Capturing Financial Volatility Through Simple Network Measures

Pedro C. Souto[1,2,3], Andreia Sofia Teixeira[1,2,4(✉)], Alexandre P. Francisco[1], and Francisco C. Santos[1,2]

[1] INESC-ID and Instituto Superior Técnico, Universidade de Lisboa, Lisbon, Portugal
{pedro.souto,sofia.teixeira,aplf,franciscocsantos}@tecnico.ulisboa.pt
[2] ATP-Group, IST-Taguspark, Porto Salvo, Portugal
[3] NOVA School of Business and Economics, Universidade Nova de Lisboa, Lisbon, Portugal
[4] LASIGE, Faculdade de Ciências, Universidade de Lisboa, Lisbon, Portugal

Abstract. Measuring the inner characteristics of financial markets risks have been proven to be key at understanding what promotes financial instability and volatility swings. Advances in complex network analysis have shown the capability to characterize the specificities of financial networks, ranging from credit networks, volatility networks, and supply-chain networks, among other examples. Here, we present a price-correlation network model in which Standard & Poors' members are nodes connected by edges corresponding to price-correlations over time. We use the average degree and the frequency of specific motifs, based on structural balance, to evaluate if it is possible, with these simple measures, to identify financial volatility. Our results suggest the existence of a significant correlation between the Index implied volatility (measured with the VIX Index) and the average degree of the network. Moreover, we identify a close relation between volatility and the number of balanced positive triads. These results are shown to be robust to a wide range of time windows and correlations thresholds, suggesting that market instability can be inferred from simple topological features.

Keywords: Financial complex networks · Financial volatility
Structural balance

1 Introduction

In recent years, it is undeniable how interconnected financial markets are becoming [2,12,19,21,26]. Modern economic agents and their institutions can operate globally in a interdependent and connected market. Proof is the most recent financial crises, in which we observed the growing importance of accounting for systematic risk, where a single financial institution can affect the global market and all its agents [4–10,28]. As a result, financial systems are a natural playground for network science. It is both convenient and insightful to describe the

L. M. Aiello et al. (Eds.): COMPLEX NETWORKS 2018, SCI 813, pp. 534–546, 2019.
https://doi.org/10.1007/978-3-030-05414-4_43

various connections between financial assets and institutions in the form of a graph. In Allen et al. [2], it is detailed the vital role of network connections in the interbank market. Banks are exposed to their peers, both by holding crossed positions (mutual exposure in their balance sheets) as well as sharing similar market portfolio, assets and liabilities (as creditors and depositors) [2,12,19]. Those so-called markets represent market players exchanging cash-flows and goods between them, being responsible for managing one of the most complex multi-agent systems humanity have ever created, permanently connecting every corner of the globe [27,29].

In this context, it remains to a large extent an open question how one can extrapolate from network properties to commonly used measures to detect risk [1,3–10,17,19,28]. At a firm level, as detailed by Onnela et al. [22], it is possible to assess firms' performance, looking at their stock price time series. It is believed that firms' valuation is based on all the available information [11,16]. This concept of "pricing" is understood as the current fair value of all company assets and the present value of future expected income flows from the current asset allocation. In other words, it measures how much the firm is worth. Nonetheless, these companies are not isolated. They are interacting with one another by exchanging cash-flows, products, clients, among others [12,20,22]. Despite the fact that is not straightforward to measure the nature of all this inner relations, stock price variations are the closest to public information it can be used to study this complex system [22,27].

Some prior studies tried to capture financial stability (or risk), looking to the inner characteristics of the network. Battiston and Caldarelli et al. seminal work gave us the insights of how it is possible to detect systemic risk looking at interbank network, in the context of asset-liabilities relations [4–10,28]. They studied the impact of several types of networks (from random to scale-free) and sources of information (the degree at which nodes can accurately measure the risks of his peers), to access the likelihood of a bankruptcy cascade effect in a distress financial period [6–9,28]. Moreover, these authors proposed some network measures, like the debt rank [4,10], to better capture the importance of each single node in a financial network in a crisis context. Boss et al. [12] presented some encouraging results in the Austrian Interbank Market proving that network metrics can explain structural changes in the environment as in many other scientific fields. In Onnela et al. [22,23], important steps were made when it was introduced the time dependence, calling for a detailed study of the co-movement between network characteristics and an external validation. However, by having the opportunity of using US financial data, namely the companies that are part of the most relevant Stock Market Index (S&P 500), it is possible to check if the network metrics mimic the volatility and financial systematic risk, by comparison to the "Fear Index", the so-called "VIX Index". This index measures the implied market risk and accounts for the short-term implied-volatility derived from all the S&P stocks and its options and structured products [15]. Despite the difficulty at fully characterize VIX Index pricing (due to the complexity of its calculations and the amount of different products the computation uses), it measures the instability of the S&P Market and it is widely used by the industry. Thus, if by using simple network measures it is possible to capture the same daily movements, we may argue that complex science can give a quicker and easy to understand answer about financial instability.

In this work, we aim to study the financial systematic risk through complex networks (simple) measures, resorting to both weighted and signed networks representations. Using as framework real US data, we build a network from price correlations among companies and measure the likelihood of capturing volatility shifts looking at the time variation in: *(i)* the network (weighted) average degree (or *strength*) and in *(ii)* particular three-node motifs (triads). On one hand, the average degree is the simplest measure capturing the level of interdependence among companies, and pictures a global and macro view of how price variations affect network connectedness. On the other hand, because structural balance theory [13,18] has already been used to study financial networks [14], we are interested in the identification of specific motifs to perceive network shifts and their impact on network volatility. This way we are able to analyze the volatility of a network with a global network measure and with specific local patterns. In both cases, we find a statistical significance when it comes to explain and replicate what happen to the VIX Index in a given period of time.

2 Methods: Using Node Degree and Motifs to Analyze Financial Networks

2.1 Financial Markets Structure

Let us now build our financial networks based on correlation matrices, as introduced before. We consider a price time series from 1992–2018, whose source is Bloomberg database[1], for a security set of 500 companies. Let us define $P_i(\tau)$ as the closing price of stock i at time τ and the daily logarithmic return of stock i as:

$$r_i(\tau) = ln[P_i(\tau)] - ln[P_i(\tau - 1)] \tag{1}$$

Then, by defining a time grouping window of bulk size T, one obtains a cube of correlations, where $\rho(x, y)_{[t,t+T]}$ is the returns correlation between firm x and firm y between t and $t + T$ (giving n data points), defined as:

$$\rho = \frac{\sum_{i=1}^{n}(x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2(y_i - \overline{y})^2}} \tag{2}$$

Having built the correlation cube, two independent studies were made. First, a weighted time-varying network was built, whose nodes were the constituents of the S&P 500 Index and their links were the correlations throughout time. By this it is meant that whenever two firms have a correlations different from zero (and ranging between -1 and 1), they will share an edge whose value is their

[1] Which is one of the most accurate database when we are dealing with financial data. The dataset has, on average, 252 days per year during 26 years.

correlation. As an example, if firm A has a price correlation in a given set of days (lets say 0.75) with firm B, the network will display two independent nodes (A and B) whose edge between them has a linkage (during this time-frame) of 0.75. From this stage, in order to capture network connectedness, we compute the time-dependent network average degree [24] as the average of the sum of the weights attached to each node (see below).

In the second study we build a signed network, in which every pair of nodes that share a correlation above a given threshold X will have a positive sign, whereas a negative sign is defined whenever the correlation value is below $-X$. The links with values between $-X$ and X were not considered to avoid adding noise or spurious edge relation for very low correlations.

Relation Between VIX and Average Degree. Given its simplicity, we chose the network average degree to obtain a global view of the network, being easy to acknowledge the strength of each node with its peers. Since that, in this case, we are dealing with a weighted network, for simplicity we extend the notion of degree of a node, to its weighted degree or strength, i.e., the sum of the relative weights of all its links [24]. Using the correlation matrix as the network adjacency matrix A (the network is relatively close to a fully-connected graph), summing row-wise (neglecting self-correlations) gives us the (weighted) degree $z_{i,t+T}$ of a node i, in the time frame $t+T$, as displayed in Eq. 2.

$$z_{i,t+T} = \frac{\sum_{j=1}^{N} A(i,j)_{[t,t+T]} - 1}{N} \tag{3}$$

By averaging over all nodes degree, we obtain the network average degree, $< z >$, for a given time window, $[t+T]$. The degree of a node can be seen as a measure of the impact of a single node in the network. Nodes with higher degree can easily spread a good or a bad economic movement, being potentially responsible for generating instability in the network. Moreover, higher values of the average degree will mean that companies are increasingly connected and interdependent, while lower values reflect independent firms price movements. Here we try to correlate the time-evolution of the network average degree with the financial volatility, which can be independently assessed through the VIX index.

Relation Between VIX, Motifs and Structural Balance. Signed networks have been used in the past to study financial portfolios (see, e.g., [14]). One of the main observations is that usually a portfolio presents high values of structural balance, being rare to have unbalanced relations. This concept of balance and unbalanced networks come from the structural balance theory [13,18]. A given network is considered to be balanced if all the cycles are balanced, otherwise it is considered unbalanced. A cycle is balanced if the product of the signs of its edges is positive (see Fig. 1). One can evaluate the "degree of balance" of a signed network as the ratio of the number of positive cycles to the total number of cycles. Let G be a signed graph, $c(G)$ be the number of cycles of G, $c_+(G)$

be the number of positive cycles of G, and $b(G)$ be the degree of balance of G. Then:

$$b(G) = \frac{c_+(G)}{c(G)} \tag{4}$$

In this work we use this measure to evaluate structural balance with cycles of size 3, following the same approach as in [14].

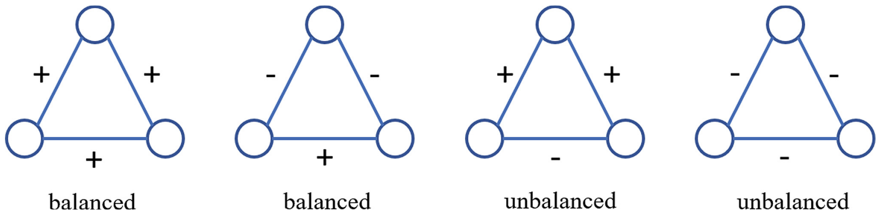

Fig. 1. Triads considered balanced and unbalanced by the structural balance theory of Harary [13,14,18].

Let $G = (V, E)$ be an undirected and signed network, with $n = |V|$ vertices (individuals) and $m = |E|$ edges (ties), and with edges labels $w = \{-1, 1\}$ between two assets (a, b): $w(a, b) = w(b, a) = 1$, if it is a positive correlation, $w(a, b) = w(b, a) = -1$ if it is a negative correlation. To calculate the degree of balance of a network we first use gtrieScanner [25][2] to obtain all triads of the network. Then, for each triad, we calculate the product of its signs and in the end we obtain the degree of balance.

As was already observed by Harary [14] financial networks tend to have high values of structural balance. We are able to observe the same in our datasets, see Fig. 6. Given this, and because when trying to relate to the VIX we want to extract the most discriminatory network characteristics effect, we removed the unbalanced triads, focusing only on those that are balanced. Additionally, since in our edge definition it was chosen firms' prices correlations we could not differentiate triads whose components were trending up versus those that were jointly falling apart, we added into each node a positive or negative sign respectively to their performance in the time horizon in study, looking for the frequency of specific motifs in the form of Fig. 2.

Therefore, as we calculate the product of the signs of each triad, we also gather the frequency of each different motif. The goal is to analyze if some specific motif can relate to VIX, always maintaining the notion of structural balance in the signs of the edges and using the signs of the nodes as supplementary information. Within such context, it is now possible to split those balanced triads with a positive impact on the network from those whose performance was poorly, relative to its peers.

[2] http://www.dcc.fc.up.pt/gtries/.

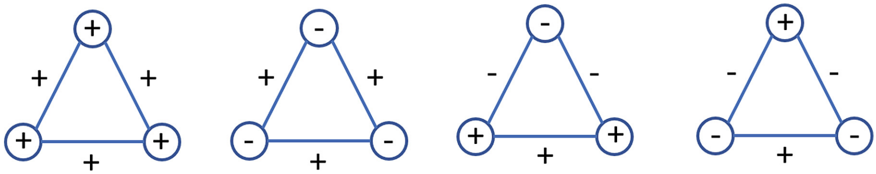

Fig. 2. Balanced triads with signs on the nodes. Those signs correspond to the performance of the firms represented by the nodes. A positive sign (+) is inputed whenever for the given time-frame node value has gone up, whereas a negative sign (−) is given when a given node lost value for the same period.

3 Results and Discussion

To answer our baseline question, which is the study of the interplay between network metrics and degree of risk or volatility, we considered the data from the S&P constituents to input in the network previously explained, as well as the VIX Index, as our exogenous and independent variable.

First, we performed one set of 1000 runs to acknowledge the sensitivity of our variables in the predictability of the average degree (summary of the results can be found in Table 1). Those variables – size of the bulk, T and the correlation cut-off threshold – are relevant to perceive if this macro view of the network can capture short or long term trends in volatility as well as if nodes with lower correlation (being responsible for lower impacts in the network) add value in the model predictability. As it is possible to picture from Table 1, the degree of a node matters at mimic financial instability. Only 8% of the tested variables were not able to accomplish at least 50% of replication, being 59.29% of the simulations statistically significant, show as proof that the network average degree was correct more time stamps than wrong (rejecting, with 95% confidence interval, the hypothesis that the measurements were different from a toss of a coin) (Fig. 4).

Moreover, it is relevant to add that even the lowest tier ranked nodes are important to increase model replication power. This can be inferred from the replication levels in Table 1 regarding the correlation cut-off threshold: as the model gets pickier at choosing the strongest relations between nodes, the model loses its capability of following the volatility index trend.

Also, Fig. 3 enlightens a very important remark: as the volatility index gets higher, network average degree tends to spike. When the fear in financial markets grows, firms specific price variations tend to be forgotten and prices move all in a similar manner. Thus, we move towards a highly connected financial structure (we can argue that the networks shrink) when instability and volatility are present, and get less connected and "relaxed" in the presence of a low systemic risk.

In our second analysis, we measure the correlation between the fraction of different motifs/triads and the volatility index VIX throughout time. We see that these time-evolving networks portray high levels of balance (Fig. 6), as has

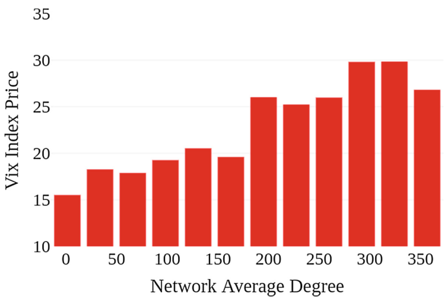

Fig. 3. VIX avg. price distribution over avg. network degree (with 11 Days and 0 correlation cut-off threshold, we got a replication power of 61.82%).

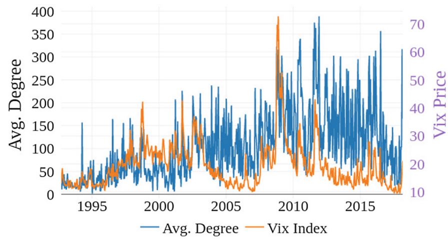

Fig. 4. VIX Index Prices and Average Network Degree Time Series (1992–2018).

Table 1. Sensitivity analysis: Z-Scores from statistical tests (green values are statistical significant with 95% confidence).

	Statistical significance (Z-Score)					Accuracy (Avg. Degree Vs. Vix Index)				
	Correlation cut-off threshold									
Number of days	0	0.2	0.4	0.6	0.8	0	0.2	0.4	0.6	0.8
5	0.9597	0.9597	0.9048	0.7402	1.2342	51.31%	51.31%	51.24%	51.01%	51.69%
6	2.8635	2.8635	2.9850	2.6208	2.0157	54.28%	54.28%	54.46%	53.92%	53.02%
7	0.3567	0.4865	0.5514	0.0973	0.4865	50.58%	50.79%	50.89%	50.16%	50.79%
8	3.7057	3.5637	3.1391	2.7868	1.5973	56.37%	56.13%	55.41%	54.81%	52.76%
9	3.5598	3.4844	3.0336	3.1836	2.4362	56.49%	56.35%	55.54%	55.81%	54.46%
10	4.4040	4.4040	4.7288	4.7288	3.6802	58.41%	58.41%	59.01%	59.01%	57.06%
11	5.9864	6.0752	5.5454	5.1095	4.4214	61.82%	61.98%	60.99%	60.17%	58.84%
12	4.0945	4.1834	3.7404	3.6523	3.2140	58.56%	58.74%	57.84%	57.66%	56.76%
13	1.7735	1.7735	1.8628	1.3283	0.6190	53.91%	53.91%	54.10%	52.93%	51.37%
14	3.2449	3.2449	3.6256	3.3398	2.6792	57.35%	57.35%	58.19%	57.56%	56.09%
15	2.3888	2.3888	2.2920	2.2920	1.5229	55.63%	55.63%	55.41%	55.41%	53.60%
17	2.8590	2.9634	2.9634	2.8590	1.8265	57.14%	57.40%	57.40%	57.14%	54.59%
19	4.7978	4.7978	4.9158	4.9158	4.2160	62.39%	62.39%	62.68%	62.68%	60.97%
21	3.1388	3.1388	2.6708	3.1388	2.0933	58.68%	58.68%	57.41%	58.68%	55.84%
23	3.7305	3.6045	3.7305	3.7305	3.4792	60.69%	60.34%	60.69%	60.69%	60.00%
25	1.5373	1.5373	1.6616	1.6616	1.1661	54.68%	54.68%	55.06%	55.06%	53.56%
29	2.8196	2.8196	2.6808	3.0991	3.2401	59.13%	59.13%	58.70%	60.00%	60.43%
31	1.9975	1.9975	1.3015	0.7514	0.4777	56.74%	56.74%	54.42%	52.56%	51.63%
33	1.5581	1.5581	1.2722	1.1298	0.2815	55.45%	55.45%	54.46%	53.96%	50.99%
35	3.0419	2.8866	2.7324	3.0419	2.4270	60.73%	60.21%	59.69%	60.73%	58.64%
37	1.6535	1.6535	1.8066	2.5841	2.4267	56.11%	56.11%	56.67%	59.44%	58.89%
39	0.3826	0.2295	-0.0765	-0.0765	-0.2294	51.46%	50.88%	49.71%	49.71%	49.12%
41	1.0221	1.1807	1.1807	1.0221	0.2350	53.99%	54.60%	54.60%	53.99%	50.92%
43	2.3748	2.3748	2.2055	2.3748	1.8703	59.35%	59.35%	58.71%	59.35%	57.42%
45	0.9903	0.8243	1.1568	1.1568	0.8243	54.05%	53.38%	54.73%	54.73%	53.38%
50	2.2938	2.4785	2.4785	2.2938	1.2172	59.70%	60.45%	60.45%	59.70%	55.22%

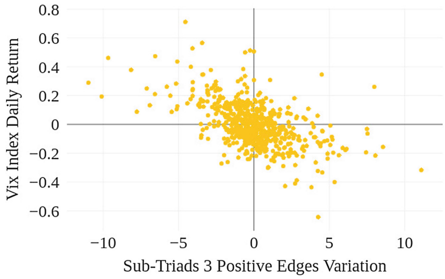

Fig. 5. Correlation VIX Index variation and balanced sub-Triad with 3 positive edges variation (with 11 Days and 0 correlation Cut-off Threshold, we got a replication power of 67.85%).

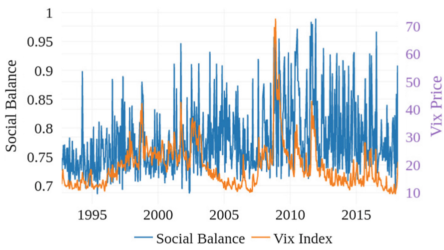

Fig. 6. VIX Index Price and Social Balance Time Series (1992–2018).

been previously found [14]. Given the observed levels of social balance, balanced triads tend to overweight the unbalanced ones, being the latter even in lower number in the presence of large volatility swings, meaning that whenever Market instability is at its highest, financial networks tend to be mostly connected and balanced. This outcome leads us to perform, within the same reasoning already developed and explained with the degree of network, a set of 50 runs to test if the likelihood of balance and the different motifs replicate the uncertainty of the market. From Table 2, we conclude that only the correlation between triads with three positive edges and the VIX index is statistically significant, and portray an Index replication consistently higher than 50%, (as displayed in Table 3).

Due to fact that only triads of fully positive edges seem to matter when mimicking the "fear Index", we split those triads whose nodes were positive in a given time-frame, from the ones that were negative in the same period of time. In Fig. 5 we show that looking to the node performance (where performance is the price variation for the time window considered), we may gain gain some additional explanatory power. In Table 2 we show the p-values from the sensitivity analysis run within the present context. As a matter of fact, we obtain significantly higher results using nodes performance for the considered period. Without having a correlation cut-off threshold and a grouping size-window of 5 trading days, triads with positive edges and positive performance of their nodes, VIX index is replicated at a rate of 70%.

The present results seem to be in line with our empirical reasoning that whenever there are times where all firms are moving together, is not because of their fundamental or intrinsic value, but mostly because of something exogenous in the financial world that spreads out into the entire network, despite its positive or negative impact. Our results suggest that when the VIX Index tend to spike, the number of triads with three positive edges and nodes tend to reduce, increasing otherwise, as shown in Fig. 5.

Table 2. Sensitivity analysis: Z-Scores from statistical tests (green values are statistical significant with 95% confidence)

		Statistical significance (Z-Scores)								
Number of days	Correlation cut-off threshold	Unbalanced	Balanced	Unbalanced	Balanced	Balanced				
		Triads (0 Pos Edges)	Triads (1 Pos Edges)	Triads (2 Pos Edges)	Triads (3 Pos Edges)	Triads (1 Pos Edges) 1/3 Pos Nodes	Triads (1 Pos Edge) 2/3 Pos Nodes	Triads (3 Pos Edges) 0 Pos Nodes	Triads (3 Pos Edges) 3 Pos Nodes	Social balance
5	0.00	−1.179	−0.795	−0.247	1.015	−12.226	10.840	−15.727	16.167	0.685
5	0.40	−1.124	−1.069	−1.124	1.344	−10.279	9.611	−15.869	16.095	−0.302
5	0.80	−469.342	−0.685	−331.124	0.521	−8.945	7.007	−15.657	15.107	−53.078
10	0.00	−3.122	−2.885	−3.919	4.729	−9.028	5.138	−10.254	9.787	3.361
10	0.40	−3.122	−3.679	−1.709	3.521	−8.301	3.441	−9.966	9.787	1.943
10	0.80	−234.229	−3.838	−147.130	3.123	−5.964	1.164	−9.776	9.224	−28.268
15	0.00	−2.098	−3.561	0.000	2.486	−4.664	3.663	−5.595	5.602	0.855
15	0.40	−3.363	−2.873	0.000	2.777	−3.958	2.777	−5.490	5.497	−0.095
15	0.80	−126.727	−1.714	−76.267	1.236	−2.484	2.292	−4.972	4.567	−21.328
30	0.00	0.403	−0.672	0.000	0.807	−4.945	1.348	−5.262	5.442	−0.134
30	0.40	−4.789	−0.403	−0.806	0.403	−4.789	0.672	−5.103	5.442	0.134
30	0.80	−62.640	0.000	−47.842	−0.403	−2.308	1.485	−3.587	3.742	−12.086

Table 3. Summary of runs accuracies: number of times the variation in the VIX Index was correctly replicated by the tested type of triads (in percentage points)

		Accuracy Versus Vix Index								
Number of days	Correlation cut-off threshold	Unbalanced	Balanced	Unbalanced	Balanced	Balanced				
		Triads (0 Pos Edges)	Triads (1 Pos Edges)	Triads (2 Pos Edges)	Triads (3 Pos Edges)	Triads (1 Pos Edges) 1/3 Pos Nodes	Triads (1 Pos Edge) 2/3 Pos Nodes	Triads (3 Pos Edges) 0 Pos Nodes	Triads (3 Pos Edges) 3 Pos Nodes	Social Balance
5	0.00	48.38%	48.91%	49.66%	51.39%	34.11%	64.24%	30.20%	70.25%	50.94%
5	0.40	48.46%	48.53%	48.46%	51.84%	36.44%	62.73%	30.05%	70.17%	49.59%
5	0.80	0.15%	49.06%	0.30%	50.71%	38.09%	59.43%	30.28%	69.12%	8.79%
10	0.00	43.99%	44.44%	42.49%	59.01%	33.48%	59.76%	31.53%	67.72%	56.46%
10	0.40	43.99%	42.94%	46.70%	56.76%	34.68%	56.61%	31.98%	67.72%	53.75%
10	0.80	0.30%	42.64%	0.75%	56.01%	38.74%	52.25%	32.28%	66.82%	13.06%
15	0.00	45.05%	41.67%	50.00%	55.86%	39.19%	58.56%	37.16%	62.84%	52.03%
15	0.40	42.12%	43.24%	50.00%	56.53%	40.77%	56.53%	37.39%	62.61%	49.77%
15	0.80	0.68%	45.95%	1.80%	52.93%	44.14%	55.41%	38.51%	60.59%	14.41%
30	0.00	51.35%	47.75%	50.00%	52.70%	34.23%	54.50%	33.33%	67.12%	49.55%
30	0.40	34.68%	48.65%	47.30%	51.35%	34.68%	52.25%	33.78%	67.12%	50.45%
30	0.80	1.35%	50.00%	2.25%	48.65%	42.34%	54.95%	38.29%	62.16%	18.47%

4 Conclusions and Future Work

In the present work, we propose two new approaches to strengthen the connection between network science and financial markets. We show that there is a close relationship between financial network characteristics and its performance. Without taking into account VIX complex pricing of volatility, network inner characteristics seem to emerge in the same fashion and magnitude. At a macro and global level, simple measures, as the average degree (or average strength), can help to replicate the short-term implied-volatility of the financial market network. As the network average degree rises, the VIX Index tends to produce a similar movement showing that in times of crisis firms get more connected and investors tend to bear their market valuation on the global macro data, leaving apart the firm intrinsic value. Reversely, when instability is lower, nodes tend to move more independently, meaning that nodes' strength is weaker, leading a less connected network. On the other hand, despite its greater complexity and time constraints, motifs are also a viable source of mimic power, giving the combination of balanced triads with knowing the performance of its constituents an out-performance considerably higher relative to the other attempts. Preliminary results indicate that the combination of multiple network features may further increase our understanding and predictive power. Work along these lines is in progress.

Further studies must be pursued for a better understanding of the financial world. In our view, there is the need to study whose firms are more often in the motifs that accurately replicate the VIX index and also to acknowledge the impact and stability of such ties throughout time. Each of these sub-graphs, define a particular kind of interactions between vertices, reflecting a meso-scale pattern that will later lead to global financial observables. In particular, it is relevant to identify or engineer sub-graphs that are more resilient and stable than the rest of the financial network, creating a portfolio with a lower likelihood of suffering in times of crisis or crashes. As future work, it seems relevant to understand if those measures are still reliable at anticipating and predicting future swings in market instability, and what are the main contributors of financial volatility and their relation with size, sector, cumulative performance, among others. Secondly, correlation networks may be spurious, i.e. induced by other variables not included in the analysis. Therefore, a deeper study is required to partial out the effect of network structure. Furthermore, producing similar studies in other markets, regions of the globe or joining them together, might be enlightening at detailing the origins of global movements or those that, despite its characteristics, easily spread throughout the financial market network.

Acknowledgments. This work was partly supported by national funds through Universidade de Lisboa and FCT –Fundação para a Ciência e Tecnologia, under projects SFRH/BD/129072/2017, PTDC/EEI-SII/5081/2014, PTDC/MAT/STA/3358/2014, and UID/CEC/50021/2013. We are grateful to Bruno Gonçalves for comments.

References

1. Afonso, G., Kovner, A., Schoar, A.: Trading partners in the interbank lending market (2013)
2. Allen, F., Babus, A.: Networks in finance. The Network Challenge, pp. 367–382 (2009)
3. Allen, F., Babus, A., Carletti, E.: Asset commonality, debt maturity and systemic risk. J. Financ. Econ. **104**(3), 519–534 (2012)
4. Bardoscia, M., Battiston, S., Caccioli, F., Caldarelli, G.: Debtrank: a microscopic foundation for shock propagation. PloS one **10**(6), e0130406 (2015)
5. Bardoscia, M., Battiston, S., Caccioli, F., Caldarelli, G.: Pathways towards instability in financial networks. Nat. Commun. **8**, 14416 (2017)
6. Bardoscia, M., Caccioli, F., Perotti, J.I., Vivaldo, G., Caldarelli, G.: Distress propagation in complex networks: the case of non-linear debtrank. PloS one **11**(10), e0163825 (2016)
7. Barucca, P., Bardoscia, M., Caccioli, F., D'Errico, M., Visentin, G., Battiston, S., Caldarelli, G.: Network valuation in financial systems (2016)
8. Battiston, S., Caldarelli, G., DErrico, M., Gurciullo, S.: Leveraging the network: a stress-test framework based on debtrank. Stat. Risk Model. **33**(3–4), 117–138 (2016)
9. Battiston, S., Caldarelli, G., May, R.M., Roukny, T., Stiglitz, J.E.: The price of complexity in financial networks. Proc. Natl. Acad. Sci. **113**(36), 10031–10036 (2016)
10. Battiston, S., Puliga, M., Kaushik, R., Tasca, P., Caldarelli, G.: Debtrank: Too central to fail? financial networks, the fed and systemic risk. Sci. Rep. **2**, 541 (2012)
11. Bodie, Z., Kane, A., Marcus, A.J.: Investment and Portfolio Management. McGraw-Hill Irwin (2011)
12. Boss, M., Elsinger, H., Summer, M., Thurner 4, S.: Network topology of the interbank market. Quant. Financ. **4**(6), 677–684 (2004)
13. Cartwright, D., Harary, F.: Structural balance: a generalization of Heider's theory (1956)
14. Davis, J.A.: Clustering and structural balance in graphs. Hum. Relat. **20**(2), 181–187 (1967)
15. Exchange, C.B.O.: The cboe volatility index–vix. White Paper (2009)
16. Fama, E.F.: Efficient capital markets: Ii. J. Financ. **46**(5), 1575–1617 (1991)
17. Griffin, K.: Testimony to the house committee on oversight and government reform. Prepared for the US House of Representatives, Committee on Oversight and Government Reform, Hearing on Hedge Funds, Washington, DC, 13 Nov 2008
18. Harary, F.: On the notion of balance of a signed graph. Mich. Math. J. **2**(2), 143–146 (1953)
19. Leonidov, A., Rumyantsev, E.: Russian interbank networks: main characteristics and stability with respect to contagion (2012). arXiv:1210.3814
20. Lo, A.: Adaptive Markets: Financial Evolution at the Speed of Thought. Princeton University Press, Princeton (2017)
21. Lo, A.W.: The adaptive markets hypothesis. J. Portf. Manag. **30**(5), 15–29 (2004)
22. Onnela, J.P., Kaski, K., Kertész, J.: Clustering and information in correlation based financial networks. Eur. Phys. J. B **38**(2), 353–362 (2004)
23. Onnela, J.P., Saramäki, J., Kertész, J., Kaski, K.: Intensity and coherence of motifs in weighted complex networks. Phys. Rev. E **71**(6), 065,103 (2005)

24. Pastor-Satorras, R., Vespignani, A.: The architecture of complex weighted network. Proc. Natl. Acad. Sci. **101**, 3747–3752 (2004)
25. Ribeiro, P., Silva, F.: Querying subgraph sets with g-tries. In: Proceedings of the 2nd ACM SIGMOD Workshop on Databases and Social Networks, DBSocial 2012, pp. 25–30. ACM, New York (2012). https://doi.org/10.1145/2304536.2304541
26. e Santos, E.B., Cont, R., et al.: The brazilian interbank network structure and systemic risk. Technical Report (2010)
27. Souto, P.: Marketopolis: a market simulation based on investors decisions. Master's thesis (2016)
28. Visentin, G., Battiston, S., D'Errico, M.: Rethinking financial contagion (2016)
29. Wyman, O.: Managing complexity: the state of the financial services industry 2015 (2015)