swiss equity markets with the EMU proxy.

However, the long run integration patterns, retrieved from the two DCC-MIDAS specifications, between the Eurozone equity and non-Eurozone market pairs, except Greece, elicit different evolutions. It is evident from the fact that predictions from the RV+Econ DCC-MIDAS specification are lagging behind in evolution to the long run correlations retrieved from RV DCC-MIDAS specification e.g. see the plots between Germany-UK, Italy-UK and Spain-Switzerland predictions, among others. Moreover, the specification using only RV tend to have sharper rises and ebbs than the specification using $RV + Econ$ specification. Surprisingly, the projections for long run correlation patterns between the pairs of Greece-Switzerland and Greece-UK from the two specifications are almost identical. This similarity in projections is also manifested between the correlation patterns between Swiss and the UK equity markets.

5.4. **Joint relationship of volatilities and correlations.** The increases in the correlations when volatility is also rising can inflate the overall portfolio risk portfolios whether constructed of basic assets or composed of derivative securities. This scenario makes the comprehension of short run and long run joint relationship between the two important to make active or passive investment decisions, constructing insurance plans and constructing hedging risk strategies, among others. Since we have estimated the short- and long-term components of dynamic volatilities and correlations through the GARCH-MIDAS and DCC-MIDAS specifications respectively, we estimate the joint relationship for both components following Cappiello et al (2006)[13].

The dynamic joint relationships are compared against the unconditional version of these joint relationships. Cappiello et al reported the average of the correlations between the variance of the country with all its associated pairwise correlations. In reporting these

[13]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.

joint relationships we delve deeper than them: we also report the within relationships between the variance of a country with the associated pair-country correlations as well. The interrelations between the two year rolling realised correlations (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[14] show that European integration levels have moved in tandem to the German stock market volatility over the full period in this study. However, increases during the post Euro and during the crisis period in German volatility 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. This entails an important implication for portfolio diversification: portfolios timing volatility and correlations could be safe hedges for spill over risks coming from either side i.e. volatility risk or market co-movements. The French and the UK stock market volatility are more correlated with its associated pairwise correlations than the benchmark German stock market in the full sample period. This positive joint relationship for the volatility of these countries and associated pairwise correlations persists in the crisis period although is negative in the post Euro period.

The unconditional joint relationships for Greek, Italian and Spain (PIIGS countries) market volatilities demonstrate the highest opposite movement to the associated pairwise correlations during the post Euro period. The joint association of stock market volatilities with their respective linked pairs, with the exception of German and Greek stock market volatilities, display a positive relationship during the crisis period. This shows the higher riskiness of timing volatilities and correlation based diversification strategies between these markets during the crisis period.

Furthermore, this demonstrates the higher riskiness of Greek assets: the associated correlations tend to move in opposite direction when Greek volatility is on the rise. Another vindication for decoupling from Greek risk from all the EU markets. Numerous studies have reported the 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 patterns need to be confirmed with the dynamic counterparts of these joint relationships.

"Please insert Table 7 about here"

[14] From here on ϕ_i or average joint relationship will 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_is using rolling or dynamic correlations are unconditional for the matter of fact.

Table 7 reports the short run joint dynamics between volatility evolution and dynamic correlations at the daily frequency from the GARCH/DCC-MIDAS specification using RV. The only consistency between ϕ_i's, in the full period, using dynamic series versus rolling series is the positive relatedness. Otherwise, on average these joint correlations are far weaker than reported in Table 6. This weakness is to the extent that for Greece and Italy dynamic equity market variance increases are arguably uncorrelated with their respective dynamic pairwise correlations. For these two countries the average joint relationship is only 0.04 and 0.09 respectively. The average joint relationship for Germany is also small i.e. 0.16 which using RV and RC was substantially higher i.e. approximately 50 percent.

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

The crisis period joint relationships are weakly positive across markets except for German stock market: the highest ϕ_i is for UK at 0.27. The negative association between the German market volatility and its pairwise EU-linkages displays the continued, although marginal benefit, for timing German volatility against the increases in dynamic correlations during this period. This pattern could be linked to important periodical realisations. Such as German market nosedived till March 2009 in response to global crisis and from there on have appreciated considerably higher to the pre-crisis index level. Therefore, during this period German market short run volatility has increased in response to positive growth in the equities followed. Germanys pairwise correlation with Greece is the only exception which is positively increased, during this period, in response to increases in the German GARCH component.

"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 tend to increase respective countrys associated pairwise correlation patterns as well. These long run dependencies are greater for EMU countries except Germany whose equity variance increases attracts mixed association with its pairwise dynamic correlations. 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 in response to increases in the German long run equity variance. Excluding joint dynamics of the Greece and Spain with Germany, the average of German joint relationships is negative in line to the earlier reported static and short run joint dynamics during the crisis period.

Importantly, the joint relationships against the benchmark German equity variance increases are negatively related to large EU markets during the crisis period i.e. France and the UK. This relationship is observed whether scrutinised dynamically or statically as well as in the long run or at the short run. Whereas, dynamic GARCH component increase in the German variance evolution attracts negative response across the board except the German-Greek pair. That is not only German conditional equity variance increases are inversely linked in the short run to its dynamic pairwise correlations but is also true for the German pairwise correlations that they are also negatively correlated with the dynamic equity increases in the remaining equity markets. This shows Germany is a stable market to not respond to each and every shock emanating from elsewhere which is not the case for other larger equity markets such as France and the UK.

Taken together these results establish few important corollaries. One, joint relationships from *RV* and *RC* series tend to overstate the magnitude of directedness considerably to that of between dynamic series from GARCH-MIDAS and DCC-MIDAS specifications. This overstatement amplifies resultant benefits or risks to develop diversification strategies and misprices insurance covers. For example, the Greek RV increases are inversely related to its pairwise correlations during the post Euro period. And the employment of these patterns could have resulted in unfavourable investment outcomes than the ones based on relationships from dynamic variance and correlation series. Two, except Germany, the average short run joint relationships show that dynamic equity variance increases accompany dynamic equity market co-movements positively 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 including Germany, as shown in Tables 8 and 9.

The peculiarity of average short run joint relationships for Germany during the crisis period enhances the benchmark credentials of German equity market in the EU in general and EMU in particular.

6. **Conclusion**

European financial markets has been reported to have increased integration levels among themselves after the introduction of Euro. This heightened co-movement is noteworthy for common currency countries. However regional EU markets not sharing common currency have also experienced increased levels of convergences in the post Euro period. We employed state-of-the-art method to estimate conditional volatilities and dynamic correlations using GARCH/DCC-MIDAS methodology. We witness different markets respond to monetary policy and business cycle linked latent variables differently. We find no particular differences in volatility or pairwise correlation predictions between specifications using RV as proxy for long run variance or specification augmented with latent factors to proxy macroeconomic conditions. This stipulates realised variance is an efficient proxy for long run variance component and this holds especially for short run volatility and integration predictions.

These predictions shows consistent evidence such that EU markets have converged substantially in the post Euro period than the pre Euro period. European equity market integration patterns using German benchmark show that dynamic pairwise correlation not got stable in the post Euro period but also achieved greater levels during the crisis period. Only exception to the increased convergence has been the divergence of Greek asset returns from the European benchmark. This Greek divergence is also available when analysed for the rest of the equity markets. This highlights the mitigation of Greek risk at the European level. Since the beginning of EDC, Greek markets divergence is substantial: towards the end of year 2013 pairwise dynamic correlations have halved from the convergence levels of approximately 80 percent witnessed at the height of global financial crisis 2007-09. This divergence is noticed at for both short run and long run predictions and for either MIDAS specification as well.

The joint relationship between the dynamic volatility and pairwise dynamic correlation predictions highlights important cross-country patterns. This analysis shows stability of Germany to proxy for European integration patterns: all markets showed a tendency to have increased positive movements between volatility and its pairwise correlation predictions except Germany during the crisis period. This establishes financial markets tend to get strangulated in contagious spirals during the crisis periods for co-movements between different dimensions of risks. This convergence increases overall risk levels and may result in far higher calamitous states which may otherwise get ignored if analysed only from increased cross-country correlation patterns. Analysing these joint relationships using rolling variance and correlation series 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 dynamic counterpart joint relationships.

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1 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 auto- correlations at 5% level at first four lags.

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 [].

Countries	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	RV	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*

Table 4: Result for the univariate part of estimation for GARCH-MIDAS (RV+Econ)

Countries	μ	α	β	m	RV	X_1^l	X_1^y	X_2^l	X_2^y	w
France	0.06*	0.08*	0.89*	-0.14	0.006*	0.33	0.60	0-0.17	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*

Table 5: Estimation of DCC-MIDAS

	RV			RV+Econ		
Countries	a	b	*w*	a	b	*w*
France - Germany	0.07*	0.76*	6.23*	0.06*	0.76*	6.58*
France - Greece	0.03*	0.95*	5.49*	0.02*	0.95*	5.04*
France - Italy	0.05*	0.93*	3.58*	0.05*	0.93*	2.82*
France - Spain	0.04*	0.93*	2.96*	0.04*	0.93*	2.91*
France - 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 corre- lation 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 corre- lation 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 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 [].

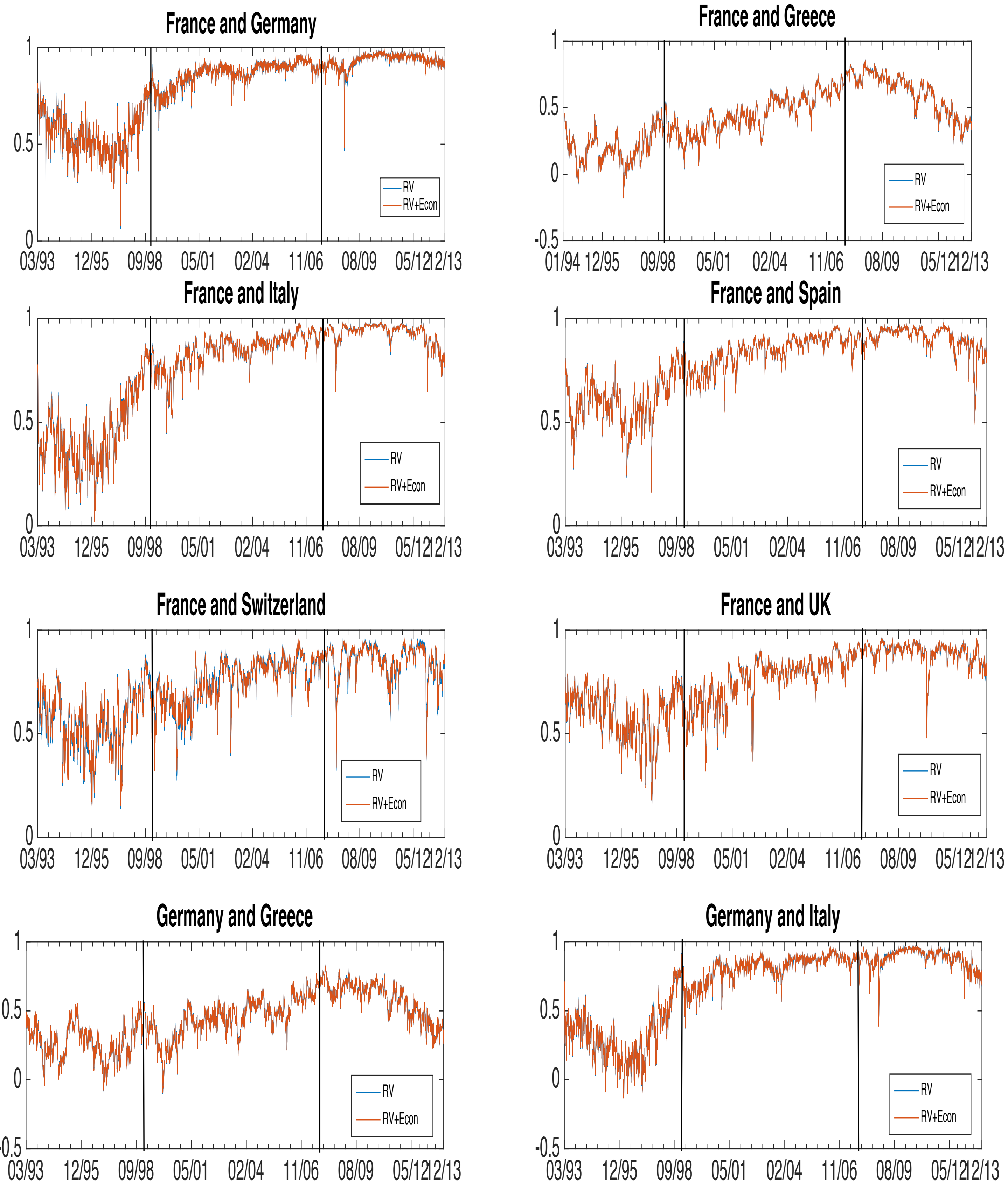
Countries	France	Germany	Greece	Italy	Spain	Swiss	UK	Average
France	-	**0.32**	**0.48**	**0.36**	**0.40**	**0.37**	**0.42**	**0.39**
	-	*(-0.16)*	*(-0.42)*	*(-0.06)*	*(-0.20)*	*(-0.26)*	*(-0.21)*	*(-0.22)*
	-	[-0.31]	[0.48]	[0.24]	[0.49]	[0.12]	[0.41]	[0.24]
Germany	**0.33**	-	**0.43**	**0.34**	**0.35**	**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]

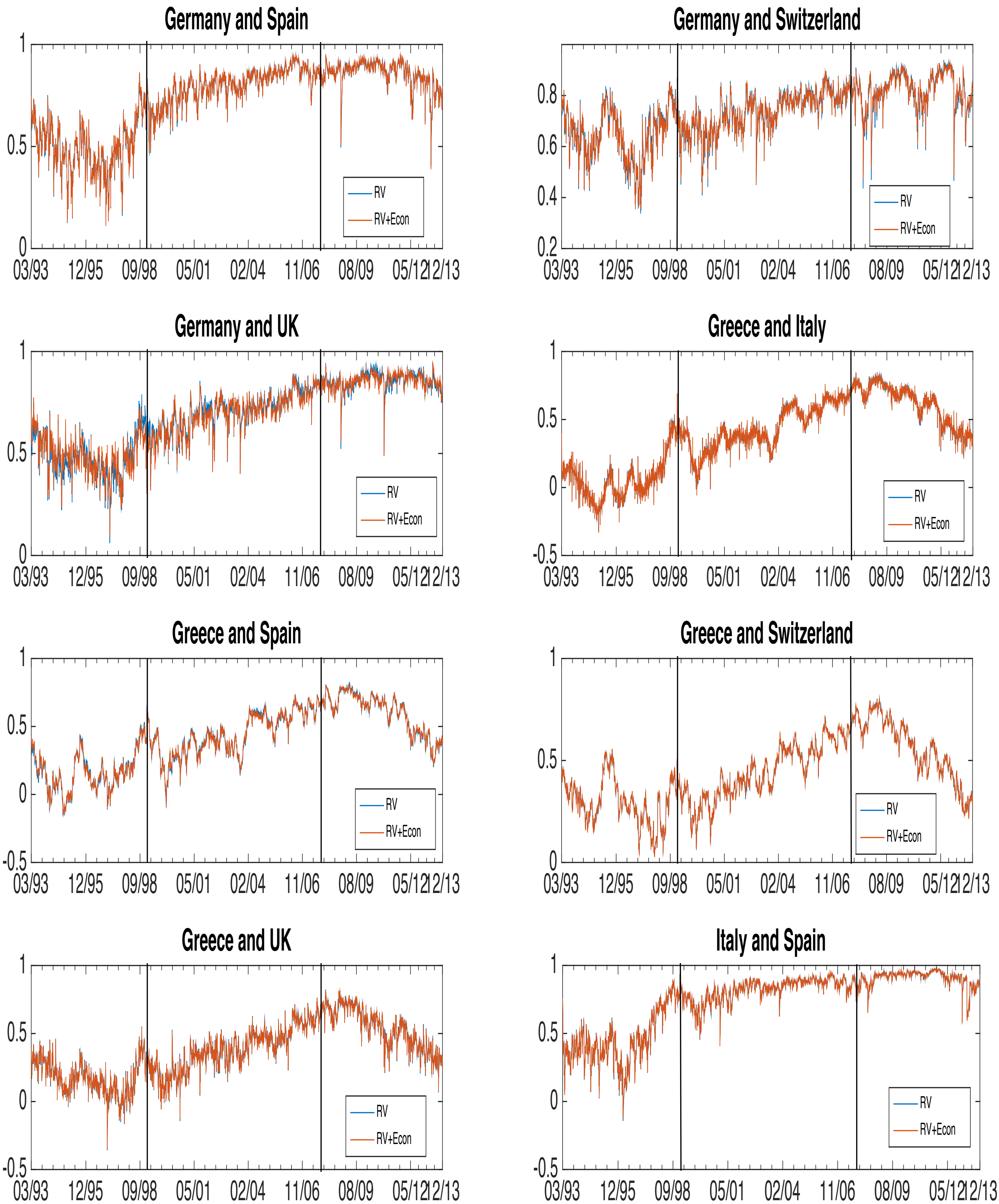
Table 9: Correlation between long-term (RV+Econ) equity variance and the corresponding pairwise equity correlations. Row defines individual volatility while columns define paired correlations. The joint correlation values for the full sample period are shown in **bold** case, since the Euro introduction 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]

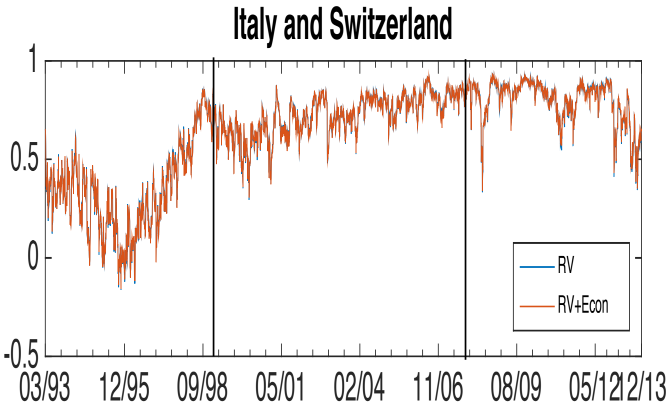
Figures:

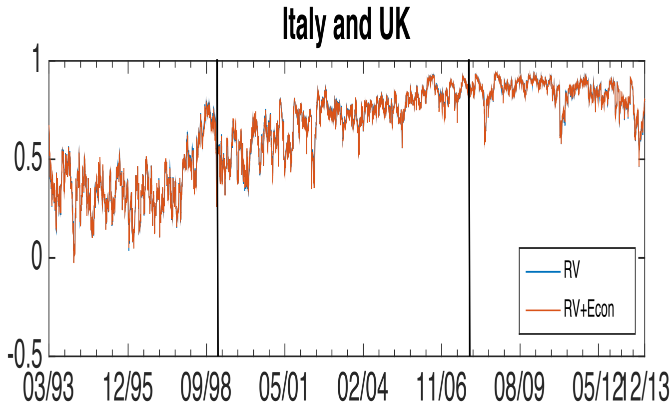
Figure 1: Short-term Pairwise-Correlations

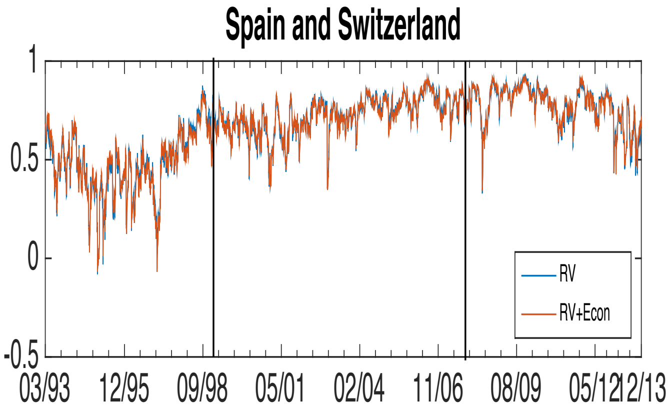


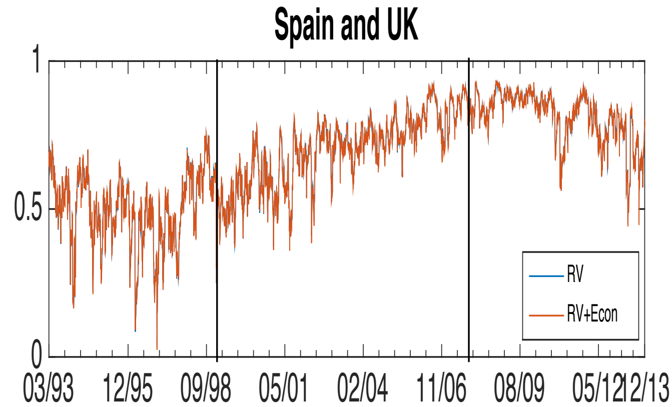


Germany and Spain
Germany and Switzerland
Germany and UK
Greece and Italy
Greece and Spain
Greece and Switzerland
Greece and UK
Italy and Spain
RV
RV+Econ
03/93
12/95
09/98
05/01
02/04
11/06
08/09
05/12
12/13


Italy and Switzerland
1
0.5
0
-0.5
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ


Italy and UK
1
0.5
0
-0.5
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ


Spain and Switzerland
1
0.5
0
-0.5
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ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1
0.5
0
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ

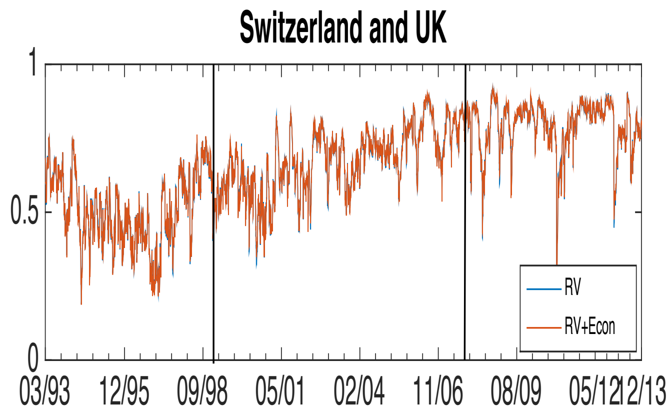
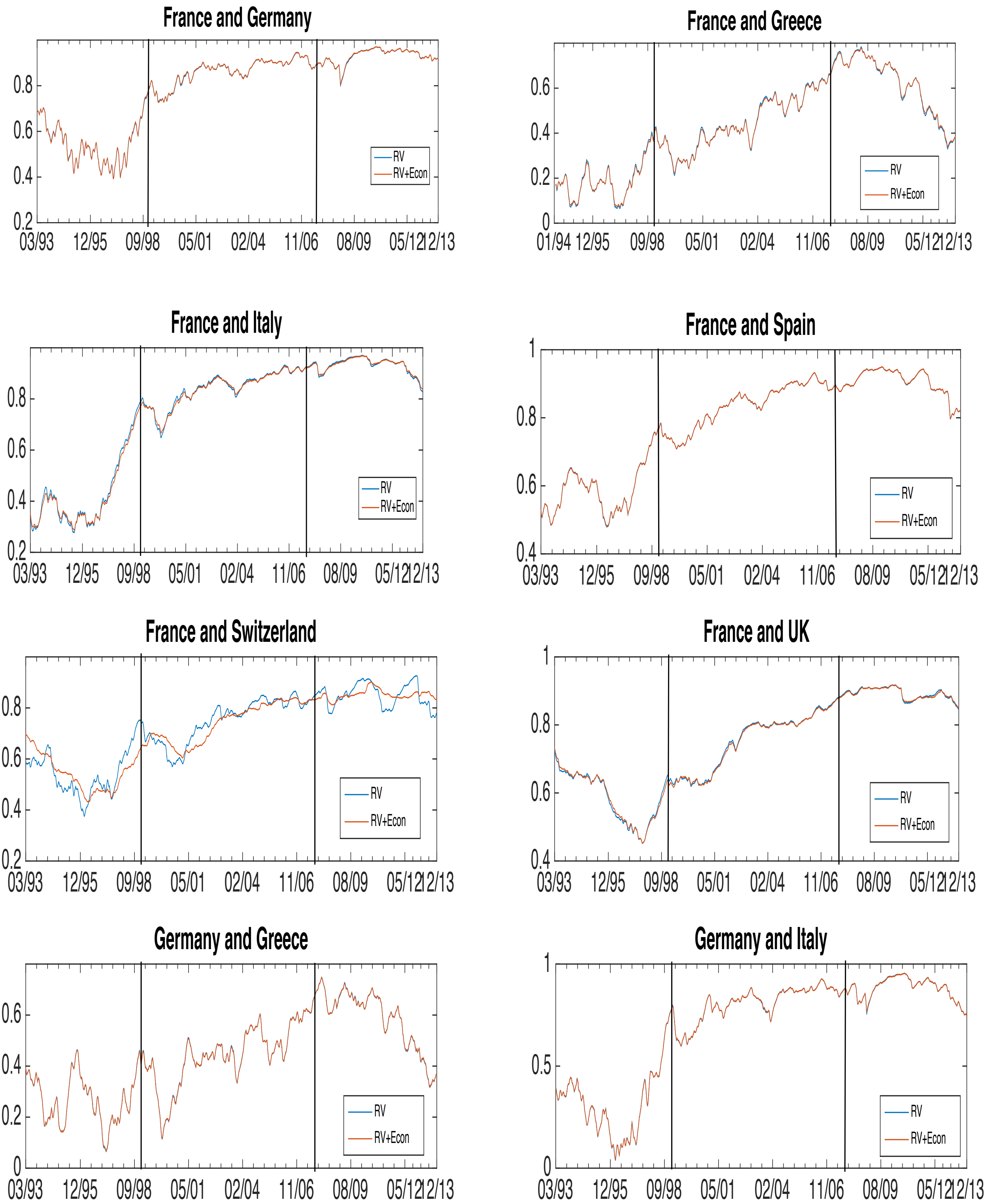
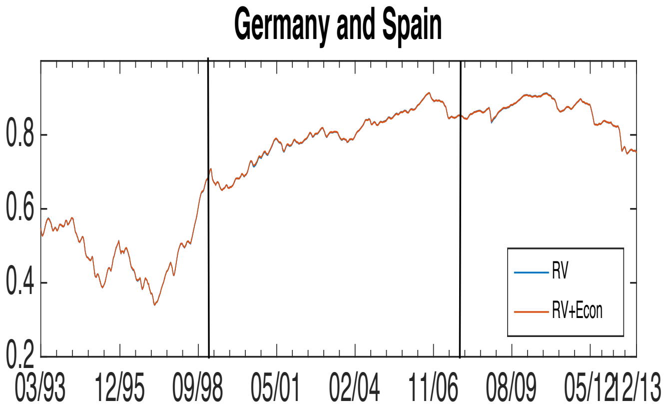
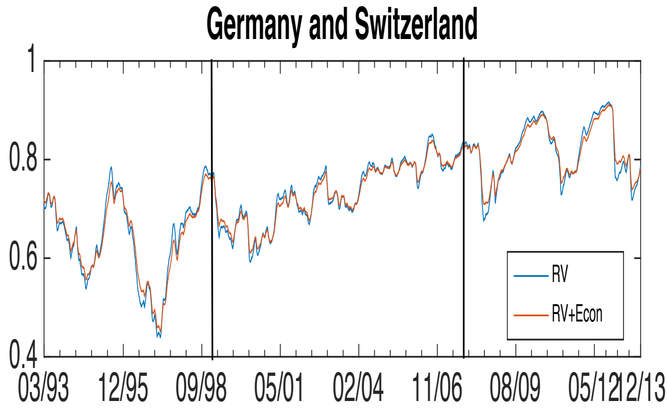
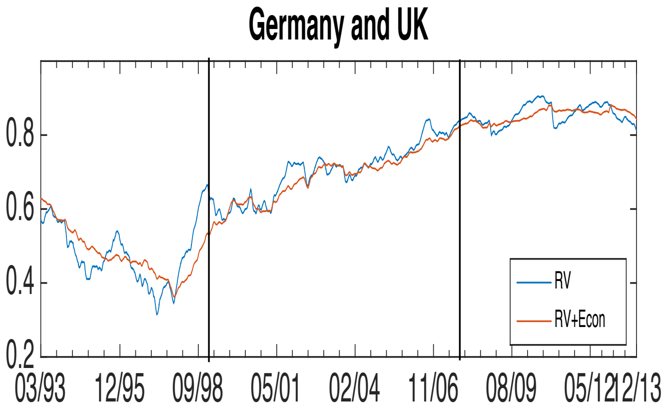

Switzerland and UK
1
0.5
0
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ

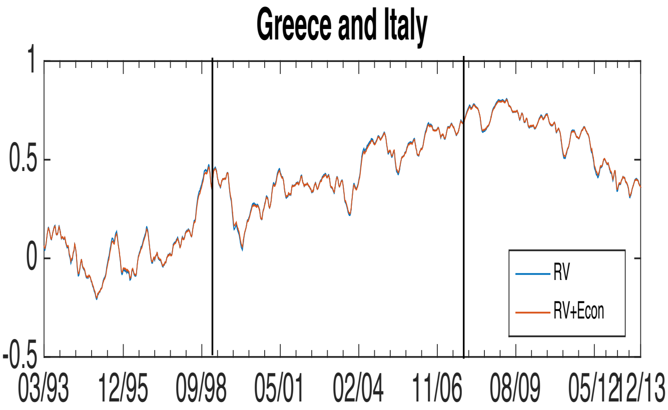
Figure 2: Long-term Pairwise-Correlations

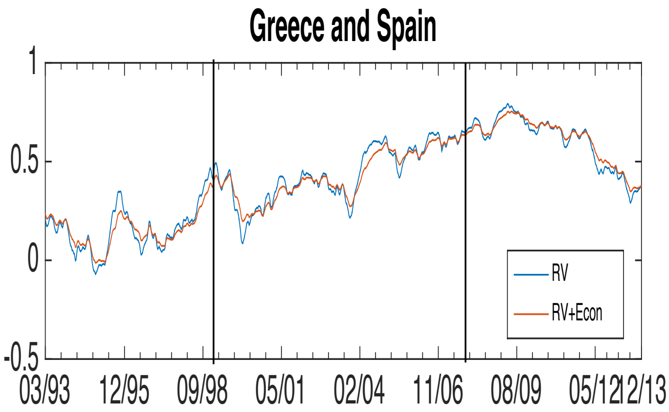


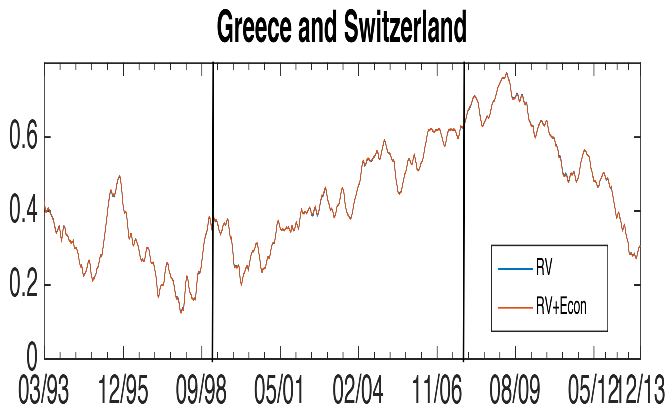

Germany and Spain
0.8
0.6
0.4
0.2
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ

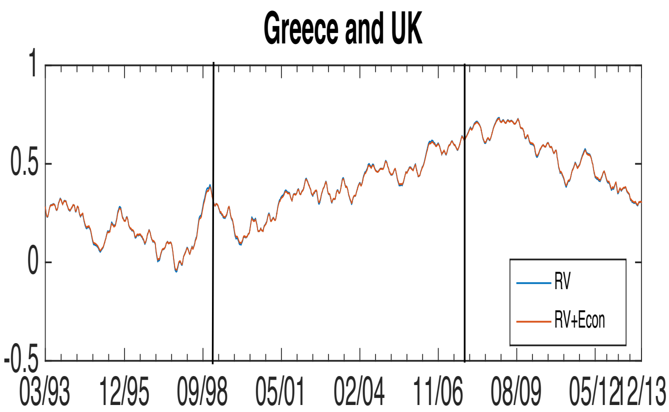

Germany and Switzerland
1
0.8
0.6
0.4
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ

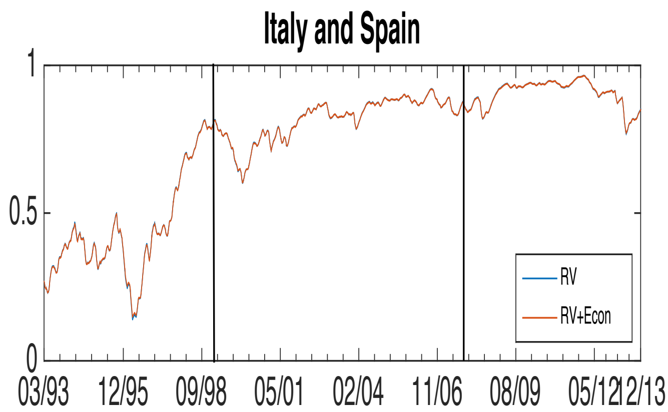

Germany and UK
0.8
0.6
0.4
0.2
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ

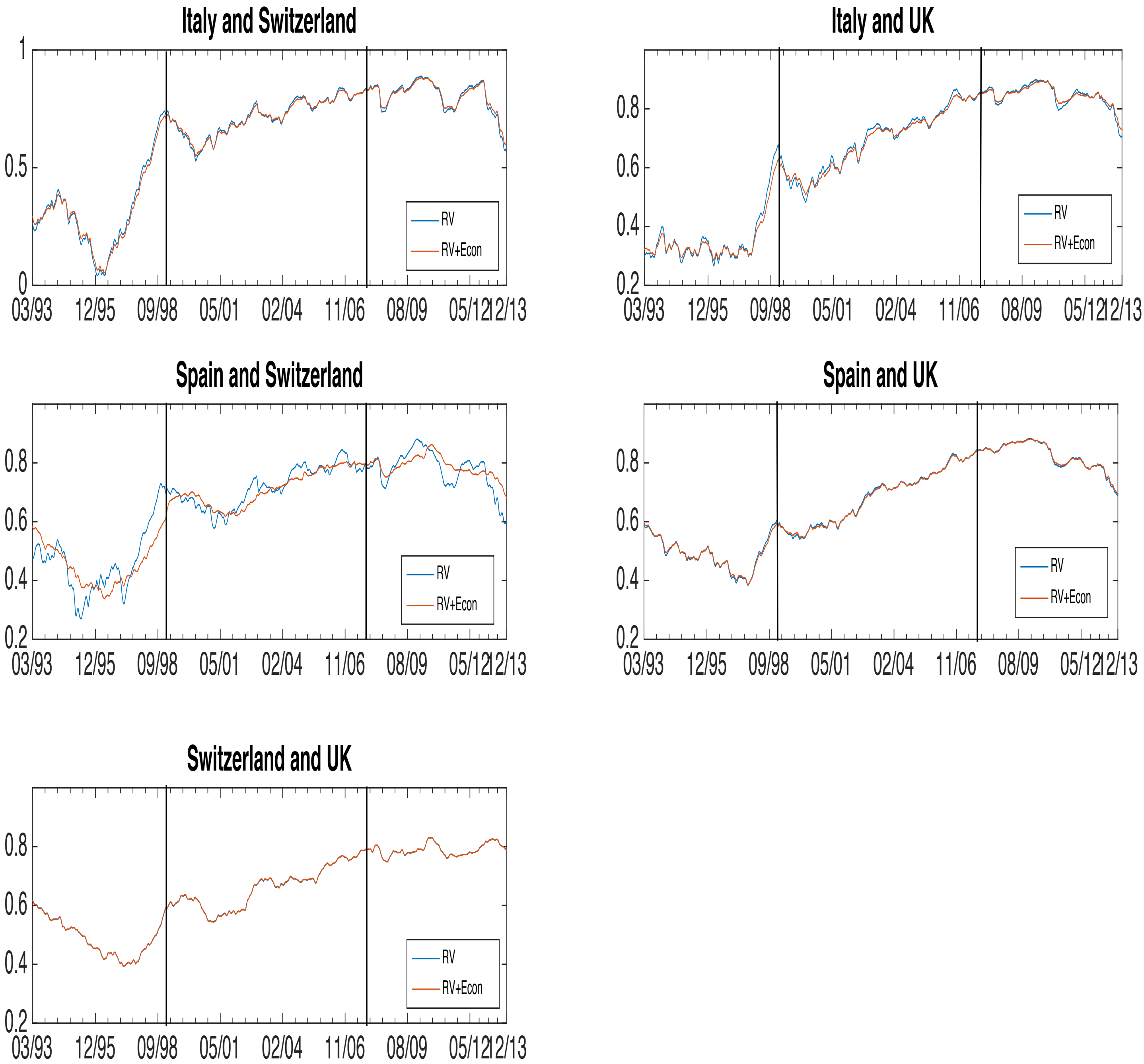

Greece and Italy
1
0.5
0
-0.5
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ


Greece and Spain
1
0.5
0
-0.5
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ


Greece and Switzerland
0.6
0.4
0.2
0
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ


Greece and UK
1
0.5
0
-0.5
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ


Italy and Spain
1
0.5
0
03/93 12/95 09/98 05/01 02/04 11/06 08/09 05/12 12/13
RV
RV+Econ


Italy and Switzerland
1
0.5
0
RV
RV+Econ
03/93
12/95
09/98
05/01
02/04
11/06
08/09
05/12
12/13
Italy and UK
0.8
0.6
0.4
0.2
Spain and Switzerland
Spain and UK
Switzerland and UK