Broker Network Connectivity and the Cross-Section of Expected Stock Returns

Tinic, Murat and Sensoy, Ahmet and Demir, Muge and Nguyen, Duc Khuong

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Murat Tiniç* Ahmet Sensoy† Muge Demir‡ Duc Khuong Nguyen§¶

Abstract

We examine the relationship between broker network connectivity and stock returns in an order-driven market. Considering all stocks traded in Borsa Istanbul between January 2006 and November 2015, we estimate the monthly density, reciprocity and average weighted clustering coefficient as proxies for the broker network connectivity. Our firm-level cross-sectional regressions indicate a negative and significant predictive relationship between connectivity and one-month ahead stock returns. Our analyses also show that stocks in the lowest connectivity quintile earn 1.0% - 1.6% monthly return premiums. The connectivity premium is stronger in terms of both economic and statistical significance for small size stocks.

Keywords— Stock market; trading networks; broker networks, network connectivity, pricing factors

JEL **-** *G11; G12; G14; G24*

*Kadir Has University, Faculty of Management, Istanbul, Turkey. Email: murat.tinic@khas.edu.tr

†Bilkent University, Faculty of Business Administration, Ankara, Turkey. Email:ahmet.sensoy@bilkent.edu.tr

‡Banking Regulation and Supervision Agency, Istanbul, Turkey. Email: mdiler@bddk.org.tr

§Corresponding author - IPAG Business School, 184 Boulevard Saint-Germain, 75006 Paris, France. Email: duc.nguyen@ipag.fr - Tel: +33 1 5363 3600 - Fax: +33 1 4544 4046.

¶International School, Vietnam National University, Hanoi, Vietnam

1 Introduction

In asset pricing theory, a stock's expected return is determined by its exposure to a number of common risk factors (Sharpe, 1964; Lintner, 1965a,b; Ross, 1976). Empirically, fundamental factors such as firm size, book-to-market ratio and price momentum are found to drive individual stock returns (Fama and French, 1993; Carhart, 1997). However, the effects of investor connectedness through trading relationship on asset prices remain to be unclear. From a theoretical point of view, Ozsoylev and Walden (2011) show that connectivity can be one of the factors that determine asset prices in an information network composed of traders because it plays a role in the flow of information through financial markets. Moreover, an increase in an agent's connectivity increases its profit when the investor network's overall connectedness is held constant, whereas an increase in the overall network connectedness is found to lower agent's profit as information disseminates through time in the network under the constancy of holding the agent's connectivity.[1] These theoretical findings imply that higher connectivity of the overall trading network could yield lower profits as more information is compounded into prices, which eventually diminishes everyone's informational rent. At the empirical level, higher connectivity of an agent has been found to indicate a better informed trader on average and thus higher profits for that agent (Ozsoylev et al., 2014; Cohen-Cole et al., 2014).

In this paper, we investigate the relationship between broker network connectivity and stock returns in an order-driven market by using a specific dataset from Borsa Istanbul where both counterparties are identified at the brokerage house level for each trade. We first construct a network for each stock where brokerage houses trading that particular stock are represented by the nodes of the network and the trade flows among them are represented by the directed links between these nodes. Each link is associated with a weight represented by the normalized cash flow of the trade, while the connectivity of each network is captured by network density (proxy for global connectivity), weighted clustering coefficient (proxy for local connectivity), and network reciprocity measures. We then examine whether broker network connectivity is a factor that influences stock prices through analyzing the relations between the constructed

[1] In a related study, Billio et al. (2017) show that network connectivity represents a factor for systematic exposure to common pricing factors, and residuals of traditional linear factor models exhibit serial-correlation and heteroskedasticity whenever network exposures are omitted from the model.

connectivity measures and future stock returns in the cross-section.[2]

To date, modelling the complex relationships across financial markets or investors as a network has gained considerable attention in finance and economics literature. Network theories have been recently applied to the analysis of contagion effect, systemic risk, and interbank risk exposures (e.g., Allen and Gale, 2000; Battiston et al., 2012; Craig and von Peter, 2014; Drehmann and Tarashev, 2013; Minoiu and Reyes, 2013; Nier et al., 2007; Diem et al., 2020; Linardi et al., 2020; Eboli, 2019; Grilli et al., 2020) as well as asset linkages across industries and sectors on the grounds of contagion risk (e.g., Ahern, 2013; Leitner, 2005; Diebold and Yilmaz, 2008; Billio et al., 2012).[3] However, due to limited data availability, only a few number of studies have been able to empirically examine the relationship between investors in the market through their trading activities or professional/personal ties, and how this relationship is reflected on their trading success. With regard to professional/personal ties, Larcker et al. (2013) show that firms with central boards of directors earn superior risk-adjusted stock returns and that a long-short position in the most-least central firms earns average annual returns of 4.68%. Ahern (2017) provides a comprehensive analysis of the social relationships which underlie illegal insider trading networks and finds that inside traders earn prodigious returns of 35% over 21 days, with more central inside traders earning greater returns. Rossi et al. (2018) show a positive relation between network centrality and risk-adjusted performance in a delegated investment management setting. Specifically, more connected managers take more portfolio risk and receive higher investor flows, consistent with these managers improving their ability to exploit investment opportunities through their network connections. More recently, Egginton and McCumber (2019) examine the relationship between stock market liquidity and the network centrality of firm executives, and show that firms whose executive officers are more central in the network of executives have higher stock liquidity.

Regarding empirical investor networks constructed via investors' trading activities, the literature is scarcer and contains only a few studies. For example, Pareek (2012) constructs an information network of

[2]The importance of brokerage houses in information diffusion is emphasized by Maggio et al. (2019) who show that brokers indeed play a key role in shaping information diffusion in the stock market.

[3]For review of different applications of network analysis in finance, see Allen and Babus (2009).

US mutual funds where two funds are connected in this network if they both take a large position in the same stock. Using network density as a measure for the speed of information diffusion in this network, the author finds that stocks with a lower network density demonstrate stronger return momentum over medium horizons and also have a delayed response to the market-wide information, consistent with the gradual information diffusion model of Hong and Stein (1999). In a similar network construction framework, Ozsoylev et al. (2014) study the trading behavior of all investors in Borsa Istanbul for the year 2005 and find that central investors earn higher returns and trade earlier than peripheral investors with respect to information events, which is consistent with the theory of information networks. For their part, Cohen-Cole et al. (2014) construct investor networks for the Dow and S&P 500 e-mini futures markets in which the links are established between the counterparties of a trade. They show that high returns are associated with high degrees of centrality irrespective of network complexity. In a recent study, Walden (2019), using account level data for all traders on the Helsinki Stock Exchange between 1998 and 2003, shows that at the investor level, more central agents make higher profits, while at the aggregate level, network topology affects the dynamics of a market's volatility and trading volume.

As far as network analysis of brokerage firms is concerned, there are, to the best of our knowledge, only two available studies, Chuang (2016) and Maggio et al. (2019). More precisely, Chuang (2016) constructs a network to model the connectivity across brokerage firms and examine the effect of information diffusion among investors on stock returns. For the sample of 95 brokerage firms and 1330 stocks traded in Taiwan Stock Exchange during the period of 2004-2011, the author finds that the centrality of brokerage firms has strong explanatory power to stock returns even after controlling for the Fama–French pricing factors and other stock characteristics. Maggio et al. (2019) investigate whether the network of relationships between brokers and investors affects the returns and whether brokers have any role in affecting how information is incorporated into prices. The authors find that although they analyze an exchange where prices are public information (not an over-the-counter market), the network of relationships between brokers and institutional investors still shapes the information diffusion in the stock market and that trades placed through more central brokers generate significantly higher abnormal returns.

The above discussions thus point out that networks serve as an influential conduit for information diffusion which is especially valuable in investment decisions with high uncertainty and information asymmetry. If networks of brokers facilitate information flow, the specific connections between them for a particular stock may reduce information asymmetry, and thereby increase the transparency and reduce the investment risk (Alós-Ferrer and Weidenholzer, 2008; Ozsoylev and Walden, 2011; Ozsoylev et al., 2014). We therefore hypothesize, in our study, that the higher the trade connectivity of brokerage houses for a particular stock, the faster the diffusion of information and the lower the expected return as private information becomes public over time in a faster manner which leads to a reduced investment risk.

Accordingly, we start with a long-short portfolio analysis to see whether a strategy based on network connectivity can provide investors with positive and significant returns. Using single and double sorted portfolios, we show that stocks in the lowest connectivity quintile can earn 1.0% to 1.6% monthly return premiums. In order to strengthen our hypothesis, we further run cross-sectional regressions and factor tests, and reveal evidence of a negative and significant relationship between brokerage firm connectedness and one-month ahead stock returns. In particular, a 1% increase in network connectivity reduces the future returns by 2%. This finding remains intact even when common factors such as market risk, firm size, and book-to-market ratio are controlled for. Moreover, we uncover that the connectivity premium is stronger in terms of both economic and statistical significance for small company stocks.

In sum, our study brings three major contributions to the related literature. First, it extends past studies on the relationship between investor/brokerage firm centrality and the future stock returns by considering, in the same framework, the impact of overall connectivity of these networks on future returns, as theoretically discussed by Ozsoylev and Walden (2011). It is plausible to assume that as information about prices becomes public over time, stock trading through brokers may allow them to extrapolate the information embedded in trade in anticipating the future prices and shaping their trading behaviour in the market. In particular, if the connectivity of broker networks improves information flow for a particular stock, this would decrease the risk involved in investing in this stock due to reduced information asymmetry. A natural question would arise as to whether connectivity obtained through brokerage house trading could affect stock returns. Specifically, are the stocks traded less densely (i.e. stocks with lower connectivity) across brokers able to generate higher returns due to the less information flow and higher opacity in the market? What role does the broker connectivity have in affecting how information is incorporated into the prices? In this paper, we answer these questions by a variety of empirical tests. Second, the results of our empirical analysis can actually provide strategies that are capable of predicting future returns since Borsa Istanbul equity market's trade book with counterparty information (only at the brokerage firm level) can be purchased from data vendors on the same day after the market is closed.[4] This is more advantageous that previous studies using proprietary investor level data because, despite the usefulness in improving our understanding of investor interactions in the market, their results have practically no use by equity traders due to ex-post data availability only. Finally, we combine the asset pricing literature with network analysis by differentiating the global and local connectivity of the agents in the network via alternative connectivity measures. Studies in other fields, such as physics or neuroscience, suggest that local clusters may have quite different topological properties from those at the level of the entire networks (Ravasz et al., 2002; Guimera and Nunes Amaral, 2005; Jie et al., 2014), and this difference can affect the dynamics of various aspects within the networks (Chen and Hero, 2015). Our analysis allows us to examine whether there exists a similar phenomenon or not in the case of empirical investor networks. In particular, we test if expected returns in the cross-section are affected differently with respect to the local vs. global connectivity of brokerage houses.

The rest of this paper is organized as follows. Section 2 describes the data used in the analysis. Section 3 explains how we measure the connectedness of the brokerage house networks. Section 4 states the hypotheses and presents the models used in our empirical analysis. The results of the analysis are reported and discussed in Section 5. Section 6 provides concluding remarks.

2 Data

We obtain the tick-by-tick trade and order quote data for all stocks traded in Borsa Istanbul (BIST) between January 2006 to November 2015 (119 months in total) from the BIST database. Each entry in our quote data set contains information about the date, time, ticker, order ID, order type, quantity

[4] In fact, this data can be obtained even in real time by subscription. See `https://www.borsaistanbul.com/en/sayfa/2727/market-data-products` for details.

and price for all company stocks. In addition, each entry has a flag for intermediary ID that provides information about the brokerage house that sent the order to the exchange. Order type shows whether the order is a buy or a sell order. This enables us to track the order arrival process for each stock with absolute precision. Regarding the trade data, it contains every single trade that took place for all stocks in BIST. Each trade contains information about date, time, ticker, quantity and price. Moreover, each trade entry has the information about the order ID for the orders on the buy- and sell-side. For each side of the trade, we match the intermediaries who sent the order to the exchange through order ID.

Our dataset enables us to form a directed and weighted network of brokerage houses for every stock traded in BIST. In our setup, for a given stock, brokerage houses represent the nodes; a realized trade between the brokerage houses represents the link across these nodes; and the size (in terms of normalized traded value) of the buy and sell activities across the brokerage houses represents the weights. Finally, the direction in this network is the direction of the cash flow (due to trading) from one brokerage house to another, i.e., link is directed from the buyer of the stock to the seller. Eventually, in any calendar month and for each stock in the market, we construct a weighted and directed network as described above. Further details regarding the broker networks are provided in Section 3.

2.1 Variables

We obtain firm-specific price and accounting variables, as well as benchmark index levels (BIST 100) from Bloomberg database. All variables are denominated in US dollars.[5] For each stock, we calculate the following variables at the end of each month.

- Size (SIZE) for a given month is the natural logarithm of the firm's market value, that is, the end-of-month price times the number of shares outstanding.
- Book-to-market ratio (BTM) for a firm is the ratio of the firm's end-of-month total equity value to its market value.
- Beta (BETA) is the market risk of a given stock i in month t, and is obtained from the market

[5] Our results are qualitatively the same when we use all variables in local currency (Turkish lira).

model given below;

$$R_{id} = \alpha_i + \beta_{it} R_{md} + e_{id} \quad d = 1, \ldots, D_t \tag{1}$$

where D_t is the number of trading days in month t. R_{id} and R_{md} are the daily returns on the stock i and the BIST100 index on a given day d, respectively. We estimate equation (1) for each stock using daily returns within each month.

- Illiquidity (ILLIQ) is a measure of the price impact of trades. For each month t, it is estimated as the ratio of the absolute monthly stock return to its traded value (Amihud, 2002) such as

$$ILLIQ_{it} = \frac{1}{D_t} \sum_{d=1}^{D_t} \frac{|R_{id}|}{VOL_{id}} \tag{2}$$

where VOL_{id} is the USD denominated trading volume for stock i on day d.

- Idiosyncratic volatility (IVOL) measures the idiosyncratic risk of a stock obtained by the standard deviation of the daily residuals, e_{id}, as presented in equation (1).That is,

$$IVOL_{it} = \sqrt{var(e_{id})} \tag{3}$$

- Reversal (REV) for each stock in month t is the return on the stock over previous month (Jegadeesh, 1990).

- Momentum (MOM) for each stock i in month t is the cumulative percentage return over the last six months. That is,

$$MOM_{it} = \frac{P_{it-1} - P_{it-7}}{P_{it-7}} \tag{4}$$

where P_{it} is the price of stock i at the end of month t.

- Max factor (MAX) is defined as the maximum daily return within a given month t (Bali et al., 2011); i.e.,

$$MAX_{it} = max(R_{id}), \quad d = 1 \ldots D_t \tag{5}$$

Table 1 provides descriptive statistics on the cross-sectional distributions of firm-specific variables. Cross-sectional mean of the returns, book-to-market ratio and reversal are all negative, indicating the existence of financially distressed firms within the sample during the analysis period. Size and book-to-market ratio exhibit larger deviation relative to other firm characteristics, as the sample includes small as well as big firms. Mean value of the beta is positive as expected, and on the average, a stock contributes to 73% of the systematic risk in the market. In terms of other firm-specific factors (MOM, ILLIQ, IVOL, MAX), they have positive means, with momentum and illiquidity measures having almost 50% variation. Reversal exhibits positive and significant correlations with MAX, idiosyncratic volatility and book-to-market ratio, indicating that average return tends to increase with those factors; whereas return is found to be negatively correlated with beta, momentum, size and reversal. In terms of magnitude, the largest negative correlation is observed between the reversal and beta. There is also high and statistically significant negative correlation between size factor and beta and idiosyncratic volatility. High and significant positive correlation between beta and MAX variable suggests that maximum daily return earned increases as systematic risk tend to increase, which is expected.

INSERT TABLE 1 HERE

3 Measuring Network Connectedness

In a weighted and directed network $G(V, E, w)$ for a particular stock $\tilde{S}$, V denotes the set of nodes (brokerage houses) in the network and $v \in V$ denotes a specific node within that set. Nodes are connected by links (cash flows across brokerage houses due to the trading of $\tilde{S}$) such that $E \subseteq V \times V$ and $(v, v') \in E$ if there is a link extending from node v to node v'. Each link is associated with a weight (normalized cash flows across any two brokerage houses) such that $w : E \rightarrow [0, 1]$. Adjacent nodes of a node v are given by $N_v = N_v^{in} \cup N_v^{out}$ where $N_v^{in} = \{v' \mid w(v', v) > 0\}$ and and $N_v^{out} = \{v' \mid w(v, v') > 0\}$. Existence of a link (v, v') (i.e. trade relationship across any two brokerage houses) is represented by $b_{v,v'} = 1$ if $w(v, v') > 0$ and 0; otherwise.

In each month t and for each stock $\tilde{S}$, we estimate the connectedness of this weighted and directed network $G(V, E, w)$ using three alternative measures, namely, network density (ND), reciprocity (RCP) and weighted clustering coefficient (WCC).

3.1 Network Density

Network density is used to estimate the *'global connectivity'* level of a network in month t for a particular stock traded across the brokerage houses. We compute network density (ND) as the number of directed links observed in the network divided by the total maximum possible number of directed links. It measures the probability of a directed connection between two brokerage houses in the network and shows how close the network is to a complete network. ND takes values between 0 and 1. Formally, it is defined as

$$ND = \frac{|E|}{|V|\times(|V|-1)}$$

where $|\ldots|$ denotes the number of elements in the considered set.

3.2 Network Reciprocity

Reciprocity is a measure of the likelihood of nodes (brokerage houses) in a directed network to be mutually linked in a given sample period. Let A be the adjacency matrix of our directed network G; i.e., $A = [a_{ij}]$ with $a_{ij} = 1$ if there is a link from brokerage house i to brokerage house j, and 0 otherwise. We measure reciprocity of G in the following traditional way,

$$RCP \equiv \frac{\sum_{i\neq j} a_{ij}}{\sum_{i\neq j} a_{ij}a_{ji}}$$

where this measure ranges between 0 and 1.[6]

3.3 Weighted Clustering Coefficient

WCC is used to estimate as the *'local connectivity'* level of a brokerage house for a particular stock and for each month in the sample. WCC tries to answer the following question: Given that a brokerage house

[6] In our analysis, we also used alternative reciprocity measures suggested by Garlaschelli and Loffredo (2004) and Squartini et al. (2013), where these methods take randomness of the mutual links and the weights of the links into account, respectively. Our results mostly remain the same, probably because we work not in time series but in the cross-section of stocks.

has connections to two other brokerage houses, what is the (weighted) probability that these two distinct counterparties also have a trading relationship so that all three form a closed triangle pattern trade flow? In estimating the weighted probability, the measure puts more weight on stronger interactions with higher amount of trade flows. WCC value ranges between 0 and 1. The higher the value of the measure, the higher the probability of the brokerage house to form tightly connected trading counterparties, weighted by the size of the trade flows across the parties.[7]

In estimating WCC, there are three main triangle patterns as shown in Figure 1. Those are 'cycle' (Figure 1-(a) and (b)), 'in' (Figure 1-(c)) and 'middle' (Figure 1-(d)) patterns. We calculate the overall WCC which takes all three types of these flow patterns into account. Since WCC is a node specific measure, we take the average of the WCC values calculated for all nodes in the network to get a network connectivity measure.[8]

INSERT FIGURE 1 HERE

3.3.1 Weighted clustering coefficient estimation

We calculate WCC as the ratio of the number of triangle pattern relationships that the node actually forms to the total possible number of the triangle pattern relationships that the node can form, weighted by the size of the flows on a triangle.[9]

[7]While our network density and reciprocity measures do not take link weight into account, WCC fully utilizes it. In recent network studies (Minoiu and Reyes, 2013; Tabak et al., 2014), considering weighted network indicators are shown to be relatively important as they are capable of providing different aspects of the network topology. Regarding the network of brokerage houses, analyzing the weighted network can be crucial as there are significant changes in the trade flows across the brokerage houses for a particular asset through the time.

[8]This approach has been used by Watts and Strogatz (1998) on various network centrality measures to analyze the network complexity. For similar applications in finance, see Minoiu and Reyes (2013); Minoiu et al. (2015).

[9]The estimation is done via the algorithm developed by Clemente and Grassi (2018). An alternative technique belongs to Fagiolo (2007), however this technique is critisized since it does not properly account for the strength of a node, resulting in a clustering coefficient that is too much sensitive to weights. For robustness, we also perform our analysis using this estimation technique. Results are qualitatively the same and they can be obtained upon request.

$$WCC(v) = \frac{\sum_{v',v'' \in N_v} w(v',v'')}{|N_v| \times (|N_v| - 1)}$$

For example, Figure 2 shows a hypothetical directional weighted network composed of six nodes and eight directional links across the nodes. For a given node v, N_v is defined to be the number of adjacent nodes of v such that $N_v = 4$, and $b(v',v'')$ is defined to be the number of links between neighbours of v, and $w(v',v'')$ is defined to be the weights associated with these nodes. Weights are normalized to 1. Then, WCC is calculated as follows:

$$WCC(v) = \frac{30 * \frac{1}{50} + 10 * \frac{1}{50}}{4 * 3} = \frac{1}{10}$$

INSERT FIGURE 2 HERE

Table 1 reports the cross-sectional descriptive statistics of our connectivity measures whereas Figure 3 provides the cross-sectional averages of these connectivity measures for each month in our sample. The average global connectivity proxied by network density (i.e., the average probability that any two brokerage house in the network of a particular stock is connected) is 19%. The average local connectivity measured by WCC (i.e., the average weighted probability that any two counterparties of a brokerage house trading a particular stock are also counterparties of themselves) is 56%. These numbers reflect the much higher intensity of local trading relationships across the brokerage houses during the analysis period compared to the whole trading connectedness. The average reciprocity measure of the network is found to be 69%, indicating the high probability of any two brokerage house in a directed and weighed network are mutually linked. This means that on the average, more than half of the trading flows are bilateral within the network.

Table 1 shows that network connectivity measures are negatively and significantly correlated with book-to-market ratio and illiquidity, whereas they are positively correlated with the other firm-specific variables. In terms of magnitude, the highest positive correlation is found to be between size factor and connectivity measures. This implies that local connectivity of a brokerage house as well as global connectivity of a network tend to increase with the market value of the company. According to Figure 3, network connectivity is almost stable during the analysis period, with an upward shift during the two years period following the global financial crisis of 2007-8, indicating denser trading flows both in terms of the number and volume of the trading relationships across brokerage houses. Average local connectivity (WCC) is found to be more volatile compared to other measures as indicated with its higher standard deviation. In particular global connectivity (ND) and reciprocity (RCP) have varied between 14% - 26%, and 61% - 75%, respectively, whereas local connectivity (WCC) has varied between 45% and 65% during the sample period. At the local level, the network appears dense, as local network connectivity does not fall below 50% for the whole sample period.

INSERT FIGURE 3 HERE

4 Methodology

4.1 Univariate Portfolio Analysis

To test the relationship between network connectivity and future returns, we first make use of portfolio analysis. Specifically, we sort the stocks in our sample into quintile portfolios based on their connectivity measures at the beginning of each month. This setting enables us to mimic an investor's portfolio who has a long position in the stocks with high network connectivity and a short position of equal size in stocks that have low network connectivity. High speed of information diffusion under high connectivity suggests that this zero-cost portfolio should have a significant and negative return. Let R_{High} and R_{Low} respectively denote the returns of top and bottom quintile portfolios, then our first hypothesis can be written as follows;

Hypothesis 1:

$$H_0 : R_{High} - R_{Low} = 0$$

$$H_A : R_{High} - R_{Low} < 0$$

4.2 Multivariate Portfolio Analysis

The pairwise correlation coefficients in Table 1 assert a significant and positive relationship between connectivity measures and firm size. To that end, on average highly connected stocks are large firms in the stock market. Moreover, although they are not as high as those between firm size and connectivity, the correlation levels between connectivity measures and beta also present the need for additional consideration. Therefore, we conduct a multivariate portfolio analysis to control for the variation in firm size and beta. We first sort stocks into quintiles based on size (beta) measures at the end of the previous quarter (month). Then, we divide each size (beta) quintile into five groups based on end-of-month connectivity estimates of the stocks in that quintile. This procedure gives us 25 different portfolios. We then follow the returns of these portfolios for one-, three- and six-months. We form zero-cost portfolios R_p for each quintile ($p = 1 \dots 5$) by subtracting the returns of the portfolio with highly connected stocks (R_p^{High}) from the returns of the portfolio with low connected stocks R_p^{Low}. The returns of the zero-cost portfolio in a multivariate setting provide us to examine the impact of network connectivity on stock returns controlling for firm size (market risk). To that end, our second hypothesis is given as follows;

Hypothesis 2:

$$H_0 : R_p = 0$$

$$H_A : R_p < 0$$

4.3 Factor Tests

For further analysis, we employ factor tests to examine the relationship between network connectivity and stock returns under the control of most popular empirical asset pricing factors. We present the standard model below;

$$R_p = \vartheta_p^1 + \vartheta_p^2 R_m + \vartheta_p^3 SMB + \vartheta_p^4 HML + \vartheta_p^5 UMD + \epsilon_p \quad p = 1 \dots 5 \tag{6}$$

where R_m represents the market (BIST100 Index), SMB is the size and HML is the value factors of Fama and French (1993), whereas UMD is the momentum factor of Carhart (1997). SMB and HML is the univariate SIZE and BTM portfolios. We then test the hypothesis that the constant terms $\vartheta^1 \equiv (\vartheta^1_1, \ldots, \vartheta^1_5)$ are jointly equal to zero.

Hypothesis 3:

$$H_0 : \vartheta^1 = 0$$
$$H_A : \vartheta^1 < 0$$

To test this hypothesis, we use the Gibbons-Ross-Shanken (GRS) test statistic (Gibbons et al., 1989).

4.4 Firm-level cross-sectional regressions

Finally, to test the relationship between network connectivity and future returns controlling for several different factors, we estimate the cross-sectional regression presented in equation (7). For each month in our sample, future returns are regressed on our network connectivity measures and various firm-specific characteristics,

$$R_{i,t+n} = \gamma_{0,t} + \gamma_{1,t} CONNECT_{i,t} + \gamma_{2,t} BETA_{i,t} + \gamma_{3,t} SIZE_{i,t} + \gamma_{4,t} BTM_{i,t} + \gamma'_{5,t} X_{i,t} + \epsilon_{i,t} \qquad (7)$$

where $R_{i,t+n}$ is the monthly return on stock i for holding periods of n months after t. We try three different holding periods; one-month, three-months and six-months. $CONNECT_{i,t}$ can be the global connectivity proxied by network density $ND_{i,t}$, average local connectivity proxied by $WCC_{i,t}$, and network reciprocity $RCP_{i,t}$. The matrix $X_{i,t}$ includes other firm-specific factors such as MOM, IVOL and ILLIQ which are described in Section 2.

Earlier theoretical works suggest that higher trade connectivity of agents for a particular asset can provide faster diffusion of information in the market, leading to lower profits as private information becomes public over time in a fast manner, reducing the information asymmetry, thereby decreasing the risk involved with this asset. Accordingly, it is plausible to test whether increased brokerage house connectivity decreases the expected returns or not after controlling for several factors. Therefore, we form our last hypothesis as follows;

Hypothesis 4:

$$H_0 : \gamma_1 = 0$$

$$H_A : \gamma_1 < 0$$

5 Results

5.1 Univariate Portfolio Analysis

In this section, we conduct univariate portfolio-level analysis where we sort sample stocks based on our network connectivity measures (ND for global connectivity, WCC for average local connectivity and RCP) and construct quintile portfolios. We form equally- and value-weighted portfolios using the stocks in each quintile and follow the returns of these portfolios for one-, three- and six-months period. Then, we mimic an investor's portfolio who has a long position in stocks with the highest broker network connectivity and a short position of equal size in stocks that have the lowest broker network connectivity. This approach enables us to examine whether the investors in BIST demand a premium for holding stocks with less broker connectedness.

The average portfolio characteristics are presented in Table 2. Specifically, Panels A, B and C of Table 2 present the average characteristics of portfolios formed using ND, WCC and RCP, respectively. In Panel A, we first observe that the network density measures of each portfolio increases monotonically as we move from low density to high density portfolios, which is a mechanical relationship due to our portfolio construction rule. Next, we document that high density portfolios usually contain companies with higher market capitalization and that have higher book-to-market ratios. In addition, we observe that high density portfolios have significantly higher betas. To that end, we can argue that stocks with high network density have higher sensitivity to market movements. Furthermore, we notice that the stocks with high network density are liquid stocks with high momentum returns and idiosyncratic volatility. Finally, we see that the lottery demand is higher for stocks that have higher network density.

——————————- **INSERT TABLE 2 HERE** ——————————-

In Figures 4, 5 and 6, we document the cumulative returns for univariate portfolios constructed using network density (ND), weighted clustering coefficient (WCC) and network reciprocity (RCP) measures with one-month holding periods. In all three figures, we observe that the USD denominated returns of zero-cost portfolios, regardless of being equally- or value-weighted, outperform the benchmark market return by a significant margin throughout our sample period.

——————————- INSERT FIGURES 4, 5 AND 6 HERE ——————————-

Furthermore, Tables 3, 4 and 5 provide the results of formal univariate portfolio analysis based on network density, weighted clustering coefficient and network reciprocity, respectively. In all three tables, Panels A, B and C respectively denote the predictive analysis for one-, three- and six-months ahead. Panel A of Table 3 shows that stocks in the lowest network density quintile have a monthly value-weighted average excess return of 20 basis points (bps). The excess returns decrease monotonically as we move from low network density portfolio to the high density one. The average value-weighted return difference between the highest and lowest density quintile is -1.1% with a significant t-statistic of -2.64, which suggests that stocks with higher density have significantly lower expected returns as hypothesised. The results are robust when we consider equally-weighted portfolios. In addition, the results do not vary depending on the selection of connectivity measures. In particular, Panel A of Table 4 (Table 5) indicates that the average excess return difference between the highest and the lowest WCC (RCP) portfolios is -1.1% (-1.4%) with a t-statistic of -2.76 (-3.69), very similar to our findings for ND based portfolios.

——————————- INSERT TABLES 3, 4 AND 5 HERE ——————————-

Furthermore, we examine whether the standard asset pricing models can explain the average return differences between high and low connectivity quintile portfolios. Specifically, we make use of the standard four-factor model that incorporates market return (R_m) along with the size (SMB) and the value (HML) factors of Fama and French (1993), and the momentum factor (UMD) of Carhart (1997). In Tables 3, 4 and 5, we also report the estimates of the constant terms ($\hat{\alpha}$) obtained from the four-factor model for each of the quintile portfolio. The estimates for the constant term gives us the abnormal returns for each quintile portfolio. In Panel A of Table 3, we observe that the lowest density portfolio has an abnormal return of 1%, whereas the highest density portfolio has an alpha of -50 bps. The abnormal return of the zero-cost portfolio is -1.6% with a t-statistic of -5.23, which is both economically and statistically significant. These results are, again, robust when we consider equally-weighted portfolios and different connectivity measures. In particular, Panel A of Table 4 (Table 5) indicates that the abnormal return of the zero-cost portfolio constructed using WCC (RCP) is -1.2% (-1.6%) which is statistically significant at 1% level.

In Panel B of Table 3, we show the returns of network density quintile portfolios with three-months holding period. The value-weighted excess return of the zero-cost portfolio is around 60 bps, statistically significant at 10% level. The abnormal returns are shown to be around 1.1% and highly significant. These results do not change when we consider different network connectivity measures. For example, in Panel B of Table 4 (Table 5), we show that the zero-cost portfolio constructed using WCC (RCP) has significant abnormal return around -1.2% (-1.3%).

In Panel C of Tables 3, 4 and 5, we document the average return and estimates for the four factor alphas for all quintile portfolios when the portfolio holding period is equal to six-months. The statistical significance of the value-weighted excess returns seems to disappear for both ND and WCC portfolios under this setting. Specifically, the value-weighted average returns of zero-cost ND and WCC portfolios are -40 bps and -30 bps respectively, both statistically indifferent from zero. Even though the constant terms in four factor models remain to be significant for all specifications of the holding periods and all network measures, a conservative interpretation might indicate that the predictive power of the network connectivity on future return diminishes for longer holding periods. Later, we test this relationship with the firm-level cross-sectional regressions as well.

Regarding univariate portfolio analysis, we finally examine the differences in return performances of the zero-cost long-short portfolios constructed based on ND versus WCC to compare whether if there exists an additional premium for strategies based on global or local broker connectivity. In Figure 7, we present the differences in cumulative returns of these two strategies for both equally- and value-weighted portfolios. We observe that the cumulative returns provided by local connectivity (WCC) based zero-cost portfolio are greater in the period from the year 2005 to 2011. However, for the rest of the sample, global connectivity (ND) based zero-cost portfolio outperforms the other. Interestingly, by the end of whole sample period, value-weighted zero-cost long-short portfolios based on global and local connectivity have almost exactly the same performance, whereas in the case of equally-weighted portfolios, global connectivity based strategy outperforms the local connectivity based one with a slight margin. In an attempt to test whether these performance differences are significant or not in the long-run, we apply the Welch (1947) two-sample t-test on the cumulative returns of these portfolios. Accordingly, we fail to reject the null hypothesis that the means of the cumulative returns are the same with corresponding p-values 0.68 and 0.94 for equally-weighted and value-weighted portfolios. Results suggest that, at least in the case of BIST, performances of the zero-cost long-short portfolio strategies based on global and local broker connectivity do not statistically differ, whether the portfolio is value- or equally-weighted.

——————————- INSERT FIGURE 7 HERE ——————————-

Overall our results suggest four main outcomes. First, stocks that are traded in networks with high broker connectivity have on average lower expected returns than stocks that are traded in networks with low broker connectivity. To that end, we argue that the investors in BIST demand a premium for holding stocks that are traded in networks with low broker connectivity, a finding that is in line with our hypothesis. Second, we show that this relationship cannot be explained by commonly used asset pricing factors. Third, we document that the predictive relationship persists for more than one-month into the future but mostly diminishes after three-months. Finally and fourth, performances of the strategies based on local and global broker connectivity are statistically indifferent in the long-run.

5.2 Multivariate Portfolio Analysis

Next, we test whether other firm-specific factors such as size and market risk have a significant impact in explaining the negative relationship between network connectivity and future returns via multivariate portfolio sorts. Specifically, to control for firm size, we sort stocks into quintiles based on end-of-quarter market capitalization.[10] Then, we sort stocks in each quintile based on monthly network connectivity proxies. For each of the initial market capitalization quintile, we form zero-cost portfolios by subtracting the returns of the portfolio with highly connected stocks from the returns of the portfolio with lowly connected stocks. This procedure enables us to control the impact of market capitalization on the relationship between broker network connectivity and future portfolio returns.[11]

Tables 6, 7 and 8 present the characteristics of 5x5 portfolios constructed using size and network density (ND), weighted clustering coefficient (WCC) and network reciprocity (RCP), respectively. In all three tables, Panel A shows the return characteristics of each portfolio along with the zero-cost portfolio constructed as the difference between high and low broker connectivity stocks for each size quantile. Similarly, Panel B (Panel C) of each table documents the average firm size (average connectivity value) of each of the portfolio.

——————————- **INSERT TABLES 6, 7 AND 8 HERE** ——————————-

For all of the network connectivity proxies, the zero-cost portfolio for the first, second and third size quintiles have negative and statistically significant returns. In particular, Table 6 shows that average portfolio return for the zero-cost network density-size portfolios for the first, second and third size quintiles are -3.5%, -1.2% and -1.8%, respectively. In Table 7, we observe that the average returns for the zero-cost WCC-size portfolios for the first three size quintiles are similar with the corresponding estimates of -3%, -1.1% and -1.9%, respectively. Finally, in Table 8, we show that respective average portfolio returns for the zero-cost RCP-size portfolios are -3.5%, -2% and -2%. For all measures, we also observe that the statistical significance of the difference in average portfolio return between high and low broker connectivity stock groups diminishes for large firms. When we sort the largest firm size quintile based

[10]We also use monthly market capitalization measures when forming portfolios. Our results are robust to this change and results can be obtained upon request.

[11]In Section 5.2, we report the results only for equally-weighted portfolios and one-month ahead investment horizon for space saving purposes. The reasons are, (i) value-weighted portfolio results are very similar to those obtained via equally-weighted portfolios, and (ii) in terms of investment horizon, conclusion is qualitatively the same with the univariate portfolio analysis performed in Section 5.1. Results with respect to alternative portfolio weighting scheme and extended investment horizons can be obtained from authors upon request.

on network connectivity measures, we observe that the difference in average returns is not statistically significant for all of the alternative connectivity measures.

We repeat the same analysis with end-of-month market risk proxy (beta) and form five different zero-cost network connectivity - beta portfolios. Tables 9, 10 and 11 present the characteristics of 5x5 portfolios constructed using market risk and network density, weighted clustering coefficient and network reciprocity, respectively. As in the case of firm size factor, in all three tables, Panel A shows the return characteristics of each portfolio along with the zero-cost portfolio constructed as the difference between high and low broker connectivity stocks for each beta quintile. Similarly, Panel B (Panel C) of each table documents the average market risk (average connectivity) of each of the portfolios.

——————————- INSERT TABLES 9, 10 AND 11 HERE ——————————-

In Panel A of Table 9, we observe that the average return for each of the zero-cost quintile portfolio is negative and statistically significant, and they vary between -70 bps and -2.4%. In Panel B, for each beta quintile (except the lowest beta quintile), we observe that beta rises monotonically as we move from low ND stocks to high ND stocks. To that end, we can say that on average, the stocks that are traded in dense broker networks have higher correlation with the overall market movements. However, we do not observe any systematic relationship in Panel C. These findings do not vary across our alternative connectivity measure WCC and RCP.

In terms of return performance, the qualitative results are similar to the case where we control for the firm size. For example, for each beta quintile, we see an almost monotonic increase in average portfolio returns as we go from group of stocks with high broker connectivity to low broker connectivity, regardless of the connectivity measure. The main difference is that when we control for the market risk, we do not see a lost of significance in the high-low connectivity zero-cost portfolios for large firms.[12] Overall, we reveal that results obtained from univariate portolio analysis in the previous section are robust when we

[12]Except the case where we use ND as the connectivity measure (see Table 9), where in the 4th quintile, zero-cost portfolio brings an average return that is statistically not different than zero.

control for the other potential factors that might influence the portfolio returns.

5.3 Factor Returns

We examine the systematic impact of broker network connectivity on stock returns through equation (6). The estimates for the abnormal return obtain by the zero-cost connectivity-size portfolios are given by the $\vartheta^1 \equiv (\vartheta^1_1, \vartheta^1_2, \vartheta^1_3, \vartheta^1_4, \vartheta^1_5)$. Table 12 provides results for our factor analysis. Panel A, B and C respectively shows the results for factor analysis where we use network density (ND), weighted clustering coefficient (WCC) and network reciprocity (RCP) as connectivity proxies.[13]

In Panel A, we observe that the coefficients for the constant term varies between -1% and -2.5%, all statistically significant at 5%. The quintile with the smallest (largest) stocks have the largest (smallest) absolute abnormal return. This is inline with the previous findings which suggest that network impact is larger for small stocks. We reject the hypothesis that the constant terms are jointly equal to zero (p-value (GRS) $<$ 0.01), indicating that the network risk is systematic in equity markets and cannot be eliminated with portfolio diversification. In Panel B, when we measure network risk with WCC, we observe that the magnitude of the abnormal returns are quite similar. The constant term for each size quintile vary between -1.1% and -2.6%, all statistically significant. Similarly, the smallest size quintile have the largest absolute abnormal return. We again reject the hypothesis that the constant terms are jointly equal to zero. In Panel C, we observe that the average abnormal return for zero-cost RCP-size portfolios vary between -50 bps and -2.5%. Again, the quintile with the smallest stocks have the largest absolute abnormal returns. Regarding RCP-size portfolios, for the fifth quintile which contains the largest stocks, we fail to reject that the return premium is statistically indifferent from zero. Even though this reduces the GRS test statistic, it is still significant at 1% level which enables us to reject that the constant terms are jointly equal to zero.

——————————- INSERT TABLE 12 HERE ——————————-

To that end, our results from multivariate portfolio and factor analyses indicate that network risk

[13] For the same reasons stated in footnote 11, we use equally-weighted portfolios with one-month ahead investment horizon in this section.

cannot be explained by existing cross-sectional return predictors. Moreover, the impact of the network premium is stronger in magnitude for the smallest stocks. Even though there is no monotonic relationship, we observe that the size quintile which has the smallest stocks have the largest negative return premium, independent of the network connectivity proxy. The size quintile which has the largest stocks usually have the smallest return premium for ND and RCP, whereas for WCC the forth quintile have a return premium of -1.1% and the last quintile have slightly larger absolute return premium of -1.2%.

5.4 Firm-level cross-sectional regressions

In this section, we analyze the predictive relationship between network density, weighted clustering coefficient and network reciprocity measures and future returns via firm-level cross-sectional regressions with one-, three- and six-month investment horizon. This setting enables us to control for various firm-specific factors such as firm size (SIZE), profitability (BTM), market risk (BETA), idiosyncratic volatility (IVOL), liquidity (ILLIQ) and historical return characteristics (REV, MOM and MAX), at the same time.

In Table 13, we present the predictive relationship between ND and future returns. Specifically, Panels A, B and C of Table 13 document the results with one-, three- and six-months investment horizon. In the first column of Panel A, we document a significant and negative relationship for one-month ahead returns which is consistent with our expectations. ND has a coefficient of -0.044 with a t-statistic of -3.33. The interpretation of the economic effect of network density is similar to our previous findings. In particular, in Table 2, we report that the average ND for high-low density portfolio is 0.29. Multiplying this difference with the average slope yields an estimated monthly premium of 1.1%.

INSERT TABLE 13 HERE

In Panel A of Table 13, columns 2 to 9 extend the univariate regression through incorporating additional firm-specific controls, one-by-one. The coefficient of ND vary between -0.051 and -0.029; all statistically significant at 1%. Column 10 shows that ND has a negative and statistically significant impact on one-month ahead returns even after controlling for all firm-specific factors. The coefficient equals to a highly significant -0.043 with a t-statistic of -3.145.

The results presented in Panel B of Table 13 show the predictive relationship between ND and three-month ahead returns. Similar to the findings presented in Panel A, we observe that univariate relationship between ND and three-month ahead returns is negative and significant with the corresponding estimate and t-statistic equalling -0.029 and -2.165, respectively. Column 10 in Panel B indicate that the significant and negative relationship persists for three-month holding period when we control for all other factors. In line with our findings in univariate analysis, we observe that the predictive relationship disappears when we take holding period as six-months. Specifically, in Panel C, we observe that the relationship between ND and six-month ahead returns is not significant in a univariate setting.

Tables 14 and 15 repeat the analysis for WCC and RCP factors. In both tables, Panels A, B and C respectively present the results for one-, three- and six-months investment horizon, in line with Table 13. All findings provide a similar picture. Specifically, for one-month specification, we observe that the coefficient estimate under the univariate regression for WCC (RCP) is -0.036 (-0.048) and highly significant with a t-statistics of -3.75 (-3.44). The corresponding estimate for the monthly return premium associated with WCC (RCP) equals to -1.5% (-1.3%). The predictive relationship between WCC (RCP) and one-month ahead returns survive under a multivariate regression setting where we control for all other firm-specific factors. Moreover, when we change the holding period to three-months, the relationship stays significant for both measures. However, in line with our previous findings, the predictive relationship disappears for six-month investment horizon for both connectivity measures.

—————————— **INSERT TABLES 14 AND 15 HERE** ——————————-

5.5 Cross-sectional persistence of network connectivity

In this section, we investigate the cross-sectional persistence of the network risk. Table 16 presents the transition matrix which shows the average probability that a stock in the broker network connectivity quintile i in one month will be in the broker network connectivity quintile j in the subsequent month. Panels A, B and C of Table 16 report these probabilities for network density (ND), weighted clustering coefficient (WCC) and network reciprocity (RCP) respectively. We expect all probabilities to be 20% if the connectivity of the broker networks for a given stock is totally at random.

—————————— **INSERT TABLE 16 HERE** ——————————

In Panel A of Table 16, we observe that with 53% probability, a stock that is in the smallest connectivity quintile will stay in the same quintile one-month later when we use ND as the connectivity measure. Similarly, approximately 61% of the stocks that are in the largest ND quintile will stay in the same quintile one-month later. These results indicate that network density risk have significant cross-sectional persistence. Furthermore, this characteristic appears to be similar when we use WCC as our connectivity proxy. In Panel B, we see that WCC portfolios also exhibit cross-sectional persistence, especially at both ends of the quintiles. Specifically, we observe that 51% (66%) of the stocks that are in the lowest (highest) WCC quintile will stay in the same quintile in the next month. Finally, In Panel C, we document that RCP portfolios also exhibit cross-sectional persistence.

Contrary to ND and WCC cases, we show that RCP portfolios do not exhibit strong cross-sectional persistence characteristics. Specifically, in Panel C of Table 16, we see that the diagonal values vary between 25.7% and 48.0%, indicating that a stock is more likely to move from one quintile to another in consecutive months rather than stay in the same quintile.

Theory indicates that the information diffusion will be higher in markets with high network connectivity. To that end, investors should demand a premium for holding stocks that have low broker network connectivity. Our results provide supporting evidence to the theory in the previous sections. On the other hand, analysis in this section slightly weakens our findings due to cross-sectional persistence. However, we also observe that the cross-sectional persistence varies depending upon the selection of connectivity estimate. In particular, considering the case of RCP measure where the probability of changing connectivity quintile is higher than 50% in all cases, our findings still have considerable level of robustness.

6 Conclusion

In this study, we examined how the brokerage houses' trading network connectivity can affect the expected returns in the cross-section of stocks. Earlier studies have shown that investor networks serve as an accelerator for information diffusion which can help investment decision making under uncertainty and information asymmetry. In our context, this would imply that the higher the broker network connectedness for a particular stock, the lower the uncertainty, thus the lower the expected returns. In line with this argument, we revealed a negative and significant relationship between brokerage firm connectedness and one-month ahead stock returns in the cross-section, with 1% increase in network connectivity reducing the next month's return by 2%. Moreover, the qualitative results still hold when we control for the common factors such as market risk, firm size, book-to-market ratio, momentum, and liquidity.

Portfolio analysis based on network connectivity confirms these findings. Connectivity based single and double sorted portfolios showed that stocks in the lowest connectivity quintile can earn significantly positive monthly return premiums ranging from 1% to 1.6%, with even higher premiums especially for small company stocks. Furthermore, in terms of the differences between global and local connectivity effects, our results showed no differentiation both qualitatively and quantitatively, and for both connectivity types, higher significant premiums have been obtained for company stocks with lower broker connectivity.

Regarding market analysis and trading strategies based on public information, the setup in our paper is the furthest we can go. For future research, using proprietary dataset can help us improve our understanding on the interaction between investor network connectedness in financial markets and expected stock returns. For example, instead of brokerage houses, analyzing the actual investor network connectivity can add more to the discussion on the role of networks in information diffusion. Moreover, identifying the institutional and retail (or foreign and domestic) investors in these trading networks, and examining the relationship between their presence in the network and future stock returns in the connectivity framework can extend our knowledge of information diffusion with respect to investor types. While a few studies have considered similar topics focusing on the relationship between centrality of investors and their trading skills (e.g., Ozsoylev et al. (2014); Cohen-Cole et al. (2014)), examining the whole connectedness of the network and its implications on expected stock returns would bring a fresh approach to the subject.

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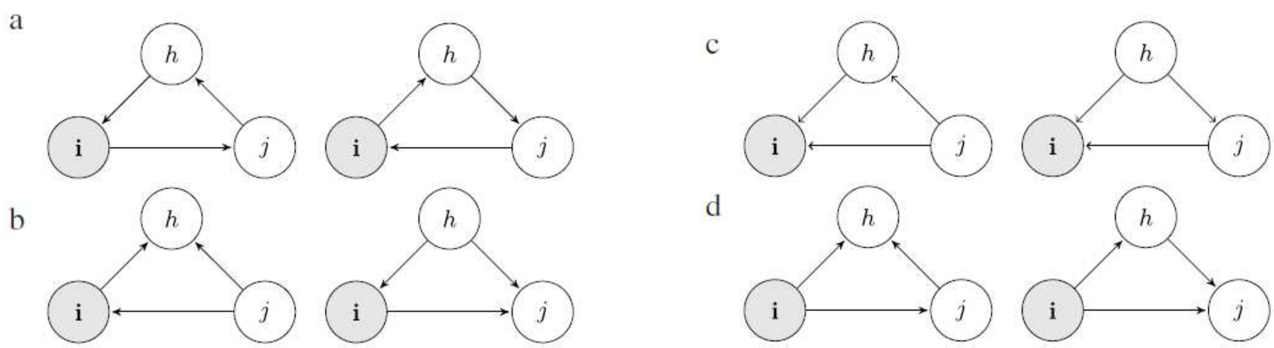
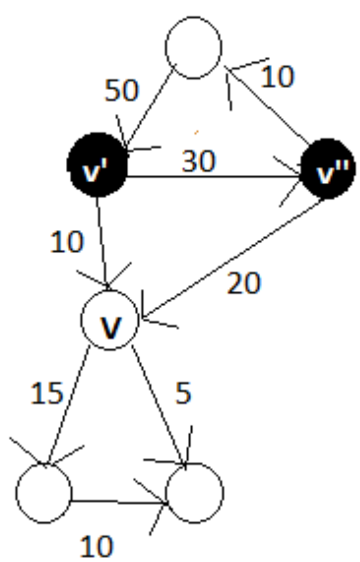
Figures and Tables

Figure 1: Triangle flows for weighted clustering coefficient



Source: Tabak et al., 2014.

Figure 2: Hypothetical directional weighted network composed of six nodes and eight directional links across the nodes



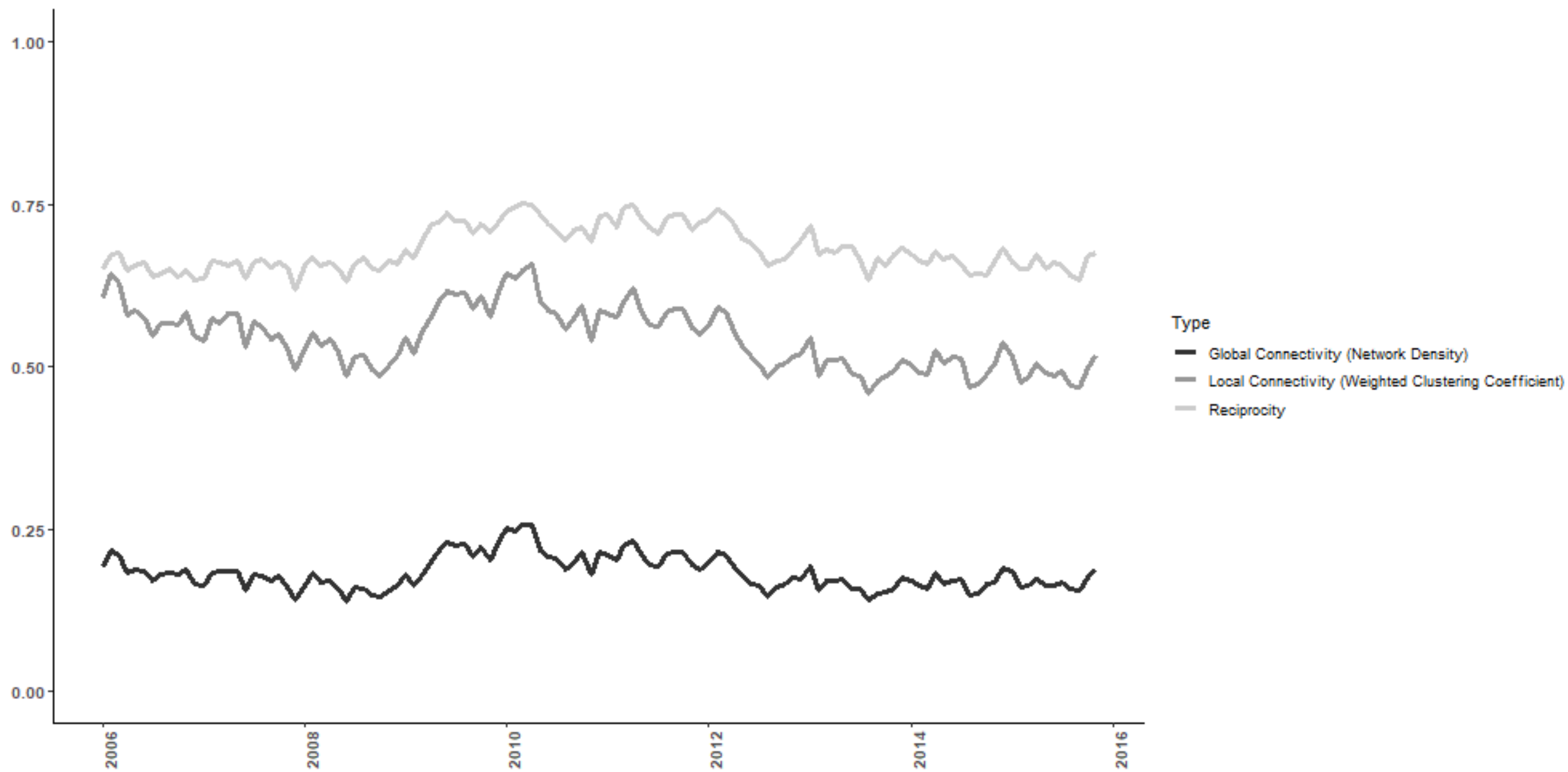


Figure 3: Average connectivity measures: In this table, we present the cross-sectional averages for network density, weighted clustering coefficient and reciprocity measures for all months between January 2006 - November 2015. We construct our network measures using intraday quotes and trades for all stocks traded in Borsa Istanbul.

Figure 4: Cumulative Returns For Univariate Global Connectivity (Network Density) Portfolios: In this figure we present the cumulative return for equally weighted and value weighted portfolios that mimics an investor who has a long position in stocks with low network density and a short position with equal size in stocks with high network density along with the cumulative returns for the market index (BIST 100). All returns are denominated in U.S. Dollars.

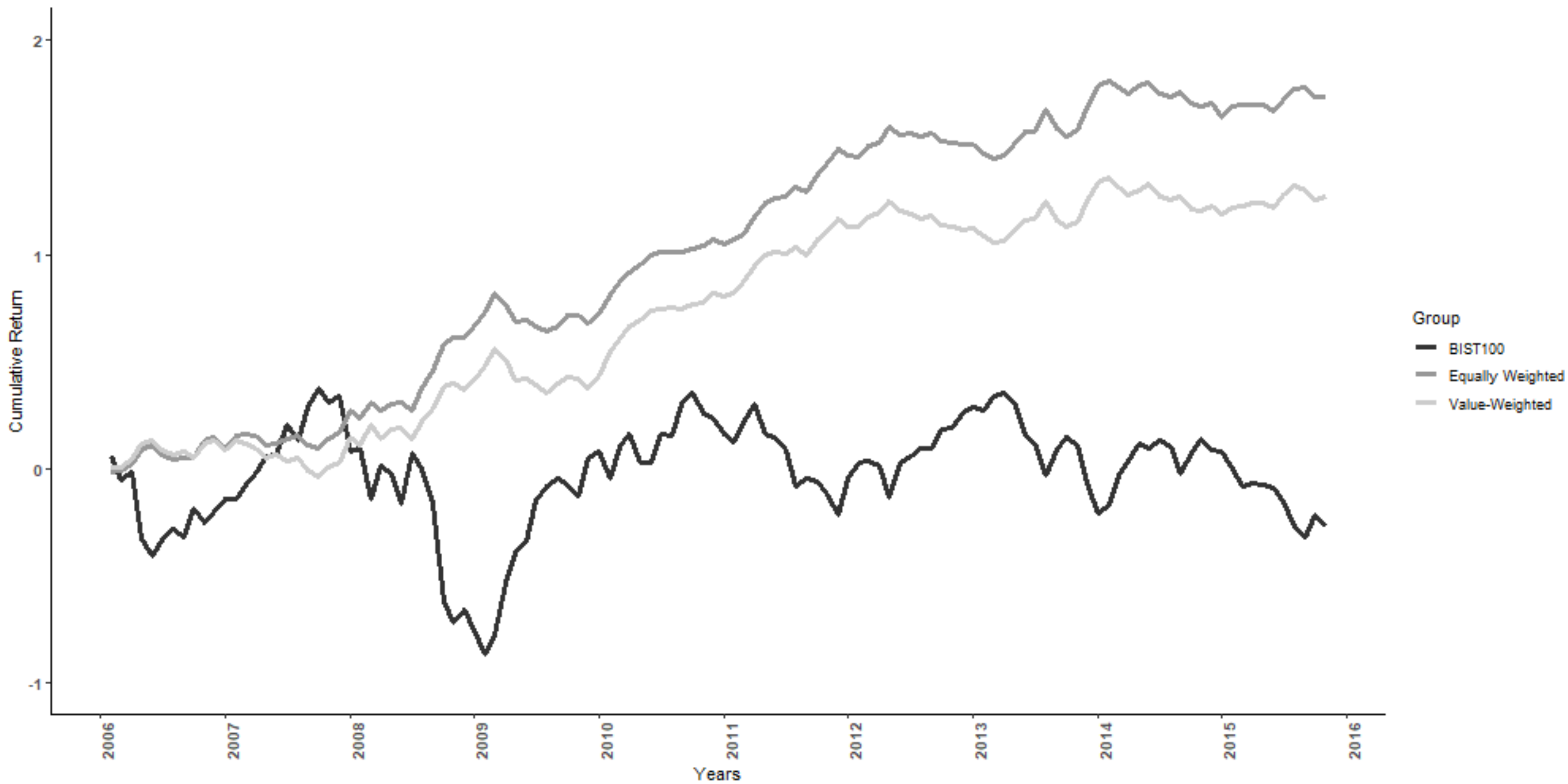


Figure 5: Cumulative Returns For Univariate Local Connectivity (WCC) Portfolios: In this figure we present the cumulative return for equally weighted and value weighted portfolios that mimics an investor who has a long position in stocks with low average local connectivity (weighted clustering coefficient) and a short position with equal size in stocks with high average local connectivity along with the cumulative returns for the market index (BIST 100). All returns are denominated in U.S. Dollars.

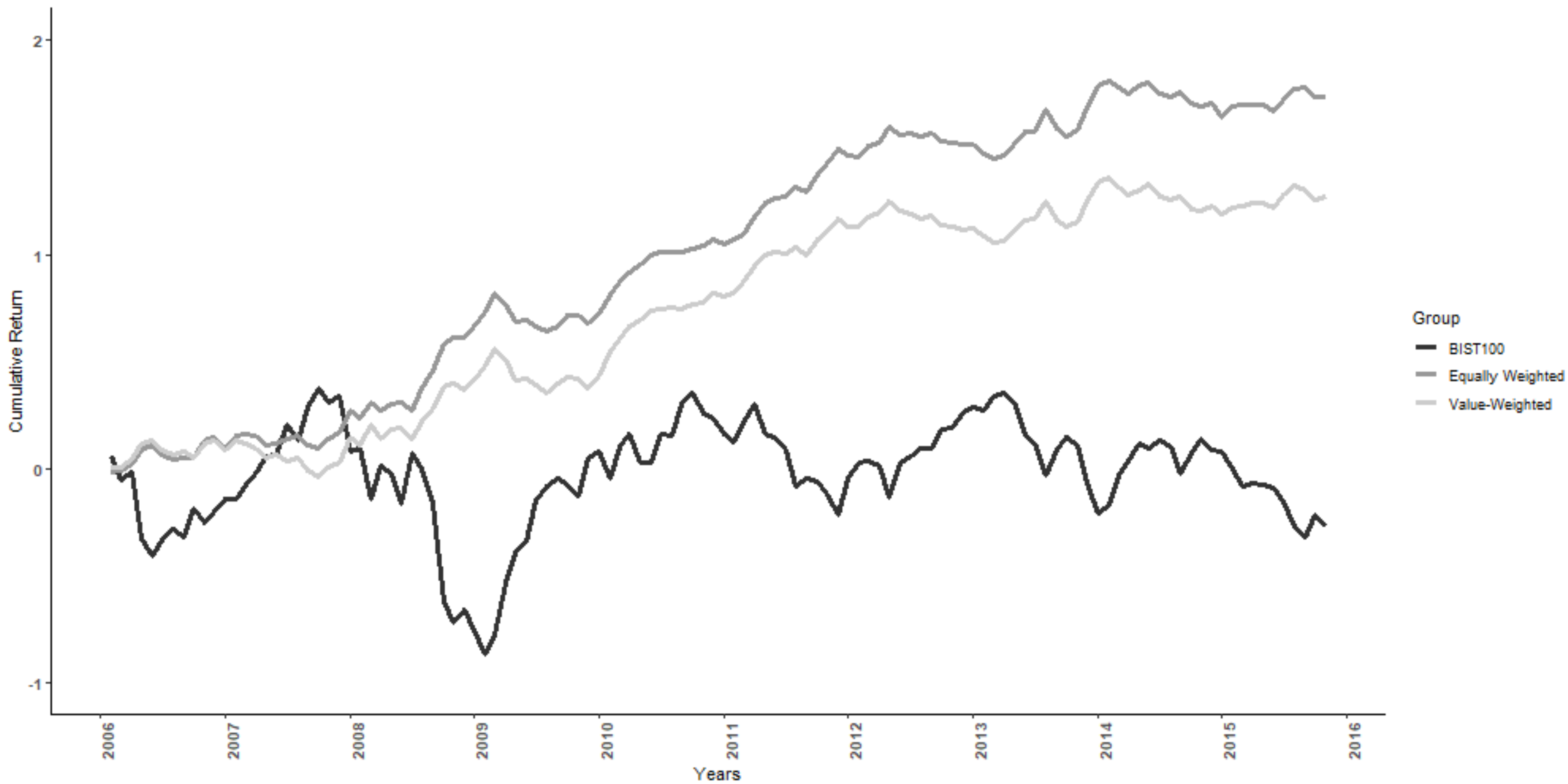


Figure 6: Cumulative Returns For Univariate Network Reciprocity Portfolios: In this figure we present the cumulative returns for equally weighted and value weighted portfolios that mimics an investor who has a long position in stocks with low network reciprocity and a short position with equal size in stocks with high network reciprocity along with the cumulative returns for the market index (BIST 100). All returns are denominated in U.S. Dollars.

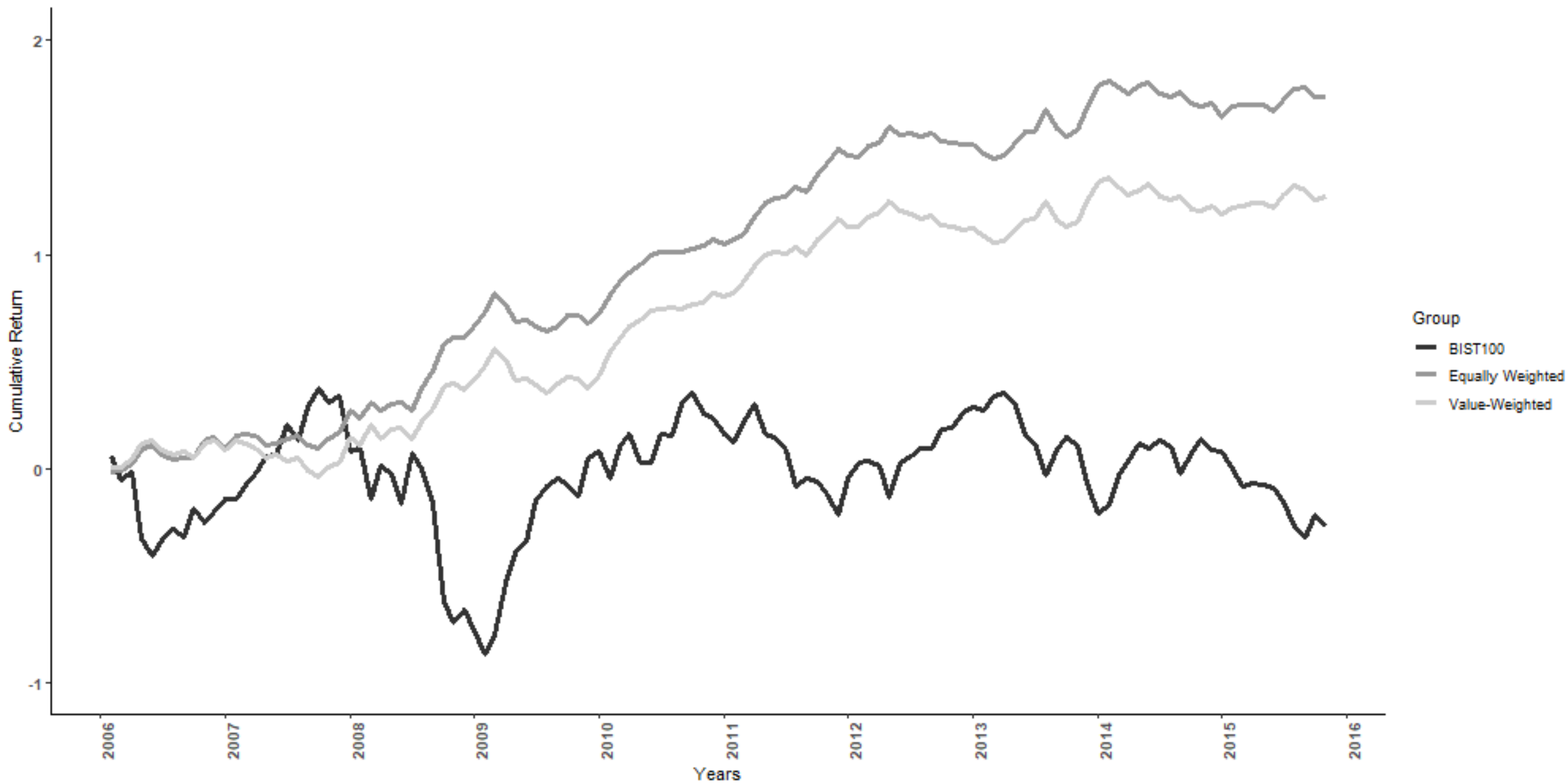


Figure 7: Difference in Univariate Portfolio Returns: In this figure, we present the difference in equally weighted and value weighted zero cost network density (ND) and weighted clustering coefficient portfolios (WCC). The portfolios mimic an investor who has a long position in stocks with low ND (WCC) and a short position with equal size in stocks with high ND (WCC). The difference is obtain via subtraticting the cumulative return of zero cost portfolio constructed with ND from the zero cost portfolio constructed with WCC in a given month. We test whether the means of cumulative return series are different or not via Welch two-sample t-test. We fail to reject the null hypothesis that the means cumulative returns are the same with corresponding p-values 0.6843 and 0.9384 for equally weighted and value weighted portfolios.

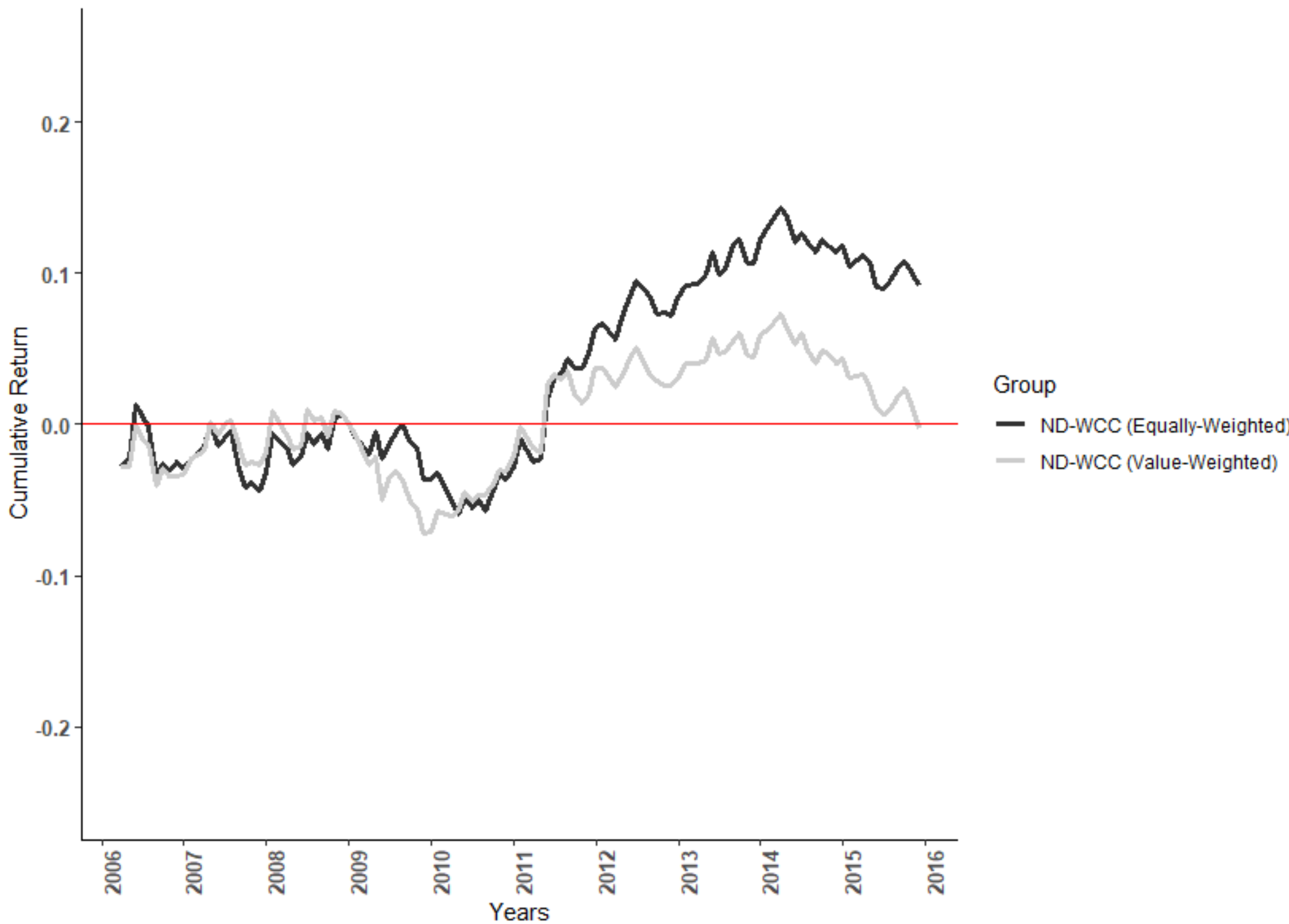


Table 1: Descriptive Statistics: In this table, we present the descriptive statistics for firm-specific factors that are calculated for all stocks that are traded in BIST between January 2006 - April 2017. **RETURN** represents the monthly log returns. **BETA** is the systematic risk factor. **SIZE** is the logarithm of the end of month market capitalization. **BTM** is the book-to-market ratio. **MOM** is the momentum variable. **ILLIQ** is the illiquidity measure. †indicates $x10^4$. **MAX** is the maximum daily return within a month. **IVOL** is the idiosyncratic volatility. **REV** is the return reversal measured by one-month lag return. ND is the network density which is also our global connectivity measure. **WCC** is the average weighted clustering coefficient, our average local connectivity measure. **RCP** denotes the network reciprocity. In Panel A, we respectively present number of observations, mean, standard deviation, minimum and maximum values for each variables in our sample. In Panel B, we present the pairwise correlations. * indicates statistical significance at 1% level

Variable	**Panel A: Descriptive Statistics**					**Panel B: Pairwise correlations**											
	Obs	**Mean**	**Std. Dev.**	**Min**	**Max**	**RETURN**	**SIZE**	**BETA**	**BTM**	**MOM**	**ILLIQ†**	**IVOL**	**MAX**	**REV**	**ND**	**WCC**	**RCP**
RETURN	37760	-0.01	0.16	-1.83	1.82	1											
SIZE	37760	4.59	1.96	-0.48	10.10	-0.01*	1										
BETA	37758	0.73	0.40	-6.72	5.01	-0.14*	0.17*	1									
BTM	37760	-0.24	0.88	-6.16	3.61	0.08*	-0.28*	0.02*	1								
MOM	37203	0.06	0.50	-0.94	20.04	-0.03*	0.09*	-0.00	-0.1401*	1							
ILLIQ†	37756	0.02	0.47	0.00	43.98	-0.00	-0.06*	-0.04*	0.0067	-0.01	1						
IVOL	37758	0.02	0.01	0.00	0.17	0.13*	-0.24*	0.0341*	-0.01*	0.11*	0.04*	1					
MAX	37760	0.06	0.04	0.00	0.90	0.22*	-0.14*	0.2065*	0.01	0.04*	0.01	0.81*	1				
REV	37328	-0.01	0.16	-1.83	1.82	-0.02*	0.07*	0.0235*	-0.09*	0.33*	0.00	0.01	-0.01	1			
ND	37760	0.19	0.11	0.00	0.70	0.11*	0.52*	0.3003*	-0.06*	0.12*	-0.06*	0.13*	0.20*	0.0392*	1		
WCC	37760	0.56	0.16	0.00	0.97	0.12*	0.52*	0.2990*	-0.07*	0.14*	-0.11*	0.12*	0.19*	0.04*	0.93*	1	
RCP	37760	0.69	0.11	0.00	0.94	0.09*	0.21*	0.2367*	-0.09*	0.09*	-0.13*	0.20*	0.25*	0.02*	0.76*	0.80*	1

Table 2: Average portfolio characteristics: This table presents average characteristics for quintile portfolios based on network connectivity measures. Specifically, Panel A, B and C respectively present the portfolios formed based on monthly network density, weighted clustering coefficient and network reciprocity measures. Low represents the portfolio consisting stocks with the lowest connectivity measures. Similarly, High represents the portfolio consisting stocks with the highest connectivity measures. The table reports the time-series averages of monthly average connectivity and various firm-specific measures for each quintile. High-Low represents the zero investment network connectivity portfolio which mimics the returns of an investor who has a long position in high connectivity portfolio and a short position of equal size in the low connectivity portfolio. t-statistics for each value is presented in parenthesis where they are corrected by the Newey-West procedure. **BETA** is the systematic risk factor. **SIZE** is the logarithm of the end of month market capitalization. **BTM** is the book-to-market ratio. **MOM** is the momentum variable. **ILLIQ** is the illiquidity measure. ‡indicates $x10^5$. **MAX** is the maximum daily return within a month. **IVOL** is the idiosyncratic volatility. **REV** is the return reversal measured by one-month lag return. **ND** is the network density which is also our global connectivity measure. **WCC** is the average weighted clustering coefficient, our average local connectivity measure. **RCP** denotes the network reciprocity.

Panel A: ND quintile portfolios

	Low	**2**	**3**	**4**	**High**	**High-Low**
ND	0.069	0.124	0.170	0.230	0.360	0.290
	(30.07)	(48.39)	(64.45)	(85.39)	(122.83)	(99.84)
SIZE	3.587	4.010	4.272	4.828	6.257	2.670
	(71.85)	(113.45)	(132.75)	(181.79)	(157.67)	(35.01)
BTM	0.163	0.182	0.242	0.286	0.313	0.150
	(7.34)	(8.47)	(11.49)	(14.34)	(12.56)	(7.64)
BETA	0.589	0.680	0.734	0.783	0.905	0.315
	(41.69)	(47.68)	(46.72)	(50.47)	(72.36)	(32.62)
ILLIQ‡	6.777	0.024	0.013	0.005	0.001	-6.775
	(4.70)	(9.25)	(8.04)	(9.68)	(9.83)	(-4.70)
MOM	0.042	0.050	0.055	0.086	0.137	0.095
	(1.69)	(1.84)	(1.91)	(2.74)	(4.08)	(7.46)
IVOL	0.019	0.019	0.022	0.024	0.025	0.006
	(54.89)	(48.50)	(53.28)	(61.48)	(68.44)	(15.79)
MAX	0.052	0.056	0.064	0.072	0.077	0.025
	(36.66)	(33.97)	(38.02)	(41.83)	(43.28)	(25.75)

Panel B: WCC quintile portfolios

	Low	**2**	**3**	**4**	**High**	**High-Low**
WCC	0.346	0.484	0.562	0.641	0.764	0.419
	(51.76)	(105.35)	(150.42)	(193.97)	(285.93)	(75.52)
SIZE	3.568	3.937	4.194	4.749	6.502	2.934
	(75.88)	(118.54)	(142.54)	(181.79)	(194.53)	(46.18)
BTM	0.132	0.184	0.261	0.303	0.307	0.174
	(6.09)	(8.30)	(12.41)	(14.70)	(12.06)	(10.05)
BETA	0.597	0.682	0.728	0.774	0.909	0.312
	(41.89)	(46.14)	(47.59)	(47.40)	(80.06)	(33.28)
ILLIQ‡	6.780	0.026	0.012	0.005	0.001	-6.780
	(4.70)	(8.58)	(8.83)	(10.30)	(9.97)	(-4.70)
MOM	0.031	0.038	0.069	0.098	0.134	0.103
	(1.24)	(1.42)	(2.37)	(3.13)	(3.98)	(8.17)
IVOL	0.019	0.019	0.022	0.025	0.024	0.004
	(54.47)	(47.58)	(52.18)	(61.85)	(65.85)	(12.63)
MAX	0.052	0.056	0.066	0.075	0.073	0.021
	(36.68)	(33.27)	(38.38)	(43.48)	(40.73)	(22.14)

Panel C: RCP quintile portfolios

	Low	**2**	**3**	**4**	**High**	**High-Low**
RCP	0.539	0.651	0.702	0.749	0.814	0.275
	(103.28)	(192.08)	(222.59)	(250.39)	(315.95)	(53.54)
SIZE	4.257	4.384	4.490	4.619	5.202	0.944
	(67.41)	(113.36)	(127.94)	(153.43)	(109.87)	(9.60)
BTM	0.163	0.128	0.196	0.292	0.406	0.243
	(7.00)	(6.23)	(8.93)	(13.27)	(17.71)	(11.84)
BETA	0.603	0.697	0.745	0.787	0.859	0.255
	(47.14)	(49.75)	(52.18)	(50.20)	(52.59)	(20.52)
ILLIQ‡	6.720	0.051	0.017	0.033	0.005	-6.710
	(4.68)	(4.12)	(8.88)	(1.40)	(4.84)	(-4.68)
MOM	0.054	0.039	0.051	0.073	0.153	0.099
	(2.13)	(1.46)	(1.79)	(2.31)	(4.55)	(7.76)
IVOL	0.019	0.018	0.020	0.023	0.030	0.011
	(56.30)	(46.12)	(51.44)	(60.47)	(72.67)	(29.40)
MAX	0.051	0.054	0.060	0.068	0.090	0.038
	(37.81)	(31.06)	(34.95)	(39.60)	(51.05)	(40.30)

Table 3: Univariate Portfolio Analysis - Quintile portfolios based on global connectivity (network density): In this table, we present the equally and value-weighted returns of quintile portfolios. At the end of each month, we sort our stocks into quintile portfolios based on global connectivity (network density) measures. We follow the portfolio returns for the next one, three and six months. Panel A,B and C present the findings for one, three and six months holding period, respectively. The four-factor α is obtained through regressing the portfolio returns on the market return (BIST100), and size (SMB) and profitability (HML) of Fama and French (1993) and the momentum factor (UMD) of Carhart (1997). High-Low represents the zero investment network density portfolio which mimics the returns of an investor who has a long position in high density portfolio and a short position of equal size in the low density portfolio. Last two rows of each panel present the t-statistic and p-values of the corresponding average return and $\hat{\alpha}$ estimates for the zero-investment (High-Low) portfolio where t-stats are corrected by the Newey-West procedure.

Panel A: Holding Period = 1 month

	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.003	0.010	0.002	0.010
2	-0.001	0.007	-0.002	0.006
3	-0.009	-0.002	-0.008	-0.001
4	-0.011	-0.005	-0.009	-0.003
High	-0.012	-0.007	-0.009	-0.006
High-Low	-0.015	-0.017	-0.011	-0.015
t-stat	(-3.59)	(-5.48)	(-2.64)	(-4.99)
p-value	0.00	0.00	0.00	0.00

Panel B: Holding Period = 3 months

	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	-0.001	0.006	-0.003	0.005
2	-0.004	0.004	-0.003	0.004
3	-0.009	-0.001	-0.007	-0.001
4	-0.008	0.000	-0.006	0.001
High	-0.010	-0.007	-0.008	-0.006
High-Low	-0.009	-0.013	-0.006	-0.011
t-stat	(-2.14)	(-4.57)	(-1.36)	(-3.99)
p-value	0.02	0.00	0.09	0.00

Panel C: Holding Period = 6 months

	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.000	0.004	-0.001	0.005
2	-0.003	0.002	-0.002	0.003
3	-0.002	0.003	-0.002	0.002
4	-0.002	0.000	-0.001	0.001
High	-0.006	-0.007	-0.005	-0.006
High-Low	-0.006	-0.011	-0.004	-0.011
t-stat	(-1.34)	(-3.50)	(-0.85)	(-3.11)
p-value	0.09	0.00	0.20	0.00

Table 4: Univariate Portfolio Analysis - Quintile portfolios based on average local connectivity (WCC): In this table, we present the equally and value-weighted returns of quintile portfolios. At the end of each month, we sort our stocks into quintile portfolios based on average connectivity measures (WCC). We follow the portfolio returns for the next one, three and six months. Panel A,B and C present the findings for one, three and six months holding period, respectively. The four-factor α is obtained through regressing the portfolio returns on the market return (BIST100), and size (SMB) and profitability (HML) of Fama and French (1993) and the momentum factor (UMD) of Carhart (1997). High-Low represents the zero investment network density portfolio which mimics the returns of an investor who has a long position in high density portfolio and a short position of equal size in the low density portfolio. Last two rows of each panel present the t-statistic and p-values of the corresponding average return and $\hat{\alpha}$ estimates for the zero-investment (High-Low) portfolio where t-stats are corrected by the Newey-West procedure.

Panel A: Holding Period = 1 month

	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.004	0.011	0.003	0.011
2	-0.001	0.007	-0.002	0.006
3	-0.010	-0.002	-0.009	-0.001
4	-0.013	-0.007	-0.010	-0.004
High	-0.010	-0.006	-0.008	-0.005
High-Low	-0.014	-0.017	-0.011	-0.016
t-stat	(-3.57)	(-5.82)	(-2.76)	(-5.23)
p-value	0.00	0.00	0.00	0.00

Panel B: Holding Period = 3 months

	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.000	0.007	-0.001	0.006
2	-0.003	0.004	-0.003	0.005
3	-0.009	-0.001	-0.008	-0.001
4	-0.009	-0.003	-0.007	-0.001
High	-0.009	-0.006	-0.008	-0.006
High-Low	-0.009	-0.013	-0.007	-0.012
t-stat	(-2.24)	(-4.92)	(-1.73)	(-4.38)
p-value	0.01	0.00	0.04	0.00

Panel C: Holding Period = 6 months

	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.000	0.003	-0.001	0.005
2	-0.002	0.004	-0.001	0.005
3	-0.001	0.003	-0.002	0.002
4	-0.005	-0.003	-0.004	-0.002
High	-0.004	-0.005	-0.003	-0.005
High-Low	-0.004	-0.008	-0.003	-0.009
t-stat	(-0.90)	(-2.85)	(-0.65)	(-2.73)
p-value	0.19	0.01	0.26	0.01

Table 5: Univariate Portfolio Analysis - Quintile portfolios based on network reciprocity: In this table, we present the equally and value-weighted returns of quintile portfolios. At the end of each month, we sort our stocks into quintile portfolios based on network reciprocity measures (RCP). We follow the portfolio returns for the next one, three and six months. Panel A,B and C present the findings for one, three and six months holding period, respectively. The four-factor α is obtained through regressing the portfolio returns on the market return (BIST100), and size (SMB) and profitability (HML) of Fama and French (1993) and the momentum factor (UMD) of Carhart (1997). High-Low represents the zero investment network density portfolio which mimics the returns of an investor who has a long position in high reciprocity portfolio and a short position of equal size in the low reciprocity portfolio. Last two rows of each panel present the t-statistic and p-values of the corresponding average return and $\hat{\alpha}$ estimates for the zero-investment (High-Low) portfolio where t-stats are corrected by the Newey-West procedure.

	Panel A: Holding Period = 1 month			
	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.001	0.008	0.000	0.007
2	0.001	0.007	0.000	0.006
3	-0.005	0.001	-0.006	0.000
4	-0.010	-0.003	-0.008	-0.002
High	-0.018	-0.010	-0.014	-0.008
High-Low	-0.019	-0.018	-0.014	-0.015
t-stat	(-4.91)	(-4.53)	(-3.69)	(-4.01)
p-value	0.00	0.00	0.00	0.00
	Panel B: Holding Period = 3 months			
	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.000	0.006	-0.001	0.006
2	-0.002	0.004	-0.003	0.003
3	-0.006	0.001	-0.004	0.002
4	-0.008	-0.002	-0.008	-0.003
High	-0.014	-0.008	-0.012	-0.007
High-Low	-0.014	-0.014	-0.011	-0.013
t-stat	(-3.57)	(-4.42)	(-2.79)	(-4.02)
p-value	0.00	0.00	0.00	0.00
	Panel C: Holding Period = 6 months			
	Equally-Weighted Portfolios		**Value-Weighted Portfolios**	
	Average Return	**Four Factor α**	**Average Return**	**Four Factor α**
Low	0.000	0.004	-0.001	0.004
2	0.000	0.003	0.001	0.005
3	-0.002	0.001	-0.001	0.000
4	-0.002	0.000	-0.002	-0.001
High	-0.009	-0.007	-0.008	-0.006
High-Low	-0.010	-0.010	-0.007	-0.010
t-stat	(-2.66)	(-3.25)	(-1.93)	(-3.22)
p-value	0.00	0.00	0.03	0.00

Table 6: Multivariate Portfolio Analysis : 5x5 portfolios on global connectivity (network density) and firm-size

This table presents the characteristics of multivariate portfolios. At the beginning of each month, we divide the sample into size quintiles based on log market capitalization of previous quarter. Then, we divide each quintile into five groups based on previous month's network density measures which proxy for global connectivity. Panel A represents the time-series average of average monthly returns in each portfolio. High-Low is the average difference between High and Low connectivity portfolios. t-stat and p-value corresponds to the t-statistics and p-value of the zero-cost difference portfolio where t-stats are corrected by the Newey-West procedure. Panel B corresponds to the time-series average of the average market capitalization of each portfolio. Panel C corresponds to the time-series averages of the average network density in each portfolio.

Panel A: Average Portfolio Return

	Small Firm	**2**	**3**	**4**	**Big**
Low ND	0.008	-0.001	0.006	0.003	-0.001
2	0.000	0.003	-0.005	0.000	-0.003
3	-0.016	-0.007	-0.014	-0.007	-0.004
4	-0.020	-0.014	-0.007	-0.009	-0.003
High ND	-0.027	-0.013	-0.012	-0.003	-0.004
High-Low	-0.035	-0.012	-0.018	-0.005	-0.002
t-stat	(-4.84)	(-1.81)	(-3.45)	(-1.05)	(-0.42)
p-value	0.00	0.04	0.00	0.15	0.34

Panel B: Average Size

	Small	**2**	**3**	**4**	**Big**
Low ND	1.207	2.418	3.446	4.603	6.268
2	2.016	3.063	3.835	4.777	6.377
3	2.380	3.322	4.109	5.012	6.540
4	2.833	3.866	4.704	5.619	7.146
High ND	3.889	5.217	6.085	7.168	8.932

Panel C: Average Network Density (ND)

	Small	**2**	**3**	**4**	**Big**
Low ND	0.059	0.070	0.073	0.073	0.071
2	0.123	0.124	0.125	0.125	0.124
3	0.169	0.170	0.170	0.171	0.171
4	0.225	0.228	0.230	0.233	0.234
High ND	0.320	0.336	0.353	0.363	0.425

Table 7: Multivariate Portfolio Analysis : 5x5 portfolios on average local connectivity (WCC) and firm-size

This table presents the characteristics of multivariate portfolios. At the beginning of each month, we divide the sample into size quintiles based log market capitalization of previous quarter. Then, we divide each quintile into five groups based on previous month's weighted clustering coefficiet estimates which proxy for average connectivity. Panel A represents the time-series average of average monthly returns in each portfolio. High-Low is the average difference between High and Low connectivity portfolios. t-stat and p-value corresponds to the t-statistics and p-value of the zero-cost difference portfolio where t-stats are corrected by the Newey-West procedure. Panel B corresponds to the time-series average of the average market capitalization of each portfolio. Panel C corresponds to the time-series averages of the average network density in each portfolio.

	Panel A: Average Portfolio Return				
	Small	**2**	**3**	**4**	**Big**
Low WCC	0.009	0.001	0.010	0.002	0.000
2	0.001	-0.002	-0.001	0.000	-0.006
3	-0.018	-0.005	-0.014	-0.007	-0.006
4	-0.027	-0.020	-0.006	-0.007	-0.005
High WCC	-0.021	-0.009	-0.009	-0.004	-0.004
High-Low	-0.030	-0.011	-0.019	-0.006	-0.003
t-stat	(-4.39)	(-1.68)	(-3.56)	(-1.19)	(-0.61)
p-value	0.00	0.05	0.00	0.12	0.27

	Panel B: Average Size				
	Small	**2**	**3**	**4**	**Big**
Low WCC	1.228	2.437	3.417	4.544	6.218
2	1.995	3.030	3.775	4.677	6.230
3	2.338	3.308	4.032	4.890	6.411
4	2.812	3.845	4.655	5.505	6.948
High WCC	4.245	5.500	6.339	7.414	9.018

	Panel C: Average Local Connectivity (WCC)				
	Small	**2**	**3**	**4**	**Big**
Low WCC	0.308	0.350	0.360	0.361	0.353
2	0.479	0.485	0.486	0.485	0.484
3	0.559	0.561	0.562	0.563	0.564
4	0.635	0.637	0.640	0.645	0.646
High WCC	0.728	0.746	0.757	0.770	0.821

Table 8: Multivariate Portfolio Analysis : 5x5 portfolios on network reciprocity (RCP) and firm-size

This table presents the characteristics of multivariate portfolios. At the beginning of each month, we divide the sample into size quintiles based log market capitalization of previous quarter. Then, we divide each quintile into five groups based on previous month's network reciprocity estimates which proxy for average connectivity. Panel A represents the time-series average of average monthly returns in each portfolio. High-Low is the average difference between High and Low reciprocity portfolios. t-stat and p-value corresponds to the t-statistics and p-value of the zero-cost difference portfolio where t-stats are corrected by the Newey-West procedure. Panel B corresponds to the time-series average of the average market capitalization of each portfolio. Panel C corresponds to the time-series averages of the average reciprocity in each portfolio.

	Panel A: Average Portfolio Return				
	Small	**2**	**3**	**4**	**Big**
Low RCP	0.005	0.004	-0.002	-0.001	-0.001
2	0.004	0.000	0.001	0.000	-0.001
3	-0.001	-0.002	-0.004	-0.005	-0.010
4	-0.016	-0.010	-0.015	-0.003	-0.003
High RCP	-0.030	-0.016	-0.022	-0.018	-0.003
High-Low	-0.035	-0.020	-0.020	-0.016	-0.002
t-stat	(-5.10)	(-3.17)	(-3.26)	(-3.07)	(-0.42)
p-value	0.00	0.00	0.00	0.00	0.34

	Panel B: Average Size				
	Small	**2**	**3**	**4**	**Big**
Low RCP	1.563	3.178	4.398	5.456	6.722
2	2.039	3.329	4.280	5.368	6.938
3	2.252	3.402	4.296	5.393	7.122
4	2.369	3.472	4.375	5.474	7.418
High RCP	2.740	3.967	4.913	6.041	8.342

	Panel C: Average Reciprocity (RCP)				
	Small	**2**	**3**	**4**	**Big**
Low RCP	0.502	0.546	0.554	0.544	0.551
2	0.651	0.651	0.651	0.650	0.651
3	0.702	0.702	0.703	0.702	0.703
4	0.748	0.749	0.749	0.749	0.750
High RCP	0.806	0.811	0.814	0.814	0.823

Table 9: Multivariate Portfolio Analysis: 5x5 portfolios on global connectivity (network density) and BETA. This table presents the characteristics of multivariate portfolios. At the beginning of each month, we divide sample into beta quintiles based on previous month estimate. Then, we divide each quintile into five groups based on previous month's network density measures which proxy for global connectivity. Panel A represents the time-series average of average monthly returns in each portfolio. High-Low is the average difference between High and Low connectivity portfolios. t-stat and p-value corresponds to the t-statistics and p-value of the zero-cost difference portfolio where t-stats are corrected by the Newey-West procedure. Panel B corresponds to the time-series average of the average market risk (BETA) of each portfolio. Panel C corresponds to the time-series averages of the average network density in each portfolio.

	Panel A: Average Portfolio Return				
	Low BETA	**2**	**3**	**4**	**High BETA**
Low ND	0.002	-0.001	0.005	0.003	0.006
2	-0.005	-0.006	-0.003	0.006	0.002
3	-0.020	-0.008	-0.006	-0.005	-0.007
4	-0.018	-0.011	-0.007	-0.008	-0.011
High ND	-0.016	-0.013	-0.007	-0.005	-0.018
High-Low	-0.018	-0.012	-0.012	-0.007	-0.024
t-stat	(-2.57)	(-2.49)	(-2.27)	(-1.37)	(-4.11)
p-value	0.01	0.01	0.02	0.09	0.00

	Panel B: Average BETA				
	Low BETA	**2**	**3**	**4**	**High BETA**
Low ND	0.197	0.462	0.590	0.717	0.986
2	0.301	0.561	0.686	0.807	1.049
3	0.292	0.606	0.747	0.882	1.144
4	0.301	0.650	0.798	0.941	1.235
High ND	0.348	0.744	0.918	1.095	1.417

	Panel C: Average Network Density (ND)				
	Low BETA	**2**	**3**	**4**	**High BETA**
Low ND	0.078	0.078	0.087	0.091	0.092
2	0.138	0.137	0.136	0.133	0.134
3	0.175	0.177	0.179	0.176	0.170
4	0.238	0.240	0.231	0.237	0.232
High ND	0.391	0.318	0.320	0.370	0.331

Table 10: Multivariate Portfolio Analysis: 5x5 portfolios on average local connectivity (WCC) and BETA. This table presents the characteristics of multivariate portfolios. At the beginning of each month, we divide sample into beta quintiles based on previous month estimate. Then, we divide each quintile into five groups based on previous month's weighted clustering coefficient estimates which proxy for average connectivity. Panel A represents the time-series average of average monthly returns in each portfolio. High-Low is the average difference between High and Low connectivity portfolios. t-stat and p-value corresponds to the t-statistics and p-value of the zero-cost difference portfolio where t-stats are corrected by the Newey-West procedure. Panel B corresponds to the time-series average of the average market risk (BETA) of each portfolio. Panel C corresponds to the time-series averages of the average network density in each portfolio.

	Panel A: Average Portfolio Return				
	Low BETA	**2**	**3**	**4**	**High BETA**
Low WCC	0.005	0.001	0.004	0.004	0.007
2	-0.006	-0.005	-0.001	0.001	0.005
3	-0.022	-0.012	-0.005	-0.002	-0.011
4	-0.021	-0.013	-0.009	-0.007	-0.016
High WCC	-0.010	-0.011	-0.006	-0.006	-0.015
High-Low	-0.015	-0.012	-0.010	-0.010	-0.022
t-stat	(-2.38)	(-2.39)	(-1.94)	(-1.76)	(-3.78)
p-value	0.01	0.01	0.03	0.04	0.00

	Panel B: Average BETA				
	Low BETA	**2**	**3**	**4**	**High BETA**
Low WCC	0.209	0.469	0.598	0.725	0.991
2	0.303	0.563	0.688	0.811	1.047
3	0.282	0.596	0.742	0.881	1.147
4	0.259	0.634	0.792	0.940	1.252
High WCC	0.382	0.751	0.918	1.089	1.403

	Panel C: Average Local Connectivity (WCC)				
	Low BETA	**2**	**3**	**4**	**High BETA**
Low WCC	0.318	0.343	0.350	0.362	0.358
2	0.482	0.482	0.484	0.483	0.487
3	0.560	0.560	0.561	0.563	0.564
4	0.639	0.639	0.639	0.643	0.643
High WCC	0.747	0.750	0.759	0.772	0.792

Table 11: Multivariate Portfolio Analysis: 5x5 portfolios on network reciprocity (RCP) and BETA. This table presents the characteristics of multivariate portfolios. At the beginning of each month, we divide sample into beta quintiles based on previous month estimates. Then, we divide each quintile into five groups based on previous month's network reciprocity estimates. Panel A represents the time-series average of average monthly returns in each portfolio. High-Low is the average difference between High and Low reciprocity portfolios. t-stat and p-value corresponds to the t-statistics and p-value of the zero cost difference portfolio where t-stats are corrected by the Newey-West procedure. Panel B corresponds to the time-series average of the average market risk (BETA) of each portfolio. Panel C corresponds to the time-series averages of the average reciprocity in each portfolio.

Panel A: Average Portfolio Return

	Low BETA	**2**	**3**	**4**	**High BETA**
Low RCP	0.003	-0.002	0.000	0.005	0.000
2	0.001	-0.003	-0.002	0.004	0.002
3	-0.008	-0.006	-0.001	-0.003	-0.003
4	-0.018	-0.014	-0.010	-0.001	-0.006
High RCP	-0.029	-0.013	-0.012	-0.015	-0.020
High-Low	-0.032	-0.011	-0.012	-0.020	-0.020
t-stat	(-4.82)	(-2.00)	(-2.12)	(-3.82)	(-3.34)
p-value	0.00	0.02	0.02	0.00	0.00

Panel B: Average BETA

	Low BETA	**2**	**3**	**4**	**High BETA**
Low RCP	0.218	0.472	0.601	0.734	0.998
2	0.326	0.574	0.702	0.827	1.060
3	0.341	0.618	0.750	0.882	1.134
4	0.326	0.649	0.797	0.942	1.221
High RCP	0.215	0.678	0.880	1.079	1.447

Panel C: Average Network Reciprocity (RCP)

	Low BETA	**2**	**3**	**4**	**High BETA**
Low RCP	0.510	0.535	0.545	0.557	0.551
2	0.650	0.649	0.650	0.651	0.653
3	0.702	0.702	0.702	0.703	0.704
4	0.748	0.748	0.749	0.749	0.750
High RCP	0.813	0.808	0.808	0.812	0.826

Table 12: Fama-French four-factor Results - We run the following regression on the time series of monthly returns of five zero-cost connectivity-size portfolios: $R_p = \vartheta_p^1 + \vartheta_p^2 R_m + \vartheta_p^3 SMB + \vartheta_p^4 HML + \vartheta_p^5 UMD + \epsilon_p$. The sample period is between January 2006 - November 2015. Panel A provides the results for multivariate portfolios constructed using the global connectivity measure (network density). Panel B provides the results for multivariate portfolios constructed using the average local connectivity measure (weighted clustering coefficient). Panel C provides the results for multivariate portfolios constructed using the network reciprocity. We provide the coefficient estimates and their respective t-statistics in the table. For goodness of fit, we provide adjusted R^2 measures along with F statistics. Last two rows, provide the Gibbons et al. (1989) test statistics for the null hypothesis that $\hat{\vartheta}^1 = 0$.

	Panel A: Global Connectivity (ND) - Size Portfolios				
	Small	**2**	**3**	**4**	**Big**
ϑ_p^1	-0.025	-0.014	-0.023	-0.013	-0.010
	(-3.42)	(-2.17)	(-4.41)	(-2.88)	(-1.94)
ϑ_p^2	0.347	0.220	0.167	0.195	0.248
	(4.94)	(3.53)	(3.35)	(4.49)	(5.05)
ϑ_p^3	-0.289	-0.867	-0.539	-0.733	-0.556
	(-1.24)	(-4.21)	(-3.27)	(-5.11)	(-3.42)
ϑ_p^4	-0.663	0.090	0.291	0.460	0.508
	(-2.85)	(0.44)	(1.76)	(3.20)	(3.12)
ϑ_p^5	0.641	0.057	-0.142	-0.218	-0.055
	(3.18)	(0.32)	(-0.99)	(-1.76)	(-0.39)
F-Stat	10.004	11.633	10.830	23.788	18.511
Adj. R^2	24%	27%	25%	44%	37%
GRS Test Statistics	7.788				
p-value (GRS)	(0.00)				

	Panel B: Local Connectivity (WCC) - Size Portfolios				
	Small	**2**	**3**	**4**	**Big**
ϑ_p^1	-0.026	-0.013	-0.021	-0.011	-0.012
	(-3.71)	(-2.06)	(-4.11)	(-2.40)	(-2.30)
ϑ_p^2	0.264	0.188	0.135	0.177	0.222
	(3.90)	(3.13)	(2.67)	(3.87)	(4.42)
ϑ_p^3	-0.620	-0.873	-0.707	-0.570	-0.678
	(-2.77)	(-4.40)	(-4.22)	(-3.78)	(-4.08)
ϑ_p^4	-0.299	0.093	0.137	0.322	0.560
	(-1.33)	(0.47)	(0.81)	(2.13)	(3.36)
ϑ_p^5	0.480	0.069	-0.073	-0.230	-0.078
	(2.48)	(0.40)	(-0.51)	(-1.76)	(-0.54)
F-Stat	8.848	10.892	9.985	15.997	17.934
Adj. R^2	21%	25%	23%	34%	37%
GRS Test Statistics	8.176				
p-value (GRS)	(0.00)				

	Panel C: Reciprocity - Size Portfolios				
	Small	**2**	**3**	**4**	**Big**
ϑ_p^1	-0.025	-0.020	-0.015	-0.023	-0.005
	(-3.40)	(-2.76)	(-2.32)	(-4.01)	(-0.93)
ϑ_p^2	0.283	0.110	0.185	-0.029	0.254
	(3.91)	(1.58)	(2.89)	(-0.52)	(4.68)
ϑ_p^3	0.502	0.016	0.022	-0.502	-0.243
	(2.10)	(0.07)	(0.10)	(-2.70)	(-1.35)
ϑ_p^4	-0.569	-0.027	-0.288	0.392	0.202
	(-2.37)	(-0.12)	(-1.36)	(2.11)	(1.12)
ϑ_p^5	0.395	-0.203	-0.046	-0.415	-0.144
	(1.91)	(-1.02)	(-0.25)	(-2.58)	(-0.93)
F-Stat	4.427	1.829	3.558	4.050	11.983
Adj. R^2	10%	3%	8%	9%	27%
GRS Test Statistics	5.353				
p-value (GRS)	(0.00)				

Table 13: Fama-MacBeth Regressions for global connectivity (network density):

This table presents the results of Fama-MacBeth regressions. $R_{i,t+h} = \gamma_{0,t} + \gamma_{1,t}ND_{i,t} + \gamma_{2,t}BETA_{i,t} + \gamma_{3,t}SIZE_{i,t} + \gamma_{4,t}BTM_{i,t} + \gamma'_{5,t}X_{i,t} + \epsilon_{i,t}$ Each month, we regress the stock returns on previous months network density measure (ND) along with the control factors BETA, SIZE, BTM, MOM, REV, ILLIQ, MAX and IVOL. Entries in the table are the time-series averages of the slope coefficients obtained from the cross-sectional regressions. Values in parenthesis present the corresponding t-statistics calculated using Newey and West (1987) standard errors. Panel A,B and C present the results for a holding period (h) of 1-month, 3 months and 6 months, respectively. ***,**,* indicates statistical significance at 1%, 5%, 10%, respectively.

Panel A: Holding Period = 1 month

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
ND	-0.044	-0.051	-0.063	-0.041	-0.044	-0.039	-0.033	-0.033	-0.048	-0.043
	(3.330)***	(4.243)***	(4.712)***	(3.074)***	(3.309)***	(3.067)***	(2.337)**	(2.302)**	(3.647)***	(3.145)***
BETA		0.008								0.002
		(2.139)**								(0.573)
SIZE			0.002							0.001
			(2.444)**							(1.317)
BTM				0.007						0.006
				(5.137)***						(5.009)***
MOM					-0.014					-0.006
					(2.334)**					(1.107)
ILLIQ						2.425				3.660
						(0.653)				(1.108)
MAX							-0.165			0.043
							(5.021)***			(0.757)
IVOL								-0.708		-0.774
								(6.155)***		(4.115)***
REV									0.005	0.010
									(0.375)	(0.707)
Intercept	0.003	-0.002	-0.003	0.003	0.001	0.001	0.012	0.016	0.002	0.007
	(0.291)	(0.275)	(0.278)	(0.321)	(0.119)	(0.143)	(1.150)	(1.578)	(0.222)	(0.671)
R^2	0.01	0.02	0.03	0.03	0.04	0.02	0.03	0.04	0.04	0.11
N	37,328	37,326	37,328	37,328	36,778	37,324	37,328	37,326	37,328	36,772

Panel B: Holding Period = 3 months

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
ND	-0.029	-0.034	-0.042	-0.027	-0.029	-0.029	-0.021	-0.023	-0.030	-0.038
	(2.165)**	(2.552)**	(3.014)***	(1.964)*	(2.191)**	(2.183)**	(1.467)	(1.590)	(2.168)**	(2.823)***
BETA		0.005								0.001
		(1.532)								(0.231)
SIZE			0.001							0.002
			(1.817)*							(1.974)*
BTM				0.006						0.005
				(4.627)***						(4.266)***
MOM					-0.013					-0.011
					(3.040)***					(2.579)**
ILLIQ						-5.147				-3.408
						(1.272)				(0.771)
MAX							-0.118			-0.036
							(3.767)***			(0.836)
IVOL								-0.407		-0.200
								(3.878)***		(1.473)
REV									-0.007	-0.005
									(0.822)	(0.465)
Intercept	-0.001	-0.003	-0.005	-0.001	-0.002	-0.001	0.004	0.006	-0.001	-0.003
	(0.079)	(0.347)	(0.506)	(0.077)	(0.240)	(0.092)	(0.422)	(0.636)	(0.096)	(0.295)
R^2	0.01	0.02	0.03	0.03	0.03	0.02	0.03	0.03	0.02	0.09
N	36,464	36,463	36,464	36,464	35,925	36,460	36,464	36,463	36,464	35,920

Panel C: Holding Period = 6 months

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
ND	-0.018	-0.021	-0.029	-0.016	-0.020	-0.016	-0.014	-0.015	-0.020	-0.026
	(1.323)	(1.549)	(2.133)**	(1.166)	(1.467)	(1.150)	(0.989)	(1.024)	(1.505)	(1.773)*
BETA		0.004								-0.000
		(1.105)								(0.002)
SIZE			0.001							0.001
			(1.474)							(1.282)
BTM				0.005						0.005
				(3.929)***						(3.787)***
MOM					-0.007					-0.004
					(1.749)*					(0.927)
ILLIQ						-3.936				-3.915
						(0.744)				(0.797)
MAX							-0.055			0.001
							(1.975)*			(0.026)
IVOL								-0.219		-0.135
								(2.549)**		(0.807)
REV									0.007	-0.000
									(0.870)	(0.018)
Intercept	0.001	-0.001	-0.003	0.001	-0.001	0.000	0.003	0.005	0.001	-0.002
	(0.092)	(0.113)	(0.286)	(0.156)	(0.113)	(0.035)	(0.336)	(0.527)	(0.057)	(0.152)
R^2	0.01	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.02	0.08
N	35,196	35,196	35,196	35,196	34,669	35,192	35,196	35,196	35,196	34,665

Table 14: Fama-MacBeth Regressions for average local network connectivity (WCC):

This table presents the results of Fama-MacBeth regressions. $R_{i,t+h} = \gamma_{0,t} + \gamma_{1,t} WCC_{i,t} + \gamma_{2,t} BETA_{i,t} + \gamma_{3,t} SIZE_{i,t} + \gamma_{4,t} BTM_{i,t} + \gamma'_{5,t} X_{i,t} + \epsilon_{i,t}$. Each month, we regress the stock returns on previous months average local connectivity measure (WCC) along with the control factors BETA, SIZE, BTM, MOM, REV, ILLIQ, MAX, and IVOL. Entries in the table are the time-series averages of the slope coefficients obtained from the cross-sectional regressions. Values in parenthesis present the corresponding t-statistics calculated using Newey and West (1987) standard errors. Panel A,B and C present the results for a holding period (h) of 1-month, 3 months and 6 months, respectively. ***,**,* indicates statistical significance at 1%, 5%, 10%, respectively.

Panel A: Holding Period = 1 month

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WCC	-0.036	-0.042	-0.051	-0.034	-0.036	-0.034	-0.029	-0.030	-0.040	-0.037
	(3.753)***	(4.640)***	(5.162)***	(3.452)***	(3.751)***	(3.584)***	(2.867)***	(2.874)***	(4.084)***	(3.804)***
BETA		0.008								0.002
		(2.223)**								(0.667)
SIZE			0.002							0.001
			(2.644)***							(1.450)
BTM				0.006						0.006
				(5.013)***						(4.938)***
MOM					-0.014					-0.006
					(2.309)**					(1.103)
ILLIQ						0.572				1.470
						(0.157)				(0.467)
MAX							-0.162			0.040
							(5.027)***			(0.712)
IVOL								-0.699		-0.748
								(6.129)***		(4.006)***
REV									0.006	0.011
									(0.439)	(0.776)
Intercept	0.015	0.011	0.013	0.014	0.013	0.014	0.022	0.027	0.015	0.019
	(1.576)	(1.284)	(1.293)	(1.512)	(1.391)	(1.396)	(2.239)**	(2.697)***	(1.662)*	(2.064)**
R^2	0.01	0.02	0.03	0.03	0.04	0.02	0.03	0.04	0.04	0.11
N	37,328	37,326	37,328	37,328	36,778	37,324	37,328	37,326	37,328	36,772

Panel B: Holding Period = 3 months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WCC	-0.022	-0.026	-0.033	-0.020	-0.022	-0.022	-0.017	-0.019	-0.023	-0.029
	(2.224)**	(2.642)***	(3.066)***	(1.981)*	(2.194)**	(2.190)**	(1.629)	(1.785)*	(2.261)**	(2.771)***
BETA		0.005								0.001
		(1.633)								(0.233)
SIZE			0.002							0.002
			(1.916)*							(1.945)*
BTM				0.006						0.005
				(4.587)***						(4.272)***
MOM					-0.013					-0.011
					(3.016)***					(2.601)**
ILLIQ						-6.086				-3.721
						(1.459)				(0.903)
MAX							-0.115			-0.040
							(3.659)***			(0.923)
IVOL								-0.396		-0.183
								(3.782)***		(1.339)
REV									-0.007	-0.004
									(0.742)	(0.386)
Intercept	0.006	0.005	0.004	0.006	0.004	0.006	0.010	0.012	0.006	0.006
	(0.726)	(0.564)	(0.485)	(0.639)	(0.516)	(0.700)	(1.121)	(1.412)	(0.749)	(0.630)
R^2	0.02	0.02	0.03	0.03	0.03	0.02	0.03	0.03	0.03	0.09
N	36,464	36,463	36,464	36,464	35,925	36,460	36,464	36,463	36,464	35,920

Panel C: Holding Period = 6 months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
WCC	-0.011	-0.012	-0.019	-0.010	-0.012	-0.009	-0.008	-0.009	-0.013	-0.015
	(1.082)	(1.202)	(1.804)*	(0.916)	(1.194)	(0.823)	(0.786)	(0.853)	(1.253)	(1.264)
BETA		0.003								-0.001
		(0.870)								(0.158)
SIZE			0.001							0.001
			(1.371)							(1.097)
BTM				0.005						0.005
				(3.901)***						(3.734)***
MOM					-0.007					-0.004
					(1.803)*					(0.979)
ILLIQ						-4.139				-5.013
						(0.855)				(1.017)
MAX							-0.058			-0.002
							(2.108)**			(0.028)
IVOL								-0.225		-0.143
								(2.650)***		(0.854)
REV									0.006	-0.002
									(0.783)	(0.153)
Intercept	0.004	0.003	0.002	0.004	0.002	0.002	0.006	0.008	0.004	0.004
	(0.429)	(0.301)	(0.276)	(0.433)	(0.250)	(0.262)	(0.637)	(0.870)	(0.445)	(0.381)
R^2	0.02	0.02	0.03	0.03	0.03	0.02	0.02	0.03	0.02	0.08
N	35,196	35,196	35,196	35,196	34,669	35,192	35,196	35,196	35,196	34,665

Table 15: Fama-MacBeth Regressions for network reciprocity:

This table presents the results of Fama-MacBeth regressions. $R_{i,t+h} = \gamma_{0,t} + \gamma_{1,t} RCP_{i,t} + \gamma_{2,t} BETA_{i,t} + \gamma_{3,t} SIZE_{i,t} + \gamma_{4,t} BTM_{i,t} + \gamma'_{5,t} X_{i,t} + \epsilon_{i,t}$. Each month, we regress the stock returns on previous months network reciprocity measures (RCP) along with the control factors BETA, SIZE, BTM, MOM, REV, ILLIQ, MAX, and IVOL. Entries in the table are the time-series averages of the slope coefficients obtained from the cross-sectional regressions. Values in parenthesis present the corresponding t-statistics calculated using Newey and West (1987) standard errors. Panel A,B and C present the results for a holding period (h) of 1-month, 3 months and 6 months, respectively. ***,**,* indicates statistical significance at 1%, 5%, 10%, respectively.

Panel A: Holding Period = 1 month

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RCP	-0.069 (5.073)***	-0.075 (5.804)***	-0.070 (5.207)***	-0.064 (4.752)***	-0.068 (4.983)***	-0.066 (4.700)***	-0.052 (3.508)***	-0.048 (3.150)***	-0.073 (5.295)***	-0.037 (2.590)**
BETA		0.006 (1.541)								-0.001 (0.252)
SIZE			0.001 (0.903)							0.000 (0.010)
BTM				0.006 (4.751)***						0.005 (4.245)***
MOM					-0.013 (2.244)**					-0.007 (1.137)
ILLIQ						3.144 (0.555)				3.724 (0.866)
MAX							-0.144 (4.219)***			0.059 (1.027)
IVOL								-0.636 (5.280)***		-0.803 (4.307)***
REV									0.007 (0.484)	0.008 (0.521)
Intercept	0.043 (3.948)***	0.042 (3.972)***	0.040 (3.560)***	0.040 (3.773)***	0.040 (3.805)***	0.040 (3.422)***	0.041 (3.987)***	0.042 (4.194)***	0.043 (4.128)***	0.032 (3.054)***
R^2	0.02	0.03	0.03	0.02	0.04	0.02	0.03	0.04	0.04	0.11
N	37,328	37,326	37,328	37,328	36,778	37,324	37,328	37,326	37,328	36,772

Panel B: Holding Period = 3 months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RCP	-0.048 (3.438)***	-0.052 (3.819)***	-0.050 (3.614)***	-0.043 (3.049)***	-0.048 (3.474)***	-0.048 (3.381)***	-0.038 (2.606)**	-0.038 (2.604)**	-0.049 (3.425)***	-0.039 (2.893)***
BETA		0.005 (1.459)								0.000 (0.044)
SIZE			0.001 (0.920)							0.001 (0.987)
BTM				0.006 (4.347)***						0.005 (3.554)***
MOM					-0.014 (3.096)***					-0.011 (2.686)***
ILLIQ						-5.930 (1.321)				-5.266 (1.128)
MAX							-0.095 (3.099)***			-0.028 (0.653)
IVOL								-0.336 (3.199)***		-0.207 (1.577)
REV									-0.006 (0.708)	-0.006 (0.560)
Intercept	0.027 (3.067)***	0.027 (3.010)***	0.026 (2.769)***	0.024 (2.746)***	0.026 (2.907)***	0.028 (2.805)***	0.026 (3.032)***	0.027 (3.193)***	0.027 (3.115)***	0.021 (2.283)**
R^2	0.01	0.02	0.03	0.02	0.03	0.02	0.02	0.03	0.02	0.09
N	36,464	36,463	36,464	36,464	35,925	36,460	36,464	36,463	36,464	35,920

Panel C: Holding Period = 6 months

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
RCP	-0.029 (2.181)**	-0.030 (2.342)**	-0.032 (2.442)**	-0.026 (1.863)*	-0.027 (2.051)**	-0.026 (1.902)*	-0.024 (1.762)*	-0.023 (1.643)	-0.031 (2.353)**	-0.019 (1.387)
BETA		0.003 (0.816)								-0.000 (0.123)
SIZE			0.001 (0.827)							0.001 (0.659)
BTM				0.005 (3.716)***						0.004 (3.331)***
MOM					-0.008 (1.968)*					-0.004 (1.058)
ILLIQ						-3.956 (0.650)				-4.381 (0.794)
MAX							-0.045 (1.649)			-0.004 (0.080)
IVOL								-0.196 (2.284)**		-0.132 (0.806)
REV									0.005 (0.552)	-0.002 (0.194)
Intercept	0.018 (2.150)**	0.016 (1.948)*	0.017 (1.983)**	0.016 (1.955)*	0.015 (1.784)*	0.016 (1.704)*	0.017 (2.077)**	0.018 (2.174)**	0.019 (2.240)**	0.010 (1.068)
R^2	0.01	0.02	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.08
N	35,196	35,196	35,196	35,196	34,669	35,192	35,196	35,196	35,196	34,665

Table 16: Transition Matrix: In this table, we present the transition probabilities. Panel A, B and C respectively present the probabilities that an average stock will move from quintile i (defined by the rows) in a given month to quintile j (defined by the columns) throughout our sample for network density, weighted clustering coefficient and network reciprocity measures. All results presented in this table are portfolios with one-month holding period.

Panel A: Network Density					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**
Quintile 1	53.2%	25.5%	13.9%	6.1%	1.4%
Quintile 2	23.4%	31.5%	26.0%	15.1%	4.0%
Quintile 3	12.9%	23.3%	28.3%	25.9%	9.6%
Quintile 4	6.6%	14.9%	23.2%	31.3%	23.9%
Quintile 5	2.7%	5.3%	9.6%	21.5%	60.8%
Panel B: Weighted Clustering Coefficient					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**
Quintile 1	51.3%	26.3%	14.8%	6.4%	1.2%
Quintile 2	23.5%	31.0%	26.9%	15.4%	3.2%
Quintile 3	14.2%	23.7%	27.8%	25.8%	8.4%
Quintile 4	7.4%	15.1%	23.3%	33.4%	20.8%
Quintile 5	2.2%	4.5%	8.1%	19.2%	66.0%
Panel C: Network Reciprocity					
	Quintile 1	**Quintile 2**	**Quintile 3**	**Quintile 4**	**Quintile 5**
Quintile 1	48.0%	25.5%	14.0%	8.4%	4.1%
Quintile 2	23.0%	27.0%	23.1%	17.9%	9.1%
Quintile 3	12.7%	21.7%	25.7%	23.9%	16.1%
Quintile 4	8.7%	15.3%	22.1%	26.7%	27.3%
Quintile 5	5.9%	10.7%	15.5%	23.5%	44.4%