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Evolution Characteristics of Complex Fund Network and Fund Strategy Identification

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Abstract: Earlier investment practices show that there lies a discrepancy between the actual fund strategy and stated fund strategy. Using a minimum spanning tree (MST) and planar maximally-filtered graph (PMFG), we build a network of open-ended funds in China's market and investigate the evolution characteristics of the networks over multiple time periods and timescales. The evolution characteristics, especially the locations of clustering central nodes, show that the actual strategy of the open-ended funds in China's market significantly differs from the original stated strategy. When the investment horizon and timescale extend, the funds approach an identical actual strategy. This work introduces a novel network-based quantitative method to help investors identify the actual strategy of open-ended funds.

Keywords: complex fund network; fund strategy; time period; timescale

1. Introduction

Investment funds provide investors many advantages, such as professional wealth management and more diversified portfolios. They are growing as a preferable option in today's investment practices. To attract more investors, many fund companies spend tremendous efforts introducing their investment strategies to investors. These strategies, commonly called the stated strategy, are publicly available to investors. Many fund managers and companies, however, often change their stated strategies, aiming to earn higher profits. The actual strategies are not known by investors. Thus, the interests of the investors are hard to protect in practice. How to get efficient and reliable information about funds' actual strategies has become a big challenge for researchers and practitioners.

As one well knows, the financial trading market is a complex system. To explore the nature of its components, a recent study has focused on financial networks [1]. Most financial networks in the literature are built on the correlation coefficient matrix R of asset returns. Nodes are used to represent assets or trade agents, while edges linking nodes denote their relationship or closeness. Current studies mostly concentrate on the topological properties of financial networks, but only a few research works explore the practical applications of financial networks [2–18]. For example, Mantegna *et al.* [2] relate the minimum spanning tree of a stock and its hierarchical tree (HT) to a taxonomy application of assets. Onnela *et al.* [3,4] examine the dynamics of the minimum spanning tree (MST) and its application to asset portfolio. They find that the optimal Markowitz portfolio lies on the outskirts of the MST. Brida *et al.* [5] employ the MST and its HT to analyze stock returns and trading volume. Gilmore *et al.* [6] use the MST obtained from European Union stock market indexes to investigate the property of equity market. Lee *et al.* [8] discuss the properties of the Korean stock market through MST on high frequency returns.

In addition, timescale is found as a key determinant impacting the property of financial networks in the study of financial network [11]. Another strand of literature concentrates on the improvement of financial network accuracy, because there always exists much noise in the financial trade. This often leads to the bias of a financial network. To eliminate the influence from noise, researchers adopt some filtering methods, among which random matrix theory (RMT) [9,15,17] and planar maximally-filtered graphs [16–18] are two efficient tools. Garas *et al.* [9] study the Athens stock market by MST and RMT and discover that the Athens stock market is related to different economic sectors, including financial services, commerce, transport, manufacturing and constructions. Tumminello *et al.* apply planar maximally-filtered graph (PMFG) to explore the influence of timescale on the top 300 biggest stock portfolios in the New York Stock Exchange during 2001–2003 and find that PMFG is able to obtain a large amount of market effective information. They also show that the smaller the timescale, the more robust the PMFGs appear [18]. Further, Coronnello *et al.* [17] employ a variety of methods, including RMT, single linkage cluster analysis (SLCA), average linkage cluster analysis (ALSA), MST and PMFG to describe how timescale impacts stock industrial clustering.

The relevant network technologies used to analyze financial market have received much attention in the recent literature. However, few studies deeply touch the fields of fund networks and fund strategy identification. Miceli *et al.* [19,20] apply MST to examine the fund strategy. Although their study stays in a static state for a certain time period, it sheds light on the fields using network studies' fund evolution and its strategy. Motivated by the previous contribution, we build up the correlation-based efficient fund network, such as MST and PMFG, to eliminate most trading noise and further help investors identify the actual investment strategy that the fund adopted. By studying the network evolution as time period lengthens and as the timescale expands, we also provide a quantitative identification for the dynamic fund's actual strategy.

The remainder of this article is organized as follows: Section 2 discusses the sample of the open-ended fund in China's market and our empirical methodology for the fund network. The results are presented and discussed in Section 3. Section 4 concludes.

2. Data and Methodology

2.1. Fund Data

The funds in China's financial market are generally classified in the following categories: (1) open-ended and closed-ended funds based on whether funds can be added and redeemed; (2) corporate and contract funds according to the organization form; and (3) stock, bond, monetary and hybrid funds according to the investment target. These rough categories, however, only help investors grasp basic information, such as fund style, risk preference, *etc.* They lack the detailed investment strategy.

In order to deeply probe the fund strategy, we retrieved 94 actively-traded open-ended contract funds from the CSMAR database. The sample period ranges from 2005 to 2012. More details of the 94 funds are listed in Table A1. Before analyzing the fund strategy and its change, we first obtain the strategy published by Tencent Finance website and Sohu Finance website as the sample fund's original stated strategy. The 94 open-ended contract funds are classified into five types of strategies: partial stock fund (56 funds), partial bond fund (21 funds), stock-bond balanced fund (12 funds), bond fund (3 funds) and principal guaranteed fund (2 funds). For the sake of clarity, the stated strategies are labeled by different colors in Table A1. Hereafter, the funds in our empirical analysis refer to the open-ended funds.

The following assumptions are made to obtain the identification from a fund network: funds with a same strategy will earn approximate returns over an identical investment horizon to a great extent. Hence, in a correlation-based network on funds' return series, these funds become close neighbors.

Observing the clustering of the fund network, we can identify the fund's actual strategy. Compared to the original stated strategy, we further detect the discrepancy between a fund's stated and its actual strategy.

2.2. Methodology

2.2.1. Selection of the Significant Correlation Coefficient

In a fund network, nodes are funds. The edges that link any two nodes are produced by their correlation coefficients. To remove most trading noise, our empirical networks only include those edges with significant correlation. Others are viewed as spuriously correlated edges and are excluded from the empirical fund networks. The financial information commonly can be expressed by the return data of the assets. In most financial analyses, the logarithm return is used to analyze the feature of trading and investment. Hence, we calculate the logarithm return of the fund net value and then get the correlation coefficient matrix R. The logarithm return $r^{\Delta t}(t)$ is the percentage change of the fund daily net value Z at time t over timescale Δt:

$$r^{\Delta t}(t) = \ln Z(t + \Delta t) - \ln Z(t) \tag{1}$$

Based on Equation (1), we further gain the Pearson correlation coefficient $\rho_{ij}^{\Delta t}$ between fund i and j as follows:

$$\rho_{ij}^{\Delta t} = \frac{\left\langle r_i^{\Delta t} r_j^{\Delta t} \right\rangle - \left\langle r_i^{\Delta t} \right\rangle \left\langle r_j^{\Delta t} \right\rangle}{\sqrt{(\left\langle (r_i^{\Delta t})^2 \right\rangle - \left\langle r_i^{\Delta t} \right\rangle^2)(\left\langle (r_j^{\Delta t})^2 \right\rangle - \left\langle r_j^{\Delta t} \right\rangle^2)}} \tag{2}$$

where $\langle \cdots \rangle$ represents the expectation operator. The fund network is constructed on the correlation coefficient matrix R. The value of $\rho_{ij}^{\Delta t}$ ranges from -1 to 1. $\rho_{ij}^{\Delta t} = 1$ means a completely positive correlation between nodes i and j and the corresponding funds have the same investment strategy. $\rho_{ij}^{\Delta t} = -1$ means a completely negative correlation and the corresponding funds have a contrary investment strategy. $\rho_{ij}^{\Delta t} = 0$ implies that there is no correlation between two funds and their strategies are independent. Therefore, from the characteristics of a correlation-based fund network obtained from R, we can deduce the fund's actual strategy.

Next, we employ the following t-test under a confidence level of $1 - \alpha = 0.95$ to test the significance of correlation coefficients. If $t > t_{0.05/2}$, we reject null hypothesis H_0 and view ρ_{ij} as a significant coefficient, and ρ_{ij} is viewed as an insignificant coefficient otherwise. Here, the matrix R only includes significant coefficients to construct a fund network after most of the trading noise is eliminated. The work in [11] adopts a similar t-test to identify significant coefficients. The expression of the t-test for a correlation coefficient is as follows:

$$H_0 : \rho = 0 \tag{3}$$

$$H_1 : \rho \neq 0 \tag{4}$$

$$t = \rho_{ij} \sqrt{\frac{n-2}{1-\rho_{ij}^2}} \sim t(n-2) \tag{5}$$

where n represents the number of observations. Hereafter, our empirical networks are constructed on the significant correlation coefficient matrix R_e.

2.2.2. Network of MST and PMFG

The MST method is a commonly-accepted method that can efficiently filter the noise in the fund networks and extract the valuable information. It presently is widely used in a variety of social behavior networks. MST is the shortest distance tree of its corresponding network. It shows most characteristics of a network in the simplest form. To obtain the MST of a fund network, we first transform correlation coefficients to a distance framework. Using the transformation d_{ij}=$\sqrt{2\left(1-\rho_{ij}\right)}$, we produce an $N \times N$ distance matrix D on which the MST is built. As one well knows, a network probably contains several different MST. This could cause error when analyzing certain fund features through a certain MST. To avoid the possible bias from multiple MSTs, we increase the precision of ρ_{ij} up to a four digit decimal. The numerical simulations indicate that this treatment ensures a unique MST corresponding to each network in our analysis.

Since an MST only has the necessary edges that connect the shortest distance, it filters a considerable amount of the valid information of a corresponding network. A PMFG [16] method is used to excavate the information underlying a fund network. The PMFG contains 3N-6 edges, but only N-1 edges on an MST. Therefore, the PMFG preserves more useful information that might be missed by an MST. Using both PMFG and MST helps us better grasp the characteristics of a fund network. PMFG is mainly used as a supplementary method to overcome the non-unique shortage of MST.

In addition, we add a hierarchical tree (HT) [2,21] as a supplement to an MST. This combination accurately detects the correlation and taxonomy of funds. Figure 1 illustrates the advantage when combing an MST and its HT. For non-unique MSTs, their HT gives a unique expression to determine the potential relationship. Correspondingly, when the nodes on an HT exhibit identical distances, its MST can precisely tell whether or not the nodes are identical. For example, the HT in Figure 1 indicates that nodes c and e have the equal distance 1 to node a, but through the corresponding MSTs, we find that only node e is closer to node a compared to the others. The distance $d_{ij}^{<}$ on the HT of Figure 1, a subdominant ultra-metric distance, represents the maximum value of the Euclidean distance linking the shortest route between nodes i and j [2,21].

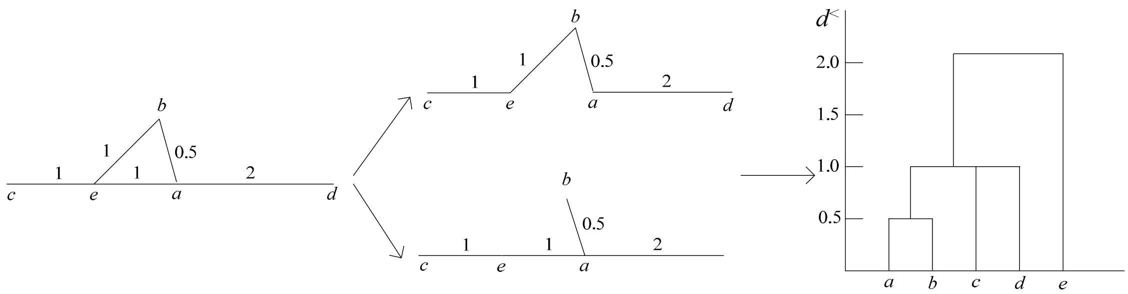

Figure 1. Illustration of two minimum spanning trees (MSTs) and their hierarchical tree (HT).

2.2.3. Characteristic Indicators of a Network

The correlation of nodes located on a fund network indicates the funds' relationship and their actual strategy. We first compute the indicator of correlation coefficient mean ρ to limn the total correlation of MST and PMFG. The bigger the value of ρ, the more correlated the nodes in the network. Funds shown by nodes in the network with a high ρ have a more similar actual strategy. Equations (6) and (7) are used to compute ρ of MST and PMFG, respectively:

$$\rho_1(\Delta t, T) = \frac{1}{N-1} \sum_{\rho_{ij} \in R_{e,T}^{\Delta t}} \rho_{ij} \tag{6}$$

$$\rho_2(\Delta t, T) = \frac{1}{3N-6} \sum_{\rho_{ij} \in R_{e,T}^{\Delta t}} \rho_{ij} \tag{7}$$

where $\rho_1(\Delta t, T)$ and $\rho_2(\Delta t, T)$ are the mean correlation coefficients of MST and PMFG on a timescale Δt over a period T, respectively, N is the edge number of the fund network and $R_{e,T}^{\Delta t}$ is the matrix built by significant correlation coefficients. Next, to reflect the network stability, we calculate the correlation coefficient variance r. The correlation coefficient variances for MST and PMFG are respectively r_1 and r_2, shown by Equations (8) and (9). A high variance denotes more diverse fund strategies.

$$r_1(\Delta t, T) = \frac{1}{N-1} \sum_{\rho_{ij} \in R_{e,T}^{\Delta t}} \left[\rho_{ij} - \rho_1(\Delta t, T)\right]^2 \tag{8}$$

$$r_2(\Delta t, T) = \frac{1}{N-1} \sum_{\rho_{ij} \in R_{e,T}^{\Delta t}} \left[\rho_{ij} - \rho_2(\Delta t, T)\right]^2 \tag{9}$$

where $r_1(\Delta t, T)$ and $r_2(\Delta t, T)$ represent the variance of the correlation coefficient of MST and PMFG on a timescale Δt over a period T, respectively. The normalized tree length (NTL) is used to measure the closeness of the network. Equations (10) and (11) give the computation of NTL for the MST and PMFG, respectively:

$$L_{NTL1}(\Delta t, T) = \frac{1}{N-1} \sum_{d_{ij} \in D_{e,T}^{\Delta t}} d_{ij} \tag{10}$$

$$L_{NTL2}(\Delta t, T) = \frac{1}{3N-6} \sum_{d_{ij} \in D_{e,T}^{\Delta t}} d_{ij} \tag{11}$$

where $L_{NTL1}(\Delta t, T)$ and $L_{NTL2}(\Delta t, T)$ are the normalized tree length of MST and PMFG on a timescale Δt over a period T, respectively, $D_{e,T}^{\Delta t}$ is the distance matrix obtained from $R_{e,T}^{\Delta t}$ and d_{ij} is the distance between nodes i and j. A shorter NTL generally denotes that the network has a greater closeness. In this case, the funds represented by network nodes exhibit a more similar strategy.

In addition, we introduce the average path length (APL) as a supplement of identifying the fund's actual strategy. It is the mean of the edges linking the shortest route between both nodes and calculated as shown in Equation (12):

$$L_{APL} = \frac{2}{N(N-1)} \sum_{i>j} l_{ij} \tag{12}$$

where l_{ij} is the edge number of the shortest path between nodes i and j. A high APL reflects that a network has a stronger compactness. The funds, therefore, are likely to appear as having a more similar strategy.

Central nodes exhibit the characteristics of nodes on the network. A central node generally links a large number of other nodes and possesses a relatively high degree of network. It is often employed as a representative of nodes surrounding it. Through observing the feature of a central node, one has to get the partial information of its neighboring nodes. We define the central nodes of a network as follows: we rank the node degrees in descending order, as shown, $K_1 > K_2 >, \ldots, > K_n$, and the nodes that satisfy the condition K_{i+1}/K_i >0.75 are defined as central nodes of the network.

3. Results and Discussion

3.1. Evolution Characteristics and Strategy Identification over a Time Period

Identifying the dynamic evolution of an open-ended fund network helps investors learn the actual change of fund investment strategy. In this section, we use a fixed timescale Δt =1 day to calculate $R_{e,T}^{\Delta t}$ over four different sample periods: 2005–2009, 2005–2010, 2005–2011 and 2005–2012. We then construct MST from $R_{e,T}^{\Delta t}$ to briefly exhibit the characteristics of the fund network.

The details of 94 open-ended contract funds, including their original stated strategies, are presented in Table A1. Each color corresponds to a fund's stated strategy, given in Table A1, to conveniently locate it in the network. We note that there are five different stated strategies in the sample: partial stock fund (red, 56 funds), partial bond fund (green, 21 funds), stock-bond balanced fund (blue, 12 funds), bond fund (yellow, three funds) and principal guaranteed fund (cyan, two funds). Figures 2–5 show the MST of 94 funds for four time periods, respectively. We find that: (1) each group on the MST includes the funds with different stated strategies; some funds show different actual strategies from their original stated strategies; (2) each group includes a central node; others surrounding it exhibit a similar actual strategy; (3) as the time period lengthens, the actual strategy greatly changes, e.g., from three types of actual strategies for the period of 2005–2009 to two types for period of 2005–2012.

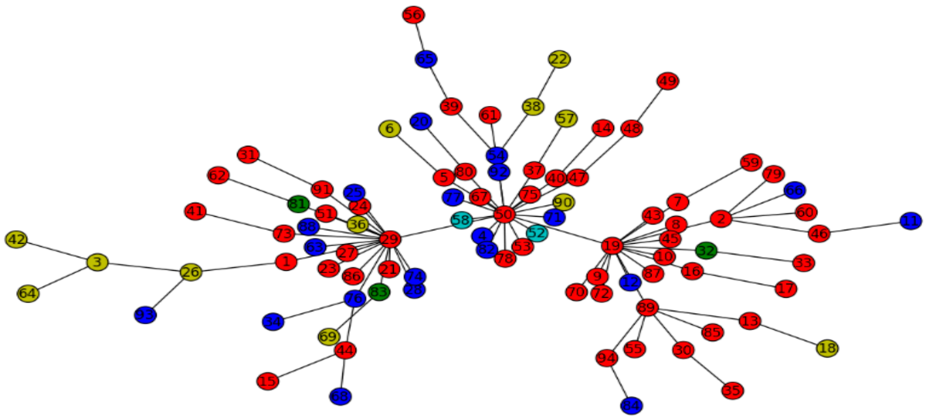

Figure 2. MST of 94 open-ended contract funds over the time period of 2005–2009.

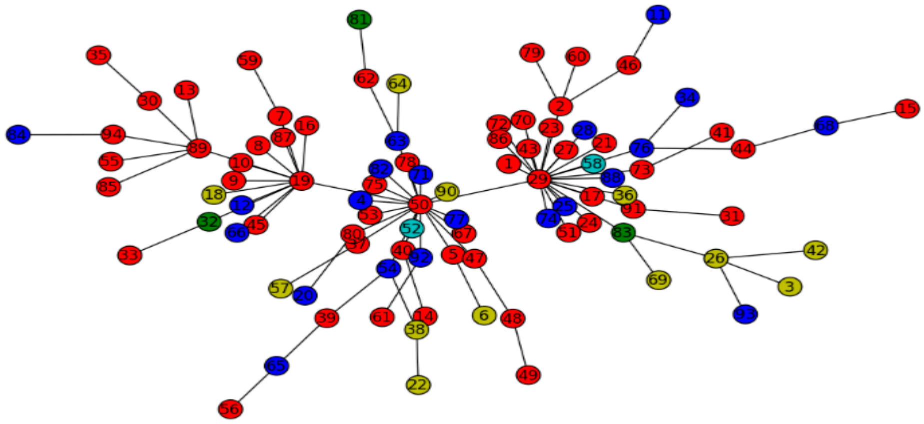

Figure 3. MST of 94 open-ended contract funds over the time period of 2005–2010.

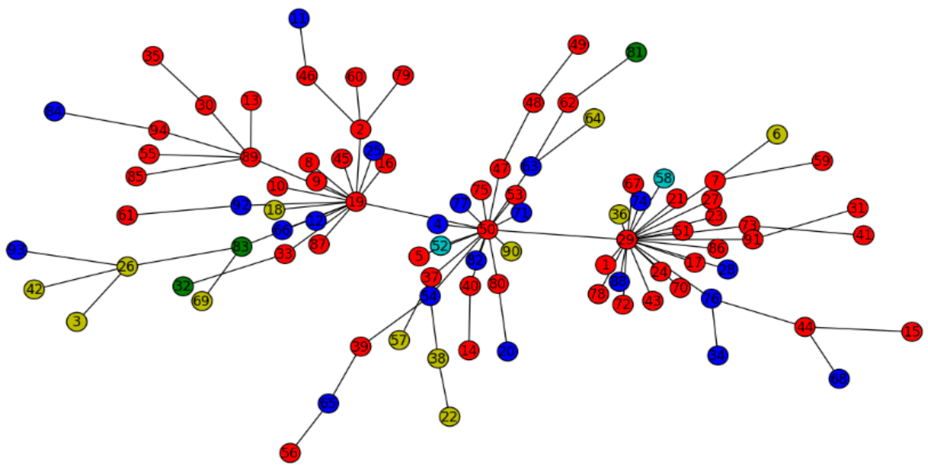

Figure 4. MST of 94 open-ended contract funds over the time period of 2005–2011.

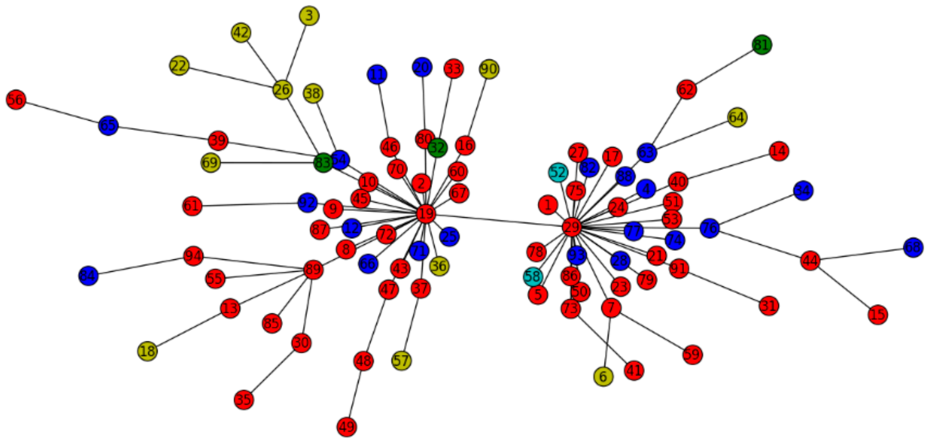

Figure 5. MST of 94 open-ended contract funds over the time period of 2005–2012.

To confirm the results above, we apply PMFG again to depict the dynamic characteristics of the fund network over the same four time periods. Figures 6 and 7 illustrate the PMFG in the periods of 2005–2009 and 2005–2012, respectively. Figure 6 shows an approximate group with the MST in Figure 2. This evidence partially supports the results of Figure 2. There also exist different groups between Figures 6 and 7 indicating that the strategies of sample funds change as the time period lengthens.

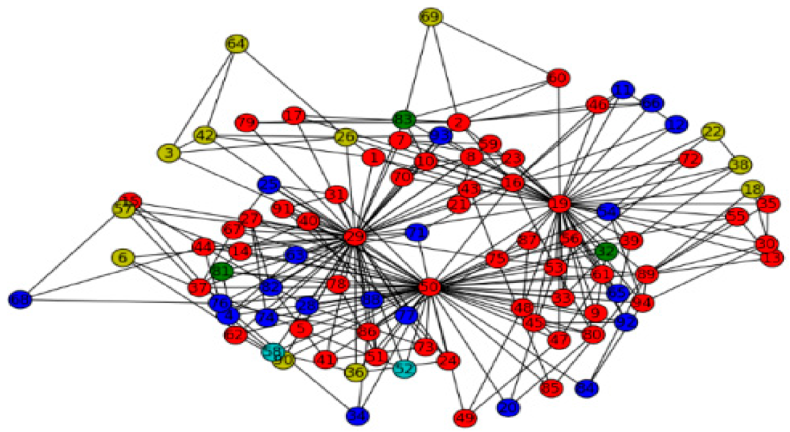

Figure 6. Planar maximally-filtered graph (PMFG) of 94 open-ended contract funds over the time period of 2005–2009.

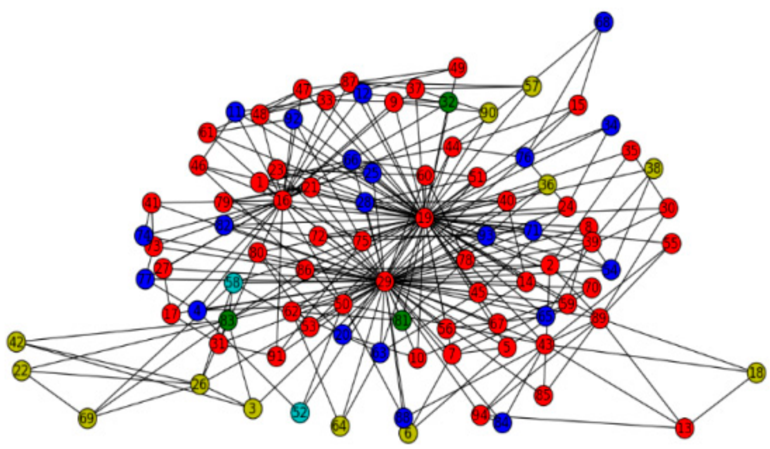

Figure 7. PMFG of 94 open-ended contract funds over the time period of 2005–2012.

Moreover, by comparing the characteristic indicators of MST with PMFG, like ρ, r, L_{NTL}, L_{APL}, degree and central node, we further study the evolution of the fund network and the fund strategy as the time period changes. Tables 1 and 2 show that as the time period lengthens: (1) the correlation of the fund network gradually increases, shown by the increasing ρ, and the fund network trends to be more stable, shown by the decreasing r; (2) the degree of closeness of the fund network also gradually increases, shown by the decreasing L_{NTL} and L_{APL}; and (3) the central node of the fund network exhibits unstable behavior, shown by the changed three top central nodes, e.g., the different $K_i(i = 1, 2, 3)$ and $K'_i(i = 1, 2, 3)$. These results suggest that the funds' actual strategies differ from their original stated strategies in investment practice and that as the time period lengthens, the closer network construction shows that the funds trend to a more identical actual strategy.

Table 1. The characteristics of the MST over four different time periods.

Time Period	ρ_1	r_1	L_{NTL1}	L_{APL1}	K_1	K_2	K_3
2005–2009	0.5642	0.0378	0.9025	4.0105	20(50)	19(29)	15(19)
2005–2010	0.5718	0.0347	0.8964	3.8813	23(29)	20(50)	13(19)
2005–2011	0.5784	0.0326	0.8916	3.9243	23(29)	17(50)	16(19)
2005–2012	0.5775	0.0323	0.8940	3.4706	30(29)	27(19)	6(89)

Note: The number, in the columns of K_i and in the parentheses, denotes the corresponding fund code of a central node on networks, and the outside number is its degree.

Table 2. The characteristics of PMFG over four different time periods.

Time period	ρ_2	r_2	L_{NTL2}	L_{APL2}	K'_1	K'_2	K'_3
2005–2009	0.4862	0.0416	0.9879	2.1716	57(50)	55(29)	47(19)
2005–2010	0.4963	0.0386	0.9796	2.1645	60(29)	54(50)	46(19)
2005–2011	0.5067	0.0363	0.9703	2.1661	60(29)	49(50)	47(19)
2005–2012	0.5039	0.0351	0.9750	2.1080	69(19)	66(29)	26(16)

Note: The number, in the columns of K_i and in the parentheses, denotes the corresponding fund code of a central node on networks, and the outside number is its degree.

Figure 8 corresponds to Tables 1 and 2. In Figure 8, two curves of MST and PMFG make a parallel movement over the period of 2009–2012; for example, the identical increasing of ρ in Figure 8a, the identical decreasing of r, L_{NTL} and L_{APL} in Figure 8b–d. This exhibits that both networks have identical evolution characteristics. Figure 8e shows that the central nodes of $K_i(i = 1, 2, 3)$ and $K'_i(i = 1, 2, 3)$ on MST and PMFG exhibit a similar change as the time period lengthens. This hints that the actual strategies of funds, represented by their central nodes, continue to adjust during the whole investment horizon.

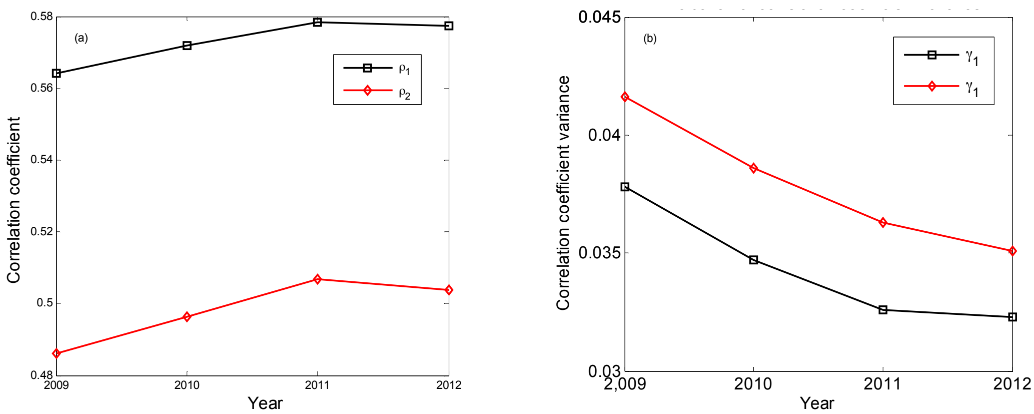

Figure 8. *Cont.*

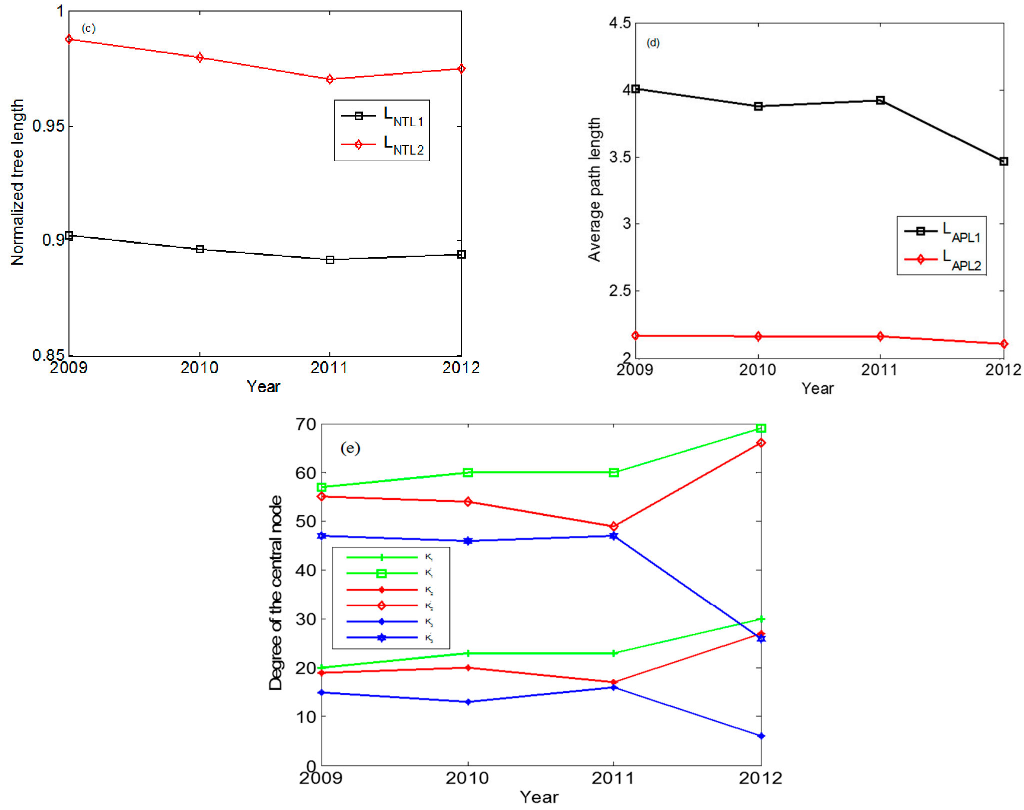

Figure 8. Comparison of the characteristic indicators of MST with PMFG over 2009–2012. (**a**) Evolution of correlation coefficient; (**b**) Evolution of correlation coefficient variance; (**c**) Evolution of normalized tree length; (**d**) Evolution of average path length; (**e**) Evolution of degree of central node.

Figures 9 and 10 present the distributions of the node degree of MST and PMFG, respectively, over four different periods. The illustrations of Figures 9 and 10 exhibit that the shapes of the degree distributions over all four periods are quite similar, especially when the degree is greater than five for MST and 10 for PMFG. In all four time periods, the number of nodes with a higher degree falls approximately into the range [1,3] for both MST and PMFG. This indicates that the nodes surround a few central nodes and conduct similar investment strategies with these dominant funds. As the time period lengthens, the nodes approach a certain node, and the funds trend to an identical strategy.

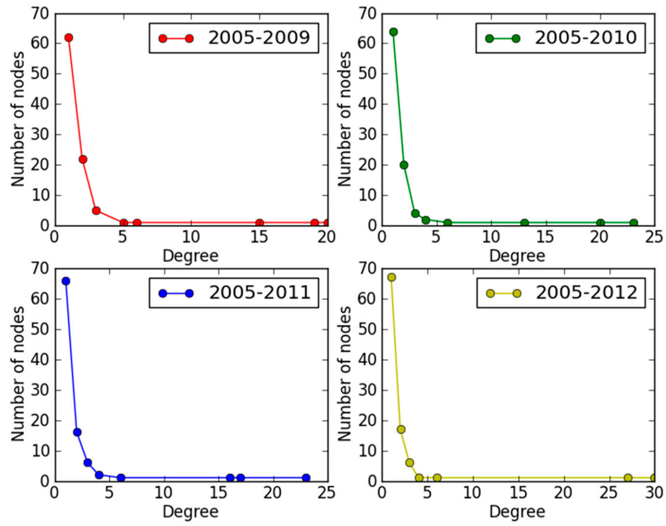

Figure 9. The distributions of the node degree for MST over four time periods.

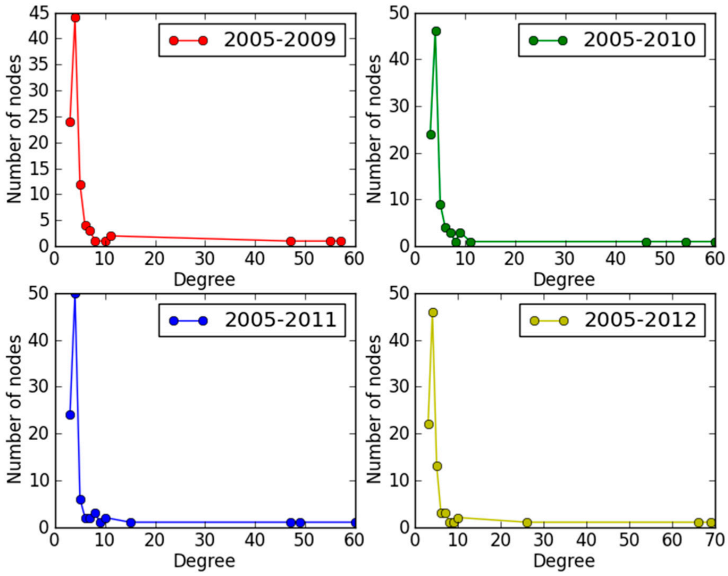

Figure 10. The distributions of the node degree for PMFG over four time periods.

In the wake of the financial crisis in 2008, China's security markets were down in the dumps. Some fund managers prefer consistent strategies to defeat a higher risk together. The evidence above perfectly explains the practical phenomena. In the network built on the relevant funds, the correlation of nodes gradually increases; the structure of the whole network becomes more compact.

3.2. Evolution Characteristics and Strategy Identification over Timescales

Most financial networks in recent research are constructed by the correlation coefficient matrix of asset returns. The calculation of return, however, depends on a certain selected timescale. The return series obtained from different timescales have distinct statistical distributions and correlations [11,22,23]. The behavior of returns on different timescales also reflects the fund investment operation over different horizons. This makes timescale a crucial factor impacting the characteristics of a fund network. To investigate such an influence, we construct MST on four typical timescales, e.g., the daily, weekly, monthly and quarterly scale, for the period from 2009–2012.

Table 3 presents the evolution of fund networks over four timescales. As the timescale expands, the networks show an increasing correlation, a declining fluctuation and a decreasing distance. The results are similar to the results presented in Tables 1 and 2 which indicate similar evolution characteristics between timescale and time period. As the timescale expands, the fund's actual strategy trends accordingly. In Table 3, we also notice that L_{APL1} has an apparently increasing tendency, which differs from the changes in Tables 1 and 2 in which L_{APL1} only slightly decreases. This shows that the compactness of the whole network significantly slows down as the timescale expands. The fund network exhibits higher correlation as the timescale expands. The investment strategy of funds gradually trends consistently. When comparing Figure 11 to Figure 12, being two significantly different scales, we find that the network structure varies dramatically over timescales. The central nodes appear to have a clear difference, supporting the evidence that funds continue to adjust their actual strategies.

Table 3. The characteristics of MST over four timescales.

Timescale	ρ_1	r_1	L_{NTL1}	L_{APL1}
daily	0.5775	0.03225	0.8940	3.4706
weekly	0.6631	0.0247	0.7947	5.2398
monthly	0.8008	0.0197	0.5943	8.8161
quarterly	0.9968	0.0003	0.0277	9.3811

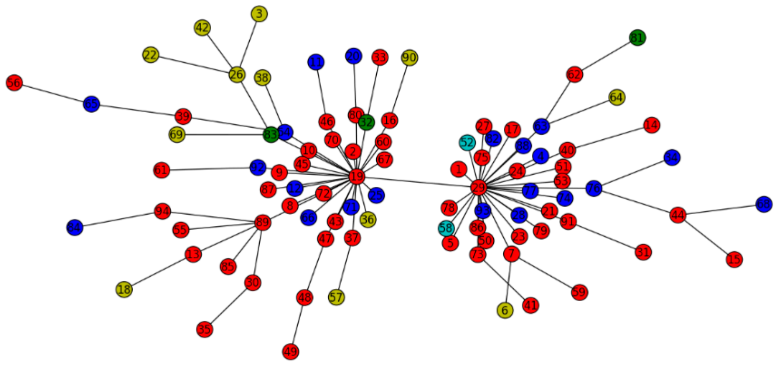

Figure 11. MST of 94 open-ended contract funds on a daily timescale over the time period of 2009–2012.

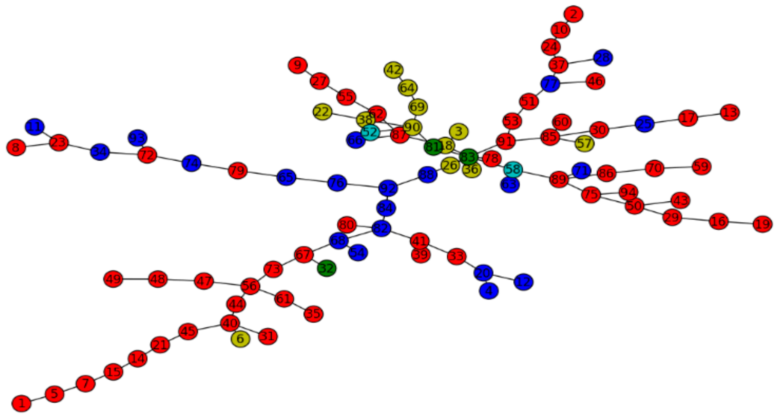

Figure 12. MST of 94 open-ended contract funds on a quarterly timescale over the time period of 2009–2012.

To clarify the details, we re-construct the HT in Figure 13 on a quarterly timescale, showing correspondence to the MST in Figure 12. According to Figure 13, one sees easily that the scattered nodes in Figure 12 surround a certain central node. Over 92 percent of nodes present very low HT distances. Their values of HT approach nearly zero. This suggests that the fund returns upon a quarterly timescale remain highly correlated. Most funds in this case conduct a consistent investment strategy, and funds do not appear to have a determinant node. The evidence from HT, shown by Figure 13, partially supports the results in Table 3 that the network becomes closer as the timescale increases. The funds, therefore, have a similar investment strategy. Figure 14, from the side of the degree distribution, also verifies the change of the central node indicated by Figures 11 and 12.

According to the evolution features of the networks, investors can identify which funds have obviously different strategies over different timescales. Investors need to properly choose the funds according to their own realistic requirements and investment preference. Additionally, investors are able to combine the funds with different actual strategies as the portfolio to diversify the risk. In addition, utilizing the networks over different timescales, the actual strategies of the funds on different horizons are identified. Investors, therefore, can choose the suitable funds according to their own investment horizons and the preference.

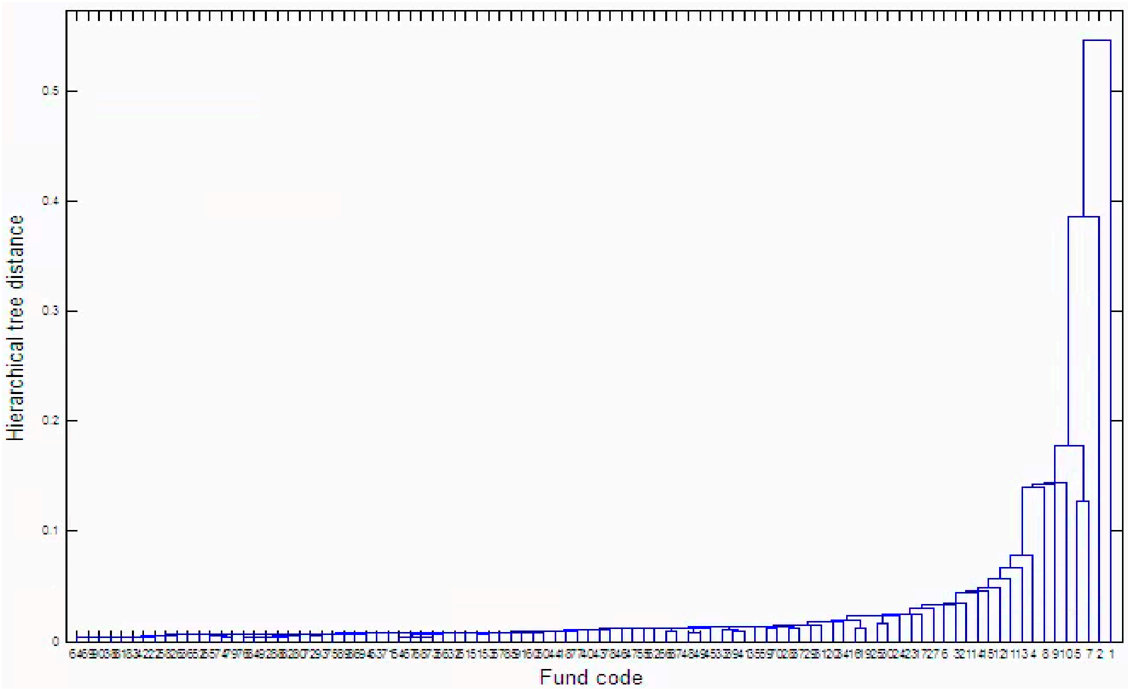

Figure 13. Hierarchical tree on a quarterly scale over the time period 2005–2012.

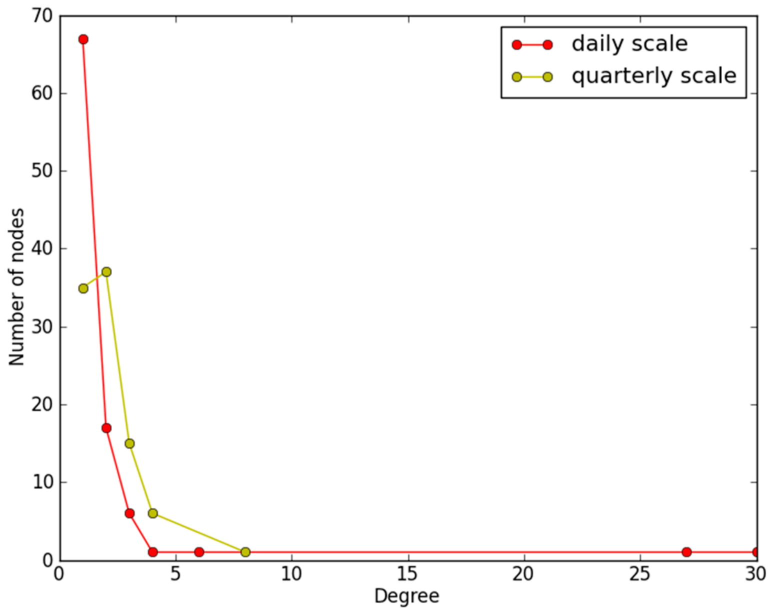

Figure 14. The distribution of the node degree of MST on two timescales over the time period of 2009–2012.

4. Conclusions

In this study, we examine the evolution of a fund network and a fund's actual strategy using 94 open-ended funds in China's finance market. Our results from the evolution of MST and PMFG are two-fold. Firstly, as the time period lengthens, the fund network presents a stronger correlation, a weaker fluctuation and a closer construction. The homogeneity of the network becomes evident. On short time periods, the network exhibits a few prominent central nodes. The fund strategy, indicated by its central node, varies as the time period changes. The fund's actual strategy significantly differs from its original stated strategy. On a longer investment horizon, the funds trend to a certain identical actual strategy, and the central nodes reduce greatly. Secondly, as the timescale expands, the fund network exhibits a tendency similar to the one of time periods. The network exhibits more correlated, stable and closer construction on a wider timescale similar to the change over time periods. The fund strategy trends more accordingly, and there still exists the evident discrepancy between the actual and stated strategy. However, since there is a discrepancy in redemption and trading between the open-ended funds and the closed-ended funds, it is hard to directly apply the above conclusions to the closed-ended funds.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix

Table A1. Ninety four sample open-ended contract funds and their stated strategies.

Fund Code	Fund Name Abbreviation	Fund Type	Corresponding Code in Network (Color)	Fund Code	Fund Name Abbreviation	Fund Type	Corresponding Code in Network (Color)
000001	HXCZ	partial stock fund	1 (red)	162202	TDZQ	partial stock fund	48 (red)
000011	HXDP	partial stock fund	2 (red)	162203	TDWD	partial stock fund	49 (red)
001001	HXZQA/B	bond fund	3 (yellow)	162204	TDJX	partial stock fund	50 (red)
002001	HXHB	stock bond balanced fund	4 (blue)	180001	YHYS	partial stock fund	51 (red)
020001	GTJY	partial stock fund	5 (red)	180002	YHBB	principal guaranteed fund	52 (cyan)
020002	GTZQA	bond fund	6 (yellow)	180003	YH88	partial stock fund	53 (red)
020003	GTJX	partial stock fund	7 (red)	200001	CCJH	stock bond balanced fund	54 (blue)
020005	GTJM	partial stock fund	8 (red)	200002	CCJT	partial stock fund	55 (red)
040001	HACX	partial stock fund	9 (red)	202001	NFWJ	partial stock fund	56 (red)
040002	HAAG	partial stock fund	10 (red)	202101	NFBY	bond fund	57 (yellow)
040004	HABL	stock bond balanced fund	11 (blue)	202202	NFBX	principal guaranteed fund	58 (cyan)
050001	BSZZ	stock bond balanced fund	12 (blue)	206001	PHCZ	partial stock fund	59 (red)
050002	BSYF	partial stock fund	13 (red)	210001	JYYX	partial stock fund	60 (red)
050004	BSJX	partial stock fund	14 (red)	213001	BYHL	partial stock fund	61 (red)
070001	JSCZ	partial stock fund	15 (red)	217001	ZSGP	partial stock fund	62 (red)
070002	JSZZ	partial stock fund	16 (red)	217002	ZSPH	stock bond balanced fund	63 (blue)
070003	JSWJ	partial stock fund	17 (red)	217003	ZSZQA	bond fund	64 (yellow)
070005	JSZQ	bond fund	18 (yellow)	217005	ZSXF	stock bond balanced fund	65 (blue)
070006	JSFW	partial stock fund	19 (red)	233001	DMJC	stock bond balanced fund	66 (blue)
080001	CSCZ	stock bond balanced fund	20 (blue)	240001	BKXF	partial stock fund	67 (red)
090001	DCJZ	partial stock fund	21 (red)	240002	BKPZ	stock bond balanced fund	68 (blue)
090002	DCZQA/B	bond fund	22 (yellow)	240003	BKZQ	bond fund	69 (yellow)
090003	DCLC	partial stock fund	23 (red)	240005	HBCL	partial stock fund	70 (red)
090004	DCJX	partial stock fund	24 (red)	255010	WCWJ	stock bond balanced fund	71 (blue)
100016	FGTY	stock bond balanced fund	25 (blue)	257010	GLAJP	partial stock fund	72 (red)
100018	FGTL	bond fund	26 (yellow)	260101	JXGP	partial stock fund	73 (red)

Table A1. *Cont.*

Fund Code	Fund Name Abbreviation	Fund Type	Corresponding Code in Network (Color)	Fund Code	Fund Name Abbreviation	Fund Type	Corresponding Code in Network (Color)
100020	FGTY	partial stock fund	27 (red)	260103	JXDL	stock bond balanced fund	74 (blue)
110001	YJPW	stock bond balanced fund	28 (blue)	260104	JSZZ	partial stock fund	75 (red)
110002	YJCL	partial stock fund	29 (red)	270001	GFJF	stock bond balanced fund	76 (blue)
110003	YJ50	partial stock fund	30 (red)	270002	GFWJ	stock bond balanced fund	77 (blue)
110005	YJJJ	partial stock fund	31 (red)	288001	HXJD	partial stock fund	78 (red)
121001	GTRH	partial bond fund	32 (green)	290002	TXXX	partial stock fund	79 (red)
121002	GTJQ	partial stock fund	33 (red)	310308	SLJX	partial stock fund	80 (red)
150103	YHYT	stock bond balanced fund	34 (blue)	310318	SLPZ	partial bond fund	81 (green)
151001	YHWJ	partial stock fund	35 (red)	320001	NAPH	stock bond balanced fund	82 (blue)
151002	YHSY	bond fund	36 (yellow)	340001	XQCJ	partial bond fund	83 (green)
160105	NFJP	partial stock fund	37 (red)	350001	TZCF	stock bond balanced fund	84 (blue)
160602	PTZQA	bond fund	38 (yellow)	360001	LHHX	partial stock fund	85 (red)
160603	PTSY	partial stock fund	39 (red)	375010	STYS	partial stock fund	86 (red)
160605	PHZG50	partial stock fund	40 (red)	398001	ZHCZ	partial stock fund	87 (red)
161601	XLC	partial stock fund	41 (red)	400001	DFL	stock bond balanced fund	88 (blue)
161603	RTZQA	bond fund	42 (yellow)	510050	50ETF	partial stock fund	89 (red)
161604	RTSZ100	partial stock fund	43 (red)	510080	CSZQ	bond fund	90 (yellow)
161605	RTLC	partial stock fund	44 (red)	510081	CSJX	partial stock fund	91 (red)
161606	RTHY	partial stock fund	45 (red)	519003	HFSY	stock bond balanced fund	92 (blue)
162102	JYZXP	partial stock fund	46 (red)	519011	HFJX	stock bond balanced fund	93 (blue)
162201	TDCZ	partial stock fund	47 (red)	519180	WJ180	partial stock fund	94 (red)

Note: We use the number and color as a tag to label the fund and its stated strategy, respectively. An identical color represents the same fund stated strategy that investors can obtain publicly before investing.

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