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# Asymmetric semi-volatility spillover effects in EMU stock markets

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ABSTRACT

The aim of this paper is to quantify the strength and the direction of semi-volatility spillovers between five EMU stock markets over the 2000–2016 period. We use upside and downside semi-volatilities as proxies for downside risk and upside opportunities. In this way, we aim to complement the literature, which has focused mainly on the contemporaneous correlation between positive and negative returns, with the evidence of asymmetry also in semi-volatility transmission. For this purpose, we apply the Diebold and Yilmaz (2012) methodology, based on a generalized forecast error variance decomposition, to downside and upside realized semi-volatility series. While the analysis of Diebold and Yilmaz (2012) is based on a stationary VAR, we take into account the long-memory behaviour of the series, by using the multivariate extension of the HAR model (named VHAR model). Moreover, we cast light on how the choice of the normalization scheme can bias the net-spillover computation in a full sample as well as in a rolling sample analysis.

## 1. Introduction

In this paper we provide evidence of asymmetry in semi-volatility transmission by capturing the asymmetric behaviour of investors in relation to downside and upside risk. To this end, we adopt the framework developed by Diebold and Yilmaz (2012) in order to analyse global and directional connectedness among five EMU stock markets over the period 2000–2016.

Our contributions to the existing literature are as follows. First, while Diebold and Yilmaz's (2012) analysis is based on the generalized forecast error variance decomposition using a stationary VAR, we estimate the multivariate extension of the HAR model proposed by Corsi (2009), which is able to capture different stylized facts associated with volatility and its dynamics. The main features captured by this model are long-memory and heterogeneity. Long memory, i.e. the slow decline of the autocorrelation function, is one of the main features of volatility series and the HAR model is able to capture the high persistence by considering long lags with a parsimonious solution. Moreover, heterogeneity, i.e. the fact that low frequency volatility has a greater impact on subsequent high-frequency volatility than conversely (Corsi, 2009), is a specific feature of volatility dynamics and is captured by means of a model specification that includes a “cascade structure” of volatilities at different frequencies. These aspects are examined in depth in Section 3.1.

Second, we provide evidence of asymmetry in semi-volatility transmission. The fact that large negative returns are more closely correlated than large positive returns (Ang & Chen, 2002) is well known in financial markets. However, much of the literature focuses on contemporaneous correlation, and asymmetries in volatility transmissions have received little attention (with the exception of the study by Barunik, Kocenda, & Vacha, 2016, focusing on the US stock market). Thanks to the use of realized estimators based on high-frequency financial data, in this paper we are able to focus on downside and upside volatilities and as a result we can distinguish between downside risk (undesirable) and upside opportunities (desirable). Moreover, the use of estimators based on high-frequency financial data has been shown to be useful in improving the forecasting accuracy of reduced form volatility models: given the persistence in volatility, high frequency estimators provide a more accurate measure of current volatility, making their use valuable for forecasting purposes (Hansen and Lunde, 2011).

Finally, we advance the understanding of normalization schemes by comparing, in a rolling estimation framework, the directional connectedness indices obtained from the row-normalization scheme suggested by Diebold and Yilmaz (2012) with the scalar-based normalization scheme proposed by Caloia, Cipollini, and Muzzioli (2016).

The paper proceeds as follows. Section 2 describes the computation

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of semi-volatilities; Section 3 presents the HAR model and describes the Diebold and Yilmaz (2012) methodology. Sections 4 and 5 contain the results of the spillover analysis in full sample and in rolling regressions. Section 6 examines the normalization issue in depth. Section 7 concludes.

## 2. Stock market semi-volatilities

The focus of the paper is on stock market semi-volatilities. Given a continuous-time stochastic process for log-prices $p_t$,if this process is assumed to be Brownian semi-martingale then:

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s \tag{1}$$

where $\mu_s$ is a drift process, $\sigma_s$ is a cadlàg process and $W$ is a Brownian motion. The quadratic variation (QV) of this stochastic process is given by:

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds \tag{2}$$

The integrated variance $\sigma^*(t) = [p_t, p_t]$ describes the ex-post variation of the stochastic process, but the main characteristic of volatility is that it is latent, so given a (complete or incomplete) information set the "true" volatility can only be proxied with some degree of error. Even if the underlying stochastic process can be thought of as a continuous-time process, volatility forecast and measurement are restricted to non-trivial discrete time intervals.

Barndorff-Nielsen and Shephard (2002) proposes to use the high-frequency based realized variance ($RV$) estimator, i.e. the sum of intraday squared returns, to proxy the quadratic variation of the stochastic process. If there are $M$ intraday (equally-spaced) observations and the sampling interval is $h = 1/M$, the daily realized variance estimator can be defined as:

$$RV = \sum_{i=1}^{M} r_i^2 \tag{3}$$

Where $r_i$ denotes intraday returns. Barndorff-Nielsen and Shephard (2002) shows that as $M \to \infty$ the realized variance estimator converges to the integrated variance, formally:

$$RV_i \overset{p}{\to} \sigma_i^2 \tag{4}$$

To capture the asymmetric behaviour of the stochastic process, Barndorff-Nielsen, Kinnebrock, and Shephard (2010) shows that nothing is lost in decomposing the RV estimator into its downside and upside semi-variance component. In fact:

$$RV = RV^- + RV^+ \tag{5}$$

and:

$$RV^- = \sum_{i=1}^{M} r_i^2 \, I(r_i < 0) \overset{p}{\to} \frac{1}{2}\int_0^t \sigma_s^2 \, ds \tag{6}$$

$$RV^+ = \sum_{i=1}^{M} r_i^2 \, I(r_i \geq 0) \overset{p}{\to} \frac{1}{2}\int_0^t \sigma_s^2 \, ds \tag{7}$$

The semi-volatility estimators are then obtained by applying the square root to the semi-variance estimators: they capture the variation due to negative and positive returns and they can be considered to be measures of downside risk and upside opportunity. In this paper, we also use the semi-volatility decomposition of the $RV$ estimator in order to ascertain whether volatility and volatility transmission exhibit a certain degree of asymmetry. The asymmetric relation between volatility and returns is a well-known stylized fact in financial markets: when prices fall, volatility increases, but when prices rise, volatility decreases to a lesser extent. In this sense, downside semi-volatility is expected to be higher than (or, at least, equal) to upside semi-volatility.

We study semi-volatility spillover effects among five European stock indices: the Dax 30 performance index, Cac 40 index, Ftse Mib index, Ibex 35 index and Aex index. The daily semi-volatility series (based on high-frequency five-minute returns) span from 2000 to 2016 and are available from the Oxford-Man Realized library. Since the distribution of variance and semi-variance series is not Gaussian, following Andersen, Bollerslev, Diebold, and Labys (2003) we choose to focus on their log-transformation to obtain approximately Gaussian measures. The transformation adopted is obtained as follows:

$$v_t^+ = \frac{1}{2}\log(RV_t^+) \quad ; \quad v_t^- = \frac{1}{2}\log(RV_t^-) \tag{8}$$

Fig. 1 shows the total volatilities as well as downside and upside semi-volatilities for the five European stock indices over the period 2000–2016. We observe that, for both types of semi-volatility, the major peaks emerge in the 2000–2002, 2008–2010 and 2010–2012 subperiods, corresponding to the "dot.com bubble" burst, the "subprime" crisis and the "sovereign debt" crisis. The latter crises were characterized by irrational responses on the part of investors such as panic and herding behaviour, and, as a result, investor reactions were strong following both good and bad news. However, we observe that the major variations correspond to falling stock prices. Tables 1 to 3 report some descriptive statistics for the log transformation of the volatility series, showing that they are approximately Gaussian, with no skewness or kurtosis.

## 3. Empirical methodology

In this section we briefly describe the empirical methodology adopted in the study, based on the HAR model (Subsection 3.1) used in the Diebold and Yilmaz (2012) (Subsection 3.2) framework.

### 3.1. The VHAR model

In order to model the volatility dynamics, we employ the multivariate extension of the HAR model (named VHAR).[1] Although VHAR does not belong to the class of long-memory models, it is able to reproduce the long-memory feature of volatility series by considering the information contained in many lags in a parsimonious way. Long-memory behaviour could also be captured by increasing the VAR order, but the dimensionality problem would be serious even for large sample sizes, so VHAR can be considered as a parsimonious version of a VAR(p) model able to embed more information without increasing the number of parameters to be estimated. Another important stylized fact captured by the VHAR model is the heterogeneous transmission of volatility, since low-frequency volatility has greater explanatory power on subsequent high-frequency volatility than conversely. This feature is taken into account by assuming a hierarchical process in which partial volatilities depend on past partial volatilities, in a cascade structure. In particular, daily, weekly and monthly volatilities are defined as:

$$\hat{\sigma}_{t+1}^{(m)} = c + \phi^{(m)} RV_t^{(m)} + \varepsilon_t \tag{9}$$

$$\hat{\sigma}_{t+1}^{(w)} = c + \phi^{(w)} RV_t^{(w)} + E_t[\hat{\sigma}_{t+1}^{(m)}] + \varepsilon_t \tag{10}$$

$$\hat{\sigma}_{t+1}^{(d)} = c + \phi^{(d)} RV_t^{(d)} + E_t[\hat{\sigma}_{t+1}^{(w)}] + \varepsilon_t \tag{11}$$

where $RV$ are three $(K \times 1)$ vectors of monthly, weekly and daily realized semi-volatilities and $\phi$ are $(K \times K)$ coefficient matrices. Using recursive substitution we obtain:

$$\hat{\sigma}_{t+1}^{(d)} = c + \phi^{(d)} RV_t^{(d)} + \phi^{(w)} RV_t^{(w)} + \phi^{(m)} RV_t^{(m)} + \varepsilon_t \tag{12}$$

Finally, the VHAR model can be formulated as follows:

$$\hat{\sigma}_t^{(d)} = c + \phi^{(d)} RV_{t-1}^{(d)} + \phi^{(w)} RV_{t-1}^{(w)} + \phi^{(m)} RV_{t-1}^{(m)} + \varepsilon_t \tag{13}$$

where $RV_t^{(w)} = \frac{1}{5}(\sum_{i=0}^{4} RV_{t-i})$ and $RV_t^{(m)} = \frac{1}{22}(\sum_{i=0}^{21} RV_{t-i})$.

[1] Similar multivariate extensions to the HAR model have been proposed by Bubàk, Kocenda, and Zikes (2011), Cubadda, Guardabascio, and Hecq (2017) and Patton and Sheppard (2013).