Wavelet analysis of variance risk premium spillovers

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Abstract

In this paper we construct a variance risk premium spillover index among France, Germany, UK, Switzerland and the US. The variance risk premium is measured by the difference between the (square) of implied volatility and expected realized variance of the stock market for next month. We also construct a spillover index for the constituents of the variance risk premium. The series under investigation exhibit long memory properties. The construction of a total spillover indicator suggested by Diebold-Yilmaz (2009) would then rely on modeling a fractionally integrated Vector Autoregressive Model, which might be subject to errors in specifying the correct lag length and the fractional differencing parameters. In order to avoid such misspecification errors, we employ wavelet analysis. In particular, we employ the Maximal Overlapping Transform and we compute the covariance matrix at different scales (associated to a frequency range). The spillover index is then obtained from the relative contribution of each (orthogonalized) shock to the variance of the other series at given scale (e.g. at a given investment time horizon).

JEL: C32, C38, C58, G13

Keywords: variance risk premium, implied variance, realized variance, long memory, MODWT, spillover index

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1. Introduction

In this paper we aim to analyze spillover among the variance risk premium series for five countries: France, Germany, UK, Switzerland and the US. Following Bollersev et al. (2009) who focus only on the US stock market (see also Bollersev et al, 2013b for a study extended to other countries stock markets), the variance risk premium is defined as the difference between the risk-neutral and statistical expectations of the future return variation. The risk neutral expectation of the stock market variance is approximated by the one-month forward looking model-free options implied variances. The statistical expectation (or expectation under the physical measure) of the stock market variance is approximated by realized variances over next month (see Carr and Wu, 2006; see also Bollersev et al., 2013). As pointed by Bollersev et al (2013a and 2013b), the variance risk premium is interpreted both as aggregate risk aversion and aggregate economic uncertainty. We also extend the analysis to spillovers among the two constituents of the variance risk premium.

Spillovers among the variance risk premia are analyzed through a time varying total spillover index obtained, following the suggestion of Diebold-Yilmaz (2009), by measuring the relative contribution of orthogonalized shocks spilling over to other markets. For this purpose, Diebold-Yilmaz (2009) rely on the variance decomposition of a stationary VAR(p).

To our knowledge, the only study analyzing the type of volatility spillovers we are interested in is the one of Jiang, et al. (2012) investigating spillovers across implied volatility indices for the US and for Europe (with emphasis on the role played by news). However, Jiang et al. (2012) focus on the relationship between first differences of implied volatilities, and not on the levels.

Since our focus is on analyzing spillovers between series exhibiting long memory (e.g. the variance risk premium and its constituents), we prefer, when building up the time varying total spillover index of Diebold and Yilmaz (2009), avoiding errors associated to a fractionally integrated Vector Autoregressive model both in terms of an incorrect VAR lag order and fractional differencing parameter[1]. For this purpose, we use the Maximal Overlapping Discrete Wavelet Transform, MODWT, to obtain a scale by scale decomposition of the covariance matrix of the fractionally integrated series under investigation (see Witcher et al., 2000). Each scale is associated to a given frequency range interpreted as a given time investment horizon. While the total spillover index of Diebold-Yilmaz (2009), based on the variance decomposition at given forecast horizon, requires the specification of the correct lag order of a VAR, we are able, through MODWT, to produce a non-parametric estimation of the variance decomposition for different investment time horizons.

The structure of the paper is as follows. Section 2 describes the issue of long memory; Section 3 describes wavelet analysis; Section 4 describes the Diebold-Yilmaz (2009) total spillover index and our contribution; Section 5 focusses on the empirical evidence and section 6 concludes.

2 Long memory

Let a time series x_t , be described by an *ARFIMA(p,d,q)* process:

$$\Phi(L)(1-L)^d y_t = \Theta(L)\varepsilon_t \tag{1}$$

where ε_t is an *iid* Gaussian process with variance σ_ε^2 . The AR component is given by a polynomial of degree p (with roots outside the unit circle):

$$\Phi(L) = 1 + \varphi_1 L + \varphi_2 L^2 + \ldots + \varphi_p L^p \tag{2}$$

and the MA component is described by a polynomial of degree q (with roots outside the unit circle):

$$\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \ldots + \theta_q L^q \tag{3}$$

The fractional differencing operator $(1 - L)^d$ can be derived from a power series expansion as follows:

[1] 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 volatilities, 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).

$$(1-L)^d = 1 + \sum_{z=0}^{\infty} \frac{\Gamma(z-d)}{\Gamma(-d)\Gamma(z+1)} L^z \qquad (4)$$

It turns out that, for $-0.5 < d < 0.5$, the process x_t is stationary and invertible. For such processes, the effect of a shock ε at time t on x at time $t+h$ decays as h increases, but the rate of decay is much lower than for a process integrated of order zero, hence the autocorrelation function for a fractionally integrated process decays hyperbolically. If $0.5 < d < 1$, then the process is non-stationary long-memory and it is characterized by an infinite variance.

There exist a number of estimation methods for the fractional integration parameter. The GPH estimator is based on the low frequency spectral behavior of the time series, and it is simply the slope of the sample log periodogram:

$$\ln P(\lambda_s) = c - d \ln(4(\sin^2(\lambda_s / 2))) + \varepsilon(\lambda_s)$$

where $P(.)$ is the periodogram of the data computed at the harmonic frequencies $\lambda_s = \frac{2\pi s}{T}$, with $s = 1, \ldots, \omega \prec T/2$, and T is the sample size.

The local Whittle estimator developed by Kunsch (1987) and by Robinson (1995b) maximizes a frequency-domain Gaussian likelihood for frequencies in the neighborhood of zero, i.e.:

$$\log\left[\frac{1}{\omega}\sum_{s=1}^{\omega}\lambda_s^{2d}P(\lambda_s)\right] - \frac{2d}{\omega}\sum_{s=1}^{\omega}\lambda_s$$

Both the GPH and local Whittle estimators provide point estimate of the fractional integration parameter which are dependent on the choice of the bandwith parameter m, that is on the number of low frequencies considered.

Moving to a multivariate approach to model dynamic spillover effects between long memory series would require the computation of dynamic multipliers by specifying fractionally integrated Vector Autoregressive Model (see Bollersev et al., 2013). As mentioned before, in this paper we want to analyze spillovers without relying on modeling a fractionally integrated Vector Autoregressive

Model, which might be subject to model misspecification in terms of lag length and in terms of the fractional differencing parameter.

3 Wavelet multiresolution analysis

Our primary focus is on the construction of a spillover index for different time investment horizon: from short to long-run. For this purpose we apply a scale by scale decomposition of variances and covariance of volatilities time series. The standard frequency-domain approach is based on the assumption that the observed time series is stationary over the time period under study. Classical Fourier analysis has a global nature; in decomposing data into sinusoidal components of various frequencies, which are localized in frequency but not in time, time information is lost except for the one conveyed in the phase. For that reason, the Fourier transform is not suitable for truly evolving (time varying) phenomena.

On the other hand, wavelet analysis allows assessing at the same time changes in the relationship among variables at different ranges of frequencies and over the time. Wavelets can be particularly useful when the time series is localized in time as well as in frequency. Discontinuities in signals can be described in terms of very short (compressed) local basis functions with a high-frequency content, whereas a fine analysis at low frequencies can be achieved using highly dilated (stretched) basis functions. In other words, the wavelet is contracted or dilated to change the scale at which one looks at a signal. The wavelet is then shifted or translated in time to correspond to different part of the signal. The procedure is called multiresolution analysis. In particular, in case of a dyadic multiresolution analysis, the dilated and translated family of wavelets functions can be defined as[2]:

$$\psi_{j,k}(t) = 2^{-j/2}\psi(2^{-j}t - k);\, j,k \in I \qquad (6)$$

[2] Given a time series with T observations, conventional dyadic multiresolution analysis applies to a succession of frequency intervals in the form of $(\pi/2^{(j)}, \pi/2^{(j-1)})$, with the decomposition level j running from 1 to J. The bandwidths are halved (down-sampled by 2) repeatedly descending from high to low frequencies. By the j^{th} round, there will be j wavelet bands and one accompanying scaling function band. At the decomposition level j, one obtains a set of $T/2^j$ mutually orthogonal wavelets functions given by equation (7), separated from each other by 2^j points.

where j and k are the integer parameters governing the scale resolution (*i.e.* 2^{-j}) and translation in time, respectively. All the wavelet basis functions, $\psi_{j,k}$, are self-similar, namely, they differ only by translation and change of scale from one another. These functions result from a *mother* wavelet, $\psi(t)$, which is any oscillating function with zero mean, finite support and unit energy, i.e.:

$$\begin{aligned}&\int_{-\infty}^{+\infty}\psi(t)dt = 0\\&\int_{-\infty}^{+\infty}|\psi(t)|^2 dt = 1\end{aligned} \tag{7}$$

The object of a wavelet analysis is to associate an amplitude (wavelet) coefficient w to each of the wavelet. The task is accomplished by the Discrete Wavelet Transform which is implemented via the pyramid algorithm of Mallat (1987). If certain conditions are satisfied, these coefficients completely characterize the signal which is resolved in terms of a coarse approximation and the sum of fine details:

$$x(t) = \sum_k v_{J,k}\phi_{J,k}(t) + \sum_j\sum_k w_{j,k}\psi_{j,k} \tag{8}$$

Here J is the highest possible level of decomposition; $\phi_{J,k}$ is the set of translated orthogonal scaling functions spanning the lower frequency range [0, $\pi/2^{(J)}$). Therefore, the first term $\sum_k v_{J,k}\phi_{J,k}(t)$ in eq. (8) is the coarse approximation of the signal, and the second term $\sum_j\sum_k w_{j,k}\psi_{j,k}$ in eq. (8) is the sum of fine details.

The scaling and wavelet coefficients $v_{j,k}$ and $w_{j,k}$ are the following projections of *x(t)* on the bases $\phi_{j,k}$ and $\psi_{j,k}$ respectively:

$$v_{j,k} = \int x(t)\phi_{j,k}(t)dt \tag{9}$$

$$w_{j,k} = \int x(t)\psi_{j,k}(t)dt \tag{10}$$

The signal can then be written as a set of orthogonal components at resolutions 1 to J:

$$x(t) = S_J + D_J + D_{J-1} + \ldots\ldots + D_1 \tag{11}$$

At level j the detail component D_j captures frequencies spanning cycles with periodicity between 2^j and 2^{j+1} and the smooth S_j captures cycles with periodicity greater than 2^{J+1} periods.

A disadvantage of the conventional dyadic wavelet analysis is the restriction on the sample size T which has to be a power of 2. A further problem lies in the fact that the DWT depends upon a non-symmetric filter that is liable to induce a phase lag in the processed data. These difficulties can be circumvented by means of the Maximum Overlapping Discrete Wavelet Transform (MODWT), through which, the filtered output at each stage of the pyramid algorithm is not subjected to down-sampling, as in DWT analysis. As a consequence, the number of coefficients generated at the j-th stage of the decomposition, are in number equal to the sample size, T, instead that equal to $T/2^j$.

4 Total spillover index

The total spillover index (for the forecast horizon *H*) put forward by by Diebold and Yilmaz (2009) is given by:

$$S = \frac{\sum_{h=0}^{H-1} \sum_{i,k=1}^{N} a_{ik}^2}{\sum_{h=0}^{H-1} trace(A_h A_h')} \tag{13}$$

The coefficients $a_{h,ik}^2$ entering the expression at the numerator are the "*cross variance shares*" or "*spillovers*", measuring the relative contribution of shock k to the variance the forecast error of series i (and viceversa). The coefficient matrix A_h includes also the "*own shares*", that is the contribution of shock i to the variance the forecast error of series i. The coefficients entering matrix A_h are obtained from a stationary VAR(p), once the residuals have been orthogonalized via Cholesky decomposition. As we can observe from eq.(13), the total spillover index provided by Diebold Yilmaz (2009) approach is based on the decomposition of the variance of forecast errors, e.g. the residuals of a VAR(p) model fitted to stationary time series. As mentioned above, our focus is on the construction of a spillover index of time series exhibiting long memory properties. In order to avoid producing a spillover indicator based on a miss-specified model both in terms of VAR lag order length and in terms of the fractional integration parameter, we rely on the MODWT to produce a scale by scale decomposition of the covariance matrix of fractionally integrated time series (see Percival and Walden, 2000; Whitcher, 2000). Each scales is associated to a given frequency range, interpreted as a given time investment horizon. Unlike the DWT, the MODWT, by producing a decomposition of a given time series into components having the same size as the original time series, is capable to explore potential structural breaks. The construction of the total spillover index is obtained in the following three stages.

1) As shown by Percival and Walden (2000) (see also Whitcher, 2000) the wavelet covariance between two fractionally integrated time series X and Y (with the orders of integration d_1 and d_2, respectively) for scale λ_j (which is equal to 2^{j-1}) is defined as: $\gamma(\lambda_j)$ and it is given by:

$$\gamma_{X,Y}(\lambda_j) = \frac{1}{N_j} \sum_{t=L_j}^{N-1} w_{jt}^{X} w_{j,t}^{Y} \tag{14}$$

where $w_{j,t}^{X}, w_{j,t}^{Y}$, are the non-boundary wavelet coefficients for the primary surplus and debt (GDP ratios) for scale λ_j; $N_j = N - L_j + 1$ and $L_j = (2^j - 1)(L-1)+1$ is the filter length at level j. The covariance formula of two fractionally integrated time series given by eq. (14) relies on the stationary property of the wavelet coefficients.. The choice of filter length depends on the trade-off between leakage and boundary affected coefficients: the longer the filter, the closer to an ideal high pass filter, but also the higher the number of boundary coefficients. For that reason, in presence of time series exhibiting an high degree of persistence, the condition suggested by Percival Walden (2000), $L \geq 2d$ (where d is the fractional integration parameter), ensuring stationary wavelet coefficients would suggest the use of a filter with length L bigger than two. However, from eq. (12), unbiased estimates for the cross covariance of the time series at scale λ_j imply considering only the non-boundary coefficients (Percival and Walden, 2000). The longer is the filter, the higher is the number of boundary affected coefficients. For robustness we consider not only the Haar filter (with filter length equal to 2), but also filters such as LA(4) and LA(8), where the number in parenthesis is the associated filter length.

2) The orthogonal shocks facilitating the computation of variance decomposition are obtained by employing a factor decomposition of the covariance matrix of the fractionally integrated time series for a given scale, employing the Cholesky decomposition (in a way similar to Diebold-Yilmaz, 2009) who rely on the Cholesky factorization of the he covariance matrix of VAR residuals).

In order to orthogonalize the innovations, we use the Cholesky decomposition of Σ_j, which is the 5×5 covariance matrix for the endogenous variables for scale λ_j, the scale specific covariance matrix of raw time series. The index j varies from 1 to 4, implying that we consider spillover indices for an investment time horizon of either 2-4 days, or 4-8 days, or 8-16 days, or 16-32 days. The Cholesky factorization of Σ_j, returning the upper triangular matrix A_j, implies a specific recursive identying scheme for the orthogonalized shocks. For robustness, we follow the suggestions of with Faust (1998) (see also Diebold-Yilmaz, 2009) considering all possible different recursive identifying schemes (which is equal 120 in case of five endogenous variables).

3) The total spillover index relative to a scale λ_j is given by:

$$S_{\lambda j} = \frac{\sum_{i,k=1}^{N} a_{ik,\lambda j}^2}{trace(A_{h,\lambda j} A_{h,\lambda j}')} \tag{15}$$

where $a_{ik,\lambda j}$ are the coefficients measuring the relative contribution of shock k to the variance of variable i for scale λ_j. Finally, similarly to Diebold-Yilmaz (2009) we produce a time varying total spillover index by using a rolling window. The first and the last ending date of the 252 day window are 13/10/2000 and 29/11/2011.

5. Data and empirical evidence

The variance risk premium at day t is defined as the difference between the risk-neutral and objective expectations of realized variance. In line with Bollersev et al. (2013a), the risk-neutral expectation of variance is measured as the end-of-month implied volatility squared and de-annualized (dividing by 12). In line with Bollersev et al. (2013a), the realized variance is the sum of squared 5-minute log returns of the S&P 500 index over the next month (using 21 days plus the squared overnight return). The daily realized variance is obtained from the OX-MAN library and the daily (annualized) implied volatility series is obtained from DATASTREAM. The sample observed at daily frequency runs from 4/1/2000 till 31/12/2011 and the countries under investigation are the US, UK, Germany, France and Switzerland.

In Table 1 we report descriptive statistics. The variance risk premia are all positive on average, ranging from a low of 8.95% for Germany to a high of 24.16% for UK on a percentage-squared monthly basis. "Selling" volatility has been highly profitable on average over the 2000-2011 period. The (average) size of the shock (measured by the standard deviation) hitting the variance risk premium and the implied variance series are similar across countries (around 30% for the variance risk premium,, and around 50% for the implied variance series). The (average) size of the shock hitting realized variances varies considerably across countries, with values equal to 41.782%, 25.085%, 50.952%, 36.530% and 25.926%, for the US, UK,, Germany, France and Switzerland, respectively. Moreover, the major source of asymmetry in the distribution of the variance risk premia series is the large kurtosis (similar findings apply to implied and realized variance series).

We turn now our focus on the long memory properties of the series under investigation. The estimation results for the fractional differencing parameter proposed by Geweke and Porter-Hudak (1983), hereafter GPH, based on a log-periodogram regression give at evidence (see Table 2) of non-stationary long memory in both implied and realized volatility time series (see Bandi and Perron, 2006 for similar results). There is also evidence of stationary long memory in the variance risk premium series (see Bollersev et al., 2013b for similar findings) with Germany as the only country exhibiting a short memory variance risk premium (given that the coefficient d is found to be not statistically different from zero). The GPH estimation results are confirmed by the Local Whittle estimator (see Table 3). Given that the variance risk premium series is integrated of an order lower than implied and realized volatility series, we can conclude that there is evidence of fractional cointegration between the realized and implied volatility time series of each country stock market.

The Figures for the time varying spillover index show that results are not sensitive to choice of the ordering of variables since the minimum, median and maximum values among the 120 recursive identifying scheme employed to orthogonalize the shocks are very close to each other.

Figures 1 gives evidence of a variance risk premium spillover index spike between 10/9/2001 and the observation immediately after (that is on 17/09/2001) when the very short term (between 2 and 4 days) variance premium spillover index raises from 31% to 45%. The interval time between 14/10/2008 and 29/10/2008 is characterized by a large drop in the spillover index from 59% to 46%. A steep rising trend in the implied variance series very short term spillover index is observed only over the last part of the sample, starting from a low of 29% the 30/10/2009 to a peak of 57.6% on 24/05/2011. Another steep rising trend can observed between 15/7/2011 and 8/8/2011 when index raises from 47% to 57%. We do not observe any spike in the spillover index for an investment time horizon above 4 days (see Figure 2-4). An investment time horizon between 4 and 8 days (see Fig. 2) is characterized by a large drop (from 63% to 48%) in the spillover index between 11/9/2008 31/10/2008 and by a steep rising trend with values of the index raising from 45% to 65% between 5/10/2009 and 23/3/2011. On the 8/8/2011 we observe the largest value, equal to 67.7%, in the spillover index. Investment time horizon between 8 and 16 days and between 16 and 32 days are not characterized by any particular structural break with values of the variance premium spillover index oscillating around an average value of 60%

From Figure 5 we can observe two volatility spikes. The first one is recorded on 17/9/2001 when there the spillover index raises from the previous day (that is, 10/9/2011) value of 35% to 51%. The second milder spike is recorded between the 3/10/2008 to 13/10/2008 when the spillover index raises from 44 to 55%. Immediately after, we can observe a large drop in the very short term spillover index, when the index falls from 57% to 28% during the interval time between 13/10/2008 and 17/10/2008. A steep rising trend in the implied variance series very short term spillover index only over the last part of the sample, starting from a low of 31% the 30/10/2009 to a peak of 59%

on 8/03/2011. Then, after a small drop to 54% there is again a constantly rising value of the spillover index from 1/1/2011 to 8/8/2011 (with values of the spillover index ranging between 54% and 60%). Moving to the investment time horizon between 4 and 8 days (see Figure 6) we can observe milder spillover spikes: from 10/9/2011 to 18/9/2011 we can observe an increase in the spillover index from 45% to 55%; from 26/9/2011 to 14/10/2011 we can observe an increase in the spillover index from 55% to 64%. Then, we can observe a constant drop till 30/10/2008 when the index reaches a value of 47%. Figure 6 shows a steep rising trend over an interval time (longer than the one observed for scale 1), from 2/11/2009 to 6/06/2011, when the spillover index raises from 48% to 67%. The very last part of the sample ending in November 2011 is characterized by values of the spillover index between 65% and 70%. From Figure 7 and 8 there is neither evidence of volatility spikes, nor of steep rising trend, although last period of the sample (starting from July 2010) is characterized by spillover index values above 70%.

From Figure 9 we can observe a steep rise in the very short term spillover index for realized variance, from 25% to 55%, between 13/6/2001 and 13/2/2002. Another steep rise in the very short term spillover index, from 19% to 70% occurs between 26/04/2004 and 9/9/2008. A mild rise in the very short term spillover index, from 36% to 49% occurs between 14/2/2011 and 7/7/2011. The spillover index for realized variance and for an investment time horizon between 4 and 8 days (see Fig 10) is characterized by an evolution over time similar to the one in Fig.9. Finally, Investment time horizon between 8 and 16 days and between 16 and 32 days are not characterized by any particular structural break with values of the realized variance spillover index oscillating around an average value of 60%

4. Conclusions

In this paper we, first, explore the long memory properties of the variance risk premium and its constituents: the expectation of stock market variance under the risk neutral and physical measure, for five countries: US, France, Germany, UK and Switzerland. The risk neutral expectation of the stock market variance is approximated by the one-month forward looking model-free options implied variances. The statistical expectation (or expectation under the physical measure) of the stock market variance is approximated by the next month realized variances. The estimation of the fractional integration parameter d by GPH and local Whittle estimator point at the existence of stationary long memory in the variance risk premium and non-stationary long memory in the constituents of the variance risk premium. One we found evidence of fractional integration, we build a total spillover index for the variance risk premium, the implied variance, and the one month realized volatility relying on a non-parametric estimation of the variance decomposition for different time investment horizon. Contrary to Diebold-Yilmaz (2009), our methodology to compute the variance decomposition and then total spillover index does not require the specification of a fractionally intergrated Vector Autoregressive Model. The method proposed in this paper is based on the Maximal Overlapping Discrete Wavelet Transform, MODWT, to obtain a scale by scale decomposition of the covariance matrix of the fractionally integrated series under investigation (see Witcher et al., 2000). Each scale is associated to a given frequency range interpreted as a given time investment horizon. The time varying spillover index plots gives evidence of few spikes and steep rising trend in the spillover index for the variance risk premium and its constituents especially for very short term time investment horizons (between 2 and 4 days and between 4 and 8 days).

References

Andersen, T. G., Bollerslev, T., 1997. Intraday periodicity and volatility persistence in financial markets. *Journal of Empirical Finance* 4, 115–158.

Baillie, R. T., Bollerslev, T., Mikkelsen, H. O., 1996. Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics* 74, 3–30.

Bandi, F. M., Perron, B., 2006. Long memory and the relation between implied and realized volatility. *Journal of Financial Econometrics* 4, 636–670.

Bollerslev T., Osterrieder D., Sizova N., and G. Tauchen (2013a) Risk and Return: Long-Run Relationships, Fractional Cointegration, and Return Predictability, *Journal of Financial Economics*, forthcoming

Bollerslev T., , Marrone J., Xu L. and H. Zhou (2013b): “Stock Return Predictability and Variance Risk Premia: Statistical Inference and International Evidence”, *Journal of Financial Quantitative Analysis*, forthcoming.

Christensen, B. J., Nielsen, M. Ø., 2006. Asymptotic normality of narrow-band least squares in the stationary fractional cointegration model and volatility forecasting. *Journal of Econometrics* 133, 343

Comte, F., Renault, E., 1998. Long memory in continuous-time stochastic volatility models. *Mathematical Finance* 8, 291–323.

Diebold, F.X. and Yilmaz, K. (2009), "Measuring Financial Asset Return and Volatility Spillovers, With Application to Global Equity Markets," *Economic Journal*, 119, 158-171.

Faust, J. 1998: “The robustness of identified VAR conclusions about money”, International Finance Discussion Papers, 610, Board of Governors of the Federal Reserve System (U.S.).

Geweke, J. & S. Porter-Hudak. (1983). The estimation and application of long memory time series models. *The Journal of Time Series Analysis*, 4-4, 221-238.

Kunsch, H. R. (1987). “Statistical Aspects of Self-Similar Processes.” In Prohorov, Y. and V.V. Sazonov (eds.), Proceedings of the first World Congress of the Bernoulli Society, Utrecht: VNU Science Press.

Jiang, G. J., Konstantinidi, E. and Skiadopoulos, George (2012) Volatility spillovers and the effect of news announcements. *Journal of Banking & Finance*, Vol.36 (No.8). pp. 2260-2273

Percival D, B, and A, T, Walden (2000), Wavelet Methods for Time Series Analysis, Cambridge University Press

Robinson, P. M. (1995a). “Log-Periodogram Regression of Time Series with Long Range Dependence.” *Annals of Statistics*, 23, 1048-1072.

Robinson, P. M. (1995b). “Gaussian Semiparametric Estimation of Long Range Dependence.” *Annals of Statistics*, 23, 1630-1661.

Velasco, C. (1999). “Non-Stationary Log-Periodogram Regression.” *Journal of Econometrics*, 91, 325-371.

Whichter P. Guttorp, and D. B. Percival. 2000. Wavelet Analysis of Covariance with Application to Atmospheric Time Series, *Journal of Geophysical Research-Atmospheres*, 105, 14941-14962.

Table 1: Descriptive Statistics

variance risk premium				
	Mean	**Std Dev**	**Skewness**	**Kurtosis**
US	17.788	32.347	-0.139	23.254
UK	24.167	31.990	3.144	23.039
GER	8.950	31.621	-2.324	17.040
FRA	22.590	34.216	1.191	12.586
SWI	19.822	31.483	3.553	33.920
implied variance				
	Mean	**Std Dev**	**Skewness**	**Kurtosis**
US	48.261	49.919	3.855	24.398
UK	46.604	46.647	3.318	19.776
GER	54.343	49.108	2.357	9.938
FRA	57.907	52.553	2.731	13.787
SWI	42.131	45.838	3.745	25.066
realized variance				
	Mean	**Std Dev**	**Skewness**	**Kurtosis**
US	30.472	41.782	4.362	27.032
UK	22.437	25.085	2.698	11.760
GER	45.393	50.952	2.437	9.758
FRA	35.316	36.530	2.489	10.753
SWI	22.309	25.926	2.634	10.741

Note: The whole sample runs from 4/1/2000 to 31/12/2011

Table 2: GPH estimates of parameter *d*

US	UK	GER	FRA	SWI
variance risk premium				
0.205	0.253	0.097	0.239	0.219
implied variance				
0.754	0.567	0.612	0.570	0.513
realized variance				
0.657	0.576	0.507	0.523	0.415

Note: The asymptotic standard error is equal to 0.088 and it is derived from the limiting distribution $\sqrt{m}\left(d_{T,m} - d\right) \rightarrow N(0, \pi^2 / 24)$, where the bandwith parameter m is set equal to the square root of the sample size. The limiting distribution was obtained by Robinson (1995a) in the presence of stationary data and by Velasco (1999) in the presence of non stationary data with $1/2 \leq d \prec 3/4$.

Table 3: Local Whittle estimates of parameter *d*

US	UK	GER	FRA	SWI
variance risk premium				
0.179	0.326	0.118	0.261	0.326
implied variance				
0.718	0.648	0.753	0.728	0.673
realized variance				
0.643	0.621	0.606	0.616	0.608

Note: Note: The asymptotic standard error is equal to 0.068 and it is derived from the limiting distribution $\sqrt{m}\left(d_{T,m} - d\right) \rightarrow N(0,1/4)$, where the bandwith parameter m is set equal to the square root of the sample size. The limiting distribution was has been derived by Robinson (1995b).

Figure 1: VP Spillover index; scale 1 (2-4 days time horizon)

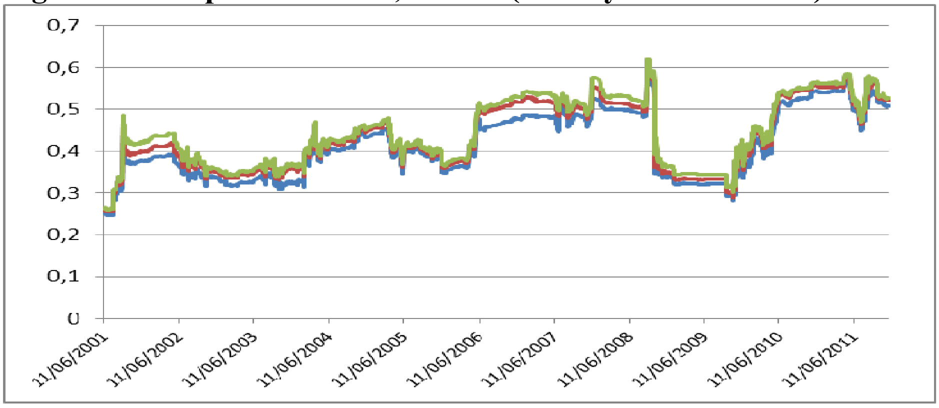

Figure 2: VP Spillover index; scale 2 (4-8 days time horizon)

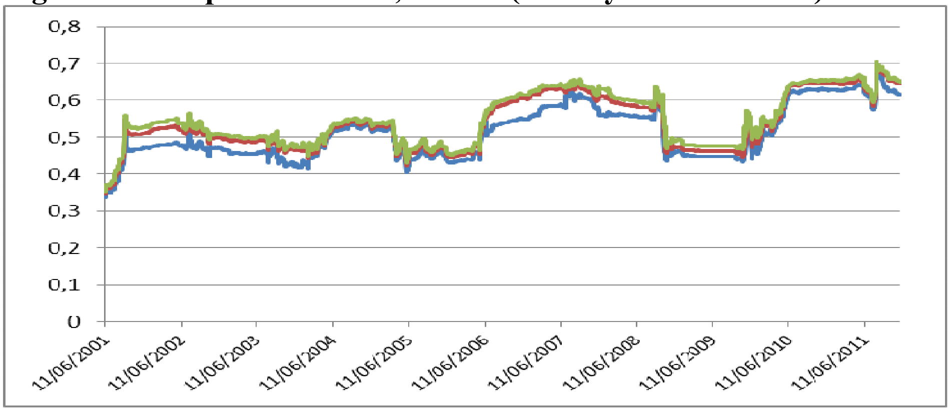

Figure 3: VP Spillover index; scale 3 (8-16 days time horizon)

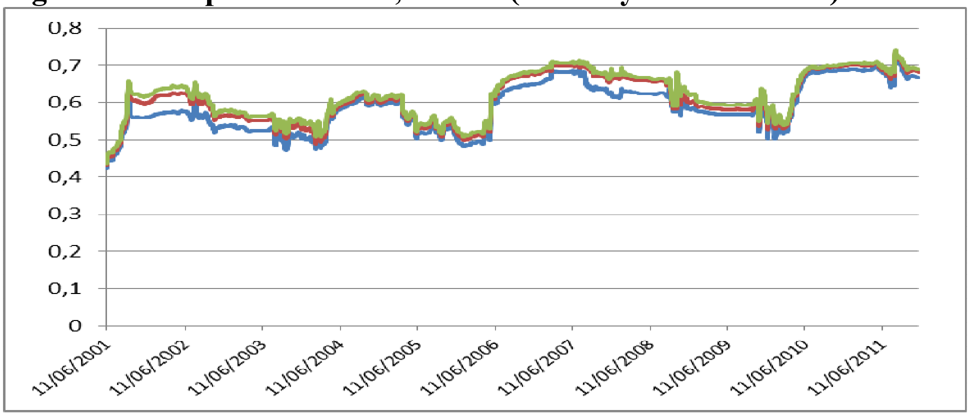

Figure 4: VP Spillover index; scale 4 (16-32 days time horizon)

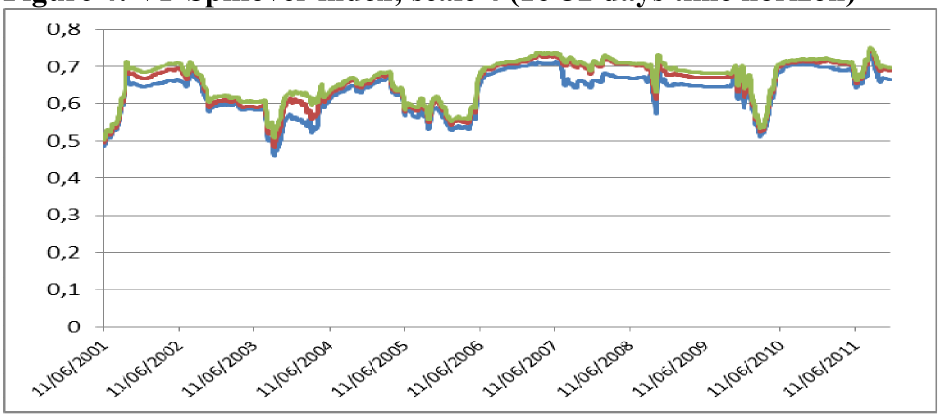

Figure 5: IV Spillover index; scale 1 (2-4 days investment time horizon)

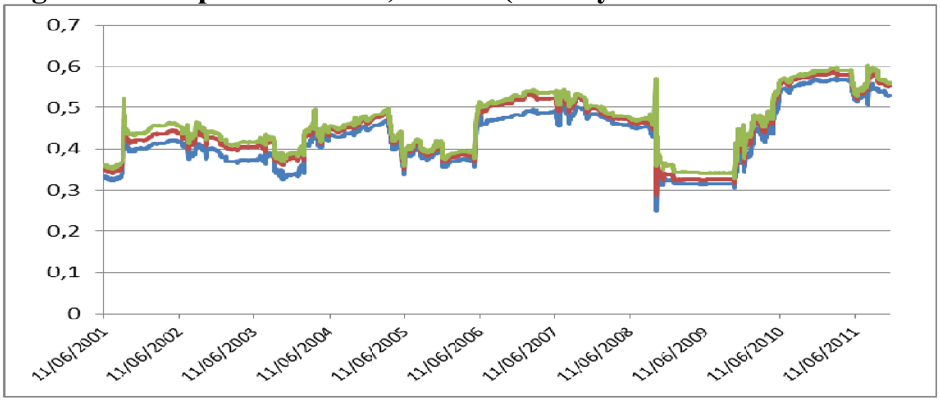

Figure 6: IV Spillover index; scale 2 (4-8 days investment time horizon)

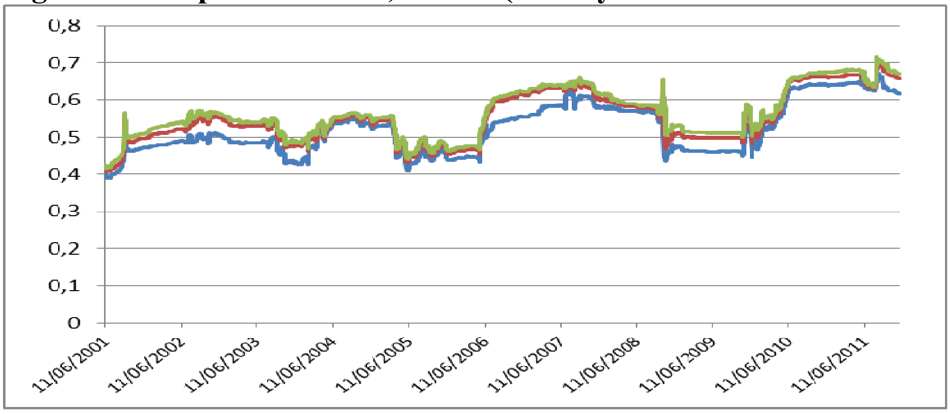

Figure 7: IV Spillover index; scale 3 (8-16 days investment time horizon)

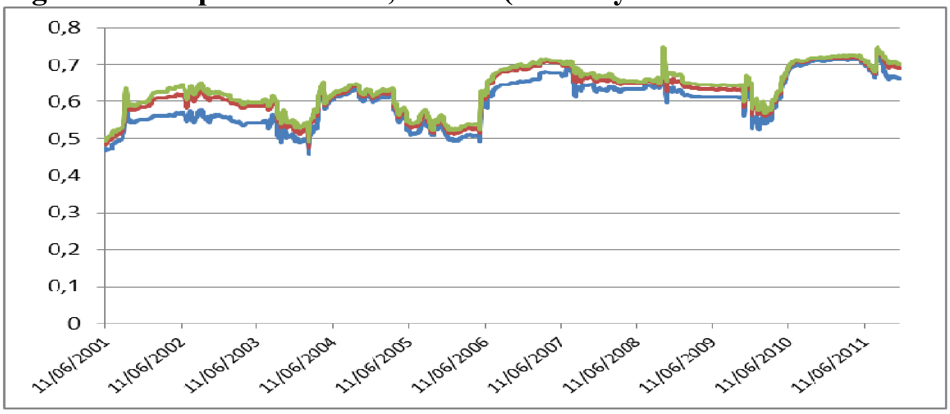

Figure 8: IV Spillover index; scale 4 (16-32 days investment time horizon)

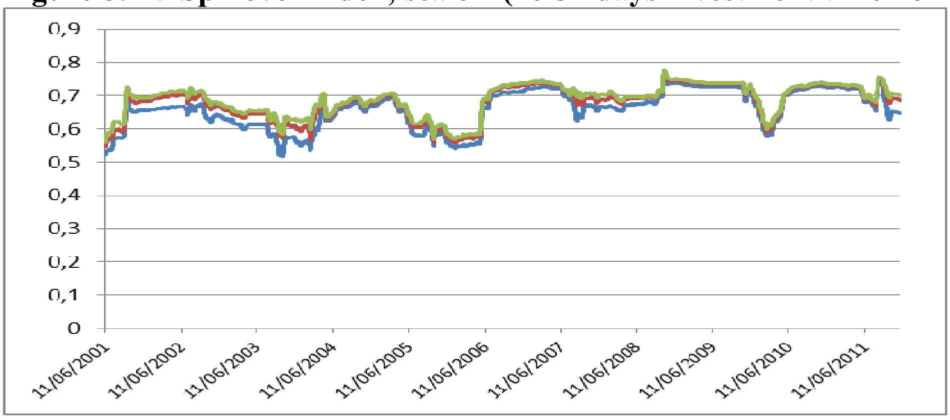

Figure 9: RV Spillover index; scale 1 (2-4 days investment time horizon)

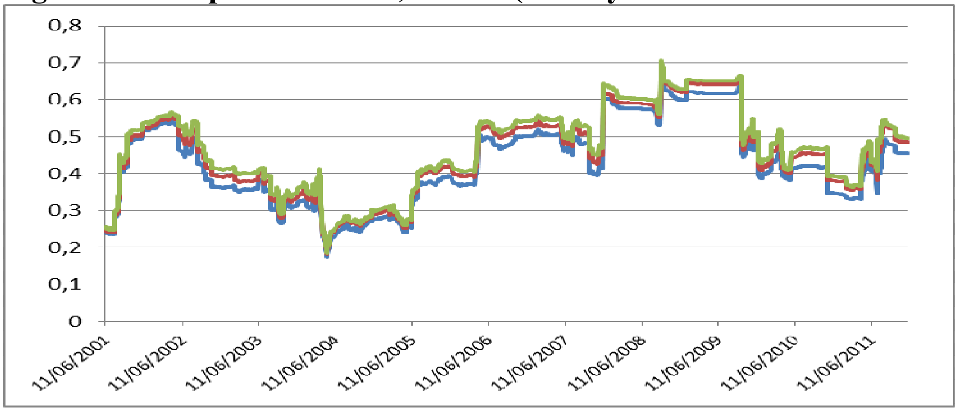

Figure 10: RV Spillover index; scale 2 (4-8 days investment time horizon)

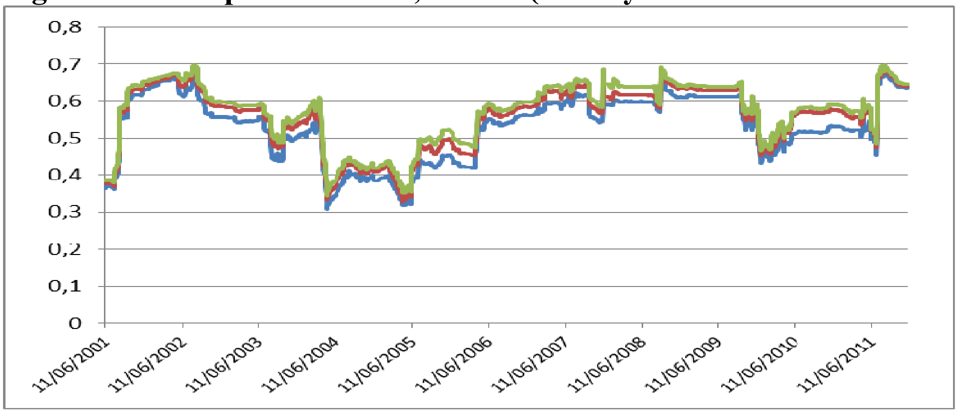

Figure 11: RV Spillover index; scale 3 (8-16 days investment time horizon)

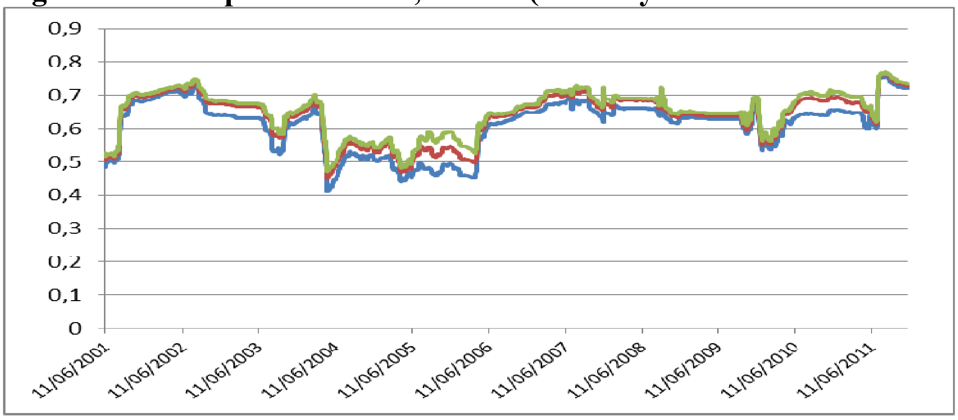

Figure 12: RV Spillover index; scale 4 (16-32 days investment time horizon)