Risk aversion connectedness in Europe

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Abstract

In this paper we construct an aggregate index of risk aversion in Europe and we assess the vulnerability and the contribution to systemic risk aversion of each country, by focusing on the volatility risk premium. For this purpose we follow Diebold-Yilmaz (2012, 2014) methodology and contribute to the latter in two main aspects. We estimate a Fractionally Integrated VAR, FIVAR, model, given the locally long memory properties of the series under investigation and we conduct a sensitivity analysis on different forecasts horizons. We pursue both a full sample analysis and a rolling analysis. The total index of risk aversion in the full sample analysis is quite stable across forecast horizons and attains a peak after the Lehman Brothers collapse. The full sample results show that France is the country contributing the least to systemic risk aversion, and it is also the country most vulnerable. Switzerland is the country least vulnerable to systemic risk aversion and Netherlands is the country contributing the most to systemic risk aversion. Rolling regression analysis shows that the index measuring contribution to systemic risk aversion is more volatile than the vulnerability indicator in Germany, France and Switzerland. The comparison with a short mamory VAR indicates that Lehman Brothers collapse is the crisis period showing a higher degree of persistence in the transmission of shocks to risk aversion.

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1. Introduction

In this paper we construct indices of total and directional connectedness in risk aversion among five European stock markets: UK, Germany, Switzerland, France, and the Netherlands, by focusing on the volatility risk premium of each country. The volatility risk premium is computed as the difference between implied and realized volatility: implied volatility is a composite measure which embeds the investor's perception on future uncertainty, whereas realized volatility measures the actual volatility experienced in the market. Therefore, the difference between the two, e.g. the volatility risk premium, represents a compensation for providing volatility insurance and, it can be considered a better proxy for risk aversion than measures based only on implied volatility, commonly known as proxies of market fear (see Muzzioli, 2013(a) and 2013(b), Bekaert and Hoerova, 2014, Bali and Zhou, 2014).

The construnction of the indices of connectedness is based on the Diebold-Yilmaz (2009; 2012; 2014) approach and, as argued by the authors, their methodology 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). We follow Buraschi et al. (2014) to compute 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) 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).

We contribute to existing literature in at least five aspects. To our knowledge, this is the first study analyzing the total and directional connectedness among volatility risk premia series. Second, while Diebold-Yilmaz (2012 and 2014) 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 long memory properties of the series under investigation[1]. Third, we provide evidence of regime shifts (in the mean) contaminating the long memory stationary features of the volatility risk premia, by following a two stage approach suggested by Qu (2011). Fourth, in order to facilitate the comparison across markets when measuring directional spillover indices, we normalize not only the ones measuring the vulnerability of each market from systemic risk aversion shocks (as in Diebold-Yilmaz (2012 and 2014)), but also the indices measuring the contribution of each market to systemic risk aversion. Last, we conduct a sensitivity analysis on different forecasts horizons, ranging from the very short-term of two days ahead to the long-term horizon equal to thirty days ahead in order to detect differences between the short memory and long memory VAR estimations and to capture the behavior of investors with different investment horizons in transmitting shocks from one market to the other.

Our empirical methodology can be divided in the following stages. First, we employ the Qu (2011) test and we find evidence of long memory stationary series contaminated by structural breaks. Moreover, we employ the Lavielle and Moulines (2000) methodology, robust to the presence of strongly dependent processes, to detect endogenously the number of regime shifts. Then we fit an *ARFIMA(p,d,q)* to estimate and make inference on the fractional integration parameter d in the different time series subsamples. In the second stage, we estimate and invert a *FIVAR* model to obtain the moving average coefficients necessary to compute the forecast error variance decomposition. The latter is used to compute the total European risk aversion index and the indices of vulnerability and contribution to systemic risk aversion in Europe.

[1] Although the study of Diebold and Yilmaz (2014) focus is on long memory daily realized volatilities (computed using intraday data), the authors still use a stationary VAR fitted to the levels of the series. To our knowledge, the only study taking into account long memory in daily realized second moments when employing the analytical tools of Diebold and Yilmaz (2009, 2012), is the one of Fengler and Gisler (2015) which is based on a restricted VAR extension of the heterogeneous autoregressive (HAR) model of Corsi (2009).

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 the corresponding moving average representation. Section 3 describes the Diebold-Yilmaz (2012, 2014) methodology. Section 4 focusses on the empirical evidence. The last section 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 jth Fourier frequency $\omega_j = 2\pi j/T$, with j=1,…,T/2, and T is the sample size. The maximum number of frequencies ω 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 "pre-whitening" 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 volatility 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 ε_t is a $kx1$ vector of white noise disturbances with covariance matrix (not diagonal) Σ; $A(L) = I_k - \sum_{i=1}^{p} A_i L^i$ 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 $d_1, d_2, \ldots, d_k$:

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

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:

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

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

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

where Γ(.) is the gamma function and $\psi_0^{(0)}=1;\ \psi_i^{(0)}=1,$ 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 Π_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:

[2] The *FIVAR* inversion following Do et al. (2013) has been computed through Gauss 6.0 by the authors.

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

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 a $kp \times kp$ matrix.

Then:

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

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

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 $(1-L)^{-d_j} = \sum_{i=0}^{\infty} \psi_i^{(d_j)} L^i$,

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:

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

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

where Π_0 is the k dimensional identity matrix**.**

3. Financial Connectedness

Following Diebold and Yilmaz (2012 and 2014), who use the generalized impulse response approach of Pesaran and Shin (1998), 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:

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

Where, Σ is the sample covariance matrix of the *k* dimensional vector of residuals (e.g. shocks) ε_t in eq. (1) and σ_{ii} is the variance of the shock to series *i*. 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.

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:

$$S_{ij}^{g}(H) = \sum_{\substack{j=1 \\ i \neq j}}^{K} \tilde{\theta}_{ij}^{g}(H) \tag{11}$$

Given the use of generalized impulse response, the sum of each row of the variance decomposition table is different from one, that is $\sum_{j=1}^{K} \theta_{ij}^{g}(H) \neq 1$. Therefore, Diebold and Yilmaz (2012; 2014) suggest to normalize each $\theta_{ij}^{g}(H)$ in (10) by the sum of each row of the variance decomposition table:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{K} \theta_{ij}^{g}(H)} \tag{12}$$

As argued by Diebold and Yilmaz (2014), the “FROM” connectedness measure described by eq.(11) is very similar to the marginal expected shortfall indicator of systemic risk proposed by Acharya et al. (2010).

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:

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

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).

While a normalization by row would ease the interpretation of the indicator FROM (measuring the vulnerability of each market), the following normalization by column:

$$\bar{\theta}^{g}_{ij}(H) = \frac{\theta^{g}_{ij}(H)}{\sum_{i=1}^{K} \theta^{g}_{ij}(H)} \tag{14}$$

would ease the interpretation of the TO indicator when making a comparison across markets.[3]

Finally, by taking the ratio of total cross variance shares to the sum of the total of cross and own shares:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{\theta}^{g}_{ij}(H)}{\sum_{i,j}^{K} \tilde{\theta}^{g}_{ij}(H)} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{\theta}^{g}_{ij}(H)}{k} \tag{15}$$

we obtain the total financial connectedness index.

4. Data and empirical evidence

Following Buraschi et al. (2013)[4], the volatility risk premium is defined as:

[3] Diebold-Yilmaz (2012, 2014) rely only on a normalization by row which, we argue, makes more difficult to compare the TO indices (measuring contribution to systemic risk) across markets.

[4] 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.

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

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.

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), Cipollini et al. (2015)) 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 a low order ARFIMA(p,d,q) according to the BIC criterion, we can observe (see rows, in Table 2, under labels Breaks and *d*) that, for the UK, only in the first sub-sample (running from the 1/2/2000 to 18/9/2008) there is mild evidence of long memory stationarity. This finding is motivated by a lower bound for the 95% confidence interval for the parameter *d* equal to 0.04 and the corresponding point estimate 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. 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 0.1. The volatility risk premium in Switzerland is the only one exhibiting long memory stationarity for most of the sample period.

More specifically, the lower bound of the 95% confidence interval and the point estimation of the fractional integration parameter is above 0.3 during the subsamples running from 11/09/2001 to 12/10/2001 and from 11/11/2008 to 23/6/2009. The French volatility risk premium shows evidence of long memory stationarity 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 stationarity for the Dutch volatility risk premium over the 1/02/2000-6/11/2011 period, and they are more pronounced for the sub-sample running from 19/9/2008 to 6/11/2011.

4.1 Total connectedness in risk aversion

We now turn our focus on the results concerning with the total connectedness among volatility risk premia. The analysis (both full sample and rolling based on a window of size equal to 500 days) is based on the estimation of VAR model with 2 lags (selected according to the Bayesian Schwarz criterion information).[5] Tables 3 and 4 report the results for the FIVAR (left Panel) and a short memory VAR (right Panel) based on the full sample analysis and report a total risk aversion index which ranges between 0.69 and 0.74, displaying a little increase over longer forecast horizons. Finally, the indexes obtained by a long memory VAR are very close to their counterparties obtained by a short memory VAR.

Fig 2 shows that the evolution over time (between 1/01/2002 and 29/8/2013) of the total connectedness index is very similar across different forecast horizons. The value of the index increases and it is less volatile if the forecast horizon increases. The highest peak of the total risk aversion index is recorded after the Lehman Brothers collapse. The total index is quite stable up to 2007, and then is going through an upward trend which ends in late 2008 right after Lehman

[5]It is important to observe that the full sample and rolling analysis is robust to different VAR order specifications. Results are available upon request.

Brother collapse. Over the 2007-2009 period the values of the index range between 0.62 and 0.74 at the 2 days horizon; between 0.675 and 0.76 at the 10 days horizon; between 0.70 and 0.77 at the 20 and 30 days horizon. An other upward trend is recorded in the period related to the second Eurozone crisis (second half of 2011).

4.2 Directional risk aversion connectedness

We now describe the empirical results on the directional connectedness indices. The full sample analysis results are reported in Table 3 (left panel for the long memory VAR, right panel for the short memory VAR) where a normalization is done by row in order to allow a better comparison of FROM indices across markets. Similarly, to ease the interpretation of the TO indices a normalization is done by column and the results are provided in Table 4 (left panel for the long memory VAR, right panel for the short memory VAR). An inspection of the index with label "TO" in Table 4 shows that, while the Netherlands is the market contributing the most to systemic risk aversion (increasing from a value equal to 0.71 for the very short term forecast horizon to values between 0.74 and 0.76 for longer forecast horizons), France is contributing the least to systemic risk aversion especially for an horizon longer than two days (with values ranging between 0.67 and 0.70). Moreover, France is also the country most vulnerable to systemic risk: an inspection of the index with label "FROM" in Table 3 shows that the index values for France range between 0.69 and 0.77 and are the highest if compared to the other countries. Switzerland is the country least vulnerable to systemic risk, since an inspection of the index with label "FROM" shows that the index ranges between 0.68 and 0.69 across different forecast horizon and it is the lowest if compared to the other countries under investigation. Finally, we can observe that the directional spillovers indices obtained by a long memory VAR are very close to their counterparties obtained by a short memory VAR (reported in the right panels of Tables 3 and 4).

The plots of the time varying indices of the directional connectedness (obtained from the rolling estimation) measuring the vulnerability of each market to systemic risk (e.g the FROM indices) and the contribution of each market to systemic risk (e.g, the TO indices) are reported in Figures 3 and 4. As observed above, to ease the interpretation the FROM indices are normalized by row, while the TO indices are normalized by column.

We start commenting on the empirical findings regarding the FROM indices (see left panel in Fig. 3). The vulnerability of UK is increasing during May 2006 – August 2008 (with values ranging from 0.60 to 0.80) and over April 2010 - November 2010 (with values ranging from 0.65 to 0.80). The intervals November 2008 - May 2010 and August 2011 onward, are characterized by a decreasing pattern with values of the index dropping from 0.80 to 0.66. A discrepancy of index values across forecast horizons occurs over October 2010-July 2011.

In Germany there are large differences of the index value across forecast horizons over the interval June 2002 - July 2004. A further large discrepancy occurs over the interval September 2008 – September 2010, for which there is evidence of increasing trend only for longer forecast horizon. The index is relatively stable around 0.70 for the rest of the sample.

In Switzerland the index exhibits an upward trend over August 2003 – December 2005 (with values ranging from 0.63 to 0.77), during May 2006 - August 2007 (with values ranging from 0.61 to 0.81) and over the period November 2010-July2011 (with values rising from 0.55 to 0.72). A long decreasing pattern of the index in Switzerland is recorded during August 2007 - October 2010 (with values falling from 0.81 to 0.55). A shorter and less volatile downward trend occurs over May 2002-Sept2003 (with values ranging from 0.80 to 0.60) and over July 2011 – August 2013 (with values of the index dropping from 0.72 to 0.63). A relatively large discrepancy across forecast horizons occurs before March 2008.

In France there is a large difference in the index values across forecast horizons especially at the beginning of the sample until July 2004. In particular, while the time varying evolution of the index is decreasing for the long forecast horizon (from 0.80 to 0.70), it is increasing from 0.60 to

0.70 for shorter forecast horizon. Since July 2004 the index in France is relatively stable (across forecast horizon) fluctuating around 0.75 till early October 2008. From Lehman Brother collapse till December 2010, the index for the longest forecast horizon rises fluctuating around 0.8 and the one associated to the shortest forecast horizon falls fluctuating around 0.7. From January 2011 onwards the index is stable around 0.75 across different forecast horizons.

In Netherlands there is evidence of an increasing trend over July 2004 - early October 2010 and during the period December 2010 – August 2013: in both periods the index is rising from 0.60 to 0.77. Finally, there is a downward trend from 0.68 to 0.60 from January 2002 till July 2004, and also a large drop from 0.75 to 0.60 over the short interval September – November 2008

We now turn our focus on the findings regarding the index measuring the contribution TO systemic risk aversion (see right Panel Figure 3). In UK the index shows a decreasing pattern from August 2002 to August 2004 (with values dropping from 0.77 to 0.65) and over August 2007-August 2008 (with values dropping from 0.80 to 0.70). There is evidence of an upward trend from August 2004 to August 2007 (from 0.65 to 0.79) and during the Lehmnan Brother collapse. Since December 2008, the index is relatively stable averaging around 0.70 and the discrepancies across forecast horizon disappear).

In Switzerland there is evidence of a downward trend from 0.75 to 0.58 over December 2002 – November 2004 and from 0.7 to 0.52 over March 2005-May 2006. Since June 2006, there is an upward trend ending in October 2008 when a peak of 0.77 is reached (followed by a large drop to 0.63 by the end of Nov2008) and over the period December 2008-November 2010, reaching a peak equal to 0.78. Since then the index value is then relatively stable averaging around 0.77. The largest discrepancy across forecast horizon occurs in the early part of the sample (till October 2004) and since December 2008.

In Germany, while index value for the short term forecast horizon is relatively stable (fluctuating around 0.70), the index for longer forecast horizon shows a more volatile time varying pattern.

More specifically, there is a huge drop (only for long forecast horizon) during the first part till October 2003 from 0.75 to 0.53, and from February 2008 till February 2010 (from 0.80 to 0.66). There is evidence of a long increasing trend from 0.55 to 0.80 over September 2003-February 2008 and over a shorter interval, from January 2010 to November 2010 (from 0.65 to 0.75). Only in the last part of the sample there are no discrepancies across forecast horizons with values close to 0.70 In France there is an increasing trend with values starting from 0.45 and reaching 0.75 in early October 2008; a shorter upward trend occurs over October 2010 and July 2011 (with values rangong from 0.65 to 0.75). A downward trend is recorded from October 2008 to October 2010 (with values dropping from 0.75 to 0.65). Discrepancies across forecast horizon occur over December 2008 and October 2010.

The plots in Fig. 3 show that among the most recent periods of financial turmoil, the one associated with Lehman Brothers collapse is the one showing the largest gap between short and long term forecast horizons for the index measuring contribution to systemic risk aversion in any country and this occurs only for Germany and France vulnerability indices. This can be the effect of the divergent behavior of investors with different forecast horizons. The Eurozone crisis period is associated with differences between short term and long term forecast horizon only in two cases: the index measuring the UK vulnerability and the one measuring contribution of Switzerland to systemic risk aversion.

Last, in Figure 4, we report the differences in the estimation of the directional connectedness indexes by using a short memory or a long memory VAR for the 30-day forecast horizon. Differently from the full sample analysis, where the difference between the outputs of the long-memory VAR and the short-memory VAR is not significant, we can see that in the rolling analysis, in particular at the longest forecast horizon of 30-day, a discrepancy between the results in the short and long memory VAR can be detected for almost all countries and in particular over the period following the Lehman Brothers collapse. The results are in line with the findings of long memory especially during the Lehman Brothers crisis period, reported in Table 2. Unreported results, which are available upon request, show that the difference between the long memory and the short memory VAR increases when switching from a short to a long forecast horizon**.**

Overall, the time varying plots in Fig 3 and 4 suggest that the transmission of shocks to volatility risk premia series during the crisis period associated with Lehman Brother collapse is more persistent than the one corresponding to first and second Eurozone crisis (associated with first half of year 2010 and second half of 2011, respectively).

5. Conclusions

In this paper we have constructed an aggregate index of risk aversion in Europe and we have also assessed the vulnerability and the contribution to systemic risk aversion of each country under investigation. In particular, we have examined the connectedness among volatility risk premia, which are considered better proxies for measuring risk aversion than plain implied volatilities. The countries considered are UK, Germany, Switzerland, France, and the Netherlands. We have followed the methodology suggested by Diebold-Yilmaz (2012, 2014) and contributed to the latter in different aspects. First, differently from Diebold-Yilmaz (2012 and 2014), we have estimated a Fractionally Integrated VAR, *FIVAR*, model, given the long memory properties of the series under investigation. Second, we have provided evidence of structural breaks contaminating the long memory stationary features of the volatility risk premia. Third, we have enhanced the comparison across markets, by normalizing not only the vulnerability of each market from systemic shocks (as in Diebold-Yilmaz (2012 and 2014)), but also the indices measuring the contribution of each market to systemic risk aversion. Last, we have conducted a sensitivity analysis on different forecasts horizons, ranging from the very short-term of two days ahead to the long-term horizon equal to thirty days ahead.

The total index of risk aversion is quite stable and attains a peak after the Lehman Brothers collapse. The full sample results results show that while France is the country contributing the least to systemic risk aversion, Netherlands is the country contributing the most. Moreover, while Switzerland is the country least vulnerable to systemic risk aversion, France is the country most vulnerable. Rolling regression analysis shows that the index measuring contribution to systemic risk aversion is more volatile than the vulnerability indicator in Germany, France and Switzerland. The comparison with a short mamory VAR indicates that Lehman Brothers collapse is the crisis period showing a higher degree of persistence in the transmission of shocks to risk aversion.

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Table 1: Descriptive Statistics of the volatility risk premium series

	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		FRA		NED	
d	***W stat***	**d**	***W stat***	**d**	***W stat***	**d**	***W stat***	**d**	***W stat***
0.111 [0.094]	1.461	0.082 [0.085]	1.424	0.222 [0.132]	1.960	0.102 [0.093]	1.459	0.082 [0.098]	1.424
Breaks	***d***	**Breaks**	***d***	**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]	1feb00 18sep08	0.060 [0.025; 0.095]	1feb00 18sep08	0.099 [0.064; 0.134]
19sep08 6nov08	0.023 [0.014; 0.033]	11sep01 8oct01	0.203 [0.193; 0.213]	11sep01 12oct01	0.350 [0.336; 0.364]	19sep08 5nov08	0.179 [0.167; 0.192]	19sep08 6nov11	0.132 [0.121; 0.144]
7nov08 29aug13	0.000 [0.091; -0.09]	9oct01 21jun02	0.141 [0.128; 0.153]	15oct01 14jun02	0.050 [NA; NA]	6nov08 6may10	0.000 [NA; NA]	7nov11 29aug13	0.000 [-0.07; 0.076]
		24jun02 19aug02	0.000 [-0.39; 0.392]	16jun02 16aug02	0.109 [0.101; 0.118]	7may10 3jun10	0.000 [-0.05; 0.059]		
		20aug02 18jan08	0.033 [0.002; 0.065]	19aug02 24sep08	0.054 [0.022; 0.086]	4jun10 29aug13	0.000 [-0.09; 0.092]		
		21jan08 18feb08	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 3: Full-Sample Connectedness Table; normalized by row.

SPILLOVER TABLE, LONG MEMORY, H=2

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.31	0.19	0.15	0.15	0.21	0.69	1.00
GER	0.16	0.32	0.16	0.17	0.19	0.68	1.00
SWI	0.16	0.20	0.32	0.15	0.18	0.68	1.00
FRA	0.16	0.20	0.14	0.31	0.19	0.69	1.00
NED	0.19	0.20	0.16	0.16	0.31	0.70	1.00
TO	0.66	0.78	0.60	0.62	0.77		TOTAL
TO+own	0.97	1.10	0.92	0.93	1.08		0.69

SPILLOVER TABLE, SHORT MEMORY, H=2

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.31	0.19	0.15	0.15	0.21	0.69	1.00
GER	0.16	0.32	0.16	0.17	0.19	0.68	1.00
SWI	0.16	0.20	0.32	0.15	0.18	0.68	1.00
FRA	0.16	0.20	0.14	0.31	0.19	0.69	1.00
NED	0.19	0.20	0.16	0.16	0.30	0.70	1.00
TO	0.66	0.78	0.61	0.62	0.77		TOTAL
TO+own	0.97	1.10	0.93	0.93	1.07		0.69

SPILLOVER TABLE, LONG MEMORY, H=10

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.29	0.16	0.19	0.14	0.23	0.71	1.00
GER	0.18	0.25	0.19	0.15	0.22	0.75	1.00
SWI	0.21	0.16	0.31	0.12	0.20	0.69	1.00
FRA	0.20	0.17	0.17	0.23	0.23	0.77	1.00
NED	0.20	0.16	0.19	0.15	0.30	0.70	1.00
TO	0.79	0.64	0.73	0.57	0.88		TOTAL
TO+own	1.08	0.90	1.05	0.80	1.18		0.72

SPILLOVER TABLE, SHORT MEMORY, H=10

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.30	0.18	0.16	0.15	0.22	0.70	1.00
GER	0.16	0.30	0.17	0.16	0.21	0.70	1.00
SWI	0.18	0.19	0.30	0.13	0.20	0.70	1.00
FRA	0.18	0.19	0.15	0.27	0.22	0.73	1.00
NED	0.19	0.18	0.17	0.16	0.30	0.70	1.00
TO	0.71	0.75	0.65	0.60	0.83		TOTAL
TO+own	1.01	1.05	0.95	0.86	1.14		0.71

SPILLOVER TABLE, LONG MEMORY, H=20

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.29	0.16	0.18	0.15	0.22	0.71	1.00
GER	0.18	0.27	0.18	0.16	0.22	0.74	1.00
SWI	0.20	0.17	0.31	0.12	0.20	0.69	1.00
FRA	0.19	0.18	0.16	0.24	0.23	0.76	1.00
NED	0.20	0.16	0.18	0.16	0.30	0.70	1.00
TO	0.77	0.67	0.71	0.58	0.87		TOTAL
TO+own	1.06	0.94	1.02	0.82	1.17		0.72

SPILLOVER TABLE, SHORT MEMORY, H=20

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.30	0.17	0.17	0.15	0.22	0.70	1.00
GER	0.18	0.28	0.17	0.16	0.22	0.72	1.00
SWI	0.20	0.18	0.30	0.12	0.20	0.70	1.00
FRA	0.19	0.18	0.15	0.25	0.23	0.75	1.00
NED	0.20	0.17	0.18	0.16	0.30	0.70	1.00
TO	0.76	0.69	0.68	0.58	0.87		TOTAL
TO+own	1.06	0.97	0.97	0.83	1.17		0.72

SPILLOVER TABLE, LONG MEMORY, H=30

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.29	0.18	0.17	0.15	0.22	0.71	1.00
GER	0.17	0.29	0.17	0.16	0.21	0.71	1.00
SWI	0.18	0.19	0.31	0.13	0.19	0.69	1.00
FRA	0.18	0.19	0.15	0.26	0.22	0.74	1.00
NED	0.19	0.18	0.17	0.16	0.30	0.70	1.00
TO	0.72	0.73	0.67	0.60	0.84		TOTAL
TO+own	1.01	1.02	0.97	0.86	1.14		0.71

SPILLOVER TABLE, SHORT MEMORY, H=30

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.30	0.16	0.18	0.14	0.23	0.70	1.00
GER	0.18	0.26	0.18	0.16	0.22	0.74	1.00
SWI	0.21	0.17	0.30	0.12	0.21	0.70	1.00
FRA	0.20	0.17	0.16	0.24	0.23	0.76	1.00
NED	0.21	0.16	0.18	0.15	0.30	0.70	1.00
TO	0.79	0.66	0.70	0.57	0.89		TOTAL
TO+own	1.09	0.92	1.00	0.81	1.19		0.72

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). Each entry of the variance decomposition table is normalized by row (see eq. 12)

Table 4: Full-Sample Connectedness Table; normalized by column

SPILLOVER TABLE, LONG MEMORY, H=2

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.32	0.17	0.16	0.16	0.19	0.68	1.00
GER	0.16	0.29	0.17	0.18	0.18	0.69	0.98
SWI	0.16	0.18	0.34	0.15	0.16	0.65	0.99
FRA	0.17	0.18	0.15	0.33	0.18	0.68	1.01
NED	0.20	0.19	0.17	0.18	0.29	0.73	1.03
TO	0.68	0.71	0.66	0.67	0.71		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.69

SPILLOVER TABLE, SHORT MEMORY, H=2

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.32	0.17	0.16	0.16	0.19	0.68	1.00
GER	0.16	0.29	0.18	0.18	0.18	0.70	0.98
SWI	0.16	0.18	0.33	0.15	0.16	0.65	0.98
FRA	0.17	0.18	0.15	0.33	0.18	0.68	1.01
NED	0.20	0.19	0.18	0.18	0.29	0.73	1.02
TO	0.68	0.71	0.67	0.67	0.71		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.69

SPILLOVER TABLE, LONG MEMORY, H=10

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.26	0.17	0.18	0.18	0.19	0.71	0.98
GER	0.18	0.30	0.20	0.21	0.20	0.79	1.09
SWI	0.17	0.16	0.27	0.13	0.15	0.62	0.89
FRA	0.19	0.20	0.17	0.30	0.21	0.78	1.08
NED	0.18	0.17	0.18	0.18	0.24	0.71	0.96
TO	0.74	0.70	0.73	0.70	0.76		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.72

SPILLOVER TABLE, SHORT MEMORY, H=10

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.29	0.17	0.17	0.17	0.19	0.70	0.99
GER	0.16	0.28	0.18	0.19	0.18	0.71	1.00
SWI	0.17	0.18	0.31	0.15	0.17	0.66	0.97
FRA	0.18	0.19	0.16	0.32	0.20	0.74	1.06
NED	0.19	0.17	0.18	0.18	0.26	0.72	0.98
TO	0.71	0.72	0.69	0.68	0.74		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.71

SPILLOVER TABLE, LONG MEMORY, H=20

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.27	0.17	0.18	0.17	0.19	0.71	0.98
GER	0.18	0.30	0.19	0.20	0.20	0.87	1.17
SWI	0.17	0.16	0.28	0.13	0.16	0.63	0.91
FRA	0.19	0.20	0.17	0.31	0.21	0.77	1.08
NED	0.18	0.17	0.18	0.18	0.25	0.72	0.96
TO	0.73	0.70	0.72	0.69	0.75		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.74

SPILLOVER TABLE, SHORT MEMORY, H=20

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.28	0.17	0.17	0.17	0.19	0.70	0.98
GER	0.17	0.30	0.19	0.20	0.19	0.75	1.05
SWI	0.18	0.17	0.29	0.14	0.16	0.65	0.94
FRA	0.19	0.20	0.17	0.31	0.21	0.76	1.07
NED	0.18	0.17	0.18	0.18	0.25	0.71	0.96
TO	0.72	0.70	0.71	0.69	0.75		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.71

SPILLOVER TABLE, LONG MEMORY, H=30

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.29	0.17	0.18	0.17	0.19	0.71	1.00
GER	0.17	0.29	0.18	0.19	0.19	0.72	1.01
SWI	0.17	0.17	0.30	0.14	0.16	0.64	0.95
FRA	0.19	0.20	0.16	0.32	0.20	0.75	1.06
NED	0.19	0.17	0.18	0.18	0.26	0.72	0.98
TO	0.71	0.71	0.70	0.68	0.74		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.71

SPILLOVER TABLE, SHORT MEMORY, H=30

	UK	GER	SWI	FRA	NED	FROM	FROM+own
UK	0.27	0.17	0.18	0.17	0.19	0.70	0.97
GER	0.18	0.30	0.19	0.20	0.20	0.77	1.08
SWI	0.18	0.17	0.28	0.13	0.16	0.64	0.92
FRA	0.19	0.20	0.17	0.31	0.21	0.77	1.08
NED	0.18	0.16	0.18	0.18	0.25	0.71	0.95
TO	0.73	0.70	0.72	0.69	0.75		TOTAL
TO+own	1.00	1.00	1.00	1.00	1.00		0.72

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). Each entry of the variance decomposition table is normalized by column (see eq. 14).

Figure 1: volatility risk premium series

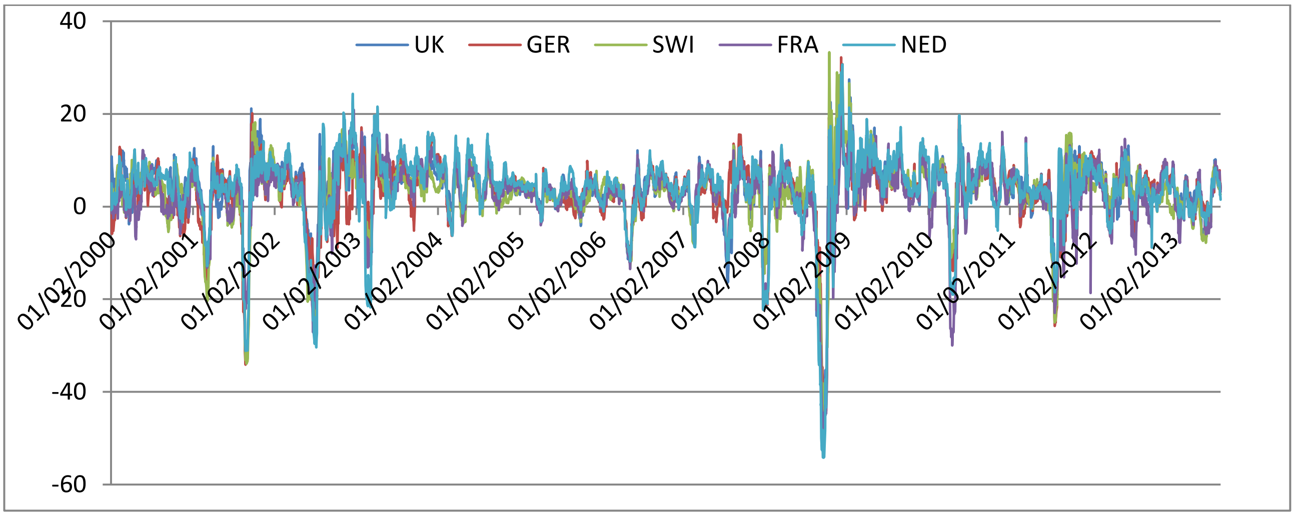
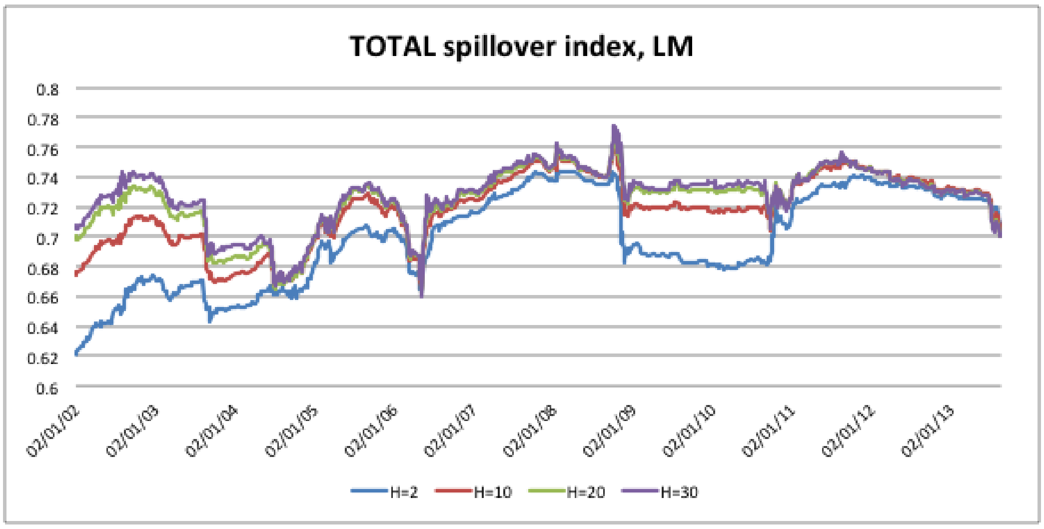


Figure 2. Total connectedness index estimated from long memory stationary VAR (top panel) and short memory stationary VAR (bottom panel)



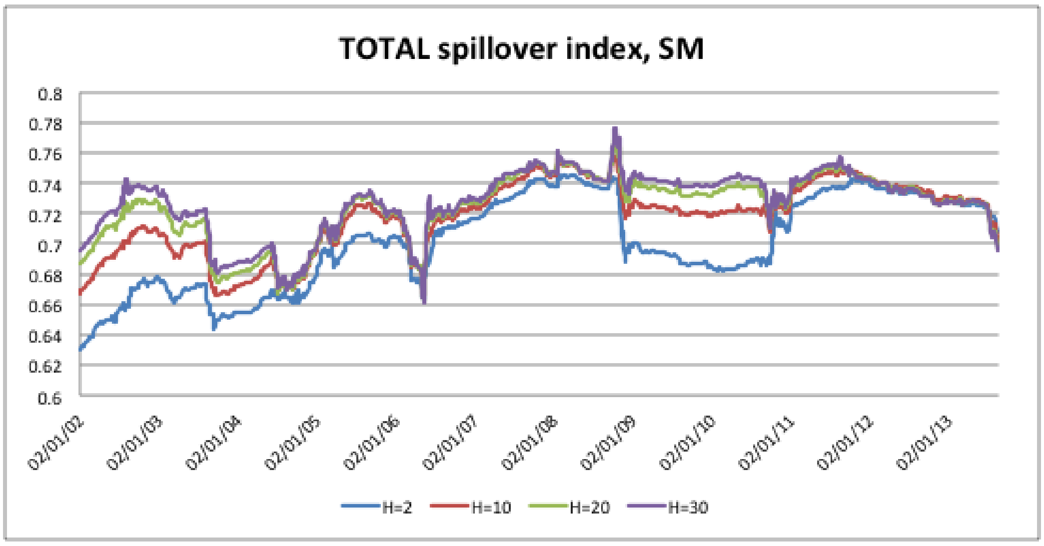


Figure 3. Directional Connectedness indices TO and FROM for different forecast horizons (long memory).

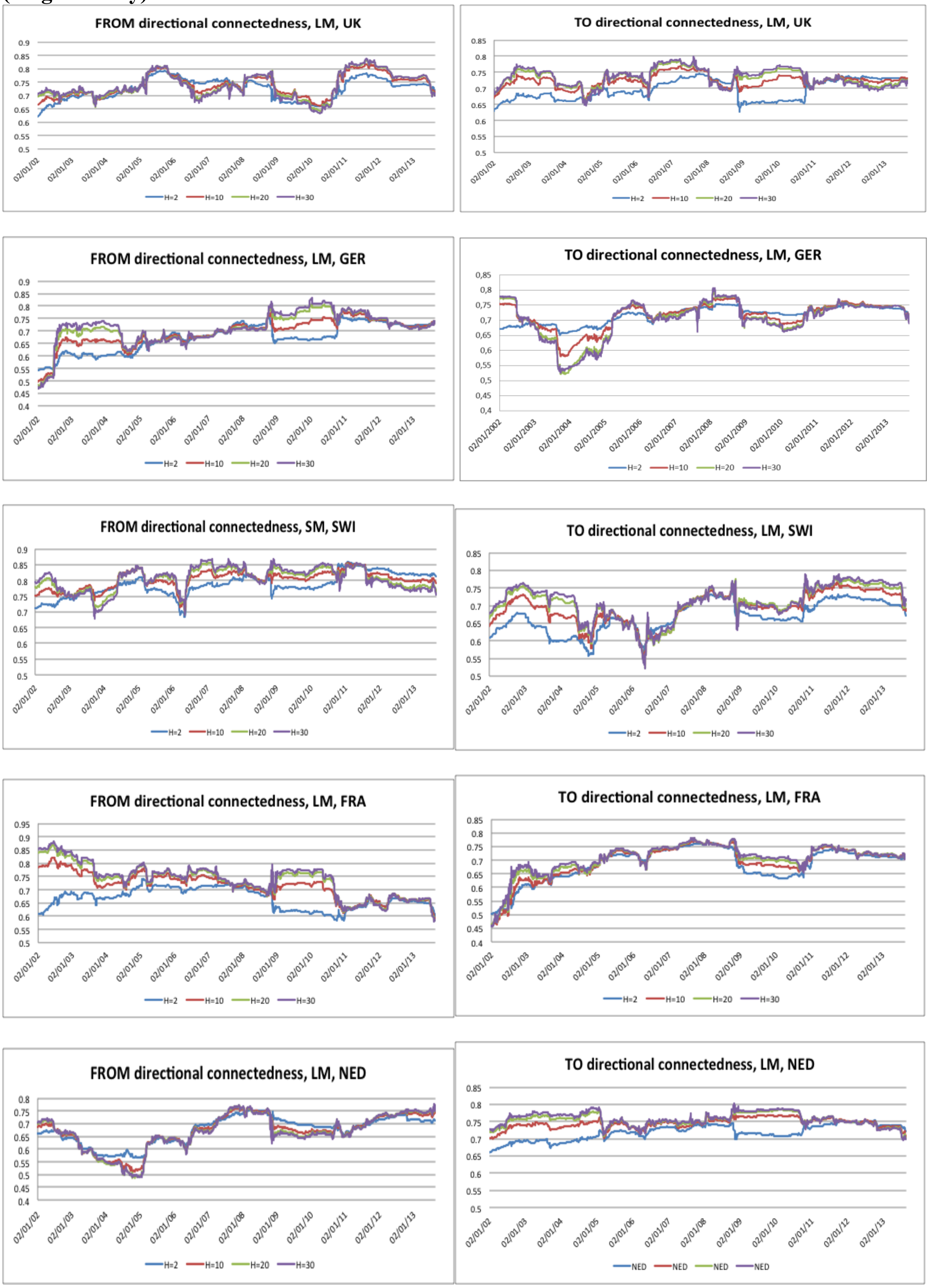


Figure 4. The comparison for the 30-days forecast horizon between short memory and long memory VAR.