Centralities in Illiquidity Transmission Networks and the Cross-Section of Expected Returns*

Bixi Jian†
McGill University

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Abstract

This paper investigates the relationship between stock illiquidity spillovers and the cross-section of expected returns. I study industry-level illiquidity spillovers in a directed network that describes the interconnections among stocks' bid-ask spreads, where the interconnections are latent and are estimated by a Granger-type measure. In the directed illiquidity transmission network, the illiquidity of high sensitive centrality (SC) industries, i.e., those active at receiving illiquidity from others, as well as high influential centrality (IC) industries, i.e., those active at transferring illiquidity to others, tends to covary with that of their neighbours and neighbours' neighbours across different horizons due to illiquidity spillovers. As a result, long run returns of the portfolios that contain stocks of central (high SC or high IC) industries may be more volatile because of weak diversification of the liquidity risk across different horizons. Thus, investors would require compensations for holding these central stocks. I confirm this conjecture and find that central industries in illiquidity transmission networks do earn higher average stock returns (around 4 % per year) than other industries. Market-beta, size, book-to-market, momentum, liquidity and idiosyncratic volatility effects cannot account for the high average return earned by central industries.

Keywords: Illiquidity spillovers; Network; Cross-Section Returns; Eigenvector Centrality; Bid-Ask Spreads; Granger Causality

JEL: G1; G12; C5; L1

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† Department of Economics, McGill University, Mailing Address: Department of Economics, McGill University, Leacock Building, 855 Sherbrooke Street West, Montreal, Quebec H3A 2T7, Canada. TEL: (1) 514 998 9885. Email: bixi.jian@mail.mcgill.ca . Web page: www.bixijian.com

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1 Introduction

Liquidity plays a central role in the functioning of financial markets. Stock market liquidity is documented as being closely related to business cycles (Næs, Skjeltorp and Ødegaard (2011)), stock market returns (Amihud (2002)) and cross-sectional returns (Pastor and Stambaugh (2003)). In a financial market where everyone is probably connected to everybody else, the illiquidity risk exposure for a firm is not only related to its idiosyncratic liquidity level and its correlation to market liquidity conditions, but also closely related to the properties of the connected individual firm. For example, a firm's poor liquidity condition could be a result of drops in liquidity of its connected firms due to illiquidity transmissions (see Oh (2013) and Cespa and Foucault (2014) among others). Current literature on illiquidity transmissions is mainly focusing on undirected commonality and aggregated contagion in liquidity,[1] and on directed illiquidity spillovers between two firms, two stocks and two markets.[2] In the recent financial crisis, however, we observe that a major market-wide liquidity problem could be a result of illiquidity spillovers originated from "important" industries, e.g., the financial industry. Not much attention is put on understanding the heterogeneity in market-wide illiquidity spillovers. To better understand this issue, this paper investigates the spillover risk of illiquidity through modeling the market-wide illiquidity spillovers in a directed network that describes the interconnections among industries' idiosyncratic illiquidity risks.[3] Then I examine the relationship between the heterogeneous roles of industries in illiquidity spillovers and the cross-section of expected returns.

When studying illiquidity spillovers in network analysis, we can explore the architecture of the spillovers as a mechanism of how individual illiquidity evolves within an "illiquidity network". This exploration involves looking into the underlying illiquidity transmission structure, rather than just superficially treating the aggregated market illiquidity as a given outcome. In network analysis, centrality is a concept referring to a node's position in the functioning of network spillovers. Actually, a directed network assumption is straightforward

[1] See Cifuentes, Ferrucci and Shin (2005), Brockman, Chung and Pérignon (2009), Hameed, Kang and Viswanathan (2010), Karolyi, Lee and van Dijk (2012), Koch, Ruenzi and Starks (2016) among the most recent studies.

[2] See, e.g., Goyenko and Ukhov (2009), Oh (2013) and Cespa and Foucault (2014).

[3] Hameed et al. (2010) document inter-industry spillover effects in liquidity, which are likely to arise from capital constraints in the market making sector.

but implicit when considering network spillovers as any financial spillover must have a direction with a source and a target. In this regard, I study network centrality in two directions: i) sensitive centrality (SC), which measures the degree of an industry being affected by others, and ii) influential centrality (IC), which measures the degree of an industry affecting others. In an illiquidity transmission network, high SC industries are the ones whose illiquidity can easily be affected by the illiquidity of other industries, while high IC industries are the one whose illiquidity can easily affect others' illiquidity. As a result, central (high SC or high IC) industries tend to play a major role in network spillovers, compared to those are isolated with others.[4] I also assume a neighbour effect: being affected by high SC industries makes an industry more likely to be a high SC industry, and affecting high IC industries makes an industry more likely to be a high IC industry as well. Thus, an industry's centrality also takes its connected industries' centralities into account, providing the characteristics of what kind of neighbours it is connected to in terms of the role in network spillovers. Implications of influential centrality in network analysis have drawn growing attention in the literature of financial systemic risk. For example, Acemoglu, Carvalho, Ozdaglar and Tahbaz-Salehi (2012) and Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) use asymmetric network structures to show the possibility that aggregate fluctuations may originate from idiosyncratic shocks to high IC firms. However, research on sensitive centrality is missing in the existing literature on financial network. I argue that SC is least as important as IC in terms of asset pricing. In this paper, I provide a comprehensive analysis on sensitive centrality and influential centrality simultaneously in a directed illiquidity network context.

Intuitively speaking, illiquidity spillovers would lead the illiquidity of a central industry to covary with that of its connected neighbours and neighbours' neighbours across different horizons due to illiquidity spillovers, thus long run returns of the portfolios that contain these central stocks may be more volatile due to weak diversification of the liquidity risk across different horizons. Since a high SC industry's illiquidity is easily affected by the illiquidity of other industries, investors will demand a premium for holding this high SC stock as agents demand compensation for not being able to use this stock to diversify the liquidity risk of others. Similarly, since it is difficult to find other stocks to diversify a high IC industry's

[4]An industry is isolated in a network means it is not connected to anybody in this network.

liquidity risk as the high IC industry's illiquidity would easily affect others' illiquidity, the high IC stocks should also earn a premium. The goal of this paper is to investigate whether such illiquidity centralities (SC and IC) are risk factors in asset pricing where industries are connected in an illiquidity network. I resolve this issue by examining the cross-sectional relationship between the illiquidity centralities and expected returns. Based on the argument stated above, my conjecture is that central stocks will earn higher average returns. The IC measured from other economic networks has already been documented as a risk factor in recent literature on network and asset pricing (see, e.g., Buraschi and Porchia (2012) and Ahern (2013)), but the result about SC is still missing. Indeed, the empirical result in this paper provides strong evidence to support my conjecture that both SC and IC industries do earn higher average returns. Interestingly, my robustness check suggests the effects of SC are even more robust than IC.

In this paper, illiquidity spillovers, network centralities and cross-sectional expected returns are to be explored together. To verify my previous conjecture, we need a new analytical procedure that includes four main steps: i) measuring industry's illiquidity, ii) estimating the illiquidity transmission network among different industries, iii) calculating centralities in the illiquidity network, and iv) examining the cross-sectional relationship between illiquidity centralities and expected returns.

First, liquidity has many dimensions; this paper focuses on a dimension associated with bid-ask spreads in stock markets, which reflects the difficulty (cost) of stocks' transactions. I use Corwin and Schultz (2012)'s bid-ask spreads estimate to measure firms' daily illiquidity. Industry's illiquidity is measured by the simple average of the individual bid-ask spreads estimates of the firms that belong to this industry.

Then adapting the financial network estimation technique suggested by Billio, Getmansky, Lo and Pelizzon (2012) and Dufour and Jian (2016), I use a Granger-type measure to estimate the directed relationships between every pair of industries in the stock market.[5] I identify the directed illiquidity spillover from industry A to industry B by testing if the marginal effect of industry A's past illiquidity on industry B's current illiquidity is positive. The estimated illiquidity transmission network can be represented by an adjacency matrix.

[5]Actually, I focus on the industry level just for feasibility of implementation.

Once we have the estimate of the adjacency matrix of the illiquidity transmission network, I take it as given and use Bonacich (1987)'s generalized eigenvector centrality measure, which is built on the neighbour effect assumption, to calculate industries' sensitive centralities and influential centralities in the illiquidity network. I re-estimate industries' centralities each year by the subsample in that year, then we obtain the annual series (1963 - 2015) of industries' centralities (SC and IC). In fact, high SC and high IC tend to coexist and are persistent in an industry. I find that industries' illiquidity sensitive and influential centralities are positively correlated in time-series and in cross-section.

Following the classic procedure used by Fama and French (1992), I examine the cross-sectional relationship between the illiquidity centralities and expected returns at portfolio level as well as at industry level. Sorting industries by their respective SC and IC at the beginning of each year, I form portfolios in 10 deciles based on SC and IC, respectively. I find that with the portfolios rebalanced annually, average return differences between industries in the highest and lowest SC deciles and average return differences between industries in the highest and lowest IC deciles exceed 4% per year. The corresponding Fama-French-Carhart four-factor alphas also exceed 4% per year. Both the return differences and the four-factor alpha differences are economically and statistically significant at all standard significance levels. Not surprisingly, industries' centralities have relation with some well-known risk factors. For example, high SC industries tend to be those industries with small average firm size and high average book-to-market and low liquidity. To ensure that it is not these characteristics, but the illiquidity centralities (SC and IC), that drive the return differences documented in this paper, I perform a battery of bivariate sorts and re-examine the raw return and alpha differences. These results are robust to controls for market-beta, size, book-to-market, momentum, liquidity and idiosyncratic volatility. Results from cross-sectional regressions corroborate this evidence. The risk premium between the highest and the lowest deciles of SC and the premium of IC estimated by the Fama-MacBeth two-step procedure are approximately 9% per year and 12% per year, respectively. A robustness check for different subperiods (1970 - 2015, 1980 - 2015, 1990 - 2015 and 2000 - 2015) suggests the effects of SC are even more robust than IC. In short, the illiquidity centralities (SC and IC) do earn premiums in the cross-section of expected returns.

The rest of this paper is organized as follows. Section 2 discusses the contributions of this paper relative to related literature. Section 3 proposes a new analytical framework for empirical studies. Section 4 provides the univariate portfolio-level analysis, the bivariate analysis and industry-level cross-sectional regressions that examine a comprehensive list of control variables. Section 4 makes a short conclusion.

2 Related Literature

This paper contributes to four strands of the literature: i) financial systemic risk with network analysis and its asset pricing implications, ii) commonality in liquidity, illiquidity contagions and illiquidity spillovers, iii) gradual information diffusion, and iv) financial network estimation.

The first stream studies financial systemic risk with network analysis and its asset pricing implications. As Andersen, Bollerslev, Christoffersen and Diebold (2012) mention, modern network theory can provide a unified framework for systemic risk measures. For example, Acemoglu et al. (2012), Elliott, Golub and Jackson (2014) and Acemoglu et al. (2015) show market architectures may function as a potential propagation mechanism of idiosyncratic shocks throughout the economy. Many of the efforts in this steam are put on studying the effect of influential centrality because high IC firms (or sectors) are very likely to be a source of market turbulences. Motivated by this intuition, Buraschi and Porchia (2012) and Ahern (2013) conduct empirical analysis on firms' fundamentals networks and on input-output networks, respectively, and find evidences support the theory implications. They document high IC firms do earn higher expected returns. This paper differs from them in two aspects. First, I stress that sensitive centrality is at least as important as influential centrality in terms of asset pricing. Sensitive centrality and influential centrality can be seen as twin concepts that built on directed network structures, but respectively characterize nodes' importance in a network in distinct directions. As discussed before, both high SC and high IC firms should earn risk premiums according to their network implications. In this paper, I provide a comprehensive analysis on high SC and high IC industries. The result related to IC is consistent with the implication of Acemoglu et al. (2012) and Acemoglu et al. (2015)'s theory in asset pricing, while SC turns out to be a more robust risk factor than IC in explaining cross-sectional returns and is thus of great importance as well. Second, I focus on a well-known risk, illiquidity risk, and its transmission structures. The illiquidity network structure is directly identified by illiquidity spillovers. Thus the interpretation of the network effects in terms of risk spillovers is more straightforward.

The second stream of literature studies commonality in liquidity, illiquidity contagions and illiquidity spillovers in financial markets. Liquidity has been shown to covary strongly across stocks[6] and commonality in liquidity can influence expected returns[7]. Both illiquidity comovements and illiquidity spillovers may describe the phenomenon of covaried illiquidity across stocks. But illiquidity comovements studies the contemporaneous relationship among cross-sectional illiquidity, while illiquidity contagions and spillovers focus more on the relationships across different horizons. Cifuentes et al. (2005) explore liquidity risk in a system of interconnected financial institutions and finds contagious failures can result from small shocks. Oh (2013) presents a model in which the contagion of a liquidity crisis between two nonfinancial institutions occurs because of learning activity within a common creditor pool. Cespa and Foucault (2014) show that cross-asset learning generates a self-reinforcing positive relationship between price informativeness and liquidity, which can lead a small drop in the liquidity of one security can, through a feedback loop, spill over and result in a large drop in market liquidity. Longstaff (2010) conducts an empirical investigation into the pricing of subprime asset-backed collateralized debt oblications (CDOs) and finds strong evidence of contagion in financial markets was propagated primarily through liquidity and risk-premium channels. These studies provide theories and empirical evidences of why illiquidity can spill over and cause contagions in financial markets across different horizons. In fact, illiquidity spillovers can happen even if there is no contemporaneous illiquidity comovement, and vice versa. The main departure of this paper from this literature is primarily in the emphasis on the network structure of illiquidity transmissions. Specifically, I focus on the asset pricing implications of the heterogeneity of illiquidity spillovers.

The third stream of the literature studies gradual information diffusion in financial mar-

[6]See Brockman et al. (2009), Hameed et al. (2010), Karolyi et al. (2012), Koch et al. (2016) among the most recent studies.

[7]See, e.g., Pastor and Stambaugh (2003) and Acharya and Pedersen (2005).

kets. It has been documented that economic links between firms can serve as the channel of gradual diffusion of information. Individual firm's returns, return volatilities and credit spreads can be predicted via firms' linkages (see Cohen and Frazzini (2008),Hertzel, Li, Officer and Rodgers (2008), Menzly and Ozbas (2010), Aobdia, Caskey and Ozel (2014), Gençay, Signori, Xue, Yu and Zhang (2015), Albuquerque, Ramadorai and Watugala (2015) and Gençay, Yu and Zhang (2016) among others). This literature implies potential effects of network structures on asset pricing, since they find firm's returns can be predicted by the returns of the firms it is connected to. Actually, gradual information diffusion may also provide a channel for risk spillovers.

The fourth strand of the literature studies the estimation on financial network structures. After all, most of financial relationships in financial markets are latent and needed to be estimated from an appropriately identified model. Billio et al. (2012) use the Granger noncausality testing to meausre connectedness in financial markets. Hautsch, Schaumburg and Schienle (2015) measures the downside risk relationship from A to B by estimating the marginal effect of the Value-at-Risk (VaR) of A's returns on B's returns. Diebold and Ylmaz (2014) and Dufour and Jian (2016) propose general network measurement frameworks to measure directed financial relationships. In this paper, illiquidity networks are estimated by a Granger-type procedure that identifies illiquidity transmissions by measuring the illiquidity prediction among industries. This method is in line with Billio et al. (2012) and Dufour and Jian (2016). We share the same estimation logic: if industry A's illiquidity transmits to industry B, then industry B's illiquidity can be predicted by industry A's illiquidity.[8] However, measuring network centrality also requires positive spillovers: if industry A's illiquidity transmits to industry B, a higher current illiquidity of industry A should increase the future illiquidity of industry B. Therefore in this paper, I estimate the direct effect in the illiquidity transmission network by testing positive prediction effects. Causality at multiple horizons could measure the illiquidity spillovers from one industry to another while simultanenously considering direct and indirect effects (see, e.g., Dufour and Jian (2016)). But the adjacency matrix representing the underlying network structure in terms of all bilateral direct effects

[8]Goyenko and Ukhov (2009) also use a Granger-type procedure to study the illiquidity spillovers between stock and bond markets.

is sufficient to calculate network centralities. So I estimate the direct effect that is measured by forecasting at horizon one: if industry A's illiquidity transmits to industry B, a higher today's illiquidity of industry A should increase tomorrow's illiquidity of industry B.

3 Analytical Framework

In this section, I provide an analytical framework to formalize and quantify illiquidity centrality for empirical analysis. I use adjacency matrix to represent a general illiquidity transmission network. Since any illiquidity transmission has direction, I categorize network centrality into: i) sensitive centrality, which measures how sensitive is a node to a random shock in a network; ii) influential centrality, which measures how influential id a node's shock affecting others in a network. Given directed network structures represented by an adjacency matrix, I use Bonacich (1987)'s generalized eigenvector centrality to measure nodes' network sensitive centrality and influential centrality. Note that illiquidity transmission networks are latent, I use Corwin and Schultz (2012)'s bid-ask spreads estimate to measure firms' daily illiquidity and apply a Granger-type specification method to empirically identify directed illiquidity network structures.

3.1 Illiquidity Transmission Network

Network analysis can be used to model and explain financial contagions. For example, Allen and Gale (2000) show that the possibility of contagion depends strongly on the completeness of the underlying network structure. For the complete network shown in Figure 1a, individuals can be insured by each others following Lucas (1977)'s diversification argument, such that microeconomic shocks would average out and thus have negligible aggregate effects. For the incomplete network shown in Figure 1b, idiosyncratic shocks may propagate throughout the entire system and an individual problem can cause a systemic failure.

In this paper, I focus on illiquidity spillovers. Industries' illiquidity may transmit to other industries via an illiquidity network. I examine financial network structures in at industry level and focus on industries' centralities in their illiquidity network. Sensitive centrality (SC) measures the degree of a node being affected by others: how sensitive is a industry to

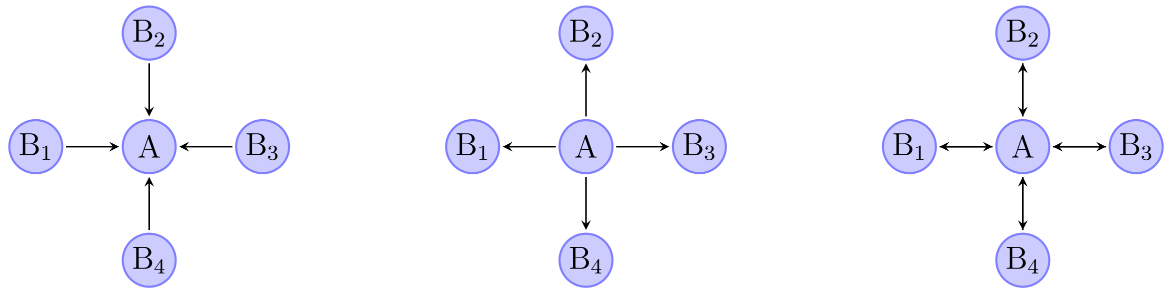
(a) Complete Network

(b) Incomplete Network

Figure 1: Financial Contagion and Network Structures

a random shock in a network. In Figure 2a, industry A is a high SC firm as illiquidity from other industries can directly transmit to it. Influential centrality (IC) measures the degree of a node affecting others: how influential of the shock of an industry affecting others in this network. In Figure 2b, industry A is a high IC industry as its illiquidity can directly transmit to all other industries. Note that a high SC industry is not necessarily low IC. Figure 2c shows a case where industry A is both high SC and high IC. I call it absolute centrality (AC). In Figure 2c, illiquidity from any other industries can directly transmit to industry A, meanwhile, industry A's illiquidity can also directly transmit to all other industries in this network. Intuitively speaking, an industry being affected by a high SC industry tends to be sensitive central as well. In Figure 3a, industry C is a high SC industry and it affects industry A. Illiquidity can easily transmit to industry C and then spillovers to industry A via industry C. Thus industry A is also a high SC industry due to industry C is sensitive central. Likewise, an industry affecting a high IC industry also tends to be influential central. In Figure 3 industry A's illiquidity can transmit to every industry in this network: directly to industry C and indirectly via industry C. Industry A is high IC since industry C is relatively influential central in the rest of the network. In this sense, our illiquidity centrality (SC and IC) has simultaneously taken directed direct effects and directed indirect effects into account.

In view of asset pricing, both high SC and IC industries' stocks are not desirable assets to hedge against a deterioration in investment opportunities. For high SC stocks, they tend to have low liquidity soon when others experiencing illiquidity during bad times. For high IC stocks, their illiquidity may spread to the whole financial network and cause market-wide



(a) Sensitive Centrality (b) Influential Centrality (c) Absolute Centrality

Figure 2: Network Centrality

(a) Affected by a sensitive central industry (b) Affecting a influential central industry

Figure 3: Neighbour to a high sensitive (influential) central industry

illiquidity and aggregate turbulences. Influential centrality could also be viewed as a source of market beta (see Ahern (2013)). Thus, as a "victim" of the illiquidity of others and a "murderer" of market turbulences, high SC stocks and high IC stocks should both earn higher expected returns. In this paper, I will empirically examine whether illiquidity network centralities (SC and IC) are risk factors priced in cross-sectional stock returns. For now, I use a simple network setting to further illustrate the intuition of why high SC and high IC firms should earn premiums, even if there is no risk or return comovement.

Example 3.1. Suppose there are only three assets (i, j, k) in the market where investors are risk-averse. Asset i's illiquidity transmits to asset j, but they are independent from asset k. In this network as shown in Figure 4, asset i and asset j are connected, and asset k is isolated. Thus, asset i is a high IC asset as it affects asset j; asset j is a high SC asset as it is affected by asset i; asset k is neither high IC nor high SC asset as it is isolated with the spillovers from asset i to asset j. I compare asset k with asset i and asset j. Asset k is a benchmark asset in this example.

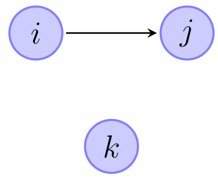


Figure 4: Simple network with high SC, high IC and isolated nodes

I assume the return of asset k at time t, R_{kt}, is independently drawn from the standard normal distribution $N(0,1)$. For asset i, its return at time t, R_{it}, is also drawn independently from $N(0,1)$. The return of asset j at time t, R_{jt}, is correlated to R_{it-1} as asset i's illiquidity at time $t-1$ can transmit to asset j's illiquidity at time t. Without loss of generality, I simply let $R_{jt} = R_{it-1}$. In this case, they all have the same expected return: $\mathrm{E}(R_{it}) = \mathrm{E}(R_{jt}) = \mathrm{E}(R_{kt}) = 0$; and the same variance of returns: $\mathrm{Var}(R_{it}) = \mathrm{Var}(R_{jt}) = \mathrm{Var}(R_{kt}) = 1$. Moreover, there exists a financial spillover, $(i \to j)$, but no contemporaneous comovement of illiquidity or returns: $\mathrm{Cov}(R_{it}, R_{jt}) = \mathrm{Cov}(R_{kt}, R_{jt}) = \mathrm{Cov}(R_{it}, R_{kt}) = 0$. Given the size (number of chosen assets) of portfolios, all of these equal-weighted portfolios seen to be equivalent to investors. However, this is not true because the spillover from asset i to asset j does play a big role in affecting long run returns.

Suppose investors can only update their portfolio (p) every two periods and let's assume the interest rate is zero for simplicity; investors will be concerned about the average return over two periods, $\frac{1}{2}(R_t^p + R_{t+1}^p)$, instead of the current return, R_t^p. Now, we consider the cases when investors have to hold a given asset z, $z = i, j, k$, and are randomly assigned another asset with equal probability of 0.5 at the beginning of day t. I denote this random two-asset portfolio as $(z, \cdot)$. Investors hold the realized portfolio of $(z, \cdot)$ over day t and day $t+1$.

There are three possible portfolios with two assets: (i,j), (i,k) and (j,k), whose corresponding returns on day t are denoted by R_t^{ij}, R_t^{ik} and R_t^{jk}, respectively, where $R_t^{ij} = \frac{1}{2}(R_{it} + R_{j_t})$, $R_t^{ik} = \frac{1}{2}(R_{it} + R_{k_t})$ and $R_t^{jk} = \frac{1}{2}(R_{jt} + R_{k_t})$. For example, $(i, \cdot)$ implies investors have to hold a random portfolio composed by asset i with probability 1 and either asset j or asset k with equal probability 0.5. At the beginning of day t, the realized portfolio could be (i,j) or (i,k), then investors hold the realized portfolio over 2 periods: day t and day $t+1$ and obtain the average return $\frac{1}{2}(R_t^{i\cdot} + R_{t+1}^{i\cdot}) = \frac{1}{2}\big(\frac{1}{2}(R_t^{ij} + R_{t+1}^{ij}) + \frac{1}{2}(R_t^{ik} + R_{t+1}^{ik})\big) = \frac{1}{8}(2R_{it} + R_{jt} + R_{kt} + 2R_{it+1} + R_{jt+1} + R_{kt+1})$. Similarly, the average return of holding asset j

for sure is $\frac{1}{2}(R_t^{j\cdot}+R_{t+1}^{j\cdot}) = \frac{1}{8}(2R_{jt}+R_{it}+R_{kt}+2R_{jt+1}+R_{it+1}+R_{kt+1})$ and the average return of holding asset k for sure is $\frac{1}{2}(R_t^{k\cdot}+R_{t+1}^{k\cdot}) = \frac{1}{8}(2R_{kt}+R_{it}+R_{jt}+2R_{kt+1}+R_{it+1}+R_{jt+1})$.

- The random portfolio $(k,\cdot)$ is superior to the random portfolio $(j,\cdot)$:

  The expected average return of $(k,\cdot)$ over two periods and the expect average return of $(j,\cdot)$ over two period are equal: $\mathrm{E}\big(\frac{1}{2}(R_t^{k\cdot}+R_{t+1}^{k\cdot})\big) = \mathrm{E}\big(\frac{1}{2}(R_t^{j\cdot}+R_{t+1}^{j\cdot})\big) = 0$. But the variance of the two-period average return of $(k,\cdot)$ is less than $(j,\cdot)$: $\mathrm{Var}\big(\frac{1}{2}(R_t^{k\cdot}+R_{t+1}^{k\cdot})\big) = \frac{7}{4}$, while $\mathrm{Var}\big(\frac{1}{2}(R_t^{j\cdot}+R_{t+1}^{j\cdot})\big) = 2$. Thus, the high SC asset j is less attractive to investors than the isolated asset asset k, because asset j will carry the shock from asset i on day t to day $t+1$ and makes the portfolios with asset j tend to be more positive correlated across different periods, which increases the return variance of holding asset j in their portfolios.

- The random portfolio $(k,\cdot)$ is superior to the random portfolio $(i,\cdot)$:

  The expected average return of $(k,\cdot)$ over two periods and the expect average return of $(i,\cdot)$ over two period are equal: $\mathrm{E}\big(\frac{1}{2}(R_t^{k\cdot}+R_{t+1}^{k\cdot})\big) = \mathrm{E}\big(\frac{1}{2}(R_t^{i\cdot}+R_{t+1}^{i\cdot})\big) = 0$. However, the variance of the two-period average return of $(k,\cdot)$ is less than $(i,\cdot)$: $\mathrm{Var}\big(\frac{1}{2}(R_t^{k\cdot}+R_{t+1}^{k\cdot})\big) = \frac{7}{4}$, while $\mathrm{Var}\big(\frac{1}{2}(R_t^{i\cdot}+R_{t+1}^{i\cdot})\big) = 2$. Thus, the high IC asset i is less attractive to investors than the isolated asset k, because asset i will transmit its shock on day t to other(s) on day $t+1$ and makes the portfolios with asset i tend to be more positive correlated across different periods, which increases the return variance of holding asset i in their portfolios.

In summary, the isolated asset k is more attractive to investors than the high SC asset j and the high IC asset i, thus investors would demand compensations for holding high SC and high IC assets. In fact, the risk diversification argument in classic portfolio theory requires weakly correlated assets, such as the isolated asset k in this example. Therefore, high SC or high IC assets may not be considered as desirable components in a portfolio in a network environment to diversify financial risks in the long run. $\square$

To model network structures mathematically, I use an adjacency matrix to model all the direct relationships in a network. Suppose there are N industries in an illiquidity network,

$A = [A_{ij}]_{i,j=1,\ldots,N}$ is an N by N matrix indicating which pairs of industries have direct illiquidity transmission. We let $A_{ij} = 1$ if and only if industry i's illiquidity will directly transmit to industry j; otherwise, $A_{ij} = 0$ if industry i's illiquidity does not directly transmit to industry j. For example, the network structures in Figure 1a and in Figure 1b can be represented by the matrices in Table 1 and in Table 2 respectively.

Table 1: adjacency matrix and the network structure in Figure 1a

	A	B	C	D
A	0	1	1	1
B	1	0	1	1
C	1	1	0	1
D	1	1	1	0

Table 2: adjacency matrix and the network structure in Figure 1b

	A	B	C	D
A	0	1	0	0
B	0	0	1	0
C	0	0	0	1
D	1	0	0	0

3.2 Eigenvector Centrality Measure

In network literature, there are some centrality measures to gauge a node's "central importance" in a network from different aspects. Among them, I use the generalized eigenvector centrality measures proposed by Bonacich (1987) to better measure illiquidity spillovers centrality in stock markets.

Given an adjacency matrix of a directed network, $A = [A_{ij}]_{i,j=1,\ldots,N}$, where N is the size of the network. $A_{ij} = 1$ if and only if industry i affects industry j, otherwise, $A_{ij} = 0$. Following Bonacich (1987), we define industry i's sensitive centrality, SC_i, as the sum of a linear function of the sensitive centralities of all the other industries that affect industry i:

$$SC_i = \sum_{j:A_{ji}=1} (\alpha + \frac{1}{\lambda} SC_j) = \sum_{j=1}^{N} A_{ji}(\alpha + \frac{1}{\lambda} SC_j), \tag{1}$$

where $\alpha \geq 0$, $\lambda > 0$. Being affected by a high SC industry j (SC_j is large) can increase industry i's sensitive centrality (SC_i) in this network. $1/\lambda$ is the weight of one's sensitive centrality measure on others'. A smaller λ means the influence of the neighbour effect is greater. In a given network, we say industry i is more sensitive central than industry j if and only if $SC_i > SC_j$.

In matrix notation, let $SC = [SC_1, ..., SC_N]'$, we have

$$\left(I - \frac{1}{\lambda}A'\right) SC = \alpha A' l, \tag{2}$$

where I is an $N \times N$ identity matrix and l is a $N \times 1$ column vector of ones.

When $\alpha = 0$, we have $\left(I - \frac{1}{\lambda}A'\right) SC = 0$ then SC is an eigenvector of the transpose of the adjacency matrix A with its eigenvalue λ. If A is an irreducible non-negative matrix, Perron-Frobenius theorem states that the only eigenvector whose components are all positive are the one associated with the biggest eigenvalue λ_{max}. In practice, we do require positive centrality measures in order to determine which one are more central in a network. Hence, the eigenvector sensitive centrality is the eigenvector associated with the biggest eigenvalue of A'.

When $\alpha > 0$, it is simply the scale of the centrality vector. Without loss of generality, we could let $\alpha = 1$. If A is an irreducible non-negative matrix and λ is greater than the biggest eigenvalue of A' in magnitude, the sensitive centrality vector has the following representation,

$$\begin{aligned} SC &= \left(I - \frac{1}{\lambda}A'\right)^{-1} A' l \\ &= A' l + \frac{1}{\lambda}(A')^2 l + \left(\frac{1}{\lambda}\right)^2 (A')^3 l + ... \end{aligned} \tag{3}$$

All elements in the sensitive centrality vector SC are positive as all the elements in equation (3) are nonnegative and A is irreducible. Moreover, the parameter $1/\lambda$ can be interpreted as a probability and SC as the expected number of directed paths in a network activated directly or indirectly to each individual.

To obtain a positive sensitive centrality vector from equation (3), the weight of one's sensitive centrality measure on others', $1/\lambda$, is at most $1/\lambda_{\text{max}}$, where λ_{max} is the biggest eigenvalue of A'.[9] If we wish to put more weight on considering the effect of being a neighbour to a high SC (IC) industry in a network, a greater weight parameter $1/\lambda$ should be selected. Therefore, in order to capture the neighbour effect as much as possible I will focus on the eigenvector centrality measure in empirical analysis hereafter.

Similar arguments apply to define a industry's influential centrality (IC). We define industry i's influential centrality, IC_i, as the sum of linear functions of the influential centralities of all the other industries who are affected by industry i:

$$IC_i = \sum_{j:A_{ij}=1} (\alpha + \frac{1}{\lambda} IC_j) = \sum_{j=1}^{N} A_{ij}(\alpha + \frac{1}{\lambda} IC_j). \tag{4}$$

Affecting a high IC industry j (IC_j is large) can increase industry i's influential centrality (IC_i) in this network. In matrix notation, let $IC = [IC_1, ..., IC_N]'$, we have $\left(I - \frac{1}{\lambda}A\right) IC = \alpha Al$. The eigenvector influential centrality is the eigenvector associated with the biggest eigenvalue of the adjacency matrix A.

Example 3.2. In Figure 5, I show a small but complex network to illustrate how the eigenvector centrality measures, sensitive centrality (SC) and influential centrality (IC), can point out the central components in this network and quantify their degrees.

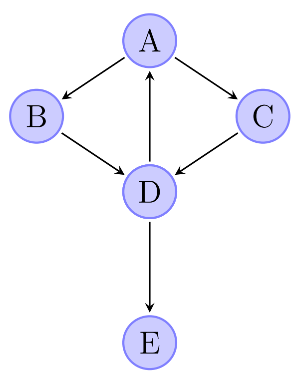


Figure 5: Eigenvector centrality of a small but complex network

The network shown in Figure 5 can be represented by the adjacency matrix in Table 3. This table also presents the calculated values of their respective eigenvector sensitive

[9]Given $\alpha > 0$, if $1/\lambda \geq 1/\lambda_{\max}$, the equation (3) does not converge and SC is not well defined in this case.

centrality and eigenvector influential centrality. The most sensitive central node is D (0.57) because it is affected by two main nodes B and C. Node A and node E are equally second sensitive central (0.45) as they are both only affected by node D. Node B and Node C are the least sensitive central (0.36) as they are only affected by node A. In terms of influential centrality, node A is the most central (0.64) because its effect can spillover to everyone in this network. Node D is second most central (0.51) as it can transmit node A's effect spilling via node B and node C to node E and back to node A. The influential centralities of node B and node C are equalled (0.40) as they only affect node D. Interestingly, the influential centrality of node E is zero, because it affects no one in this network.

Table 3: adjacency matrix and eigenvector centrality measures

	A	B	C	D	E	IC
A	0	1	1	0	0	0.64
B	0	0	0	1	0	0.40
C	0	0	0	1	0	0.40
D	1	0	0	0	1	0.51
E	0	0	0	0	0	0.00
SC	0.45	0.36	0.36	0.57	0.45	

□

3.3 Bid-Ask Spreads Measure for Illiquidity Risk

In general, illiquidity risk in financial markets is a financial risk that a given financial asset or security cannot be traded quickly enough in the market without impacting the market price. Liquidity has many dimensions. This study focuses on a dimension associated with bid-ask spreads. In stock markets, the spread is the difference between the bid and ask prices for a particular stock. The bid price corresponds to the highest price the demand side is willing to pay; the asking price corresponds to the lowest price the supply side is willing to sell. In other words, the bid-ask spread reflects the divergence of the demand side and the supply side for a stock. Wider the divergence makes the transactions more difficult to make, since investors have to pay more "spread cost" to buy or sell a stock.

Thus, the level of the illiquidity risk of a stock increases with the size of its bid-ask spreads. The interconnections of industries' bid-ask spreads can be interpreted as industries' illiquidity risk transmission network.

In this paper, I use Corwin and Schultz (2012)'s bid-ask spreads estimate, which only requires stock' daily high and low prices, to measure firms' illiquidity risk. We assume that there is a spread of S%. Because of the spread, observed prices for buys are higher than the actual values by (S/2)%, and observed prices for sells are lower than the actual values by (S/2)%. If we further assume that the daily high price is buyer-initiated and the daily low price is seller-initiated, then we will have $H^O = H^A(1 + S/2)$ and $L^O = L^A(1 - S/2)$, where $H^O(L^O)$ is the observed high (low) price and $H^A(L^A)$ is the actual high (low) price. Following Corwin and Schultz (2012), the bid-ask spread estimate on day t is

$$S_t = \frac{2(e^\alpha - 1)}{1 + e^\alpha}, \tag{5}$$

where $\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}$, $\beta = \left[\ln\left(\frac{H^O_{t-1}}{L^O_{t-1}}\right)\right]^2 + \left[\ln\left(\frac{H^O_t}{L^O_t}\right)\right]^2$ and $\gamma = \left[\ln\left(\frac{\max\{H^O_{t-1}, H^O_t\}}{\min\{L^O_{t-1}, L^O_t\}}\right)\right]^2$.

This bid-ask spread estimate has several advantages for our empirical analysis. First, this estimate is very easy to compute. No optimization problem needs to be solved. Second, this estimate only requires the daily observations of high price and low price. High price and low price are available in almost all stock databases. Third, the daily bid-ask spreads S_t for any given stock can be estimated from low-frequency (daily) sample observations.

3.4 Granger Causality and Network Estimation

Once we have firms' estimates of their respective daily bid-ask spreads, we want to uncover the underlying network structures of how firms' bid-ask spreads spill over to each other. Following Billio et al. (2012) and Dufour and Jian (2016), this paper uses a Granger-type procedure (see, e.g., Granger (1969) and Sims (1972)) to identify the existence of directed relationships between every pair of nodes in the illiquidity risk network.

To identify the dynamic structures of the underlying illiquidity transmission network, I divide the whole daily panel sample into annual subsamples. Suppose in year y we have τ_y days in this annual subsample, and we have N_y firms' estimates of their respective daily bid-ask spreads: $[S_{1t}, S_{2t}, ..., S_{N_k t}]_{t=1}^{\tau_y}$. I assume the illiquidity risk network structure is fixed in each given year but can vary year by year. In year y, the network structure can be represented by an N_y by N_y adjacency matrix: $A^y = [A^y_{ij}]_{i,j=1,...,N_y}$. where $A^y_{ij} = 1$ if and only if firm i's bid-ask spreads can affect firm j's bid-ask spreads; otherwise, $A^y_{ij} = 0$.

To estimate the directed relationship from firm i to firm j, A_{ij}, I use the following regression model,

$$S_{jt} = \beta_0 + \beta_i S_{it,p} + \beta_j S_{jt,p} + \beta_Z Z_{t,p} + \epsilon_{jt}, \qquad t = 1, ..., \tau_k, \tag{6}$$

where S_{jt} is firm j's spread on day t, $S_{it,p} = [S_{it-p}, ..., S_{it-1}]'$ is the past recent p days' observations of firm i's spreads, and $S_{jt,p} = [S_{jt-p}, ..., S_{jt-1}]'$ is the past recent p days' observations of firm j's spreads. $Z_{t,p} = [Z^1_{t,p}, ..., Z^S_{t,p}]'$ is the past recent p days' observations of S state variables, $Z^s_{t,p} = [Z^s_{t-p}, ..., Z^s_{t-1}]$ for $s = 1, ..., S$. β_0 is a scalar parameter, β_i is a row vector correspond to $S_{it,p}$, β_j is a row vector correspond to $S_{jt,p}$ and β_Z is a row vector correspond to $Z_{t,p}$. Then the general Granger-type procedure for identifying network structures becomes a testing problem ($H_0 : \beta_i = 0$, $H_1 : \beta_i \neq 0$):

$$A^k_{ij} = \begin{cases} 1, & \text{reject } H_0 \\ 0, & \text{can not reject } H_0 \end{cases} \tag{7}$$

Some notes of caution are needed here. First, selecting state variables Z is important. One of the drawbacks of using the bilateral Granger noncausality testing in network estimation comes from spurious effects. If the regression model in equation (6) does not include the common factor(s) that are orthogonal to firm j's past spreads but correlated to firm i's past spreads and firm j's current spread, we may reject H_0 even if there is no effect from firm i to firm j.

Second, the choice of day lag p is somewhat arbitrary, however, I suggest $p = 1$ for the network analysis in this paper. Setting $A^k_{ij} = 1$ implies we expect to see firm i's spread yesterday will affect firm j's spread today. When $p = 1$, the noncausality implication is in line with the direct effect interpretation in network adjacency matrix. Moreover, note that we only have one year daily observations in each subsample, thus small p can increase the estimation precision, especially when we add some state variables in the regression model.

Furthermore, measuring network centrality requires positive spillovers: if firm i's illiquidity transmits to firm j, a higher today's illiquidity of firm i should increase tomorrow's illiquidity of firm j. When β_i is univariate, a more appropriate way to identify network structures is by testing whether $\beta_i > 0$.

Third, in order to ensure the adjacency matrix to be irreducible, the underlying illiquidity risk network should be strongly connected and not too sparse. Thus, the significance level selected for testing cannot be too low, otherwise the estimated network may be too sparse.

4 Illiquidity Network Centrality and the Cross-Section of Expected Returns

In the previous section I have discussed how to estimate illiquidity network structures by daily bid-ask spread estimates and how to apply eigenvector centrality measure to measure nodes' centralities in the network. This section explores the empirical relation between the cross-section of expected returns and the illiquidity centrality (SC and IC). For feasibility of implementation, the illiquidity network and the cross-section of expected returns are examined at industry level.

4.1 Data

The first dataset includes all the stock information from the Center for Research in Securities Prices (CRSP) for stocks traded in New York Exchange (NYSE), American Stock Exchange (AMEX), and NASDASQ with share codes 10 or 11 from January 1963 through December 2015. I use daily stock high prices and low prices to calculate daily bid-ask spread estimates. I use share prices and shares outstanding to calculate market capitalization. The first 3 digits of the Standard Industry Classification (SIC) code indicate the industry level. Industry's returns and bid-ask spreads are defined as the simple average of the returns and bid-ask spreads for the stocks belong to the industry. The second dataset is COMPUSTAT, which is used to obtain the equity book values for calculating the book-to-market ratios of individual firms and the book-to-market ratios of industry defines as the simple average of the book-to-market ratios of individual firms belong to the industry. The third dataset is from the Kenneth French's data library to obtain risk-free rates and four-factor portfolios returns. These variables are defined in detail in the Appendix and will be discussed when they are used in the analysis.

4.2 Illiquidity Network Centralities

Using daily stock high prices and low prices I calculate daily bid-ask spreads estimates $S_{i_k t}$ for individual stock i_k that belongs to industry i on date t, with the adjustments suggested in Corwin and Schultz (2012). Industry i's bid-ask spread estimate on date t, $S_{it} = \frac{1}{n_i}\sum_{i_k \in i} S_{i_k t}$, where n_i is the number of stocks belong to industry i on date t. In year y, we have τ_y daily observations of N_y industries' daily bid-ask spreads estimates: $[S_{1t}, S_{2t}, ..., S_{N_y t}]_{t=1}^{\tau_y}$.

To identify N_y industries' illiquidity network structure $A^y = [A^y_{ij}]_{i,j=1,...,N_y}$ in year y, I use the following regression equation:

$$S_{jt} = \beta_0 + \beta_i S_{it-1} + \beta_j S_{jt-1} + \beta_Z Z_{t-1} + \epsilon_{jt}, \qquad t = 2, ..., \tau_y. \tag{8}$$

The directed relationship from industry i to industry j is specified as: $A^y_{ij} = 1$ if and only if $\beta_i > 0$; otherwise, $A^y_{ij} = 0$. The state variable Z_{t-1} includes: 1) average bid-ask spreads estimates of the stocks belong to the major group of industry j on day $t-1$, where the major group is indicated by the first two digits of SIC codes; 2) average bid-ask spreads estimates of all stocks on day $t-1$. By controlling major industry average illiquidity and market average illiquidity of industry j, a positive marginal effect ($\beta_i > 0$) of the illiquidity of industry i on day $t-1$ on the illiquidity of industry j on day t can be safely interpreted as the illiquidity spillover from industry i to industry j: increase in the illiquidity of industry i today leads the illiqudity of industry j up tomorrow. I use the simple t-statistic on one tail test at significance level 0.1 to test whether $\beta_i > 0$ in equation (8). I repeat this procedure for every pair of industries. After implementing $N_y \times N_y$ OLS regressions and testings on equation (8), we find all the directed relationships in the network and uncover the underlying illiquidity transmission network structure in year y, A^y.

Given each year y, we already have its adjacency matrix A^y by the procedure described above. I calculate sensitive centralities and influential centrality for each industry by the eigenvector centrality measure. More central industry will have a higher centrality measure in cross-section, however note that eigenvector is set to have unit norm, thus eigenvector centrality measures are not comparable directly across different years. To fix this problem, I rescale the industries' centrality measures for each year, such that the sum of squares of industries' centrality measures in year y equals the size of the network in this year (N_y). After rescaling, more central industries given a year will still have higher centrality measures in cross-section as they are rescaled by the same weight. In addition, centrality measures in different years are comparable in terms of relative centrality in their respective networks. If the centrality measure of an industry is greater than 1, which is the root mean square of all industries' centrality measures in the network, it implies the industry is a relatively central industry, and vice versa. In any given year y, we have industry i' sensitive centrality measure (SC_{iy}) and its influential centrality measure (IC_{iy}) such that $\frac{1}{N_y}\sum_i SC_{iy}^2 = 1$ and $\frac{1}{N_y}\sum_i IC_{iy}^2 = 1$. $SC_{iy} = 1$ ($IC_{iy} = 1$) means (approximately) that industry i does not have an unusually large or small degree of centrality in year y, irrespective of the number of industries in the illiquidity network in year y (N_y), and I call these industries as "middle-industry".

Table 4 presents summary statistics of the empirical distributions of illiquidity network centralities in cross-section across different years from 1963 to 2015. The network centralities are estimated for every year from January 1963 to December 2015. There are 53 years from 1963 to 2015. In these years, there are 310 industries in illiquidity networks on average. Panel A presents summary statistics for sensitive centrality. The yearly median of the medians of cross-sectional sensitive centrality measures is 0.96, which is close to 1 of middle-industry. In contrast, for influential centrality in panel B the yearly median of the medians of cross-sectional influential centrality measures is only 0.73, but the yearly median of the 75% quantiles of cross-section influential centrality measures is 1.09, which is close to 1 of middle-industry. It implies high influential industry ($IC_i > 1$) is minority in illiquidity networks in average years. Compared to the sensitive centrality median 'max-min' spread (1.29 = 1.71 - 0.42), the influential centrality has a wider median 'max-min' spread (2.54 = 2.71 - 0.17). In cross-section, illiquidity influential centralities have a wider spread than illiquidity sensitive centralities. For both sensitive centrality and influential centrality, most of their cross-sectional empirical distributions from 1963 to 2015 are right-skewed and have heavier tails than normal distribution. Right-skewed network distribution is often documented in economic and social network literature (see e.g., Jackson et al. (2008)).

To investigate the empirical relation between sensitive centrality and influential centrality of a given industry in illiquidity networks, Table 5 presents the descriptive statistics of industries' time-series correlations. I only calculate the time-series correlations between sensitive centrality and influential centrality for those industries have more than 10 years centralities observations in sample. Then we have 395 industries' sensitive centralities and influential centralities time-series correlations and their respective p-values to null hypothesis of no correlation. The average sensitive centrality and influential centrality correlation is 0.42; the 25% quantile of the sensitive centrality and influential centrality correlations is 0.32; for most ($> 75\%$) industries the p-values are less than 0.1. It means the changes of illiquidity sensitive centrality for most industries tends to go with the direction of their changes in influential centrality. If an industry get more connections to others, its illiquidity will have more chances to affect others as well as being affected by others. High SC (or IC) industries in the illiquidity network tend to be high absolute centrality.

4.3 Univariate Portfolio-Level Analysis

Table 6 presents the equal-weighted and value-weighted average monthly returns of decile portfolios that are formed by sorting the industries based on the illiquidity network centralities (SC and IC) respectively estimated in past calendar year. Centrality measures are estimated every year from January 1963 to December 2014. Industry's returns are calculated by the equal-weighted returns of stocks belong to the industry, and value-weighted portfolios are the average industry returns weighted by industry's total market capitalizations. For example, I estimate industries' centrality measures in 2000 with the sample from January 2000 to December 2000, and form the portfolios from January 2001 to December 2001 based on the industries' centrality measures in 2000. Portfolios are rebalanced yearly. Portfolio 1 (Low SC (IC)) is the portfolio of industries with the lowest SC (IC) in the past calendar year, and portfolio 10 (high SC (IC)) is the portfolio of industries with the highest SC (IC) in the past calendar year.

In Panel A sorted by sensitive centrality, the equal-weighted raw return difference between decile 10 (high SC) and decile 1 (low SC) is 0.36% per month (4.32% per year) with a corresponding Newey-West (1987) t-statistics of 3.66. In addition to the raw returns, Table 6 also presents the intercepts (Fama-French-Carhart 4-factor alphas) from the regression of the equal-weighted portfolio returns on a constant, the excess market return, the size factor, the book-to-market factor, and the momentum factor, following Fama and French (1993) and Carhart (1997). The difference in alphas between the high SC and low SC equal-weighted portfolios is 0.45% per month (5.40% per year) with a Newey-West t-statistic of 3.72. This difference is economically significant and statistically significant at all conventional levels. Similar significant results also apply to value-weighted portfolios. The value-weighted raw return difference between decile 10 (high SC) and decile 1 (low SC) is 0.38% per month (4.56% per year) with a corresponding Newey-West t-statistics of 2.15; the difference in alphas between the high SC and low SC value-weighted portfolios is 0.49% per month (5.88% per year) with a Newey-West t-statistic of 2.65.

Taking a closer look at the value-weighted average returns and alphas across deciles, it is clear that they are not strictly monotonic increasing as SC increases. The average returns of decile 1 to 9 are very close, in the range of 1.24% to 1.47% per month, but decile 10 (high SC) average return jumps significantly to 1.82% per month. The alphas for the first 9 decile are close too, from 0.61% to 0.84%, but again the alpha for the decile 10 jumps up to 1.23%. A similar pattern also exists for equal-weighted average returns and alphas. The average return and alpha for the high SC decile portfolio are significantly higher than those in decile 1 to 9. It implies investors dislike the high SC portfolio industries' stocks especially. The most sensitive central industries are the most exposed to idiosyncratic illiquidity spillovers from other industries, thus investors may demand a premium to hold these high SC portfolio due to with they too sensitive to others' illiquidity.

In Panel B sorted by influential centrality, the equal-weighted raw return difference between decile 10 (high IC) and decile 1 (low IC) is 0.40% per month (4.80% per year) with a Newey-West t-statistic of 3.19. The difference in alphas between the high IC and low IC equal-weighted portfolio is 0.48% per month (5.67% per year) with a t-statistic of 3.35. Similar significant results also apply to value-weighted portfolios. The value-weighted raw return difference between decile 10 (high SC) and decile 1 (low SC) is 0.31% per month (3.27% per year) with a corresponding Newey-West t-statistics of 2.33; the difference in alphas between the high SC and low SC value-weighted portfolios is 0.31% per month (3.27% per year) with a Newey-West t-statistic of 2.31. The difference of average returns and alphas between high IC and low IC portfolios are economically and significant and statistically significant.

Again, the average returns and alphas across deciles for the equal-weighted and value-weighted portfolios are not strictly monotonic increasing as IC increases. But the high (low) IC portfolio still has the highest (lowest) average return and alpha across deciles. The highest influential centrality industries transfer their idiosyncratic illiquidity risk to many others and leave investors no place to hide in the stock market. Therefore, the illiquidity risk with holding the high IC portfolio is the most difficult to be hedged. The high IC stocks should earn a premium.

Comparing Panel A and Panel B, we can see that the average returns and alphas spreads between high SC and low SC and the spreads between high IC and low IC are close. Moreover, the patterns of average returns and alphas across deciles sorted by SC and by IC are similar. Note that we have already found the changes of illiquidity sensitive centrality for an industry tends to go with the direction of its change in influential centrality across different years in Table 5. Even though we find high SC and high IC portfolios earn significantly higher average returns and alphas compared with low SC and low IC portfolios respectively, these spreads may be generated from similar portfolios components. Table 7 presents the distribution of industries across deciles sorted by SC and sorted by IC. The ith row and jth column element in the table is the time-series average of the percentage ratios of the number of the industries in portfolio j sorted by IC, as well as in portfolio i sorted by SC, over the total number of the industries in portfolio i sorted by SC. We can find from the table that industries in high (low) decile portfolios sorted by SC are more likely to be in high (low) decile portfolios sorted by IC. The table entries around diagonal are clearly greater than those in off-diagonal positions. On average, 23.02 percent of decile 1's industries sorted by SC belong to decile 1 portfolio sorted by IC; 28.89 percent of decile 10's industries sorted by SC belong to decile 10 portfolio sorted by IC. In other words, about 3/4 of the industries that belong to the decile 1 (10) portfolio sorted by SC do not belong to the decile 1 (10) portfolio sorted by IC. These industries can tell apart the risk associated with SC and the risk associated with IC in their respective 10-1 portfolio[10]. The return and alpha differences of the 10-1 portfolios sorted by SC and IC respectively are not generated from similar portfolio components.

The 10-1 portfolios are constructed to capture the risk premium associated with sensitive centrality and influential centrality in the illiquidity network. In Table 6, we have found solid evidence that the 10-1 portfolios sorted by SC and sorted by IC are respectively both statistically and economically significant, however, it is still possible that we may just by "luck" pick up the well-performed industries in decile 10 and poor-performed industries in decile 1 as our portfolio formations are rebalanced annually. It is desirable for a trading strategy to utilize annually rebalanced portfolio as its transaction cost will be much lower than the strategies rebalanced monthly or even daily. But annually rebalancing does not provide many opportunities for changes in portfolio components. It would cast doubt on the reliability of the statistical properties for a trading strategy with low turnovers.

To examine this issue more carefully, we look at the transition matrix of industries in portfolios sorted by SC and sorted by IC. Table 8 presents the probability transition matrix of industries in different decile portfolios in successive two years. The ith row and jth column element in the 10 by 10 table is the time-series average of the percentage ratios of the number of the industries in portfolio i in year y shifting to portfolio j in year $y+1$ over the number of the industries in portfolio i in year y. If portfolio formations are purely random, industries are equally distributed in different deciles; all the entries in the transition matrix should equal 10(%). The range of the table entries is from 7.22 to 12.44 for deciles sorted by SC in Panel A; the range of the table entries is from 5.64 to 15.44 for deciles sorted by IC in Panel B. The maximum probability of an industries stay at the same decile in two successive years is only 12.44 (15.44) for decile sorted by SC (IC). In other words, it is quite unlikely that we pick up the well-performed industries consistently in decile 10 and poor-performed industries in decile 1 just by "luck" in Table 6 because most of industries do not stay at the same decile in two successive years and go to other different deciles with approximately equal probability. Taking a closer look at the tables, we can find the table entries around diagonal are a little

[10]Long the high decile portfolio and short the low decile portfolio.

bit greater than those in off-diagonal positions. In Panel A, for example, the probability of an industry in decile 10 (High SC) shifting to decile 1 (Low SC) next year has the lowest value of 8.25% for industries from decile 10, while the probability of an industry in decile 10 (High SC) staying at decile 10 (High SC) next year has the highest value of 12.44%. It is in line with our intuition since we expect a relatively low (high) SC industry in this year will be more likely to be relatively low (high) SC industry in next year. Similar arguments also apply to deciles sorted by IC in Panel B. In conclusion, the results documented in Table 6 are trustworthy in term of statistics since industries in different deciles reshuffle enough in each year, even though our annually rebalancing does not provide many opportunities for changes in portfolio components.

In finance literature, market beta, book-to-market, illiquidity, momentum and idiosyncratic volatility are well-known risk factors of pricing returns in the cross-section at firm level (see Fama and French (1992), Fama and French (1993), Amihud (2002), Pastor and Stambaugh (2003), Jegadeesh and Titman (1993), Ang, Hodrick, Xing and Zhang (2006) among others). Though I study illiquidity network centralities at industry level, it would be important to investigate whether industries' sensitive centrality measures and influential centrality measures have relation with these well-know risk factors. To get a clearer picture of the component in portfolios sorted by sensitive centrality and influential centrality, Table 9 presents summary statistics for the industries in the deciles sorted by SC in Panel A and those sorted by IC in Panel B. Specifically, the table reports for each decile the simple average across the years and across the industries of various characteristics for the industries: the average firm market capitalization (in millions of dollars, labeled FSIZE), the industry market capitalization (in millions of dollars, labeled ISIZE), the market beta (labeled BETA), the book-to-market (labeled BM), the average stock bid-ask spreads estimate (in percent, labeled SPREAD), the average Amihud (2002) illiquidity measure (scaled by 10^6, labeled RTV), the average industry monthly return in the past calendar year prior to portfolio formation (in percent, labeled MOM), and the industry idiosyncratic volatility over the past calendar year prior to portfolio formation (labeled IVOL). Definitions of these variables are given in the Appendix.

In Panel A sorted by sensitive centrality, as SC increases across deciles industry market capitalization increases but firms' average market capitalization exhibits little change in a range from 1.13 millions of dollars to 1.22 millions of dollars with less than 10% in variation. In others words, an industry's sensitive centrality is irrelevant to its average firm size, but a bigger industry, which has more firms and has bigger market capitalization, tends to have a higher sensitive centrality measure. It can be partially explained by the fact that an industry with more firms would have greater exposure to illiquidity spillovers in stock market. In contrast to the conjecture that sensitive centrality may serve as a source of market beta in financial network analysis (see Ahern (2013)), industries' market betas are almost the same across different deciles in our illiquidity network. Momentum and idiosyncratic volatility are also almost the same across deciles. As SC increases across the deciles, firms' average book-to-market ratio increases slightly. The value industries, which have higher average firms' book-to-market ratios, tend to have higher sensitive centrality measure. In additon to Corwin and Schultz (2012)'s bid-ask spreads estimate to measure illiquidity, I also consider a more widely used illiquidity measure proposed by Amihud (2002), which measures firm's illiquidity as the sensitivity of firm's absolute returns to its trading volume in dollars. Not surprisingly, those industries with higher sensitive centrality measures tend to have greater bid-ask spreads and return-to-volume (RTV). These results may provide an explanation of the value-premium known at least since Fama and French (1992). A motivation of the value-premium is that value firms are consistent bad performers in periods of systemic downturns. It may be because in the periods of systemic downturns value firms are more sensitive to market illiquidity thus poor liquidity make their returns further lower during these periods.

In Panel B sorted by influential centrality, as IC increases across deciles firms' average market capitalization decreases. Industries with small firms are more suitable distress vehicles than industries with large firms whose relatively large trading volumes could serve as temporary buffers to slow down illiquidity propagation.[11] Interestingly, the industry market capitalization exhibits an U-shape across deciles. A bigger industry, which has more firms and small caps on average, tends to has a higher influential centrality measure. As IC increases across deciles, industries' market betas decrease slightly (influential industries are

[11]Buraschi and Porchia (2012) find small firms have higher influential centrality in a network connecting firms' fundamentals.

less correlated to market returns); industries' book-to-market increases slightly (high book-to-market industries may be a source of systemic distress). Similar to the pattern across deciles sorted by SC, as IC increases across deciles illiquidity measures (SPREAD and RTV) are higher. Momentum and idiosyncratic volatility are also almost the same across deciles.

Given these differing characteristics, there is some concern that the 4-factor model used in Table 6 to calculate alphas is not adequate to capture the true difference in risk and expected returns across the portfolios sorted by SC and the portfolios sorted by IC. The 4-factor model does not control for the differences in expected returns due to differences in industry size or illiquidity. In the following two subsections I provide different ways to deal with the potential interaction of the illiquidity centrality measures with industry size, book-to-market and liquidity.

4.4 Bivariate Portfolio-Level Analysis

In this section I examine the relation between illiquidity causality measures and future industry returns after controlling for average firm market capitalization, industry market capitalization, market beta, book-to-market, illiquidity measured by return-to-volume, average industry monthly return in the past calendar year prior to portfolio formation, and industry idiosyncratic volatility over the past calendar year prior to portfolio formation. For example, I control for industry capitalization by first forming 5 decile portfolios ranked based on industry capitalization. Then, within each industry size decile, I sort industries into portfolio ranked based on sensitive centrality and portfolio ranked based on influential centrality so that decile 1 (decile 10) contains industries with lowest (highest) centrality measures.

Table 10 presents average industry return across the 5 control deciles to produce decile portfolio with dispersion in SC but with similar levels of the control variables. For each column controlling variables, the equal-weighted average return difference between the high SC and low SC portfolios are still all economically and statistically significant. After controlling for firms' average size, industry size, market beta, book-to-market, momentum and idiosyncratic volatility, the equal-weighted average return differences between the high SC and low SC portfolios are 0.29% (3.14%), 0.32% (3.84%), 0.28% (3.36%), 0.28% (3.36%), 0.29% (3.48%), and 0.30% (3.60%) per month (per year), with Newey-West t-statistics of

2.83, 3.27, 2.78, 2.83, 3.19 and 3.17, respectively. The corresponding values for the equal-weighted average risk-adjusted return differences are 0.40% (4.80%), 0.39% (4.68%), 0.31% (3.72%), 0.37% (4.44%), 0.35% (4.20%) and 0.40% (4.80%) per month (per year), with t-statistics of 2.71, 2.97, 2.93, 2.76, 3.46 and 2.67, which are also highly significant. Note that the absolute return to trading volume in dollars (RTV) illiquidity measure proposed by Amihud (2002) is a much more popular way to measure illiquidity in literature, for brevity hereafter I only use Amihud (2002)'s RTV measure to control the illiquidity risk to make the results in this paper comparable to existing studies.[12] We found that industries sensitive centralities are positive correlated with industry size, book-to-market and illiquidity (SPREAD and RTV)in Panel A of Table 9. After controlling each of these variables (ISIZE, BM and RTV), the average returns and alphas of the 10-1 portfolios sorted by SC remain significant. But the average return and alpha of the 10-1 portfolios decrease most after controlling RTV. After controlling RTV, the average return of the 10-1 portfolios decreases to 0.20% per month (2.4% per year) with a Newey-West t-statistic of 2.20; the alpha of the 10-1 portfolios decreases to 0.29% per month (3.48% per year) with a t-statistic of 2.11. Nevertheless, these results of high-low spread of the portfolios sorted by SC are still economically and statistically significant. For the double sorted value-weighted decile returns portfolios exhibit very similar significant results, except after controlling industry size the average returns of the 10-1 portfolios decrease to 0.21% per month (2.52% per year) with a t-statistic of 1.54, which is insignificant for conventional significance levels.

Table 11 presents average industry return across the 5 control deciles to produce decile portfolio with dispersion in IC but with similar levels of the control variables. For each column controlling variables, almost all the equal-weighted average returns and alphas of 10-1 IC portfolios are economically and statistically significant, and are close to those sorting only by SC in Table 6. After controlling for firms' average size, industry size, market beta, book-to-market, momentum and idiosyncratic volatility, the equal-weighted average return differences between the high SC and low SC portfolios are 0.35% (4.2%), 0.36% (4.32%), 0.31% (3.72%), 0.34% (4.08%), 0.35% (4.20%), 0.25% (3.00%) per month (per year), with t-statistics of 3.16, 2.99, 2.60, 2.85, 3.37, 2.11, respectively. The corresponding 10-1 alphas

[12]The results of using SPREAD to control illiquidity risk are very similar.

are 0.45% (5.40%), 0.45% (5.40%), 0.34% (4.08%), 0.44% (5.28%), 0.38% (4.56%) and 0.34% (4.08%) per month (per year), with t-statistics of 3.41, 3.11, 2.59, 3.21, 3.51 and 2.67, which are also both economically and statistically significant. The only exception is the average return of the 10-1 portfolio after controlling RTV, which is 0.16% per month with a t-statistic of 1.42. But the 10-1 alpha after controlling RTV is 0.27% per month (3.24% per year) with a t-statistic of 2.24, which is also significant. However, the 10-1 IC portfolios are not always significant for the value-weighted portfolio returns, even though their averages returns and alphas are all positive.

In summary, these results indicate that for both the equal-weighted and value-weighted portfolios, the well-known cross-sectional effects at firm level such as size, market beta, book-to-market, liquidity, momentum and idiosyncratic volatility can not explain the high returns to high SC industries, while similar robust results do not apply to the high returns to high IC industries except for the case of equal-weighted portfolios sorted by IC.

4.5 Industry-Level Cross-Section Regressions

So far we have tested the significance of illiquidity sensitive centrality (SC) and illiquidity influential centrality (IC) as determinants of the cross-section of future returns at portfolio-level. The portfolio-level analysis has the advantage of being non-parametric in the sense that we do not impose a functional form on the relation between illiquidity centrality measures and future return. But the portfolio-level analysis misses a large amount of information in the cross-section via aggregation. Moreover, it fails to control for multiple effects simultaneously. In this section, I examine the cross-sectional relation between the centrality measures (SC and IC) and expected returns at the industry level using Fama and MacBeth (1973) two-step regressions.

I present the time-series averages of the slope coefficients from the regression of industry returns on sensitive centrality (SC), influential centrality (IC), market beta (BETA), average of logs of firms' market capitalizations (FSIZE), log of industry market capitalization, average of logs of firms' book-to-market (BM), illiquidity (RTV), momentum (MOM), and idiosyncratic volatility (IVOL). The average slopes provide standard Fama-MacBeth tests for determining which explanatory variables on average have non-zero premiums. Monthly cross-sectional regressions are run for the following econometric specification and nested versions:

$$
\begin{aligned}
R_{i,t,y+1} =& \lambda_{0,t,y} + \lambda_{1,t,y}\mathrm{SC}_{i,y} + \lambda_{2,t,y}\mathrm{IC}_{i,y} + \lambda_{3,t,y}\mathrm{BETA}_{i,y} + \lambda_{4,t,y}\mathrm{FSIZE}_{i,y} + \lambda_{5,t,y}\mathrm{ISIZE}_{i,y} \\
&+ \lambda_{6,t,y}\mathrm{BM}_{i,y} + \lambda_{7,t,y}\mathrm{RTV}_{i,y} + \lambda_{8,t,y}\mathrm{MOM}_{i,y} + \lambda_{9,t,y}\mathrm{IVOL}_{i,y} + \epsilon_{i,t,y+1}
\end{aligned}
$$

where $R_{i,t,y+1}$ is the realized return on industry i in month t in year $y+1$, the predictive cross-section regression are run on the lagged values of SC, IC, BETA, FSIZE, ISIZE, BM, RTV, MOM, and IVOL, which are all calculated or estimated with the sample from January to December in year y. This setting assures the associated trading strategy is rebalanced annually.

Table 12 reports the time-series average of the slope coefficients $\lambda_{i,t,y}$ $(i = 1, ..., 9)$ over the 624 months from January 1964 to December 2015 for all industries in the illiquidity networks that are estimated annually from 1963 to 2014. The Newey-West adjusted t-statistics are given in parentheses. The univariate regressions show a positive and statistically significant relation between illiquility sensitive centrality and the cross-section of future industry returns; and a positive and statistically significant relation between illiquility influential centrality and the cross-section of future industry returns. The average slope, $\lambda_{1,y}$, from the monthly regressions of realized returns on SC alone is 0.82 with a t-statistic of 2.05. The economic magnitude of the associated effect is higher than that documented in Table 6 and Table 10 for the univariate and bivariate sorts. The spread in average SC between decile 10 and decile 1 is 0.93 (1.50 - 0.57). Multiplying this spread by the average slope yields an estimate of the monthly risk premium of 0.76% per month (9.12% per year). The average slope, $\lambda_{2,y}$, from the monthly regressions of realized returns on IC alone is 0.69 with a t-statistic of 1.70. The economic magnitude of the associated effect is also higher than that documented in Table 6 and Table 11. The spread in average IC spread between decile 10 and 1 is 1.64 (1.96 - 0.32). Multiplying this spread by the average slope yields an estimate of the monthly risk premium of 1.13% month (13.56% per year).

Conditional on 6 other variables (BETA, FSIZE, BM, RTV, MOM and IVOL), the economic magnitudes and the significance levels of $\lambda_{1,y}$ and $\lambda_{2,y}$ remain almost unchanged. The average slope coefficient on SC, $\lambda_{1,y}$, conditional on the 6 control variables, is 0.88 with a t-statistic of 2.14; the average slope coefficient on IC, $\lambda_{2,y}$, conditional on the 6 control variables, is 0.79 with a t-statistic of 1.95. Since we have found in Table 7 that SC and IC are cross-sectional positive correlated, our primary interest is the full specification with SC, IC, and the 6 control variables. In this specification, the average slope coefficient on SC is 0.83 with a t-statistic of 2.00; the average slope coefficient of IC is 0.62 with a t-statistic of 1.92.[13] Theses results are very similar to the univariate regressions.

In the last specification in Table 12, I exclude SC and IC in the full specification regression to investigate the effect of dropping SC and IC to other control variables in explaining the cross-section returns at industry level. In the last specification, the average slope coefficient on RTV is 0.81 and significant, while those average slope coefficient on RTV in the specification with either SC or IC or both are smaller than 0.81 and statistically insignificant. It implies the illiquidity risk premium associated with RTV can be captured by SC and IC but not vice versa.

The table shows only SC, IC and MOM are consistently significant under the regressions of all specifications in the table. Many well-known cross-sectional effects at firm level such as market-beta, size, book-to-market, liquidity, and idiosyncratic volatility are not robustly significant in explaining the cross-section returns at industry level. The size effect measured by ISIZE is significantly positive with a t-statistic of 2.10 only in the full specification; the book-to-market effect measured by BM is significantly positive only in the full specifications excluding either SC or IC; the liquidity effect measured by RTV is significantly positive only in the specification without SC and IC. The signs of these effects are in line with those documented in literature. Note that these variables in this paper are measured at industry level and renewed annually, return dispersions associated with these variables could be small due to firms' aggregations into industry level. The momentum effect, however, is surprisingly robust at industry level.

As a robustness check for the significant effects of SC and IC, Table 13 presents the cross-sectional regression results of the full specification model under different subperiods

[13]Controlling SPREAD instead of RTV in the full specification has little effect on the results. In such specification, the average slope coefficient on SC is 0.94 with a t-statistic of 2.18; the average slope coefficient of IC is 0.76 with a t-statistic of 2.27.

(1970 -2015, 1980 - 2015, 1990 - 2015 and 2000 - 2015). SC is positive and statistically significant at the level of 0.1 in all subperiods. IC is also positive and statistically significant at the level of 0.1 in all subperiods except the most recent and shortest subsample period of 2010 - 2015, while the mean of coefficients for IC of 2010 - 2015 is still positive. Another observation is the effects of SC and IC measured by their respective mean coefficients are even larger in recent decades.

The clear conclusion is that the cross-sectional regressions provide strong corroborating evidence for an economically and statistically significant positive relation between the illiquidity centrality measures (SC and IC) and future returns, consistent with our conjecture that illiquidity centralities (sensitive centrality and influential centrality) are an important idiosyncratic risk that should be priced in financial markets, and they indeed earn risk premiums in the cross-sectional stock returns at industry level. Moreover, SC is a more robust risk factor than IC in explaining cross-sectional returns.

5 Conclusion

This paper proposes a new analytical framework to study centralities in an illiquidity transmission network and its asset pricing implication in the cross-section of expected stock returns. I document a statistically and economically significant relation between lagged illiquidity centralities (sensitive centrality and influential centrality) and future returns. This result is robust to controls for numerous other potential risk factors. The result related to influential centrality is consistent with the asset pricing implication of Acemoglu et al. (2012) and Acemoglu et al. (2015)'s theory, while I find sensitive centrality is an even more robust risk factor than influential centrality in explaining cross-sectional returns. In summary, I find strong evidence that the illiquidity network centralities (SC and IC) may be important risk factors in asset pricing with network structures of securities.

This paper differs from the existing literature studying commonality in liquidity, illiquidity spillovers and contagions in that I consider illiquidity spillovers in a network environment with focus on industries' illiquidity interconnections, instead of basing it on simple two-agents settings or on contemporaneous correlation-based analysis. Moreover, I consider network centrality in two directions: i) sensitive centrality (SC), which measures the degree of a node being affected by others; and ii) influential centrality (IC), which measures the degree of a node affecting others. Existing literature related to financial network centrality is mostly motivated by the systemic risk studies that suggest idiosyncratic shocks to an influential firm may cause aggregate market failures, so they tend to only consider influential centrality. I argue that sensitive centrality is at least as important as influential centrality in terms of asset pricing. Indeed, I find strong evidence in illiquidity network to support this conjecture. I find that SC and IC are positively correlated in time-series and in cross-section and each adds to the explanation of cross-sectional returns even given the other measure.

The approach used in this paper can be applied to study many other financial networks, such as return network, volatility network, and credit-spread network. An interesting direction for further research may be studying direct and indirect network effects in a unified framework with the general network measurement method proposed by Dufour and Jian (2016). After all, the adjacency matrix can only tell us about direct effects. If we want to study financial spillovers and propagations in depth, measuring indirect effects is also necessary. In this paper I assume the illiquidity network is unweighted. But weighted economic effects of financial spillovers could provide us more insights to understand the strength of underlying financial networks. Of course, different network centrality measures have to be selected accordingly. I leave a detailed analysis of these issues to future work.

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Appendices

A Variable Definitions

1. SPREAD: SPREAD is the average of daily Corwin and Schultz (2012)'s bid-ask spreads estimates within a year for the firms belong to the same industry specified by the first three digits of SIC codes.

2. RTV: RTV is the average of daily Amihud (2002)'s illiquidity estimates ($\text{RTV}_{i,t}$) within a year for the firms belong to the same industry specified by the first three digits of SIC codes.

$$\text{RTV}_{i,t} = \frac{|R_{i,t}|}{VOLV_{i,t}} \tag{9}$$

   where $\text{RTV}_{i,t}$ is firm i's illiquidity estimate on day t. $R_{i,t}$ is firm i's return on day t. $VOLV_{i,t}$ is firm i's trading volume in dollars on day t.

3. ISIZE: ISIZE is the average of daily sum of market capitalizations within a year for the firms belong to the same industry specified by the first three digits of SIC codes:

$$\text{ISIZE}_{i,t} = \sum_{i_k \in i} MC_{i_k,t} \tag{10}$$

   where $MC_{i_k,t}$ is firm i_k's market capitalization (stock's price times shares outstanding in millions of dollars) on day t, and firm i_k belongs to industry i.

4. FSIZE: FSIZE is the average of daily average of market capitalizations within a year for the firms belong to the same industry specified by the first three digits of SIC codes:

$$\text{FSIZE}_{i,t} = \frac{1}{n_i} \sum_{i_k \in i} MC_{i_k,t} \tag{11}$$

   where $MC_{i_k,t}$ is firm i_k's market capitalization (stock's price times shares outstanding in millions of dollars) on day t, and firm i_k belongs to industry i. n_i is the number of firms belong to industry i.

5. BM: Following Fama and French (1992), I compute a firm's book-to-market ration in month t using the market value of its equity at the end of December of the previous year and the book value of common equity plus balance-sheet deferred taxes for the firm's latest fiscal year ending in prior calendar year.

$$\mathrm{BM}_{i,t} = \frac{1}{n_i} \sum_{i_k \in i} \mathrm{BM}_{i_k,t} \tag{12}$$

where $\mathrm{BM}_{i,t}$ is industry i's book-to-market in month t. $\mathrm{BM}_{i_k,t}$ is firm i_k's book-to-market in month t, for firm i_k belongs to industry i. n_i is the number of firms belong to industry i. Industry's book-to-market in year y is the simple average of monthly industry's book-to-market in year y.

6. BETA: To take into account nonsynchronous trading, I follow Scholes and Williams (1977) and Dimson (1979) and use the lag and lead of the market portfolio as well as the current market when estimating beta:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_{1,i}(R_{m,d-1} - r_{f,d-1}) + \beta_{2,i}(R_{m,d} - r_{f,d}) + \beta_{3,i}(R_{m,d+1} - r_{f,d+1}) + \epsilon_{i,d}, \tag{13}$$

where $R_{i,d}$ is the average return of the stocks belong to industry i on day d, $r_{f,d}$ is the risk-free rate on day d and $R_{m,d}$ is the market return on day d. I use simple OLS to estimate equation 13 for each industry using daily returns within a year. The market beta of industry i in year y is defined as $\hat{\beta}_i = \hat{\beta}_{1,i} + \hat{\beta}_{2,i} + \hat{\beta}_{3,i}$.

7. IVOL: I use a simple CAPM model specification to estimate the yearly idiosyncratic volatility of a firm:

$$R_{i,d} - r_{f,d} = \alpha_i + \beta_i(R_{m,d} - r_{f,d}) + \epsilon_{i,d}, \tag{14}$$

where $\epsilon_{i,d}$ is the firm i' idiosyncratic return on day d. The idiosyncratic volatility of firm i in year y is defined as the standard deviation of daily OLS residuals in year y:

$$\mathrm{IVOL}_{i,t} = \sqrt{\widehat{\mathrm{var}(\hat{\epsilon}_{i,d})}}. \tag{15}$$

The idiosyncratic volatility of an industry in year y is the average of the idiosyncratic volatilities of the firms belong to that industry in year y.

8. MOM: The momentum variable of firm i for every months in year $y+1$ is the simple average of firm i' daily returns in year y. The momentum of an industry is the simple average of the momentums of the firms belong to that industry.

Table 4: Summary statistics of illiquidity network centralities panels. Centrality measures are estimated every year from January 1963 to December 2015. Column descriptive statistics provide characteristics of the empirical distribution of cross-section centrality measures in a given year. Row descriptive statistics provide characteristics of each column's descriptive statistics across different years (1963 - 2015). Skewness is unbiased skew, for those are greater than 0 are right-skewed; kurtosis is unbiased kurtosis using Fisher's definition of kurtosis (kurtosis normal = 0). Panel A presents summary statistics for sensitive centrality; Panel B presents summary statistics for influential centrality.

Panel A: Sensitive Centrality

	Cross-section Centrality Measures									
	count	mean	std	min	25%	50%	75%	max	skewness	kurtosis
count	53	53	53	53	53	53	53	53	53	53
mean	310.28	0.95	0.28	0.39	0.75	0.90	1.12	1.83	0.51	0.21
std	42.87	0.05	0.13	0.14	0.15	0.12	0.04	0.30	0.40	0.59
min	222	0.81	0.15	0.15	0.35	0.54	1.01	1.44	-0.26	-0.74
25%	282	0.94	0.19	0.25	0.67	0.89	1.10	1.60	0.24	-0.14
50%	311	0.98	0.21	0.42	0.83	0.96	1.11	1.71	0.45	0.08
75%	332	0.98	0.34	0.52	0.86	0.97	1.14	2.09	0.80	0.43
max	393	0.99	0.59	0.62	0.88	1.00	1.24	2.47	1.69	2.99

Panel B: Influential Centrality

	Cross-section Centrality Measures									
	count	mean	std	min	25%	50%	75%	max	skewness	kurtosis
count	53	53	53	53	53	53	53	53	53	53
mean	310.28	0.85	0.49	0.18	0.52	0.72	1.05	2.84	1.38	2.34
std	42.87	0.10	0.14	0.11	0.17	0.17	0.14	0.62	0.53	2.22
min	222	0.41	0.22	0.00	0.05	0.11	0.26	1.62	0.27	-1.14
25%	282	0.82	0.41	0.12	0.41	0.63	1.01	2.46	1.09	1.16
50%	311	0.87	0.49	0.17	0.51	0.73	1.09	2.71	1.37	1.78
75%	332	0.91	0.57	0.23	0.65	0.84	1.12	3.18	1.54	2.55
max	393	0.98	0.91	0.44	0.84	0.97	1.35	4.92	3.57	11.94

Table 5: Summary statistics of the time-series correlations of sensitive and influential centralities of given industries. Centrality measures are estimated every year from January 1963 to December 2015. I only calculate the time-series correlations between sensitive centrality and influential centrality for those industries have more than 10 years centralities observations in sample. Column statistics provide time-series correlations of any given industry and its p-value to null hypothesis of no correlation. Row descriptive statistics provide characteristics of each column's statistics across different industries.

	corr	p-value
count	395	395
mean	0.42	0.09
std	0.19	0.19
min	-0.37	0.00
25%	0.32	0.00
50%	0.45	0.00
75%	0.55	0.07
max	0.82	0.96

Table 6: Return and alpha on portfolios of stocks sorted by illiquidity network centralities. Decile portfolios are formed every year from January 1964 to December 2014 by sorting industries based on the sensitive centrality (SC) in Panel A and based on the influential centrality (IC) in Panel B. Centrality measures are estimated every year from January 1963 to December 2014. Industry returns are calculated by the equal-weighted returns of stocks belong to the industry. Portfolio 1 (10) is the portfolio of industries with lowest (highest) centralities in the past calendar year. The tables reports the equal-weighted and value-weighted average monthly returns, the 4-factor Fama-French-Carhart alphas on the equal-weighted and value-weighted portfolios, and the average centrality of industries in the past calendar year. The last two rows present the differences in monthly returns and the differences in alphas with respect to the 4-factor Fama-French-Carhart model between portfolios 10 and 1 and the corresponding t-statistics. Average raw and risk-adjusted returns are given in percentage terms. Newey-West (1987) adjusted t-statistics are reported in parentheses.

Panel A: Sorted by sensitive centrality

	Equal-Weighted		Value-Weighted		
Decile	Average Return	4-factor Alpha	Average Return	4-factor Alpha	SC
Low SC	1.06	0.31	1.44	0.74	0.57
2	1.11	0.42	1.35	0.64	0.68
3	1.18	0.42	1.36	0.67	0.75
4	1.26	0.52	1.44	0.76	0.81
5	1.24	0.53	1.47	0.82	0.87
6	1.07	0.33	1.32	0.61	0.94
7	1.28	0.59	1.42	0.80	1.02
8	1.26	0.62	1.26	0.72	1.12
9	1.12	0.47	1.43	0.84	1.26
High SC	1.42	0.76	1.82	1.23	1.50
10-1	0.36	0.45	0.38	0.49	
	(3.66)	(3.72)	(2.15)	(2.65)	

Panel B: Sorted by influential centrality

	Equal-Weighted		Value-Weighted		
Decile	Average Return	4-factor Alpha	Average Return	4-factor Alpha	IC
Low IC	1.05	0.33	1.26	0.62	0.32
2	1.20	0.52	1.55	0.89	0.44
3	1.18	0.47	1.42	0.74	0.52
4	1.20	0.48	1.37	0.76	0.60
5	1.22	0.53	1.50	0.83	0.68
6	1.18	0.45	1.45	0.82	0.77
7	1.17	0.49	1.54	0.87	0.89
8	1.19	0.48	1.41	0.76	1.06
9	1.16	0.45	1.35	0.72	1.33
High IC	1.44	0.81	1.57	0.93	1.96
10-1	0.40	0.48	0.31	0.31	
	(3.19)	(3.35)	(2.33)	(2.31)	

Table 7: Distribution of industries across deciles sorted by sensitive centrality and sorted by influential centrality. Centrality measures are estimated every year from January 1963 to December 2014. Decile portfolios are formed every year from January 1964 to December 2015 by sorting industries based on the sensitive centrality (SC) and based on the influential centrality (IC). Portfolio 1 (10) is the portfolio of industries with lowest (highest) centralities in the past calendar year. The ith row and jth column element in the table is the time-series average of the percentage ratios of the number of the industries in portfolio j sorted by influential centrality, as well as in portfolio i sorted by sensitive centrality, over the total number of the industries in portfolio i sorted by sensitive centrality.

By sensitive centrality	By influential centrality									
	Low IC	2	3	4	5	6	7	8	9	High IC
Low SC	23.02	16.29	12.07	11.18	8.32	7.95	5.66	5.61	4.53	3.48
2	16.90	13.53	12.94	12.58	10.57	7.98	8.18	6.04	5.11	4.28
3	14.32	12.15	12.86	10.99	11.21	9.54	9.57	7.24	6.21	4.01
4	9.84	11.61	12.89	11.64	12.13	10.87	10.05	7.19	7.29	4.60
5	8.64	12.20	9.82	10.54	10.57	11.52	10.15	11.29	7.29	6.10
6	8.15	9.22	10.90	11.18	10.69	10.36	12.57	10.84	8.36	5.84
7	5.25	8.49	8.45	11.13	10.81	10.91	11.42	11.77	11.28	8.60
8	4.84	6.23	6.97	7.22	10.87	10.54	12.21	12.82	12.95	13.47
9	4.34	4.77	6.91	5.94	7.34	8.51	10.90	12.98	17.38	19.05
High SC	3.01	3.88	4.72	6.12	6.06	6.87	7.94	12.68	17.94	28.89

Table 8: Transition matrix of industries in portfolios sorted by illiquidity network centralities. Centrality measures are estimated every year from January 1963 to December 2014. Decile portfolios are formed every year from January 1964 to December 2015 by sorting industries based on the sensitive centrality (SC) in Panel A and based on the influential centrality (IC) in Panel B. Portfolio 1 (10) is the portfolio of industries with lowest (highest) centralities in the past calendar year. The ith row and jth column element in the table is the time-series average of the percentage ratios of the number of the industries in portfolio i in year y shifting to portfolio j in year $y+1$ over the number of the industries in portfolio i in year y.

Panel A: Sorted by sensitive centrality

	To									
From	Low SC	2	3	4	5	6	7	8	9	High SC
Low SC	11.39	10.58	11.05	10.56	7.22	8.75	8.78	9.12	8.91	8.25
2	10.90	9.04	9.96	9.78	9.79	9.81	8.19	8.77	8.96	8.96
3	9.95	8.98	10.60	8.89	10.30	9.62	9.82	8.72	9.33	8.64
4	9.35	11.01	8.65	9.99	10.19	8.13	9.58	9.56	9.33	9.36
5	9.05	9.65	8.43	10.24	10.27	9.78	10.41	9.10	9.13	9.04
6	10.00	9.79	9.42	9.01	9.06	8.87	10.30	9.80	9.24	9.13
7	8.63	9.01	10.28	9.55	10.43	8.28	10.06	9.18	10.50	9.67
8	8.78	8.43	8.37	9.51	9.44	10.63	9.20	10.86	9.87	10.44
9	7.78	9.33	9.06	8.14	10.26	9.67	9.46	10.33	10.52	10.99
High SC	8.25	8.57	8.57	9.22	8.53	8.61	10.13	11.33	10.19	12.44

Panel B: Sorted by influential centrality

	To									
From	Low IC	2	3	4	5	6	7	8	9	High IC
Low IC	10.86	11.20	11.28	10.77	9.83	9.86	10.07	7.41	6.52	7.54
2	10.87	11.64	10.74	9.74	11.71	7.47	9.95	8.11	7.69	7.15
3	12.92	9.85	10.43	9.17	10.58	8.45	8.89	9.39	7.62	8.07
4	9.42	10.82	11.33	10.55	9.73	8.94	8.64	8.60	8.47	7.94
5	11.27	9.99	9.91	9.62	8.24	8.90	8.76	9.17	9.61	8.90
6	8.70	8.84	8.19	8.42	9.91	10.49	9.50	11.03	9.80	9.81
7	8.69	11.38	8.51	8.49	9.48	9.58	9.90	8.58	11.21	9.63
8	8.05	7.76	8.56	9.71	8.42	10.91	10.14	10.58	11.72	10.16
9	6.27	7.55	8.64	9.32	8.36	8.40	11.50	10.85	11.34	13.09
High IC	7.05	5.64	7.08	8.17	9.00	9.31	9.23	12.28	12.13	15.14

Table 9: Summary statistics for decile portfolios sorted by illiquidity network centralities. Centrality measures are estimated every year from January 1963 to December 2014. Decile portfolios are formed every year from January 1964 to December 2015 by sorting industries based on the sensitive centrality (SC) in Panel A and based on the influential centrality (IC) in Panel B. Portfolio 1 (10) is the portfolio of industries with lowest (highest) centralities in the past calendar year. The table reports for each decile the simple average across the years and across the industries of various characteristics for the industries: the average stock market capitalization (in millions of dollars, labeled FSIZE), the industry market capitalization (in millions of dollars, labeled ISIZE), the market beta (labeled BETA), the book-to-market (labeled BM), the average stock bid-ask spreads estimate (in percent, labeled SPREAD), the average Amihud (2002) illiquidity measure (scaled by 10^6, labeled RTV), the average industry monthly return in the past calendar year prior to portfolio formation (in percent, labeled MOM), and the industry idiosyncratic volatility over the past calendar year prior to portfolio formation (labeled IVOL).

Panel A: Sorted by sensitive centrality

Decile	FSIZE($\$10^6$)	ISIZE($\$10^6$)	BETA	BM	SPREAD(%)	RTV(10^{-6})	MOM(%)	IVOL
Low SC	1.22	14.86	0.89	2.59	1.84	4.82	0.08	0.28
2	1.13	16.05	0.87	3.17	2.09	6.63	0.08	0.29
3	1.18	15.51	0.87	3.19	2.16	6.56	0.07	0.28
4	1.25	19.02	0.87	2.89	2.25	7.11	0.08	0.27
5	1.19	18.00	0.87	3.41	2.11	7.70	0.08	0.28
6	1.17	20.97	0.88	3.08	2.21	7.25	0.08	0.27
7	1.13	20.06	0.88	2.77	2.32	7.85	0.09	0.28
8	1.28	25.64	0.86	3.82	2.41	7.51	0.08	0.28
9	1.18	20.25	0.85	3.28	2.55	6.02	0.08	0.26
High SC	1.18	30.09	0.87	4.36	2.64	7.53	0.08	0.27

Panel B: Sorted by influential centrality

Decile	FSIZE($\$10^6$)	ISIZE($\$10^6$)	BETA	BM	SPREAD(%)	RTV(10^{-6})	MOM(%)	IVOL
Low IC	1.37	21.20	0.94	2.93	1.59	4.63	0.08	0.26
2	1.29	23.67	0.89	2.76	1.75	6.74	0.08	0.28
3	1.34	20.01	0.90	3.10	1.76	4.78	0.08	0.27
4	1.27	17.25	0.88	4.06	1.92	6.64	0.08	0.27
5	1.15	15.75	0.87	2.92	1.88	6.06	0.08	0.28
6	1.12	16.97	0.87	3.32	2.12	6.58	0.07	0.28
7	1.26	18.67	0.85	3.23	2.43	7.35	0.08	0.28
8	1.00	18.96	0.84	2.88	2.57	8.14	0.08	0.28
9	1.16	19.12	0.84	3.72	3.06	8.70	0.07	0.28
High IC	0.94	28.72	0.82	3.68	3.48	9.34	0.07	0.28

Table 10: Returns on portfolios of industries sorted by sensitive centrality after controlling for FSIZE, ISIZE, BETA, BM, RTV, MOM, and IVOL. Centrality measures are estimated every year from January 1963 to December 2014. Double-sorted, equal-weighted and value-weighted decile portfolios are formed every year from January 1964 to December 2015 by sorting industries based on sensitive centralities after controlling for average firm market capitalization, industry market capitalization, market beta, book-to-market, return-to-volume, industry momentum, and industry idiosyncratic volatility. In each case, I first sort the industries in to 5 deciles using the control variable, then within each decile, I sort industries into 10 decile portfolios based on the sensitive centralities over the previous calendar year so that decile 1 (10) contains industries with the lowest (highest) SC. This table presents average industry returns across the 5 control deciles to produce decile portfolio with dispersion in SC but with similar levels of the control variable. "10-1 Return" is the difference in average monthly returns between the High SC and Low SC portfolios. "10-1 Alpha" is the difference in 4-factor alphas on the High SC and Low SC portfolios. Newey-West (1987) adjusted t-statistics are reported in parentheses.

	Equal-Weighted Returns							Value-Weighted Returns						
Decile	FSIZE	ISIZE	BETA	BM	RTV	MOM	IVOL	FSIZE	ISIZE	BETA	BM	RTV	MOM	IVOL
Low SC	1.10	1.04	1.05	1.03	1.13	1.04	1.07	1.57	1.50	1.29	1.28	1.40	1.27	1.47
2	1.12	1.15	1.15	1.18	1.17	1.09	1.13	1.54	1.54	1.38	1.45	1.41	1.30	1.31
3	1.18	1.19	1.22	1.19	1.12	1.27	1.14	1.57	1.57	1.31	1.33	1.37	1.43	1.45
4	1.23	1.19	1.24	1.25	1.23	1.21	1.28	1.55	1.62	1.48	1.51	1.43	1.49	1.51
5	1.13	1.20	1.12	1.09	1.31	1.17	1.18	1.57	1.64	1.31	1.30	1.59	1.37	1.44
6	1.08	1.04	1.13	1.21	1.11	1.16	1.12	1.39	1.35	1.38	1.33	1.35	1.32	1.33
7	1.22	1.32	1.18	1.19	1.19	1.13	1.28	1.59	1.64	1.34	1.27	1.34	1.45	1.59
8	1.25	1.19	1.16	1.28	1.15	1.29	1.13	1.63	1.61	1.20	1.40	1.31	1.34	1.35
9	1.21	1.24	1.36	1.27	1.22	1.25	1.28	1.62	1.63	1.55	1.58	1.48	1.37	1.49
High SC	1.39	1.36	1.33	1.31	1.33	1.33	1.37	1.84	1.71	1.55	1.50	1.68	1.51	1.75
10-1 Return	0.29	0.32	0.28	0.28	0.20	0.29	0.30	0.27	0.21	0.26	0.23	0.29	0.24	0.29
	(2.83)	(3.27)	(2.78)	(2.83)	(2.20)	(3.19)	(3.17)	(2.05)	(1.54)	(1.94)	(1.71)	(2.41)	(1.95)	(1.85)
10-1 Alpha	0.40	0.39	0.31	0.37	0.29	0.35	0.40	0.38	0.29	0.34	0.33	0.39	0.31	0.40
	(2.71)	(2.97)	(2.93)	(2.76)	(2.11)	(3.46)	(2.67)	(2.41)	(1.96)	(2.46)	(2.26)	(2.41)	(2.57)	(2.10)

Table 11: Returns on portfolios of industries sorted by influential centrality after controlling for FSIZE, ISIZE, BETA, BM, RTV, MOM, and IVOL. Centrality measures are estimated every year from January 1963 to December 2014. Double-sorted, equal-weighted) and value-weighted decile portfolios are formed every year from January 1964 to December 2015 by sorting industries based on influential centralities after controlling for average firm market capitalization, industry market capitalization, market beta, book-to-market, return-to-volume, industry momentum, and industry idiosyncratic volatility. In each case, I first sort the industries in to 5 deciles using the control variable, then within each decile, I sort industries into 10 decile portfolios based on the sensitive centralities over the previous calendar year so that decile 1 (10) contains industries with the lowest (highest) SC. This table presents average industry returns across the 5 control deciles to produce decile portfolio with dispersion in SC but with similar levels of the control variable. "10-1 Return" is the difference in average monthly returns between the High SC and Low SC portfolios. "10-1 Alpha" is the difference in 4-factor alphas on the High SC and Low SC portfolios. Newey-West (1987) adjusted t-statistics are reported in parentheses.

	Equal-Weighted Returns							Value-Weighted Returns						
Decile	FSIZE	ISIZE	BETA	BM	RTV	MOM	IVOL	FSIZE	ISIZE	BETA	BM	RTV	MOM	IVOL
Low IC	1.10	1.12	1.15	1.12	1.14	1.07	1.15	1.53	1.54	1.29	1.27	1.43	1.37	1.42
2	1.17	1.19	1.14	1.14	1.22	1.24	1.08	1.60	1.59	1.36	1.38	1.35	1.42	1.34
3	1.23	1.12	1.15	1.22	1.19	1.15	1.15	1.75	1.57	1.41	1.41	1.49	1.42	1.37
4	1.20	1.19	1.23	1.14	1.15	1.11	1.18	1.61	1.47	1.40	1.32	1.37	1.37	1.51
5	1.12	1.23	1.13	1.21	1.20	1.24	1.21	1.53	1.77	1.35	1.38	1.46	1.41	1.59
6	1.04	1.19	1.21	1.16	1.19	1.16	1.36	1.34	1.58	1.42	1.38	1.43	1.38	1.58
7	1.15	1.12	1.16	1.15	1.22	1.17	0.95	1.67	1.58	1.46	1.43	1.51	1.38	1.29
8	1.29	1.25	1.26	1.20	1.12	1.19	1.36	1.61	1.74	1.43	1.46	1.42	1.47	1.68
9	1.14	1.12	1.15	1.17	1.25	1.22	1.21	1.59	1.52	1.30	1.37	1.42	1.50	1.52
High IC	1.45	1.47	1.46	1.45	1.30	1.42	1.40	1.68	1.69	1.57	1.47	1.53	1.48	1.51
10-1 Return	0.35	0.36	0.31	0.34	0.16	0.35	0.25	0.14	0.15	0.27	0.20	0.09	0.11	0.09
	(3.16)	(2.99)	(2.60)	(2.85)	(1.42)	(3.37)	(2.11)	(1.36)	(1.26)	(2.41)	(1.82)	(0.92)	(1.03)	(0.65)
10-1 Alpha	0.45	0.45	0.34	0.44	0.27	0.38	0.34	0.21	0.24	0.30	0.24	0.21	0.13	0.18
	(3.41)	(3.11)	(2.59)	(3.21)	(2.24)	(3.51)	(2.67)	(1.85)	(1.62)	(2.38)	(2.07)	(1.90)	(1.12)	(1.38)

Table 12: Industry-level cross-sectional return regressions. Each month from January 1964 to December 2015 I run an industry-level cross-section regression of the return in that month on subsets of lagged predictor variables including sensitive centrality (SC), influential centrality (IC), FSIZE, ISIZE, BETA, BM, RTV, MOM, and IVOL. Centrality measures (SC and IC) are estimated every year from January 1963 to December 2014. Industry returns are calculated by the equal-weighted returns of stocks belong to the industry. For example, the industry return of each month in 2001 are regressed on the the lagged predictor variables estimated with the sample from January 2000 to December 2000. In each row, the table reports the time-series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses).

SC	IC	BETA	FSIZE	ISIZE	BM	RTV	MOM	IVOL
0.82								
(2.05)								
	0.69							
	(1.70)							
0.88		0.48	0.47	-0.52	0.91	0.50	0.66	0.04
(2.14)		(1.41)	(1.02)	(-1.30)	(2.18)	(1.32)	(2.57)	(0.06)
	0.79	0.49	0.47	-0.52	0.90	0.50	0.63	0.13
	(1.95)	(1.43)	(1.02)	(-1.3)	(2.18)	(1.32)	(2.38)	(0.20)
0.83	0.62	0.49	-0.58	0.87	0.57	0.68	0.65	0.27
(2.00)	(1.92)	(1.02)	(-1.46)	(2.10)	(1.52)	(1.45)	(2.52)	(0.39)
		0.65	0.45	0.51	-0.44	0.81	0.64	0.50
		(1.52)	(1.41)	(1.10)	(-1.09)	(1.93)	(2.44)	(0.71)

Table 13: Industry-level cross-sectional return regressions in subperiods (1970 -2015, 1980 - 2015, 1990 - 2015 and 2000 - 2015). Each month from January in each starting year (1970, 1980, 1990 and 2000) to December 2015 I run an industry-level cross-section regression of the return in that month on lagged predictor variables including sensitive centrality (SC), influential centrality (IC), FSIZE, ISIZE, BETA, BM, RTV, MOM, and IVOL. Centrality measures (SC and IC) are estimated every year from January 1963 to December 2014. Industry returns are calculated by the equal-weighted returns of stocks belong to the industry. For example, the industry return of each month in 2001 are regressed on the the lagged predictor variables estimated with the sample from January 2000 to December 2000. In each row, the table reports the subsample time-series averages of the cross-sectional regression slope coefficients and their associated Newey-West (1987) adjusted t-statistics (in parentheses).

Subperiods	SC	IC	BETA	FSIZE	ISIZE	BM	RTV	MOM	IVOL
1970 - 2015	0.89	0.68	0.50	-0.62	0.97	0.65	0.75	0.70	-0.09
	(1.89)	(1.87)	(0.93)	(-1.36)	(2.05)	(1.50)	(1.39)	(2.74)	(-0.14)
1980 - 2015	0.90	0.70	0.46	-0.83	0.87	0.53	0.68	0.67	-0.11
	(1.69)	(1.75)	(0.75)	(-1.69)	(1.70)	(1.14)	(1.14)	(2.49)	(-0.16)
1990 - 2015	1.24	0.94	0.81	-0.89	1.16	0.84	0.88	0.50	-0.29
	(1.94)	(1.80)	(1.03)	(-1.49)	(1.78)	(1.45)	(1.12)	(1.83)	(-0.36)
2000 - 2015	1.93	0.96	1.15	-0.32	1.43	1.46	1.26	0.83	-1.13
	(2.10)	(1.34)	(0.91)	(-0.52)	(1.51)	(1.76)	(1.11)	(2.14)	(-0.91)