Investment Communities: Behavioral Attitudes and Economic Dynamics

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Abstract

Using a real-world data set encompassing the daily portfolio holdings and exposures of complex investment funds, we derive a set of quantitative attributes to capture essential behavioral features of fund managers. We find the existence and stability of three investment attitudes, namely the conservative, the reactive, and the pro-active profiles, defining communities that respond differently when facing external shocks. The conservative community has behavioral similarities that tend to decrease due to external shocks, the reactive community members greatly increase their activity level especially during turmoil phases, while delegated investors in the pro-active community are more resilient to turbulence and counterbalance the impact of the events by adjusting their portfolio exposures in advance. We show that exogenous shocks only temporarily perturb the behavioral traits of the communities which then go back to their original states once the distress is embedded.

Keywords: Investment Funds; Tensor Decomposition; Community Detection; Managers Behavioral Attitudes

JEL classification: C15; G11; G4.

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1 Introduction

"The age of asset management is upon us". These words were pronounced by Andrew Haldane, the chief economist of the Bank of England, to stress the increasing influence of the investment industry on financial markets and the potential risk this poses on financial stability (Haldane et al., 2014). The industry of assets under management is, indeed, growing rapidly; it has approximately doubled its size over the past decade, showing a trend that seems not to decline in the near future. PriceWaterhouseCoopers, for instance, has estimated that the industry of assets under management could touch around USD100 trillion by 2020, reaching USD400 trillion by 2050[1].

Delegated investors[2] are concerned with their relative performance compared to their peers. Searching for alpha, i.e. extra-returns with respect to a benchmark, has the potential to inject spillover effects into the financial system, possibly generating frictions in market liquidity similar to a bank run (Feroli et al., 2014). Such adverse dynamics are more likely to arise from asset managers behaving in a correlated fashion. In other words, while during market upswings managers are likely to look for yield in an attempt to outperform their benchmarks, in market downturns they quest for safety to boost relative return rankings, possibly causing a flight to quality effect (Davis and Madura, 2012).

A vast literature has addressed the issues of funds' dynamic asset allocation and stock-picking decisions by examining how excess returns relative to benchmarks are obtained (Barras et al., 2010; Christopherson et al., 2009; Grinblatt et al., 1995; Grinold, 1989; Sharpe et al., 1999). Nevertheless, the behavioral features driving managers in their allocation choices are far from being well analyzed and investigated (Hsieh et al., 2011). The scope of this paper is, hence, to analyze the behavioral features that drive managers in their allocation choices. Besides sector, asset type, geographical and market portfolio compositions, we want to disentangle similarities in the behavior of professional investors in terms of e.g. trading intensity, derivative exposures and position concentration. In particular, we are interested in studying how extreme events reveal coordinated behaviors usually hidden by almost perfectly balanced portfolio dynamics to provide the potential for a better understanding of fund managers' activities.

We employ a micro-level data set of complex portfolio holdings for constructing a vector of behavioral features that describe the investment decisions of managers. We focus on the year 2015 due to the relevant macroeconomic and geopolitical events that heavily perturbed financial markets as, for instance, the Greek austerity packages, the elections in UK as well as the major monetary changes that occurred both in Europe and in the US. We investigate the patterns of co-occurrences of behavioral traits through time to determine similarities and differences across the behaviors of professional investors in the light of the economic and geopolitical events affecting market dynamics. We focus on the behavioral responses of managers to market instability, investigating their attitudes towards risk and uncertainty by introducing an intrinsically temporal approach that allows to simultaneously identify communities and track their activity over time (Pecora and Spelta, 2017; Spelta, 2017). Our primarily interest is in strong, or dominant, relation-

[1] See *https://www.pwc.com/gx/en/industries/financial-services/asset-management/publications/asset-management-2020-a-brave-new-world.html.*

[2] The terms delegated investors, fund managers and asset managers are used as synonymous in the paper.

ships that tie together managers' behavioral features. As these types of relationships are more difficult to be broken, they reveal the "true" and persistent structures of managers' behavioral attitudes, emphasizing the relationships between e.g. the use of mental models and the representation of the financial markets by delegated investors (Johnston-Laird, 1983; Johnson-Laird, 2010).

In particular, besides the Minimal Spanning Tree (MST) analysis of the time constrained similarity networks built from managers' behavioral attributes, a coefficient of residuality is defined to capture the structural evolution of primary linkages (Mantegna and Stanley, 1999; Onnela et al., 2002; Spelta and Araújo, 2012). The residuality coefficient captures not only the changes in the threshold that insures connectivity of the whole network, but it also measures the variations in the relative amounts of strong and weak ties, contributing to identifying the coordinated behaviors arising, for instance, during financial crisis periods. Strong linkages are then analyzed from a geometric perspective showing that the systematic information characterizing managers' behaviors actually belongs to a space of few dimensions (Seber, 2009), where we have applied a multidimensional decomposition technique to identify persistent communities with homogeneous behavioral features.

Our work relies on a particular tensor decomposition approach, the so-called CP decomposition (whose label refers to the two most popular techniques, namely the "Candecomp", developed by Carroll and Chang (1970), and the "Parafac" proposed by Harshman (1970)). This approach basically stands for a singular value decomposition (SVD) applied to multidimensional array; it also reflects the fact that an evolving network can be described as a time-ordered sequence of adjacency matrices that represent the state of a given system at a certain time. These adjacency matrices are, then, arranged in a single mathematical object that is the three-way tensor.

The intrinsically temporal nature of the methodology allows us also to investigate managers' activity patterns and temporal correlations during various market phases. Our study reveals the existence of three communities characterized by different investment behavioral traits: conservative, reactive and pro-active. The analysis of the activity level of the communities as a function of time shows how fund managers with a conservative behavior respond to external shocks by decreasing their similarities. The opposite happens to reactive fund managers that, instead, increase their synchronization during unexpected events. Those fund managers can also be named pro-cyclical to differentiate them from the last group, i.e. the pro-active funds, whose members tend to anticipate possible market shocks (thus deserving also the label of counter-cyclical funds managers).

More importantly, our temporal analysis confirms that, besides a general increase in the synchronization between managers' behaviors during turbulent periods, communities react differently when facing exogenous shocks. We observe a temporary perturbation in the configuration of the traits characterizing a community only in the neighborhood of major distress events, which vanishes once the turbulence has been internalized by market participants. These findings contribute to the debate on the interdependence between market dynamics and the impact of events causing systemic instability since the agents considered in the study, i.e. professional investors, are those that are more likely to interpret market signals in a timely manner.

The paper is structured as follows: Section 2 describes the data set and presents the methodology applied to identify communities via a temporal clustering decomposition.

This section is also devoted to the description of the behavioral indicators used to characterize managers' investment attitudes. Section 3 exhibits the results of the study focusing on the arising communities of managers and providing the characterization and stability analysis of their behavioral traits over time. Finally, Section 4 concludes and provides the economic discussion about the results.

2 Data and methodology

2.1 Behavioral features data

In the present paper, we employ a data set that contains the daily portfolio allocations of 22 open-ended funds[3] in the year 2015. More than 4 thousands constituents belonging to 70 different countries are present in the data set. The funds' size ranges from 12 M/Euro to 2.3 B/Euro. The data covers information on fund returns, on the total values of the assets under management (AUM), and on the portfolio constituents (e.g., their market values, prices, and quantities). The constituents include several financial instruments, ranging from stocks to bonds and derivatives. Each position is classified according to the asset class, market, sector and geographical location of the issuer. The data set granularity supports its use for studying the behavioral commonalities among asset managers.

Investment funds have been typically studied in terms of portfolio compositions, focusing in particular on their performances, by examining how excess returns relative to benchmarks are obtained based on, for instance, dynamic asset allocations and stock-picking decisions (Barras et al., 2010; Christopherson et al., 2009; Fama and French, 1993; Grinblatt et al., 1995; Grinold, 1989; Sharpe et al., 1999). Portfolio allocation has been usually described by discriminating between different geographical, sectoral and asset type classes corresponding to each portfolio constituent. Indeed, the typical approach for asset management is to allocate funds into specific areas, e.g., US vs. Eurozone, or according to certain sectors or asset types, e.g., automotive vs. financial or bonds vs. equities.

Differently from previous literature on investment strategies, which focuses on indicators for standard portfolio compositions to characterize competing funds (Benartzi and Thaler, 2001; Fung and Hsieh, 1997; Sharpe, 1992), we exploit information extracted from data that is usually not fully publicly available to identify and characterize the behavioral traits of managers. In order to study the dynamics of these behavioral features, we introduce a list of attributes as proxies to map different investment profiles. We propose to examine three relevant dimensions to characterize how behavioral features affect asset managers in their portfolios allocation. The first dimension is the use of derivatives for hedging or speculating purposes. This indicator helps to detect manager's willingness to accept risk when making investment decisions. The second dimension is the manager's intensity of trading, which is the ratio of the market value of trades in one day to the value of the fund AUM. Finally, we quantify the investment concentration level among different asset classes, which is related to the trade-off that delegated investors face between using specialization to gain extra returns and the benefit of increasing diversification to mitigate risk. Although these attributes are far from being a complete and exhaustive

[3]We do not have information about funds' identity therefore we have identified them with progressive numbers from id1 to id22.

representation of the investment behavioral profiles, however, they enrich the basic perspective provided by public categories (e.g., classifications based on geographical, sectoral and asset classes), thus significantly enhancing our understanding of funds managers' behaviors.

For each fund i in time t we construct a daily vector $\mathbf{y}_i(t)$ of synthetic indicators representing both the portfolio composition and the investment strategy preferences of fund managers. We use these investment styles to map behavioral criteria that delegated investors apply when examining and selecting among competing allocation possibilities. The vector $\mathbf{y}(t)$, therefore, includes measures of both the portfolio composition and manager responses to external signals, e.g., trading intensity, use of derivatives, attitude to stock selection and asset diversification. In particular, we apply a principal component analysis on the categories for market, geographical, sectoral and asset classes to extract a list of 10 features related to portfolio composition. To measure a manager's propensity to trade, we use the ratio between the market value of trades in one day and the value of the assets under management (hereinafter, the turnover index or TI). The hedging coefficient (HC), which indicates whether equity derivatives are used for hedging or for speculation purposes, has been derived as a proxy to measure the managers' willingness to accept risk. Finally, to capture the trade-off between specialization and diversification, the Herfindahl-Hirschman index (HHI), that quantifies the investment concentration/diversification among equities, corporate and government bonds markets, has been calculated. Finally, to limit the potential noise in daily observations, all measures at time t are averaged over the preceding 10 days. Our results are robust enough across windows ranging from 5 to 15 days (see Tables in Appendix B).

2.2 The distance matrix

Once we have constructed the daily vectors of fund managers' behavioral features, we compute a measure of similarity for each pair of the N funds by adopting the cosine metric used in information retrieval for sparse and multidimensional settings. Given two funds whose time-t behavioral characteristics are collected in vectors $\mathbf{y}_i(t)$ and $\mathbf{y}_j(t)$, the time-t cosine (cos) of the angle between them is:

$$\cos(\mathbf{y}_i(t), \mathbf{y}_j(t)) = \frac{< \mathbf{y}_i(t), \mathbf{y}_j(t) >}{||\mathbf{y}_i(t)||||\mathbf{y}_j(t)||}. \tag{1}$$

where $< \circ >$ indicates the inner product and $|| \circ ||$ the Euclidean norm. The distance matrix $\mathbf{D}\,(t)$ is computed as:

$$\mathbf{D}_{ij}\,(t) = 1 - \cos(\mathbf{y}_i(t), \mathbf{y}_j(t))$$

The stronger the similarity (i.e., the force that connects two fund managers' behavioral characteristics), the shorter the length of the links connecting the funds. In other words, pairs of funds that are dissimilar receive higher weights since they are placed far away from each other, while values approaching zero are assigned to pairs with highly similar characteristics.

The fully-connected nature of $\mathbf{D}\,(t)$ does not aid in the determination of whether there are relevant patterns taking place in the system. The analysis of the systems, whose topological signature is a complete (fully-connected) network, demands the corresponding representation of the system where sparseness replaces completeness in a suitable way. To accomplish this purpose we first derive the Minimal Spanning Tree (MST) representation of fund managers' behavioral similarities.

2.3 The Minimal Spanning Tree

For each time t from the $N \times N$ distance matrix $\mathbf{D}$, we apply the nearest neighbor method to perform the hierarchical clustering. At the initial step, we consider N clusters corresponding to the N funds. Then, at each subsequent step, two clusters l_i and l_j are merged into a the same single cluster if:

$$d\left(l_i, l_j\right) = \min\left\{d\left(l_i, l_j\right)\right\}$$

with the distance between clusters being defined as:

$$d\left(l_i, l_j\right) = \min\left\{d_{pq}\right\}$$

with $p \in l_i$ and $q \in l_j$. These operations are repeated until a single cluster emerges. This clustering process is also called the single link method since one obtains the MST of a network. Given a connected graph, the corresponding MST is a tree of $N-1$ edges that provides the minimum value of the sum of the edge distances. More specifically, the hierarchical clustering procedure takes $N-1$ steps to be completed when the graph is composed by N nodes, and it exploits, at each step, a particular distance $d_{i,j} \in \mathbf{D}$ to merge two clusters into a single one. Let $C = \{d_q\}, q = 1, ..., N-1$, be the set of distances $d_{i,j} \in \mathbf{D}$ used at each step of the clustering procedure, and $L = \max\{d_q\}$. It follows that $L = d_{N-1}$. By determining the threshold distance value (L), which ensures the full connectivity between funds' features, we are able to define a representation of $\mathbf{D}$ with sparseness replacing fully-connectivity in a suitable way. In particular we consider strong ties those links that have a weight less than L. Those links represent high similarities between pairs of funds' behavioral characteristics vectors. In formula:

$$\hat{\mathbf{D}}_{ij} = \begin{cases} \mathbf{D}_{ij} & if \;\; d_{ij} < L \\ 0 & otherwise \end{cases}$$

In so doing, we do not assume an a priori specification for the degree of sparseness of $\mathbf{D}$ letting stronger similarities in the pruned network $\hat{\mathbf{D}}$ to spontaneously emerge from the dynamic of the system.

Having defined $\hat{\mathbf{D}}$ we can also compute the number S of redundant elements in $\hat{\mathbf{D}}$, namely the number of distances d_{ij} that, although assuming values smaller than L, do not need to be considered in the hierarchical clustering procedure leading to the MST. In a connected graph, S is called the cyclomatic number since it provides the cardinality of the cycles of the graph. Here, cycles and trees may or may not emerge in the resulting structures of the graph. In particular, clustered networks show a high cyclomatic number, while on the opposite scenario the networks resemble a tree-like structure and, consequently, present low clustering values.

2.4 The Principal Coordinates Analysis

To facilitate the detection of commonalities between the behaviors of delegated investors, we mitigate the course of data dimensionality by applying the Principal Coordinates Analysis (Seber, 2009) to the matrix $\hat{\mathbf{D}}$ containing strong similarities. We determine the centering matrix as follows:

$$\mathbf{H} = \mathbf{I} - N^{-1}\mathbf{1}\mathbf{1}^T$$

where $\mathbf{I}$ is the $N \times N$ identity matrix, and $\mathbf{1}$ is a vector of N ones. The eigenvalue and eigenvectors of the matrix:

$$\mathbf{B} = \mathbf{H}\left(-\frac{1}{2}\hat{\mathbf{D}}\right)\mathbf{H}$$

are then determined for each day (t). The coordinates in the lower-dimensional space are recorded in a matrix $\mathbf{\Lambda}_s = \mathbf{A}_s\mathbf{G}_s^{(1/2)}$, where $\mathbf{A}_s$ refers to the eigenvectors that correspond to the s largest eigenvalues of $\mathbf{B}$, and $\mathbf{G}_s^{(1/2)}$ contains the square root of the s largest eigenvalues along the diagonal elements.

By looking at the decay of the eigenvalues of the scalar product $\mathbf{X} = \mathbf{\Lambda}_s\mathbf{\Lambda}_s^T$ in Figure 10 (Appendix A), we see that the first three-dimensions capture the structure of the deterministic similarities and behavioral trends that are driving the system. Therefore, we embed $\hat{\mathbf{D}}$ in a three-dimensional space ($s = 3$), obtaining, for each t, the configuration matrix $\mathbf{\Lambda}_3$ that contains the coordinates of funds managers' behavioral traits in the reduced space. The resulting multivariate geometric spaces, where each fund is uniquely identified by a set of coordinates, provide the basis for the computation of the CP decomposition and of the community detection analysis. In other words, the scalar product matrix $\mathbf{X} = \mathbf{\Lambda}_3\mathbf{\Lambda}_3^T$ is the primary object of the cluster analysis.

2.5 The CP decomposition

Starting from the evolving scalar product matrix $\mathbf{X}$ obtained at each time t, we build a 3-way tensor (Bro, 1997; Kolda and Bader, 2009) $\mathcal{X} \in R^{N \times N \times T}$, where the index $N = 22$ represents funds and $T = 219$ denotes days. Thus, the tensor is composed of 219 slices, $\mathbf{X} \in R^{22 \times 22}$. The tensor $\mathcal{X}$ encompasses both the topological and temporal information of the evolving behavioral characteristics of funds managers. To reveal the community structure of such behavioral traits and their activity patterns, lower-dimensional factors need to be identified and extracted from the data. To this end, we use the CP decomposition (Bro, 1997; Kolda and Bader, 2009; Pecora and Spelta, 2017; Spelta, 2017) to represent the tensor as a suitable product of lower-dimensional factors.

Solving this problem consists in finding the R rank-1 tensors that best approximate the tensor $\mathcal{X}$. This multidimensional decomposition is, thus, analogous to a community detection where the number of communities is set a priori: the number of lower-dimensional factors we select to approximate the tensor is the number of communities (and activity patterns) we obtain. Assuming that the number of components is fixed (at the end of the section we relax this hypothesis by introducing a test to choose the proper number of communities), we compute a CP decomposition with R lower-dimensional factors that best approximates $\mathcal{X}$, i.e., to find

$$\min_{\widehat{\mathcal{X}}} \left\| \mathcal{X} - \widehat{\mathcal{X}} \right\|_F^2 \;\; with \;\; \widehat{\mathcal{X}} = [\sigma; \mathbf{U}, \mathbf{V}, \mathbf{W}] = \sum_{r=1}^{R} \sigma_r \mathbf{u}_r \circ \mathbf{v}_r \circ \mathbf{w}_r \tag{2}$$

where $|| \circ ||_F^2$ represents the Frobenius norm, R is a positive integer and $\mathbf{V} \in R^{N \times R}$, $\mathbf{U} \in R^{N \times R}$, $\mathbf{W} \in R^{T \times R}$ and $\sigma = \|\mathbf{V}\| \, \|\mathbf{U}\| \, \|\mathbf{W}\|$.

The problem is solved by using an Alternating Least Squares (ALS) Algorithm (Bro, 1997) dividing the minimization into three-dimensional sub-problems by unfolding the tensor $\mathcal{X}$. Meaning rearranging the elements of $\mathcal{X}$ into three matrices $\mathbf{X}_{(1)}, \mathbf{X}_{(2)}$ and $\mathbf{X}_{(3)}$. The three resulting matrices have a size of $N \times NT$, $N \times NT$ and $T \times NN$, respectively. In this way problem (2) is equivalent to the minimization of the difference between each of the modes and their approximation in terms of factors.

$$\min_{\mathbf{U}} \left\| \mathbf{X}_{(1)} - \mathbf{U}\mathbf{M}_{VW}^T \right\|_F^2$$

where $\mathbf{M}_{VW} = \mathbf{V} \odot \mathbf{W}$ and $\mathbf{X}_{(1)}$ is the $N \times NT$ unfolded matrix of $\mathcal{X}$,

$$\min_{\mathbf{V}} \left\| \mathbf{X}_{(2)} - \mathbf{V}\mathbf{M}_{UW}^T \right\|_F^2$$

where $\mathbf{M}_{UW} = \mathbf{U} \odot \mathbf{W}$ and $\mathbf{X}_{(2)}$ is the $N \times NT$ unfolded matrix of $\mathcal{X}$ and

$$\min_{\mathbf{W}} \left\| \mathbf{X}_{(3)} - \mathbf{W}\mathbf{M}_{UV}^T \right\|_F^2$$

where $\mathbf{M}_{UV} = \mathbf{U} \odot \mathbf{V}$ and $\mathbf{X}_{(3)}$ is the $T \times NN$ unfolded matrix of $\mathcal{X}$.

After computing the Karush-Kuhn-Tucker conditions, we compute the gradient of the local cost functions. The stationary points can be found via the following updates:

$$\mathbf{U} \leftarrow \frac{1}{\mathbf{M}_{VW}^T \mathbf{M}_{VW}} \mathbf{X}_{(1)} \mathbf{M}_{VW}$$

$$\mathbf{V} \leftarrow \frac{1}{\mathbf{M}_{UW}^T \mathbf{M}_{UW}} \mathbf{X}_{(2)} \mathbf{M}_{UW}$$

$$\mathbf{W} \leftarrow \frac{1}{\mathbf{M}_{UV}^T \mathbf{M}_{UV}} \mathbf{X}_{(3)} \mathbf{M}_{UV}$$

being the scalar product matrices symmetric, this implies $\mathbf{U} = \mathbf{V}$. To choose the correct number communities, usually multiple CP decompositions with different number of components are computed until "good" enough one is found. However, when data are noisy, the model fit alone cannot determine the best rank approximation, therefore, we follow Bro and Kiers (2003) by employing the Core Consistency Diagnostic (Corcondia) to compare results obtained from different numbers of components. The Corcondia test determines whether, for a fixed number of components, the model is better described by a Tucker decomposition (Tucker, 1966) or by a CP decomposition. The Tucker method essentially decomposes a tensor into a set of matrices and one small core tensor. We notice that the tensor decomposition described by Equation (2) can be written, in scalar notation as:

$$\widehat{\mathcal{X}} = \sum_{n=1}^{R} \sum_{n=1}^{R} \sum_{t=1}^{R} g_{mmn}^1 u_{in} v_{jn} w_{kt} \tag{3}$$

where $g^1_{mmn} = \delta_{ij}\delta_{jk}\delta_{ik}$ is the unit superdiagonal tensor. This form is a special representation of a more general tensor decomposition, the Tucker decomposition, where g_{mmn}, known as the core tensor, encodes the interactions between the three factors and does not have to be superdiagonal. The Corcondia test, in other words, compares g^1_{mmn} with g_{mmn} and is written as follows:

$$Corc(R) = 1 - \frac{\sum_{n=1}^{R}\sum_{n=1}^{R}\sum_{t=1}^{R}(g_{mmn} - g^1_{mmn})^2}{\sum_{n=1}^{R}\sum_{n=1}^{R}\sum_{t=1}^{R}(g^1_{mmn})} \tag{4}$$

A Corcondia test close to 100% indicates that the CP decomposition better explains the data with respect to a Tucker model. If the data cannot be described by a trilinear decomposition or too many communities are employed, the Corcondia will be close to zero (or even negative). In practice the core consistency decreases slowly for an increasing number of components and then sharply falls when the correct number of components is exceeded. Finally, the number of components that should be chosen corresponds to the last high consistency value[4].

After having solved the model, a post-processing of the results provides additional information about the organizational principles of behavioral features. Information about the community structure of funds managers' behavioral similarities and about their temporal activity have been found through the leverage analysis. Leverage can be seen as an influence measure, which ranges between zero and one and expresses the deviation from the average data distribution. A high value of the influence measure indicates an influential variable, while a low value stands for the opposite (Bro, 1997). The leverage within the r-th community has been computed as:

$$\mathbf{c}_r = diag\left(\mathbf{u}_r\left(\mathbf{u}_r^T\mathbf{u}_r\right)^{-1}\mathbf{u}_r^T\right)$$

$$\tau_r = diag\left(\mathbf{w}_r\left(\mathbf{w}_r^T\mathbf{w}_r\right)^{-1}\mathbf{w}_r^T\right)$$

The vector $\mathbf{c}_r$ encompasses the leverage of each funds in the r-th community, while the vector τ_r encompasses the leverage of each day in the sample, i.e., the level of the r-th community activity in the t-th working day. Managers' behaviors with high leverage values in the r-th component are placed together into the same community as they are highly influential within that community. Similarly, a high leverage in the time dimension of the r-th community indicates a high activity in that community at time t, or, in other words, that in the t-th working day members within that community are very similar in their behavioral features.

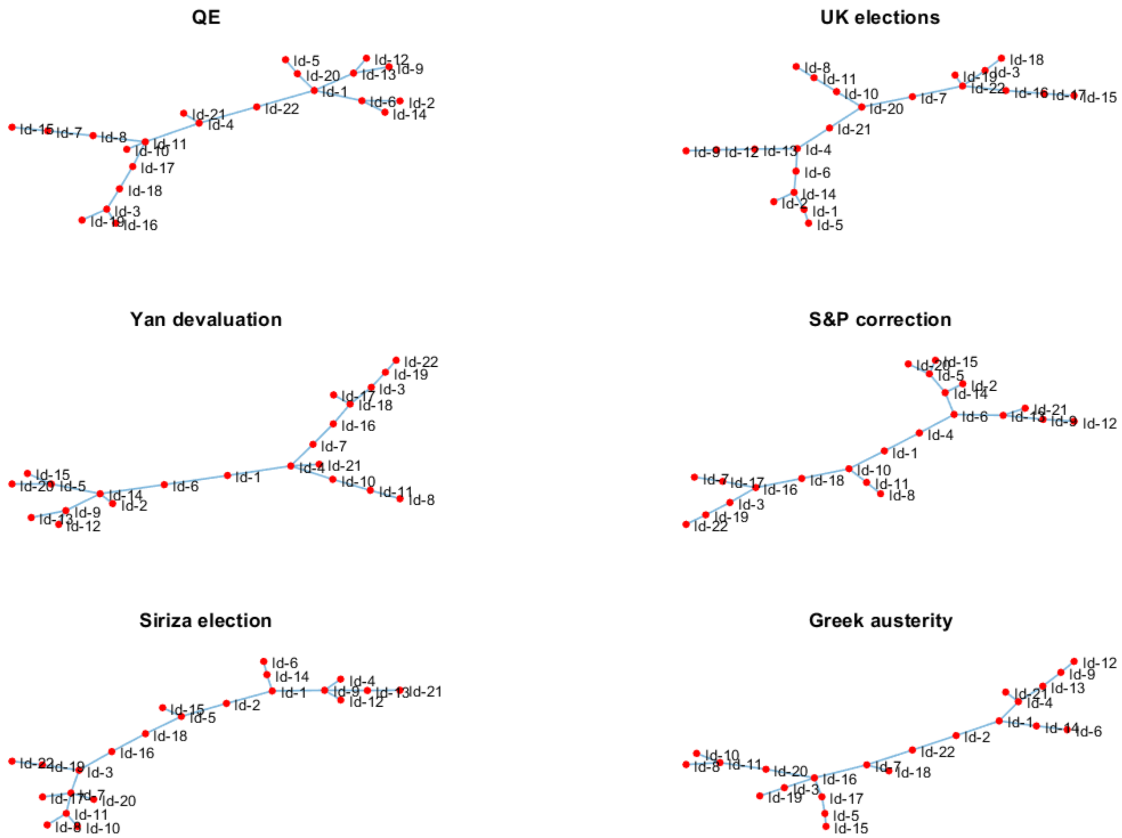
3 Results

In order to gain a deeper understanding of the structure inferred from the data, we have reported the MST configurations obtained during different turmoil phases, namely, the QE, the election in the UK, the Yuan devaluation, the S&P correction, the Siriza elections and the Greek austerity package. The roles of the different funds in allowing the

[4]Figure 11 in Appendix A shows the goodness of fit and displays the Corcondia test values for different number of factors on the right

network to be connected are presented in Figure 1. For instance, there are no funds with a prominent role in terms of centrality (the degree ranges from 1 to 3), meaning that all funds have been impacted equally by the different events. Moreover, the position of the funds on the MST is not stable over time meaning that different events shape the network of similarities in different ways. Nevertheless, it has to be notice that the MST contains, by construction, only $N - 1$ edges and therefore most of the information could be lost if the other connections are not taken into account.

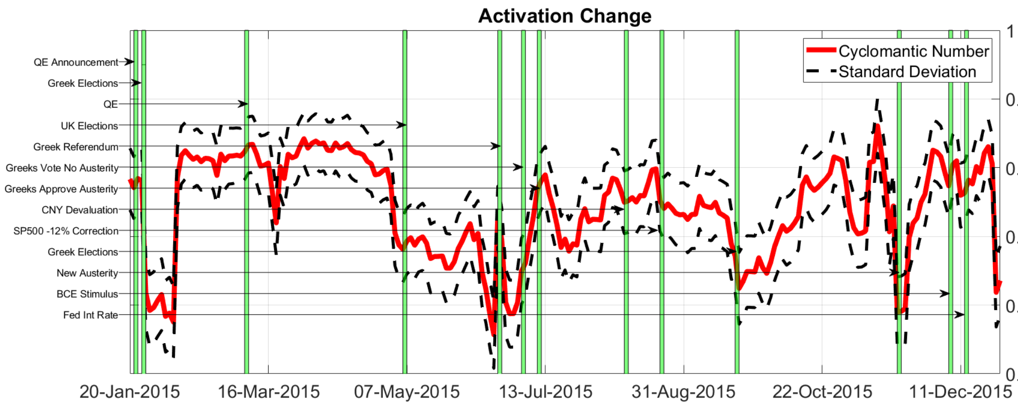
Figure 1: Minimal Spanning Tree. For different and relevant economic events of the year 2015 we have reported the MST configuration of fund similarities. Notice that no fund play a dominant role in connecting the network and that a fund's position in the network does not remain stable over time.



3.1 Identification of Synchronization Phases

During economic booms and normal times, financial markets tend toward randomness, whereas in the crisis periods the structure of financial markets is reinforced in the topological sense, as shown by the clustering coefficient (see Onnela et al. (2002)). The number S of redundant elements emphasizes such structural changes that take place on the network structure.

Figure 2: Cyclomatic Number. The red line shows the daily values of the cyclomatic number S, i.e. the number of distances d_{ij} that, although being smaller than L, does not need be considered in the hierarchical clustering process leading to the MST, along with the standard deviation in black. Green bars represent economic and geopolitical events that stormed the financial markets in 2015.

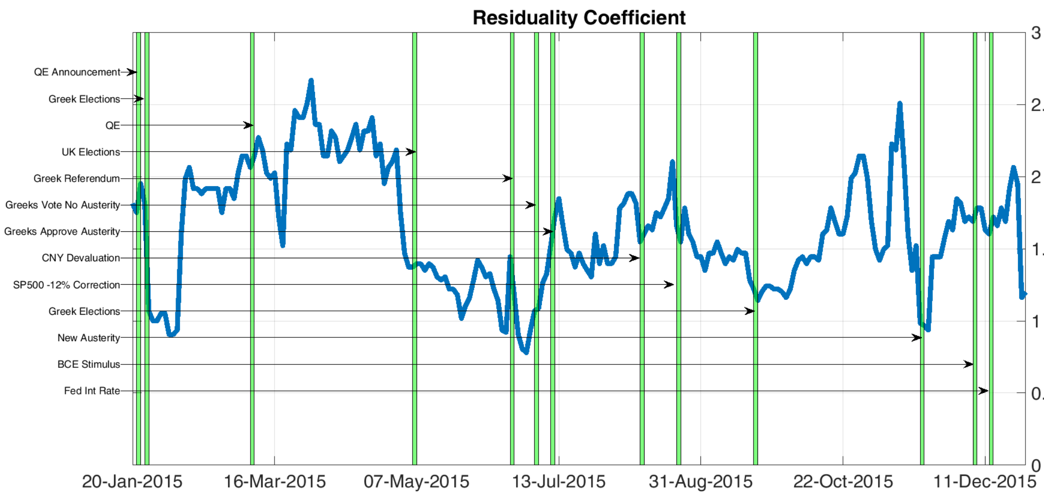


Not surprisingly, increasing clusterization tend to be a consequence of disturbed periods as reported in Figure 2.

Moreover, in the distressed periods high similar positions (namely, "synchronization") emerge in financial markets, thus, reinforcing their topological structures (Onnela et al., 2002). To capture this feature in the behavioral traits of the delegated investors we define a residuality coefficient as:

$$\rho(t) = \frac{\sum_{d(t)_{ij} > L(t)} d(t)_{ij}^{-1}}{\sum_{d(t)_{ij} < L(t)} d(t)_{ij}^{-1}}$$

Figure 3: Residuality Coefficient. The blue line shows the daily values of the residuality coefficient i.e. ratio of the similarities between funds' behavioral characteristics that lie above and below the MST threshold or, in other words, the ratio between weak and strong ties. Green bars represent economic and geopolitical events that stormed the financial markets in 2015. One can see that around January, July and November 2015, the index reaches the lowest values due to the influence of the geopolitical events that occurred in this period. Funds managers' behavioral similarities increase significantly during these occasions.



Residuality relates the relative strengths of the similarities above and below the MST threshold and provides evidence for the structural changes that toke place during market turmoils. Figure 3 shows the values of $\rho(t)$ for the year 2015 and allows for capturing the main differences in the behaviors of fund managers between turmoil phases and "business as usual" days. Figure 3 indicates that the lowest values of $\rho(t)$ correspond to the Greek and English elections, to the Greek austerity referendum and to the new austerity packages. The decrease of the residuality coefficient observed in Figure 3 is due to that the distance values below $L(t)$ tend to be smaller (shorter) than those above the threshold, i.e. strong ties intensify, showing that synchronization between behavioral traits' similarities increase significantly during these major geopolitical events.

3.2 Identification of Behavioral Community

We are also interested in discovering homogeneous traits at the community level that may reveal the different mental models and investment practices employed by delegated investors. A tensor decomposition with 3-factors ($R = 3$) explains 75% of the data variability and the Corcondia test around 90%, indicates that the CP decomposition is suitable for qualifying the structure of the data we employ. We partition the behavioral traits of fund managers into three communities by employing a soft partition scheme. We compute membership probabilities[5] of each fund inside each community by normalizing the leverage of the i-th fund in the r-th community. Denoting by $\mathbf{c}_r^i$ the leverage value of the i-th fund in the r-th community, allows us to compute the degree membership $\hat{\mathbf{c}}_r^i$ inside community r as follows:

$$\hat{\mathbf{c}}_r^i = \frac{\mathbf{c}_r^i}{\sum_{r=1}^{R} \mathbf{c}_r^i}$$

Figure 4 shows the membership probabilities of each fund. Most of the funds have a degree of membership concentrated in one community meaning that they strongly and exclusively belong to that particular community for most of the time and have well defined behavioral traits. We find that this tendency is reflected in funds id1, id2, id5, id6 and id14 which strongly belong to Community-1 or in funds id4, id9, id10, id12, id13 and id15 that compose Community-2 and in funds id3, id19, id21 and id22 that pertain to Community-3. Other funds (namely id7, id8, id11, id16 id17 id18 and id20), instead, have a dispersed degree of membership and belong to more than one community. These funds seem to have mixed behavioral characteristics inherited from the different communities.

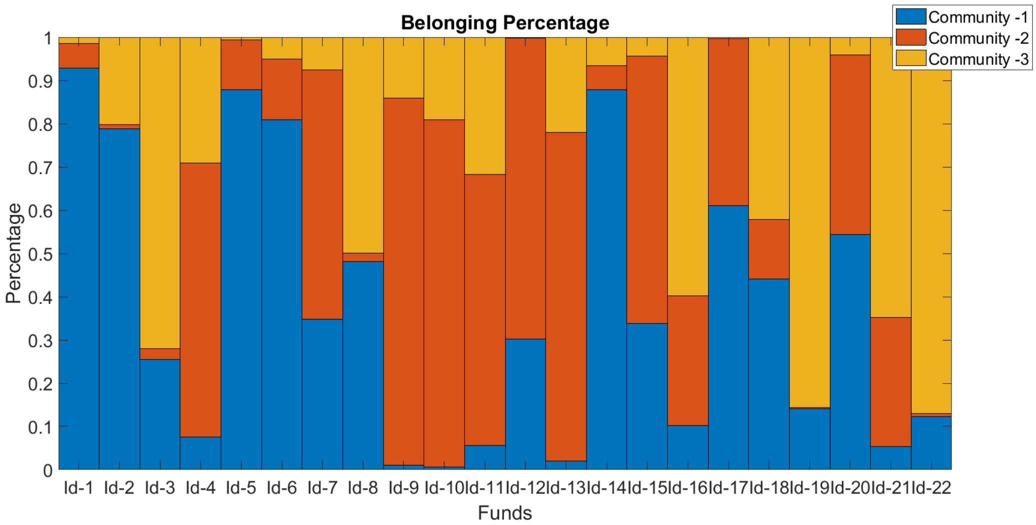
3.3 The Features of Behavioral Communities

We identify the behavioral characteristics of each community by examining its features values over time. The features of a community have been identified as the weighted sum of the features of the community constituents, where the weights are the degree membership of each fund in that community[6].

[5] Such membership distribution is used to assign funds to communities. We apply a hard partition scheme in which we assign each fund to the community where the fund has the highest impact in terms of strength.

[6] If a fund is assigned to the first community with a degree membership of .7, that community will have the 70% of the characteristics of the fund.

Figure 4: Community memberships. For each fund, the probability of belonging to one of the three identified communities has been reported. Most funds, having an unimodal membership distribution, exclusively belong to only one community. Funds id1, id2, id5, id6 and id14 strongly belong to Community-1 (blue) while funds id4, id-9, id10, id12 ,id13 and id15 compose the second community (red). Community-3 (yellow) refers to funds id3, id19, id21 and id22. The other funds, having a membership distribution that is closer to uniform, belong to different communities at the same time.



Figures 5-7 show these values along time in the upper panels and the average value in the bottom panels. Some interesting results emerge. Generally speaking, the average features of each community are stable over time but in some cases, during crisis phases, we can observe a perturbation in the configuration of the traits characterizing a community and this is specially true for the HC coefficient reported in Figure 5. Community-1 has on average the highest hedging coefficient followed by Community-3 and Community-2 (bottom panel), nevertheless Community-3 displays the biggest drop of the HC coefficient in the interval June-July 2015, i.e., during the turbulent phase dominated by the UK election and Greek events (see upper panel).

Also, the time series of the HHI index reported in Figure 6 show some breaks in connection with the most relevant economical and geopolitical events. For instance, all of the communities have the highest concentration on fund positions, but the high concentration of members in Community-1 decreases after the approval of the austerity measures by the Greek parliament, while the contrary occurs for the members of Community-2 and Community-3 which pass from a lower concentration in the summer to a higher concentration after July, thus returning back to their past levels.

By looking at the TI shown in Figure 7, Community-1 displays the lowest values along the entire time window meaning that members of this community infrequently adjust their portfolios. Members of Community-2 and Community-3, on the other hand, behave the opposite having a high average turnover value.

Finally, although portfolio compositions matter for the characterization of funds conducts, these dimensions do not appear to fully characterize a community. For instance, as Figures 12-15 in Appendix A emphasize, all the three communities primarily invest in developed markets especially in Italy and Europe. Beside that, members of Community-1 mostly invest in equity instruments, while Community-2 is more oriented to Corporate bonds and Community-3 to Government Bonds.

Figure 5: Hedging Coefficient (HC). The figure displays in the upper panel the changes of the Hedging coefficient of each community over time. The bottom panel shows the average values over time. Besides the highest value of the HC index of Community-1, it is interesting to note how Community-3 decreases the HC during crisis periods.

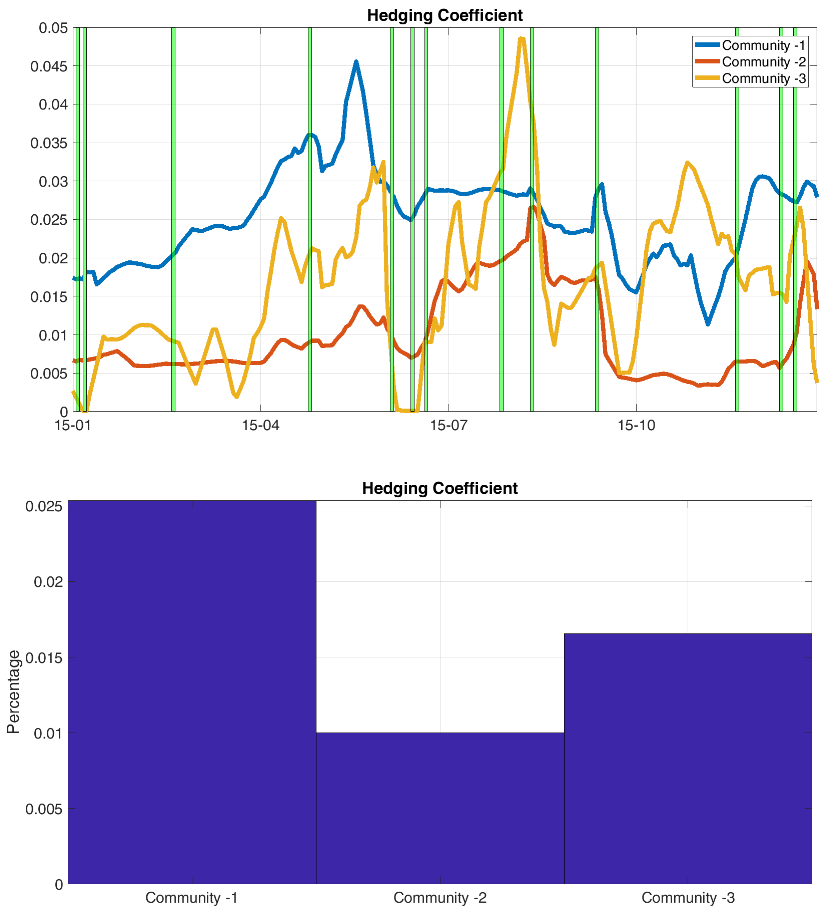


Figure 6: Herfindhal-Hirshman Index (HHI). The figure displays in the upper panels the dynamics in time of the Herfindhal index computed on various asset classes for each community. The bottom panel shows the average values over time. All the communities are highly concentrated on fund positions and less on the other asset classes. This behavior, however, is not constant over time but shows abrupt changes during crisis periods.

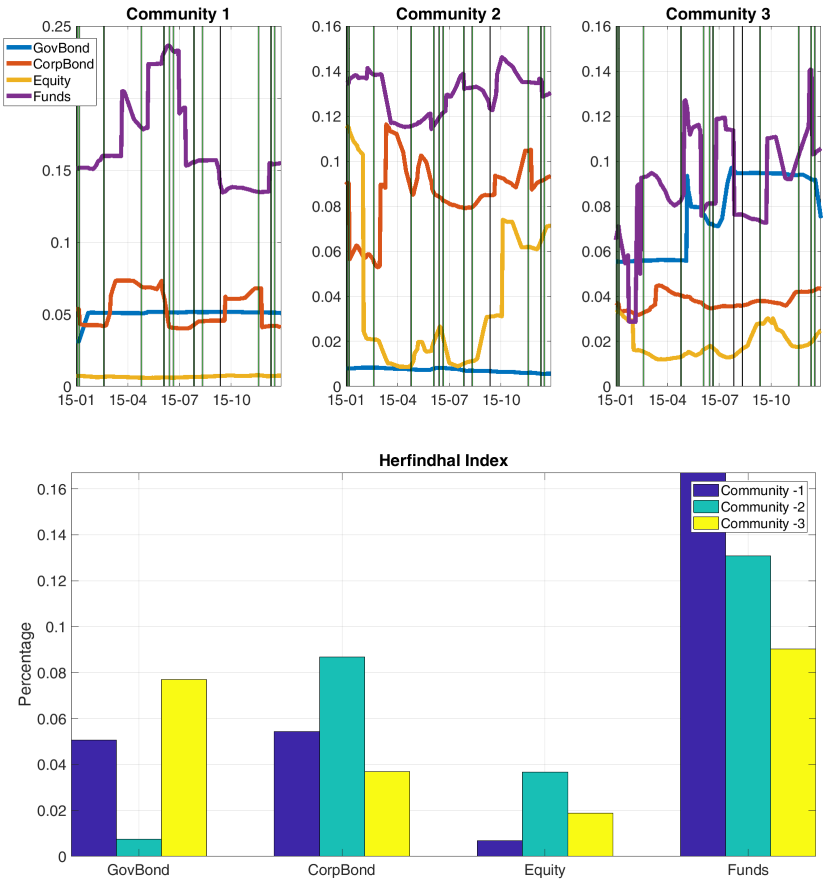
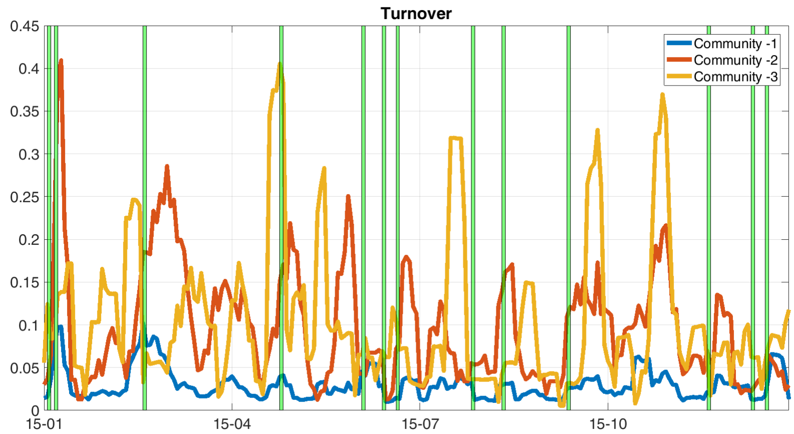
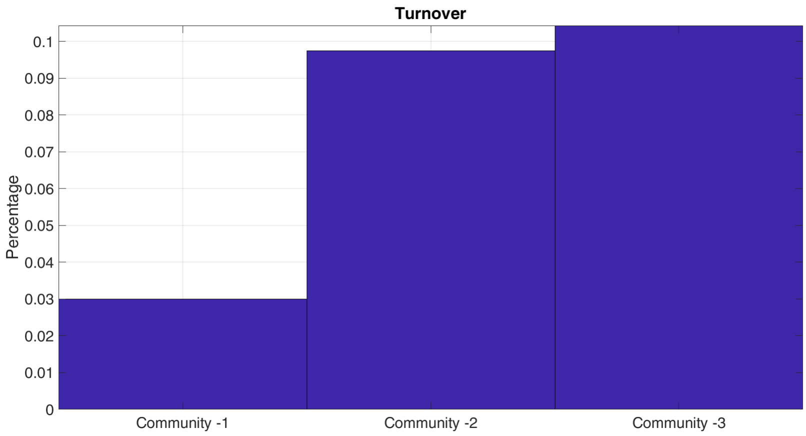


Figure 7: Turnover Index (TI). The figure displays in the upper panel the turnover movements of each community over time. The bottom panel shows the average values over time. Community-1 has the lowest turnover and this characteristic is stable over time. On the other hand communities 2 and 3 have a high and fluctuating turnover.

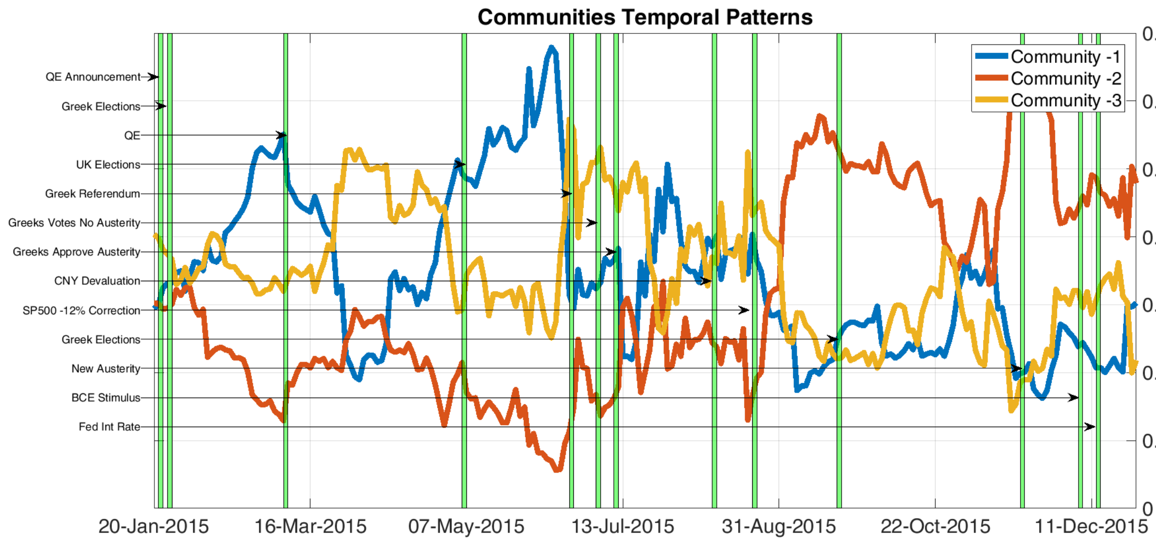




3.4 Analysis of Community Synchronization

The tensorial decomposition, by taking into consideration both spatial and temporal features, allows us to investigate how the different communities responded to external events that perturbed the markets. As in the previous case, we normalize the leverages related to the temporal components and obtain the temporal activity patterns of each community over time. The probabilities ($\hat{\tau}_r$) are shown in Figure 8 and represent the level of synchronization of the funds' behavioral features within each community along the reference period. In other words, these probabilities reflect how the behavioral similarities of each community respond to external factors.

Figure 8: Temporal Activity Patterns The level of synchronization of behavioral similarities within each community is described by the three colored lines. The blue line represents Community-1, the activity patter of Community-2 is shown in red and the yellow line corresponds to the synchronization of Community-3 members. Green bars represent relevant economic and geopolitical events. One can see that these events bring breaks in the synchronization level of the communities. Members of Community-1 decrease their activity while the contrary occurs for Community-2. Community-3 instead seems to be less affected by external events.



To gauge the level of synchronization within communities we focus on major distress events that occurred in the year 2015. Again, the austerity measures imposed on Greece turned out to be among the most shocking events. In addition, the synchronization level of behavioral traits within communities was also heavily affected by the introduction of the Quantitative Easing (QE) and by the macroeconomic conditions as expressed by the S&P500 correction of August. In particular, Community-1 decreased its activity during most of the events in 2015, meaning that the behavioral similarities of its members tended to reduce because of external forces. The contrary happened to Community-2, whose members increased their behavioral similarities during the same period. Community-3, instead, seems to be less affected by external events as it maintained a stable level of activity. In other words, fund managers in Community-1 and Community-2 seem to be less sensitive to external shocks, although presenting opposite trends, while fund managers of Community-3 appear to be more resilient against market turmoils exhibiting synchronization levels less dispersed. These traits would have remained largely hidden if we had stopped our investigation at the system level without deepening the analysis at the community level.

The cross-correlation between the temporal pattern of the three communities and the CBOE volatility index (VIX) is performed to investigate whether a change in the synchronization level of behavioral traits of a community lags/leads the market volatility. In other words, we aimed at quantifying the manager response to changes in the market volatility level through variations in the synchronization intensity reflected by the temporal community patterns. The cross-correlation function (CC) of the two time series is the product-moment correlation as a function of k lags between the series[7]. In formula:

$$CC_{\hat{\tau}_r,VIX}(k) = \frac{CV_{\hat{\tau}_r,VIX}(k)}{\sqrt{CV_{\hat{\tau}_r,\hat{\tau}_r}(0)\, CV_{VIX,VIX}(0)}}$$

where $\hat{\tau}_r$ and VIX represent the temporal pattern of community r and the volatility index, respectively, and $c(k)$ is the the cross-covariance function (CV) defined as:

$$CV_{\hat{\tau}_r,VIX}(k) = \frac{1}{N}\sum_{t=1}^{N-k}\left(\hat{\tau}_{r,t} - \overline{\hat{\tau}_r}\right)\left(VIX_{t+k} - \overline{VIX}\right) \;\; ; k = 0, 1, ..., (N-1)$$

$$CV_{\hat{\tau}_r,VIX}(k) = \frac{1}{N}\sum_{t=1-k}^{N}\left(\hat{\tau}_{r,t} - \overline{\hat{\tau}_r}\right)\left(VIX_{t+k} - \overline{VIX}\right) \;\; ; k = -1, ..., -(N-1)$$

where variables with upper bars indicate the average value.

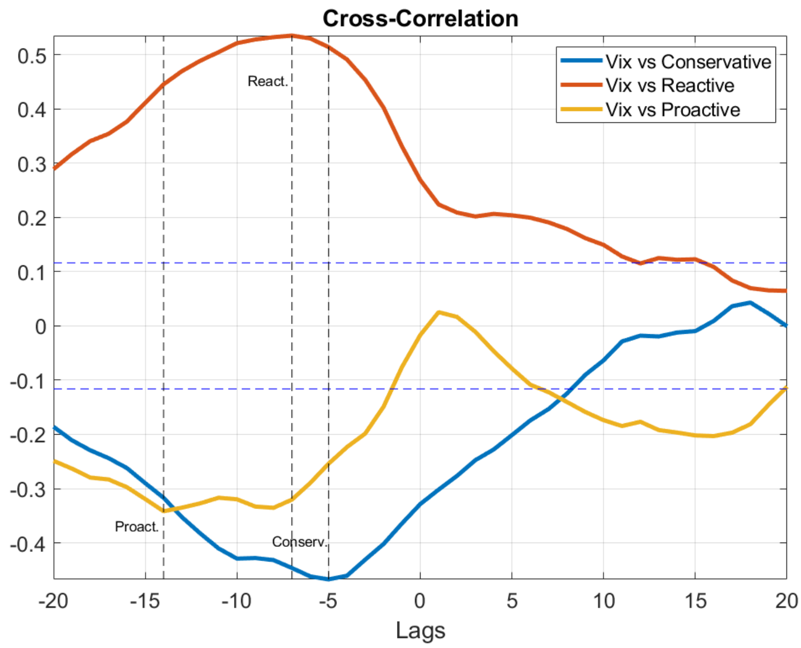
Figure 9 shows the correlation coefficients between the temporal component of the different communities with the VIX index for different time lags. The high positive/negative significant cross-correlation at negative lags shows how fund managers, being expert managers aware of market dynamics in a timely way, anticipate the market volatility. The strong positive (negative) values of Community-2 (Community-1) emphasize that an increasing (decreasing) synchronization between the behavioral features of the community members leads to an increased market volatility. Moreover, the fact that the instantaneous correlation (i.e., lag equal to zero) between the temporal pattern of Community-3 and the VIX is not statistically significant, differently from the lag-0 correlations of the temporal patterns of Community-1 and Community-2, means that funds in Community-3 seem to be more able to fully anticipate market shocks, promptly re-adjusting their portfolios in advance, while those in the other communities appear slightly less forward-looking (correlation values with positive lags remain significant).

To summarize our main findings, we provide a nomenclature for the communities we have identified. Funds in Community-1 have low TI values and infrequently adjust their portfolios, thus deserving the name "conservative" funds. Moreover, members of Community-1 have a high HC indicator, meaning that they rely on hedging strategies. Differently, members in Community-2 are more prone to change portfolio allocations (high TI) and have a low HC value. Funds in this community are "reactive" in their portfolio investment behavior and try to exploit these investment features in their allocation strategies. Members of Community-3 are, instead, characterized by a high TI and a mild HC indicator. In addition, members of Community-3 seem to be more prone to anticipating external events than the other funds justifying their "pro-active" labeling. The

[7] Contemporaneous correlation is indicated by $k = 0$.

cross-correlation reported in Figure 9 supports the idea that these funds may represent the "first mover" in interpreting market signals confirming our behavioral identification approach by showing that these features are revealed by the use of a multidimensional perspective applied to a granular data set. Although portfolio compositions matter for the characterization of funds' conduct, our analysis highlights that more weight should be given to the behavioral traits of investment managers.

Figure 9: Cross-Correlation. The figure shows the correlation coefficients between the temporal component of the different communities and the VIX index for different lags. Lag-0 cross-correlation is interpreted as the instantaneous correlation between the temporal community patterns of the community and the volatility index. High positive/negative cross-correlation at negative lags shows the leading power of the temporal community patterns.



4 Discussion and conclusion

The technique presented in the paper is the first attempt to map behavioral funds profiles through time both at a system and at a community level. Our approach captures the heterogeneity in managers' investment behaviors and provides rich information about how their allocation decision processes change with external events that impact the market dynamic.

Although portfolio compositions display some differences among the emerging communities, the additional behavioral attributes that we propose help to depict peculiar and persistent traits that characterize each community. Our analysis also enables us to identify the heterogeneous responses of delegated investors to external shocks. We have shown that the behavior fund managers becomes more similar around the days of relevant economical and geopolitical events by revealing a more uniform pattern but, beside that, we have also indicated the existence of different levels of synchronization between the behavioral traits of each community.

We believe that the behavioral commonalities detected by this study are relevant for several reasons. First, our findings confirm that behavioral traits play an important role in expert decision-making processes. Second, we show that exogenous shocks perturb the different communities in various ways. Some behavioral attitudes are reinforced during the out-of-equilibrium phase, while other traits weaken. However, communities appear only temporarily perturbed by major economic and geopolitical shocks, returning back to their original states once the distress is embedded. This important finding expands our understanding on how financial turmoil spreads throughout an economical system.

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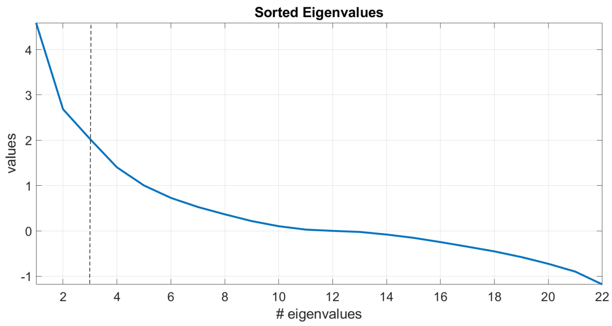
Appendix A

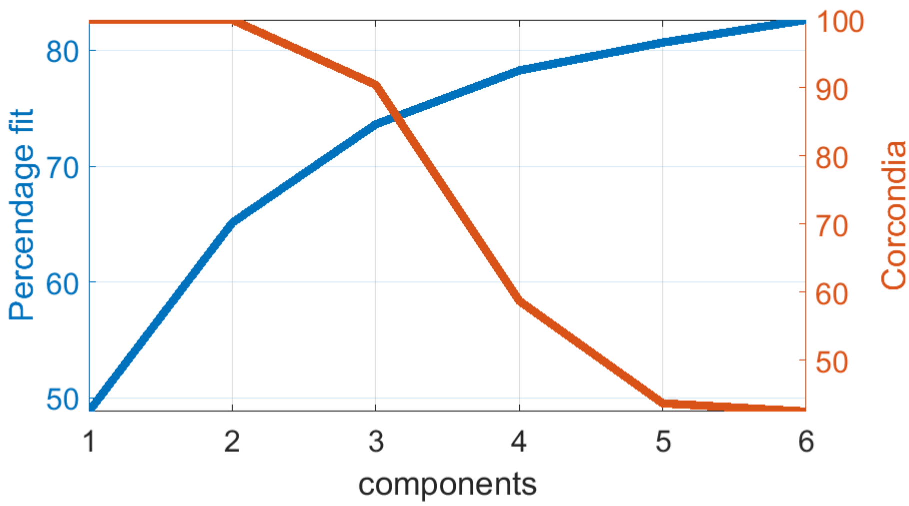
Figures 10 show the decay of the first 20 eigenvalues of the scalar product matrix $\mathbf{X}(t) = \mathbf{\Lambda}(t)\mathbf{\Lambda}(t)^T$ averaged over time. From the figure clearly emerges that the first three dimension capture the structure of the deterministic similarities and behavioral trends that are driving the system.

Figure 10: The Scalar Product Matrix Eigenvalues. The plot exhibits average value of the first 20 eigenvalues of the scalar product matrix $\mathbf{X}(t) = \mathbf{\Lambda}(t)\mathbf{\Lambda}(t)^T$. The the decay of the eigenvalues shows that the first three dimensions contain the deterministic structure of the data. The rest of the space may be seen as being generated by random fluctuations.



Figures 11 shows the value of the Corcondia test for different number of communities along with the percentage fit.

Figure 11: Model Fit and Corcondia Test. The figure reports the goodness of fit (blue) and the values of the Corcondia test (red) for different number of components. The percentage fit is shown on the left y-axis while the Corcondia values are put on the right y-axis. A 3-factors model explains 75% of the data variability and the Corcondia test around 90% suggests adequacy of the model.



Figures 12-15 show the portfolio composition values of the communities along time in the upper panels and the average value in the bottom ones. The figure emphasize, all the three communities primarily invest in developed market especially in Italy and Europe. Beside that, members of Community-1 mostly invest in equity while Community-2 is more oriented to Corporate bonds and Community-3 to Government Bonds.

Figure 12: Market Composition. The figure displays in the upper panels the dynamic along time of the market composition of each community. The bottom panel shows the average values along time. All the communities are highly concentrated on developed market and this behavior is not affected by external events.

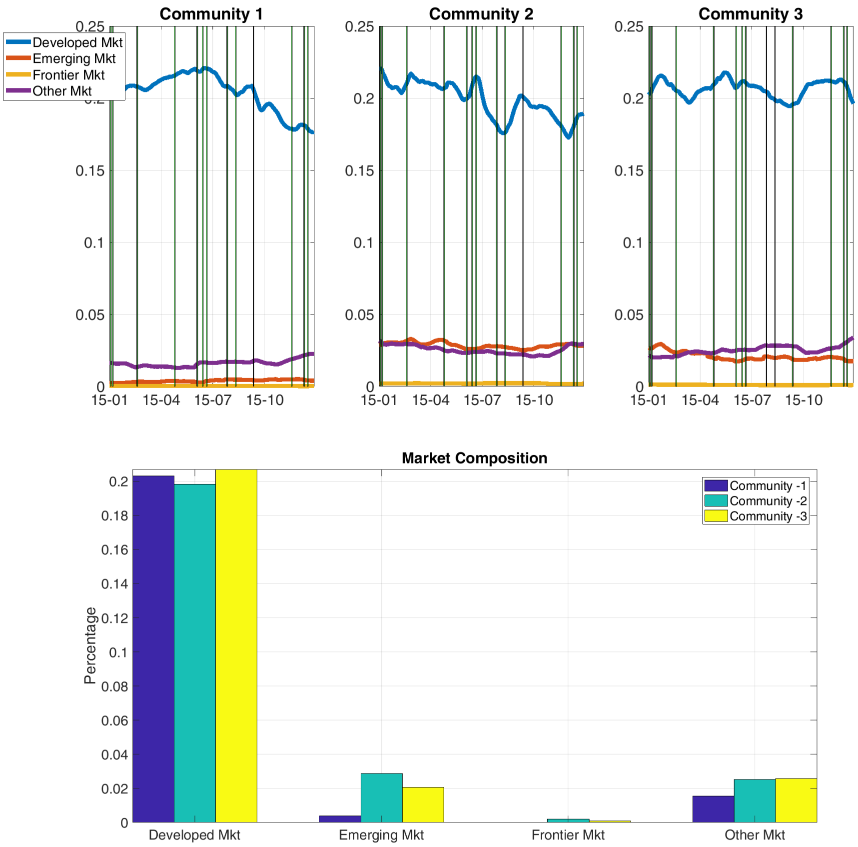


Figure 13: Sector Composition. The figure displays in the upper panels the dynamic along time of the sectoral composition of each community. The bottom panel shows the average values along time. All the communities are well concentrated on Government bonds but communities 1 and 2 also encompasses equity assets form financial, consumers and technology sectors.

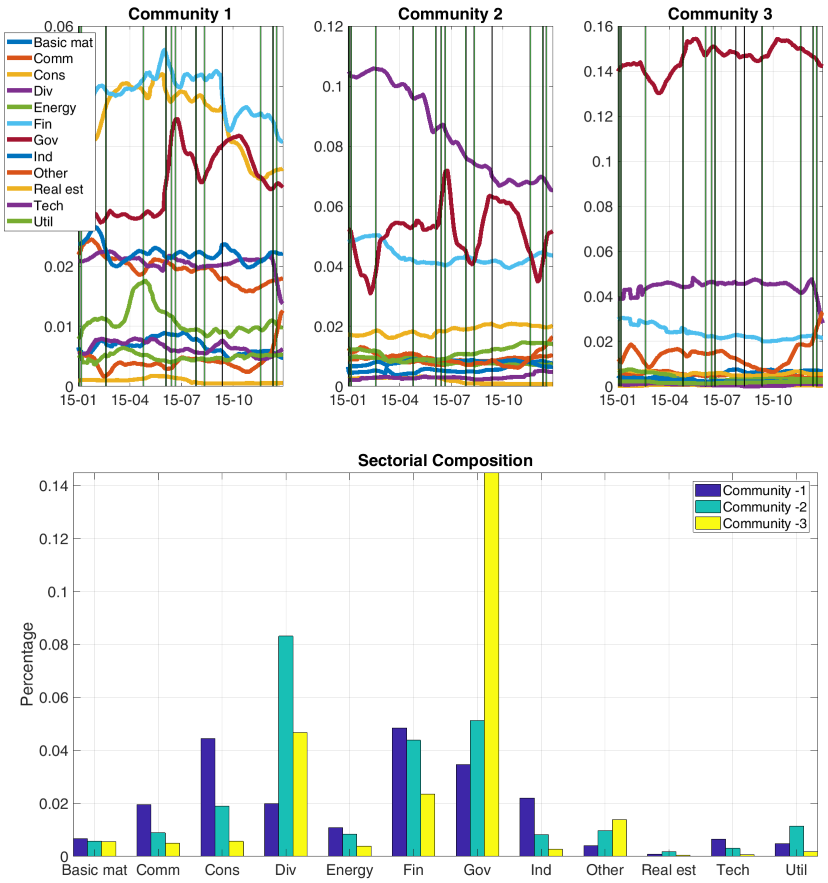


Figure 14: Geographical Composition. The figure displays in the upper panels the dynamic along time of the geographical composition of each community. The bottom panel shows the average values along time. All the communities are quite concentrated on European markets, especially Italy.

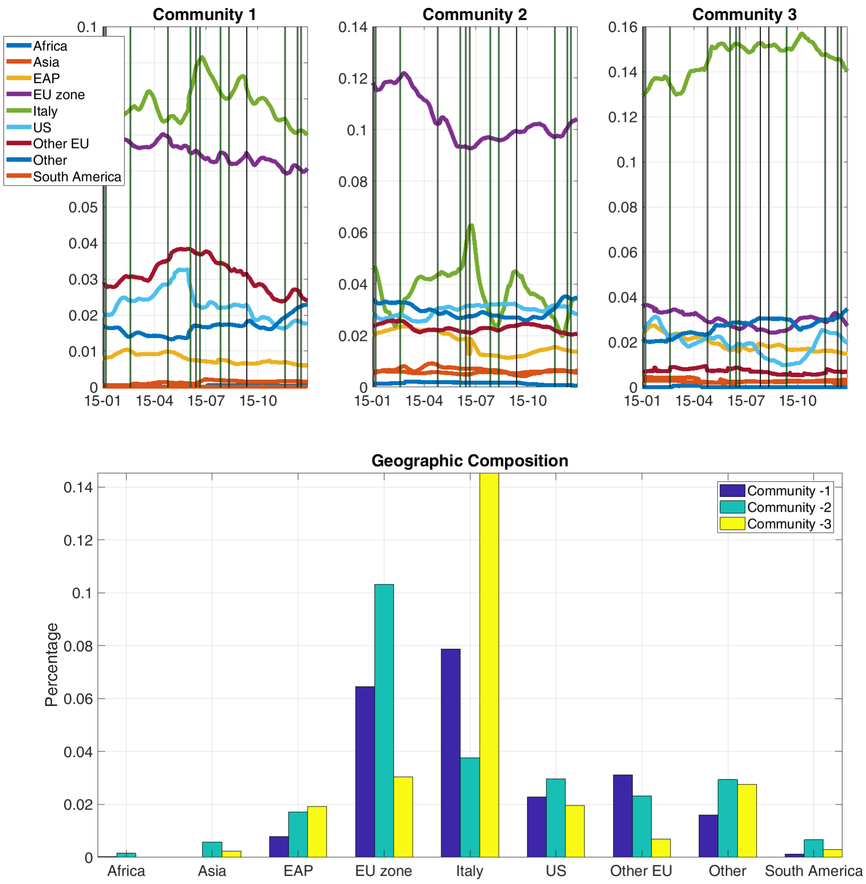
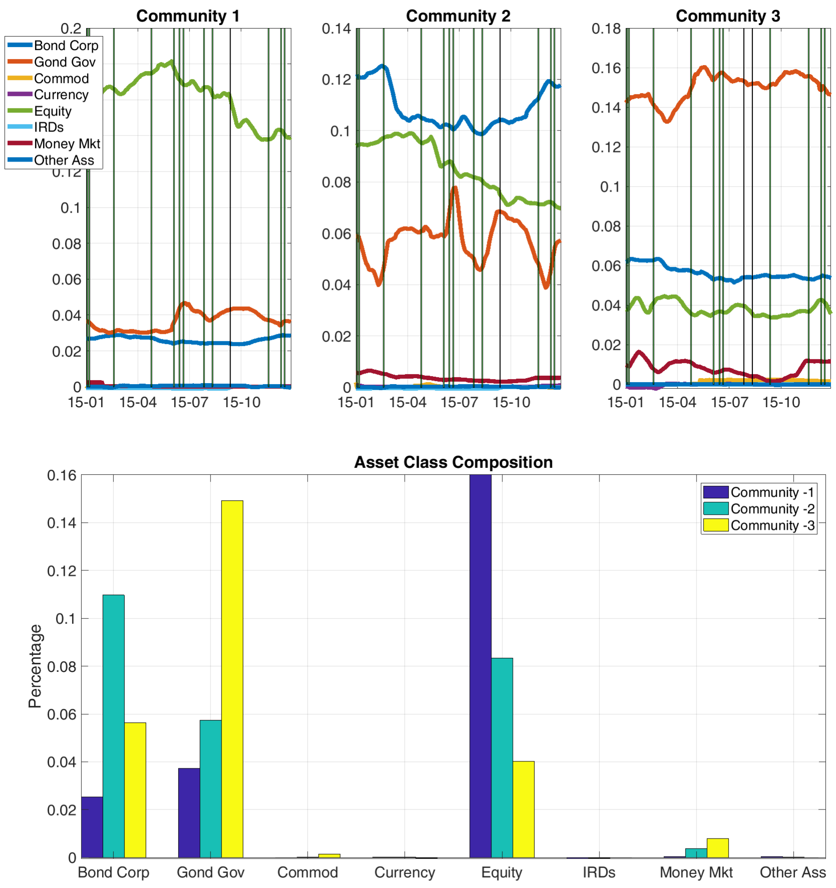


Figure 15: Asset Composition. The figure displays in the upper panels the dynamic along time of the asset composition of each community. The bottom panel shows the average values along time. Community-1 is concentrated on Equity, Community-3 on Government bonds while Community-2 members have more disperse assets composition.



Appendix B

All the results presented in the Main Text are obtained averaging the data over a rolling window of 10 days. To insure robustness in the results we have also performed the same operations using other two different window levels, namely 5 and 15 days. Here we report the tables regarding the sensitivity analysis of the results to changes in the moving windows. Results are robust across different window specifications. This exercise helps also in identifying the behavioral characteristics of each community.

Table 1: Funds Compositions. The table reports market, geographical, sectoral, and asset classes compositions, respectively. Column **Obs** indicates the number of constituents for each group. Columns **5d, 10d, and 15d-MW** refer to compositions in percentage computed over a rolling window in the interval of $5, 10, 15$ days. **Mean** and **Std** stand for the mean value and its corresponding standard deviation computed over the whole sample.

	Obs	Mean 5d-MW	Std 5d-MW	Mean 10d-MW	Std 10d-MW	Mean 15d-MW	Std 15d-MW
Developed Market	3494	0.8721	0.0195	0.8728	0.0189	0.8735	0.0182
Emerging Market	291	0.0511	0.0056	0.051	0.0054	0.0509	0.0053
Frontier Market	14	0.0027	0.0001	0.0027	0.0001	0.0027	0.0001
Other	304	0.0742	0.0157	0.0736	0.0151	0.073	0.0145
Africa	4	0.0011	0.0003	0.0012	0.0002	0.0012	0.0002
Asia	44	0.0088	0.0012	0.0088	0.0011	0.0087	0.0011
East Asia and Pacific	398	0.1579	0.0211	0.1577	0.0183	0.1577	0.0171
Eurozone	1396	0.1666	0.0167	0.1666	0.0157	0.1664	0.0153
Italy	461	0.2769	0.0474	0.2774	0.0458	0.2777	0.045
North America	956	0.2371	0.0156	0.2371	0.0119	0.2373	0.0102
Other Europe	469	0.0654	0.0145	0.0656	0.0139	0.0659	0.0134
Other Geograph. Areas	335	0.0779	0.0163	0.0774	0.0158	0.0768	0.0151
South America	40	0.0084	0.0008	0.0084	0.0007	0.0084	0.0006
Basic Materials	165	0.0309	0.0074	0.0308	0.007	0.0307	0.0066
Communications	229	0.044	0.008	0.0439	0.0077	0.0438	0.0075
Consumer	642	0.1578	0.0204	0.1578	0.0196	0.158	0.0191
Diversified	218	0.1229	0.026	0.123	0.0254	0.1229	0.0248
Energy	183	0.0371	0.0119	0.037	0.0115	0.037	0.0113
Financial	531	0.1663	0.0105	0.1665	0.0099	0.1668	0.0094
Gvt	305	0.2432	0.0587	0.2435	0.0577	0.2435	0.0571
Industrial	264	0.0873	0.0078	0.0874	0.0074	0.0875	0.0071
Other Sector	1295	0.0281	0.0145	0.0274	0.0133	0.0268	0.0118
Real Estate	23	0.0096	0.0016	0.0096	0.0016	0.0096	0.0016
Technology	150	0.0589	0.0089	0.059	0.0084	0.0592	0.0082
Utilities	98	0.0141	0.0021	0.0141	0.0018	0.0141	0.0016
Bond Corp	598	0.2018	0.0227	0.2014	0.0221	0.2008	0.0216
Bond Gvt	325	0.254	0.057	0.2542	0.0559	0.2542	0.0553
Commodity	8	0.0006	0.0013	0.0005	0.0011	0.0005	0.0008
Currency	139	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002
Equity	2952	0.5297	0.0532	0.5301	0.0512	0.5309	0.0501
Interest Rate Deriv.	39	-0.0004	0.0003	-0.0004	0.0003	-0.0004	0.0003
Money Mkt	33	0.0141	0.0061	0.014	0.0059	0.0138	0.0057
Other Asset type	9	0.0001	0.0002	0.0001	0.0002	0.0001	0.0002

Table 2: Belonging Percentage. The table reports the belonging percentage of each fund inside each community. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving windows of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
Id-1	0.92	0.07	0.01	0.93	0.06	0.01	0.96	0.04	0.00
Id-2	0.76	0.02	0.22	0.77	0.01	0.22	0.72	0.00	0.27
Id-3	0.27	0.01	0.71	0.27	0.02	0.71	0.30	0.03	0.67
Id-4	0.07	0.58	0.35	0.08	0.63	0.29	0.09	0.65	0.26
Id-5	0.87	0.11	0.02	0.87	0.12	0.01	0.87	0.12	0.01
Id-6	0.81	0.16	0.02	0.81	0.14	0.05	0.82	0.14	0.04
Id-7	0.41	0.51	0.08	0.34	0.58	0.08	0.27	0.63	0.10
Id-8	0.42	0.03	0.55	0.46	0.02	0.52	0.42	0.01	0.57
Id-9	0.02	0.80	0.18	0.01	0.84	0.14	0.01	0.88	0.11
Id-10	0.00	0.87	0.12	0.01	0.81	0.19	0.00	0.74	0.26
Id-11	0.05	0.68	0.27	0.05	0.63	0.32	0.04	0.59	0.37
Id-12	0.27	0.70	0.02	0.30	0.70	0.00	0.30	0.70	0.00
Id-13	0.02	0.71	0.26	0.02	0.75	0.22	0.03	0.78	0.19
Id-14	0.92	0.05	0.04	0.88	0.06	0.06	0.89	0.06	0.05
Id-15	0.22	0.70	0.08	0.34	0.62	0.04	0.47	0.51	0.02
Id-16	0.14	0.25	0.61	0.11	0.30	0.59	0.12	0.33	0.55
Id-17	0.55	0.45	0.00	0.61	0.39	0.00	0.65	0.33	0.02
Id-18	0.43	0.14	0.43	0.45	0.14	0.41	0.51	0.12	0.37
Id-19	0.17	0.00	0.83	0.15	0.00	0.84	0.18	0.00	0.82
Id-20	0.51	0.48	0.01	0.55	0.42	0.03	0.53	0.44	0.03
Id-21	0.05	0.25	0.71	0.05	0.29	0.66	0.03	0.33	0.64
Id-22	0.16	0.06	0.78	0.14	0.01	0.86	0.11	0.00	0.89

Table 3: Temporal Activity Patterns. The table reports aggregate statistics of the temporal activity patterns of the three communities. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	Min	1st Q	Mean	Median	3rd Q	Max	Std
Time Activ. C1 5d-MV	0.16	0.26	0.34	0.32	0.43	0.70	0.12
Time Activ. C2 5d-MV	0.16	0.24	0.34	0.33	0.41	0.68	0.12
Time Activ. C3 5d-MV	0.18	0.24	0.34	0.32	0.44	0.67	0.12
Time Activ. C1 10d-MV	0.06	0.20	0.31	0.26	0.45	0.68	0.14
Time Activ. C2 10d-MV	0.06	0.20	0.31	0.26	0.45	0.66	0.15
Time Activ. C3 10d-MV	0.04	0.18	0.31	0.26	0.47	0.61	0.15
Time Activ. C1 15d-MV	0.11	0.26	0.34	0.34	0.43	0.54	0.10
Time Activ. C2 15d-MV	0.14	0.29	0.35	0.34	0.40	0.57	0.09
Time Activ. C3 15d-MV	0.08	0.27	0.35	0.33	0.42	0.57	0.10

Table 4: Communities Market Composition. The table reports aggregate statistics of the main market compositions of the three communities. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
Developed Mkt	0.22	0.19	0.20	0.22	0.19	0.20	0.23	0.19	0.20
Emerging Mkt	0.01	0.03	0.02	0.01	0.03	0.02	0.01	0.03	0.02
Frontier Mkt	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Other Mkt	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

Table 5: Communities Geographical Composition. The table reports aggregate statistics of the main geographical compositions of the three communities. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
Africa	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Asia	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00
EAP	0.01	0.02	0.02	0.01	0.02	0.02	0.01	0.02	0.02
EU zone	0.07	0.09	0.04	0.07	0.09	0.04	0.07	0.09	0.04
Italy	0.10	0.04	0.13	0.09	0.04	0.13	0.10	0.04	0.13
US	0.03	0.03	0.02	0.03	0.03	0.02	0.02	0.03	0.02
Other EU	0.03	0.02	0.01	0.03	0.02	0.01	0.03	0.02	0.01
Other	0.02	0.03	0.03	0.02	0.03	0.02	0.02	0.02	0.03
South America	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00

Table 6: Communities Sectorial Composition. The table reports aggregate statistics of the main sectorial compositions of the three communities. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
Basic mat	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Comm	0.02	0.01	0.01	0.02	0.01	0.01	0.02	0.01	0.01
Cons	0.04	0.02	0.01	0.04	0.02	0.01	0.04	0.02	0.01
Div	0.03	0.07	0.04	0.03	0.07	0.05	0.03	0.07	0.05
Energy	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00
Fin	0.05	0.04	0.03	0.05	0.04	0.03	0.05	0.04	0.02
Gov	0.06	0.05	0.12	0.06	0.05	0.12	0.07	0.05	0.12
Ind	0.02	0.01	0.00	0.02	0.01	0.00	0.02	0.01	0.00
Other	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Real est	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Tech	0.01	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00
Util	0.01	0.01	0.00	0.01	0.01	0.00	0.01	0.01	0.00

Table 7: Communities Asset Class Composition. The table reports aggregate statistics of the main asset class compositions of the three communities. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
Bond Corp	0.04	0.09	0.06	0.04	0.10	0.06	0.04	0.10	0.05
Gond Gov	0.06	0.05	0.13	0.06	0.05	0.13	0.07	0.05	0.12
Commod	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Currency	0.00	0.00	-0.00	0.00	0.00	-0.00	0.00	0.00	-0.00
Equity	0.15	0.09	0.04	0.15	0.08	0.05	0.15	0.08	0.06
IRDs	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
Money Mkt	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.01
Other Ass	0.00	0.00	-0.00	0.00	0.00	-0.00	0.00	0.00	-0.00

Table 8: Communities Hedging Coefficient (HC). The table reports aggregate the Hedging Coefficient of the three communities. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window. We simplify the framework by focusing on the geographical segmentation. HC takes a value of 0 if both signs of the market exposures are concordant (this indicates that the strategy is not an hedging strategy). It is equal to 1 when the market exposures of the derivatives are larger than those of the underlying equity instruments and the signs are discordant. Whenever the ratio is in $[-1; 0]$, the HC is the absolute value of the ratio of the market exposures. If there is a derivatives exposure but the corresponding underlying equity assets are not present, then the value for HC is put equal to zero since this is not a hedging position.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
HC	0.02	0.01	0.01	0.02	0.01	0.01	0.03	0.01	0.01

Table 9: Communities Concentration Index. The table reports aggregate statistics of Herfindahl-Hirschman Index (HHI) for different asset classes in the three communities. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
GovBond	0.06	0.01	0.06	0.06	0.01	0.06	0.06	0.01	0.06
CorpBond	0.06	0.08	0.04	0.06	0.08	0.04	0.06	0.08	0.04
Equity	0.01	0.03	0.02	0.01	0.03	0.02	0.01	0.03	0.02
Funds	0.17	0.13	0.10	0.17	0.12	0.09	0.18	0.12	0.09

Table 10: Communities Turnover. The table reports aggregate statistics of communities' turnover (TI). TI in t for fund f is computed as $TI_{f,t} = \frac{\sum_{i=1}^{N} |Q_{i,t} - Q_{i,t-1}| \times P_{i,t}/FX_{i,t}}{NAF_{f,t}}$, where $FX_{i,t}$ is the exchange rate and $NAF_{f,t}$ is the total market value in t. We consider the absolute value of these quantities since we are interested in the portion of the portfolio which varies due to quantity changes. C1 represents Community-1, C2 represents Community-2 and C3 represents Community-3. 5d-MV means that the results have been obtained using a moving window of 5 days while 10d-MV reefers to a 10 days moving window and 15d-MV to a 15 days moving window.

	C1 5d-MV	C2 5d-MV	C3 5d-MV	C1 10d-MV	C2 10d-MV	C3 10d-MV	C1 15d-MV	C2 15d-MV	C3 15d-MV
Turn Over	0.05	0.09	0.09	0.05	0.09	0.09	0.05	0.09	0.09