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# Volatility risk premia and financial connectedness

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## Abstract

*In this paper we use the Diebold Yilmaz (2009 and 2012) methodology to construct an index of connectedness among five European stock markets: France, Germany, UK, Switzerland and the Netherlands, by using volatility risk premia. The volatility risk premium, which is a proxy of risk aversion, is measured by the difference between the implied volatility and expected realized volatility of the stock market for next month. While Diebold and Yilmaz focus is on the forecast error variance decomposition of stock returns or range based volatilities employing a stationary VAR in levels, we account for the (locally) long memory stationary properties of the levels of volatility risk premia series. Therefore, we estimate and invert a Fractionally Integrated VAR model to compute the cross forecast error variance shares necessary to obtain the index of total connectedness and the net contribution of each series to total connectedness.*
*The results show that, over January 2000-August 2013, the index of total connectedness among volatility risk premia has been relatively stable with an increasing role played by France and with a positive (but decreasing) role played by Germany and the Netherlands. Non EMU countries such as the UK and Switzerland are negative net contributors to the index.*

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## 1. Introduction

In this paper we construct an index of co-movements in risk aversion among five European markets: UK, Germany, Switzerland, France, and the Netherlands, by focusing on the volatility risk premium of each country. We follow Buraschi et al (2014) to construct the daily volatility risk premium as the difference between a risk neutral measure of expected volatility formulated at time $t$ for the next 30-days (derived from model-free implied volatility extracted from a panel of index options, and proxied by the market volatility index) and future (next month) physical expectation of volatility (extracted from realized square log-returns over next month). The choice of the countries under investigation is made in order to have both EMU and non EMU countries and is based on the availability of a volatility index traded in each country (the only country excluded is Belgium since its market volatility index VBEL has been traded only for a limited time period and it is not traded nowadays). Since the volatility risk premium represents compensation for providing volatility insurance, it can be considered a better proxy for risk aversion (see Muzzioli, 2013; Bekaert and Hoerova, 2014) than measures based only on implied volatility (commonly known as proxies of market fear). We follow Diebold-Yilmaz (2009, 2012) approach to construct an index of co-movements: both an index of total connectedness and of directional connectedness are computed. As Diebold and Yilmaz (2014) argue, the connectedness framework provide a unifying framework for a variety of systemic risk measures, including the CoVaR approach of Adrian and Brunnermeier (2008) and the marginal expected shortfall approach of Acharya et al. (2010). While Diebold-Yilmaz (2009 and 2012) focus on the variance decomposition of a stationary VAR (fitted to stock returns or range based volatilities), we concentrate on the estimation of Fractionally Integrated VAR, *FIVAR*, model, given the (locally) stationary long memory properties of the series under investigation[1]. More specifically, we provide evidence of regime shifts (in the mean) contaminating the long memory stationary features of the

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[1] Although Diebold and Yilmaz (2014) focus is on long memory daily realized volatilities (computed using intraday data), they still use a stationary VAR fitted to the levels of the series.

volatility risk premia, by following a two stage approach suggested by Qu (2011). In the first stage we employ the Qu (2011) test for the null of long memory stationarity versus the alternative of structural breaks. The rejection of the null leads to the second stage of the analysis which investigates whether the structural breaks contaminate either a short or a long memory time series. In particular, we employ the Lavielle and Moulines (2000) methodology, robust to the presence of strongly dependent processes. This method allows detecting endogenously the number of regime shifts (in the mean). Then we fit an *ARFIMA(p,d,q)* to estimate and make inference on the fractional integration parameter *d* for the different time series segments.

When turning our focus on multivariate analysis, we follow Do et al. (2013) to invert the *FIVAR* model to obtain the moving average coefficients necessary to compute the forecast error variance decomposition necessary to obtain the index of total connectedness and of total directional connectedness for the proxies of risk aversion.

The structure of the paper is as follows. Section 2 describes the issue of long memory and structural breaks, the Fractionally Integrated VAR model and corresponding moving average representation; Section 3 describes the Diebold-Yilmaz (2009, 2011) methodology; Section 4 focusses on the empirical evidence and section 5 concludes.

## 2. Long memory and multivariate analysis

A long-memory process is characterized by a spectral density which is unbounded at the origin and by an autocorrelation function decaying at a hyperbolic rate at long lags. A series is stationary long memory if the fractional differencing parameter (required transforming the series into a short memory stationary process) *d* is between -0.5 and 0.5. If the fractional differencing parameter *d* is greater than 0.5 and less than 1, then the series is non stationary long memory.

Evidence of long memory in volatility measures is well documented. The studies of Baillie et al. (1996), Andersen and Bollerslev (1997), Comte and Renault (1998) give evidence of long-run

dependencies, described by a fractionally integrated process, in GARCH, realized volatiles, and stochastic volatilities models, respectively. More recently, empirical studies show that the volatility implied from option prices exhibits properties well described by fractionally integrated process (see Bandi and Perron, 2006 and Christensen and Nielsen, 2006). Evidence of a stationary long memory in the variance risk premium is found in studies where there is evidence of fractional cointegration between implied and realized volatilities (see Bandi and Perron, 2006; Christensen and Nielsen, 2006; Bollerslev et al., 2013 among the others) of an order, greater than zero and lower than the degree of fractional integration for each volatility series.

The use of multivariate long memory models to financial time series has been recently advocated by Andersen et al. (2001), employing a VAR model to fractionally differenced exchange rates; by Cassola and Morana (2008) who employ a Vector Autoregressive Model with a common factor following an ARFIMA process to explore co-movements among Euro short term interest rates. Moreover, Bollerslev et al. (2013) use a co-fractional VAR to model long run and short run dynamics of realized variance, implied variance and stock return in the US market.

### 2.1 Long memory, structural breaks and volatility risk premium

The full sample estimation of the fractional integration parameter d is based on the local Whittle estimator. More specifically, we focus on the local Whittle function suggested by Kunsch (1987) defined over the frequency domain, implying the minimization of the profiled likelihood function:

$$R(d) = \log G(d) - 2d \frac{1}{m} \sum_{j=1}^{m} \left[ \log \omega_j \right]$$

where $G(d) = \frac{1}{m} \sum_{j=1}^{m} \left[ \omega_j^{2d} I_j \right]$

where $I_j$ is the sample periodogram at the j$^{\text{th}}$ Fourier frequency $\omega_j = 2\pi j/T$, with j=1,…,T/2, and T is the sample size. The maximum number of frequencies $\omega$ involved in the estimation of the fractional integration parameter is given by *m*.

In this paper we account for the spurious effects of structural breaks in detecting long memory time series we employ a two stage approach suggested by Qu (2011). In the first stage, we use the *W* statistics developed by Qu (2011) to test for the null of stationary long memory vs the alternative of structural breaks described either as a regime change or a smoothly varying trend. The *W* test statistics is based on the derivatives of the profiled local Whittle likelihood function and it does not require the specification on the way structural breaks occur under the alternative hypothesis. Moreover, as suggested by Qu (2011), we employ a "prewhitening" procedure that reduces the short memory component (which might spuriously affect the values of the *W* test statistics) while maintaining the same limiting distribution for the test. The "prewhitening" procedure involves the selection of low order *ARFIMA(p,d,q)* model and filtering the series using the estimated autoregressive and moving average coefficients. If the comparison of the test statistics with tabulated critical values (see Qu, 2011) leads to rejection of the null, then, in a second stage, we employ the method of Lavielle and Moulines (2000) to detect multiple points for strongly dependent processes. In particular, Lavielle and Moulines (2000) suggest that segmentation of a time series is based on the minimization of a penalty function (measuring the difference between the actual series and the segmented series). Given the focus on volatililty risk premia we are interested in time series segmentation only in terms of mean shifts. In particular, the best number of segments *K* is given by the last value of *K* for which the second derivative of a standardized penalty function is greater than a threshold S, which according to numerical experiments, is set equal to 0.75 (see Lavielle, 2005).

## 2.2 Fractionally Integrated VAR, FIVAR

The multivariate long memory we use in this study is a Fractionally Integrated VAR process *FIVAR(d,p)*:

$$A(L)D(L)y_t = \varepsilon_t \tag{1}$$

where $y_t$ is a time series vector of $k$ endogenous variables, and $\varepsilon_t$ is a *kx1* vector of white noise disturbances with covariance matrix (not diagonal) $\Sigma$; $A(L) = I_k - \sum_{i=1}^{p} A_i L^i$ is the matrix of coefficients polynomial in the lag operator $L$ and *D(L)* is *kxk* diagonal matrix characterized by $k$ degrees of fractional integration $d_1, d_2,\ldots,d_k$ :

$$D(L) = \begin{bmatrix} (1-L)^{d_1} & 0 & \ldots & 0 \\ 0 & (1-L)^{d_2} & .. & 0 \\ \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & (1-L)^{d_k} \end{bmatrix}$$

where $(1-L)^{d_j}$ is the difference operator of order $d_j$.

## 2.3 Vector Moving Average

If all the roots of the $|A(z)| = \left| I_k - \sum_{i=1}^{p} A_i z^i \right| = 0$ fall outside the unit circle and all series are long memory stationary, that is $|d_j| < 1/2$, for $j = 1,2,..k,$ then the FIVAR model given by eq.(1) can be inverted in order to obtain the infinite order moving average representation:

$$y_t = D(L)^{-1} A(L)^{-1} \varepsilon_t = \Phi(L)\varepsilon_t \tag{2}$$

where $D(L)^{-1}$ is a diagonal matrix with the element of the main diagonal described as follows:

$$(1-L)^{-d_j} = \sum_{i=0}^{\infty} \frac{\Gamma(i+d_j)}{\Gamma(d_j)\Gamma(i+1)} = \sum_{i=0}^{\infty} \psi_i^{(d_j)} L^i \tag{3}$$

where $\Gamma(.)$ is the gamma function and $\psi_0^{(0)} = 1$, $\psi_i^{(0)} = 0$ for $i \neq 1$.

Following Do et al. (2013), the Vector Moving Average representation is obtained in two steps.[2] In first step we obtain the coefficient matrices $\Pi_i$ of the inverted AR components for the forecast horizon $i$. More specifically, we can rewrite a VAR($p$) for the fractionally differenced vector $z_t = D(L)y_t$ as a first order system:

$$
\begin{bmatrix} z_t \\ z_{t-1} \\ : \\ : \\ z_{t-p+1} \end{bmatrix} =
\begin{bmatrix} A_1 & A_2 & & A_p \\ I & 0 & 0 & 0 \\ : & : & : & : & : \\ 0 & 0 & 0 & 0 \\ 0 & 0 & I & 0 \end{bmatrix}
\begin{bmatrix} z_{t-1} \\ z_{t-2} \\ : \\ : \\ z_{t-p} \end{bmatrix} +
\begin{bmatrix} \varepsilon_t \\ 0 \\ : \\ : \\ 0 \end{bmatrix}
$$

which can be written in compact form:

$$\bar{z}_t = \bar{A}\bar{z}_{t-1} + \bar{\varepsilon}_t \tag{4}$$

where $\bar{A}$ is an $kp \times kp$ matrix.

Then:

$$\Pi_i = \bar{e}\,\bar{A}^{i}\,\bar{e}' \tag{5}$$

The selection matrix $\bar{e}$ has $k$ rows and $kp$ columns $\bar{e} = \begin{bmatrix} I & \bar{0} & \cdots & \bar{0} \end{bmatrix}$ with $I$ being the $k \times k$ identity matrix; $\bar{A}^i = \prod\limits_{h=1}^{i} \bar{A}$.

In the second step, since $\Phi(L) = D(L)^{-1}\Pi(L)_t$, we can observe that the $j^{th}$ row of $\Phi(L)$, that is $^{(j)}\Phi(L)$ can be written as:

$$^{(j)}\Phi(L) = (1-L)^{-d_j} e'_j \Pi(L) \tag{6}$$

where $e_j$ is $kx1$ selection vector with 1 in row $j$ and zeros elsewhere. Since $(1-L)^{-d_j} = \sum\limits_{i=0}^{\infty} \psi_i^{(d_j)} L^i$, then we can rewrite eq. (6) as:

$$^{(j)}\Phi(L) = \left[ \sum_{i=0}^{\infty} \psi_i^{(d_j)} L^i \right]\left[ \sum_{i=0}^{\infty} e'_j \Pi_i L^i \right] \tag{7}$$

By expanding the multiplication of eq.(7), Do et al. (2013) show that the moving average coefficients for the forecast horizon $h$ are:

$$^{(j)}\Phi_h = \sum_{i=0}^{h} \psi_i^{(d_j)} e'_j \Pi_{h-i} \qquad \text{for } h = 1,2,\ldots$$

$$^{(j)}\Phi_h = e'_j \Pi_0 \qquad\qquad \text{for } h = 0 \tag{8}$$

Using the generalized impulse response approach of Pesaran and Shin (1998) and, under the assumption of multivariate Gaussian distribution for $\varepsilon_t$, the scaled (by one standard deviation) effect of a shock to the system (at time t) on the expected value of the $kx1$ vector $y$ at time $t+h$ is given by:

$$\Phi_h^g = \Phi_h \Sigma \Xi \tag{9}$$

where $\Xi = \begin{bmatrix} \sigma_{11}^{-1/2} & 0 & ... & 0 \\ 0 & \sigma_{22}^{-1/2} & ... & 0 \\ ... & ... & ... & ... \\ 0 & 0 & ... & \sigma_{kk}^{-1/2} \end{bmatrix}$ and $\sigma_{ii}$ is the variance of the $i^{th}$ shock in the system.

## 3. Financial Connectedness

Following Diebold and Yilmaz (2012 and 2014), the contribution of shock to market $i$ to the variance of the $H$ step ahead forecast error for market $j$, $\theta_{ij}^g(H)$, is given by:

$$\theta_{ij}^g(H) = \frac{\sigma_{ii}^{-1/2} \sum_{h=0}^{H-1} \left( e_i' \Phi_h e_j \right)^2}{\sum_{h=0}^{H-1} \left( e_i' \Phi_h \Sigma \Phi_h' e_j \right)^2} \tag{10}$$

For $i \neq j$, the above expression describes the "cross variance shares" (that is the contribution of shock $i$ to the variance of the forecast error of series $j$), while for $i = j$, the above expression captures the "own shares" (that is the contribution of shock $i$ to the variance of the forecast error of the same series). Equation (10) describes the generic element $i,j$ of the variance decomposition table.

Since the sum of each row of the variance decomposition table is different from one, that is $\sum_{j=1}^{K} \theta_{ij}^g(H) \neq 1$, Diebold and Yilmaz (2012) suggest to normalize each $\theta_{ij}^g(H)$ by the sum of each row of the variance decomposition table:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum\limits_{j=1}^{K} \theta_{ij}^{g}(H)}$$

implying $\sum\limits_{j=1}^{k} \widetilde{\theta}_{ij}^{g}(H) = 1$ and $\sum\limits_{i,j=1}^{K} \widetilde{\theta}_{ij}^{g}(H) = k$.

The total financial connectedness index is given by taking the ratio of total cross variance shares to the sum of the total of cross and own shares:

$$S^{g}(H) = \frac{\sum\limits_{\substack{i,j=1 \\ i \neq j}}^{K} \widetilde{\theta}_{ij}^{g}(H)}{\sum\limits_{i,j}^{K} \widetilde{\theta}_{ij}^{g}(H)} = \frac{\sum\limits_{\substack{i,j=1 \\ i \neq j}}^{K} \widetilde{\theta}_{ij}^{g}(H)}{k} \tag{11}$$

The index of total directional connectedness (see Diebold and Yilmaz, 2014) received by market $i$ from the rest of the system is measured by the sum of row $i$ of the variance decomposition table less the element measuring the own share in the $i$-$th$ row:

$$S_{ij}^{g}(H) = \sum\limits_{\substack{j=1 \\ i \neq j}}^{K} \widetilde{\theta}_{ij}^{g}(H) \tag{12}$$

The index of total directional connectedness (see Diebold and Yilmaz, 2014) transmitted from market $j$ to the rest of the system is measured by the sum of column $j$ of the variance decomposition table less the element measuring the own share in the $j$-$th$ column:

$$S_{ji}^{g}(H) = \sum\limits_{\substack{i=1 \\ i \neq j}}^{K} \widetilde{\theta}_{ij}^{g}(H) \tag{13}$$

As argued by Diebold and Yilmaz (2014), the "from"-connectedness measure described by eq.(12) is very similar to the marginal expected shortfall indicator of systemic risk proposed by Acharya et al. (2010). The "to"-connectedness measure described by eq.(13), measures the contribution of a single market (asset) to the system, in a fashion very similar to CoVaR indicator of systemic risk suggested by Adrian and Brunnermeier (2008).

The index of net total directional connectedness (see Diebold and Yilmaz, 2014), useful to assess whether a market is net donor or recipient is given by difference between eq. (12) and (13).

## 5. Data and empirical evidence

Following Buraschi et al. (2013)[3], the volatility risk premium is defined as:

$$VRP(t) = IV(t) - RV(t+1)$$

Both addends are in percentage values, $IV(t)$ is the risk neutral expectation at time $t$ of volatility between t and $t+1$, proxied by the annualized implied volatility index of the stock market index; $RV(t+1)$ is the square root of the annualized realized variance between t and t+1 of the stock market index return (obtained from the sum of squared log returns of 21 days occurring between t and t+1). All series are obtained from DATASTREAM. The sample observed at daily frequency runs from 1/2/2000 till 29/08/2013 and the countries under investigation are the UK, Germany, Switzerland, France and Netherlands, given that they are the only countries in Europe in which a volatility index for the underlying stock market index is traded.

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[3] Differently from other papers in the "financial" literature (see e.g. Carr and Wu 2009) where the variance risk premium is defined as the difference between physical and risk neutral variance, here we follow the "econometric" literature where the variance risk premium is defined in the opposite way as the difference between risk neutral and physical variance.

In Figure 1 we can observe the plots of the time series under investigation. In particular, we can observe a synchronized behavior of the five series throughout the sample with a large negative peak in correspondence of the Lehman Brothers collapse (September/October 2008)

In Table 1 we report descriptive statistics. The volatility risk premia are all positive on average, ranging from the lowest value of 2.567 for France to the highest value of 3.793 for UK on a percentage annualized basis. This means that "selling" volatility has been highly profitable on average over the 2000-2013 period. The findings are consistent with the literature (see e.g. Carr and Wu (2009), Bollerslev et al. (2014)) where a negative variance risk premium (if measured as the difference between physical and risk neutral variance, as opposite to our way of measuring it) is usually detected: in other words investors are willing to accept (gain) a significantly negative (positive) return being long (short) in a variance swap, in order to be hedged (in exchange to be exposed to) against peaks of variance.

We turn now our focus on the long memory properties of the series under investigation using the full sample of daily observations. Visual inspection of the time series plots in Fig.1 would suggest the presence of level shifts which might "spuriously" affect the estimation results of the fractional integration parameter. The full sample estimation results are given in the first row of Table 2 and the large standard errors relative to the point estimates of $d$ based on the minimization of the profiled likelihood function would suggest no evidence of long memory. In order to account for the role played by structural breaks, we employ Qu (2011) test for the null hypothesis that a given time series is a stationary long-memory process against the alternative hypothesis that it is affected by regime change or a smoothly varying trend. The values of the $W$ statistics (see first row of Table 2) compared to the tabulated critical values reported in the footnote to Table 2, suggest rejection of the null of long memory stationarity. Then, given the evidence of structural breaks we investigate whether they contaminate a short memory or a stationary long memory process. For this purpose, in the second stage of the analysis we detect the optimal number of time series segments based on

mean shifts through the minimization of a contrast function by Lavielle and Moulines (2000) and by Lavielle (2005). The optimal number of time series sub-samples for UK, Germany, Switzerland, France and Netherlands, is equal to 3, 11, 8, 5 and 3. From the estimation of the selected low order ARFIMA(p,d,q) model according to the BIC criterion, we can observe (see rows, in Table 2, under labels Breaks and d) that, for the UK, only the first sub-sample (running from the 1/2/2000 to 18/9/2008) there is evidence of long memory stationarity, given that the lower bound for the 95% confidence interval for the parameter *d* is equal to 0.04 and the point estimate is equal to 0.08. As for the German volatility risk premium, there is evidence of long memory stationarity over the sample period between 1/2/2000 and 21/6/2002, given that the lower bound for the 95% confidence interval for the parameter *d* does not fall below 0.128 and the point estimate varies between 0.141 and 0.203. Then, the long memory stationary features are displayed over the following sub-samples: 21/1/08 -18/2/08, 6/10/08-7/11/08, and 4/8/2011-3/9/2011, given that the lower bound for the 95% confidence interval for the parameter *d* does not fall below 10%. The volatility risk premium in Switzerland is the only one exhibiting long memory stationarity for most of the overall sample period with both the lower bound of the 95% confidence interval and the point estimation of the fractional integration parameter above 0.3 during the subsamples running from 11/09/01 to 12/10/2001 and from 11/11/08 to 23/6/2009. The French volatility risk premium shows evidence of long memory stationary only over a short sub-sample period: 19/9/2008-5/11/2008, since the point estimates of the fractional integration parameter *d* is equal to 0.179 and the lower bound for the 95% confidence interval is equal to 0.167. Finally, there is evidence of long memory stationary for the Dutch volatility risk premium over the 1/2/2000-6/11/2011 period, and they are more pronounced for the sub-sample running from 19/9/2008 to 6/11/2011. To summarize, from Table 2 we can observe that only the French volatility risk premium can be considered as a short memory stationary process for most of the sample period under investigation.

We now turn our focus on the results concerning with the total connectedness among volatility risk premia. The analysis (both full sample and rolling) is based on the estimation of VAR model with 2 lags (selected according to the Bayesian Schwarz criterion information).[4] The plot of daily measures of total connectedness, starting on 1/01/2002 and ending on 29/8/2013 (see Fig. 2), based on the rolling analysis (using a window of size equal to 500 observations), shows values of the index ranging between 68% and 76%. While, the plot of the time varying measure of the total index shows a relatively stable evolution over time around a mean value equal to 73.1% (see the full sample analysis results in Table 3), on the other hand, there is an high degree of heterogeneity in the indices of directional connectedness both across countries and over time: these latter findings are the object of the following discussion.

We first focus on the full sample analysis results. The row sum of the pairwise connectedness measures results in the total directional connectedness "from others" to each one of the volatility risk premium. Similarly, the column sum of all pairwise connectedness measures results in the corresponding volatility risk premium total directional connectedness "to others".

More specifically, from Table 3, we can observe that EMU countries such as France, Netherlands and Germany are the countries with the lowest degree of directional connectedness from others (with values equal to 0.692, 0.676, 0.694, respectively) and with the highest degree of directional connectedness to others (with values of the index equal to 0.735, 0.916, 0.782, respectively). Non EMU countries such as Switzerland and UK are the countries with the highest degree of directional connectedness from others (with values of the index equal to 0.785 and 0.719 respectively) and lowest degree of directional connectedness to others (with values equal to 0.436 and 0.696 respectively). Consistently with previous findings, we can observe (see Table 3) that France,

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[4] It is important to observe that the full sample and rolling analysis is robust to different VAR order specifications (from 2 to 8 lags) and to different forecast horizon (2, and 5 days ahead). Results are available upon request.

Netherlands and Germany have a positive index of net total directional connectedness to others, (e.g. they are net donors); UK and, especially Switzerland are net recipients, since they have a negative index of net total directional connectedness to others.

Inspections of time varying plots (see Fig 3-7) of net directional connectedness reveal interesting patterns. We first concentrate on non EMU countries. Figure 3, showing the time varying UK net contribution to volatility risk premia connectedness, suggests that, while UK is a net recipient on average (confirming the full sample analysis results), there has been a positive contribution between mid-October 2007 and end of June 2010 (that is during the period of financial turmoil involving sub-prime crisis, Lehman Brothers collapse, and the first Eurozone crisis, motivated by the EU' failure to act to contain the Greek crisis) with a peak of 30% reached on 23/02/2010. Inspection of Figure 5 shows that Switzerland has been a negative net contributor to volatility risk premia throughout the period of investigation, with the highest value of the index, which is equal to 0% recorded on mid-November 2008.

We now describe the empirical findings for EMU countries. Inspection of Figure 4 shows that, on average, Germany is a positive net contributor to the European connectedness to volatility risk premia, although the rolling analysis shows a steady decrease throughout the 2002-2013 sample period analyzed. In particular, there has been a steep decrease in the index from 80% to -10% during the period running from mid-May 2002 to December 2003, and then a steady rise with values of the index averaging 20% till August 2013, with the exception of the negatives values during the interval period running from mid-2009 to August 2011 (corresponding to the second Eurozone crisis period, August 2011, following troubles experienced by Italy and Spain). Figure 6 shows that, since early 2006 France has become a positive net contributor to the European connectedness to volatility risk premia, with the highest values ranging between 20% and 40% during November 2010 – August 2013. Finally, inspection of Figure 7 shows that the Netherlands are a positive net contributor to the European connectedness to volatility risk premia. In particular,

the rolling analysis shows a steady decrease of the index from 80% in January 2005 to 0% in June 2007, a rebound till November 2010 (when the index reaches a value equal to 40%) and a steady decrease toward zero 0 in the last part of the sample.

**Conclusions**

The focus of this paper is on co-movements between volatility risk premia, that is on proxies of stock market risk aversion among five European countries (UK, Germany, Switzerland, France, Germany and the Netherlands). We compute the index of total connectedness and total directional connectedness following Diebold-Yilmaz (2009, 2012) to measure co-movements. While Diebold-Yilmaz (2009 and 2012) rely on the variance decomposition of a stationary VAR (since they concentrate on stock returns or range based volatilities), we focus on the estimation of a Fractionally Integrated VAR, FIVAR, model, to account for the evidence of long memory in the volatility risk premia. More specifically, in the first stage of the analysis, we find evidence that the series under investigation are long memory stationary contaminated by (unconditional mean) regime shifts. In a second stage of the analysis, we follow Do et al. (2013) to invert the FIVAR model giving the moving average coefficients necessary to obtain the forecast error variance decomposition table and to construct the pairwise, the total connectedness and the directional connectedness indices. The empirical evidence suggests that, over January 2000-August 2013, the index of total connectedness among volatility risk premia has been relatively stable around 73%, with an increasing role played by France and with a positive (but decreasing) role played by Germany and the Netherlands. Non EMU countries such as the UK and Switzerland are negative net contributors to volatility risk premia connectedness, with a positive contribution of UK occurring between mid-October 2007 and end of June 2010.

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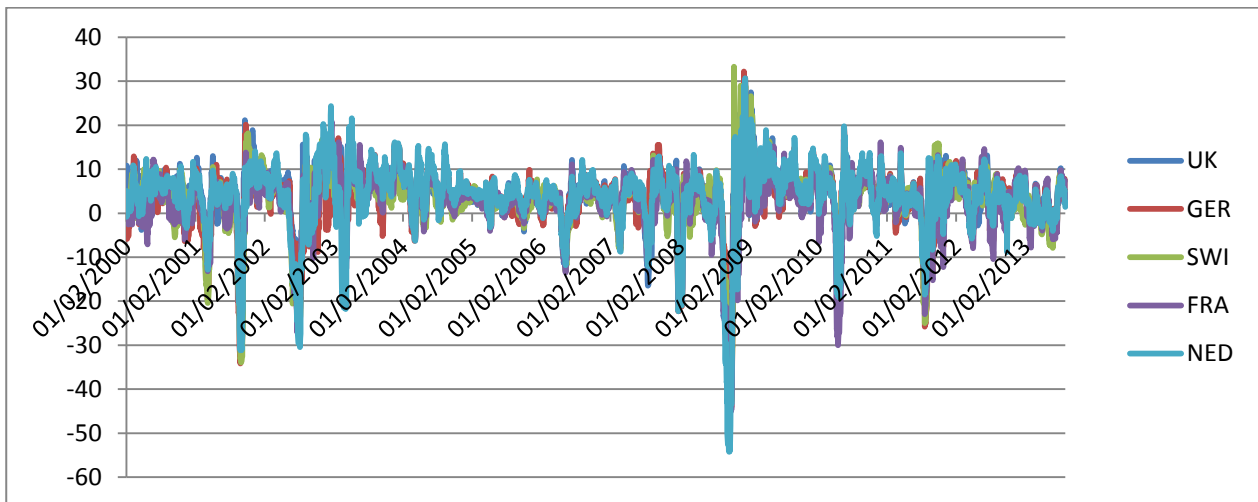
**Figure 1: volatility risk premia series**



**Table 1: Descriptive Statistics**

|  | Descriptive Statistics | | | |
|---|---|---|---|---|
|  | **Mean** | **Std Dev** | **Min** | **Max** |
| **UK** | 3.793 | 6.638 | -45.541 | 27.476 |
| **GER** | 3.116 | 7.117 | -44.853 | 32.181 |
| **SWI** | 3.111 | 7.251 | -44.141 | 33.269 |
| **FRA** | 2.567 | 7.427 | -50.963 | 28.230 |
| **NED** | 3.778 | 8.031 | -54.207 | 30.640 |

**Note**: The whole sample runs from 1/2/2000 to 29/08/2013.

**Table 2: Long memory estimation results for the volatility risk premia.**

| UK | | GER | | SWI | |
|---|---|---|---|---|---|
| **Full sample estimate of *d*** | ***W stat*** | **Full sample estimate of *d*** | ***W stat*** | **Full sample estimate of *d*** | ***W stat*** |
| 0.111 [0.094] | 1.461 | 0.082 [0.085] | 1.424 | 0.222 [0.132] | 1.960 |
| **Breaks** | ***d*** | **Breaks** | ***d*** | **Breaks** | ***d*** |
| 1feb00 18sep08 | 0.080 [0.046; 0.114] | 1feb00 10sep01 | 0.194 [0.177; 0.214] | 1feb00 10sep01 | 0.139 [0.119; 0.159] |
| 19sep08 6nov08 | 0.023 [0.014; 0.033] | 11sep01 8oct01 | 0.203 [0.193; 0.213] | 11sep01 12oct01 | 0.350 [0.336; 0.364] |
| 7nov08 29aug13 | 0.000 [0.091; -0.091] | 9oct01 21jun02 | 0.141 [0.128; 0.153] | 15oct01 14jun02 | 0.050 [NA; NA] |
| | | 24jun02 19aug02 | 0.000 [-0.39; 0.392] | 16jun02 16aug02 | 0.109 [0.101; 0.118 |
| | | 20aug02 18jan08 | 0.033 [0.002; 0.065] | 19aug02 24sep08 | 0.054 [0.022; 0.086] |
| | | 21jan08 18feb8 | 0.156 [0.144; 0.168] | 25sep08 10nov08 | 0.159 [0.148; 0.169] |
| | | 19feb08 3oct08 | 0.000 [NA; NA] | 11nov08 23jun09 | 0.378 [0.364; 0.393] |
| | | 6oct08 7nov08 | 0.181 [0.163; 0.199] | 24jun09 29aug13 | 0.161 [0.133; 0.188] |
| | | 8nov08 3aug11 | 0.059 [0.033; 0.086] | | |
| | | 4aug11 2sep11 | 0.106 [0.096; 0.116] | | |
| | | 5sept11 29aug13 | 0.000 [-0.13; 0.134] | | |

**Note:** The entries in the first row (columns 1, 3 and 5) are the full sample Local Whittle point estimate of the fractional integration parameter *d* (standard errors in parenthesis). The entries in the first row (columns 2, 4 and 6) are the values of the *W* statistics developed by Qu (2011) for the null hypothesis that a given time series is a stationary long-memory process against the alternative hypothesis that it is affected by regime change or a smoothly varying trend. The tabulated critical values for 10% and 5% level of significance are 1.118 and 1.252, respectively (see Qu, 2011). The remaining rows (under the Breaks label) give the breakpoints (in the mean) describing each time series segment. The optimal number of segments (for instance, this number is equal to 3 for UK) is obtained using the method of minimizing a contrast function by Lavielle and Moulines (2000) and by Lavielle (2005). The remaining rows (under the d label) give the sub-sample estimates of the fractional integration parameter *d* (95% confidence interval bands in parenthesis) fitting the best ARFIMA(p,d,q) according to the BIC criterion.

**Table 2 cont'd: Long memory estimation results for the volatility risk premia.**

| FRA | | NETH | |
|---|---|---|---|
| **Full sample estimate of *d*** | *W stat* | **Full sample estimate of *d*** | *W stat* |
| 0.102 [0.093] | 1.459 | 0.082 [0.098] | 1.424 |
| **Breaks** | ***d*** | **Breaks** | ***d*** |
| 1feb00 18sep08 | 0.060 [0.025; 0.095] | 1feb00 18sep08 | 0.099 [0.064; 0.134] |
| 19sep08 5nov08 | 0.179 [0.167; 0.192] | 19sep08 4nov11 | 0.132 [0.121; 0.144] |
| 6nov08 6may10 | 0.000 [NA; NA] | 7nov11 29aug13 | 0.000 [-0.07; 0.076] |
| 7may10 3jun10 | 0.000 [-0.05; 0.059] | | |
| 4jun10 29aug13 | 0.000 [-0.09; 0.092] | | |

**Table 3: Full-Sample Connectedness Table; forecast horizon = 10 days**

| | *UK* | *GER* | *SWIS* | *FRA* | *NED* | **FROM** |
|---|---|---|---|---|---|---|
| *UK* | *0.280* | *0.187* | *0.113* | *0.180* | *0.238* | *0.719* |
| *GER* | *0.159* | *0.305* | *0.113* | *0.196* | *0.225* | *0.694* |
| *SWI* | *0.186* | *0.209* | *0.214* | *0.167* | *0.222* | *0.785* |
| *FRA* | *0.168* | *0.196* | *0.097* | *0.307* | *0.230* | *0.692* |
| *NED* | *0.182* | *0.189* | *0.112* | *0.191* | *0.323* | *0.676* |
| **TO** | *0.696* | *0.782* | *0.436* | *0.735* | *0.916* | ***0.713*** |
| **NET** | *-0.022* | *0.087* | *-0.348* | *0.043* | *0.240* | |

**Note**: We follow Diebold-Yilmaz (2014) in the description of the Full-Sample Connectedness Table. The full sample VAR(2) analysis stars is Feb 2, 2000 through August 29, 2014. The ij-th entry of the upper-left 5x5 sub-matrix gives the ij-th pairwise directional connectedness: the percent of h-day-ahead forecast error variance of country i due to shocks from country j. The rightmost ("FROM") column gives total directional connectedness (from): row sums (from all others to i). The bottom ("TO") row gives total directional connectedness (to); i.e., column sums (to all others from j). The bottom ("NET") row gives the difference in total directional connectedness (to-from). The bottom-right element (in boldface) is total connectedness (mean "from" connectedness, or equivalently, mean "to" connectedness).

**Figure 2: total financial connectedness (rolling estimation; window size = 500); forecast horizon = 10 days**
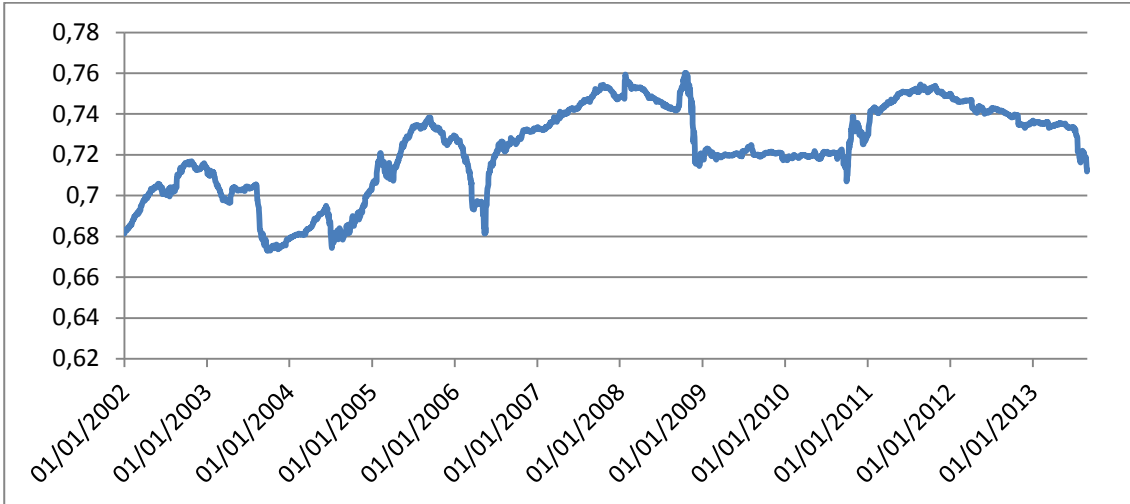


**Figure 3: net contribution to total financial connectedness from UK (rolling estimation; window size = 500); forecast horizon = 10 days**
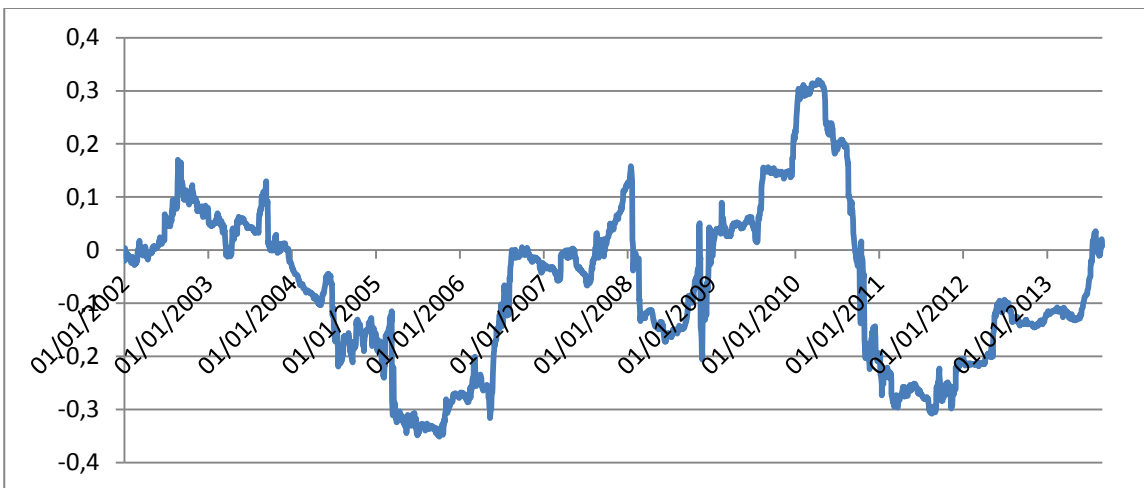


**Figure 4: net contribution to total financial connectedness from Germany (rolling estimation; window size = 500); forecast horizon = 10 days**
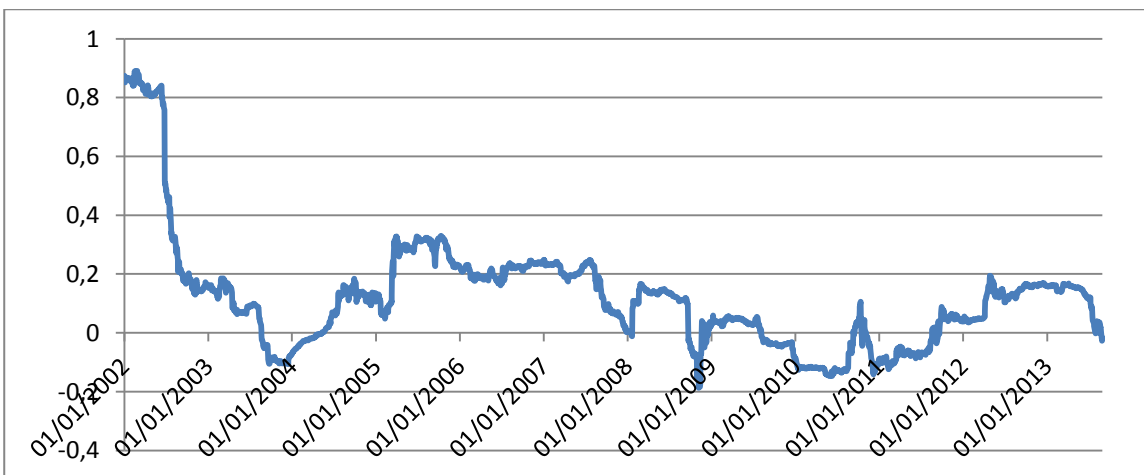
**Figure 5: net contribution to total financial connectedness from Switzerland (rolling estimation; window size = 500); forecast horizon = 10 days**
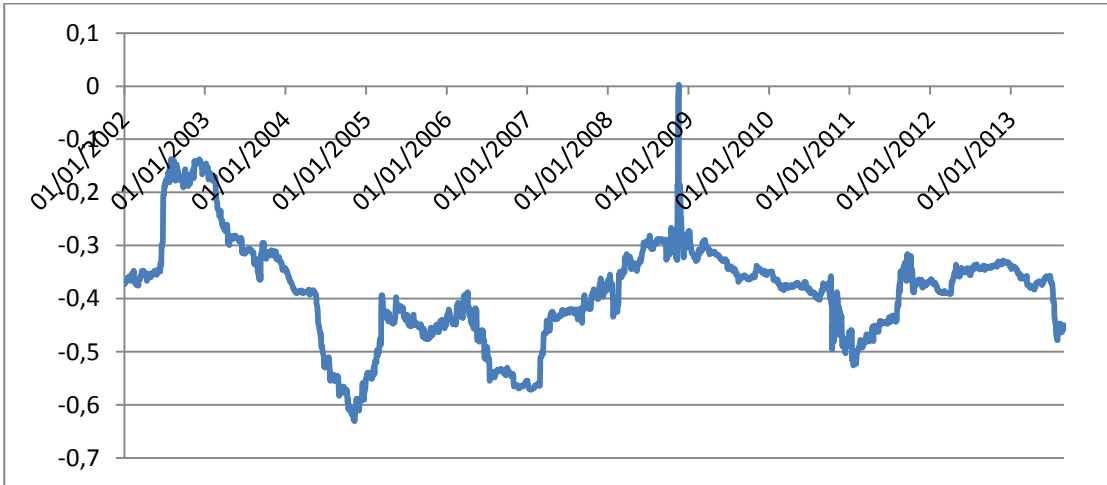


**Figure 6: net contribution to total financial connectedness from France (rolling estimation; window size = 500); forecast horizon = 10 days**
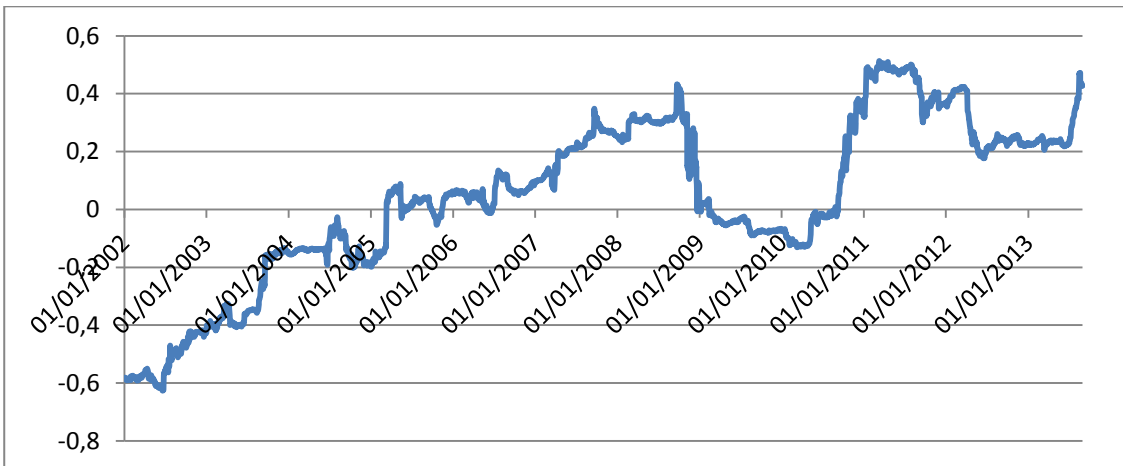


**Figure 7: net contribution to total financial connectedness from Netherlands (rolling estimation; window size = 500); forecast horizon = 10 days**