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SPILLOVER EFFECTS IN THE VOLATILITY OF FINANCIAL MARKETS

Edoardo Otranto

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Spillover Effects in the Volatility of Financial Markets[*]

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Abstract

Recent econometric and statistical models for the analysis of volatility in financial markets serve the purpose of incorporating the effect of other markets in their structure, in order to study the spillover or the contagion phenomena. Extending the Multiplicative Error Model we are able to capture these characteristics, under the assumption that the conditional mean of the volatility can be decomposed into the sum of one component representing the proper volatility of the time series analyzed, and other components, each representing the volatility transmitted from one other market. Each component follows a proper dynamics with elements that can be usefully interpreted. This particular decomposition allows to establish, each time, the contribution brought by each individual market to the global volatility of the market object of the analysis. We experiment this model with four stock indices.

Keywords: MEM, realized volatility, volatility transmission.
JEL Classification: C32, C51, C58.

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1 Introduction

The increasing degree of financial integration in terms of international investments and financial movements across borders has provided frequent cases of volatility transmission among markets (spillover effects, financial contagion, comovements,...; see, for example, Forbes and Rigobon, 2002, Gallo and Otranto, 2008, Brenner et al., 2009). From a statistical point of view, this phenomenon has favored the development of models devoted to incorporating the effects of other markets on the volatility of a given market. For example, Engle et al. (1990a) consider simple GARCH models (Bollerslev, 1986) providing the possibility that the conditional variances are affected by additional information in the form of squared innovations occurring in other markets. Simple approaches are referred in Pericoli and Sbracia (2003), who propose Probit/Logit models in which dummy variables represent existing crises in another market, or Leading Indicators models, where variables linked to economic fundamentals or to foreign markets are included among the regressors. Many contributions were developed in the frame of Markov Switching models (Hamilton, 1990): Edwards and Susmel (2001, 2003) suggest a bivariate version of the Markov Switching ARCH model (Hamilton and Susmel, 1994) for weekly international stock returns and interest rates, tracking co-dependence in volatility regimes, driven by an ergodic Markov Chain; Baele (2005) studies the effect of globalization on market interdependence, using a Markov switching model where switching occurs in the spillover parameters; Gallo and Otranto (2007, 2008) adopt a Multi-Chain Markov Switching model (Otranto, 2005) in which the probability of the state of each market (high or low volatility regime) depends on the state of another market.

In our view, an important aspect to be considered in this framework is the fact that the volatility transmission is not constant along time, but depends on the particular period considered; it is likely that the so-called dominant markets (e.g. the USA market) show their influence in the volatility of the other markets very frequently, whereas other markets show their effects only in particular periods and in correspondence of particular turmoils (a clear example is represented from the Greek crisis in 2011-12). In modeling volatility, an important task is to capture the effect of the volatility of other markets in time-varying terms.

In this paper we propose an extension of the Multiplicative Error Model (MEM hereafter) of Engle (2002) to include this characteristic, but working within a univariate framework. The MEM approach is particularly interesting because, while maintaining the simple structure of the GARCH model, it is able to modelize non negative observations without resorting to the log transformation and to provide conditional expectations of the variables studied and not the expectations of the logarithms. In particular we adopt the Asymmetric MEM (AMEM) specification of Gallo and Otranto (2012) (a particular case of the extended MEM illustrated in Gallo and Engle, 2006) to take into account the effect of the sign of returns on volatility.

The MEM structure is obtained from the product of two factors, one representing the mean level of the volatility and the other a positive disturbance. Our extension considers the possibility that the first factor can be decomposed into the sum of several unobserved components (sub-factors), one representing the proper volatility of the market under study and the others interpreted as the volatility transmitted into this from the other markets.

Each sub-factor follows a sort of Threshold GARCH model (Zakoïan, 1994) and each part of the corresponding equation can be usefully interpreted, distinguishing among effects due to the recent information, persistence effect of the transmitted volatility, and effects due to negative returns in the other markets. We call this model the AMEM with Spillover effects (SAMEM). As a final result, the SAMEM allows to evaluate the presence and the weight of the volatility transmission from each market and to measure how this influences the market under investigation.

The aims of this paper could also be achieved using a multivariate approach, as in Cipollini et al. (2006), but the computational effort is very high given the large number of parameters and equations to be considered. In the SAMEM approach the framework is univariate, but there is the possibility to capture all the effects considered from the multivariate case, with a reduced number of coefficients.

The paper is organized as follows: the next section will describe the SAMEM, underlying its main characteristics to analyze the volatility transmission from n markets to a given one; Section 3 is devoted to an empirical illustration of the model, experimenting it on four volatility indices: S&P500, Nikkei 225, Hang Seng, Euro Stoxx 50. Final remarks will conclude the paper.

2 The Model Proposed

Let $\boldsymbol{z}_t = (y_t, \boldsymbol{x}_t)'$ a $(n+1) \times 1$ vector of variables, each one representing the volatility relative to a certain financial market; in particular y_t represents the volatility at time t of the market to be analyzed, whereas $\boldsymbol{x}_t$ contains the other n variables. We hypothesize that the volatility y_t can be decomposed into the product of two factors: μ_t and a non negative disturbance ε_t with mean, conditional on the information at time $t-1$ (call it $\boldsymbol{\Psi}_{t-1}$), equal to 1. As a consequence, μ_t can be interpreted as the conditional mean of y_t. Similarly to Engle and Gallo (2006), we hypothesize that $\varepsilon_t|\boldsymbol{\Psi}_{t-1}$ follows a Gamma distribution with coefficients a and $(1/a)$; the dependence on only one unknown parameter provides the hypothesized mean and a certain flexibility of the distribution with respect to, for example, an exponential with parameter equal to 1, as in Engle (2002).

In the original MEM (Engle, 2002), the μ_t factor is parameterized as a GARCH model (Bollerslev, 1986), whereas Engle and Gallo (2006) provide more general specifications, with the dependence on other variables and dummies to capture the asymmetric behavior of financial markets in front of negative returns. We adopt a particular case of Engle and Gallo (2006), developed by Gallo and Otranto (2012), the AMEM.

The conditional mean of the volatility, μ_t, will incorporate all the effects, whether explicited or not in the model, affecting the level of the volatility, including the transmission of the volatility from other markets. We propose to decompose the factor μ_t in $n+1$ sub-factors:

$$\mu_t = \zeta_t + \sum_{i=1}^{n} \xi_{i,t} \tag{2.1}$$

where ζ_t represents the volatility of the analyzed market due to its proper dynamics and internal shocks (*proper volatility*), whereas $\xi_{i,t}$ represents the part of the volatility due to the volatility transmission from the $i-th$ market with volatility x_{it} included in $\boldsymbol{x}_t$

(*transmitted volatility*). We suppose that both ζ_t and each $\xi_{i,t}$ follow a GARCH type dynamics.

Summing up, the model we propose (the SAMEM), is characterized from the following set of equations:

$$\begin{array}{l} y_t = \mu_t \varepsilon_t \qquad \varepsilon_t | \mathbf{\Psi}_{t-1} \sim Gamma(a, 1/a) \text{ for each } t \\ \mu_t = \zeta_t + \sum_{i=1}^{n} \xi_{i,t} \\ \zeta_t = \omega + \sum_{h=1}^{p_0} \alpha_{0,h} y_{t-h} + \sum_{j=1}^{q_0} \beta_{0,j} \zeta_{t-j} + \gamma_0 D_{0,t-1} y_{t-1} \\ \xi_{i,t} = \sum_{h=1}^{p_i} \alpha_{i,h} x_{i,t-h} + \sum_{j=1}^{q_i} \beta_{i,j} \xi_{i,t-j} + \gamma_i D_{i,t-1} x_{i,t-1} \end{array} \tag{2.2}$$

where $D_{r,t}$ is a dummy variable assuming value 1 when the return of the corresponding market (with volatility y_t for $r = 0$, $x_{r,t}$ for $r = 1, \ldots, n$, respectively) is negative, 0 otherwise. In the last equation we do not insert the constant to avoid problems with the identification of parameters. If all the $\beta_{i,j}$ coefficients ($i = 0, \ldots, n$, $j = 1, \ldots, q_i$) are constrained to zero, we obtain a basic AMEM with the effect of predetermined variables (the $x_{i,t}$ in this case), as in Engle and Gallo (2006). It is clear that the SAMEM is more complete with respect to an AMEM with additive effects of other variables, because model (2.2) contains also an inertial effect of the volatility of the other markets, represented by $\sum_{j=1}^{q_i} \beta_{i,j} \xi_{i,t-1}$.

Model (2.2) differs from other factor models for the analysis of the volatility, generally developed in a multivariate framework to avoid the cumbersome computations and to guarantee a positive definite conditional covariance matrix (see, for example, Diebold and Nerlove, 1989, who develop a sort of factor multivariate stochastic volatility model, and Engle et al., 1990b, who work in a similar way using multivariate GARCH). Moreover our model is only formally similar to the Composite MEM of Brownlees et al. (2012), in which μ_t is the sum of a short and a long run component. There is some similarity with the Component MEM of Brownlees et al. (2011), who consider multiplicative factors, representing intra-daily periodic and non-periodic dynamics and daily components.

Recently, also a multivariate version of MEM has been developed by Cipollini et al. (2006) to include in each equation of volatility the effects of the volatility of other markets. It is important to notice that model (2.2) does not correspond to a single equation of the Multivariate MEM; the latter (considering the simple case of a GARCH(1,1) dynamics for the conditional mean) is given by:

$$\mu_t = \omega + \alpha_0 y_{t-1} + \beta_0 \mu_{t-1} + \gamma_0 D_{0,t-1} y_{t-1} + \sum_{i=1}^{n} \alpha_{i,1} x_{i,t-1} + \sum_{i=1}^{n} \beta_{i,1} \mu_{i,t-1} + \sum_{i=1}^{n} \gamma_i D_{i,t-1} x_{i,t-1} \tag{2.3}$$

where $\mu_{i,t-1}$ is the average of the volatility of market i at time $t-1$. In this case we need a multivariate framework because $\mu_{i,t-1}$ is not observable and other n expressions as (2.3) and n equations as the first one of (2.2) are necessary to consider the volatilities of the other n markets. Moreover, a computational problem is added in considering the multivariate distribution of the vector of disturbances and for the large number of coefficients; Cipollini et al.(2007) propose to put $\beta_{i,1} = 0$ for each $i = 1, \ldots, n$, to estimate the system equation by equation adopting Gamma marginal distributions, and then using copula functions to retrieve the simultaneous correlation among innovations.[1]. Dealing with a

[1] More recently, Cipollini et al., (2009) propose a semiparametric approach to avoid the constraints about

univariate framework, as in (2.2), we do not need to explicit models for the volatility of the other markets because each sub-factor is relative to the dynamics of the market studied. The components ζ_t and $\xi_{i,t}$ have a different interpretations with respect to μ_t and $\mu_{i,t}$ in (2.3); in fact they are not conditional means of the volatility of each markets, but the effect of each market on the conditional mean of the volatility of the market of interest, with the possibility to interpret each component, as we will see at the end of this section.

Model (2.2) does not present particular estimation problems; it is possible to make explicit the likelihood function and to maximize it. On the other hand, this simple extension provides a lot of information. Firstly, it is possible to calculate the percentage of the explained volatility due to the transmission from other markets; it is given by:

$$tv_t = \frac{\sum_{i=1}^{n} \xi_{i,t}}{\mu_t} = 1 - \frac{\zeta_t}{\mu_t} \tag{2.4}$$

where $\frac{\zeta_t}{\mu_t}$ is the fraction of proper volatility.

Moreover, for each market it is possible to estimate the contribution of each market i to the volatility y_t by:

$$tv_{i,t} = \frac{\xi_{i,t}}{\mu_t} \tag{2.5}$$

Again, each element of the ζ_t and $\xi_{i,t}$ equations in (2.2) can have a proper interpretation:

- $\sum_{h=1}^{p_0} \alpha_{0,h} y_{t-h}$ is the part of the proper volatility due to the recent information about the volatility of the analyzed market (call it α-*proper volatility*);
- $\sum_{h=1}^{p_i} \alpha_{i,h} x_{i,t-h}$ is the part of the transmitted volatility due to the recent information about the market i (α-*transmitted volatility from* i) ;
- $\sum_{j=1}^{q_0} \beta_{0,j} \zeta_{t-j}$ is the inertial component of the proper volatility (β-*proper volatility*);
- $\sum_{j=1}^{q_i} \beta_{i,j} \xi_{i,t-j}$ is the inertial component of the transmitted volatility from market i (β-*transmitted volatility from* i);
- $\gamma_0 D_{0,t-1} y_{t-1}$ is the effect due to negative returns in the analyzed market (γ-*proper volatility*);
- $\gamma_i D_{i,t-1} x_{i,t-1}$ is the effect due to negative returns in the market i (γ-*transmitted volatility from* i);

In practical terms, the great advantage of model (2.2) is the possibility to consider a lot of effects, as in the multivariate MEM, while working in a simple univariate framework.

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the $\beta_{i,1}$ coefficients.

3 An Illustrative Application

We experiment our approach on four volatility series using indices representative of the financial markets of USA, Asia and Europe: they are the Standard $\&$ Poor's 500 index (hereafter SP), the Nikkei 225 (N), the Hang Seng (HS) and the Euro Stoxx 50 (ES). A large debate emerged in the econometric literature on the choice of the best way to compute volatility; while this is not concluded, it seems to have reached a mature stage, and the realized volatility is now indicated as the best proxy (Andersen et al., 2000). There are several ways to compute it (see, for a review, Andersen et al., 2003, 2010); many authors indicate the realized kernel volatility as a measure with desirable properties, such as the robustness to market microstructure noise (Barndorff-Nielsen et al., 2006). For the four indices analyzed here, the realized variance series are taken from the *Oxford-Man Institute's realised library* version 0.1 (Heber et al., 2009). The original data are transformed and expressed as percentage annualized volatility, i.e. the square root of the realized variance multiplied by $\sqrt{252} * 100$.

Figure 1 shows the dynamics of the four series for the period between January 3, 2000 and November 4, 2011. From the graphs it is possible to notice many peaks common to all the series; in particular, at the beginning of the series, it is possible to observe the final effects of the dot-com bubble, which has its climax in March 2000, the steep surge in volatility following the twin towers terrorist attack, the 2007-2011 global financial crisis, started in USA, followed by the late 2000s recession and the 2010 European sovereign debt crisis.

3.1 Model Comparison

We have estimated three kinds of models: four univariate SAMEM as in (2.2) with $p_0 = \ldots, p_n = q_0 = \cdots = q_n = 1$; four univariate AMEM ($p_0 = q_0 = 1$), which corresponds to (2.2) with $\mu_t = \zeta_t$, so that the last n equations are not considered; a multivariate AMEM (call it Vector AMEM-VAMEM), with the following specification:

$$\begin{aligned} \boldsymbol{z}_t &= \boldsymbol{\mu}_t \odot \boldsymbol{\varepsilon}_t \\ \boldsymbol{\mu}_t &= \boldsymbol{\omega} + \boldsymbol{A}\boldsymbol{z}_{t-1} + \boldsymbol{B}\boldsymbol{\mu}_{t-1} + \boldsymbol{\Gamma}\boldsymbol{d}_{t-1} \odot \boldsymbol{z}_{t-1} \end{aligned} \tag{3.1}$$

where $\odot$ is the Hadamard (element–by–element) product; $\boldsymbol{\omega}$, $\boldsymbol{A}$, $\boldsymbol{B}$, $\boldsymbol{\Gamma}$ are unknown coefficient matrices having dimension $(4, 1)$, $(4, 4)$, $(4, 4)$, $(4, 4)$ respectively; $\boldsymbol{d}_{t-1}$ is a $(4, 1)$ vector containing four dummies as $D_{r,t}$ in (2.2), one for each series of returns; $\boldsymbol{\varepsilon}_t$ is a $(4, 1)$ vector of disturbances with marginal densities $Gamma(a_i, 1/a_i)$ ($i = 1, \ldots, 4$) that we suppose independent to reduce the number of unknown coefficients. Notice that the maximum number of coefficients to be estimated for each SAMEM is 14, for each AMEM is 5, for the VAMEM is 56.

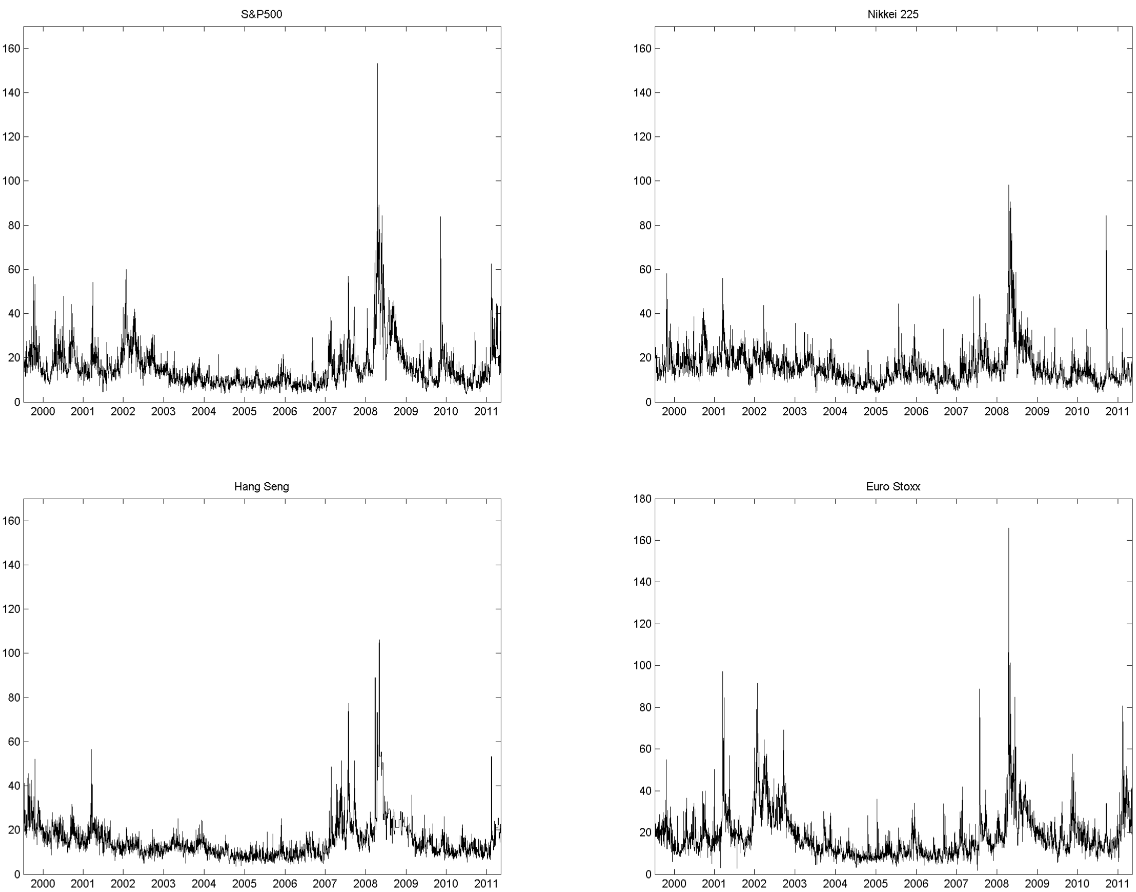
We start from a full specification of the models, with the maximum number of coefficients, and, in the case of coefficients identically equal to zero (which involve a non positive definite hessian to calculate standard errors), we remove them. This will provide a feasible specification of the models.

We show the estimation results in Table 1. We have re-labeled the indices of the coefficients with the symbol of the market. For example, if the variable studied y_t is the

Table 1: Estimates of AMEM, SAMEM and VAMEM coefficients (standard errors in parentheses), p-value of the Ljung-Box statistics at lag 1, likelihood based criteria and loss functions for four series of realized kernel volatility.

	S&P500			Nikkei 225			Hang Seng			Euro Stoxx		
	AMEM	SAMEM	VAMEM	AMEM	SAMEM	VAMEM	AMEM	SAMEM	VAMEM	AMEM	SAMEM	VAMEM
a	13.831	15.545	15.225	14.772	16.927	16.528	15.761	17.924	17.677	13.405	15.621	14.950
	(0.478)	(0.391)	(0.384)	(0.491)	(0.427)	(0.416)	(0.670)	(0.452)	(0.446)	(0.490)	(0.393)	(0.376)
ω	1.035	0.199	0.503	1.348	0.497	0.803	1.355	0.489	0.559	1.137	0.30	0.651
	(0.024)	(0.090)	(0.061)	(0.088)	(0.086)	(0.088)	(0.03)	(0.069)	(0.076)	(0.085)	(0.059)	(0.072)
α_{SP}	0.300	0.270	0.304		0.060			0.059			0.167	
	(0.010)	(0.019)	(0.018)		(0.014)			(0.011)			(0.019)	
β_{SP}	0.576	0.615	0.608									
	(0.008)	(0.020)	(0.020)									
γ_{SP}	0.105	0.081	0.085		0.050	0.054		0.034	0.032		0.092	0.080
	(0.006)	(0.007)	(0.021)		(0.009)	(0.007)		(0.008)	(0.005)		(0.011)	(0.009)
α_N		0.000		0.361	0.319	0.360						
		(0.000)		(0.026)	(0.019)	(0.019)						
β_N		0.655		0.510	0.562	0.515						
		(0.059)		(0.006)	(0.024)	(0.023)						
γ_N		0.001		0.080	0.053	0.054					0.007	
		(0.005)		(0.006)	(0.008)	(0.008)					(0.009)	
α_{HS}		0.004			0.020		0.439	0.373	0.395			
		(0.002)			(0.014)		(0.018)	(0.019)	(0.019)			
β_{HS}		0.956					0.465	0.559	0.553			
		(0.019)					(0.014)	(0.022)	(0.021)			
γ_{HS}		0.000			0.032	0.017	0.000					
		(0.000)			(0.009)	(0.006)	(0.001)					
α_{ES}		0.019								0.307	0.217	0.314
		(0.012)								(0.029)	(0.018)	(0.020)
β_{ES}		0.175								0.576	0.676	0.586
		(0.127)								(0.033)	(0.021)	(0.021)
γ_{ES}		0.049	0.023		0.031	0.021				0.095	0.059	0.059
		(0.001)	(0.006)		(0.007)	(0.006)				(0.007)	(0.007)	(0.009)
$p(Q_1)$	0.002	0.182	0.108	0.001	0.003	0.054	0.103	0.530	0.550	0.000	0.010	0.029
Log-lik	-8427.59	-8239.76		-8508.01	-8290.28		-8198.85	-7986.21		-8983.89	-8738.95	
AIC	5.460	5.344		5.512	5.377		5.307	5.180		5.820	5.667	
BIC	5.470	5.371		5.522	5.404		5.317	5.207		5.830	5.695	
RMSE i.s.	5.247	5.144	5.175	4.855	4.610	4.648	4.781	4.630	4.672	6.167	5.923	5.990
MAE i.s.	3.200	3.166	3.186	3.168	3.053	3.089	2.806	2.706	2.727	3.758	3.586	3.670
RMSE o.s.	6.100	6.040	6.213	4.800	4.892	4.912	4.062	4.006	4.269	6.028	5.606	6.153
MAE o.s.	1.926	1.920	1.946	1.661	1.684	1.673	1.583	1.570	1.590	2.010	1.959	2.037

Figure 1: Realized kernel volatility of four indices.



volatility of the S&P500 index, α_{SP}, β_{SP} and γ_{SP} will correspond to $\alpha_{0,1}$, $\beta_{0,1}$ and $\gamma_{0,1}$ respectively in the third equation of (2.2). We call them *proper volatility coefficients*. In alternative, if the S&P500 volatility corresponds to the variable $x_{1,t}$, then α_{SP}, β_{SP} and γ_{SP} will correspond to $\alpha_{1,1}$, $\beta_{1,1}$ and $\gamma_{1,1}$ in the fourth equation of (2.2). We call them *transmitted volatility coefficients*. Considering the VAMEM in (3.1) and supposing that the order of the variables is the one of Table 1 (SP, N, HS, ES), each row of the matrix $\mathbf{\Gamma}$ is composed by the corresponding rows of the Table relative to the γ coefficients of VAMEM. In other words:

$$\mathbf{\Gamma} = \begin{bmatrix} 0.085 & 0 & 0 & 0.023 \\ 0.054 & 0.054 & 0.017 & 0.021 \\ 0.032 & 0 & 0 & 0 \\ 0.080 & 0 & 0 & 0.059 \end{bmatrix}$$

Similarly for $\boldsymbol{A}$ and $\boldsymbol{B}$.

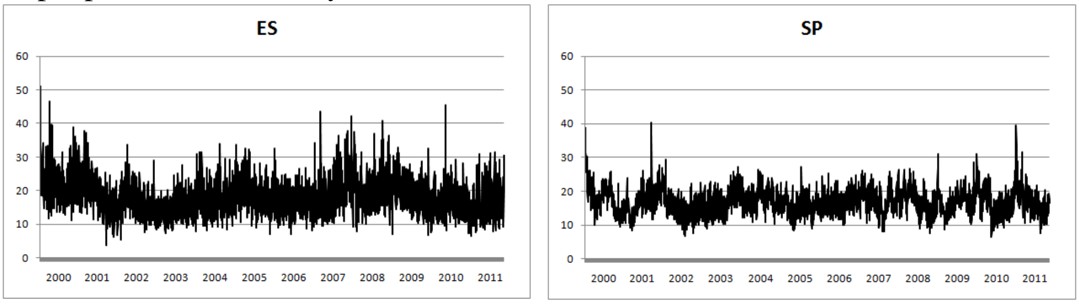
The coefficient a of the Gamma distributions are larger for the AMEM with respect to the other two models, so that its variance of disturbances is larger. This results is due to the fact that the SAMEM and the VAMEM can capture some dynamics of the volatility series with the presence of volatility transmission effects. A similar interpretation holds for the high value of the constant ω in the AMEM; the lower values of SAMEM and VAMEM indicate that these models are able to capture some dynamic aspects, using the volatility transmission effects, which are not captured by the AMEM.

Considering the proper volatility coefficients α, β, γ, we can note that the persistent coefficient β is not large (in many empirical studies it is around 0.9) and that the asymmetric coefficient γ is small but significant in most of the cases. Only in the HS case no proper asymmetric effect is present. It is interesting to notice the different identification of transmitted volatility coefficients in the SAMEM and the VAMEM. The only transmitted volatility effect present in VAMEM is the asymmetric one, in particular from the S&P500 index (the γ_{SP} coefficient is always present in the four VAMEM equations), whereas the α and β transmitted volatility coefficients are not included in the final selected model. In practice, the VAMEM approach indicates that the only transmission volatility effects are verified in presence of negative shocks in the other markets. On the other side, the SAMEM considers different effects for the four indices. The SAMEM which models the volatility of S&P500 contains all the coefficients relative to the effects of the other markets; in particular, it seems to depend on the effect of negative returns in the European markets (which is consistent with the effects of recent episodes of crises in Europe) and from a strong inertial volatility transmission from China; as well known, China is the largest foreign owner of U.S. Treasury bonds, supporting the value of the dollar. Its rapid economic growth and its emergence as a major economic power are the reasons China exerts a great influence on the U.S. economy (see Elwell and Labonte, 2007). The Nikkei index seems to depend mainly on the most recent negative returns of the other markets, similarly to the VAMEM case (the only significant α parameter, among the volatility transmission coefficients, is the one relative to S&P500). The volatility of the Hang Seng and the Euro Stoxx indices depend only on the US volatility in terms of the most recent information with asymmetric effect.

The first value of the last part of Table 1 shows the p-value of the Ljung-Box statistics to verify the autocorrelation of residuals at lag 1, denoted with $p(Q_1)$. This is an interesting statistics because Gallo and Otranto (2012), analyzing the realized kernel volatility of the S&P500 index, show that the AMEM presents a strong residual autocorrelation, which is captured inserting Markov switching coefficients in the model. In practice, they show that the autocorrelation is due to the presence of regimes with different dynamics. Observing Table 1, we notice that VAMEM is able to capture the residual autocorrelation at a significance level of 1%, present in the AMEM residuals (excluding the Hang Seng case, which is cleaned of autocorrelation with all the models), but the SAMEM also shows a similar performance, excluding the Nikkei case. A natural conclusion is that the presence of the volatility effects of other markets helps to better specify the model.

The comparison of the three alternative models is made in terms of likelihood-based criteria (AIC and BIC) and in terms of loss functions. The AIC and BIC are compared only for the univariate models (for the VAMEM we have just one likelihood function) and show a clear evidence in favor of the SAMEM. The loss functions (Root Mean Squared Errors-RMSE- and Mean Absolute Error-MAE) are showed for the in sample (i.s.) and out-of-sample (o.s.) cases. For the o.s. case we have cut-off the last 400 observations of the data set, re-estimated the models and calculated the 1-step ahead forecasts, adding one observation with each step. The i.s. loss functions indicate SAMEM as the model

Figure 2: Percentage of transmitted volatility in EuroStoxx and S&P500 indices in the sample period from January 3, 2000 to November 4, 2011.



which best fits the four series and AMEM the worst. The better behavior of SAMEM is confirmed also in terms of o.s. forecasts, where the VAMEM does not show a good performance; the only exception is the Nikkei case, where the best performance is obtained with the AMEM and the worst with the SAMEM. Maybe, in this case, the general-to-specific procedure to select the model does not work adequately.

3.2 Interpretation of the SAMEM Results

Observing the differences among the loss functions, both for the i.s. and o.s. cases, it seems that the SAMEM is clearly better than the two other models for the analysis of the volatility of the Euro Stoxx index. To better understand the information derived from the SAMEM, we choose to analyze in greater detail the results relative to this case.

A first relevant information derived from the SAMEM is the part of explained volatility transmitted from the other markets with respect to the proper volatility. In Figure 2 we show the dynamics of the indicator (2.4), in percentage terms, for the ES index along the full sample interval considered, compared with the same indicator for SP. The stronger effect of the other markets on the European volatility is noticeable, if compared to the US case; in particular we notice that, on average, the percentage of transmitted volatility is 18.11 toward ES (with a variance equal to 33.48), whereas it is 16.78 toward SP, with a more restricted variability (variance equal to 16.75). In some cases, the tv_t indicator is greater than 40%, showing a clear spillover effect from other markets.

In Figure 3 we show the estimated volatility of ES (which follows the profile of the original kernel volatility series, shown in Figure 1) pointing out (in correspondence of the rectangles along the line at level 100 of the y axis) the seven points in which $tv_t > 0.40$. These points correspond to the following dates: 5 January 2000, 5 April 2000, 28 February 2007, 12 and 13 December 2007, 30 September 2008, 7 May 2010. Note that these points do not necessarily corresponde to the highest peaks of the volatility but it is interesting to underline that they correspond to particular events in the United States, which have caused turmoil in financial markets. In particular, the first two dates refer to the end of the long dot-com bubble, which has shown its main effects at the beginning of 2000; in February 2007 the U.S. subprime mortgage crisis began to affect the financial sector, when HSBC, the world's largest bank, wrote down its holdings of subprime-related Mortgage-Backed Securities; in the middle of December 2007 we have

Figure 3: Estimated volatility of EuroStoxx index, using the SAMEM, in the sample period from January 3, 2000 to November 4, 2011. The rectangles indicate the dates in which the transmitted volatility is more than 40%.

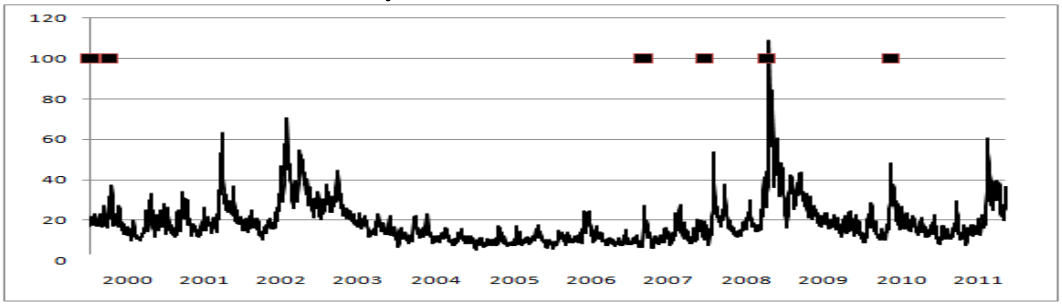
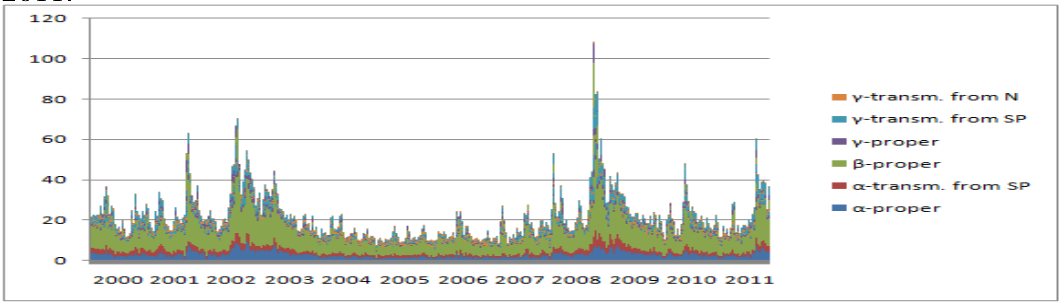


Figure 4: Composition of the estimated volatility of EuroStoxx index, using the SAMEM (excluding the constant part), in the sample period from January 3, 2000 to November 4, 2011.

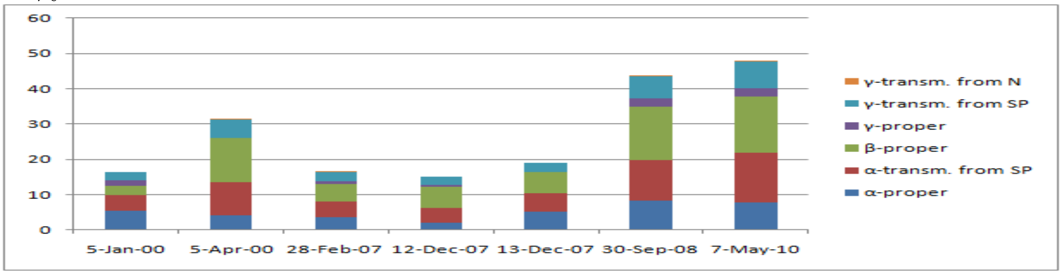


the confirmation that the financial crisis has affected the full year and the beginning of the global recession; September 2008 is the month in which Lehman Brothers and other important financial institutions failed, causing the highest peaks in volatility in the whole time span considered; finally, on 6 May 2010, the US market shows an abrupt crash, known as the Flash Crash, due (maybe only in part)[2] to the news relative to the Greek crisis, in which many US indices plunged about nine percent only to recover those losses within minutes. The day after this high volatility level was transmitted to the European markets.

The dating proposed suggests that the main changes in volatility of ES are due to episodes of crises in the U.S.A.; actually, separating the effects of the proper and transmitted volatilities in the SAMEM, following the scheme illustrated at the end of Section 2, we can notice in Figure 4 that large part of the volatility of ES can be explained in terms of inertial proper effects (β-proper volatility), but, in particular around the cited crisis periods, the transmission volatility effects due to recent information from SP (α and γ-transmitted volatility from SP) seem to have a relevant role. On the other side, the

[2]Some analysts have detected "an erroneous trade for a basket of stocks which caused shares for companies such as Procter & Gamble Co., one of the market's most stable blue-chip stocks, to fall 35% in two minutes" (The Wall Street Journal of May 7, 2010).

Figure 5: Composition of the estimated volatility of EuroStoxx index, using the SAMEM (excluding the constant part), in the dates in which the transmitted volatility is more than 40%.



γ-transmitted volatility from N seems to have a small incidence in the previous periods.

Details about the composition of the volatility in correspondence of the seven previous dates are shown in Figure 5. The α and γ-transmitted volatilities from SP have a large weight in the explained volatility of ES, especially in the peak of September 2008 and May 2010, confirming a central rule of the news (in particular the negative information) from a dominant market such as the U.S. On the other hand, in these dates the effect of the N index is almost null.

4 Final Remarks

We have proposed a new model, which extend the capabilities of the MEM family to capture spillover and other effects of volatility transmission from a set of markets to another one. The main advantage of this model seems to be the possibility to distinguish several possible effects, separating the proper volatility of the market object of study from the transmitted volatility from other markets; moreover, within each proper and transmitted effect, we can distinguish among effects due to the most recent information, effects due to the bad news (recent negative returns) and inertial effects.

From a computational point of view, the SAMEM is very simple to estimate and, using a general-to-specific specification, we are able to obtain feasible models. An advantage is the possibility to work in a univariate framework, reducing the number of coefficients to be estimated, but, at the same time, obtaining very good results in terms of goodness-of-fit and forecasting performance. In the example illustrated in this work, we have obtained better performance indices in three of the four cases studied.

Of course, a multivariate approach is more elegant from a formal point of view, and more apt to capture the correlations existing among the disturbances of different markets. Anyway, for the purpose analyzed here, a simpler approach which provides the information about the volatility transmission dynamics seems to be easier and yet provides a very satisfying performance, as commented before, also with respect to the multivariate case.

Formally, an extension of model (2.2) to the multivariate case is possible, but it would imply $(n+1)$ equations of the ζ_t type and $(n+1)n$ equations of the ξ_t type, and the coefficients of a multivariate Gamma (or other multivariate distributions with positive support) making the model unfeasible. The alternative would be to consider common factors for the $(n + 1)$ variables, as in Engle et al. (1990b), following a similar approach to the one of the Dynamic Factor Models of Forni et al. (2005) and Stock and Watson (2002), developed in a macroeconomic framework. With this, however, we would lose the possible interpretation of the factors, that we have described at the end of Section 2.

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