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FINANCIAL CLUSTERING IN PRESENCE OF DOMINANT MARKETS

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Financial Clustering in Presence of Dominant Markets

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Abstract

Clustering financial time series is a recent topic of statistical literature with important fields of applications, in particular portfolio composition and risk evaluation. The risk is generally linked to the volatility of the asset, but its level of predictability also plays a basic role in investment decisions. In particular, the classification of a certain asset could be linked to its dependence on the volatility of a dominant market: movements in the volatility of the dominant market can provide similar movements in the volatility of the asset and its predictability would depend on the strength of this dependence. Working in a model based framework, we base the classification of the volatility of an asset not only on its volatility level, but also on the presence of spillover effects from a dominant market, such as the U.S. one, and on the similarity of the dynamics of the asset and the dominant market. The method is carried out using an extended version of the Multiplicative Error Model and is applied to a set of European assets.

Keywords: MEM, unconditional volatility, spillover effect, common dynamics, AR distance.
Jel classifications: C32, C38, G11.

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1 Introduction

Clustering financial time series is a topic which creates an increasing interest in statistical literature, with several practical aspects largely used in portfolio management, the study of risk, the classification of volatility (see, for example, Pattarin et al., 2004, Otranto, 2008 and 2010, Lisi and Otranto, 2010, De Luca and Zuccolotto, 2011). In particular, the possibility of classifying markets by homogeneous degrees of volatility is a useful tool for financial actors to provide balanced portfolios or funds with different degrees of risk. Recent works have underlined how, in the last few decades, the increasing level of globalization of world economies (see, for example, Forbes and Chinn, 2004) has provided increasing levels of interdependence and spillover effects in financial markets. This fact has important consequences in investor choices. For example, if an asset seems to be sensitive to the U.S. variations with a lag (spillover effect), the movements in the U.S. stock indices could help to forecast the movements of the asset of interest. The spillover effects are evident during periods of turmoil, in correspondence with particular shocks, such as the Lehman Brothers' crack in September 2008 (see, for example, Bordo, 2008, and Frank and Hesse, 2009).

In this framework, it is important to distinguish between the volatility proper of the asset and the volatility transmitted by the dominant market. For this reason, a basic tool is capturing and quantifying the spillover effect in the volatility of a certain financial time series. This purpose can be achieved using several approaches, for example operating in a classical GARCH framework, but also extending the recent Multiplicative Error Model (MEM).

The GARCH models put forth by Engle et al. (1990) consider the dependence of the conditional variances on squared innovations occurring in other markets. The extension of the multivariate ARCH models to include changes in regime (Edwards and Susmel 2001, 2003) implies the possibility to observe if switches from a regime of low to high volatility (or vice versa) in a pair of markets are contemporaneous or lagged.[1] Gallo and Otranto (2008) propose a battery of tests to detect and distinguish the several possible scenarios (spillover, interdependence, co–movements, independence).

A recent strand of econometric literature is devoted to model unbiased measures of volatility, more efficient with respect to the estimated volatility derived from the GARCH models. Gallo and Otranto (2007, 2008) analyze the spillover effects in financial markets using the range as a measure of volatility, which is a very good alternative to the most frequently used proxy, the so–called realized volatility (see, for example, Andersen et al., 2000, 2003), which requires, for its computation, a large collection of intra–daily data. Engle (2002) and Engle and Gallo (2006) introduce the Multiplicative Error Model (MEM) to represent the (non–negative) volatility levels with multiplicative disturbances without resorting to logarithms. This has the great advantage of producing direct forecasts of volatility and not of log–volatility; moreover the Quasi Maximum Likelihood interpretation ensures consistency of parameter estimators. A first extension of this

[1]The latter implies that one market leads the movements of the other one.

model, present also in Engle and Gallo (2006), provides the inclusion of asymmetric effects in the dynamics of volatility, depending on the sign of returns; this model is called Asymmetric MEM (AMEM). Otranto (2013) has extended this model to include asymmetric spillover effects, developing a factorial model with two unobserved components representing the *proper* volatility of the asset and the volatility due to spillover effects respectively. He calls this model the Asymmetric MEM with Spillover effects (SAMEM).

A different characteristic is the similarity of the dynamics of the assets of interest and that of the dominant market: the movements of the volatility of the assets are similar to the movements of the volatility of the dominant market, also in quiet periods.[2] The similarity of the dynamics can be studied in terms of similarity of the models representing the dynamics of the volatilities. For this purpose Piccolo (1990) proposed an AR distance between ARMA processes, extended to the GARCH case in Otranto (2008), which can be easily extended to the AMEM case.

In this work we propose to classify the markets in terms of unconditional volatility levels, spillover effects from a dominant market and similar dynamics of volatility with respect to a dominant market. For this purpose we will develop some indicators derived from the SAMEMs, which are the models chosen to represent the volatility. We will use a hierarchical clustering algorithm to classify the assets according to these indicators, representing the previous three characteristics.

We will consider the US market as the origin of the spillovers. This choice is natural because of the dominance of this market in the world finance; for example, the collapse of the US housing prices and the consequent subprime mortgage crises started in the US in the summer 2007 were transmitted first to the US financial market and then to all the world markets with a clear spillover effect (Penny Angkinand et al., 2010). This fact has generated different reactions in the world markets and also in the single assets.

The paper is organized as follows: in the next section we briefly recall the SAMEM and we introduce the main tools used in this analysis. In Section 3 we apply our methodology to a set of 37 assets belonging to the Euro Stoxx 50 index, using the S&P500 index to represent the US market; in the same section we will provide evidence for the robustness of the classification in terms of the unconditional volatility derived from the SAMEM, comparing it with the same indicator derived from the AMEM, and we will emphasize the differences in classification when we consider or not the effects of the dominant market. Some final remarks will conclude the paper.

2 Statistical Tools

In this section we will describe the tools (models, indices, distances and classification algorithm) that will be adopted to perform the classification proposed.

[2]As said, the spillovers are typical in turmoil periods and their effect is transmitted with a lag; the similarity of dynamics is referred to similar movements in the full span considered.

2.1 The model

The AMEM is discussed in Engle and Gallo (2006), who develop the MEM basic idea of Engle (2002). The main hypothesis of the model is that the volatility y_t of a certain financial asset is obtained as the product of the time varying conditional expectation of y_t (call it μ_t) and a stochastic non-negative error term ε_t, which follows a Gamma distribution depending only on one unknown coefficient a. The unobservable factor μ_t follows a GARCH(1,1) dynamics with asymmetric effects due to the sign of the zero median returns r_t of the asset at the previous time. Formally:

$$\begin{aligned}
&y_t = \mu_t \varepsilon_t, \qquad \varepsilon_t \sim Gamma(a, 1/a) \qquad \forall t \\
&\mu_t = \omega + \alpha y_{t-1} + \beta \mu_{t-1} + \gamma D_{t-1} y_{t-1} \\
&D_t = \begin{cases} 1 & \text{if } r_t < 0 \\ 0 & \text{if } r_t \geq 0 \end{cases}
\end{aligned} \tag{2.1}$$

The Gamma distribution is used because, as shown in Engle and Gallo (2006), it is a very flexible distribution to represent a non-negative disturbance; moreover the dependence on just one parameter provides a mean equal to 1, so that μ_t is the expected value of y_t (the variances of ε_t and y_t are $1/a$ and μ_t^2/a respectively). Under sufficient conditions for the stationarity of the model ($\omega > 0$; $0 \leq \alpha, \beta, \gamma$; $\alpha + \beta + \gamma/2 < 1$), the unconditional mean of volatility is given by:

$$u_A = \frac{\omega}{1 - \alpha - \beta - \gamma/2} \tag{2.2}$$

It could be considered as the *long–run level* of volatility, which represents a sort of level of risk of the asset.

The extension of model (2.1) to include spillover effects was provided by Otranto (2013). The idea is that the conditional mean μ_t can be decomposed into the product of two factors,[3] representing the volatility transmitted from the dominant market (the spillover effect; call it ξ_t) and the *proper* volatility of the asset (call it ζ_t), which includes the volatility due to idiosyncratic effects, eventually also including spillover effects from other markets. The SAMEM adopted here is defined as:

$$\begin{aligned}
&y_t = \mu_t \varepsilon_t \qquad \varepsilon_t \sim Gamma(a, 1/a) \text{ for each } t \\
&\mu_t = \zeta_t + \xi_t \\
&\zeta_t = \omega_0 + \alpha_0 y_{t-1} + \beta_0 \zeta_{t-1} + \gamma_0 D_{0,t-1} y_{t-1} \\
&\xi_t = \alpha_1 x_{t-1} + \beta_1 \xi_{t-1} + \gamma_1 D_{1,t-1} x_{t-1}
\end{aligned} \tag{2.3}$$

where $D_{i,t}$ is a dummy variable assuming value 1 when the return of the corresponding market is negative, 0 otherwise; $i = 0$ represents the market (asset) with volatility y_t, $i = 1$ represents the dominant market with volatility x_t.

Substituting ζ_t and ξ_t in the second equation of (2.3) with the two successive equations, the

[3]In Otranto (2013) a general case with more factors is illustrated.

unconditional expected value of μ_t is given by:

$$u_S = \frac{\omega_0 + \frac{1-\beta_0}{1-\beta_1}(\alpha_1 + \gamma_1/2)\bar{x}}{1 - \alpha_0 - \beta_0 - \gamma_0/2} \tag{2.4}$$

where $\bar{x}$ is the mean of the volatility of the dominant market. We expect that the difference between u_A and u_S, calculated on the same time series, is not large because both the indices represent the unconditional mean of the full volatility. In equation (2.4) we can separate the effect of the dominant market from the rest of the volatility. This is given by:

$$t_S = \frac{(\alpha_1 + \gamma_1/2)\bar{x}}{1 - \beta_1} \tag{2.5}$$

The ratio

$$f_S = \frac{t_S}{u_S} \tag{2.6}$$

will provide the fraction of the full volatility level due to the spillover effect from the dominant market.

2.2 AMEM distance

Another important aspect is relative to the dynamics of the volatility in the time span considered. Similar dynamics could underline similar co–movements, which could be interpreted as similar behaviors of the assets. To compare them, it is necessary to define a distance measure between the dynamic parts of the data generating processes. Otranto (2008) introduced the idea of a distance between GARCH processes, a simple extension of the AR metric proposed by Piccolo (1990). Let A and B be a certain asset and the dominant market respectively. For our purposes, we consider that both the asset and the dominant market follow an AMEM, as in (2.1), and we will extend the AR metric in this framework; then we will extend this metric to measure the distance between a SAMEM (representing the dynamics of asset A) and an AMEM (representing the dynamics of the dominant market B).

First, we explicit the ARMA representation of the AMEM (2.1) for the volatility series $y_{i,t}$ ($i = A, B$); it is given by :

$$y_{i,t} = \omega_i + (\alpha_i + \gamma_i D_{i,t-1} + \beta_i) y_{t-1} - \beta_i (y_{i,t-1} - \mu_{t-1}) + (y_{i,t} - \mu_t) \tag{2.7}$$

Then we rewrite the ARMA(1,1) representation in (2.7) as an AR(∞) process; following the iterative procedure illustrated in Brockwell and Davis (1996) to explicit the AR coefficients in correspondence of each lag, it is easy to show that:

$$y_{i,t} = \sum_{j=0}^{\infty} \left[(\alpha_i + \gamma_i D_{i,t-1}) \beta_i^j \right] y_{i,t-j-1}$$

Substituting the dummy with its expected value (recalling that the returns have zero median, it is equal to $\frac{1}{2}$), the AR distance is defined as the Euclidean distance between the two sequences of AR coefficients of the volatilities of asset A and market B; extending the results of Otranto (2010), this *AMEM distance* is given by:

$$d_A = \left[\frac{(\alpha_A + \gamma_A/2)^2}{1-\beta_A^2} + \frac{(\alpha_B + \gamma_B/2)^2}{1-\beta_B^2} - \frac{2(\alpha_A + \gamma_A/2)(\alpha_B + \gamma_B/2)}{1-\beta_A\beta_B}\right]^{1/2}. \tag{2.8}$$

Along the lines of Otranto (2010), it is possible to show that (2.8) is a metric. If $d_A = 0$, the two volatilities follow the same dynamics; in practice values of d_A near to zero show evidence for very similar movements in the volatilities of A and B.

Estimating a SAMEM for asset A with $x_t = y_{Bt}$, there are two different equations expressing the dynamics of y_{At}, one relative to ζ_t and the other to ξ_t. We can consider the *proper volatility AMEM distance*:

$$d_\zeta = \left[\frac{(\alpha_{0A} + \gamma_{0A}/2)^2}{1-\beta_{0A}^2} + \frac{(\alpha_B + \gamma_B/2)^2}{1-\beta_B^2} - \frac{2(\alpha_{0A} + \gamma_{0A}/2)(\alpha_B + \gamma_B/2)}{1-\beta_{0A}\beta_B}\right]^{1/2} \tag{2.9}$$

and the *transmitted volatility AMEM distance* between A and B:

$$d_\xi = \left[\frac{(\alpha_{1A} + \gamma_{1A}/2)^2}{1-\beta_{1A}^2} + \frac{(\alpha_B + \gamma_B/2)^2}{1-\beta_B^2} - \frac{2(\alpha_{1A} + \gamma_{1A}/2)(\alpha_B + \gamma_B/2)}{1-\beta_{1A}\beta_B}\right]^{1/2}. \tag{2.10}$$

To derive the global distance between asset A and market B we could use a weighted mean of d_ζ and d_ξ, using the proportions of proper and transmitted volatility present in the asset A as weights. In other words, we define the statistic:

$$d_S = d_\zeta(1 - f_S) + d_\xi f_S \tag{2.11}$$

where f_S is derived from (2.6).[4]

2.3 The classification steps

The grouping of the set of financial time series can be made using classical clustering algorithms. For this purpose we will use the agglomerative hierarchical clustering method, adopting the complete linkage criterion and the Euclidean distance to merge the two most similar clusters at each step. The number of clusters k is detected with the support of a quality index, the C

[4]The statistic (2.11) is the sum of two metrics, so it is again a metric. Anyway, we will use it as an index to measure the distance between the dynamics of the volatility of the asset A and the dynamics of the volatility of the dominant market B.

index (Hubert and Schultz, 1976), defined as:

$$C = \frac{S_W - S_{min}}{S_{max} - S_{min}} \tag{2.12}$$

where S_W is the sum of the distances over all pairs of patterns from the same cluster. Let n be the number of those pairs; S_{min} and S_{max} are the sum of n smallest and largest distances, respectively, between all the pairs of points in the entire data set. The C index falls in the interval $[0, 1]$; smaller values of C indicate a better clustering performance. In our strategy, starting from the cluster with 1 group, following the hierarchical clustering, we will choose the clustering with k groups if its C index is lower than the C index of the cluster with $k - 1$ groups and not greater than the C index of the cluster with $k + 1$ groups.

For the purposes of this paper, we perform three sets of experiments:

1. **Classification of the unconditional volatilities**: We compare the classifications of the assets obtained from (2.4) (SAMEM-based classification) and from (2.2) (AMEM-based classification). If they are similar, this would be evidence for the robustness of the classification because different models provide similar clustering. The similarity of the clustering can be based on the Rand index (Rand, 1971, Hubert and Arabie, 1985):

$$R_a = \frac{\sum_{i=1}^{k}\sum_{j=1}^{k'}\binom{n_{ij}}{2} - [\sum_{i=1}^{k}\binom{n_i}{2}][\sum_{j=1}^{k'}\binom{n_j}{2}]/\binom{n}{2}}{[\sum_{i=1}^{k}\binom{n_i}{2} + \sum_{j=1}^{k'}\binom{n_j}{2}]/2 - [\sum_{i=1}^{k}\binom{n_i}{2}][\sum_{j=1}^{k'}\binom{n_j}{2}]/\binom{n}{2}},$$

   where k is the number of groups in the SAMEM clustering, whereas k' is the number of groups in the AMEM clustering; n_i and n_j represent the number of series belonging to the group i of the SAMEM clustering and the group j of the AMEM clustering respectively; n_{ij} is the number of series belonging to the group i in the SAMEM case and assigned to the group j in the AMEM clustering. R_a lies in the interval $[0, 1]$ and it is equal to 1 in the case of coincidence between the two classifications, whereas it is 0 when the differences between them are at their maximum.

2. **Other SAMEM–based classifications**: the clustering algorithm is used to classify the series according to the following criteria:

   (a) classifying the series with similar proportion of transmitted volatility (2.6);

   (b) classifying the series with similar dynamics with respect to the dominant market, using the statistic (2.11).

3. **Multiple classification**: the several characteristics of the assets derived from the SAMEM specification (u_S, f_S and d_S) are considered simultaneously, obtaining groups of series with similar unconditional volatility levels, similar proportions of transmitted volatility from a dominant market, similar dynamics with respect to the dominant market.

3 Empirical Evidence for European Assets

We have considered 37 of the 50 assets compounding the Euro Stoxx 50 index. The list of the assets considered is shown in Appendix A, where we show the symbols which we will use hereafter, the starting date and the number of observations considered for each time series. The dominant market is the US and we use the S&P500 index to represent it. The bivariate SAMEM analysis involves the use of pairs of series with different lengths, due to different closing days of each market; for each model we have considered only the common dates of the two series. For each series the volatility has been measured using the intra–daily log–range with the correction proposed by Parkinson (1980), given by:

$$y_{i,t} = \left[ln(p^h_{i,t}) - ln(p^l_{i,t})\right] \left[\frac{1}{4} ln(2)\right]^{1/2}$$

where $p^h_{i,t}$ and $p^l_{i,t}$ are the highest and lowest price respectively, of the asset (market) i during the day t. For a comparative analysis of the properties of the daily range with respect to alternative measures of volatility, see Patton (2011).

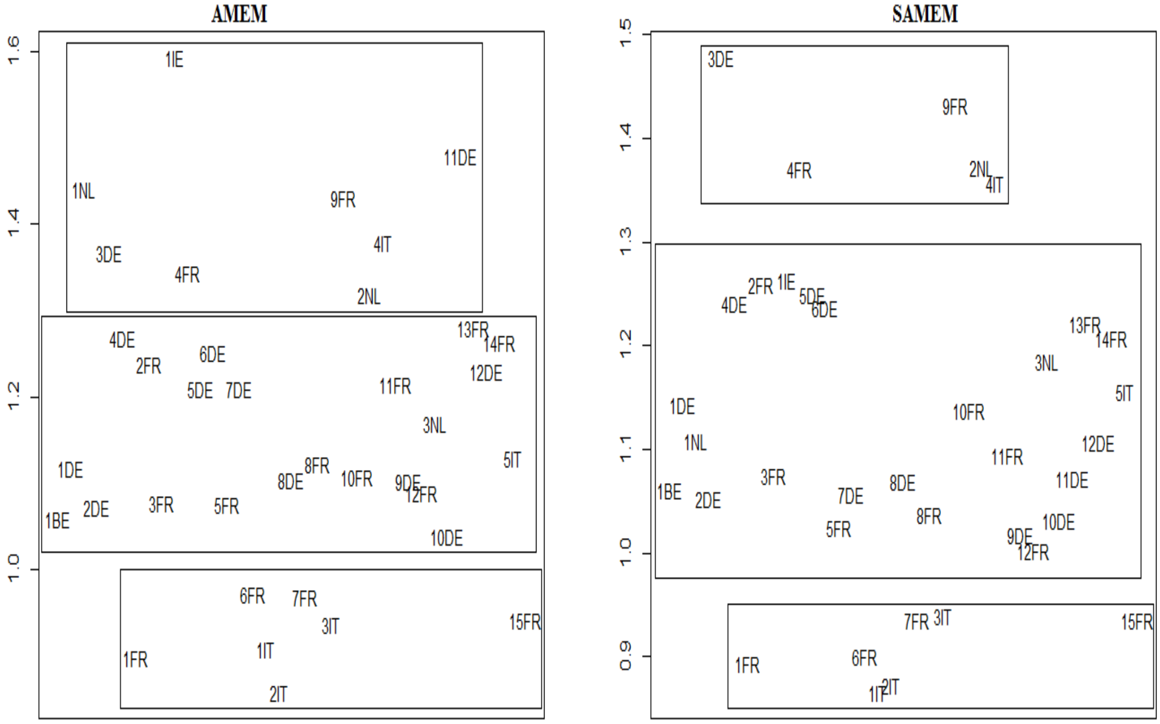
We perform the three sets of experiments described in the previous section, distinguishing them by subsections. For this purpose 37 SAMEMs and 37 AMEMs are estimated; the tables with the estimation results are shown in Appendix B.

3.1 Classification of the unconditional volatilities

First, we have applied the clustering algorithm described in the previous section to classify the 37 assets by different levels of unconditional volatility, obtained alternatively from the AMEM (equation (2.2)) and the SAMEM ((equation (2.4)). In both cases we obtain three groups, that can be interpreted as groups of low (L), medium (M) and high (H) unconditional level of volatility; they are illustrated in Figure 1.

Observing the SAMEM classification (right panel) we notice that a large part of the assets (25 assets) belong to the medium group, with an average level of volatility equal to 1.12, whereas the low and high unconditional volatility groups are composed of 7 (average level equal to 0.91) and 5 (average level equal to 1.40) assets respectively. Also the groups seem clearly separated in the graph, in the sense that the presence of a *jump* between the levels of two groups seems clear. It is interesting to notice that the cluster of low volatility is composed only by French and Italian assets, whereas eleven of the twelve German assets belong to the cluster of medium volatility. The AMEM classification (left panel) shows small differences with respect to the SAMEM case: the only different classification is relative to three assets (11DE, 1IE, 1NL) which belong to group M in the SAMEM classification, whereas they are included in group H in the AMEM classification. The average levels of each group in the AMEM case are 0.93,

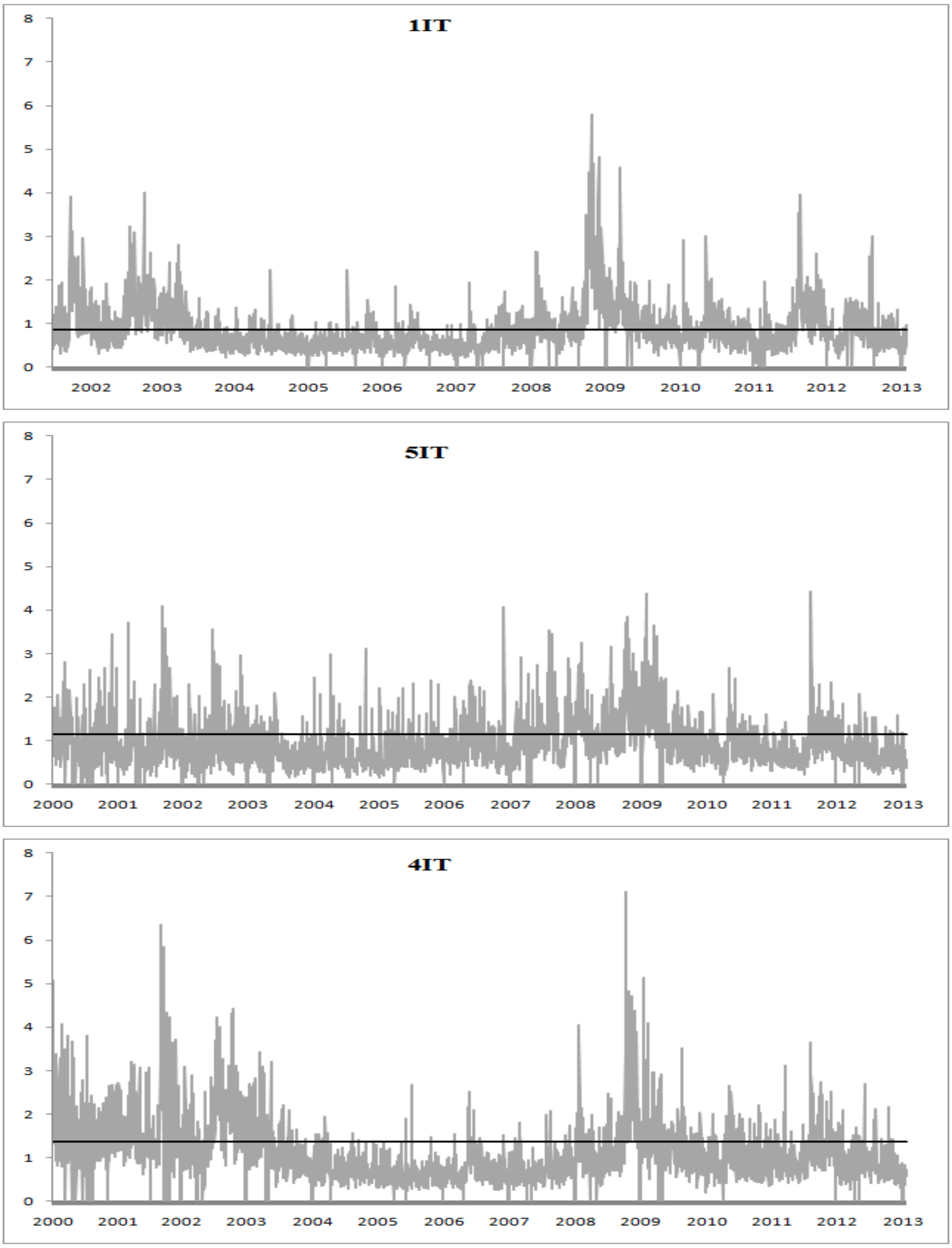
Figure 1: Clustering based on the unconditional volatility (left panel) derived from the AMEM and from the SAMEM (right panel)



1.20, 1.37 respectively. A Rand Index equal to 0.85 is a further support to the intuition that the two classifications are very similar, so the classification of the unconditional volatility derived by the SAMEM can be considered as a robust starting point for our successive experiments.

The different behavior of the series belonging to different groups is clear observing Figure 2, where the volatility of three Italian series (one for each group) is shown. It is evident how the series belonging to the first group (1IT) has small levels of volatility, with some jumps in correspondence to the main global shocks, such as the Afghan war in October 2001 and the Iraqi war in March 2003, or the more evident 2008-09 financial crisis. The series belonging to Group M (5IT) shows more similar levels of volatility in the span considered, with a higher level (in average) with respect to the previous one. The last series (4IT), belonging to Group H, has a similar behavior with respect to 1IT, but the peaks and the general level of volatility are higher. The horizontal lines, in correspondence of the unconditional level of volatility u_S of each series, represent the long–run level of the volatility of each series.

Figure 2: Volatility series of three assets, belonging to different unconditional volatility level groups, derived from the SAMEM (1IT to Group L, 5It to Group M, 4IT to Group H). The black lines are in correspondence to the unconditional volatility level.



3.2 SAMEM-based classification

The 37 assets have been classified for different levels of unconditional volatility (2.4). Stopping our classification at this point and interpreting the volatility as a proxy of risk, we could conclude that the group H is the most risky, whereas the group L the most tranquil because less volatile.

Following our procedure, the 37 assets in terms of proportion of transmitted volatility are now classified with respect to the total. In the right panel of Figure 3 we can observe the composition of the 4 groups obtained following the C index criterion; in this case the lowest group is the one with the lowest proportion of transmitted volatility, whereas the highest group is the one most affected by the volatility of the dominant market. In particular, it can be noted that a large part of the assets (15 assets) belong to the cluster with a low-medium (LM) proportion of transmitted volatility (average proportion equal to 0.13), whereas both the clusters of low (L) and medium-high (MH) transmitted volatility are composed of 9 assets, with an average proportion equal to 0.06 and 0.19 respectively. Four assets (with an average equal to 0.26) compose the cluster with high (H) proportion of transmitted volatility. To understand the differences between the four clusters, we show in Figure 4 the proportion of transmitted volatility from S&P to four German assets (ratios $\frac{\xi_t}{\zeta_t+\xi_t}$): 4DE (belonging to cluster H), 12DE (cluster MH), 9DE (cluster LM), 7DE (cluster L). It is evident how the transmitted volatility is almost constant in the series 7DE, whereas it follows the US shocks in the other cases, with different magnitude. The horizontal black lines, representing the value of f_S for each series, show that this ratio is a synthesis (a sort of average) of the information deriving from the graphical inspection.

It is apparent that this classification seems really different from the previous one and our feeling is confirmed in Table 1, where the 37 assets are classified in terms of the two criteria. In particular the two classifications can be considered independent, as confirmed by a chi-squared statistic equal to 6.09, with the corresponding p-value (derived from a chi-squared distribution with 6 degrees of freedom) equal to 0.41.

Table 1: Distribution of the assets in terms of unconditional volatility clustering and proportion of transmitted volatility clustering

Proportion of Transm. vol.	Unc. Vol. L	M	H	Total
L	1	6	2	9
LM	5	9	1	15
MH	0	7	2	9
H	1	3	0	4
Total	7	25	5	37

Figure 3: Clustering based on the unconditional volatility (left panel) and the proportion of transmitted volatility (right panel) derived from the SAMEM.

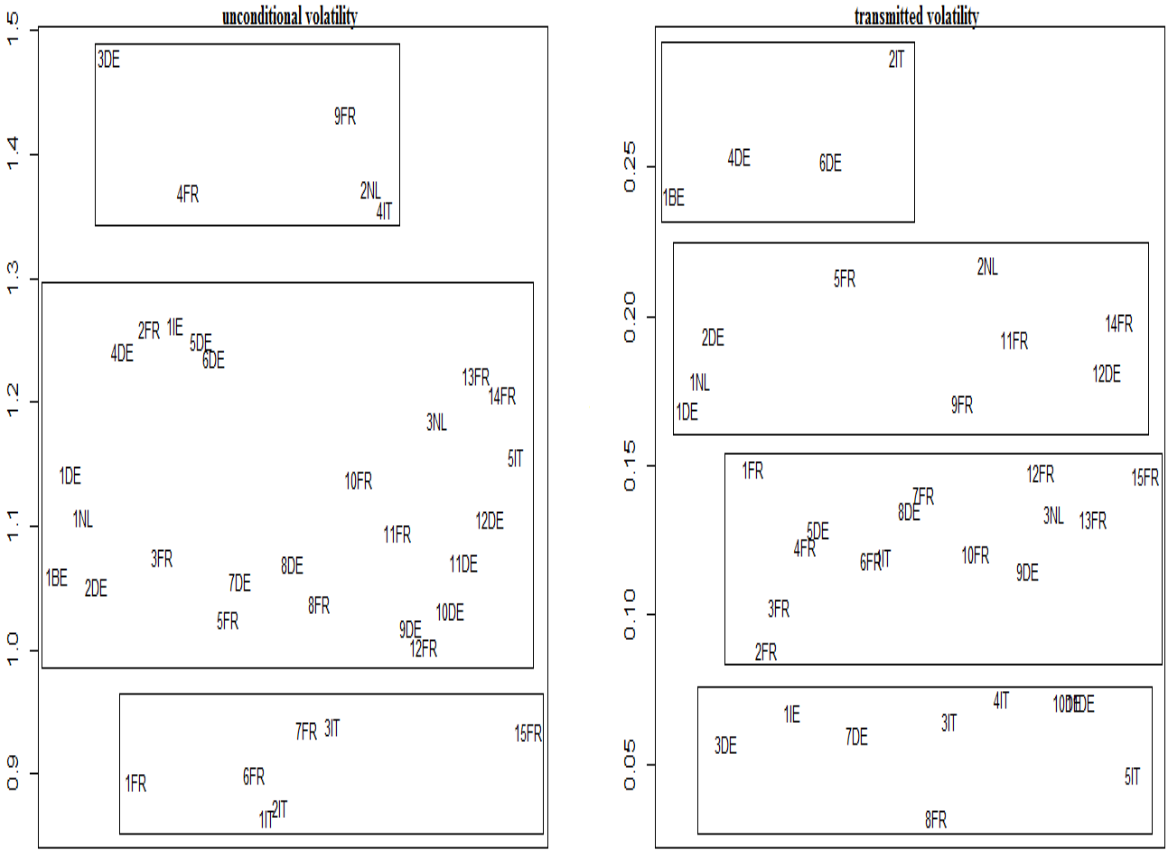
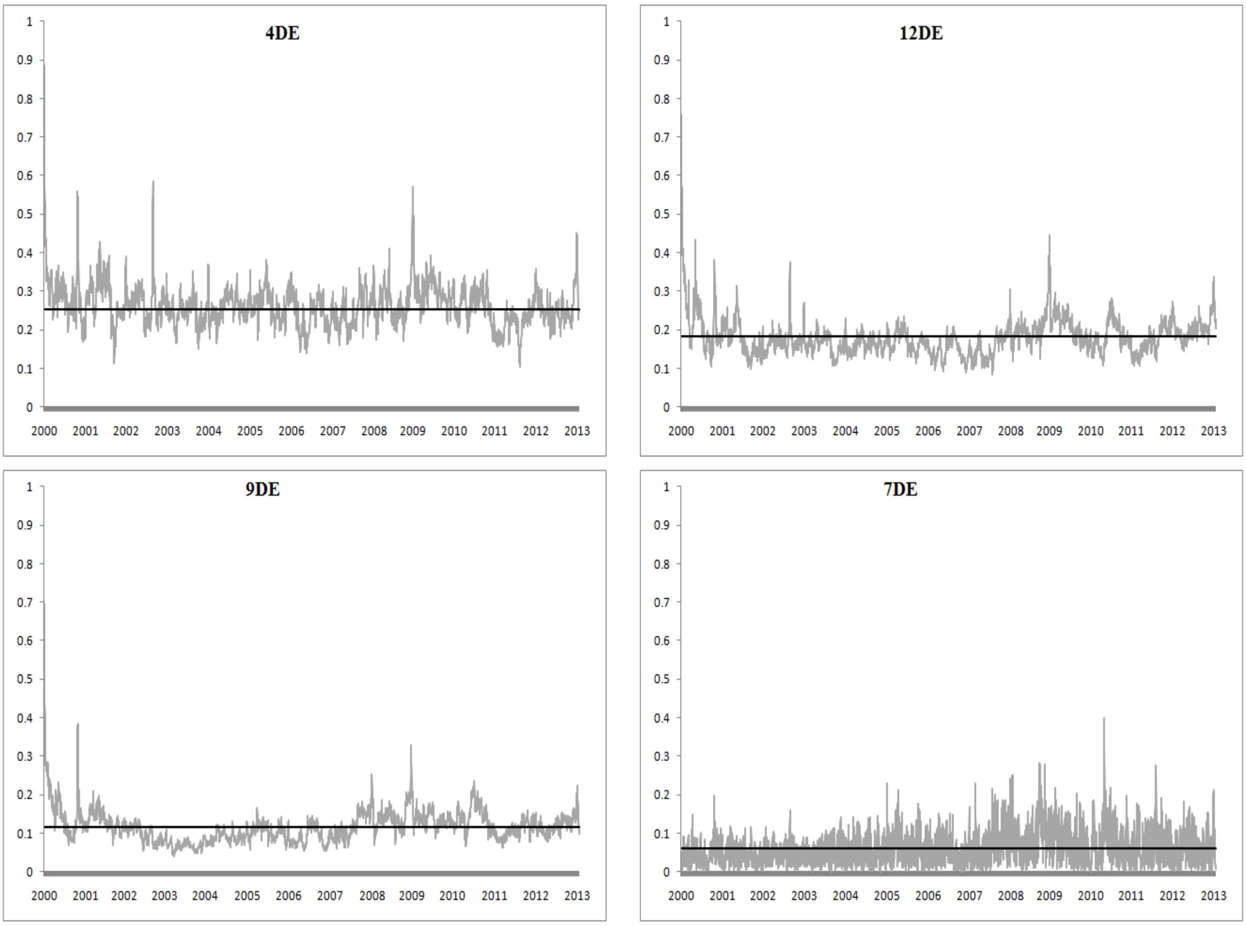


Figure 4: Series of the proportion of transmitted volatility of four assets, belonging to different f_S ratios groups, derived from the SAMEM (4DE to Group H, 12DE to Group MH, 9DE to Group LM, 7DE to Group L). The black lines are in correspondence of the f_S ratio of each series.



The lesson we learn from this experiment is that, if we consider the risk of an asset linked to the unforecastable movements of the price of the asset, the unconditional volatility level can not be interpreted as a proxy of the risk because it considers the full dynamics of the volatility, included the part due to spillover effects that could be expected observing the movements of the dominant market. A more correct risk-based classification of the 37 assets is illustrated in Figure 5; each panel represents the three different groups of unconditional volatility (from the lowest on the left to the highest on the right). Within each panel, the assets by different degrees of transmitted volatility are classified; the groups at the top of each panel are characterized by a high proportion of transmitted volatility. In practice, based on this classification, the less risky asset is 2IT, whereas the assets more risky are 3DE and 4IT.

On the other hand, in particular for investments and disinvestments in the short term, it might be convenient to classify the assets in terms of similar dynamics with respect to the dominant market, using the distance (2.11). We have re-run the clustering algorithm for this index, obtaining the results illustrated in Figure 6. Six clusters are obtained, but several assets follow a dynamics very similar to the S&P index, with a d_S statistic close to zero; we label the six groups with the letters from A to F, where A is the group with more similar dynamics with respect to S&P, whereas F the most different. The three clusters in the lower part of the graph (A, B and C), which contains the three groups of assets with more similar dynamics with respect to the S&P index, contain 29 of the 37 assets. The assets 3DE and 2NL (which belong to the group of high unconditional volatility, but with low and medium-high proportions of transmitted volatility respectively) show the lowest similarity in the dynamics with respect to S&P (Group F). Notice that 4FR and 4IT belong to Group A, but they were classified as assets with high unconditional volatility. In practice the movements of the volatility of an asset that, at a first stage, we could evaluate as risky, could be in part expected following the US market movements.

Figure 5: SAMEM-based classification within the three unconditional volatility groups (L, M, H) in terms of proportion of transmitted volatility

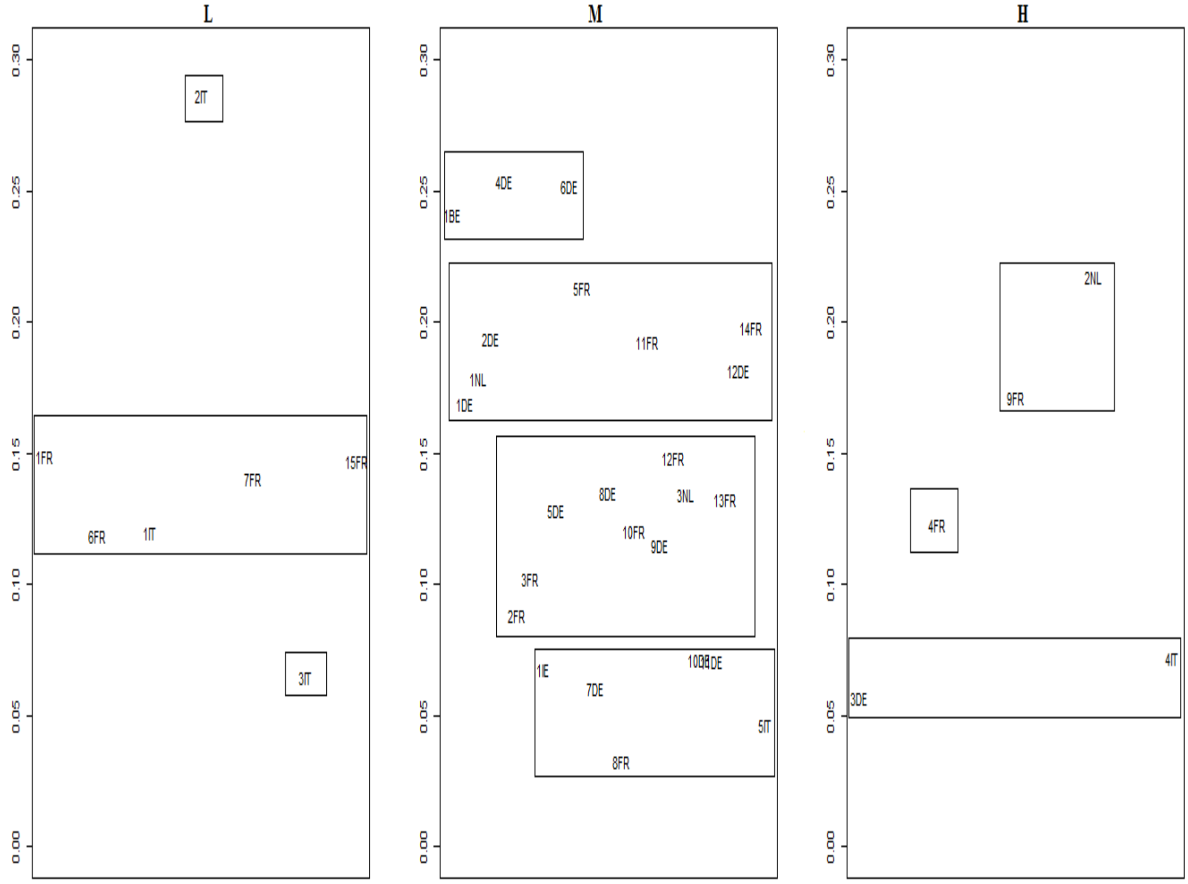
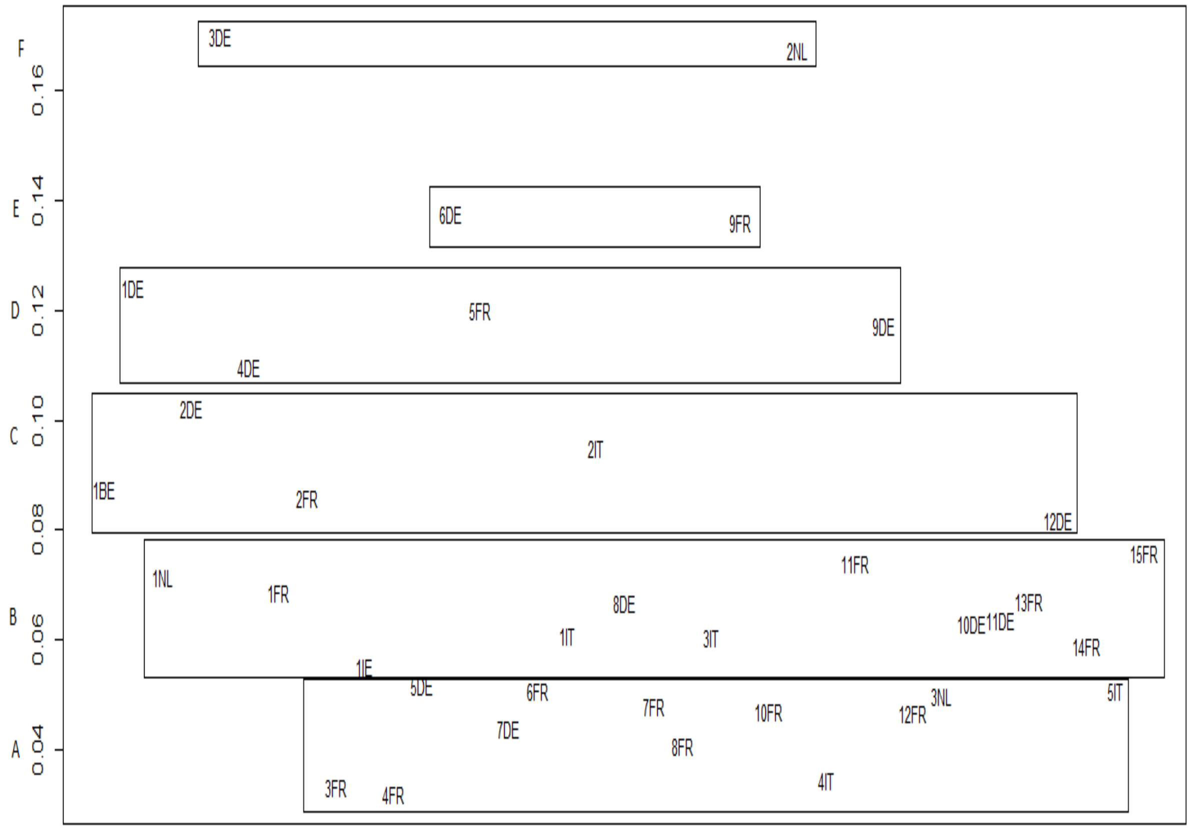


Figure 6: SAMEM-based classification in terms of distance from the S&P model.



To show that the statistic d_S in (2.11) really measures the similarity in the dynamics of the volatility of an asset A and the volatility of the dominant market B, we have calculated the following loss functions (Root Mean Squared Difference of Variations -RMSDV- and Mean Absolute Difference of Variations -MADV):

$$\begin{aligned} RMSDV &= \sqrt{\textstyle\sum_t \left(\Delta y_{A,t} - \Delta y_{B,t}\right)^2} \\ MADV &= \textstyle\sum_t \left|\Delta y_{A,t} - \Delta y_{B,t}\right| \end{aligned} \tag{3.1}$$

where $\Delta y_{i,t} = y_{i,t} - y_{i,t-1}$ $(i = A, B)$. In practice we verify if variations in asset A are similar, in sign and magnitude, with respect to the variations in market B. In the extreme case of equal movements, the two loss functions are equal to zero. In Table 2 we show the average values of $RMSDV$ and $MADV$ within each group. It can be noted how the two indicators increase when the group is more distant with respect to the benchmark represented by the S&P dynamics, confirming the interpretation of the distance as a measure of the similarity between the dynamics of two volatility series.

Table 2: Average values of two loss functions within each group obtained classifying the assets by d_S (standard deviations in parentheses).

Group	RMSDV	MADV
A	0.035	0.056
	(0.031)	(0.013)
B	0.086	0.058
	(0.022)	(0.013)
C	0.096	0.064
	(0.018)	(0.011)
D	0.117	0.079
	(0.015)	(0.008)
E	0.152	0.100
	(0.024)	(0.012)
F	0.182	0.110
	(0.040)	(0.017)

3.3 Multiple classification

As a consequence of the previous comments, a logical classification of the assets is based on a clustering which considers simultaneously the level of volatility, the proportion of transmitted volatility and the similarity of the dynamics. In other words, we classify the 37 series considering the variables u_S, f_S and d_S. The hierarchical algorithm and the C index identify nine clusters, as shown in Table 3; the mean of each variable within each cluster helps to interpret the groups.

The groups are ordered by increasing unconditional volatility, but their characteristics are clearly different; in the following points they are briefly described.

- Group 1: it is characterized by a low volatility level but a high degree of transmitted volatility. Its dynamics is not very different from the one of S&P (Group C in terms of the clustering based on d_S). The asset 2IT is the only one belonging to this group and seems to be the less risky asset.
- Group 2: a low volatility level, but also a lower proportion of transmitted volatility with respect to the previous group and a higher similarity in the dynamics with respect to S&P.
- Group 3: a medium-low level of volatility with a small transmitted volatility proportion.
- Group 4: a medium-low level of volatility with a higher transmitted volatility proportion.
- Group 5: a medium-high level of volatility with a medium transmitted volatility proportion and a strong similar dynamics with respect to S&P.
- Group 6: a medium-high level of volatility with a high transmitted volatility proportion and a different dynamics with respect to S&P.

Table 3: Multiple SAMEM–based classification in terms of u_S, f_S, d_S.

Group 1			Mean			
		u_S	f_S	d_S		
		0.873	0.287	0.095		
			Assets			
2IT						
Group 2			Mean			
		u_S	f_S	d_S		
		0.925	0.127	0.059		
			Assets			
1FR	6FR	7FR	12FR	15FR	1IT	3IT
Group 3			Mean			
		u_S	f_S	d_S		
		1.052	0.084	0.061		
			Assets			
7DE	8DE	9DE	10DE	11DE	3FR	8FR
Group 4			Mean			
		u_S	f_S	d_S		
		1.084	0.196	0.094		
			Assets			
1BE	1DE	2DE	12DE	5FR	11FR	1NL
Group 5			Mean			
		u_S	f_S	d_S		
		1.211	0.103	0.058		
			Assets			
5DE	2FR	10FR	13FR	1IE	5IT	3NL
Group 6			Mean			
		u_S	f_S	d_S		
		1.229	0.235	0.102		
			Assets			
4DE	6DE	14FR				
Group 7			Mean			
		u_S	f_S	d_S		
		1.364	0.097	0.033		
			Assets			
4FR	4IT					
Group 8			Mean			
		u_S	f_S	d_S		
		1.402	0.194	0.152		
			Assets			
9FR	2NL					
Group 9			Mean			
		u_S	f_S	d_S		
		1.479	0.057	0.170		
			Assets			
3DE						

- Group 7: a high level of volatility with a low transmitted volatility proportion and a strong similar dynamics with respect to S&P.
- Group 8: a high level of volatility with a medium-high transmitted volatility proportion and a different dynamics with respect to S&P.
- Group 9: a high level of volatility with a low transmitted volatility proportion and a different dynamics with respect to S&P. The only asset belonging to this group, 3DE, is clearly the most risky asset.

4 Final Remarks

The volatility of a certain asset is often considered as a proxy of the risk of the same asset and the classifications are made according to this idea. But the degree of risk is particularly linked to the possibility of expecting the volatility movements, in particular to the sensitivity of the asset to the shocks or the dynamics of a dominant market; in this case, the investor possesses important information which can guide his choices. In a clustering framework it is important to identify measures to evaluate the propensity to absorb the spillovers deriving from a dominant market, and the similarity of the dynamics of the volatility series overtime. We propose a model-based approach, developing the SAMEM of Otranto (2013), which extends the AMEM of Engle and Gallo (2006) to include the spillover effects deriving from dominant markets. Extending the definitions of unconditional volatility and AR distance (Piccolo, 1990) we are able to define three measures representing the volatility level, the proportion of transmitted volatility and the similarity of the dynamics, respectively. Applying a hierarchical algorithm and obtaining the number of clusters following a quality criterion (C index), our approach provides groups of assets different with respect to the classification based only on the volatility levels: groups with similar volatility levels are split according to different degrees of dependence and similarity with respect to the dominant market.

Of course this approach could be extended to include also other variables of interest, such as the volume of exchanges, economic indicators or statistical indicators (such as the degree of asymmetry, the autocorrelation, etc.; see, for example, Wang et al., 2006).

The choice of a stopping rule, such as the one based on the value of the C index, helps users in the detection of the number of groups, which is automatic. Of course, users possessing statistical skills could base their choice on the number of clusters observing the dendrogram or using alternative stopping rules. The C index criterion favors the clear separation of the groups with an optimal clustering quality; on the other hand it could favor a large number of groups, but, in the portfolio choices, this could be an advantage because the investor can choose among several different portfolio compositions with different degrees of risk.

The choice of the MEM approach is due to the recent development of this family of models and the possibility to model a measure of the volatility directly, without resorting to the use of logarithms or other transformations. Of course, it is possible to extend our approach using different models, which can incorporate the effects of dominant markets on the asset of interest and that can provide measures of the spillover effects as in the SAMEM case.

The experiments could be repeated using alternative measures of volatility (we have used the intra-daily log-range) or considering several dominant markets (as in the general SAMEM formulation of Otranto, 2013).

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A Appendix A: The data set

The data set used in the experiments illustrated in this work is referred to 37 of the 50 assets composing the Euro Stoxx 50 index, downloaded from the website of Yahoo Finance. We have selected only the series available for the period 2000-2012. All the series end on 18 January 2013 (except CRG.IR that ends in 15/10/2012). The starting date is different, depending on the availability of the data. In Table 4 we show the code used for each asset in the Figures and Tables, the starting date and the number of observations.

Table 4: List of the 37 assets considered in the classification experiments

Code	Market	Asset	Starting date	Observations
1BE	Belgium	ANHEUS.-BUSCH INBEV	01/12/2000	3148
1DE	Germany	Allianz SE	03/01/2000	3361
2DE	Germany	BASF SE	03/01/2000	3376
3DE	Germany	Bayer AG	03/01/2000	3374
4DE	Germany	Bayerische Motoren Werke Aktiengesellschaft	03/01/2000	3374
5DE	Germany	Daimler AG	03/01/2000	3375
6DE	Germany	Deutsche Bank AG	03/01/2000	3375
7DE	Germany	Deutsche Telekom AG	03/01/2000	3376
8DE	Germany	E.ON SE	03/01/2000	3380
9DE	Germany	M	03/01/2000	3235
10DE	Germany	RWE AG	28/11/2000	3385
11DE	Germany	SAP AG	03/01/2000	3375
12DE	Germany	Siemens Aktiengesellschaft	03/01/2000	3395
1FR	France	Danone	23/02/2000	3394
2FR	France	BNP Paribas SA	03/01/2000	3384
3FR	France	Carrefour SA	03/01/2000	3395
4FR	France	AXA Group	03/01/2000	3390
5FR	France	VINCI S.A.	03/01/2000	3394
6FR	France	Essilor International SA	03/01/2000	3384
7FR	France	Total SA	03/01/2000	3387
8FR	France	France T	03/01/2000	3395
9FR	France	Societe Generale Group	03/01/2000	2578
10FR	France	GDF Suez S.A.	03/01/2000	3395
11FR	France	LVMH Moet Hennessy Louis Vuitton	03/01/2000	3395
12FR	France	L'Oreal SA	03/01/2000	3088
13FR	France	Compagnie de Saint-Gobain	03/01/2000	3395
14FR	France	Schneider Electric S.A.	03/01/2000	3395
15FR	France	Unibail-Rodamco SE	03/01/2000	3395
1IE	Ireland	CRH PLC	01/01/2003	2493
1IT	Italy	Enel SpA	09/07/2001	3003
2IT	Italy	Eni SpA	18/06/2001	2992
3IT	Italy	Assicurazioni Generali S.p.A.	03/01/2000	3378
4IT	Italy	Intesa Sanpaolo S.p.A.	03/01/2000	3336
5IT	Italy	UniCredit S.p.A.	03/01/2000	3395
1NL	Holland	ASML Holding NV	03/01/2000	3385
2NL	Holland	ING Groep N.V.	01/01/2003	3388
3NL	Holland	ROY.PHILIPS	01/08/2000	3366

B Appendix B: Parameter Estimates

In this Appendix we show the estimation results for the AMEM (Table 5) and SAMEM (Table 6) coefficients that we have used to derive the indicators representing the unconditional volatilities (2.2) and (2.4), the proportions of transmitted volatility (2.6) and the distances (2.11) . To save space we have not inserted the standard errors of each estimator; this information is available on request.

Table 5: Estimate of AMEM coefficients for each asset and S&P500.

Asset	ω_0	α_0	β_0	γ_0	a
1BE	0.03	0.14	0.81	0.04	3.93
1DE	0.03	0.16	0.78	0.07	3.77
2DE	0.03	0.14	0.80	0.07	3.65
3DE	0.02	0.24	0.73	0.04	2.96
4DE	0.02	0.14	0.82	0.04	3.55
5DE	0.03	0.13	0.82	0.05	3.52
6DE	0.02	0.16	0.80	0.05	3.44
7DE	0.02	0.14	0.83	0.03	4.05
8DE	0.02	0.12	0.83	0.06	5.18
9DE	0.01	0.12	0.84	0.04	4.33
10DE	0.01	0.14	0.82	0.06	3.44
11DE	0.02	0.12	0.83	0.07	4.55
12DE	0.02	0.12	0.85	0.05	3.92
1FR	0.02	0.16	0.81	0.02	4.29
2FR	0.03	0.16	0.78	0.07	4.46
3FR	0.02	0.13	0.84	0.04	4.33
4FR	0.02	0.13	0.83	0.07	4.28
5FR	0.03	0.15	0.79	0.05	3.83
6FR	0.02	0.15	0.79	0.07	3.91
7FR	0.01	0.13	0.83	0.05	4.02
8FR	0.02	0.16	0.80	0.04	3.91
9FR	0.03	0.14	0.81	0.04	4.38
10FR	0.02	0.20	0.75	0.07	5.13
11FR	0.02	0.18	0.78	0.05	4.57
12FR	0.01	0.11	0.85	0.06	4.87
13FR	0.01	0.12	0.84	0.06	3.46
14FR	0.02	0.13	0.82	0.07	2.47
15FR	0.01	0.14	0.82	0.06	3.98
1IE	0.01	0.09	0.90	0.00	3.27
1IT	0.03	0.14	0.79	0.07	4.87
2IT	0.03	0.15	0.79	0.06	3.87
3IT	0.02	0.17	0.79	0.06	3.96
4IT	0.02	0.11	0.85	0.06	4.40
5IT	0.04	0.14	0.79	0.03	3.66
1NL	0.02	0.10	0.86	0.04	3.76
2NL	0.02	0.13	0.82	0.05	3.59
3NL	0.03	0.16	0.79	0.04	5.79
S&P500	0.01	0.07	0.85	0.12	6.50

Table 6: Estimate of SAMEM coefficients for each asset

Asset	ω_0	α_0	β_0	γ_0	a	α_1	β_1	γ_1
1BE	0.04	0.13	0.76	0.02	4.04	0.50	0.17	0.07
1DE	0.02	0.17	0.73	0.07	3.80	0.96	0.01	0.00
2DE	0.04	0.14	0.73	0.06	3.69	0.93	0.01	0.03
3DE	0.00	0.26	0.72	0.00	2.99	0.40	0.00	0.16
4DE	0.01	0.16	0.76	0.04	3.58	0.98	0.01	0.00
5DE	0.03	0.13	0.81	0.02	3.55	0.62	0.06	0.09
6DE	0.00	0.18	0.72	0.05	3.46	0.99	0.01	0.00
7DE	0.01	0.14	0.83	0.02	3.42	0.49	0.00	0.10
8DE	0.03	0.13	0.78	0.04	3.93	0.58	0.04	0.11
9DE	0.02	0.18	0.75	0.05	4.61	0.97	0.00	0.01
10DE	0.03	0.15	0.80	0.02	5.86	0.59	0.00	0.10
11DE	0.02	0.13	0.81	0.06	3.46	0.98	0.00	0.01
12DE	0.02	0.12	0.78	0.06	3.49	0.97	0.00	0.02
1FR	0.03	0.15	0.78	0.00	4.37	0.46	0.06	0.11
2FR	0.02	0.16	0.78	0.05	4.50	0.57	0.03	0.09
3FR	0.02	0.12	0.83	0.02	4.41	0.66	0.00	0.12
4FR	0.02	0.11	0.84	0.04	4.34	0.53	0.05	0.15
5FR	0.06	0.16	0.68	0.05	3.88	0.91	0.01	0.03
6FR	0.03	0.13	0.81	0.01	4.12	0.73	0.00	0.09
7FR	0.02	0.11	0.82	0.04	5.26	0.58	0.04	0.10
8FR	0.01	0.13	0.83	0.05	4.03	0.98	0.00	0.00
9FR	0.00	0.19	0.73	0.06	3.99	0.98	0.00	0.01
10FR	0.02	0.13	0.81	0.02	4.46	0.44	0.06	0.13
11FR	0.02	0.11	0.80	0.06	4.45	0.97	0.00	0.02
12FR	0.02	0.12	0.82	0.01	4.40	0.46	0.08	0.10
13FR	0.02	0.12	0.81	0.07	4.57	0.97	0.00	0.01
14FR	0.03	0.11	0.82	0.02	3.98	0.53	0.12	0.12
15FR	0.05	0.14	0.77	0.01	3.73	0.46	0.06	0.11
1IE	0.01	0.10	0.88	0.00	3.27	0.96	0.00	0.01
1IT	0.02	0.13	0.80	0.04	3.96	0.56	0.02	0.10
2IT	0.04	0.12	0.72	0.06	4.99	0.85	0.03	0.05
3IT	0.02	0.15	0.81	0.02	3.94	0.56	0.00	0.09
4IT	0.02	0.12	0.83	0.04	3.62	0.44	0.02	0.13
5IT	0.02	0.13	0.82	0.05	2.47	0.58	0.00	0.07
1NL	0.00	0.13	0.82	0.05	3.77	1.00	0.00	0.00
2NL	0.00	0.21	0.68	0.08	5.21	0.99	0.00	0.01
3NL	0.02	0.11	0.82	0.05	4.90	0.96	0.00	0.02

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