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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 μ_s is a drift process, σ_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:

$$RV_i \xrightarrow{p} \sigma_i^2 \tag{4}$$

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:

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

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

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 ϕ 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).

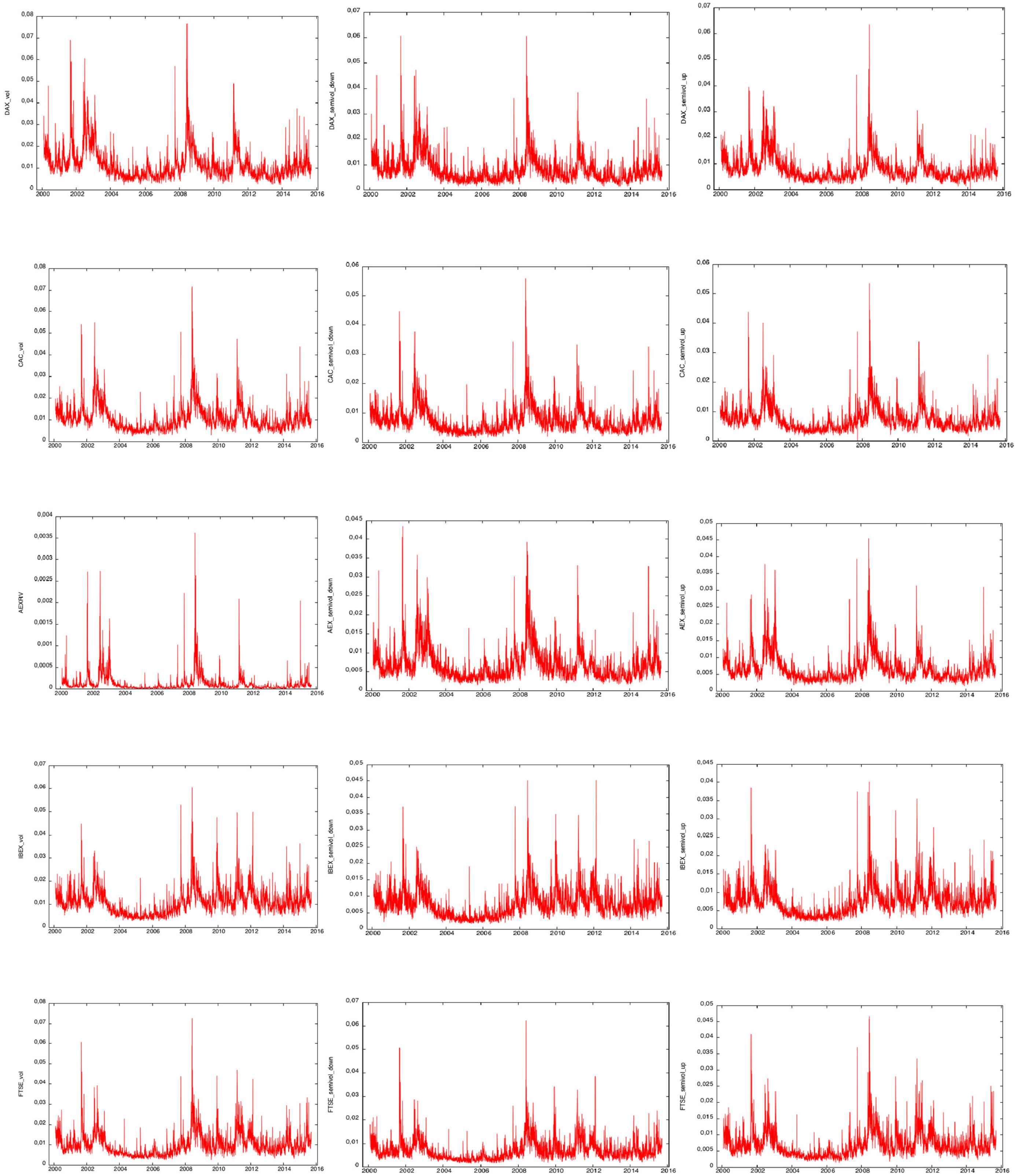

Fig. 1. Volatility (left), downside semi-volatility (middle) and upside semi-volatility (right) of the Dax index, Cac 40 index, Aex index, Ibex 35 index and Ftse Mib index.

While in the original HAR model every partial volatility has an AR (1) structure, in its multivariate setting, every partial volatility has a VAR(1) structure. Following Fengler and Gisler (2015), we reformulate the VHAR model as a restricted VAR(22) model:

$$x_t = \sum_{i=1}^{22} \beta_i x_{t-i} + \varepsilon_t \tag{14}$$

where the coefficients β's are subject to the following constraints:

Table 1
Descriptive statistics: log downside semi-volatility.

	Mean	Std. dev.	Max	Min	Skewness	Kurtosis
Dax	−4.96	0.553	−2.80	−6.49	0.29	0.02
Cac 40	−5.02	0.507	−2.88	−6.47	0.28	0.05
Aex	−5.12	0.529	−3.13	−6.52	0.42	0.02
Ibex 35	−4.98	0.517	−3.09	−6.41	−0.07	−0.16
Ftse Mib	−5.08	0.528	−2.77	−6.49	0.20	−0.09

Table 2
Descriptive statistics: log upside semi-volatility.

	Mean	Std. dev.	Max	Min	Skewness	Kurtosis
Dax	−4.95	0.506	−2.75	−6.61	0.40	0.30
Cac 40	−5.02	0.475	−2.92	−6.42	0.36	0.22
Aex	−5.12	0.494	−3.08	−6.45	0.53	0.24
Ibex 35	−4.98	0.484	−3.21	−6.25	−0.02	−0.14
Ftse Mib	−5.08	0.495	−3.06	−6.53	0.32	−0.07

Table 3
Descriptive statistics: log total volatility.

	Mean	Std. dev.	Max	Min	Skewness	Kurtosis
Dax	−9.17	0.509	−5.13	−12.19	0.35	0.16
Cac 40	−9.31	0.474	−5.27	−11.99	0.34	0.17
Aex	−9.52	0.496	−5.62	−12.20	0.50	0.14
Ibex 35	−9.23	0.482	−5.61	−11.76	−0.06	−0.16
Ftse Mib	−9.42	0.474	−5.24	−11.90	0.28	−0.03

$$\beta_i = \begin{cases} \phi^{(d)} + \frac{1}{5}\phi^{(w)} + \frac{1}{22}\phi^{(m)} & \text{for } i = 1 \\ \frac{1}{5}\phi^{(w)} + \frac{1}{22}\phi^{(m)} & \text{for } i = 2, \dots, 5 \\ \frac{1}{22}\phi^{(m)} & \text{for } i = 6, \dots, 22 \end{cases} \tag{15}$$

and the ϕ's are obtained from the estimation of the model given by Eq. (13).

3.2. Diebold and Yilmaz's (2012) methodology

Following Diebold and Yilmaz (2012), volatility spillovers are based on a forecast error variance decomposition computed on a generalized impulse-response. In order to describe the effects of shocks over time on the future expected values of the endogenous variables, the generalized impulse response function by Koop, Pesaran, and Potter (1996) is given by the difference between the expected value of the endogenous variables (conditional to a shock hitting the variables at time t) and their unconditional expected value, and it can be formulated as follows:

$$G.\,I.\,(h, \delta, \Omega_{t-1}) = E(x_{t+h} \mid \varepsilon_t = \delta, \Omega_{t-1}) - E(x_{t+h} \mid \Omega_{t-1}) = A_h \delta \tag{17}$$

where h is the forecast horizon. The impulse responses are independent of the information set Ω_{t-1}, but depend on the dynamics $A(L)$ and on the compositions of shocks defined by the vector δ.

As an initial step, in order to capture the responses to a shock, we reformulate our constrained VAR(22) in its state space representation, as a large scale VAR(1):

$$z_t = Az_{t-1} + \varepsilon_t \tag{18}$$

where $z_t = D(L)y_t$ and A is the $(Kp \times Kp)$ companion matrix, the first K rows of which contain the coefficient matrices of the constrained VAR (22).

Then we obtain the H step ahead impulse responses by exploiting the following relations:

$$\Pi = e' A^{(H)} e \tag{19}$$

where:

$$A^{(H)} = \prod_{h=1}^{H-1} A \tag{20}$$

where $A_0 = I_N$ and $e = |I_K \;\; 0_K \;\; \dots \;\; 0_K|$ is a $(K \times Kp)$ selection matrix. For every given forecast horizon $h = 1, \dots, H$ the Π matrix contains the inverted AR components. While the traditional approach uses the Cholesky decomposition of the variance-covariance matrix of the residuals to obtain orthogonal shocks, the "generalized approach" usually considers the historical distribution of the errors, thus allowing the shocks to be correlated. Since the log-volatility series are nearly Gaussian, following Pesaran and Shin (1998) we use the closed-form formula for the decomposition of the system variance. As a result, the generalized forecast error variance decomposition for the forecast horizon H is given by:

$$\theta_{ij}^{g} = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} e_i' A_h \Sigma A_h e_i} \qquad i, j = 1, \dots, N \tag{21}$$

where $\theta_{ij}{}^{g}$ denotes the fraction of the H-step ahead forecast error variance of x_i due to shocks to x_j for $i, j = 1, \dots, N$. When $i \neq j$ the contribution to the forecast error variance is named cross-variance share or simply spillover. The generalized forecast error variance decomposition is the most commonly used in the literature, since the traditional approach achieves orthogonality by means of Cholesky factorization and the resulting variance decompositions are sensitive to variable ordering. In the traditional approach, the orthogonality of the shocks makes the sum of the contributions equal to one. In the generalized approach, however, since the covariance between the shocks δ_i is nonzero, the sum of all the contributions is not (necessarily) equal to 1. Diebold and Yilmaz (2012) suggest normalizing the entries of the variance decomposition table to make it row-stochastic.

Unlike Diebold and Yilmaz (2012), we choose to normalize the entries of the variance decomposition by a scalar factor. The total spillover index is obtained by taking the ratio of total cross-variance shares over the total (own and cross) variance shares, formally:

$$T.\,S.\,I.^{g}\,(H) = \left(\frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \theta_{ij}^{g}}{\sum_{i,j=1}^{K} \theta_{ij}^{g}} \right) * 100 \tag{22}$$

The total spillover index is a proxy for the system overall connectedness. The directional spillovers, i.e. the spillovers received and transmitted by each single market, are defined as follows. The directional spillover received by market i from all the other markets j (named FROM others) is obtained as:

$$DS^{g}_{\cdot\to}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{K} \theta_{ij}^{g}}{\sum_{j=1}^{K} \theta_{ij}^{g}} \tag{23}$$

while the directional spillover transmitted by market i to all the other markets j (named TO others) is:

$$DS^{g}_{\to\cdot}(H) = \frac{\sum_{\substack{i=1 \\ i \neq j}}^{K} \theta_{ij}^{g}}{\sum_{i=1}^{K} \theta_{ij}^{g}} \tag{24}$$

Finally, we derive a measure of net contribution (NET) for every market i for the forecast horizon H by subtracting the gross volatility transmitted and the gross volatility received as:

$$NET_i^{\cdot}(H) = DS^{g}_{\to\cdot}(H) - DS^{g}_{\cdot\to}(H) \tag{25}$$

A positive value of the NET spillover measure means that the market i has been, on average, a net donor in terms of volatility transmission, while a negative sign of the NET spillover indicates that the market has been a net receiver. Note that, as we choose not to normalize the values of the variance decompositions, the only spillover measures that are equal to the ones computed in the framework suggested by Diebold and Yilmaz (2012) are the TOTAL spillover index and the FROM directional spillover. On the contrary, the spillover transmitted has a different value from the one in row-normalization, and, as a result, also the measure of NET contribution will be different. We present a comparison of the two different normalization schemes in Section 6. Following our previous work (Caloia et al., 2016) the decision not to normalize the entries of the variance decomposition table by row was taken for the following reasons:

– Diebold and Yilmaz (2012) state that as an alternative to row-normalization, it is possible to normalize by column and compare the results, though directional spillovers values are not robust to this choice.
– Row (column) normalization means respecting the order of magnitude of the entries of the variance decomposition table only by row (by column). As a result, the NET spillovers obtained from Eq. (25) are the result of the subtraction of two incomparable values. Because of this, the NET spillovers may have the wrong ranking and the opposite sign (as shown in Caloia et al., 2016, this effect holds for series characterized by various degrees of correlation and persistence).
– The scalar-factor normalization allows us to obtain scaled (and therefore more comparable) spillover measures while preserving the ranking and the sign of the net spillovers.

4. Empirical evidence: Full sample analysis

In this section we present the results obtained from the full sample analysis. The spillovers obtained are based on the generalized forecast error variance decomposition computed on the estimate of the VAR(22) model subject to restrictions on the parameter estimates as defined by the VHAR model.

Full sample analysis results are reported in Tables 4 and 5 for downside and upside semi-volatilities respectively, referring to the forecast horizons $H = 5$ (Panel I), $H = 10$ (Panel II) and $H = 22$ (Panel III).

More specifically, Tables 4 and 5 are connectedness tables, where the pairwise spillovers are reported along with the measures of vulnerability of one market to system-wide shocks (e.g. the FROM indices) and of the contribution of one market to systemic risk (e.g. the TO indices). While in Table 5 it can be seen that the full sample results for the upside log-semi-volatility series show that the net contributions of all markets (except France with a slightly positive sign) are about zero, (since the index FROM nearly matches the index TO), the full sample results for the downside log-semi-volatility series paint a different picture. Germany is the largest net donor, given that the NET index is equal to 0.072 for the 5-day forecast horizon increasing to 0.090 and 0.085 for the 10-day and 22-day forecast horizon, respectively. Italy and Spain are net receivers and the Italian stock market is the largest net receiver given that the NET index is equal to −0.104 for the 5-day forecast horizon increasing to −0.117 and − 0.116 for the 10-day and 22-day forecast horizon, respectively. By examining the signs of the NET spillovers reported in Tables 4 and 5, we see that the asymmetries in volatility transmission emerge strongly in the full sample set-up: the role of Spain and Italy (net receiver markets) as well as of France and the Netherlands (net donor markets) does not change with the semi-volatility measure, whereas on the other hand, Germany is on average a net donor of downside semi-volatility spillovers and a net receiver of upside semi-volatility spillovers. In other words, Spain and Italy (France

Table 4
Spillover table for downside semi-volatility.

	GER	FRA	NED	SPA	ITA	FROM others + own	FROM others	FROM others %
Panel I: H = 5								
GER	0.250	0.192	0.174	0.147	0.147	0.911	0.661	72.58%
FRA	0.193	0.238	0.203	0.179	0.187	1	0.762	76.18%
NED	0.183	0.204	0.242	0.149	0.153	0.930	0.688	73.99%
SPA	0.173	0.198	0.182	0.228	0.173	0.955	0.727	76.11%
ITA	0.183	0.204	0.193	0.184	0.225	0.989	0.764	77.23%
TO others + own	0.982	1.036	0.994	0.887	0.885			
TO others	0.733	0.798	0.752	0.659	0.660			TOTAL
TO others %	74.5%	77.02%	75.67%	74.28%	74.55%			75.2%
NET	0.072	0.036	0.064	−0.068	−0.104			
Panel II: H = 10								
GER	0.245	0.190	0.173	0.145	0.146	0.899	0.654	72.74%
FRA	0.191	0.234	0.200	0.177	0.184	0.986	0.752	76.26%
NED	0.186	0.205	0.224	0.163	0.165	0.942	0.718	76.24%
SPA	0.178	0.201	0.186	0.213	0.173	0.951	0.738	77.58%
ITA	0.189	0.209	0.198	0.189	0.215	1	0.785	78.53%
TO others + own	0.989	1.039	0.982	0.886	0.883			
TO others	0.744	0.805	0.758	0.673	0.668			TOTAL
TO others %	75.2%	77.46%	77.20%	75.94%	75.68%			76.3%
NET	0.090	0.053	0.039	−0.065	−0.117			
Panel III: H = 22								
GER	0.245	0.191	0.174	0.145	0.146	0.902	0.657	72.82%
FRA	0.192	0.235	0.201	0.177	0.183	0.988	0.754	76.26%
NED	0.184	0.203	0.220	0.164	0.167	0.938	0.718	76.57%
SPA	0.177	0.199	0.184	0.213	0.172	0.946	0.733	77.48%
ITA	0.189	0.209	0.198	0.189	0.215	1	0.785	78.50%
TO others + own	0.987	1.037	0.978	0.888	0.884			
TO others	0.742	0.803	0.758	0.675	0.669			TOTAL
TO others %	75.1%	77.38%	77.51%	76.01%	75.68%			76.3%
NET	0.085	0.049	0.040	−0.058	−0.116			

Note: The generalized forecast error variance decomposition is normalized by the maximum row sum. The directional spillover received (FROM others) is the off-diagonal row sum of the VDT, the directional spillover transmitted (TO others) is the off-diagonal column sum, the net contribution measure (NET) is the difference between the directional spillovers TO and FROM. The total spillover index (TOTAL) is obtained as the average of the directional spillover received. The column FROM others + own and the row TO others + own correspond to the row sum and the column sum of the elements of the forecast error variance decomposition, respectively. The column FROM others % shows the ratio between FROM others and FROM others including own. The row TO others % shows the ratio between TO others and TO others including own. Panel I is for the forecast horizon 5-day, Panel II for the forecast horizon 10-day and Panel III for the forecast horizon 22-day.

Table 5
Spillover Table for upside semi-volatility.

	GER	FRA	NED	SPA	ITA	FROM others + own	FROM others	FROM others %
Panel I: H = 5								
GER	0.202	0.199	0.198	0.196	0.195	0.991	0.789	79.58%
FRA	0.194	0.205	0.200	0.196	0.196	0.991	0.787	79.33%
NED	0.198	0.202	0.204	0.198	0.198	1	0.796	79.64%
SPA	0.195	0.200	0.199	0.203	0.198	0.995	0.792	79.56%
ITA	0.195	0.200	0.200	0.199	0.203	0.997	0.794	79.63%
TO others + own	0.984	1.007	1.000	0.993	0.990			
TO others	0.781	0.802	0.797	0.790	0.787			TOTAL
TO others %	79.43%	79.65%	79.65%	79.51%	79.50%			79.5%
NET	−0.007	0.015	0.000	−0.002	−0.006			
Panel II: H = 10								
GER	0.202	0.199	0.198	0.196	0.195	0.990	0.787	79.57%
FRA	0.195	0.205	0.200	0.196	0.196	0.991	0.787	79.34%
NED	0.198	0.202	0.203	0.199	0.198	1	0.797	79.65%
SPA	0.194	0.200	0.199	0.203	0.197	0.994	0.791	79.56%
ITA	0.195	0.200	0.200	0.199	0.203	0.996	0.793	79.63%
TO others + own	0.983	1.006	1.000	0.992	0.989			
TO others	0.781	0.801	0.796	0.789	0.787			TOTAL
TO others %	79.43%	79.65%	79.65%	79.53%	79.49%			79.6%
NET	−0.006	0.015	0.000	−0.001	−0.007			
Panel III: H = 22								
GER	0.202	0.199	0.198	0.195	0.195	0.989	0.787	79.54%
FRA	0.195	0.205	0.200	0.197	0.197	0.995	0.790	79.43%
NED	0.198	0.202	0.203	0.199	0.198	1	0.797	79.65%
SPA	0.194	0.200	0.199	0.203	0.197	0.993	0.790	79.57%
ITA	0.194	0.200	0.200	0.199	0.203	0.996	0.793	79.62%
TO others + own	0.984	1.006	1.000	0.993	0.990			
TO others	0.782	0.801	0.797	0.790	0.787			Total
TO others %	79.44%	79.65%	79.66%	79.56%	79.49%			79.6%
NET	−0.005	0.011	0.000	0.000	−0.006			

Note: See note to Table 4.

and the Netherlands) are net receivers (donors) of both downside risk and upside opportunities, while Germany is a net donor of downside risk and a net receiver of upside opportunities.

5. Empirical evidence: Rolling sample analysis

In this section we present the results obtained from the rolling sample analysis, based on a moving window of 1000 observations. The focus of this section is on the NET spillover measures, in order to identify how the role of each market changed over time. Moreover, we focus on the asymmetry of the NET spillovers to see the different impact of positive and negative returns on the linkages between the various markets. Figs. 2 and 3 report the net spillover plots for downside and upside log-semi-volatility series, respectively, for the 5-day, 10-day and 22-day forecast horizons. We can observe that France displays a positive net contribution in terms of risk transmission for both downside and upside semi-volatilities throughout the sample. In particular, for the downside semi-volatility, there is a downward trend in the last part of the sample starting in early 2012, offsetting the upward trend occurring between 2008 and 2011. The upside semi-volatility of France displays a similar pattern as the one of the downside semi volatility in the first part of the sample, especially if we refer to the fall of the NET index from 2006 to early 2008 and to the rebound which occurs immediately thereafter until early 2009. Although in the first part of the sample the German net spillover index is negative both for downside and upside semi volatility, after early 2008 Germany increasingly becomes a net donor especially for downside semi volatility. Although Italy and Spain are net receivers of downside semi volatility, both markets show an upward trend in terms of the net contribution in the last part of the sample starting from 2013. Similarly, Italy and Spain are net receivers of upside semi volatility, and especially Spain shows a downward trend in terms of net contribution throughout the sample. Finally, the NET spillover index for the Netherlands changes from positive to negative from 2012 for the upside and from 2013 for the downside semi volatilities until the end of the sample. In summary, the results show that first there is considerable time variation in the role of each country in risk transmission towards the other EMU countries considered. In some cases, the role of a market confirms and becomes predominant (France) while in other cases, we observe that as time goes by the role of a market changes (Germany, Spain). Second, although the time-varying patterns of the downside and upside NET indexes are similar and highly correlated, we observe that in specific market periods asymmetries emerge and one particular market can at the same time transmit downside volatility and receive upside volatility or vice versa. Finally, we observe that the role of each country tends to be clearer during tranquil periods, while during the crisis we observe that the role is almost null for all the markets, meaning that positive or negative innovations in each country suddenly transmit to all the others, regardless of the specific market affected.

6. Normalization schemes

In this section we show, in a rolling regression framework, the impact of the row-normalization scheme suggested by Diebold and Yilmaz (2012) on NET spillovers. The row-normalization scheme is widely used in the literature aimed at detecting spillovers through the generalized forecast error variance decomposition. In our previous work (Caloia et al., 2016) we showed, by means of simulated data characterized by different degrees of persistence and correlation, that the row-normalization scheme (as well as the equivalent column normalization scheme) produces errors in the ranking and the sign of the NET spillovers.

In this section, we confirm the findings of Caloia et al., 2016 showing how the errors in sign persist over time in a rolling regression

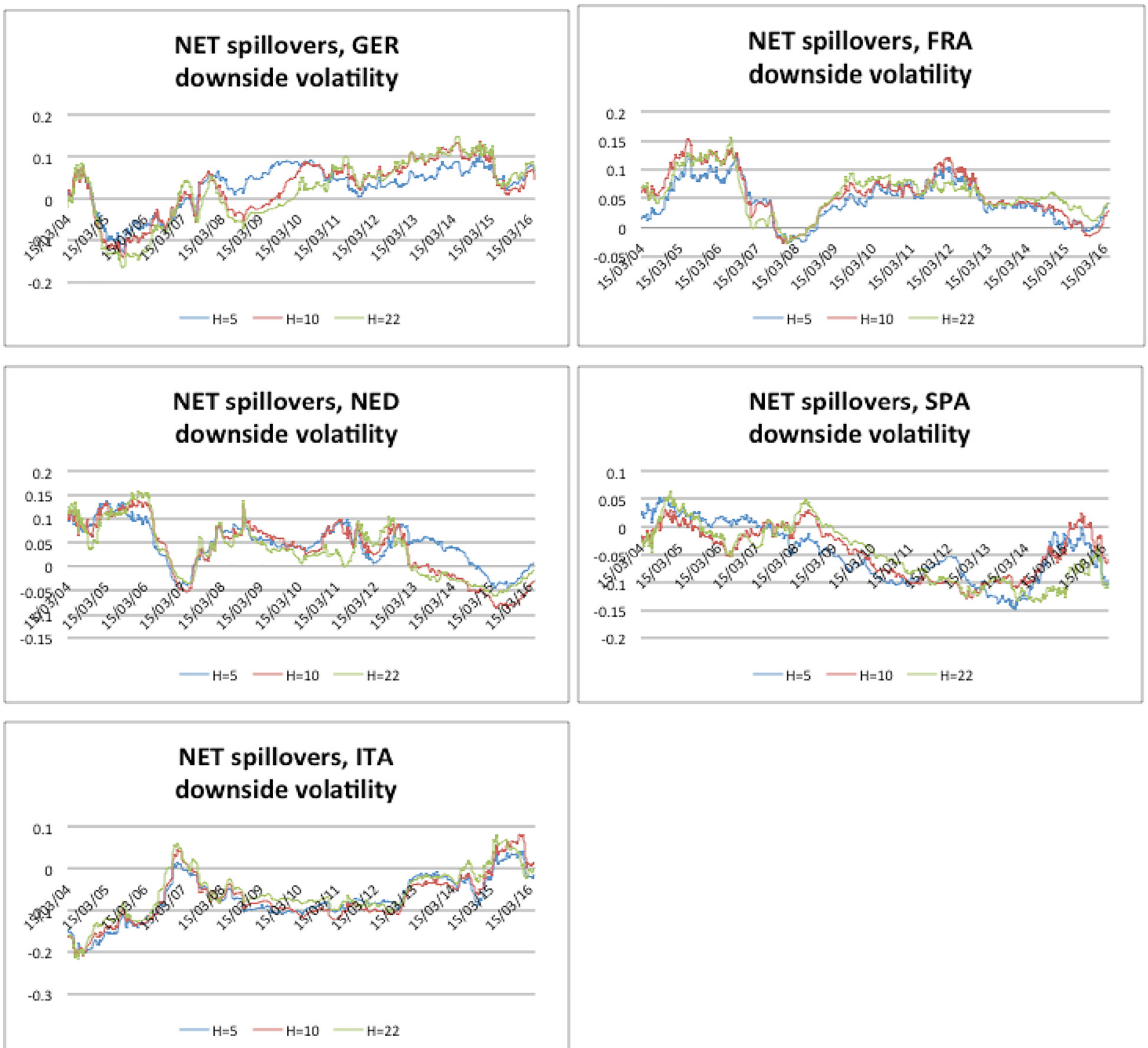

Fig. 2. Net spillovers, downside semi-volatility.
Note: the plots display the measures of net contribution (NET spillovers) obtained from rolling regressions for the five EMU countries over the period 2004–2016 for different forecast horizons: H = 5 (blue line), H = 10 (red line) and H = 22 (green line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

framework. In Fig. 4 we compare, for the case of the Netherlands,[2] the NET spillovers obtained from a variance decomposition table normalized by row as in Diebold and Yilmaz (2012) and the NET spillovers obtained from a variance decomposition table scalar normalized, for the three forecast horizons. Scaling the VDT values make the comparison of the spillovers easier and, at the same time, preserves the ranking and the sign of the NET spillover measures defined by the non-normalized VDT (Caloia et al. (2016)). In this example the scalar normalization factor was set equal to the maximum row sum. In Fig. 4 we observe numerous differences in the sign of the NET spillovers under the two normalization schemes: in many cases the row-normalized NET measure states that the market under investigation is currently a net donor in terms of semi-volatility spillover while the scalar normalized NET spillover states the opposite. One clear example is the upside semi-volatility NET spillover for the Netherlands: for H = 5, for almost the entire 2012–2016 period, this market was a net receiver of upside semi-volatility, but the row-normalized NET spillover detects a positive net contribution, i.e. this normalization scheme misconceives the Netherlands as a net donor market.

In order to further investigate the frequency of errors in sign for the five countries, we report in Table 6 the total number of errors in sign (i.e. the number of errors in the NET spillovers due to row-normalization) for the 5-day, 10-day and 22-day forecast horizons. For each forecast horizon, the total number of possible errors for each single market is 3049 ($N - w$,where w is the moving window of 1000 observations). For $H = 10$ the row-normalized downside semi-volatility NET spillovers amount to a total of 1705 sign errors, while the corresponding number of errors for the upside semi-volatility series is 2634. For the downside log-volatility series, the number of sign errors seems to grow with the length of the forecast horizon: for $H = 5$ there are 1708 sign errors and for $H = 22$ there are 1798 sign errors. For the upside volatility series, the number of errors are 2304 for the one-week forecast horizon and 1734 for the one-month forecast horizon.

The highest number of errors is 2634 (upside semi-volatility

[2] Similar pictures are obtained for the other four countries under investigation and are available upon request.

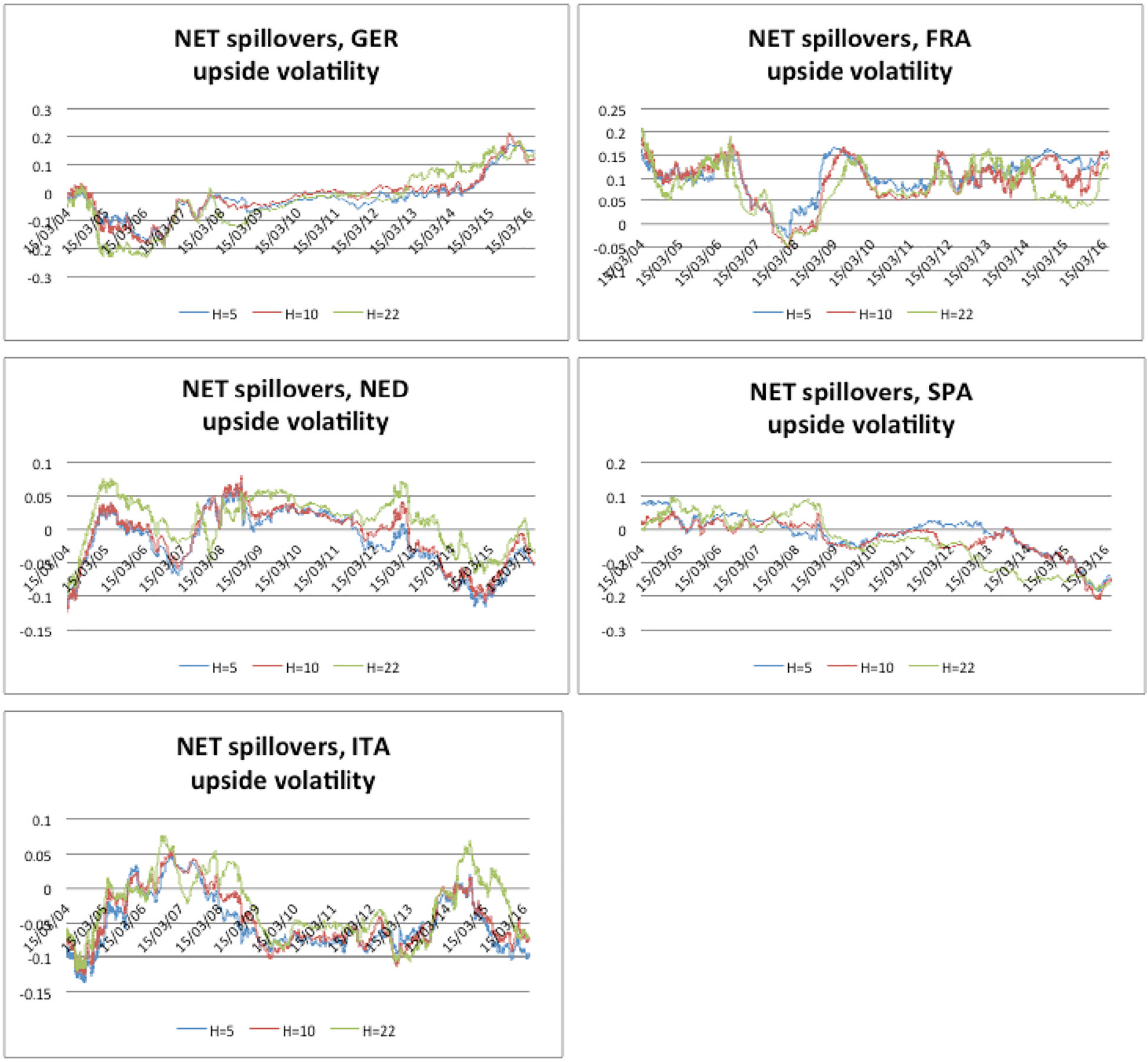

Fig. 3. Net spillovers, upside semi-volatility.
Note: the plots display the measures of net contribution (NET spillovers) obtained from rolling regressions for the five EMU countries over the period 2004–2016 for different forecast horizons: H = 5 (blue line), H = 10 (red line) and H = 22 (green line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

H = 10) while the lowest number of errors is 1705 (downside semi-volatility, H = 10), meaning that in our experiment the total number of errors is at least 11% and not > 17% of the total number of observations. The market for which net spillovers are misconceived the most is the Netherlands for the upside volatility series: in fact for the one-week and two-week horizons the row-normalization produces > 1000 sign errors out of a total of 3049.

7. Concluding remarks

The focus of this paper was on the asymmetry in risk transmission between five major EMU stock markets: Germany, France, the Netherlands, Italy and Spain. In order to provide evidence of asymmetry in volatility transmission, we used upside and downside semi-volatilities as proxies for upside opportunities and downside risk. Semi-volatility transmission was investigated in the Diebold and Yilmaz (2012) framework (see also Barunik et al., 2016 focusing on the US stock market). While Diebold and Yilmaz's (2012) analysis was based on a stationary VAR, we computed the generalized forecast error variance decomposition using a VHAR model in order to account for the high persistence of the semi-volatility data and its heterogeneous transmission.

We provided evidence of asymmetry in risk transmission by means of a comparison of the results (net spillovers) obtained from downside and upside semi-volatility series. We found that, over the 2000–2016 period, France and the Netherlands were net donors, while Italy and Spain were net receivers of both downside risk and upside opportunities. As a result, the status of Spain and Italy as peripheral countries in risk transmission appears to be confirmed. On the other hand, Germany was a net receiver of upside semi-volatility and a net donor of downside semi-volatility. In a rolling sample analysis we showed that the behaviour of the five countries changed during the sample period: while France and the Netherlands reduced their role as donors of downside risk from the beginning of the sample to the end, Italy decreased its role as a receiver, Spain became less vulnerable and Germany increased its role. For upside volatility the behaviour was less clear, with Germany

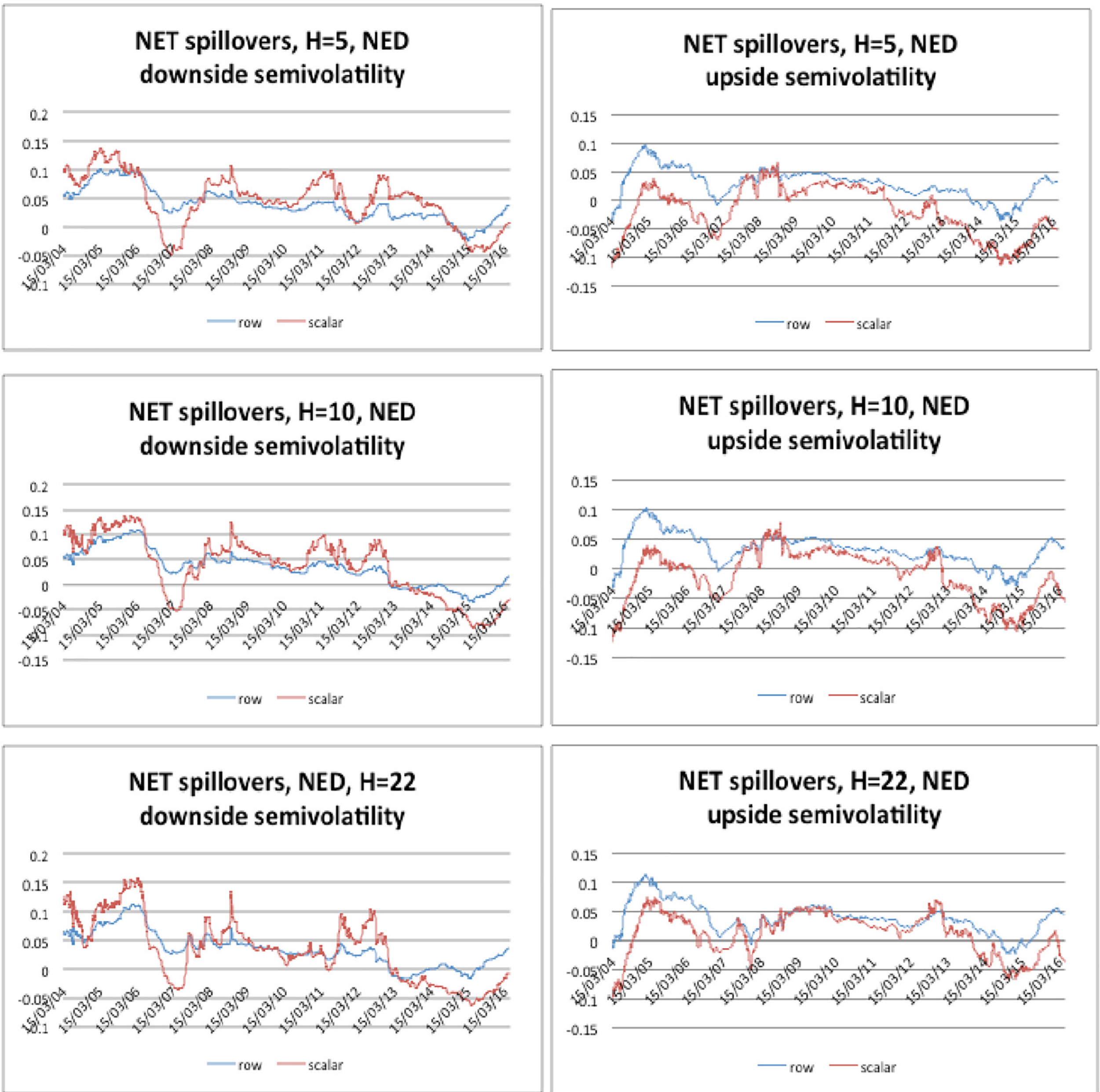

Fig. 4. Comparison among normalization schemes: the case of the Netherlands
Note: this figure compares, for both the downside semi-volatility (left) and upside semi-volatility (right), NET spillovers normalized by row (in red) and NET spillovers normalized by the maximum row sum (in blue) for the Aex index over the three different forecast horizons (H = 5, H = 10, H = 22). The comparison is based on rolling regressions results. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6
Errors in sign.

	GER	FRA	NED	SPA	ITA	Total
Panel I: downside semi-volatility						
H = 5	483	370	302	307	246	1708
H = 10	425	348	315	437	180	1705
H = 22	400	228	568	222	380	1798
Panel II: upside semi-volatility						
	GER	FRA	NED	SPA	ITA	Total
H = 5	157	107	1292	634	115	2305
H = 10	660	280	1060	326	308	2634
H = 22	114	273	729	134	484	1734

Note: The Table shows the number of errors in sign of NET spillovers when using the row-normalization scheme of the generalized forecast error variance decomposition values. The errors refer to the NET spillovers computed for the downside semi-volatility series (Panel I) and the upside semi-volatility series (Panel II).

increasing its role and Spain decreasing it, while France, the Netherlands and Italy displayed different spikes and turns during the sample period. Finally, we stressed the importance of choosing a scalar-based normalization scheme different from the row sum which is the one traditionally used in the empirical literature, in order to obtain more reliable net spillover measures.

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