Characteristics of Real Futures Trading Networks

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Abstract

Futures trading is the core of futures business, and is considered as a typical complex system. To investigate the complexity of futures trading, we employ the analytical method of complex networks. First, we use real trading records from Shanghai Futures Exchange to construct futures trading networks, in which vertices are trading participants, and two vertices have a common edge if the two corresponding investors simultaneously appear in at least one trading record as a purchaser and a seller respectively. Then, we conduct a comprehensive statistical analysis on the constructed futures trading networks, and empirical results show that the futures trading networks exhibit such features as scale-free structure with interesting odd-even-degree divergence in low degree region, small-world effect, hierarchical organization, power-law betweenness distribution, and shrinkage of both average path length and diameter as network size increases. To the best of our knowledge, this is the first work that uses real data to study futures trading networks, and we argue that the research results can shed light on the nature of real futures business.

Keywords: Complex networks, Futures trading networks, Scale-free scaling, Small-world effect
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1. Introduction

Since the works of Watts & Strogatz [1] and Barabási & Alberta [2] were published, complex networks, as a new scientific area, have caught a tremendous amount of interest [3–7]. Complex networks can describe a wide range of real-life systems in nature and society, and show various non-trivial topological characteristics not occurring in simple networks such as regular lattices and random networks. There are a number of frequently cited examples that have been studied from the perspective of complex networks, including World Wide Web [8–11], Internet [12], metabolic networks [13], scientific collaboration networks [14], online social networks [15, 16], public transport networks [17, 18], airline flight networks [19] and human language networks [20–22]. Empirical studies on these networks mentioned above have largely motivated the recent curiosity and concern about this new research area so that a number of techniques and models have been explored to improve people's perception of topology and evolution of real complex systems [23–28]. As growing in importance and popularity, complex network

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theory becomes a powerful tool with intuitive and effective representations to analyze complex systems in a variety of fields, including financial market [29].

In the literature, a number of papers have been dedicated to studying financial market from the perspective of complex networks. The major difference among these works lies in the types of networks to be constructed from financial data for characterizing the organization and structure of financial market. Some existing works constructed stock networks whose connectivity is defined by the correlation between any two time series of stock prices [30–34]. Some others established directed networks of stock ownership describing the relationship between stockholders and companies [35, 36]. Networks of market investors based on transaction interaction between the investors were also investigated. For example, Franke et al analyzed irregular trading behaviors of users in an experimental stock market [37], while Wang et al studied the evolving topology of such a network in an experimental futures exchange [38].

The study on financial investor networks can provide clues to reveal the true complexity in financial market, especially futures market. In a real futures market, the futures trading model serves as a matching engine to execute all eligible orders from various market participants, and the interactions among the participants form a complex exchange network, which is termed as *futures trading network* (FTN in short) in this paper. Simply, a FTN consists of a set of trading participants, each of which has at least one connection of direct exchange action to another on the futures contracts.

In this paper, we try to provide a comprehensive study on the characteristics of futures trading networks established with genuine trading data from Shanghai Futures Exchange. To the best of our knowledge, this is the first work that uses real futures trading data to construct networks. So we think the empirical results may unveil the financial trading behavior and shed light on the nature of futures market.

The rest of this paper is organized as follows. FTN construction method is introduced in Section 2, including trading data set and the detail of network construction. Section 3 presents the empirical results of FTNs. Section 4 concludes the paper.

2. Construction of Futures Trading Networks

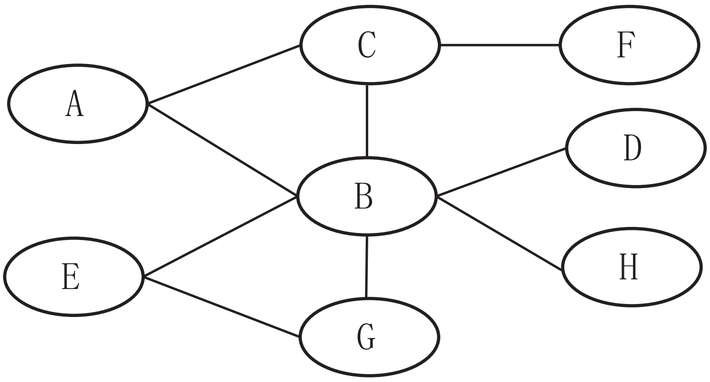
In this section, we first introduce the real trading data from Shanghai Futures Exchange, which will be used to construct futures trading networks, and then present the detail of futures trading networks construction.

2.1. Dataset

To construct futures trading networks, we use real trading records from Shanghai Futures Exchange, which is the largest one in China's domestic futures market and has considerable impact on the global derivative market. Trade records are generated by matching orders or quotes from buyers and sellers according to a certain rule of price/time priority (first price, then time) in the electronic trading platform of the futures exchange. There are hundreds of thousands of matching results reported from the exchange in one typical trading day. We use a dataset involving all futures commodities in the derivative market from July to September of 2008. For the trading records, we use virtual and unique IDs to represent the trading participants, and all other information is filtered for privacy preservation reason.

2.2. *Network Construction*

Since a trading record contains the IDs of both the buyer and the seller, we are able to establish a futures trading network. The construction process is as follows. A vertex represents a participant in a trading record, and an edge, meaning a trade relation, is established between two participants if their IDs appear in the same trading record at least once. An example of FTN comprising nine records is shown as Fig. 1. Here, A-H are IDs of trading participants. Each row in the right part of Fig. 1 represents a trading record, and the Seller and Buyer columns are the IDs of seller and buyer in each trading record.



seller	buyer
A	B
A	C
B	C
B	D
B	E
B	G
B	H
C	F
E	G

Fig. 1. An example of futures trading network constructed from a dataset with nine trading records.

Following the above process, we first create the largest network with the whole dataset containing three months' trading records, this network is denoted as FTN-all. Then, we construct three sub-networks based on three subsets of the whole dataset above according to futures commodity classification of Shanghai Futures Exchange. These three sub-networks are termed as FTN-met, FTN-rub and FTN-oil, which involve only futures commodity metal (concretely including copper, aluminum, zinc and gold), natural rubber and fuel oil respectively. Thus, we have totally four FTNs, their detailed information is given in Table 1.

Table 1. The details of the four FTNs. FTN-all is based on the whole dataset containing three months' trading records from July to September of 2008, FTN-met, FTN-rub and FTN-oil are three sub-networks of FTN-all, they correspond to three subsets that involve only trading records of futures commodity metal, natural rubber and fuel oil respectively.

Label	Futures Commodity	Number of vertices	Number of edges
FTN-all	all	100994	8068676
FTN-met	metal	75262	3226119
FTN-rub	natural rubber	55828	3364557
FTN-oil	fuel oil	52208	1657268

3. Properties of Futures Trading Networks

In what follows, we study the characteristics of FTNs constructed above, our focus is on topological features and dynamical properties. Extensive empirical results are presented.

3.1. Scale-free Behavior

Degree distribution *P(k)* is one of the most import statistical characteristics of a network, and one of the simplest properties that can be measured directly, whose definition is the probability that a random vertex in a network has exactly k edges. In many real complex networks, *P(k)* decays with k in a power law, following $P(k) \sim k^{-\lambda}$. A network owning such a property is called scale-free network [2].

The degree distributions of FTN-all, FTN-met, FTN-rub and FTN-oil are shown in Fig. 2(a), (b), (c) and (d). We can see that the $P(k)$ of all the four networks follows power-law distribution with the same λ value, which is about 1.5. This implies that highly connected vertices have larger chances of occurring and dominating the connectivity. Actually, these vertices correspond to a few active speculators who send numerous orders to the exchange, and consequently obtain more opportunities to make deals with the others. Their trading behaviors also account for the fact that FTNs dynamically expand in accordance with the rule of preferential attachment by continuously adding new vertices during the lifetime of the networks.

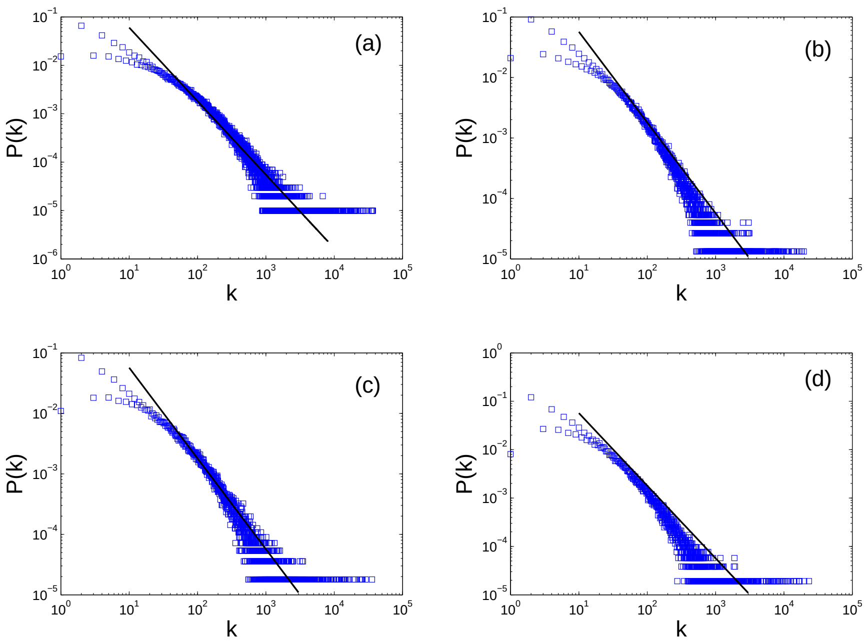


Fig. 2. Degree distributions of FTN-all, FTN-met, FTN-rub and FTN-oil. All the four fitting lines in the subplots have the same slope and follow $P(k) \sim k^{-1.5}$.

In Fig. 2, we also can see the fact that in low-degree region, the probability of even degree is larger than that of odd degree following the former, which forms a divergence. As the degree increases, the two branches gradually converge and the difference is averaged out. The branch of even degree conforms to power law more than that of the odd. For this observation, one reasonable explanation is that most participants with a small number of trading transactions are unwilling to hold the positions long term, which are open not long ago, and close them soon. To a certain extent, due to the randomicity of counter part during the execution, two matches (open and close) of a participant are more possible to be involved in different counter parties, thus two degrees will be added to the corresponding vertex. This observation reveals that there are few hedgers with long-term position in real trading, which is consistent with the fact of low delivery ratio in the futures market.

Now let us consider weighted futures trading networks where vertex strength is a significant measure [39]. In this paper, the vertex strength is defined as follows. Suppose that the weight of an edge between two vertices is the number of times they appear in the same trade record, the strength S of a vertex is defined as the total weight of all edges connecting it. As shown in Fig. 3, the relationship between the strength and degree of all vertices in FTN-all shows a nontrivial power law scaling $S \sim k^{\beta}$, which demonstrates the fact that active market participants get more active. Such a scale-free behavior being correlated to the occurrence frequency of a trading participant provides another justification for the power-law degree distribution of the networks.

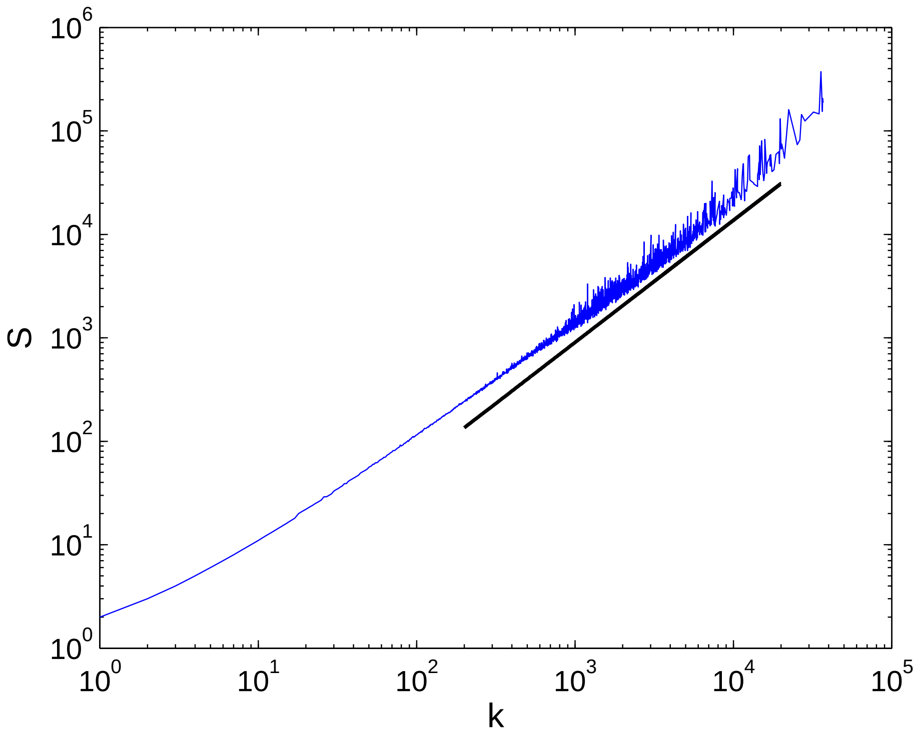


Fig. 3. Plot of the vertex strength S as a function of degree k in FTN-all, the slope is about 1.18.

3.2. Small-world Effect

For complex networks, average path length and clustering coefficient are two important measures of small-world effect.

In a network, the average path length (say L) is defined as the number of edges in the shortest path between any two vertices, averaged over all pairs of vertices. It plays an important role in transportation and communication in a network. We can obtain $L = (2/n(n-1)) \sum_{i \geq j} d_{ij}$. The longest shortest path among all pairs of vertices is called the diameter of the network.

The clustering coefficient C_i of a vertex i is defined as the ratio of the total number e_i of edges that actually exist between all its k_i immediate (nearest) neighbors and the number $k_i(k_i - 1)/2$ of all possible edges between them, that is, $C_i = 2e_i/k_i(k_i - 1)$. The clustering coefficient C of the whole network is the average of C_i over all vertices, i.e., $C = (1/n) \sum C_i$. The clustering coefficient measures the probability that two neighbors of a vertex are connected and reveals the local cliquishness of a typical neighborhood within a network.

In recent empirical studies, many real systems show small-world effect by two crucial factors: average path length and diameter is relatively small despite often the large network size, which grows nearly logarithmically with the number of vertices, and the clustering coefficient is larger than that of a comparable random network having the same number of vertices and edges as the real network.

We also notice small-world effect in FTN-all. On one hand, the average path length L and diameter D are small, their values are 2.470 and 6 respectively, while the values are 2.774 and 4 in an equivalent random network with the same parameters. On the other hand, the network is highly clustered. The clustering coefficient of FTN-all is 0.0480, which is larger than that of the random network (the value is 0.0016). These results are presented in Table 2.

Table 2. Small-world effect shows in FTN-all with large clustering coefficient C and small average path length L and diameter D, contrary to a random network with similar parameters (total number of vertices V, total number of edges E or average number of edges per vertex $< k >$)

Label	V	E	$< k >$	k_{max}	C	L	D
FTN-all	100994	8068676	159.8	36878	0.0480	2.470	6
random	-	-	-	218	0.0016	2.774	4

The ratio of $C_{FTN-all}$ and C_{rand} is relatively small in comparison with other real systems [4]. This implies no adequate evidence of local cliquishness of a typical neighborhood within FTN-all, which may be due to the randomicity of counter part during execution. Furthermore, the small L and D is because of 1) the existence of hub vertices (conforming to the large maximum degree k_{max} in Table 2), which are bridges between different vertices separated in the network; and 2) new connections generated between the existing vertices without direct links previously, which provide more shortcuts to the network. The shortest path distribution in Fig. 4 shows that most of the shortest paths are 2 or 3, which helps to explain the small-world effect.

3.3. Hierarchical Organization

To examine the hierarchical organization feature of a network, we check *C(k)*, the average clustering coefficient of all vertices with the same degree k. If *C(k)* follows a strict scaling law, the network is viewed as the presence of hierarchical organization. Some real networks, such as World Wide Web, actor network and Internet, display the hierarchical topology [40].

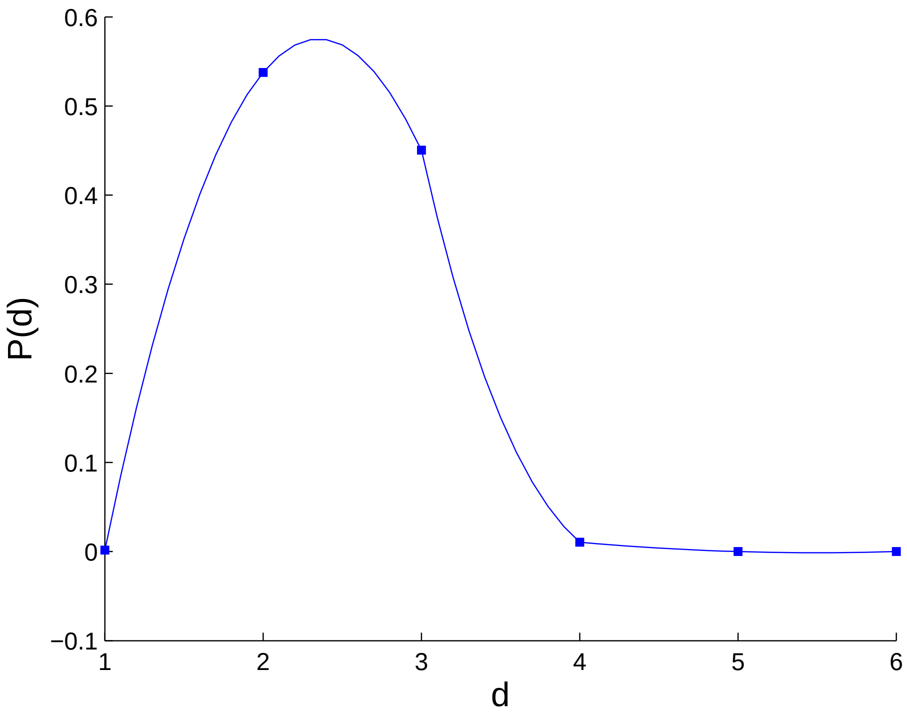


Fig. 4. Shortest path distribution indicating that most of the shortest paths are 2 or 3.

For FTN-all, as indicated in Fig. 5, the main part of *C(k)* obeys a scaling law of $k^{-0.8}$, which implies that the network has a hierarchical architecture. Although the majority of bargainers making a few deals have a few links (low k), most of these links join hub vertices that connect to each other, resulting in a big *C(k)*. The high-k vertices are hub bargainers, and their neighbors being low-k vertices are seldom linked to each other, leading to a smaller *C(k)*. This implies that ordinary investors are part of such clusters with high cohesiveness and dense interlinking except the hubs that play a bridging role to connect many separate small communities together into a complete network. To some extent, the hub investors flourish the market and improve the market's liquidity.

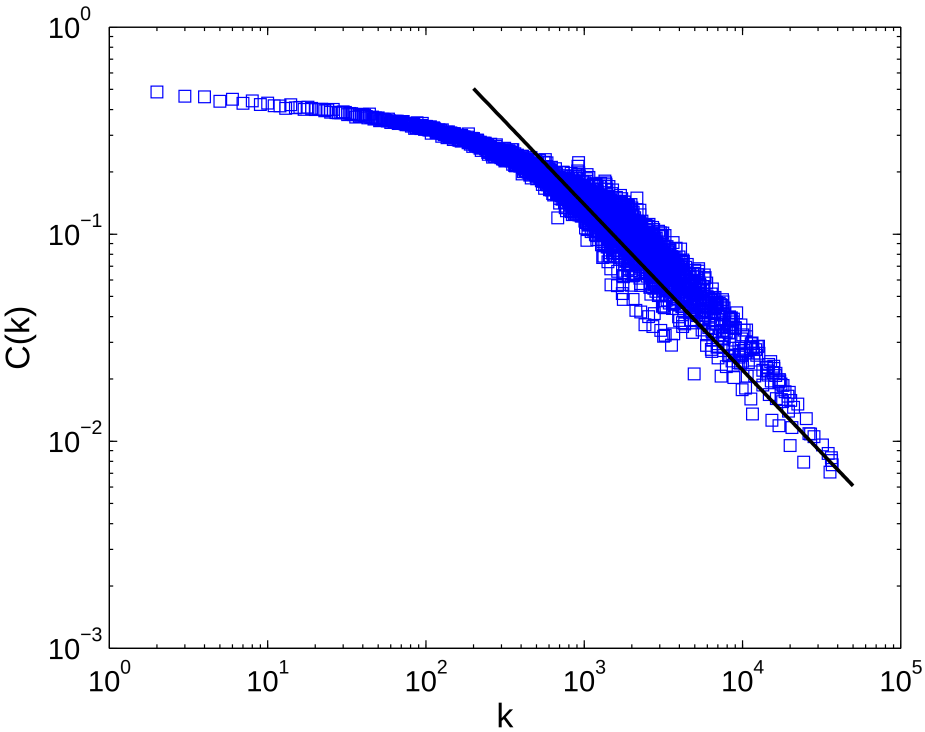


Fig. 5. Clustering coefficient *C(k)* as a function of the vertex degree k with a exponent of -0.80

3.4. Betweenness Distribution

Betweenness is a measure of the centrality of a vertex in a network, and also a measure of the influence a vertex has over the spread of information through the network [41].

The betweenness of a vertex is defined to be the fraction of shortest paths between pairs of vertices in a network that go through it. If there is more than one shortest path between two vertices, the value of each such path is weighted by one over the number of shortest paths. To be precise, the definition is as follows: $b(i) = \sum b_{jk}(i)/b_{jk}$ where $b_{jk}(i)$ is the number of geodesic paths from j to k containing i, while b_{jk} is the total number of geodesic paths linking j and k.

By exploring the betweenness distribution *P(b)* of FTN-all, we find it following a power law function, i.e., $P(b) \sim b^{-\omega}$ with ω=0.8. The result is illustrated in Fig. 6.

Information communication (e.g. money or asset transfer) exists in FTNs, and money flow is considered as the index of marke. The power-law distribution demonstrates that the vertices having high betweenness own such a potential to control information flow passing between vertex pairs of the network. Accordingly, the participants with high betweenness centrality play decisive role in promoting market boom and enhancing financial function.

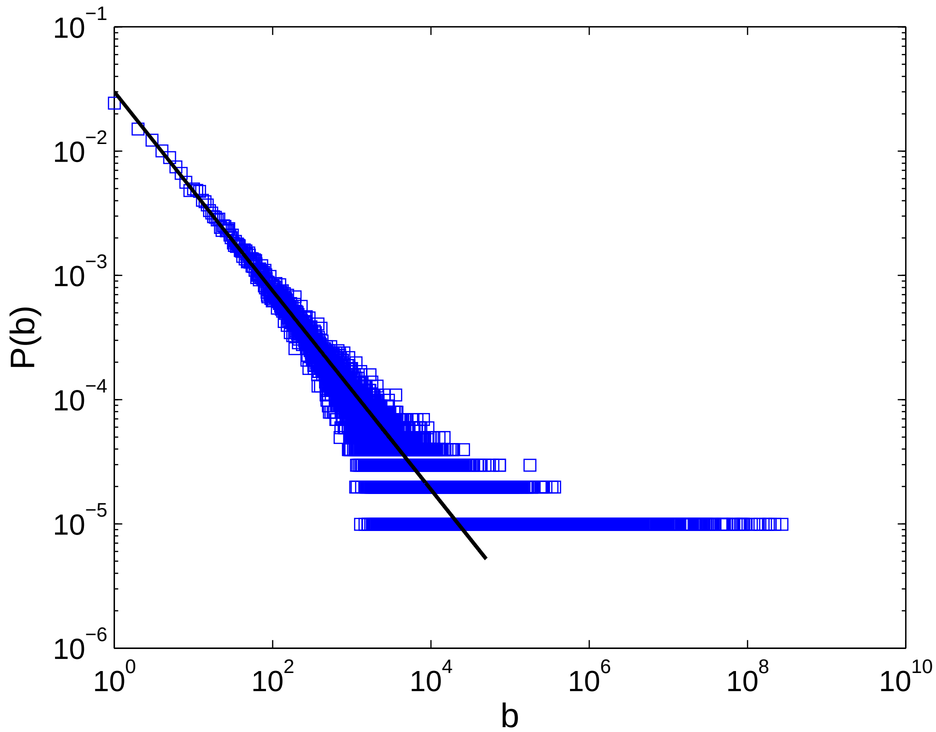


Fig. 6. Betweenness distribution following a power law function with $P(b) \sim b^{-0.8}$

3.5. Power-Law Evolution

We have now explored topological properties in static FTNs. Here we will check some dynamic characteristics of the FTN-all network by considering its evolutional process, which can characterize the real trading behaviors of futures market.

Like many real-life systems [10, 12, 13], FTN-all also shows accelerated growth [42] in Fig. 7(a), which manifests that the number of edges increases faster than the number of vertices. Furthermore, the relationship between the number of edges and the number of vertices in FTN-all follows a power law function $e(t) \sim v(t)^{\alpha}$, where *e(t)* and *v(t)* respectively denote the numbers of edges and vertices of the network at time t, and α is the exponent. Such relationship is termed densification power law by Leskoverc et al. [43]. We can see that the fitting curve in Fig. 7(a) consists of two segments with different slopes, 1.8 and 3.3 respectively. We notice that the critical point of the broken fitting line exactly locates at the end of the first trading day, meaning that the mechanism of intraday edge's growth in FTN-all is totally different from that after the first day.

Besides, we observe that the average degree and density of FTN-all super-linearly grow with the network size, and both show broken lines in the logarithmic plots of Fig. 7(b) and (c), similar to Fig. 7(a). The variations of both average degree and density over time are directly related to the change of edges' number. The average degree $\overline{k}(t)$ and density *d(t)* are respectively evaluated by $\overline{k}(t) = 2e(t)/v(t)$ and $d(t) = 2e(t)/v(t)(v(t) - 1)$, and thus we obtain $\overline{k}(t) \sim v(t)^{\alpha-1}$ and $d(t) \sim v(t)^{\alpha-2}$. In Fig. 7(b), the two slopes of the broken line are 0.8 and 2.3 respectively, and in Fig. 7(c) they are -0.2 and 1.3 respectively, which explains why the broken line of the density first falls and then rises. According to Fig. 7(a), (b) and (c), FTN-all is becoming denser as the network size increases.

In Fig. 7(d), the maximum degree $k_{max}(t)$ of FTN-all grows in power law: $k_{max}(t) \sim v(t)^{\beta}$ where the slope β is 1.7. This observation illustrates that the active participants in the futures market keep vigorous all the time, and the day traders (these who frequently buy and sell futures within the same trading day so that all positions will customarily be closed before the market close's on that day) constitute the core part of the active participants.

In some real complex networks [1, 9], the average path length scales logarithmically with the number of vertices, and the diameter slowly grows with network size. However, in FTN-all we notice that the average path length deceases as the number of vertices increases, so does the diameter. The average path length decays in a power law with a slope of -0.27 in Fig. 7(e), while the diameter of FTN-all deceases as shown in Fig. 7(f). With the network size's growing, the simultaneous shrinkage of both the average path length and the diameter in FTN-all provides another evidence of densification in the network.

The exposed properties above indicate that the vertices in FTN-all become closer with each other as the network size grows. These properties attribute to the real trading behavior of futures market. The deals are resulted from two sources: trading of new investors who just enter the market, and transactions between the existing participants. The new investors make a few deals because of caution and carefulness, while the existing participants, especially the day traders, generate a large number of transactions. The latter provide many chances to make deals between the participants without any trading relationship before, which results in the new links between the vertices that have no direct connections previously in FTN-all, and consequently accounts for the properties mentioned above. Additionally, the different dominant sources of edge addition determine the discontiguous slopes in the logarithmic plots. In the first trading day, almost all investors are newcomers, so the edge growth from new investors is the dominant factor. After that day, the number of new investors and their transactions tend to remain steady, and the edges generated between the existing participants outnumber those generated by the new investors. The conversion of the edge growth's driving factors explains the existence of two different exponents in the power law underlying the network's evolution.

4. Conclusion

Futures trade networks in financial business have been analyzed from the perspective of complex network. We constructed FTNs by using real trading records covering three months' operation in Shanghai Futures Exchange. We found a number of interesting statistical properties of the networks, including scale-free behavior, small-world effect, hierarchical organization and power-law evolution characteristics. Some unique features of the FTNs are possibly due to the

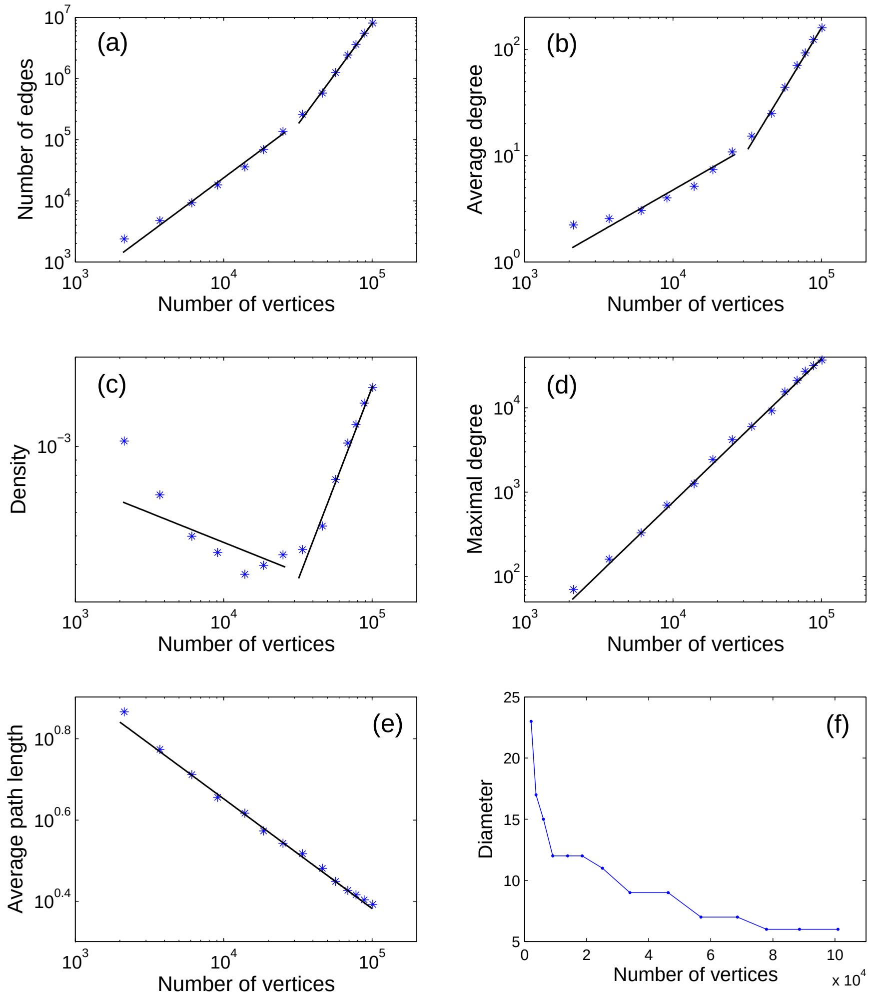


Fig. 7. (a) The number of edges vs. the number of vertices in log-log scale for FTN-all, a power law is witnessed with the slopes of 1.8 and 3.3 respectively in the evolution process. The critical point locates at the end of the first trading day. (b) Average degree super-linearly grows in a power law with the slopes of 0.8 and 2.3 respectively. (c) Density changes over time in an approximate power law of the slopes -0.2 and 1.3, and the slope values account for the reason why the curve first falls and then rises. The conversion of edge growth's driving factors results in the different slopes in the power law underlying the network's evolution. (d) Maximum degree grows in a power law with regard to network size, and the slope is 1.7. (e) Average path length decays in a power law with a slope of -0.27. (f) Diameter decreases as the number of vertices increases.

randomicity of counter part during deal execution and the continuous generation of new links between previously-unconnected vertices, which play important roles in determining the structures of futures trade networks.

As only undirected graphs are considered in this paper, it is worthy of further studying the directed FTNs based on trading direction, such as from buyer to seller, which reflects information flow, for example, money flow. In Section 3.1, we simply established the weighted FTN-all to demonstrate that active market participants get more active, but it is obviously not enough. Actually, we can construct weighted FTNs or weighted and directed FTNs to investigate the market behavior of active parts. Moreover, the generation model of FTNs is also an important issue for further exploration, as it can provide valuable insight on financial trade monitoring and risk control.

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References

[1] D. J. Watts, S. H. Strogatz, Collective dynamics of 'small-world' networks, Nature 393 (1998) 440.
[2] A.-L. Barabási, R. Albert, Emergence of scaling in random networks, Science 286 (1999) 509.
[3] M. E. J. Newman, The structure and function of complex networks, SIAM Rev. 45 (2003) 167.
[4] R. Albert, A.-L. Barabási, Statistical mechanics of complex networks, Rev. Modern Phys. 74 (2002) 47.
[5] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, D.-U. Hwang, Complex networks: Structure and dynamics, Phys. Rep. 424 (2006) 175.
[6] L. da. F. Costa, F. A. Rodrigues, G. Travieso, P. R. V. Boas, Characterization of complex networks: A survey of measurements, Adv. Phys. 56 (2007) 167.
[7] C. Song, S. Havlin, H. A. Makse, Origins of fractality in the growth of complex networks, Nature Physics 2 (2006) 275.
[8] B. A. Huberman, L. A. Adamic, Growth dynamics of the world-wide web, Nature 410 (1999) 131.
[9] R. Albert, H. Jeong, A.-L. Barabási, Diameter of the world-wide web, Nature 401 (1999) 130.
[10] A. Broder, R. Kumar, F. Maghoul, P. Raghavan, S. Rajagopalan, R. Stata, A. Tomkins, J. Wiener, Graph structure in the web, Comput. Netw. 33 (2000) 309.
[11] A.-L. Barabási, R. Albert, H. Jeong, G. Bianconi, Power-law distribution of the world wide web, Science 287 (2000) 2115.
[12] M. Faloutsos, P. Faloutsos, C. Faloutsos, On power-law relationships of the internet topology, Comput. Commun. Rev. 29 (1999) 251.
[13] H. Jeong, B. Tombor, R. Albert, Z. N. Oltvai, A.-L. Barabási, The large-scale organization of metabolic networks, Nature 407 (2000) 651.
[14] M. E. J. Newman, The structure of scientific collaboration networks, Proc. Natl. Acad. Sci. USA 98 (2001) 404.
[15] K. Subrahmanyam, S. M. Reich, N. Waechter, G. Espinoza, Online and offline social networks: Use of social networking sites by emerging adults, Journal of Applied Developmental Psychology 29 (2008) 420.
[16] F. Fu, L. H. Liu, L. Wang, Empirical analysis of online social networks in the age of web 2.0, Physica A 387 (2008) 675.
[17] M. Kurant, P. Thiran, Layered complex networks, Phys. Rev. Lett. 96 (2006) 138701.
[18] B. B. Su, H. Chang, Y.-Z. Chen, D. R. He, A game theory model of urban public traffic networks, Physica A 379 (2007) 291.
[19] D.-D. Han, J.-H. Qian, J.-G. Liu, Network topology and correlation features affiliated with european airline companies, Physica A 388 (2009) 71.
[20] A. E. Motter, A. P. S. de Moura, Y.-C. Lai, P. Dasgupta, Topology of the conceptual network of language, Phys. Rev. E 65 (2002) 065102.
[21] S. M. G. Calderia, T. C. P. Lobão, R. F. S. Andrade, A. Neme, J. G. V. Miranda, The network of concepts in written texts, Eur. Phys. J. B 49 (2006) 523.
[22] S. G. Zhou, G. B. Hu, Z. Z. Zhang, J. H. Guan, An empirical study of chinese language networks, Physica A 387 (2008) 3039.

[23] R. Albert, A.-L. Barabási, Topology of complex networks: Local events and universality, Phys. Rev. Lett. 85 (2000) 5234.
[24] G. Bianconi, A.-L. Barabási, Competition and multiscaling in evolving networks, Europhys. Lett. 54 (2001) 436.
[25] C. P. Zhu, S. J. Xiong, Y. J. Tian, N. Li, K. S. Jiang, Scaling of directed dynamical small-world networks with random responses, Phys. Rev. Lett. 92 (2004) 218702.
[26] L. K. Gallos, R. Cohen, P. Argyrakis, A. Bunde, S. Havlin, Stability and topology of scale-free networks under attack and defense strategies, Phys. Rev. Lett. 94 (2005) 188701.
[27] M. E. J. Newman, A measure of betweenness centrality based on random walks, Social Networks 27 (2005) 39.
[28] M. Tumminello, T. Aste, T. Di Matteo, R. N. Mantegna, A tool for filtering information in complex systems, Proc. Natl. Acad. Sci. USA 102 (2005) 10421.
[29] L. da F. Costa, O. N. Oliveira Jr., G. Travieso, F. A. Rodrigues, P. R. V. Boas, L. Antiqueira, M. P. Viana, L. E. C. da Rocha, Analyzing and modeling real-world phenomena with complex networks: A survey of applications.arXiv:0711.3199.
[30] R. N. Mantegna, Hierarchical structure in financial markets, Eur. Phys. J. B 11 (1999) 193.
[31] G. Bonanno, G. Caldarelli, F. Lillo, R. N. Mantegna, Topology of correlation-based minimal spanning trees in real and model markets, Phys. Rev. E 68 (2003) 046130.
[32] J.-P. Onnela, A. Chakraborti, K. Kaski, J. Kertész, , A. Kanto, Asset trees and asset graphs in financial markets, Physica Scripta T106 (2003) 48.
[33] J.-P. Onnela, K. Kaski, J. Kertész, Clustering and information in correlation based financial networks, Eur. Phys. J. B 38 (2004) 353.
[34] R. K. Pan, S. Sinha, Collective behavior of stock price movements in an emerging market, Phys. Rev. E 76 (2007) 46116.
[35] D. Garlaschelli, S. Battiston, M. Castri, V. D. P. Servedio, G. Caldarelli, The scale-free topology of market investments, Physica A 350 (2005) 491.
[36] S. Battiston, J. F. Rodrigues, H. Zeytinoglu, The network of inter-regional direct investment stocks across europe, Adv. Complex Syst. 10 (2007) 29.
[37] M. Franke, B. Hoser, J. Schröder, On the analysis of irregular stock market trading behavior, GfKl (2007) 355.
[38] S. C. Wang, J. J. Tseng, C. C. Tai, K. H. Lai, W. S. Wu, S. H. Chen, S. P. Li, Network topology of an experimental futures exchange, Eur. Phys. J. B 62 (2008) 105.
[39] A. Barrat, M. Barthélemy, A. Vespignani, Weighted evolving networks: coupling topology and weights dynamics, Phys. Rev. Lett. 92 (2004) 228701.
[40] E. Ravasz, A.-L. Barabási, Hierarchical organization in complex networks, Phys. Rev. E 67 (2003) 026112.
[41] L. C. Freeman, A set of measures of centrality based on betweenness, Sociometry 40 (1977) 35.
[42] S. N. Dorogovtsev, J. F. F. Mendes, Effect of the accelerating growth of communications networks on their structure, Phys. Rev. E 63 (2001) 025101.
[43] J. Leskovec, J. Kleinberg, C. Faloutsos, Graph evolution: Densification and shrinking diameters, ACM Trans. Knowl. Discov. Data 1 (2007) 2.