Essays on the Dynamics of Liquidity Networks

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Abstract

This dissertation presents three essays on liquidity interrelationships between firms in the Standard and Poor's 500 (S&P500) index using network theory. Liquidity is the ease of trading securities in the financial market. It varies over time and differs significantly across firms. The principal challenge for market participants is the variability and uncertainty in liquidity. In simple terms, market liquidity risk relates to the inability to trade at a fair price with immediacy. Many studies investigate liquidity co-movement of assets and the associated risk. However, almost no empirical work has been devoted to investigating the possibility of liquidity interrelationship through a liquidity network.

In the first essay, I investigate if a liquidity network among 1,174 firms included in the S&P500 exists using 30 years of data, employing a lead-lag liquidity network method to analyse liquidity interrelationships beyond contemporaneous spillover effects. I find an intertemporal liquidity network where 84% of the firms exhibit statistically significant connectivity in at least one direction during the sample period. The degree and manner of liquidity communication vary across the firms and are dynamic over time. Furthermore, I show that individual firms' characteristics, such as the level and change in liquidity, firm size, and return volatility, can explain their network structure. The outcome emphasizes the fragility of the liquidity system through the firms' connectivity which can be a new factor to consider when evaluating firms' expected rate of return.

The second essay explores the relationship between the firm-level liquidity shock transmission through the liquidity network and the role that firm-size plays in the transmission process. I find that the transmission of the liquidity shock depends on the firm size. The greater intensity shocks influence the transmission more through larger firms than small firms. I also find that with one unit increase in the size differences between firms, the odds of firms not being connected in the network increases by 2.5%, suggesting similar-size firms tend to have

more connectivity. Furthermore, looking at size-based portfolios, I find that although all the portfolios transmit shock significantly to one another, their explanatory power varies. Most portfolios tend to send out more shocks to the next largest quantiles. The outcome overall suggests that diversification against liquidity shock transmission is possible by including different firm sizes.

Finally, I investigate the impact of the COVID-19 pandemic on liquidity interlinkages of U.S. industry groups. I document that sectors differ in their liquidity interactions during the pre-COVID period, with some sectors more interlinked than others. I also document that the crisis induced by COVID-19 had a significant effect on the liquidity network, with virtually all sectors becoming more interconnected relative to the pre-COVID period. The effect varies across industries, with the real estate sector being the most affected and telecommunication services the least. Overall, due to higher interconnectedness, liquidity risk became harder to diversify.

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Statement of Contribution

DRC 16

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STATEMENT OF CONTRIBUTION
DOCTORATE WITH PUBLICATIONS/MANUSCRIPTS

We, the candidate and the candidate's Primary Supervisor, certify that all co-authors have consented to their work being included in the thesis and they have accepted the candidate's contribution as indicated below in the *Statement of Originality*.

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(This form should appear at the end of each thesis chapter/section/appendix submitted as a manuscript/ publication or collected as an appendix at the end of the thesis)

CHAPTER 1

Introduction

This chapter provides an overview of the thesis. In particular, Section 1.1 outlines the motivation, contribution and the need to explore the area of liquidity connectivity and its associated risk. Section 1.2 presents a brief overview of the findings of three empirical studies. Section 1.3 lists research outputs from the thesis. Finally, Section 1.4 provides the structure of the remainder of the thesis.

1.1 Motivation and Contribution to the Literature

Traditionally, market microstructure focused on attributes of individual assets. Researchers then discovered a commonality in liquidity (Chordia et al., 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001). That is, the liquidity of individual assets co-moves with market liquidity (Chordia et al., 2000). The commonality in liquidity has received much attention since it influences expected return (Acharya & Pedersen, 2005; Pástor & Stambaugh, 2003). Also, there is evidence of liquidity spillover (Cespa & Foucault, 2014). The fact that the liquidity of individual firms co-moves and propagates from one to another implies connectivity. Nevertheless, to the best of my knowledge, there has been no attempt to capture stock market liquidity connectivity through a possible network of interrelated firms.

Modeling market liquidity as a network facilitates capturing the liquidity interdependence and interrelationship across firms. In my three essays, I utilize the Granger-causality network analysis proposed by Billio et al. (2012). The intertemporal nature of the Granger-causality network enables me to look beyond the contemporaneous liquidity movement. The lead-lag connections are not arbitrary; understanding them provides new insights to link microlevel behaviour with the macrolevel phenomenon. For example, through this liquidity connectivity, we might be able to anticipate and therefore control channels through which liquidity shock propagates into the market in times of financial distress.

In my first essay (Chapter 2), I explore whether an intertemporal liquidity network exists. I look at the liquidity network structure and capture its dynamics over time by utilizing the addition and deletion of the Standard and Poor's 500 (S&P500) constituents through 30 years of the sample period. Then I investigate whether firm-specific factors can explain the liquidity network. The outcome of the first essay shows that some firm characteristics, such as liquidity and firm size, explain the liquidity connectivity, motivating the idea of looking deeper into the association between firm size and liquidity shock propagation through the network. Hence, in the second essay (Chapter 3), I investigate whether the firm size can explain firm-level liquidity shock propagation. In particular, I explore where firm-level liquidity shock transmits to by employing firm size and size-sorted portfolios. Lastly, in essay 3 (Chapter 4), I focus on the most recent external shock that has influenced the financial markets. Therefore, I analyse the influence of the COVID-19 systematic shock on the structure of liquidity interconnectedness in the U.S. sectors.

My first essay contributes to the literature in three significant ways. Firstly, I provide empirical evidence that the liquidity network exists and is dynamic over time. This is an important point because the intertemporal nature of the liquidity network implies the predictability of firm liquidity by using its liquidity connectivity to others in the network. Secondly, I contribute to the literature on liquidity spillover by identifying the sources of liquidity transmissions within a liquidity network. Cespa and Foucault (2014) suggest that liquidity spillovers occur through a cross-asset learning mechanism. However, they call upon future research to examine the magnitude of the effect and whether some assets are more pivotal for liquidity spillovers. Thirdly, I provide empirical evidence of a relationship between individual firms' characteristics and their liquidity network structure.

My second essay contributes to the literature on liquidity-risk diversification by detecting the destination of liquidity shock transmission through the firm-size channel. I provide evidence that firm-level liquidity shock transmission in the network depends on the level of firm size. My findings also add to the literature on the relationship between market efficiency and liquidity by showing that firms tend to transmit information to similar-sized firms and portfolios.

My last essay adds to the literature on connectivity and systematic risk propagation. COVID-19's impact on the financial market is one of the most mainstream research fields. There is evidence of asymmetry in reaction and recovery across and within asset classes (Yarovaya et al., 2020). Utilizing two liquidity measures, my study shows that interconnectivity among the U.S. industry groups increased substantially when the COVID-19 shock hit the stock market. However, the crisis brought about by the pandemic has affected various sectors differently.

1.2 Main Findings

This section highlights the main findings of the three essays. In the first essay, I model market liquidity as a network and investigate the liquidity ties between the assets through five network measures. I establish connectivity through a Granger-causality network. My empirical evidence illustrates a dynamic liquidity network in the U.S. stock market over 30 years of the sample period. While a firm contributes to the liquidity of others, it is simultaneously influenced by their liquidity. Of the firms, 84% exhibit statistically significant connectivity in at least one direction during the sample period. Moreover, out of possible pairwise causality combinations, more than 12% of pairs have statistically significant relationships.

Furthermore, I look at firm-level characteristics using fixed-effect panel-regression analysis to investigate what explains the cross-sectional differences in the firms' network structure. I find that smaller, riskier firms (measured by market capitalization and return volatility) with lower liquidity and a greater change in liquidity tend to explain the firm network structure the most.

My second essay provides evidence that shock transmission depends on the level of firm size. The greater intensity shocks influence the transmission more through larger firms than small firms. That is, if a smaller firm experiences the same magnitude of shock, it influences the liquidity network less. This relationship holds for the subsamples of positive and negative shocks, suggesting that the way liquidity shock propagates into the system is independent of its sign. My outcome is in line with Chordia et al. (2014), who observe that shock in order flow is reflected in large stock prices within a month, while the smaller, less visible firms take over 6 months to reflect the effect entirely. I also find that with one unit increase in the size differences between firms, the odds of firms not being connected in the network increases by 2.5%, suggesting similar-size firms tend to have more connectivity.

Lastly, my third essay documents that liquidity interconnectedness varied across industries before the COVID-19 pandemic. However, when the COVID-19 hit the stock market, virtually all the industry groups in the S&P500 experienced a uniform increase in connectedness. More specifically, there was an increase in the mean of interconnectedness from 40.1% to 62.7%. As a potential consequence of higher interconnectedness, return correlations have increased in the COVID-19 period for most industries.

1.3 Research Outputs From the Thesis

The third essay contained in this thesis is published in the *Finance Research Letters* journal.

Essay 1:

This essay was presented at the following conferences:

Farzami, Y., Gregory-Allen, R., Molchanov, A. (2019, February). The dynamics of liquidity interconnectedness. *Proceedings of the 23^rd^ New Zealand Finance Colloquium* (*NZFC*), *PhD Symposium*, New Zealand.

Farzami, Y., Molchanov, A., Gregory-Allen, R. (2019, July). The dynamics of liquidity interconnectedness. *Proceedings of the 11th Financial Management Association* (*FMA*) *Asia/Pacific Conference and Doctoral Student Consortium*, Ho Chi Minh City, Vietnam.

Essay 2:

The early version of Essay 2 was presented at the following conference:

Farzami, Y. (2019, July). The dynamics of liquidity interconnectedness. *Proceedings of the 11th Financial Management Association* (*FMA*) *Asia/Pacific Conference and Doctoral Student Consortium*, Ho Chi Minh City, Vietnam.

Essay 3:

<u>Publication:</u>

Farzami, Y., Gregory-Allen, R., Molchanov, A., & Sehrish, S. (2021). COVID-19 and the liquidity network. *Finance Research Letters*, *42*, 101937.

This essay was presented at the following seminar:

Farzami, Y., Gregory-Allen, R., Molchanov, A. (2020, September). COVID-19 and the liquidity network. *Proceedings of Massey University Seminar Series*, Auckland, New Zealand.

1.4 Structure of the Thesis

The remainder of this thesis is organized as follows. Chapter 2 comprises the first essay, which examines the existence of a liquidity network and its characteristics. Chapter 3 contains the second essay, which looks at firm-level shock transmission through a liquidity network. Chapter 4 presents the third essay, an event study investigating the impact of the COVID-19 pandemic across industry groups in the U.S. market. Chapter 5 outlines the main findings and their implications for future research directions. Supplementary information, such as descriptive statistics and robustness check outcomes, are reported in the appendices.

CHAPTER 2

The Dynamics of the Liquidity Network

2.1 Introduction

Liquidity is the ease of trading securities in the financial market. It varies over time and differs significantly across assets. The principal challenge for market participants is the variability and uncertainty in liquidity. Due to its dynamic and ever-changing nature, market liquidity could be considered a complex system. In such a system, the interaction between the individual agents (firms) gives rise to the collective behaviors of the system (market liquidity). A firm's liquidity itself depends on the dynamics of supply and demand, which in turn are influenced by macroeconomic forces. It is the interaction between all these forces that cause the emergence of market liquidity. Hence, to be able to anticipate the behavior of such a complex system, extracting meaningful relationships across its element is the first step. Motivated by this principle, I employ the Granger-causality network method to capture liquidity sequence, interdependence, and interrelationship across the firms and over time in the U.S. stock market.

Liquidity of a firm co-moves with that of the market (Chordia et al., 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001), and there is a liquidity spillover effect across assets (Cespa & Foucault, 2014). The commonality in liquidity and liquidity spillover implies liquidity connectivity, and connectivity suggests the existence of a network. I conjecture there is a liquidity network through which liquidity information flows. I model market liquidity as a network to investigate how firms' liquidity bonds together through their lead-lag relationships. These connections are not arbitrary, and understanding them will give us new insights to better link microlevel behavior with the macrolevel phenomenon. For example, through this liquidity connectivity, we might be able to anticipate and therefore control channels through which liquidity shock propagates into the market in times of financial distress.

Unlike traditional correlational techniques, lead-lag liquidity network analysis can identify the patterns of liquidity interactions across firms, emphasizing there is more to firms' liquidity relationship than the contemporaneous liquidity movement. Liquidity connectivity, however, has not received much attention. Even the focus of the literature on assets' liquidity spillover relies on either the cause of liquidity spillover or on examining the impact of liquidity transmission on other variables of interest.[1] For example, Cespa and Foucault (2014) suggest liquidity spillovers through a cross-asset learning mechanism. However, they call upon future research to examine the magnitude of the effect and whether some assets are more pivotal for liquidity spillovers. Therefore, identifying the sources of liquidity spillover or the channels through which liquidity transmits from one asset to another is still an open area for investigation.

I contribute to the literature in three significant ways. Firstly, I provide empirical evidence that the liquidity network exists and is dynamic over time by examining a sample period of 30 years. This is important because the intertemporal nature of the liquidity network implies the predictability of firm liquidity by using its liquidity interconnections with others in the liquidity network. Secondly, I contribute to the literature on liquidity spillover by identifying the sources of liquidity transmissions within a liquidity network. Thirdly, I provide empirical evidence of a relationship between individual firms' characteristics and their liquidity network structure. My paper is also the first to recognize market liquidity as a complex system and captures its dynamic nature with an intertemporal network-based technique. Additionally, the empirical outcomes of this study offer a new avenue for future research. Answering the following questions will contribute to asset pricing and liquidity-risk literature: Should liquidity connectivity be taken to account for portfolio diversification purposes? Is a firm liquidity network structure a priced source of risk?

[1] See, for example, Angelidis and Andrikopoulos (2010), Chordia et al. (2011).

Two key rationales suggest the existence of an intertemporal liquidity network. Firstly, firms vary in the speed of information reflected in their prices. The differences in firms' information diffusion are due to the cost of processing and reacting to the new information or the limit to arbitrage constraints (Barberis et al., 2005; Holden & Subrahmanyam, 2002). While larger liquid firms with fewer arbitrage constraints are likely to reflect the information to a relatively more significant extent, smaller illiquid ones tend to reflect information to a much lesser extent. That might lead to a lead-lag liquidity network. The directionality of the lead-lag relationship is also an important point of consideration. Chordia et al. (2011) examine the relationship between information transmission and firms' cross-autocorrelations and show that low large-stock liquidity dictates stronger lead-lag relations from larger to smaller firms. They also propose an alternative hypothesis where the low liquidity of smaller firms might cause a delay in the transmission of information into their prices. In this scenario, arbitragers who seek to close the pricing gap between large and small firms cause a delay in information diffusion. This suggests that the lead-lag effect increases when small-stock illiquidity is high (firms are riskier).

The second rationale for the lead-lag relationship is through cross-asset learning. Cespa and Foucault (2014) propose that liquidity providers learn information about an asset from the prices of other assets (cross-asset learning), leading to liquidity spillovers, a source of fragility. Their model suggests cross-asset learning makes assets' liquidity interlinked. In their theoretical model, they show that if the liquidity of one asset drops, its price becomes less informative for liquidity providers in another asset. Therefore, the liquidity of other assets drops as well. Given that, in reality, it takes time for the liquidity providers to adjust the liquidity of an asset through the information received from the liquidity of another, I might detect lead-lag connectivity.

I analyse the different aspects of the liquidity network following Billio et al. (2012), where connectivity is established through the Granger-causality test, and the network is measured by *Out-degree*, *In-degree*, *In+out-degree*, *Closeness* and *Eigenvector* centrality. My empirical evidence illustrates that there is a liquidity network in the U.S. stock market, which is dynamic over 30 years of the sample period. The five network measures vary across the firms and over time. While a firm contributes to the liquidity of others, it is simultaneously influenced by their liquidity. Of the firms, 84% (993 out of 1174) exhibit statistically significant connectivity in at least one direction during the sample period. Among 54,816,084 possible pairwise causality combinations, more than 12% of pairs have statistically significant relationships.[2] The cross-sectional degree of connectivity rises significantly during the global financial crisis (GFC). This magnifying effect is in line with the literature on commonality in liquidity and is empirically confirmed in an event study of the COVID-19 pandemic by Farzami et al. (2021).

Furthermore, I look at firm-level characteristics using fixed-effect panel-regression analysis to investigate what explains the cross-sectional differences in the firms' network structure. I find that smaller, riskier firms (measured by market capitalization and return volatility) with lower liquidity and a greater change in liquidity tend to explain the firm liquidity interactions within the network.

One might expect to see that larger liquid firms with fewer arbitrage constraints are dominant in explaining the network structures due to their greater price informativeness. However, liquidity improves market efficiency and hampers return predictability (Chordia et al., 2008; D. Chung & Hrazdil, 2010). Thus, a different rationale for the lead-lag relationship is that the low liquidity of smaller firms causes a delay in the transmission of information into

[2] The number of possible pairwise Granger-causality combination is computed from the outcome of 36-month rolling window, where I restrict my regression to 36 months of observations for each pair within a 36-month rolling window.

their prices. This suggests that lead-lag predictability increases when firms are riskier.[3] Such a network can be perceived negatively, where the smaller, riskier firms can broadcast the liquidity information to others. My empirical outcome supports the latter rationale, which may be the main reason we see liquidity dry-ups in times of financial distress. The firm-size effect will be explored further in Chapter 3, where I examine whether liquidity shock transmits differently between size-sorted firms and portfolios.

The remainder of this chapter is structured as follows. Section 2.2 presents a review of the related literature, Section 2.3 describes the data and methodology, Section 2.4 provides empirical results and discussion of the liquidity network, Section 2.5 discusses and provides empirical evidence of the firm-level network determinants, and Section 2.6 concludes this study.

2.2 Literature Review

Three main types of liquidity are central bank liquidity, funding liquidity, and market liquidity. In this section, I bring together relevant literature on market liquidity and its evolution. In particular, Section 2.2.1 reviews asset liquidity, liquidity co-movement, and systematic risk. Section 2.2.2 looks at the determinants of liquidity co-movement. Section 2.2.3 is about the liquidity preferences of institutional traders. Section 2.2.4 reviews the literature on market efficiency and liquidity. Lastly, Section 2.2.5 presents the literature on complexity and the liquidity network

2.2.1 Asset Liquidity, Liquidity Co-Movement, and Systematic Risk

Literature often recognizes asset liquidity as an elusive notion. It is a concept that is hard to observe directly but that reflects several aspects of security trading. Generally, liquidity is

[3] This hypothesis was first suggested by Chordia et al. (2011) to explain cross-autocorrelation in stock returns. However, their empirical results were in favour of the increased cross-autocorrelation in returns where illiquidity of large firms increases.

defined as the ability to trade large quantities, at short notice, with low cost and minimum price impact. Therefore, it is evident that liquidity has several dimensions. W. Liu (2006) categorizes different aspects of liquidity into four main dimensions, namely: trading quantity, trading speed, trading cost, and price impact. Existing measures of liquidity mainly capture one dimension of liquidity. For example, the measure of bid-ask spread in Amihud and Mendelson (1986) captures the trading cost dimension, while Datar et al. (1998) address the trading quantity dimension with their turnover measure. Two more comprehensive measures have been introduced by Amihud (2002) and Pástor and Stambaugh (2003). Their liquidity measures employ the concept of price impact to capture the price reaction to trading volume.

One of the key reasons investors care about asset liquidity is its substantial influence on expected return. This impact arises from the increased risk of trading on illiquid securities (Amihud & Mendelson, 1986; Jacoby et al., 2000). The relationship between return and illiquidity is positive and significant across stocks and over time. Moreover, unexpected market illiquidity decreases contemporaneous stock prices. This happens because higher realized illiquidity increases expected illiquidity, raising expected stock returns and lowering stock prices (Amihud, 2002). Chaieb et al. (2021) have recently conducted a study on this relation. The authors provide empirical evidence that noninvestable stocks (securities that can only be held by foreign investors), earn a higher liquidity premium than freely investable ones due to limited risk-sharing and higher illiquidity.

Market liquidity is dynamic over time. Factors such as market return, volatility, and interest rates influence market liquidity (Chordia, Roll, & Subrahmanyam, 2001). Researchers have also discovered a commonality in liquidity (Chordia et al., 2000; Hasbrouck & Seppi, 2001; Huberman & Halka, 2001). That is, the liquidity of individual assets co-moves with market liquidity. The commonality in liquidity has received much attention since it influences expected return (Acharya & Pedersen, 2005; Pástor & Stambaugh, 2003).

In one early paper in this area, Chordia et al. (2000) utilize quoted spread, quoted depth, and effective spread to test any market- and industry-wide liquidity movement. Controlling for individual liquidity determinants such as volatility, volume, and price, their outcome suggests a significant liquidity commonality exists in the New York Stock Exchange market. The authors also identify the influence of inventory risk and the presence of asymmetric information on the common liquidity movement. Soon after, Hasbrouck and Seppi (2001) apply principal components and canonical correlation analyses to identify common factors in the time variation of return and liquidity proxies for Dow Jones Industrial Average components. Their outcome explains two thirds of the common return movement and a relatively small part of liquidity commonality.

At the same time, another line of research has developed which investigates liquidity cross-asset covariation as a systematic risk of liquidity. In this relation, some scholars believe the risk that arises from liquidity co-movement is not diversifiable (Acharya & Pedersen, 2005; K. H. Lee, 2011). For instance, Huberman and Halka (2001) propose that neither inventory risk nor an asymmetric information-based approach explains the systematic component of the temporal variation of liquidity. However, they confirm the existence of liquidity co-movement in a time series of 240 stocks. The authors speculate that the common movement is due to the presence and effect of noise trading.

Furthermore, Brockman and Chung (2002) argue that events such as a financial crisis strongly suggest liquidity provision is subject to systematic factors. Other factors that influence systematic liquidity are market volatility and market liquidity changes. There are empirical and theoretical studies that suggest volatility and liquidity influence systematic risk through the impact of liquidity supply by market makers and money managers across many stocks (Brunnermeier & Pedersen, 2008; Hameed et al., 2010; Kamara et al., 2008; Vayanos, 2004). To be more precise, in a declining market, the capital available to market participants decreases, forcing them to reduce their stock holdings which causes common liquidity movement and correlation in asset returns.

More recent studies in liquidity commonality take a broader view of this concept by exploring international stock markets, presenting the evidence of global liquidity factors, or investigating the nexus of liquidity commonality in different asset classes. Brockman et al. (2009) carry out a comprehensive study of commonality in liquidity to examine systematic liquidity factors in 47 stock exchanges. According to their findings, across most of the world's stock exchanges, firm-level variations in liquidity are substantially influenced by exchange-level changes. There is also strong evidence of asset liquidity covariation in bond, exchange rate, and commodity markets (Mancini et al., 2013; Marshall et al., 2013).

2.2.2 Liquidity Co-Movement Determinants

Given all the previous exploration and evidence of liquidity covariations across the assets, a fundamental question arises: What are the driving forces of liquidity co-movement? The literature in this area attempts to explain the economic factors underlying this phenomenon through using supply and demand forces theories. According to the supply-side hypothesis, when the market is declining or volatile, financial intermediaries provide less liquidity due to funding constraints which in return causes an increase in liquidity co-movements (Brunnermeier & Pedersen, 2008; Coughenour & Saad, 2004; Gromb & Vayanos, 2002; Hameed et al., 2010; Kyle & Wei, 2001). On the other hand, the demand-side explanation suggests that common ownership of financial institutions leads to correlated trading patterns, which causes common movements of liquidity. In studying cross-country liquidity commonality, Karolyi et al. (2012) conclude that commonality is more consistent with demand-side than supply-side explanations. They believe the funding liquidity hypothesis and the evidence provided for the potential role of funding constraints from financial intermediaries are weak.

One reason for correlated trading is the institutional herding hypothesis. This hypothesis suggests that institutional investors often tend to trade by inference from each other's trades (Sias, 2004). They often rebalance their portfolios and hold stocks with similar characteristics, such as large-cap stocks and constituents of exchange-traded fund (ETF) indices. Moreover, previous research also reports that unidirectional trading on the same information leads to correlated movement of liquidity (Corwin & Lipson, 2011; Kamara et al., 2008; Karolyi et al., 2012; H. Liu & Wang, 2013). In the same respect, Harford and Kaul (2005) hypothesize that indexing and correlated industry events lead to correlated order flow as the institutional traders tend to trade on common information.

Moreover, to identify the influence of correlated demand on the commonality in liquidity, H. Liu and Wang (2013) propose a tractable equilibrium model with asymmetric information and imperfect competition among market makers. The authors suggest that common liquidity movement is greater in significantly declined and more volatile markets. More importantly, liquidity correlation decreases with information asymmetry. This implies that inside information could be one of the sources of correlated trading among informed traders. In addition, the authors study the price impact of an informed trader's trades on stock prices as another measure of liquidity. They find that the price impact on one stock is dependent on the characteristics of the other stock and can be nonmonotonic in private information quality. More recently, in a sample of the Taiwan Stock Exchange, Lowe (2014) finds that the main reason that some stocks have more significant liquidity covariation than others is their higher aggregated ownership by qualified foreign institutional investors. He then endorses the habitat investing and style trading explanations of the demand-side hypothesis in liquidity commonality. Based on these explanations, liquidity covariation across the stocks may relate to some firm characteristics, such as market capitalization. Empirical evidence shows that firms with larger market capitalization demonstrate more liquidity commonality (Corwin & Lipson, 2011). Moreover, securities that are heavily invested in by informed traders, such as mutual funds, have a more significant liquidity covariation (Koch et al., 2016).

Literature built on the demand hypothesis suggests liquidity covariation is a priced source of risk that magnifies in the circumstances such as the absence of information asymmetry, high market volatility, and financial distress. This implies that it is unlikely to observe a common movement of liquidity under normal market conditions since it is dependent on certain conditions that unite the actions of either liquidity demanders or liquidity suppliers. For instance, correlated trading across institutions occurs through two sources, common ownership and correlated liquidity shocks. The common ownership channel leads to liquidity commonality when institutions which own identical assets trade in the same direction with similar investment styles based on the same information sources. These assets then experience correlated liquidity demand and their liquidity co-moves.

However, there is strong evidence of different trading styles and liquidity preferences of informed investors in the literature that challenges the idea of correlated demand for institutional investors.

2.2.3 Liquidity Preferences of Institutional Traders

Style and habitat-based explanations suggest that common factors reflect correlated trading decisions within specific groups of traders. Many studies illustrate the diversity of institutional investors' investment styles and liquidity preferences. As the variety in investment styles leads to substantially different demands for the immediacy of trades, differences in order submission strategies likely cause different trading costs (Keim & Ananth, 1995). Another critical point is the likelihood of traders' exposure to identical information. Private information is not frequently available. Even if it were, informed traders are less likely to react to the same information uniformly. Keim and Ananth (1995) utilize conference calls and insider-trading data to test this hypothesis. They find that private information influences transient institutions' trading behavior but not dedicated and quasi–indexing institutions. This is because while the first group has short-term trading incentives, and thus prefers to sell shares before the impact of bad news on the stocks, the latter group has long investment horizons, and it may not be optimal for them to act upon the information. Yan and Zhang (2007) emphasize the heterogeneity of informed investors' investment horizons. In addition to investment objectives and styles, they propose other factors that differentiate sophisticated traders from one another. The authors recognize legal restrictions, competitive pressures, and institutions' informational roles as essential elements. Moreover, they suggest that institutions with short-term trading incentives are better informed than those with long-term ones; therefore, they benefit from an informational advantage.

As mentioned in Section 2.2.2, liquidity commonality literature suggests that correlated institutional trading is one reason for liquidity co-movement in the stock market. On the other hand, a growing body of literature is exploring mutual fund heterogeneity in trading style and the underlying reasons for these differences. For instance, in a study on return predictability conducted by Lou (2012), a flow-driven return effect can fully explain the fund's performance. The funds that face inflows reduce their illiquid stock holdings, whereas those experiencing outflows tend to sell more of their liquid stocks. Another example is a study on time-varying fund manager skills by Kacperczyk et al. (2014). The authors propose that even fund managers vary significantly in their skill sets and capabilities, and only a subset of fund managers can create value by processing firm-specific and economy-wide shocks.

More recently, two other studies have been conducted on mutual fund investment strategies. The first study, by Ben-Rephael (2017), focuses on the trading decisions of equity mutual funds during 10 periods of market uncertainty. The outcome of this study suggests that mutual fund managers tend to sell off illiquid stocks only when market liquidity starts to decline. This behavior is consistent with retail investor withdrawals in response to bad performance. In times of financial distress, fund managers' response to withdrawals might lead to a drop in illiquid stock prices (flight-to-liquidity). However, carrying out an unconditional analysis, the authors do not witness any statistical or economic significance to support fund managers collectively tilting their portfolio toward liquid or illiquid assets when there is no extreme market uncertainty. The second study discusses herding behavior in mutual funds. According to empirical results reported by Deng et al. (2018), the funds' herding behavior is due to the poor information environment and low disclosure quality. In summary, the correlated demand explanation of commonality in liquidity and financial institution heterogeneity in trading styles and liquidity preferences is somewhat conflicting. I suggest that a liquidity network should exist that makes liquidity interactions across the firms possible over time and not only under particular circumstances.

2.2.4 Liquidity and Market Efficiency

Market efficiency has long been the subject of debate among finance scholars. Strictly speaking, a market is efficient if equity prices adjust to new information without delay. As a result, no arbitrage opportunities exist to allow investors to achieve above-average returns. This hypothesis tries to explain the asset price formation through two primary assumptions. 1: The market is frictionless, so there are no transaction costs, taxes, or restrictions on trade (e.g., short-sale constraints); 2: The market is perfectly competitive, where any trader can buy/sell an infinite quantity of security without changing its price. These two assumptions refer to a perfectly liquid market where the price is a random walk, and no return predictability is possible. However, empirical evidence shows that the past order flow predicts short-horizon asset return (Chordia et al., 2005; Cushing & Madhavan, 2000).

Chordia et al. (2005) explain that if market makers have limited risk-bearing capacity, persistent order imbalance (excessive buy/sell orders) makes prices deviate from fundamental values, leading to return predictability. In this scenario, arbitragers such as floor brokers and floor traders who might be able to detect such deviations may submit arbitrage trades, which in turn might speed up the convergence of prices to fundamental values. In reality, however, the price deviation cannot be easily mitigated through arbitrage submission because orders are negatively influenced by illiquidity. This mechanism links liquidity with market efficiency (Chordia et al., 2008; D. Chung & Hrazdil, 2010). Another factor preventing an immediate price conversion to the fundamental values is the limit of arbitrage. Specialized performance-based arbitragers use the investors' capital for the trade. Therefore, when prices move significantly from fundamental values, they might bail out of the market where their participation is most needed (Shleifer & Vishny, 1997).

We know that the collection and process of information take time (Holden & Subrahmanyam, 2002). The price of different securities reacts to information at a different pace, leading to commonality in the return of securities with a similar speed of information diffusion (Barberis et al., 2005).

In short, not all informed investors reflect the new information to the full extent due to the limit to arbitrage constraints. While liquid firms with fewer arbitrage constraints are likely to reflect the information to a relatively more considerable extent, illiquid ones tend to reflect information much less. The immediate reflection of the information in the price of liquid firms might mitigate the chance of predictability. However, illiquid firms take time to reflect the new information in their prices. Therefore, we might detect an intertemporal network.

2.2.5 Liquidity Network and Complexity

In Sections 2.2.1 and 2.2.2, I reviewed the literature on liquidity commonality, which either utilizes the common approach of cross-sectional correlation in liquidity movement or follows Chordia et al.'s (2000) market model. The popularity of these approaches is due to their simplicity and efficiency in capturing the contemporaneous liquidity movement across securities. However, it is likely that there is more to the asset liquidity relationship than their contemporaneous correlations.

Liquidity varies over time and differs significantly across securities, making the predictability of liquidity hard to pursue (Foucault et al., 2013). The lack of literature in liquidity forecasting is indeed discouraging. Market liquidity possesses the most prominent features of a complex system. One of the most appropriate ways to reveal a complex behavior is to employ various network theories, such as social network theory and graph theory (e.g., Choi & Liker, 1995; Wasserman & Faust, 1994). A system is considered complex if it consists of many components (agents) that are in the process of spontaneous change. The agents have varying degrees of linkages with others through which information and resources can flow. They are also dynamic and self-organized (Choi et al., 2001; Holland, 1995). Hence, capturing the complexity of liquidity interlinkages through network analysis might reveal the relationships that cannot be revealed otherwise.

It is not uncommon to capture the complexity of a financial market by using network theory—for example, Billio et al. (2012) use an innovative intertemporal pairwise Granger-causality network to capture stock return interconnection among four types of financial institutions. They find that all four sectors have become highly interlinked over the past decade, leading to an increased systemic risk level in the finance and insurance industries through a complex and time-varying network of relationships. Other leading works that use network perspectives in economic contexts and introduce economic perspectives in network contexts include Acemoglu et al. (2010), Allen et al. (2012), and Diebold and Yilmaz (2014).

Since completing the last draft of this thesis, a paper by Brunetti et al. (2021) has been made available about liquidity interconnectedness in the interbank market. The paper explores interconnectivity in the overnight-lending market. The authors propose that increased interconnectivity may increase systemic risk. However, they suggest that too little connectivity might hamper the market's functioning. Their focus is on a liquidity network where the connections are established between aggressive borrowers (lenders) and passive lenders (borrowers) in the overnight-lending market. Given the absence of empirical work in this area, this sudden shift of interest from commonality in liquidity-to-liquidity network indicates a need to explore the complex nature of the liquidity system from a different perspective.

2.3 Data

To investigate the liquidity network in the U.S. stock market, I use the S&P500 index as the main data source. There are a couple of reasons for choosing the S&P500 index as the primary source of information. Firstly, indexing has become excessively mainstream among investors in the past decade. According to the *Wall Street Journal*, up until September 2019, nearly US$1.36 trillion in net flows was added to U.S. equity mutual funds and exchange-traded funds that mimic market indexes (Lim, 2019). Hence, market participants benefit from exploring the possible liquidity network that links the index's constituents.

Moreover, S&P500 is one of the most popular indexes that reflects the U.S. economy and maintains an adequate variety of firms. Based on the Morningstar database (as cited in Berger, 2017), 13% of S&P500 firms are mid-cap companies. Berger (2017) mentions in *Forbes* that the index considered a "blend" fund because it combines growth and value companies. Another advantage of an index firm compared with a nonindex firm is that it has the minimum number of missing observations due to frequent trading.

I collect the S&P500 constituents list from *Bloomberg*. There are 1,174 firms on the list from January 1990 to December 2019. The reason for selecting 1990 as a starting point is the availability of the constituents list through Bloomberg. Using the list of the components, I obtain the daily data on stock prices, returns, volumes, and market capitalizations from the Centre for Research in Security Prices (CRSP). The daily CRSP price is the daily closing price of a security. If unavailable, the number in the price field is replaced with a bid/ask average.

The daily return values are calculated as the daily change in the total value of investment while the dividend is reinvested. The volume is the total volume traded within the day. I use historical CUSIP as the common identifier to match the Bloomberg list of constituents with the daily CRSP data. In a few cases of CUSIP unavailability, I alternatively use the ticker and company name to match the data. It is worth pointing out that, prior to any analysis, I detect and remove all missing prices and returns. According to CRSP, the missing observations can happen if there is a missing price at time *t* due to the suspension in trading or trading in an unknown exchange. Moreover, a valid, current price but no valid, previous price might lead to a missing return. In the end, my panel data include all the additions and deletions in the index during the 30 years of the sample period.

2.4 Methodology

Market participants care about liquidity as it influences their expected return. Nevertheless, anticipating liquidity is difficult to pursue due to its dynamic and complex nature. Asset liquidity co-movement with market liquidity has provided the foundation of liquidity determinants. The concurrent assets' liquidity movement implies connectivity, and looking into liquidity connectivity gives a new insight into liquidity predictability. I hypothesize that an intertemporal liquidity network might exist due to the differences in firms' ability to adjust to the new information. In such a network, firms are linked through their lead-lag liquidity. Modeling market liquidity as a network enables me to see the possible differences in liquidity interactions and interdependence beyond co-movement across the firms. Therefore, in this section, I utilize the Granger-causality network method proposed by Billio et al. (2012) to capture the liquidity network structure. I first establish connectivity through the Granger-causality test across the firms and over time. Then I look at five different network measures to identify the possible cross-sectional differences in the way firms communicate liquidity. Last, I employ a fixed-effect panel-regression model to test whether firm-specific characteristics could explain their liquidity network structure over time.

2.4.1 Liquidity Proxy

The liquidity proxy used in this paper is based on the Amihud (2002) illiquidity measure. This measure is widely used to capture systematic risk and commonality in liquidity in the literature (See, e.g., Acharya & Pedersen, 2005; Hasbrouck & Seppi, 2001; Kamara et al., 2008). It adheres to the notion of liquid markets as those facilitating trading with the most negligible impact on price. It is the daily ratio of absolute stock return to dollar volume. There are other acceptable liquidity measures, such as bid-ask spreads used in Chordia et al. (2000) or price impact utilized in Sadka (2006). The first measure is only available from the end of 1992, and the latter requires intraday data. I use the Amihud (2002) measure mainly to avoid noisy intraday data and because it enables me to study for a more extended period. I construct my monthly liquidity proxy by calculating the equally weighted average of the daily liquidity. The focus on the monthly frequency is to avoid noise in prices at a lower frequency and to ensure that the linkages across securities are not derived from temporary price deviations.

Following Karolyi et al. (2012) and H. C. Lee et al. (2014), I add a constant to the Amihud (2002) price-impact measure and take logs to minimize the impact of outliers. I then multiply the result by -1 to arrive at a variable which is increasing in the liquidity value. Lastly, I use the change in monthly liquidity as my main proxy to make the data stationary[4].

The daily Amihud liquidity measure ($Amihud_{i,t}$) is as shown in Equation 1 and the monthly change in liquidity ($\Delta Aliq_{i,m}$) shown in Equation 2 as follows:

$$\mathrm{Amihud}_{\mathrm{i,t}} = \left[-\log\left(1 + \frac{|\,\mathrm{R}_{\mathrm{i,t}}\,|}{\mathrm{P}_{\mathrm{i,t}}\,\mathrm{VO}_{\mathrm{i,t}}}\right)\right] \times 10^{6} \tag{1}$$

[4] I use augmented Dickey-Fuller (ADF) to test the stationarity of the panel data. While some of the pairwise time series are stationary, some other have a unit root. The data is stationary at the first difference.

$$\Delta \mathrm{Aliq}_{\mathrm{i,m}} = \mathrm{Amihud}_{\mathrm{i,m}} - \mathrm{Amihud}_{\mathrm{i,m-1}} \tag{2}$$

where $R_{i,t}$ is the return for firm *i* on day *t* and $P_{i,t}\, Vo_{it}$ is the dollar volume for firm *i* on day *t*. $Amihud_{i,m}$ is an equally weighted average of daily liquidity for firm *i* in month *m*.

2.4.2 Linear Granger-Causality Test

I first conduct a pairwise Granger-causality test to investigate the lead-lag relationship between all the firms included in the S&P500. To observe any changing properties of the series over time, I apply a 36-month rolling-window technique utilizing the following model. Every window carries a pairwise 36-month change in liquidity (*ΔAliq*) for all the N firms included in the S&P500 index on that particular date interval and rolls over by 1 month to the next window.

The model presents the linear interrelationship between two stationary time series. Time series *j* Granger-causes time series *i* if past values of *j* contain information that aids the prediction of *i* above and beyond the information contained in past values of *i* alone.

$$\begin{aligned} \Delta \mathrm{Aliq}^{\mathrm{i}}_{\mathrm{t+1}} &= \alpha^{\mathrm{i}} + \beta^{\mathrm{i}}\, \Delta \mathrm{Aliq}^{\mathrm{i}}_{\mathrm{t}} + \gamma^{\mathrm{ij}}\, \Delta \mathrm{Aliq}^{\mathrm{j}}_{\mathrm{t}} + \varepsilon^{\mathrm{i}}_{\mathrm{t+1}} \\ \Delta \mathrm{Aliq}^{\mathrm{j}}_{\mathrm{t+1}} &= \alpha^{\mathrm{j}} + \beta^{\mathrm{j}}\, \Delta \mathrm{Aliq}^{\mathrm{j}}_{\mathrm{t}} + \gamma^{\mathrm{ji}}\, \Delta \mathrm{Aliq}^{\mathrm{i}}_{\mathrm{t}} + \varepsilon^{\mathrm{j}}_{\mathrm{t+1}} \end{aligned} \tag{3}$$

where $\Delta Aliq_t^i$ and $\Delta Aliq_t^j$ are the monthly change in liquidity at time *t* for firm *i* and *j*, respectively, α^i and α^j are constants and $\beta^i, \beta^j, \gamma^{ij}, \gamma^{ji}$ are coefficients of the model. Also ε_{t+1}^i and ε_{t+1}^j account for uncorrelated white noise.[5] In this equation, there exists a lead-lag relationship among the series when γ^{ij} or γ^{ji} are different from zero.

[5] I use the "Bayesian information criterion" (BIC; see Schwarz, 1978) as the model-selection criterion to determine the optimal number of lags for each pair of security in time-series manner. Then I take the mode of BIC for the entire sample period. In addition, to make sure the standard errors and *t*-statistics of the coefficients are robust, I control for heteroscedasticity and utilize rectified p-values as my main results. It is worth pointing out that I only consider outcome to be statistically significant when $\gamma^{ij}\, \Delta Aliq_t^j$ could explain $\Delta Aliq_{t+1}^i$ and $\gamma^{ji}\, \Delta Aliq_t^i$ causes $\Delta Aliq_{t+1}^{j}$.

Next, to establish connectivity between firms, I allocate 1 and 0 to the linear Granger-causality outcomes based on their statistical significance at 5%. There is a connection between *j* and i if the Granger-causality test outcome is statistically significant at 5%. Otherwise, there is no connection, and I assign 0. *j*'s relationship with itself is not considered a connection.[6]

$$(\mathrm{j} \rightarrow \mathrm{i}) = \begin{Bmatrix} 1 \ \text{ if j} \ \ \text{Granger\_causes i} \\ 0 \qquad\qquad \text{otherwise} \end{Bmatrix}$$
$$(\mathrm{j} \rightarrow \mathrm{j}) = 0 \tag{4}$$

2.4.3 *Degree of Granger-Causality*

The degree of Granger-causality (*DGC*) measures the fraction of statistically significant Granger-causal relationships among all *N* (*N-1*) pairs of securities available in each period:

$$\mathrm{DGC} \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} (j \rightarrow i) \tag{5}$$

where *N* is the number of firms in each period, and $(j \rightarrow i)$ is the causality indicator. For better illustration, let us imagine a network of three firms *A*, *B*, and *C*. There are six possible numbers of connections at time *t: AB, BA, AC, CA, BC*, and *CB.* If only two of these pairs significantly Granger-causes one another, the *DGC* at time *t* would be $(\frac{2}{6}) \times 100$= 33.3%. Higher *DGC* among assets is evidence of higher liquidity connectivity.

2.4.4 *Liquidity Network Measures*

In this section, I introduce the five network metrics employed by Billio et al. (2012) to evaluate the importance of individual firms in the liquidity network structure, where each metric captures a different type of importance.

[6] To obtain more robust estimation, we restrict the pairs with less than 36 observations (36 months) prior to conducting the Granger-causality test.

2.4.4.1 Number of Connections. Based on network theory, the number of connections (degree centrality) refers to the direct connection between firms in the network. Degree centrality shows how many links a firm has.

Out-degree, In-degree, and *In+out-degree* each represent one aspect of a directed graph of liquidity. While directionality of the connections is the main point of focus for *Out-* and *In-degree*, *In+out-degree* means overall connectivity. Given that my network is based on liquidity ties, it is fundamentally different when a firm Granger-causes the liquidity of other firms with its lagged value (has an *Out-degree*) or Granger-caused by a lagged liquidity of the other firms (has an *In-degree*). For simplicity, I define "send" to mean "Granger-causes" and "receive" to mean "Granger-caused by" and use those terms throughout the thesis.

In a liquidity network, a firm sending out liquidity more than it receives means it influences the liquidity of others more than it is influenced by them. A firm has greater overall connectivity if it possesses a higher *In+out-degree.*

Out-degree:
$$(\mathrm{j} \rightarrow \mathrm{S}) = \frac{1}{N-1}\sum_{i\neq j}(j \rightarrow \mathrm{i}) \qquad 6$$

In-degree:
$$(\mathrm{S} \rightarrow \mathrm{j}) = \frac{1}{N-1}\sum_{i\neq j}(\mathrm{i} \rightarrow j) \qquad 7$$

In+out-degree
$$(\mathrm{S} \leftrightarrow \mathrm{j}) = \frac{1}{2(N-1)}\sum_{i\neq j}(\mathrm{i} \rightarrow j) + (\mathrm{j} \rightarrow \mathrm{i}) \qquad 8$$

where *S* represents the system in the above three network metrics and *N* is the number of firms. *Out-degree* measures a fraction of firms that are significantly Granger-caused by firm *j*. *In-degree* measures a fraction of firms that significantly Granger-causes *j*.

In+out-degree is the summation of the two measures. One of the key conditions to calculate these three metrics is $i \neq j$.

2.4.4.2 Closeness. By measuring Closeness (*Clos*) among firms in the liquidity system, I look beyond the first level of connections (i.e., the second, third, and fourth till the *N-1* layer of relationships). This is built around the notion that liquidity information could be transmitted through indirect linkages. While the first level of connectivity gives us information about the directionality and the magnitude of the links, *Clos* reveals how liquidity information is transmitted throughout the network.

Clos determines how distant a firm is from others in the system. The distance between two firms is the length of the shortest path between them. The shorter the distance between the firms, the faster the information transmission of liquidity is between them. Therefore, the smaller the *Clos* value, the closer the firms are to each other.

In order to employ this measure, firstly, all the causality paths between *j* and *i* are identified. Thus, from firm (node) *j* to *i* there exists a series of firms as:

$$(\mathrm{j} \rightarrow \mathrm{k}_1) \times (\mathrm{k}_1 \rightarrow \mathrm{k}_2) \times \ldots \left(\mathrm{k}_{\mathrm{p}-1} \rightarrow \mathrm{i}\right) \equiv \left(\mathrm{j} \overset{\mathrm{p}}{\rightarrow} \mathrm{i}\right) = 1 \quad (9)$$

where *P* is the pathway between firm *j* to *i*. k_2 to k_{p-1} are the firms that transmit liquidity from *j* to *i* through their direct connections.

Secondly, the shortest path among those paths (*P*) is selected and defined as *Pji:*[7]

$$\mathrm{P}_{\mathrm{ji}} \equiv \mathrm{Min}_{\mathrm{P}} \left\{\mathrm{P} \in [1, \mathrm{N}-1]: \left(\mathrm{j} \overset{\mathrm{P}}{\rightarrow} \mathrm{i}\right) = 1\right\} \quad (10)$$

In this relation, if *j* causes *i* directly, *Pji* equals 1; however, if *j* does not cause *i* at all, *Pji* is equivalent to (*N-1*).

Given *Pji* is the shortest path between node *j* and *i*, the Closeness measure for firm *j* is defined as:

[7] To find the shortest path between the nodes, the unweighted graph in the PROC OPTNET procedure in SAS is utilized, which employs a breadth-first search (BFS) algorithm.

$$Clos = \frac{1}{N-1} \sum_{i \neq j} P_{ji} \ \left(j \overset{P}{\rightarrow} i\right) \qquad 11$$

where P_{ji} is the shortest path between the two firms through which liquidity information transmits, and *N* is the number of firms in the liquidity network at each given time.

2.4.4.3 Eigenvector Centrality. Eigenvector centrality (*Eig*) reflects the idea that not all connections are equal in the liquidity network. Having a connection with a well-connected firm is more critical and thus scored higher in the network than being linked to a less connected firm. To score the connections, the following adjacency matrix *A* is defined as:[8]

$$[A\,]_{ji} = (j \rightarrow i) \qquad 12$$

To identify the central firms in the liquidity network for each period, I compute *Eig* using the following equation:

$$\lambda v = \mathrm{A} v \qquad 13$$

where v is the Eigenvector and λ is the Eigenvalue. The central Eigenvector is the one that corresponds to the largest Eigenvalue.[9] A firm with a larger Eigenvector is a firm that is connected to well-connected firms. It is noteworthy that the larger the network (adjacency matrix of A), the greater the number of iterations of the above calculation for achieving the largest Eigenvalue associated with the leading Eigenvector. (Appendix A illustrates the

[8] I construct an adjacency matrix of *[A]ji* for each period using the outcome of the 36-month rolling window. *[A]ji* is a squared nonsymmetric matrix (where *j* causes *i* does not necessarily mean *i* causes *j*).

[9] To measure Eigenvector centrality, I employ a power iteration method using SAS/IML software. This method is an algorithm that computes the largest Eigenvalue (in absolute value) with its associated Eigenvector for any matrix provided that the largest Eigenvalue is real and distinct. In each iteration a normalization is performed to prevent the Eigenvector from growing in value. The common way of normalizing Eigenvector is by dividing Eigenvector components to their square roots using the following formula for a network consist of four firms $\frac{1}{\sqrt{A^2+B^2+C^2+D^2}}$.

detailed analysis of Eigenvector centrality for a directional network of four firms through an example.)

Similarly, a firm's Eigenvector centrality is defined as proportional to the sum of the scores of all nodes connected to it. Mathematically, this is expressed as:

$$v_j = \sum_{i=1}^{N} [A]_{ji} v_i \qquad (14)$$

where v_j is the Eigenvector centrality of j.

2.5 Empirical Evidence of the Liquidity Network

In this section, I discuss and report the empirical findings of this research. Initially, I explain the outcome of the linear Granger-causality, which is the first step for establishing connectivity across firms over time. Next, the detailed findings of the network analysis are presented and discussed.

2.5.1 Linear Granger-Causality Test

To better visualize the interrelationship among the firms, I depict the liquidity network diagram of 993 firms in Figure 2.1. The interlinkages result from 657,346 pairwise Granger-causality tests over the sample period from January 1990 to December 2019. A total of 75,965 pairs (11.56%) established statistically significant relationships. The firms are color-coded from dark red to bright yellow based on weighted In+out-degree (*In&Out*), *w*here firms with a greater value of *In&Out* exhibit a brighter color than those with a lower weight. Also, firms are size-coded based on Eigenvector (*Eig*). Firms with higher Eigenvector centrality are shown with larger node sizes than those with lower *Eig* values. The network diagram illustrates three key points of the liquidity network. Firstly, firms vary in degree of connectivity measured by *In&Out.* Secondly, firms differ in their pivotal role in the liquidity network measured by *Eig*.

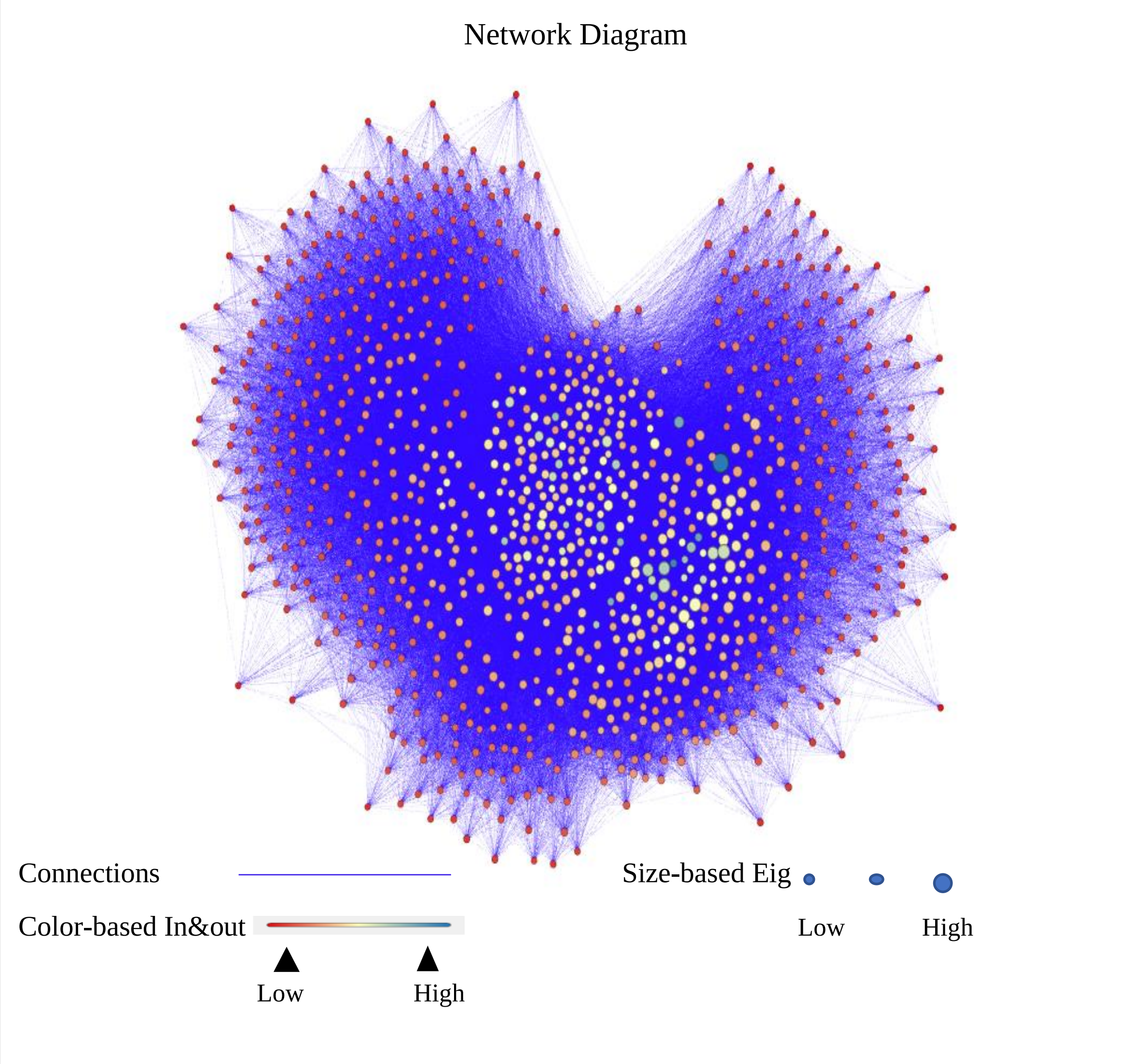
Thirdly, firms with a higher degree of connectivity tend to have greater *Eig.* These relationships are further confirmed through the correlation result in Table 2.3.

From this point onward, I discuss the network measure outcomes calculated based on the rolling window of the Granger-causality test. The dynamics of the *DGC* and its percentage change (*%Change-DGC*) are demonstrated in Figure 2.2. *DGC* is the outcome of a 36-month rolling-window regression at a 5% significance level which captures the liquidity linkages across the firms over the sample period. My outcome shows strong evidence of a liquidity network throughout the 30 years of the sample period. More than 10% of the firms are a part of the network at each given time. An increase in *DGC* (depicted in blue) indicates increased liquidity connectivity across the firms, which reaches its peak at the time of the GFC when up to 30% of the firms in the sample become interlinked.[10] Moreover, *%Change-DGC* (depicted in orange) shows more than 60% increase in *DGC* during the crisis time.

[10] To ensure the dynamics of the *DGC* were robust, I computed the *DGC* by considering 0.1%, 1%, and 10% significance level at a time and plotted the outcome. I observed that the time-series of the *DGC* exhibits the same pattern of connectivity regardless of the level of statistical significance.

Figure 2.1

The Network Diagram of Pairwise Granger-Causality



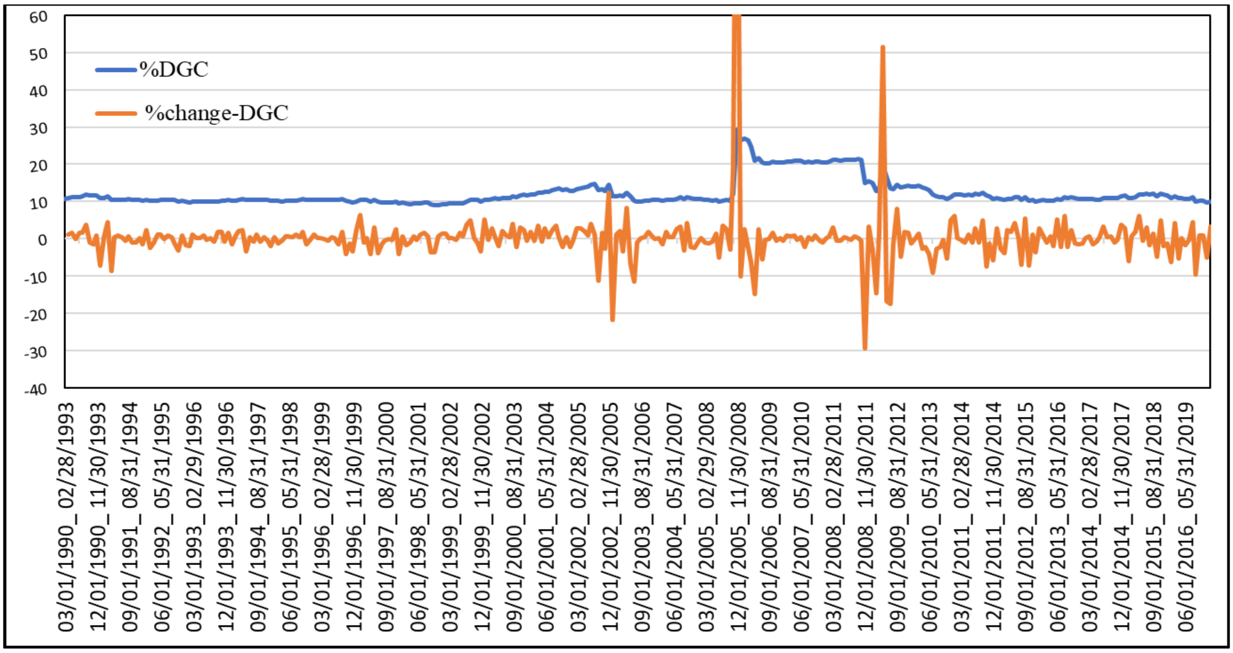
Note: The network diagram of pairwise linear Granger-causality relationships of 993 firms at a 5% statistical significance level. The test is conducted on the monthly changes in liquidity ($\Delta Aliq$) in the S&P500 index during the sample period from January 1990 to December 2019. The network diagram resulted from 657,346 pairwise regressions where 75,965 pairs (11.56%) established statistically significant relationships.

The firms (nodes) in the network diagram are color-coded based on weighted *In&Out* and size-coded based on *Eig*. The firms' colors range from dark red to bright yellow, where firms with brighter colors carry higher weighted *In&Out* than those of dark red.

Each dark blue ray illustrates sending (*out*) or receiving (*In*) liquidity connections to/from other securities in the liquidity network. The statistical significance is based on rectified heteroscedasticity.

Figure 2.2

Degree of Granger-Causality Over Time.



Note: Time series of degree of Granger-causality (DGC) with a 36-month rolling window from January 1990 to December 2019. %DGC is the fraction (in percentage) of statistically significant (at 5%) pairwise linear Granger-causal relationships among monthly liquidity of *N*(*N-1*) pairs of those stocks available in each period. %change-*DGC* is the percentage change of the degree of Granger-causality.

2.5.2 The Liquidity Network and Its Dynamics

Table 2.1 illustrates the descriptive statistics of network metrics in Panel A and the Pearson correlation matrix in Panel B. The descriptive statistics include a time-series mean, median, standard deviation, minimum, maximum, and the 25th and 75th percentiles.

All the network metrics of liquidity (*Out-degree, In-degree, In+out-degree, Closeness,* and *Eigenvector*) are calculated based on the 36-month rolling window. My descriptive statistics show that all the variables have a mean greater than the median and are slightly positively skewed. The zero minimum in the statistics for *Out, In,* and *Eig* is worth mentioning. It shows that some of the firms in the sample do not have statistically significant Granger-causal relationships and hence don't receive/send liquidity from/to other network members. Specifically, there is only one firm in the sample that does not send liquidity to others (*Out=0*) but receives liquidity from the system; therefore, the value of *Clos* for the stated firm is equivalent to (*N-1*). This is why the largest maximum value and standard deviation belong to *Clos* (*Max=315, SD=*0.*905*).[11] Therefore, I drop this observation from my *Clos* variable to prevent spurious outcomes caused by extreme values for the panel-regression analysis in Section 2.6.2, where I regress firm-specific variables on the *Clos*. The deviation from the mean for the rest of the network's metrics is not as dispersed.

Furthermore, to measure the strength of linear association among the network metrics, Pearson correlation is utilized and presented in Table 2.1.[12] The test is carried out on the monthly outcomes of the network measures during the sample period. The correlation outcome illustrates a meaningful and statistically significant relationship between all five network measures at a 1% level. The negative correlation between *Out* and *In* implies that firms that tend to send out liquidity to the system have less tendency to receive liquidity. Therefore, they might have more influence on the rest of the firms (*Out,In*=-0.023). In general, the correlation between the variables is consistent with my expectations, giving confidence in the findings. For example, *Out* and *Eig* have a positive and significant correlation (*Out,Eig=*0.818), suggesting that firms that send out more liquidity to others are more pivotal in the liquidity system. At the same time, the correlation between *Clos* and *Eig* (*Clos,Eig*=-0.120) and *Clos* and *Out* (*Clos,Out=*-0.140) are both inverse and significant, suggesting an increase in the pivotal power of a firm decreases its distance from others. Conversely, the correlation between *In* and *Clos* and *In* and *Eig* suggests that firms that tend to be influenced by others' liquidity;

[11] The maximum *Closeness* is less than *N-1*=499 due to the restriction applied in pairwise Granger-causality rolling window regression. I only retain the pairs that have 36 months of observation. Pairs might have less than 36 months of matched observations for two reasons: either because of entering the S&P500 index in the middle or end of a window (date-interval) or due to utilizing the first difference and lag in the model.

[12] I also consider the Spearman correlations between all variables and find that the results for the network measures correlation are consistent with the Pearson correlation (See Appendix B) .

transmit the liquidity information slower and are less pivotal in the liquidity network (*In, Clos=0.008; In, Eig*= -0.148).

Table 2.1

Summary Statistics and Pearson Correlation of Network Metrics

Panel A: Descriptive statistics							
	Mean	Median	SD	Min	Max	P25	P75
Out	0.121	0.098	0.084	0.000	0.973	0.074	0.136
In	0.121	0.101	0.078	0.000	1	0.077	0.137
In&Out	0.121	0.106	0.057	0.013	0.645	0.087	0.137
Clos	1.998	1.942	0.905	1.027	315.000	1.884	2.009
Eig	0.044	0.039	0.023	0.000	0.327	0.029	0.053

Panel B: Pearson Correlations among Network's metrics					
	Out	In	In&out	Clos	Eig
Out	1				
In	-0.023***	1			
In&Out	0.726***	0.671***	1		
Clos	-0.140***	0.008***	-0.099***	1	
Eig	0.818***	-0.148***	0.504***	-0.120***	1

Note: Panel A and Panel B respectively report the summary statistics and Pearson correlations of S&P500 network metrics from January 1990 to December 2019. Out-degree (*Out*), In-degree (*In*), In+out-degree (*In&Out*), Closeness (*Clos*), and Eigenvector centrality (*Eig*) are network measures calculated from 36-month rolling-window Granger-causality outcomes with statistical significance at 5%. *Out* measures a fraction of firms that are significantly Granger-caused by *j*; *In* represents a fraction of firms that significantly Granger-cause *j*; and *In&Out* is the summation of the two. *Clos* measures the averaged shortest path between a firm and all other firms reachable from it. *Eig* estimates the sum of the Eigenvector centralities of all the firms Granger-caused by firm *j*.
*, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

2.6 The Liquidity Network and Firm-Specific Characteristics

2.6.1 Firm-Specific Characteristics

The first step to better understanding what might explain the liquidity network is to look at firm-level characteristics. It is intuitive to assume the complex interplay between liquidity demanders and suppliers might be reflected in the firms' liquidity to some extent. Therefore, I investigate whether firm-level liquidity (*Aliq*) and change in liquidity (Δ*Aliq*) can explain their liquidity network structure. I am interested in examining the change and the level because firm liquidity is dynamic, so investigating the change in liquidity might have a different impact on a firm's liquidity connectivity than that of the level. The reason for expecting such a different impact on the network can be explained from the market participants' perspective. A more remarkable change in liquidity might signal firm instability. Hence such an asset might be perceived as riskier than a firm with less variability. Therefore, the impact of the liquidity change on a firm network structure is likely different from the liquidity level. Another point is that if firm liquidity levels were constant, investors would not change their portfolios to meet their liquidity needs. Similarly, liquidity providers would not need to adjust their stock inventory on the information received from the liquidity of other securities. Therefore, liquidity information spillovers would be less likely, and the liquidity network might not have existed.

I also examine the relationship between firm size and liquidity network metrics across the firms and over time. Firm size has been known to influence liquidity and commonality in liquidity (Asness et al., 2018; Chordia et al., 2000; Kamara et al., 2008). Small firms are less liquid than larger ones (Amihud & Mendelson, 1986) and face more liquidity risk (Acharya & Pedersen, 2005). Hence, they require higher expected returns. While larger firms reflect the information to a much greater extent, the price of the smaller firms is less informative. The differences in information diffusion speed on the price might influence the liquidity lead-lag connection. Therefore, it is crucial to see if there is a size effect in explaining the liquidity network.

Moreover, firm performance (measured by market-to-book ratio) and stock liquidity have a positive relationship (Fang et al., 2009). The influence of firm characteristics and co-movement in market liquidity is also established (Moshirian et al., 2017). Generally, riskier firms are less desirable to trade, so they require a higher expected return. Intuitively, it takes longer for information to diffuse into the price of the riskier firm compared to that of the stable one. Therefore, following Fang et al. (2009) and Moshirian et al. (2017), I consider return volatility, debt-to-equity ratio, book-to-market ratio, and return-on-equity ratio as proxies of the firms' financial and economic environment and explore their relationship with the liquidity network.

The definition, computation, and sources of the firm-level variables are reported in Table 2.2, and their descriptive statistics are reported in Table 2.3.

Table 2.2

Firm-Level Characteristics, Definitions and Sources

Variable	Abbrev.	Description	Source
Firm Liquidity	*Aliq*	Monthly liquidity is calculated by averaging the daily measure of Amihud (2002) liquidity for firm *i* in month *m*.	The Center of Research in Security Prices (CRSP), and own computation
Firm Change in Liquidity	$\Delta Aliq$	The monthly first difference measure of Amihud (2002) liquidity for firm *i* in month *m*.	The CRSP, and own computation
Firm Size	*Mcap*	Natural log of market capitalization in millions. Where *Mcap* is: daily $Abs\ (price_t)\times$ $Share\ outstanding_t$ averaged to monthly.	The CRSP, and own computation
Return Volatility	*σRet*	The monthly standard deviation of daily return.	The CRSP, and own computation
Debt-to-Equity Ratio	*DE*	Total liabilities to shareholders' equity (common and preferred).	Wharton Research Data Services (WRDS Beta)
Book-to-Market-Ratio	*BM*	Natural log of the book value of equity as a fraction of the market value of equity.	WRDS Beta
Return-on-Equity Ratio	*ROE*	Net income as a fraction of average book equity based on the most recent two periods, where the book value of equity is defined as the sum of total parent stockholders' equity and deferred taxes and investment-tax credit.	WRDS Beta

2.6.2 Panel-Regression Analysis

I aim to examine the association between firm-specific characteristics on the five network measures of *Out, In, In&Out, Clos, Eig.* In particular, I am interested in investigating the explanatory power of the liquidity (*Aliq*), changes in liquidity (*ΔAliq*), firm size (*Mcap*), return volatility (*σRet*), debt-to-equity ratio (*DE*), book-to-market ratio (*BM*), and return-on-equity ratio (*ROE*) on the firm-level network of liquidity.

Using the following model, I regress firm-level variables on five network metrics at a time. I perform 45 separate panel fixed-effect regressions where I regress the liquidity network measures on one of the firm-specific factors independently and report the outcome in Table 2.4.

$$Network^{*}_{i,t} = \alpha_{i,t} + \beta_1 * \text{FirmSpec}_{i,t} + \vartheta_I + \eth_T + \varepsilon_{i,t} \quad 15$$

where $Network^{*}_{i,t}$ is one of the market-adjusted estimated metrics of liquidity network for firm i in month t ($Network^{*}_{i,t} = Out, In,$ etc.).[13] $FirmSpec_{i,t}$ is one of the firm-specific-factors for firm i at month t ($FirmSpec_{i,t} = AveAliq^{*}_{i,t}$, $RankAveAliq^{*}_{i,t}$, $Ave\Delta Aliq^{*}_{i,t}$, $RankAve\Delta Aliq^{*}, etc.$). ϑ_I and $\eth_T$ refer to industry fixed-effect and year fixed-effect coefficients, respectively.

To control for unobserved factors, I hold the year and industry effects constant across firms in all panel-regression analyses.[14] Moreover, I use market-adjusted network measures in all the panel regressions as my response variables. This is to take a more conservative approach and adjust for the possible impact of market network dynamics on the network structure of individual firms. The t-statistics for all the panel regressions are based on Newey and West's (1987) autocorrelation and heteroscedasticity consistent standard errors.

My main hypothesis predicts $\beta_1 > 0$. I do not have precise theoretical predictions on the coefficient sign of all the explanatory variables. However, given that risk and connectivity have been known to have a positive relationship, I expect to see a rise in overall connectivity

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[13] Market-adjusted network measures are calculated as follows:

$\text{Network}^{*}_{\text{i,t}} = \text{Network}_{\text{i,t}} - \text{Network}_{\text{Mkt,t}}$

where $Network_{i,t}$ is an estimated network metric for firm *i* at month *t* and $Network_{Mkt,t}$ is the equally weighted average of a network measure across all the firms in the sample at time *t*.

Market-adjusted change in liquidity is calculated as follows:

$Ave\Delta Aliq^{*}_{i,t} = Ave\Delta Aliq_{t,i} - Ave\Delta Aliq_{t,Mkt}$ where $Ave\Delta Aliq_{t,i}$ is the the change in monthly liquidity averaged over 36 months and $Ave\Delta Aliq_{t,Mkt}$ is the equally weighted average of $Ave\Delta Aliq$ across all the firms in the sample at the same date interval .

[14] I control for the impact of time and industry by creating year and industry dummy variables for each cross-section. In total, I have (27-1) dummies for year and (66-1) dummies for industry. I utilize the firm's two-digit standard industrial classification codes (SIC) to allocate dummy variables to the firms.

(measured by *In&Out*) when firms' level of riskiness (proxied by *change in liquidity*, *return volatility*, *DE ratio*) increases. One can also expect an increase in the level of liquidity (*Aliq*) and efficiency in generating profit (measured by *ROE*) to improve the firm influence on others in the network measured (by *Eig, Out,* and *Clos*).

$AveAliq^{*}_{i,t}$ is my first independent variable, which represents the market-adjusted *Aliq* for firm *i* averaged over 36 months. To check the robustness of Model 15, I also perform a rank regression to ensure that possible outliers of $AveAliq^{*}_{i,t}$ have not driven the result. To do so, I first score the firms based on their average liquidity from *1 to N* for each 36-month date interval, where firms with the lowest value of market-adjusted liquidity ($AveAliq^{*}_{i,t}$) score 1, and firms with the greatest value of $AveAliq^{*}_{i,t}$ rank as *N*. Then, I use this scoring system to define a new variable as $RankAveAliq^{*}$ and regress it independently on each of the network metrics ($Network^{*}_{i,t}$) defined in Equation 15. The outcome of the rank regression is reported in Table 2.4. I use the same approach to regressing $Ave\Delta Aliq^{*}_{i,t}$ and $RankAve\Delta Aliq^{*}$ on the $Network^{*}_{i,t}$ [15].

The rest of the firm-specific variables are defined as follows: Firm size (*Mcap*) is the value of the monthly average of market capitalization. Return volatility(σRet) is the concurrent monthly standard deviation of daily return. The *DE* is the quarterly ratio of total liabilities to shareholders' equity (common and preferred). The *BM* is the quarterly book value of equity as a fraction of the market value of equity. The quarterly *ROE* is the net income as a fraction of the average book value of equity based on the most recent two periods, where the book value of equity is defined as the sum of total parent shareholders' equity-deferred taxes and investment-tax credit.

[15] I assign the same score to the firms where their liquidity values are identical.

It is worth pointing out that financial ratios often contain unintended extreme values that need to be controlled. My *BM* ratio contains no negative value, and I use the natural logarithm to mitigate the outlier effect for this variable. To deal with the influence of outliers, I winsorize the extreme observations in the *DE* ratio to one percentile.

2.6.3 Empirical Evidence and Discussion

Panel A in Table 2.3 shows the descriptive statistics of the six firm-specific factors utilized in the regression analysis, while Panel B shows the Pearson correlation matrix between them.[16]

The descriptive statistics show that firm size (*Mcap*), return volatility (*σRet*), and *BM* have a normal distribution during the sample period given their close mean and median *Mean*(*Mcap*)=16.215, *Median*(*Mcap*)=16.192; *Mean*(*σRe*)=0.018, *Median*(*σRep*)=0.015; *Mean*(*BM*)=-0.933, *Median*(*BM*)=-0.877. The sample mean for the *DE* ratio is 3.110, and for *BM* and *ROE* have a mean of -0.933 and 0.166, respectively. Although liquidity level and change are positively skewed and dispersed, I don't transform them *STD*(*AveAliq*)= 8.442; *STD*(*AveΔAliq*) = 0.308. Instead, I perform a rank regression analysis to minimize the possible impact of outliers on the linear regression outcome.

The correlation between the firm-specific factors shows that liquidity level and change in liquidity have an inverse and significant correlation (*AveAliq*, *AveΔAliq=-0.095*). This negative correlation suggests that more liquid firms experience less change in liquidity. Moreover, my correlation outcome between *Mcap* and *AveAliq* shows a positive and significant relationship, suggesting larger firms are more liquid. This relationship is in line with the previous studies that find larger firms have less transaction costs (Amihud, 2002; Chordia et al., 2000). Given the negative correlation between *AveAliq* and *AveΔAliq*, the inverse and statistically significant relationship between the firm size and liquidity change is not

[16] The Pearson and Spearman correlation among the network metric and the firm-specific factors is reported in Appendices B and C.

unexpected (*Mcap*, *AveΔAliq*= -0.054). Moreover, *Mcap* is positively and significantly correlated with *ROE* (*Mcap*, *ROE=0.058*) and negatively associated with *σRet,* (*Mcap*, *σRet*=- 0.184).

Most of the firm-specific factors show statistically significant association to one another at 1%. The correlation between *ROE* and *BM* is significant and inverse (*ROE*, *BM*=- 0.170), suggesting that firms with greater *BM* possess less *ROE.* These are intuitive outcomes in line with studies on the relationship between financial ratios and cross-sectional return (See Nagel, 2005). While *σRet* and *BM* have an inverse correlation with *AveAliq* (*AveAliq*, *σRet*=-0.047; *AveAliq, BM*=-0.079), *ROE* and *AveAliq* are positively correlated (*AveAliq*, *ROE=0.025*), suggesting liquid firms are more efficient in generating profit than illiquid firms. This relationship might seem to contradict Amihud's (2002) hypothesis that illiquid assets require a higher expected return. However, *ROE* and expected return vary in what they measure. While expected return is about how much profit a specific investment can generate from trading a financial asset, *ROE* considers a company's net income and shareholders' equity to evaluate how effectively a firm uses the shareholder's equity to generate profit.

Table 2.4 presents the estimation result of 45 separate panel-regression analyses to address whether firm-specific characteristics explain firms' liquidity network structure. I independently regress market-adjusted outcome of liquidity network measures on the firm-specific factors, where I control for the industry and year effect. I find that 7 out of 9 explanatory variables contain valuable information for explaining the liquidity network measures (*Out**, *In**, *In&Out**, *Clos**, *Eig**) at a 1% significance level.

As I stated earlier, *AveAliq** and *AveΔAliq** are negatively correlated, and my fixed-effect outcome reflects this inverse relationship. Specifically, an increase in average liquidity (*AveAliq**) decreases *Out** and *Eig** by 13.4% and 4.5%, respectively, suggesting more liquid firms tend to send out less liquidity and are less pivotal in sending liquidity information in the network. However, looking at the liquidity change, I witness an increase in $Ave\Delta Aliq^{*}$ increases the *Out** and Eig^{*}. The rank regression coefficient signs for all the network measures are matched with that of $AveAliq^{*}$ and $Ave\Delta Aliq^{*}$, confirming the robustness of the outcomes. The only exception is the In-degree (In^{*}), which has a negative rank regression sign for the coefficient of $Ave\Delta Aliq^{*}$ that might be due to the sensitivity of the measure to the nonnormal nature of $Ave\Delta Aliq^{*}$.

Solely looking at one rank increase of liquidity change ($RankAve\Delta Aliq^{*}$) the Out-degree (*Out**) rises by 6.1%, and In-degree (In^{*}) decreases by 2.23%. Suggesting a rise in liquidity change increases the ability of firms to send out liquidity to other firms and reduces their ability to receive liquidity from others (to influence others more than getting influenced by them). It also increases firms' pivotal role in the system by 7.6%. In general, firms with greater change in liquidity tend to play a greater role in sending out liquidity to others, are more pivotal in the liquidity network and transfer liquidity information faster. In contrast, firms with more stable liquidity that experience less change and have a greater level of liquidity tend to be less influential in the liquidity network. Even comparing the strength of beta coefficients of the two rank explanatory variables for the five measures, we see a greater beta coefficient for the $RankAve\Delta Aliq^{*}$ in comparison with that of $RankAveAliq^{*}$.

Looking at financial ratios, I find the same relationship pattern, where riskier firms (measured by return volatility) have a more significant impact on the liquidity network. For instance, comparing *BM* and *σRet* over the different metrics of the liquidity network, *σRet* indicates more economic significance and explanatory power than *BM*. An increase in *σRet* leads to a rise in *Out** by more than 17% and decreases In^{*} by 6%. Additionally, the rise in *σRet* elevates the information transmission across the firms and improves their pivotal role in the network. My outcome might seem surprising at first glance. However, it directs the attention toward the association between the firms’ riskiness and the ability of the firms to influence the liquidity system through the lead-lag ties; and aligns with the literature on liquidity and market efficiency and liquidity and returns predictability. Illiquid firms with greater return volatility are less desirable for traders for reasons such as the limit to arbitrage constraints (see Shleifer & Vishny, 1997). Lack of desirability causes a delay in the transmission of information into stock prices and creates predictability opportunities. Chordia et al. (2008) find that predictability diminishes when bid-ask spreads are narrower, and Lesmond et al. (2004) find more predictability in relatively illiquid securities.

The firm-size effect on the network measures is another factor that shows a risk-predictability association. My outcome shows that smaller firms tend to be more influential in the liquidity network. That is, an increase in firm size decreases the firm's ability to send out liquidity to others; it also reduces the centrality of the firms. As expected, *Clos* has a positive and significant coefficient in relation to size, suggesting that an increase in firm size makes firms more distant from others in the liquidity network. The small adjusted r-square of the regression results is not unexpected since research on the determinants of commonality in liquidity also exhibit small r-square output (e.g., Chordia et al., 2000; Koch et al., 2016)

In summary, my empirical result shows that the liquidity network exists in the U.S. market and is dynamic throughout the sample period. Firms are different in their liquidity network structures. While some firms are the influencers in the network, others tend to be influenced through their liquidity ties. The degree of the liquidity network seems to rise in times of financial turmoil. Moreover, some firm-specific factors such as liquidity level, change in liquidity, firm size, return volatility and book-to-market ratio can explain the differences in the firms’ liquidity network structure.

Table 2.3

Summary Statistics and Pearson Correlation of Firm-Specific Characteristics

Panel A: Summary statistics							
	Mean	Median	SD	Min	Max	P25	P75
AveAliq	-1.273	-0.217	8.442	-714.079	-0.001	-0.779	-0.085
AveΔAliq	0.015	0.001	0.308	-48.270	53.737	-0.000	0.008
Mcap	16.215	16.192	1.302	10.447	20.927	15.362	17.026
σRet	0.018	0.015	0.012	0.000	0.357	0.011	0.022
DE	3.110	1.739	4.537	-9.029	26.620	0.992	3.246
BM	-0.933	-0.877	0.802	-8.826	12.450	-1.376	-0.387
ROE	0.166	0.140	0.921	-152.429	37.037	0.077	0.215

Panel B: Pearson correlation							
	AveAliq	AveΔAliq	Mcap	σRet	DE	BM	ROE
AveAliq	1						
AveΔAliq	-0.095***	1					
Mcap	0.068***	-0.054***	1				
σRet	-0.047***	-0.021***	-0.184***	1			
DE	0.037***	0.000	0.083***	0.030***	1		
BM	-0.079***	-0.003	-0.286***	0.065***	-0.033***	1	
ROE	0.025***	0.000	0.058***	-0.103***	0.055***	-0.170***	1

Note: Panel A and Panel B respectively report the summary statistics and Pearson correlation of S&P500 firm-specific characteristics from January 1990 to December 2019. I sourced firm-specific variables from CRSP and WRDS Beta databases.

Liquidity average *AveAliq* is the monthly liquidity averaged over 36 months multiplied by 1,000. The average change in liquidity *AveΔAliq* refers to the monthly change in liquidity averaged over 36 months multiplied by 1,000. Firm size (*Mcap*) is the monthly market capitalization in logarithm, market capitalization = daily absolute price × share outstanding. Return volatility (*σRet*) is the concurrent monthly standard deviation of daily return. Debt-to-equity ratio (*DE*) is the total monthly liabilities to shareholders' equity winsorized at 1st and 99th percentile. Book-to-market ratio (*BM*) refers to the monthly book value of equity as a fraction of the market value of equity in logarithm. Return-on-equity ratio (*ROE*) is the monthly net income as a fraction of average book equity based on the most recent two periods, where the book value of equity is defined as the sum of total parent stockholders' equity and deferred taxes and investment-tax credit.

*, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.4

Determinants of the Network—Firm Level

Variables	Out*	In*	In&Out*	Clos*	Eig*
$AveAliq^{*}$	-0.134 (-3.28)*** 0.011	0.073 (4.69)*** 0.020	-0.028 (-1.58) 0.013	0.217 (2.91)*** 0.000	-0.045 (-3.00)*** 0.007
Rank $AveAliq^{*}$	-0.035 (-11.59)*** 0.021	0.21 (5.82)*** 0.020	-0.013 (-3.90)*** 0.013	0.006 (6.06)*** 0.000	- 0.060 (-19.36)*** 0.010
$Ave\Delta Aliq^{*}$	5.969 (4.70)*** 0.012	1.365 (2.24)*** 0.019	3.258 (5.56)*** 0.014	-12.089 (-2.94)*** 0.010	2.699 (4.98)*** 0.009
Rank $Ave\Delta Aliq^{*}$	0.061 (21.68)*** 0.015	-0.023 (-8.62)*** 0.020	0.034 (12.25)*** 0.015	-0.063 (-22.23) 0.013	0.076 (25.87)*** 0.013
Mcap	-0.001 (-4.60)*** 0.011	0.002 (8.02)*** 0.021	0.001 (4.07)*** 0.014	0.003 (10.47)*** 0.010	-0.001 (-11.36)*** 0.008
BM	0.002 (6.68)*** 0.013	-0.002 (-7.28)*** 0.019	0.000 (0.08) *** 0.014	-0.003 (-4.62)*** 0.021	0.0004 (3.88)*** 0.009
σRet	0.174 (5.75)*** 0.012	-0.06 (-2.83)*** 0.019	0.113 (3.44) *** 0.014	-0.685 (-3.86)*** -0.000	0.082 (9.84)*** 0.009
DE	-0.000 (-1.35) 0.013	0.000 (1.04) 0.018	-0.000 (-0.38) 0.014	0.000 (-0.60) 0.011	-0.000 (-0.25) 0.010
ROE	-0.000 (-0.66) 0.013	0.000 (0.700) 0.018	-0.000 (-0.39) 0.014	-0.000 (-0.88) 0.021	-0.000 (-0.1) 0.009

Note: Regression coefficients, *t*-statistics, and adjusted *R*-square for equations 15 from January 1990 to December 2019. Where *AveAliq**, *RankAveAliq**, *AveΔAliq**, *RankAveΔAliq**, *Mcap*, σRet, *DE*, *NPM*, and *ROE* are regressed on the outcome of firm-level network measures by holding the effect of year and industry constant. $Out^{*}, In^{*}, Clos^{*}, and\ \ Eig^{*}$ are market-adjusted network metrics averaged over 36-month percentiles. The liquidity average *AveAliq** refers to the market-adjusted monthly liquidity averaged over 36 months. *Rank AveAliq** is the rank of $AveAliq^{*}$. Average change in liquidity *AveΔAliq** refers to the market-adjusted monthly change in liquidity averaged over 36 months multiplied by 1,000. *Rank AveΔAliq** is the rank of $Ave\Delta Aliq^{*}$. Firm size (*Mcap*) is the monthly market capitalization calculated as daily absolute price × share outstanding in logarithm. Return Volatility (*σRet*) is the concurrent monthly standard deviation of daily return. The debt-to-equity ratio (*DE*) is the total quarterly liabilities to shareholders' equity winsorized at 1st and 99th percentile. Book-to-market ratio (*BM*) refers to the quarterly book value of equity as a fraction of the market value of equity in logarithm. Return-on-equity ratio (*ROE*) is the quarterly net income as a fraction of average book equity based on the most recent two periods, where book equity is defined as the sum of total parent stockholders' equity and deferred taxes and investment-tax credit.

The *t*-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) standard errors. The coefficients of $RankAveAliq^{*}$, $RankAve\Delta Aliq^{*}$are standardized. A standardized regression coefficient is computed by dividing a parameter estimate by the ratio of the dependent variable's sample standard deviation to the regressor's sample standard deviation. The first number in the table presents the coefficient of the fixed-effect model, the second value in the parenthesis is the *t*-statistics, and the third value is adjusted R-square.

*, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

2.7 Conclusion

My study suggests that market liquidity is complex, and there is more to the liquidity nexus across the firms than their contemporaneous relationship and co-movement. Therefore, I employ the lead-lag liquidity network method to capture liquidity sequence, interdependence and interrelationship across the firms.

Utilizing S&P500 addition and deletion constituents, I provide empirical evidence that there is a liquidity network during the 30 years of the sample. I show the liquidity network is dynamic and varies across the firms. While a firm contributes to the liquidity of others, it is simultaneously influenced by their liquidity. During the sample period, 84% of the firms (993 out of 1,174) exhibit statistically significant connectivity in at least one direction (*In-degree or Out-degree*). More than 12% of pairs have statistically significant relationships among all the possible pairwise causality combinations. The cross-sectional degree of connectivity rises significantly during the GFC. This magnifying effect is in line with the literature on commonality in liquidity.

Moreover, I find that some firm-specific characteristics such as level of liquidity, liquidity change, firm size, return volatility, and book-to-market ratio can explain the cross-sectional differences in the firm liquidity network structure. The outcome seems to direct the attention toward the association between the firm riskiness and the ability of the firms to influence the liquidity system through their network ties. There is evidence of significant size effect over all five network measures where the smaller riskier firms (measured by return volatility) seem to influence firms within the liquidity network the most. This is a somewhat surprising but not unintuitive result. One might expect firms with larger market capitalization would play a central role in the network due to their greater liquidity and price informativeness. However, the illiquidity of smaller firms might cause the information to be reflected into their prices with a delay. This suggests that lead-lag predictability increases when firms are riskier, which may be why we see liquidity dry-ups in times of financial distress.

Recognizing the existence of the liquidity network opens a new path for future research. An important research issue open for investigation is to see if the liquidity network is priced and if it exists in different asset classes. Also, other potential determinants might explain the cross-sectional differences in the network structure, such as firms' information environment.

CHAPTER 3

Firm-Level Liquidity Shock Transmission and Firm Size

3.1 Introduction

Liquidity is time-varying and subject to persistent shocks (negative liquidity shock leads to lower future liquidity). It also spills over across securities and markets. Firm-level liquidity shocks are positively related to contemporaneous returns and predict the return continuation for up to 6 months (Bali et al., 2014). Unlike systematic liquidity risk, firm-level liquidity risk is not priced in and might be diversifiable through trading (Fernando, 2003). Investigating how firm-level liquidity shock transmits through the liquidity network could, therefore, provide new insight for investors to anticipate their expected return and possibly reduce the adverse impact of the shock effect on their portfolios.

We now know that liquidity/illiquidity spills over across assets (Angelidis & Andrikopoulos, 2010; Cespa & Foucault, 2014; Chordia et al., 2011), and liquidity connectivity is a channel of illiquidity-risk propagation. Consequently, assets with a greater level of liquidity ties could be perceived riskier than less interlinked assets in times of market distress. A systematic event such as the COVID-19 pandemic increases the liquidity network connectivity and influences all the sectors in the U.S. economy (Farzami et al., 2021), making diversification less effective. In a network where securities are interlinked through their lead-lag liquidity connectivity, one might expect firm-level liquidity shocks to transmit through these interlinkages. In contrast to systematic liquidity shocks that simultaneously affect all assets, stock-level liquidity shock captures a firm's public information and, therefore, might propagate the information through detectable channels. However, our understanding of the relationship between the firm-level liquidity shock transmission and the liquidity network is, at best, limited.

Generally, investors are willing to pay 0.5%–2% per annum over the actuarial probability of a crisis to receive liquid funds at the onset of deterioration of market liquidity (Ang et al., 2014). In fact, as stated by Longstaff (2001), "there is a widespread view in Wall Street that the liquidity of a security is the major determinant of its value" (p. 2). Although liquidity does not consider an independent alpha factor, it is a crucial driver of transaction costs and net returns (Amihud & Mendelson, 1986). In other words, when constructing investment portfolios, trading costs, which are a direct function of the liquidity level of a stock, erode the expected alpha. Thus, detection of liquidity shock transmission matters due to the risk of illiquidity spillovers and its impact on the stock return; hence can add much value to the investment process.

The link between liquidity and market efficiency has been in the spotlight. Specifically; the speed through which the financial markets incorporate information has motivated many scholars (see, e.g., Avramov et al., 2006; Chordia et al., 2008, 2011; Hou & Moskowitz, 2005; Mitchell et al., 2002; Sadka & Scherbina, 2007). Due to their trading cost and associated risk, illiquid small firms take more time to incorporate market information and converge to fundamental values. Empirical evidence shows that firm size impacts the transmission of liquidity (e.g., Chordia et al., 2011) and liquidity co-movement (e.g., Kamara et al., 2008; Koch et al., 2016), motivating the consideration of liquidity shock transmission through the firm size in the network.

In Chapter 2, I provide empirical evidence that firms' liquidity can partially explain their network structure. I also show that small firms send out more liquidity and large firms receive more; therefore, it could be expected that the difference in size explains the shock transmission. The suggestion that firm-level liquidity shocks transmit differently across different firm sizes leads to the following questions: Does firm size matter in transmitting shock? Who are the recipients of the transmission?

In this chapter, I argue that given the size effect in the liquidity network and how small-/large-cap firms vary in incorporating information into their prices, the liquidity shock transmission might be more detectable and, therefore, diversifiable through firm size/size-sorted portfolios. If firms transmit their shock more to their similar-sized counterparts, it is possible to diversify against liquidity shocks by including dissimilar firm sizes into investment portfolios. Conversely, if firms tend to send out shocks to dissimilar firm size, then the diversification approach would be including similar-size assets.

Two possible channels through which firm-level shock transmission might occur include information diffusion channels (Hong et al., 1999; Barberis et al., 2005; Holden & Subrahmanyam, 2002) and Cross-asset learning mechanism (Cespa & Foucault, 2014). Both channels might cause shock spillover when the firms have a high degree of correlation. For example, suppose that two stocks, A and B, are in the same industry or have similar characteristics. If there is a sudden liquidity shock in A due to an unexpected announcement/ event, the shock can spillover from A to B either through portfolio adjustment of investors or inventory adjustment of the liquidity suppliers. Specifically, suppose A and B are large firms that many investors actively trade. Then assume there is a liquidity shock due to the release of a negative earning announcement of company A at time *t*. The liquidity decrease in stock A at time *t* concerns the investors about the liquidity of stock B. Therefore, traders are considering rebalancing their portfolio by selling A and B. This could take place any time between time *t* to time *t+1*. Consequently, the selling pressure that stock B experiences lead to order imbalance for B and, hence, the illiquidity of stock B. Through this mechanism, the shock of A transmits to stock B.

To look into the detail of the transmission flow, I divide my analysis into three sections. I first check if shock transmission depends on the firm size. I use a fixed-effect panel regression where I regress the transmission measure on the interaction between shock and firm size. In the second part of the analysis, I test whether the firms are inclined to transmit the shock to others with the same information transmission immediacy. For this part of the analysis, I use fixed-effect logistic model. At last, to look deeper into the shock destination, I construct pairwise size-based quantiles and focus my analysis on the shock transmission between quantiles excluding firms' liquidity connectivity within quantiles.

My empirical outcome shows that an increase in shock (in absolute value) increases liquidity transmission significantly at 1%, holding other factors constant. More importantly, the shock transmission depends on the level of firm size. The greater intensity shocks influence the transmission more through larger firms than small firms. This implies that although smaller firms generally send out more connectivity ties, larger firms create more out connections after receiving a large shock. This relationship holds for the subsamples of positive and negative shocks, suggesting that the way liquidity shock propagates into the system is independent of its sign. My outcome is in line with Chordia et al. (2014), who observe that shock in order flow is reflected in large stock prices within a month, while the smaller, less visible firms take over 6 months to reflect the effect entirely.

Another interesting observation is that firms are more prone to be connected to the nearest firm size. Specifically, with one unit increase in the size differences, the odds of firms being disconnected rises by 2.5%. This suggests that the probability of the firms transmitting shock to similar-sized firms is higher. One explanation for this outcome could be that liquidity providers adjust their inventories by learning from the liquidity of similar-sized firms. Another possibility is that similar-sized firms reflect the information with the same immediacy; therefore, they tend to transmit the shock to one another. The outcome of the portfolio analysis confirms this result by showing that although all the size quantiles transmit shock significantly to one another at 1%, their explanatory power varies. Most portfolios tend to send out more shocks to the next largest quantiles. Overall, the outcome suggests that the traditional method of diversification through different firm sizes is effective against liquidity shock transmission in the liquidity network.

I contribute to the emerging literature on liquidity connectivity and the literature on liquidity-risk diversification in two distinct ways. Firstly, I provide evidence that liquidity shock transmission in the network depends on the of firm size. Secondly, I show that firms tend to transmit shocks to similar-sized firms. My findings also add to the literature on the relationship between market efficiency and liquidity by showing the difference in information transmission between firm size and size-based portfolios, implying that the way information is reflected in the firms' prices matters. The outcome has practical implications regarding the liquidity-risk diversification process and is robust to the negative and positive liquidity shock subsamples.

The rest of the chapter is organized as follows: Section 3.2 provides an in-depth review of the related literature. Section 3.3 describes the data. Section 3.4 presents the methodology used in this research. Section 3.5 discusses the empirical results. Lastly, Section 3.6 concludes the study.

3.2 Literature Review

This section reviews the empirical and theoretical work of scholars in the field in two subsections. In Section 3.2.1, I review papers on the liquidity shock and stock return relationship. Section 3.2.2 discusses the literature on portfolio-risk diversification through asset liquidity, the role of firm size in the diversification process, and a few existing works on size and liquidity transmission.

3.2.1 Liquidity Shock and Stock Returns

The literature on market liquidity has evolved from focusing on the firm-level relationship with asset return to the importance of systematic liquidity and its determinants.

Works on firm-level (idiosyncratic level) liquidity and asset prices argue that investors holding illiquid assets are compensated by higher future returns (Amihud, 2002; Amihud & Mendelson, 1986; Brennan & Subrahmanyam, 1996; Jacoby et al., 2000; Jones, 2002), emphasizing that firm illiquidity is an asset characteristic associated with risk. On the other hand, there is a systematic, or market-wide, component to firm liquidity fluctuations (see Amihud, 2002; Chordia et al., 2000; Huberman & Halka, 2001). In this relation, Pástor and Stambaugh (2003) show that systematic liquidity risk is a priced risk factor. They develop a measure of aggregate (market-wide) liquidity based on daily price reversals. They show that assets whose returns covary highly with this aggregate liquidity measure earn higher expected returns than those whose returns exhibit low covariation with aggregate liquidity.

One of the earliest works that divides liquidity shocks into two different components is conducted by Fernando (2003). The paper attempts to find the fundamental determinants of market-wide liquidity movement. The author uses the intuition of Karpoff (1986), who suggests that investors have different liquidity needs and that noninformational trading results from differences in the personal valuation of assets. Fernando (2003) argues that the liquidity shocks that cause investors to revise their personal valuations have systematic (common across all investors) and idiosyncratic components. Common factors in liquidity imply that liquidity shocks apply systematically across investors and are transmitted across securities causing market-wide effects. He then shows that systematic and idiosyncratic liquidity shocks differ significantly in their impact on asset prices, trading volume and volatility. He suggests that given that firm-level liquidity shock drives the demand for liquidity, investors can potentially diversify their risk by trading. He then concludes that commonality is the outcome of covariation in investor heterogeneity rather than systematic liquidity shocks. Later, Acharya and Pedersen (2005) model the effect of liquidity shock on the stock's liquidity and contemporaneous and future returns in a theoretical framework. They develop a liquidity-adjusted capital asset pricing model (CAPM) that, besides standard market beta, considers three types of liquidity risk: namely, risk related to commonality in liquidity with the market liquidity, return sensitivity to market liquidity, and liquidity sensitivity to market returns. Their model illustrates that a persistent negative shock to a security's liquidity results in low contemporaneous returns and high predicted future returns.

Although a few of the works above talk about liquidity shocks and their effect on the expected return, finding a firm-specific liquidity shock proxy that is reliable and straightforward to compute is indeed challenging. To elaborate, the existing literature either refers to the direct and well-defined information releases and company events as firm-level liquidity shocks or considers order imbalances as liquidity shocks (see, for example, Avramov et al., 2006; Coval & Stafford, 2007). Similarly, in theoretical works, it is assumed that the liquidity shocks arise due to events that change the investors' marginal valuation of the risky assets (see Karpoff, 1986; Michaely & Vila, 1995, 1996).

Several years ago, Bali et al. (2014) proposed three different firm-level liquidity shock proxies and investigated their influence on assets' return in a comprehensive empirical work. The authors provided evidence that firm-level liquidity shocks are positively related to contemporaneous returns and predict the return continuations for up to 6 months. Moreover, they show that portfolios sorted based on long and short liquidity shocks generate a significant return of 0.70% to 1.20% per month, respectively. Motivated by their work, Chordia et al. (2014) explore the relationship between shocks to order-flow volatility and stock returns. They find that shocks to order-flow volatility strongly predict stock returns, even after controlling the characteristics that can influence the stock return. They provide empirical evidence that the shock effect varies between large and small firms. While the shock is reflected in large stock prices within a month, the smaller, less visible firms take over 6 months to reflect the effect entirely. They also find a significant positive correlation between shocks to order-flow volatility and existing illiquidity proxies. The strong positive correlation between shock and illiquidity proxy is reassuring because it implies that the liquidity proxy used in this study for establishing the network is sufficient to capture the shock transmission effect.

The theoretical and empirical preceding works emphasize the effect of liquidity shock on contemporaneous and future stock returns. Given that there is a liquidity network among the securities, investigating the channel through which firm-level liquidity shock transmits through the liquidity network matters.

3.2.2 Diversification, Firm Size and Liquidity Transmission

Risk management has become one of the focal points of firms, and market imperfections are one of the drivers of this focus. A common way to reduce risk is through diversification strategies. Markowitz's (1952) well-known paper about portfolio diversifications shows that it is not an asset's own risk that is important to an investor but rather the security's contribution to the variance of her entire portfolio (its covariance with all the other securities). The single period model of Markowitz was later extended to a multiperiod setting by Samuelson (1975) and then to continuous time by Merton (1969).

The traditional portfolio diversification approach assumes that investors can continuously trade unlimited amounts of securities without any constraints; however, in reality, there are liquidity constraints that make the investment in less liquid assets more expensive, in extreme cases, even impossible sometimes. Longstaff (2001, 2009) shows that asset illiquidity significantly impacts the optimal portfolio choices of investors, leading them to abandon diversification as a strategy. This might be because highly leveraged investors cannot trade unlimited amounts of securities without exposure to the risk of bankruptcy; they might even give up a large percentage of available gains. Moreover, Lo et al. (2003) discovered that even portfolios close to each other on the traditional mean-variance efficient frontier could vary significantly in their liquidity characteristics. The authors suggest three ways to incorporate liquidity directly into a portfolio-optimization program as follows: 1) utilizing a liquidity filter for including securities into the liquidity-optimized portfolio, 2) constraining the portfolio-optimization program to yield a mean-variance efficient portfolio with a minimum level of liquidity, and 3) adding the liquidity metric into the mean-variance objective function directly. They conclude their research by providing empirical evidence that a simple form of liquidity optimization can significantly reduce a portfolio's liquidity-risk exposure without sacrificing a great deal of expected return per unit risk. In a similar work, Kinlaw et al. (2013) propose a method for incorporating liquidity benefits in portfolio choice. The authors map units of liquidity into units of expected return and risk to capture the possible rise in expected portfolio utility. Hence, if any fraction of a portfolio is static, investors bear an illiquidity cost that they should consider when forming portfolios. In the most recent research on liquidity-risk diversification, Ghabri et al. (2021) show that including Bitcoin in a portfolio leads to potential gains by diversifying the liquidity risk and enhances the Sharpe ratio under the mean-variance liquidity framework. Therefore, the literature is rich with evidence of portfolio diversification benefits through liquidity risk and reward consideration.

The relationship between firm size and expected return is also well established. Small stocks in the US (stocks with lower market capitalizations) have higher average returns than large stocks, an effect not accounted for by the higher market beta of small stocks (Banz, 1981; Fama & French, 1992; Reinganum, 1981). Knez and Ready (1996) argue that size-based strategies are too costly to trade. The transaction cost makes it difficult to take advantage of the market anomalies. Firm size has always been a matter of importance in the literature on liquidity and liquidity risk. Firm size matters because small firms are less liquid (Amihud & Mendelson, 1986) and face more liquidity risk (Acharya & Pedersen, 2005), requiring higher expected returns. Chordia et al. (2011) find that informed trading is transmitted from large to small stocks with lag. This lead-lag relation increases with lagged large-stock illiquidity. The authors show that this relationship is more pronounced before macroannouncements, when information-based trading is more likely, and weaker afterwards (when information asymmetries are lower). More recently, Asness et al. (2018) conducted a comprehensive study on whether the size effect on financial studies is overrated. They argue that the size premium holds if a firm's junk is accounted for. Their empirical evidence shows that a significant size premium emerges that is stable through time, robust to specification, not concentrated in microcaps, more consistent across seasons, and evident for nonprice-based measures of size. Their results hold in 30 different industries and 24 international equity markets. The authors show that small, quality stocks are less liquid than large, quality stocks, and likewise, small, junk stocks are less liquid than large, junk ones.

The relationship between liquidity shock and expected return, the benefits of diversification through liquidity-optimized portfolios, and the size effect of information transmission are independently well documented. However, there is a gap in the literature for linking these crucial findings and exploring them from a different angle. Investigating the liquidity shock transmission across different size-sorted portfolios introduces a possible practical way to manage the risk associated with firm-specific liquidity shocks.

3.3 Data

Section 3.3 discusses the data employed in this study. As this essay is closely related to Essay 1, I utilize the same liquidity data and sample period for this study. Therefore, the data and analysis involve occasional reference to the previous work.

In brief, I utilize the S&P500 index as the primary data sample. The S&P500 constituents list is collected from Bloomberg from January 1990 to December 2019 (see Chapter 2, Section 2.3). I obtain the daily data on stock prices, returns, volumes, and market capitalizations (firm-size proxy) from the CRSP. I calculate the Amihud (2002) liquidity measure by following Karolyi et al. (2012) and H. C. Lee et al. (2014) as my liquidity measure (see Chapter 2, Section 2.4.1, Liquidity Proxy).

3.4 Methodology

In the following sections, I test two hypotheses through three different models. I first test if the shock transmission depends on the level of firm size. Next, I investigate where the shocks transmit to. The methodology section consists of the following: Section 3.4.1 explains the construction of the shock network. Section 3.4.2 discusses the firm-level shock proxy and its computation. Section 3.4.3 presents the panel-regression analysis where I regress the transmission measure on the interaction between firm size and shock. Section 3.4.4 investigates where the shocks go through logistic regression. Lastly, I explain and conduct a robustness check using size-sorted portfolios in Section 3.4.5.

3.4.1 Formation of the Shock Network

My base analysis for this essay is on the outcome of the firm-level rolling window of monthly Granger-causality (See 2.4.2, Linear Granger-Causality Test). Therefore, I use the Granger-causality outcome to construct a shock network. Given that the interest of this chapter is shock transmission, constructing a shock network is a necessary step. The shock network contains only firms with significant liquidity connections with other firms at a given time (36-month window). All the firms with no significant Granger-causal relationship are deleted from the shock network. I then map my firm-level shock proxy to the firm-level rolling-window dataset and exclude firms that do not meet the shock criteria (see Section 3.4.2). I have 968 firms during the sample period in the S&P500 shock network. Employing the shock network, I conduct the firm-level analysis by computing the *Out-degree* transmission metrics. It is noteworthy that this essay's *out-degree* computation is identical to that of Chapter 2. As a robustness test, I cluster the shock network into five size-based quantiles (portfolios) at each given time and calculate the transmission metric between portfolios. The formation of the size-based portfolio is then discussed in detail in Section 3.4.5.

3.4.2 Liquidity Shock Proxy

As mentioned earlier, a systematic shock is external and influences all the securities simultaneously. Therefore, any impactful systematic event such as COVID-19 can be considered to investigate its impact on securities. However, finding a firm-specific shock proxy is not as straightforward. The existing literature either refers to the direct and well-defined information releases and company events as the firm-level liquidity shock or considers order imbalances as liquidity shocks (see, for example, Avramov et al., 2006; Coval & Stafford, 2007). Similarly, theoretical works assume that liquidity shocks arise due to events that change the investors' marginal valuation of the risky assets (see Karpoff, 1986; Michaely & Vila, 1995, 1996).

One of the contributions of my paper is to look at the firm-level liquidity shock propagation into the network during normal market conditions. This requires a proxy reflecting unanticipated and continuous shocks to firm-level liquidity during the sample period. In this paper, I utilize the liquidity shock proxy introduced by Bali et al. (2014). There are a couple of advantages to using this proxy: firstly, the shock calculation is independent of the company's information release or company events, such as earning releases and mergers and acquisitions; hence it is continuous. Secondly, it is positively correlated with the spread shock measure constructed by Bali et al. (2014) with an average correlation coefficient of 43%, reflecting order imbalances. Last, but not least, the measure or its mutation is used in other well-referenced works to account for firm-level liquidity shocks (see example: Atilgan et al., 2020; K. H. Chung & Chuwonganant, 2018).

The first step for shock computation is to calculate Amihud's (2002) illiquidity measure as follows:

$$ILLIQ_{i,t} = Avg\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right] \qquad 1$$

Where $R_{i,d}$ and $VOLD_{i,d}$ are the daily return and dollar trading volume for stock *i* on day *d*, respectively. A stock must have at least 15 daily return observations in month *t*. The Amihud illiquidity measure is scaled by 10^6.

The idiosyncratic liquidity shock *(denoted LIQU)* is defined as the negative difference between *ILLIQ* and its past 12-month average:

$$LIQU_{i,t} = -\left(ILLIQ_{i,t} - \mathrm{AVGILLIQ}_{\mathrm{i|t-12,t-1}}\right) \qquad 2$$

where $AVGILLIQ_{i|t-12,t-1}$ is the mean of illiquidity over the past 12 months.[1] Positive (negative) liquidity shocks indicate an increase (decrease) in liquidity relative to its past 12-month average. It is worth mentioning that firms with less than 6 months of observation are excluded from the sample due to the filtration above.

I employ absolute shock value instead of the level in my main analysis. There are two views in this regard. One might argue that different liquidity shock proxies capture different types of liquidity information. Bali et al. (2014) believe that, compared with the well-defined information events studied in the literature, liquidity shocks are not well defined, and their pricing implications are harder for average investors to interpret. Similarly, Hirshleifer et al. (2013) make a case that investors would "have greater difficulty processing information that is less tangible" (p. 1); therefore, the elusive nature of liquidity news can be subject to investors'

[1]When a firm enters the network, I only require illiquidity values for the past 6 months in order to preserve observations. Firms are excluded from the network if 12-months moving average can’t be calculated.

attention constraints. Even if traders do pay attention to the liquidity shock, they will allocate more attention to systematic shocks and less to stock-specific shocks (Peng & Xiong, 2006). Thus, a strong case can be made for solely focusing on the shock transmission; it should not matter whether the shock is positive or negative because average investors have difficulty exploiting the opportunity to trade on them.

However, the counter-argument would be that positive and negative liquidity shocks differ. A positive shock represents more liquidity, whereas a negative one means a lack of it. While the positive shock can be considered an exploitable trading opportunity, the negative one is a risk factor. As a result, shocks might vary in how they influence the network.

Although there is no research on the shock–network relationship, the literature examines the liquidity shock and return connection.[2] Therefore, to address this concern, I have created two subsamples where I test the robustness of my outcome by taking to account the positive and negative shocks independently one at a time (see Appendix D).

3.4.3 Shock Transmission and Firm Size: Panel-Regression Analysis

The transmission proxy of the liquidity shock is the measure of *out-degree* utilized in Chapter 2 (see Section 2.4.4.1). My shock network is based on bidirectional liquidity ties. It is fundamentally different when a firm Granger-causes the liquidity of other firms with its lagged value (has an *Out-degree*) or Granger-caused by a lagged liquidity of the other firms (has an *In-degree*). In this essay, I focus on the *out-degree*. The intuition behind this focus is simple. A firm influences the network when its lagged value can predict another firm's value at ex-ante. Simply put, when a firm is subject to a liquidity shock, it transmits it through its liquidity ties to other firms. Therefore, it is critical to identify the agents that influence others the most to suggest any risk-management techniques.

[2] For example, Acharya and Pedersen (2005) suggest that a persistent negative shock (negative liquidity shocks predict lower future liquidity) results in low contemporaneous returns and high future returns, and vice versa.

To examine whether liquidity shock and size together influence the lead-lag liquidity network beyond their independent impact, I employ the following fixed-effect regression:

$$Out_{jt} = \alpha + \beta_1 \, LIQU\_Abs_{j,t-1} + \beta_2 \, Mcap_{j,t-1} + \beta_3 \, LIQU\_Abs_{j,t-1} \times Mcap_{j,t-1} + \vartheta_I + \eth_T + \varepsilon_{j,t} \quad 3$$

Where *Out* is the *Out-degree* monthly estimated measure of liquidity network. *Out* is measured as the sum of all the significant Granger-causal connections (at 5%) from firm *j* to others at time *t* divided by the number of all firms (except firm *j)* at time *t.* $LIQU\_Abs_{j,t-1}$ is the monthly shock of firm *j* liquidity in absolute value at *t-1.* $Mcap_{j,t-1}$ is the proxy of firm size, which is the monthly average of the market capitalization of firm *j* at time *t-1.*[3] $LIQU\_Abs_{j,t-1} \times Mcap_{j,t-1}$ is the interaction term between the firm-level monthly liquidity shock and monthly market capitalization of firm *j* at time *t-1.* ϑ_I and $\eth_T$ refer to industry fixed-effect and year fixed-effect coefficients, respectively. I control year and industry effects by creating dummy variables for each cross-section. There are (27-1) dummies for the year and (66-1) dummies for the industry.[4] I also regress *Out* on $LIQU\_Abs_{j,t-1}$ and $Mcap_{j,t-1}$ in a separate regression by excluding the interaction term to establish the relationship between shock, size and transmission of liquidity.

It is worth explaining the introduction of the shock at time *t-1* in the above model. The logic is built on the intertemporal nature of the connectivity through the Granger-causality test. Firm *j* could have a liquidity tie with firm *i* at time *t,* if the lagged value of *j* can explain the value of *i* at time *t.* Therefore, for detecting the firm-level shock transmission through a lead-lag network measure of *Out-degree*, the shock needs to be imposed into the system when firm

[3] *Mcap* is daily *Abs* $(price_t) \times Share\ outstanding_t$ averaged into monthly. The daily data is acquired from CRSP.

[4] I utilize the firm's two-digit standard industrial classification codes (SIC) to allocate dummy variables to the firms.

j establishes connectivity at *t-1*. The same logic also applies to the firm-size proxy of *Mcap* in the model.

3.4.4 Where Do the Shocks Go? Fixed-Effects Logistic Model

Knowing where the shocks go is crucial and has portfolio diversification implications. Therefore, I use my shock network and employ a logistic model to test if differences between the firm sizes make or break the *Out* connections.

Given the firms' pairwise relationships, I code a binary *Out-degree* variable where *Out* connections are equal to zero (*Out-con=0)* if firm *j* does not cause firm *i,* and *Out-con*=1 otherwise. The primary explanatory variable is the firm-size differences (in absolute value) between firm *j* and firm *i*. I employ the following model where *Out-con=1* is the base category:

$$ln\left(\frac{Out-con_{jt}=1}{Out-con_{jt}=0}\right) = \alpha + \beta_1\, DIFFMcap_{j,t-1} + \vartheta_I + ð_T + \varepsilon_{j,t} \tag{4}$$

Where *Out-con* is the outcome of the monthly pairwise Granger-causal relationship between firm *j* and *i* at time *t* coded as 0 or 1. $DIFFMcap_{j,t-1}$ is the monthly difference between the market capitalization of firm *j* and firm *i* in absolute value at *t-1*. $Mcap_{j,t-1}$ is the proxy of firm size, which is the monthly average of the market capitalization of firm *j* at time *t-1*. ϑ_I and $ð_T$ refer to industry fixed-effect and year fixed-effect coefficients, respectively.

A positive coefficient of $DIFFMcap$ means that for a unit increase in firm size differences, the log odds of no connection increase. In other words, it is more likely that firms send out significant *Out* connections to the ones with similar firm size. Conversely, a negative β_1 refers to an increase in log odds of out connections when there is one unit increase in firm-size differences. If the manner in which information is reflected in the prices matters in how firms communicate shock, I expect to see a positive coefficient for $DIFFMcap$.

3.4.5 Size-Based Portfolios and Shock Transmission

In this section, I attempt to examine whether the transmission of firm-level liquidity shock differs across the size-sorted portfolios. Utilizing the shock network, I index firms into five quantiles based on their market capitalization and then restrict their link to out-of-quantile connections *(Out-Q)*. Understanding how firm-level liquidity shocks transmit into the liquidity network of size-based quantiles lends new insight into liquidity-risk management. Then, I explore the relationship between the liquidity shock, firm size and the portfolio-level network-transmission proxy through a panel-regression analysis.

My network is established through a 36-month rolling window of a bidirectional pairwise lead-lag Granger-causality outcome. To construct size-based portfolios, I initially rank all of the securities at each date interval (window) into five quantiles (*Q*) based on their market capitalization. By doing so, I get a time series of size-based quantiles during the 30 years of my sample period [5]. Then I construct pairwise size-based quantiles at each time *t*. When firms indexed in each quantile are linked through their Granger-causal relationship to other firms from their own and other quantiles. Next, I remove all the within-quantile connectivity and form 20 subsamples ($5Q \times 5Q\text{-}1$). The 20 subsamples are the result of all possible mutations of the portfolios with each other. It is worth mentioning that the network is directional.

The following are examples of pairwise size-based quantiles:

Subsample1: Q1 to Q2,

Subsample2: Q1 to Q3,

…

[5] The number of firms in each date interval varies throughout the sample period. This is due to the data cleaning and filtration. For example, I require a minimum 6 months of liquidity observation, for the shock calculation so I lose some of the firms. In a perfect scenario with 325 months of rolling window liquidity data and each quantile consisting of 100 firms, I would have 325*100=32,500 observations for time series of each quantile. There are approximately 500 firms at each date interval and 100 firms in each size-based portfolio at the time.

Subsample20: Q5 to Q4.

After forming the pairwise size-based quantiles, I compute the *Out-Q* connectivity in the next section for every subsample.

The following equation presents the measure of liquidity transmission. *Out-Q* is a more granular version of Billio et al. (2012) *portfolio-conditional number of connections* measure. The only difference between my *Out-Q* measure and *portfolio-conditional number of connections* is that Billio et al.'s (2012) method looks at *Out* connections to all other portfolios. In contrast, my *Out-Q* approach enables me to compute firm-level shock transmission to every other portfolio independently. Precisely, each firm in my subsample consists of four *Out-Q* values, each representing the total liquidity ties the firm has to each quantile at a time. Monthly *Out-Q* is therefore computed as follows:

Out-Q

$$\big((j\,|\alpha_r) \rightarrow (i\,|\alpha_s)\big) = \frac{1}{N}\sum_{k=1}^{N}(i_k\,|\alpha_s) \qquad 5$$

Where *Out-Q* for firm j of quantile α_r is the percentage of firms i in quantile α_s that are significantly Granger-caused by firm j (with $r, s\ \in \{1,..,5\}\ and\ r \neq s$). N is the number of securities in quantile α_s.

In simple terms, if firm $(j\,|\alpha_r)$ transmits liquidity information to all the firms indexed in α_s then firm *j Out-Q to* α_s is equal to 1.

To look at the shock transmission at a more granular level, I employ the following model to regress *Out-Q* network measure on the firm-level shock for each subsample (*Subsample1 … Subsample20*) independently and acquire 20 beta coefficients.

$$\big((\mathrm{j}\,|\alpha_\mathrm{r}) \rightarrow (\mathrm{i}\,|\alpha_\mathrm{s})\big) = \beta_{0_{\alpha,t}} + \beta_1\, LIQU\_Abs_{j,\alpha_r,t-1} + \vartheta_I + \eth_T + \epsilon_{\alpha,t} \qquad 6$$

Where Out_Q is estimated connectivity measures of the liquidity network for firm *j* at time *t* indexed in quantile α_r concerning another quantile α_s (with $r, s \in \{1, .., 5\}\ and\ r \neq s$). $LIQU\_Abs_{j,\alpha_1,t-1}$ is the monthly liquidity shock of firm *j* indexed in α_r at *t-1*. ϑ_I and $\eth_T$ refer to the industry fixed-effect and year fixed-effect coefficients, respectively. I control the impact of time and industry by creating year and industry dummy variables for each cross-section (every year within a subsample). I have 30 years of sample data and use the 36-month rolling-window regression. Therefore, I construct 26 dummy variables (27 years-1) for year and 66-1 dummies for the industry.

I adjusted the t-statistics for heteroskedasticity and autocorrelation using Newey and West's (1987) standard errors.

3.5 Empirical Result and Discussion

I divide my empirical findings into three key sections: The first section establishes the relationship between the firm-level liquidity shock transmission and firm size through a fixed-effect panel-regression analysis. The second section explores how the change in firm size influences the shock network through a logit model. Lastly, I briefly review the outcome of the size-based portfolio-level shock transmission.

3.5.1 Shock Transmission and Firm Size: Firm Level

Table 3.1 illustrates the descriptive statistics of monthly idiosyncratic liquidity shock in absolute value (*LiqU-Abs*), market capitalization (*Mcap*) as the firm-size proxy, and Out-degree (*Out*) as the transmission measure in the shock network. The descriptive statistics include a time-series mean, median, standard deviation and 5th and 95th percentile for each variable during the sample period.[6]

[6] The descriptive statistics of the positive and negative liquidity shock subsamples is reported in Appendix E.

My statistic on the transmission proxy of *Out* shows that, on average, firms send out liquidity connections of 12.45% to the liquidity system (*Mean=0.1245*). The *Mcap* (firm-size proxy) is presented in natural logarithm to be consistent with Essay 1[7]. On average, the monthly firm size is more than 16.0673, with a standard deviation of 1.2628.

Table 3.1

Summary Statistics of Firm-Level Liquidity Shock and Liquidity Transmission

Variable	Mean	Median	SD	5th	95th
LIQU-Abs	0.5907	0.0539	5.6465	0.0019	2.0121
Mcap	16.0673	16.0342	1.2628	14.0183	18.3065
OUT	0.1245	0.10070	0.0864	0.0481	0.2930

Note: The summary statistics of the monthly firm-level liquidity shock and liquidity transmission of S&P500 constituents from January 1990 to December 2019. Where *LIQU* is the liquidity shock measured as the negative difference between *ILLIQ* and its past 12-month average. *LIQU*-Abs is the absolute value of liquidity shock scaled by 1,000 at time *t-1*. Out-degree (*Out*) is a network measure calculated from a 36-month rolling window of Granger-causality outcomes with a statistical significance at 5%. *Out* measures a fraction of firms significantly Granger-caused by *j* at month *t*. *Mcap* is the natural log of monthly market capitalization in millions at month *t-1*.

Table 3.2 shows the outcome of Equation 3. However, before discussing the influence of interaction between shock and size on liquidity transmission, I establish the relationship between shock and firm size with the transmission measure. My empirical outcome shows that while an increase in firm size reduces the transmission significantly, an increase in liquidity shock significantly increases it (at 1%), holding all else constant. I then test my hypothesis that the effect of liquidity shock-transmission changes depending on the size of the firms by introducing an interaction between the firm size and liquidity shock. The outcome illustrates that the interaction term significantly contributes to the information transmission's predictive ability (statistically significant at 1%). The effect of shock on *Out*, therefore, depends on the

[7] I test the relationship between the firm size in level and that of the transmission proxy of *Out* and the outcome of the regression holds.

level of firm size. The positive coefficient of the interaction term, in particular, suggests that larger size shocks influence the transmission more through larger firms than the smaller ones. The outcome is in line with the findings of Chordia et al. (2014), who show that shock in order flow is reflected in large stock prices within a month, while the smaller, less visible firms take over 6 months to reflect the effect entirely.

Moreover, to test whether the impact of different types of shock on transmission varies, I employ the same model by regressing the subsample of positive and negative shocks on the size-based pairwise portfolios at a time. The outcome of the regression is reported in Appendix D. I find that the transmission effect through the negative and positive shocks subsample is similar to that of the absolute shock sample.

Table 3.2

Firm-Level Liquidity Shock, Size and Liquidity Transmission

Independent variable	LIQU-Abs	MCAP	LIQU-Abs× MCAP
Out	-0.0058 (-5.61)*** 0.1587	-0.0005 (-6.17)*** 0.1587	0.0004 (5.93)*** 0.1587
Out	0.0004 (4.48)*** 0.1576	-0.0019 (-7.49)*** 0.1576	---
Number of obs	125,930	125,930	125,930
Year fixed effect	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes

Note: Regression coefficients, *t*-statistics, and adjusted *R*-square for the following two models:

1- $Out_{jt}=\alpha+\beta_1\ LIQU\_Abs_{j,t-1}+\beta_2\ Mcap_{j,t-1}+\beta_3\ LIQU\_Abs_{j,t-1} \times Mcap_{j,t-1}\ +\vartheta_I + ð_T + \varepsilon_{j,t}$

2- $Out_{jt}=\alpha+\beta_1\ LIQU\_Abs_{j,t-1}+\beta_2\ Mcap_{j,t-1} + \vartheta_I + ð_T + \varepsilon_{j,t}$

The sample includes S&P500 constituents spanning from January 1990 to December 2019. Where *LIQU* is the monthly firm-level liquidity shock measured as the negative difference between *ILLIQ* and its past 12-month average, at time *t-1*. *LiqU-Abs* is the absolute value of liquidity shock scaled by *1,000* at time *t-1*. *Mcap* is the monthly market capitalization at time *t-1* in logarithm. *LiqU_Abs*Mcap* is the interaction term between the firm-level liquidity shock in absolute value and market capitalization. *Out* is the monthly firm-level measure of liquidity transmission. ϑ_I and $ð_T$ are the industry and year fixed effect.

The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West's (1987) standard errors. The first number in the table presents the coefficient of the fixed-effect model, the second value in the parenthesis is the t-statistics, and the third value is adjusted R-square.
*, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

3.5.2 Where Do the Shocks Go?

Table 3.3 reports the outcome of fixed-effect logistic regression, where I regress the binary outcome of the pairwise Granger-causality test on the size differences between the firms. The logit model results reveal whether the closer sized firms tend to send out the shock to one another more. I design my binary dependent variable so that if a firm significantly connects to (Granger-causes) another firm, it gets the Out-connection=1; otherwise, the Out connections are equal to 0. I use the probability of the Out-connection to be significant as my base and expect to see an odd ratio above 1 with a positive and significant coefficient.

My outcome in Table 3.3 is in line with my expectation and shows a positive coefficient of 0.0251 which is significant at 1%. The odd ratio of greater than 1 (odd ratio=1.025) suggests that one unit increase in size difference between firms results in 2.5% increase in odds of firms not having significant out connections. In other words, the larger the size differences between firms, the more likely it is that the out connections will be insignificant. I further check the robustness of my result by looking into size-sorted portfolios.

Table 3.3

Firm-Level Logistic Regression

Independent variable	$DIF - Mcap$
Out-con (sig Out-con=1, Insig Out-con=0)	0.0251 (1.025)***
Year fixed effect	Yes
Industry fixed effect	Yes

Note: Regression coefficients and odd ratio for the fixed-effect logistic regression of the S&P500. The number of observations of the firms' pairwise connectivity is 54,179,479, which span from January 1990 to December 2019. The dependent binary variable is *Out* connections (*Out-con*). *Out-con*=1 if firm *j* Granger-causes firm *i*, and *Out-con=0* otherwise. The reference of the dependent variable for the model is *Out-con=1*. The primary explanatory variable is the firm size differences in absolute value between firm *j* and firm *i*. *Mcap* is the proxy of the firm size and it is the natural log of monthly market capitalization in millions at month *t-1*.

The odd ratio is reported in parenthesis. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

3.5.3 Analysis of Size-Sorted Portfolios

In this section, I discuss the outcome of the size-sorted portfolio regression. Appendix F shows the outcome of the fixed-effect regression analysis performed on 20 pairwise size-sorted subsamples. Each time I regress the network measure of *Out-Q* on the absolute shock. My finding suggests that although all portfolios significantly transmit the liquidity shock to others (at a 1% level), their explanatory power of this transmission (measured by their beta coefficient) varies. Most quantiles tend to have the largest beta coefficient when transmitting the shock to the next larger quantile or the closest one. For example, with one unit increase in absolute shock, *Q1* sends the shock to *Q2* and *Q3 by* 0.38 and 0.37 percentage points respectively. Similarly, *Q2, Q3* and Q4 show the same transmission pattern, where the most explanatory power goes to the next larger quantiles. The only exception is the largest portfolio of *Q5*, where the most shock transmission is to *Q3* and *Q4* as there is no higher size-based quantile than Q5[8]. Notably, the large coefficient of *Q5* resulted from the fact that shocks indexed in this portfolio are far smaller than in other portfolios. Specifically, the summary statistics of the liquidity shock in Panel B of Appendix G show, on average, *Q5* shock is smaller than *Q1* by 94.73%. Nevertheless, the large difference in shock quantile portfolio is not unexpected as Bali et al. (2014) also witnessed a significant percentage increase in their liquidity shock-based portfolio, where shock in Decile 10 is 246.355% larger than that of Decile 1 in their sample of NYSE, AMEX and NASDAQ. My outcome also shows a similar pattern for four out of five quantiles, when I employ the subsample of the negative shocks and repeat the regression (see Appendix H)[9].

[8] I test the equality of coefficients to ensure my interpretation of the outcome is robust. I examine if the largest and smallest *Out-Q* coefficients are significantly different for each quantile. My outcome confirms that four of the five portfolios' coefficients (*Q2, Q3, Q4* and *Q5*) are statistically different, confirming that portfolios vary in transferring shock. To be more specific, while the largest and smallest coefficient in *Q2* and *Q3* are statistically significant at *10%,* the null hypothesis of coefficient equality is rejected for *Q4* and *Q5* at 1%.

[9] The outcome of pairwise size-sorted transmission of positive shock subsample is available upon request.

Overall, my findings point to the benefit of diversifying portfolios with different firm sizes to shield against the liquidity shock transmission effect.

3.6 Conclusion

Liquidity is time-varying and subject to persistent shocks. It also spills over across securities and markets. Firm-level liquidity shocks positively relate to contemporaneous returns and predict the return continuation. Unlike systematic liquidity shock that simultaneously influences all the firms in the liquidity system, firm-level liquidity shocks might transmit through detectable channels. The literature shows that firm size impacts the transmission of liquidity (e.g., Chordia et al., 2011) and liquidity co-movement (e.g., Kamara et al., 2008; Koch et al., 2016). I also found a significant firm-size effect that explains network connectivity in my Essay 1, where small firms predominantly tend to influence the liquidity network by having greater *out-degree* and *Eigenvector centrality.* Therefore, in this essay, I investigate whether liquidity shock transmission can be explained through firm-size differences.

My empirical outcome shows that shock transmission depends on the level of firm size. The greater intensity shocks influence the transmission more through larger firms than small firms. The outcome is robust with absolute shock and the subsamples of the negative and positive shocks. Moreover, looking into firm-size differences and their impact on the transmission, my logistic regression outcome reveals that the odds of *Out* connections being significant decreases when firm size are further apart, suggesting that firms transmit more shock to similar-sized firms. One explanation for this outcome could be that similar-sized firms reflect the shock with the same immediacy; therefore, they tend to transmit the shock to one another. Another possibility is that liquidity providers adjust their inventories by learning from the liquidity of similar-sized firms.

Lastly, I check the robustness of my findings by constructing pairwise size-based quantiles and focus my analysis on *Out-Q* connections. I find that although size-based portfolios all significantly transmit the shock to one another (at 1%), their explanatory power varies. Most portfolios tend to have higher explanatory power (measured by beta coefficient) when transmitting the shock to the next larger size quantile or the quantile nearest to them. That is in line with the logistic regression outcome and suggests diversification against liquidity shock transmission might be possible by including different firm sizes.

In summary, I contribute to the emerging literature on liquidity connectivity and the literature on liquidity-risk diversification by providing empirical evidence that liquidity shock transmission varies through different firm sizes and size-sorted portfolios. My findings also add to the literature on the relationship between market efficiency and liquidity by showing the difference in the information transmission across different firm sizes and size-based portfolios. Moreover, the outcome has practical implications regarding the liquidity-risk portfolio diversification.

CHAPTER 4

COVID-19 and the Liquidity Network

4.1 Introduction

Traders and investors have faced considerable liquidity challenges as a result of the COVID-19 outbreak. Bid-ask spreads of S&P 100 stocks have increased almost four times compared to the levels in January this year, with a similar pattern in Russell 2000 stocks (Mittal et al., 2020). Moreover, they report that the average cost for a fixed available amount of liquidity was 20.5 basis points during the outbreak, compared to the usual 2.9.

Variability and uncertainty of liquidity is one of the principal challenges for market participants, and current literature either focuses on co-movement between an asset and market liquidity or liquidity spillover (Cespa & Foucault, 2014; Chordia, Subrahmanyam, & Anshuman, 2001; Huberman & Halka, 2001). The fact that liquidity co-moves and propagates from one asset to others implies connectivity. Hence, I model market liquidity as a network to detect how the network components (firms) exchange liquidity with one another, and how this has changed in the current COVID-19 crisis. To that end, I employ a lead-lag liquidity network method proposed by Billio et al. (2012) to compare the liquidity interrelationship across firms in the U.S. stock market pre- and during the COVID-19 effect.

Assets connectivity is a risk factor which makes portfolio diversification of market participants ineffective during market distress. COVID-19 has a ripple effect on economies because of global interlinkages of supply chains and trading activities (Ozili & Arun, 2020). Some recent studies analyze the spillover effects of COVID-19 on global stock markets and identify transmission channels in terms of returns and volatility, at firm and market-level (Akhtaruzzaman et al., 2020; Selmi & Bouoiyour, 2020). However, the impact of the pandemic on the liquidity network hasn't been the center of much attention. Network analysis reveals the patterns of liquidity interactions across firms and over time. It enables us to investigate whether the liquidity transmission channel has changed from the normal market condition due to the pandemic effect.

Considering the spillover characteristics of liquidity, I believe a firm that has its liquidity less connected with other firms in the market during the pandemic may act as a safe haven for investors in times of crisis. My study examines the impact of COVID-19 on the liquidity network of S&P 500 firms and the shift in network characteristics across sectors in the US before and during the COVID-19 period. More specifically, I focus on two network characteristics – liquidity that a particular sector sends to others *(Out-to-Others)*, and liquidity that it receives from other sectors *(In-from-Others).*

The crisis brought by the pandemic has affected various sectors differently. Early analysis of the pandemic has documented that in the first 2 months of 2020, prices for energy, retailing, and transportation decreased substantially compared to the healthcare sector (Ramelli & Wagner, 2020). According to Mazur et al. (2020), stocks in natural gas, food, healthcare, and software industries have earned positive returns during the market crash of March 2020, as compared to the petroleum, real estate, entertainment, and hospitality sectors. There is also evidence of asymmetry in reaction and recovery across and within asset classes (Yarovaya et al., 2020). This further motivates us to perform the analysis at the industry level. However, as industry constituents are often very few, I use industry groups (subsectors).

I expect to see an increase in the liquidity linkages across the sectors due to the pandemic effect, both in terms of *Out-to-Others* and *In-from-Others*. However, the composition of this change is expected to vary across the sectors. I conjecture that well-interconnected firms significantly disseminate liquidity shocks to other firms in the network. Hence, if negatively impacted industries have strong lead-lag interlinkages within the network, they are likely to contribute to increasing illiquidity in the market significantly (increased *Out-*

to-Others). On the other hand, the least affected industries are expected to be the source of liquidity transmission within the network.

I believe the network transformation reflects how liquidity providers and active institutional investors react toward the uncertainty caused by COVID-19. Liquidity providers have a specific inventory level that is adjusted based on a normal market condition. To facilitate liquidity with their limited inventory, they increase their premium. Therefore, asset liquidity becomes negatively correlated with market volatility. This might lead to an assets' pairwise correlation (Vayanos, 2004). There is empirical evidence of the COVID-19 effect on the market liquidity caused by the withdrawal of liquidity suppliers (Foley et al., 2020). The authors show that this liquidity supply withdrawal is correlated with the increase in margin requirement by 400%. They also show this effect is more pronounced in indexed securities that electronic market makers provide their liquidity. Investors, on the other hand, become more risk-averse and gravitate their portfolios toward liquid assets, which in turn, put selling pressure on illiquid assets even more (Ben-Rephael, 2017). I expect to see that the liquidity network will be influenced by the complex interplay between the liquidity demanders and suppliers in during the crisis. Our results illustrate that COVID-19 significantly influences the liquidity interconnectedness across the industry groups.

4.2 Brief Review of the Literature

Investors generally care about liquidity because it influences their expected return (Amihud & Mendelson, 1986; Jacoby et al., 2000). Another critical reason that makes liquidity crucial is the risk associated with lack of it (illiquidity). Illiquidity pushes agents to abandon diversification and choose polarized portfolios instead (Longstaff, 2009). Sometimes liquidity dries up even in liquid markets, disrupting trade between market participants. For example, Anderson and Gascon (2009) note that the commercial paper market froze in the 2008–2009 financial crisis and in 1970 when the Penn Central railroad collapsed. In both cases, the Federal

Reserve stepped in to help to restore liquidity. These illiquidity crises occur in many asset markets.

Similarly, Næs et al. (2011) show that stock market liquidity dry-ups are a forerunner of real economic crises. The authors show that this effect is not new, and there has been a link between liquidity and the business cycle. Moreover, systematic liquidity shocks affect investors' optimal behavior. Martınez et al. (2005) argue that aggregate liquidity restrictions can characterize a recession, and stocks tend to perform poorly during recessions. Therefore, it is reasonable to expect a higher return on stocks that are highly and positively sensitive to systematic liquidity shocks.

Another phenomenon in times of financial distress is the significant increase in commonality in liquidity. When the markets are declining or volatile, financial intermediaries provide less liquidity due to funding constraints which in return cause an increase in liquidity co-movements (Brunnermeier & Pedersen, 2008; Coughenour & Saad, 2004; Gromb & Vayanos, 2002; Hameed et al., 2010; Kyle & Wei, 2001).

The liquidity of financial markets seems to show a different pattern of behavior when exposed to a sudden change. For example, in response to the GFC, European bank correlation networks experienced increased connectedness showing that banks' equity returns were moving closely together during the crisis (Brunetti et al., 2019). Given the importance of liquidity in the well-functioning of the financial system, it is necessary to explore the impact of the COVID-19 pandemic on the stock market's liquidity. In particular, investigating any pattern of change in the liquidity connectedness might aid market participants to better adjust their trading strategies in such timings.

4.3 Data and Methodology

I investigate how the COVID-19 shock impacts the liquidity network across USA industry groups. I consider a sample of all firms listed on the S&P 500 Index from January 1

2012 to July 17 2020, incorporating additions and deletions as obtained from the Compustat Capital IQ database. I collect daily total returns data, and share trading volume from the Datastream and Bloomberg databases, respectively. After adjusting for missing observations and errors, I have a sample of 704 firms. For our industry-conditional analysis, I assign firms into one of the 24 industry groups according to the Global Industry Classification Standard (GICS) code.

4.3.1 Liquidity Measure and Linear Granger-causality

To measure stock liquidity, I base the liquidity measure on Amihud (2002). This measure is widely used to capture systematic risk and commonality in liquidity.[1] It is the daily ratio of absolute stock return to dollar volume, and adheres to the notion of a liquid market as one that facilitates trading with the least price impact. Following H. C. Lee et al. (2014), I calculate liquidity as:

$$Amihud_{i,d} = \left[-\log\left(1 + \frac{|\,R_{i,d}\,|}{P_{i,d}\,VO_{i,d}}\right)\right] \times 10^{6} \tag{1}$$

where $R_{i,d}$ is Abs(return), $P_{i,d}$ is the adjusted closing price, and $VO_{i,d}$ is the trading volume of stock *i* at day *d*. I calculate weekly liquidity as the average of daily liquidity each week. Weekly frequency enables us to capture the dynamics of the COVID-19 impact, while avoiding the noise in higher frequency data.

For our primary analysis, I follow the Granger-causality network method proposed by Billio et al. (2012), conducting a pairwise linear Granger-causality test to investigate the lead-lag relationship among all the firms in our sample. The following model presents the linear interrelationship between two stationary time series.[2] Time series *j* Granger-causes time series

[1] See, e.g., Acharya and Pedersen (2005), Hasbrouk and Seppi (2001), Kamara et al. (2008).

[2] We use the augmented Dickey–Fuller (ADF) test on our panel data, finding no evidence of a unit root.

i if past values of j contain information that aid the prediction of i above and beyond the information contained in past values of i alone:

$$\begin{aligned} \mathrm{Aliq}^{\mathrm{i}}_{\mathrm{t+1}} &= \alpha_{\mathrm{i}} + \beta^{\mathrm{i}}\,\mathrm{Aliq}^{\mathrm{i}}_{\mathrm{t}} + \gamma^{\mathrm{ij}}\,\mathrm{Aliq}^{\mathrm{j}}_{\mathrm{t}} + \varepsilon^{\mathrm{i}}_{\mathrm{t+1}} \\ \mathrm{Aliq}^{\mathrm{j}}_{\mathrm{t+1}} &= \alpha_{\mathrm{j}} + \beta^{\mathrm{j}}\,\mathrm{Aliq}^{\mathrm{j}}_{\mathrm{t}} + \gamma^{\mathrm{ji}}\,\mathrm{Aliq}^{\mathrm{i}}_{\mathrm{t}} + \varepsilon^{\mathrm{j}}_{\mathrm{t+1}} \end{aligned} \tag{2}$$

where $Aliq_t^i$ and $Aliq_t^j$ are the weekly liquidity at time t for firm i and j respectively, α_i and α_j are constants and $\beta^i, \beta^j, \gamma^{ij}, \gamma^{ji}$ are coefficients of the model, and ε_{t+1}^i and ε_{t+1}^j account for uncorrelated white noise.[3] In this equation, there exists a lead-lag relationship among the series when γ^{ij} and γ^{ji} are different from zero. Following Billio et al. (2012), I define a causality indicator (j$\rightarrow i$), which is 1 if j Granger-causes i, and 0 otherwise.

Next, I calculate the DGC to measure the fraction of statistically significant Granger-causal relationships (at 5%) among all $N(N\text{-}1)$ pairs of securities available in each period:

$$\mathrm{DGC} \equiv \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} (j \rightarrow i) \tag{3}$$

where N is the number of firms in each period, and (j$\rightarrow i$) is the causality indicator.

To observe the dynamics of *DGC* over time, I use a 13-week rolling window, calculating pairwise Granger-causality of those 13-weeks' DGC [4]. Higher *DGC* among assets is evidence of higher liquidity interconnections across the firms.

[3] We use the Bayesian information criterion (BIC; see Schwarz, 1978) as the model-selection criterion to determine the optimal number of lags for each security pair. Then we generalize the outcome using the mode of *BIC* for the entire sample period.

[4] We eliminate pairs with less than 12 weeks of observations.

4.3.2 Industry-Conditional Number of Connections

As I am interested in investigating the liquidity interactions across different industries, I calculate DGC separately for ($j \rightarrow i$), when firms i and j are in different industry groups. Given 24 industry groups indexed by $\propto, \beta = 1, \dots, 24$, within the system of S, I then compute the following three measures:

Out-to-others (*Out*):

$$\left((j \mid \propto) \rightarrow \sum_{\beta \neq \alpha} (S|\beta) \right) = \frac{1}{N_{\alpha \neq \beta}} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left((j \mid \propto) \rightarrow (i|\beta) \right) \tag{4}$$

In-from-others (*In*):

$$\left(\sum_{\beta \neq \alpha} (S|\beta) \rightarrow (j| \propto) \right) = \frac{1}{N_{\alpha \neq \beta}} \sum_{\beta \neq \alpha} \sum_{i \neq j} \left((i|\beta) \rightarrow (j|\alpha) \right) \tag{5}$$

In+Out-Others *(In&out):*

$$\left((j| \propto) \leftrightarrow \sum_{\beta \neq \alpha} (S|\beta) \right) = \frac{\sum_{\beta \neq \alpha} \sum_{i \neq j} \left((i|\beta) \rightarrow (j|\alpha) \right) + \left((j \mid \propto) \rightarrow (i|\beta) \right)}{2\left(N_{\alpha \neq \beta}\right)} \tag{6}$$

where *Out-to-Others* is the percentage of firms in other industry groups that are significantly Granger-caused by group j, *In-from-Others* is the percentage of firms in group j that are significantly Granger-caused by firms in other groups, and *In+Out-Others* is the sum of the two. $\propto$ represents the group that firm j belongs to in the system of S. β is the group that firm i belongs to, and N is the number of firms. For simplicity and ease of exposition, I define "send" to mean "Granger-causes", and "receive" to mean "Granger-caused by" and use those terms throughout the paper.

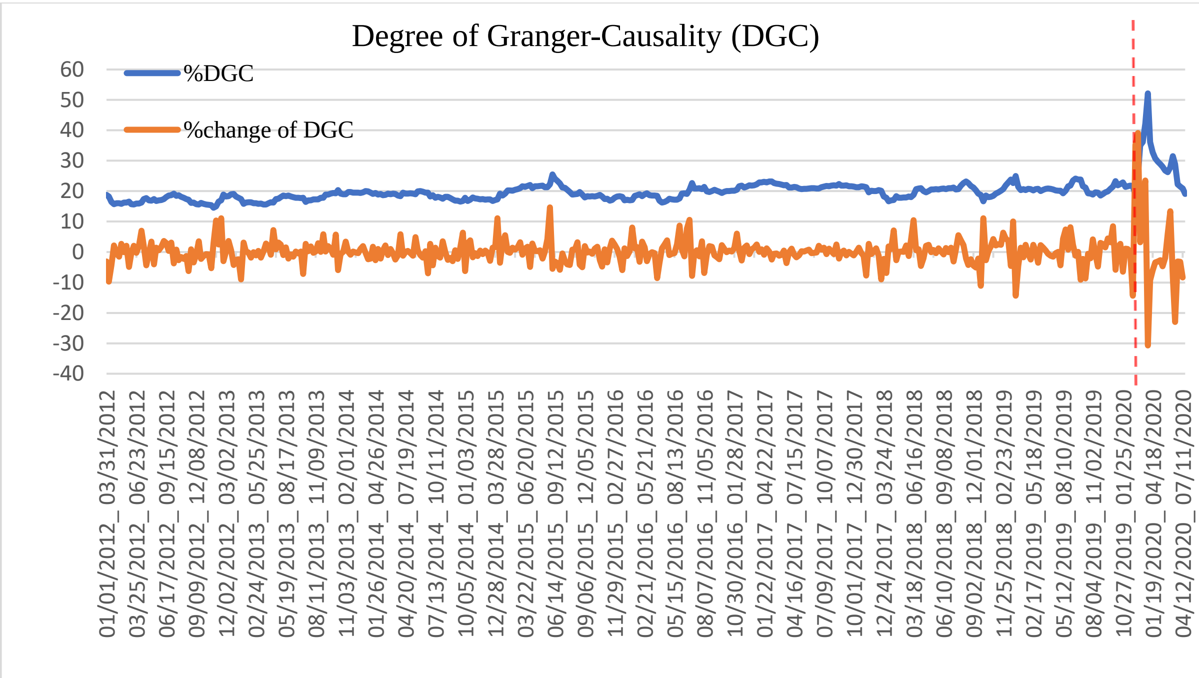
4.4 Empirical Results and Discussion

4.4.1 The Degree of Liquidity Network Across Firms

Figure 4.1 illustrates the dynamics of *DGC* and its percentage change across all the firms our sample. Aside from a few small spikes, it is relatively stable until the first week of March 2020 when it jumps 35% and then 39% the following week, suggesting a significant COVID-19 impact. I followed this up with a series of t-tests, using 2012–2019 as the base, to confirm that the abnormal *DGC* impact was during that time.[5]

Figure 4.1

Degree of Granger-Causality Over Time



Note: Time series of degree of Granger-causality (DGC) with 13-weeks rolling window from 08Jan2012 to 17July2020. %DGC is the fraction (in percentage) of statistically significant (at 5%) pairwise linear Granger-causal relationships among weekly liquidity of N (N-1) pairs of those stocks available in each period. % change of DGC is the percentage change of DGC.

[5] We ran a simulation, to confirm the veracity of these results.

4.4.2 Liquidity Network Characteristics

Table 4.1 reports descriptive statistics of the liquidity network metrics for each industry group during the pre-COVID period, and Table 4.2 for the COVID period. In Panel A of both tables are descriptive statistics for all firms in our sample. There is compelling evidence of an overall increase in interconnectedness, as evidenced by an increase in mean (*In&Out)* from 40.1% to 62.7%.

In Panel B for both tables, I consider averages for industry groups. In the pre-COVID period *Telecommunication Services* is the most connected industry group (*In&Out* = 65.2%), while the least connected is *Commercial and Professional Services* (*In&Out* = 31.8%).[6] The last column reports the percentage difference in *In & Out (%Dif In&Out).* The strongest net sender is *Insurance* with the difference at 34.1%, and the biggest net receiver is *Telecommunication Services* with the difference at -87.7%.

During the COVID-19 period (Table 4.2), *Media and Entertainment* is the most connected (*In&Out* = 71.4%), and *Transportation* the least connected (*In&Out* = 53.7%). *Food and Staples Retailing* is the strongest net sender (47.5%) and *Media and Entertainment* is the strongest net receiver (-36%).

[6] Market capitalization appears to be the main variable explaining the differences in interconnectedness. Firm size has been proven to be one of the main variables explaining synchronicity in liquidity (see, for example, Kamara et al., 2008; Koch et al., 2016).

Table 4.1

Pre-COVID-19 Period Liquidity Network Characteristics

Panel A: Descriptive Statistics

	Mean	Median	SD	Min	Max	P25	P75
Out	19.2%	19.2%	2.7%	13.2%	27.9%	17.2%	21.1%
In	20.8%	18.6%	8.8%	9.5%	69.9%	14.5%	24.3%
In+out	40.1%	38.0%	9.5%	25.3%	90.9%	33.5%	44.4%

Panel B: Network ranking

Industry Groups	In+out	Rank	Out	Rank	In	Rank	%Dif In&Out	Rank
Telecommunication Services	65.2%	1	18.3%	24	46.9%	1	-87.7%	24
Banks	49.7%	2	18.6%	22	31.1%	2	-50.6%	23
Media & Entertainment	49.2%	3	18.9%	21	30.3%	3	-46.2%	22
Pharmaceuticals, Biotechnology	45.6%	4	19.3%	12	26.4%	4	-31.1%	21
Food & Staples Retailing	45.1%	5	19.1%	15	25.9%	5	-30.2%	20
Household & Personal Products	44.6%	6	19.6%	2	24.8%	6	-23.0%	19
Semiconductors	43.8%	7	19.5%	7	24.3%	7	-21.6%	18
Technology Hardware & Equipment	42.7%	8	19.5%	10	23.2%	8	-17.2%	16
Software & Services	42.0%	9	19.1%	19	22.9%	9	-18.1%	17
Consumer Services	39.5%	10	19.1%	17	20.3%	10	-6.1%	15
Retailing	39.0%	11	19.2%	14	19.7%	11	-2.7%	14
Food, Beverage & Tobacco	38.1%	12	19.1%	16	19.0%	12	1.0%	13
Energy	37.5%	13	19.6%	4	17.8%	13	9.6%	11
Capital Goods	36.9%	14	19.5%	8	17.4%	15	11.8%	9
Automobiles & Components	36.9%	15	19.1%	18	17.7%	14	7.7%	12
Diversified Financials	36.1%	16	19.0%	20	17.0%	16	10.9%	10
Health Care Equipment & Service	35.5%	17	19.5%	9	15.9%	17	20.3%	8
Transportation	34.6%	18	19.8%	1	14.8%	18	28.7%	7
Materials	33.7%	19	19.6%	5	14.2%	19	32.1%	6
Utilities	33.6%	20	19.6%	3	13.9%	21	33.8%	3
Insurance	33.5%	21	19.6%	6	13.9%	22	34.1%	1
Consumer Durables & Apparel	33.5%	22	19.4%	11	14.0%	20	32.2%	5
Real Estate	33.0%	23	19.3%	13	13.7%	23	33.8%	2
Commercial & Professional Services	31.8%	24	18.5%	23	13.3%	24	33.3%	4

Note: Panel A presents the summary statistics of linear Granger-causality relationships (at the 5% level of statistical significance) among the weekly liquidity of all the firms included in *S&P500* during the estimation period of 08/01/2012 to 29/12/2019. Panel B reports the industry-wise mean and industry-wise ranking of mean values for all the variables during the estimation period. *Out*, *In*, and *In+Out variables* are the average percentage of other industry groups in the system that are significantly Granger-caused by an industry group *j*, the average percentage of other industry groups in the system that significantly Granger-cause industry group *j*, and the summation of the two, respectively. *%Dif In&Out* is the percentage difference between *In* and *Out* calculated as $\frac{Out-In}{\frac{Out+In}{2}}$. The ranks are assigned in descending order. The table is sorted by rank of In+out. All the measures are winsorized at the 5th and 95th percentile.

4.4.3 Changes in Liquidity Network, Pre- to COVID-19 Period.

Comparing Tables 4.1 and 4.2, the main story is the uniform increase in connectedness for all industry groups. From pre-COVID to COVID, virtually all metrics for all industry groups have increased. Consistent with that, the mean for each metric has increased. Further, a difference-in-means test shows that for all metrics the differences are significant at a 1% level.

Table 4.3 looks at the change in metrics directly. All industry groups have experienced an increase in connectedness according to both *Out* and *In&Out* metrics. The *In* metric has increased for 21 out of 24 industries. This further demonstrates that market-wide connectedness has increased during the COVID period.

As a robustness check, I re-estimate connectedness measures using proportional bid-ask spread. The results are consistent. Mean connectedness as measured by *In&Out* increases from 40.6% to 78.7%. The summary statistics of proportional quoted spread is reported in Appendix I.

Table 4.2

COVID-19 Impact Period Liquidity Network Characteristics

Panel A: Descriptive Statistics

	Mean	Median	SD	Min	Max	P25	P75
Out	32.1%	31.1%	8.1%	13.4%	61.8%	26.3%	36.7%
In	30.6%	29.6%	8.6%	14.2%	58.8%	23.9%	36.2%
In+out	62.7%	61.4%	11.1%	40.9%	95.5%	54.3%	70.7%

Panel B: Network ranking

Industry Groups	In+out	Rank	Out	Rank	In	Rank	%Dif In&Out	Rank
Media & Entertainment	71.4%	1	29.3	17	42.1%	1	-36.0%	24
Retailing	70.1%	2	31.4%	14	38.6%	3	-20.5%	20
Software & Services	68.0%	3	39.4%	2	28.5%	13	32.0%	6
Telecommunication Services	67.7%	4	28.8%	18	38.9%	2	-30.0%	22
Technology Hardware & Equipment	67.4%	5	32.7%	9	34.7%	5	-5.9%	15
Semiconductors & Semiconductor	66.7%	6	40.0%	1	26.7%	20	39.8%	2
Utilities	66.3%	7	28.5%	21	37.8%	4	-28.1%	21
Automobiles & Components	65.7%	8	38.3%	3	27.4%	16	33.1%	4
Consumer Services	63.9%	9	37.1%	4	26.8%	19	32.3%	5
Health Care Equipment & Service	63.2%	10	28.5%	20	34.7%	6	-19.4%	19
Banks	62.9%	11	35.1%	7	27.8%	14	23.1%	9
Capital Goods	61.8%	12	28.6%	19	33.2%	9	-14.7%	17
Materials	61.6%	13	30.1%	16	31.6%	10	-5.0%	14
Real Estate	61.6%	14	28.0%	22	33.6%	8	-18.3%	18
Pharmaceuticals, Biotechnology	61.5%	15	31.5%	13	30.0%	12	4.6%	13
Insurance	60.4%	16	35.8%	5	24.6%	22	37.2%	3
Diversified Financials	59.5%	17	31.7%	12	27.8%	15	13.4%	12
Food, Beverage & Tobacco	59.4%	18	32.1%	10	27.4%	17	15.9%	10
Commercial & Professional Services	59.3%	19	34.3%	8	25.0%	21	31.3%	7
Household & Personal Products	59.3%	20	32.0%	11	27.3%	18	15.7%	11
Consumer Durables & Apparel	59.1%	21	24.7%	24	34.5%	7	-33.2%	23
Energy	57.5%	22	26.8%	23	30.7%	11	-13.8%	16
Food & Staples Retailing	56.9%	23	35.2%	6	21.7%	24	47.5%	1
Transportation	53.7%	24	30.7%	15	22.9%	23	29.1%	8

Note**:** Panel A presents the summary statistics of linear Granger-causality relationships (at the 5% level of statistical significance) among the weekly liquidity of all the firms included in *S&P500* during the impact period of 08/03/2020 to 20/06/2020. Panel B reports the industry-wise mean and industry-wise ranking of mean values for all the variables during the impact period. The percentage difference between *In* and *Out* is also reported. *Out*, *In*, and *In+Out* are the average percentage of other industry groups in the system that are significantly Granger-caused by an industry group *j*, the average percentage of other industry groups in the system that significantly Granger-cause group *j*, and the summation of the two, respectively. *%Dif In&Out* is the percentage difference between *In* and *Out* calculated as $\frac{Out-In}{\frac{Out+In}{2}}$. The ranks are assigned in descending order. The table is sorted by rank of *%Dif In&Out*. All the measures are winsorized at the 5th and 95th percentile.

Table 4.3

Liquidity Network Change Analysis

Industry Groups	%change In+out	Rank	%change out	Rank	%change In	Rank
Utilities	97.3	1	45.3	21	171.2	1
Real Estate	86.6	2	45.3	22	145.5	2
Commercial & Professional Services	86.3	3	84.8	6	88.7	8
Materials	82.7	4	53.5	18	122.9	4
Insurance	80.2	5	82.9	8	77.1	9
Retailing	79.9	6	63.7	12	95.8	6
Health Care Equipment & Services	78.1	7	46.2	20	117.7	5
Automobiles & Components	78.0	8	100.3	3	55.0	12
Consumer Durables & Apparel	76.6	9	26.8	24	145.4	3
Capital Goods	67.6	10	46.7	19	91.2	7
Diversified Financials	64.7	11	66.8	11	62.8	11
Software & Services	62.0	12	106.6	1	24.7	18
Consumer Services	61.7	13	94.1	4	31.8	17
Technology Hardware & Equipment	57.9	14	67.9	9	50.0	14
Food, Beverage & Tobacco	56.0	15	67.6	10	44.3	15
Transportation	54.9	16	55.2	16	54.6	13
Energy	53.3	17	36.5	23	72.5	10
Semiconductors & Semiconductor	52.1	18	104.5	2	9.9	21
Media & Entertainment	45.2	19	54.8	17	39.2	16
Pharmaceuticals, Biotechnology	34.8	20	63.2	13	13.9	19
Household & Personal Products	32.9	21	62.7	14	10.3	20
Banks	26.4	22	88.9	5	-10.7	22
Food & Staples Retailing	26.0	23	83.8	7	-16.4	23
Telecommunication Services	3.9	24	57.3	15	-16.9	24

Note: Industry-wise percentage change between pre-COVID period to COVID impact period of all the liquidity network metrics resulted from the linear Granger-causality relationships (at the 5% level of significance). The sample consists of all the firms included in *S&P500* during pre-COVID period of 08/01/2012 to 29/12/2019 and the COVID-19 impact period from 08/03/2020 to 20/06/2020.

%ChangeOut reports industry-wise percentage change between *Out* pre-COVID period to COVID-19 period.

%ChangeIn presents industry-wise percentage change between *In* pre-COVID period to COVID-19 period, and *%Change In+Out* shows the industry-wise percentage change between averaged *Out+In* pre-COVID period to COVID-19 period. The difference is calculated from COVID-19 minus pre-COVID. The ranks are assigned in descending order. The table is sorted by rank of *%Change In+Out.*

4.5 Conclusions

I analyze the impact of the COVID-19 pandemic on liquidity interconnectedness. I employ a lead-lag liquidity network method, allowing us to examine liquidity interactions beyond contemporaneous spillover effect. I use a Granger-causality methodology to measure connections of liquidity, utilizing S&P 500 firms, divided into industry groups.

I document that the degree of liquidity interconnectedness varies across industries in the pre-COVID period. *Telecommunication Services* is the most interconnected sector within the liquidity network, while *Commercial and Professional* Services is the least connected. Differences in connectedness are related to firm-level differences in market capitalization. I also document that interconnectedness has increased substantially between pre-COVID and COVID periods, with all industry groups increasing in their overall connectivity measure. The impact of the COVID-19 pandemic is similarly uneven, with *Utilities* being the most affected and *Telecommunication Services* the least.

As a result of higher interconnectedness, liquidity risk became harder to diversify. As a potential consequence, return correlations have increased in the COVID period for the majority of industries.[7] Some earlier work (e.g., Driessen & Laeven, 2007) shows that benefits of international diversification have been declining over the past decades. Our findings suggest that benefits of cross-industry diversification have declined as well, making investors potentially more exposed to further market downturns.

A number of observations may provide venues for future research. First, industries that were less connected in pre-COVID period tended to experience higher growth in connectedness. Second, net senders in the network appear to become more interconnected than net receivers in the COVID period.

[7] Unreported results are available upon request.

CHAPTER 5

Conclusion

This chapter concludes the thesis by summarizing the three essays' main results in Section 5.1. Section 5.2 documents potential directions for future research.

5.1 Major Findings and Conclusion

The field of liquidity connectivity and risk associated with this phenomenon is in its infancy. Market liquidity is complex, and there is more to the liquidity nexus across firms than their contemporaneous relationship. In this thesis, I provide valuable information through empirical evidence that there is an intertemporal liquidity network in S&P500 from January 1990 to December 2019. By investigating the lead-lag liquidity network, I can detect the patterns of liquidity communication. These patterns are essential pathways of liquidity information communication among firms, and understanding them provides a strong tool for managing market liquidity dry ups.

My key conclusion from the first essay is the existence of an intertemporal liquidity network in the S&P500 during the sample period of 30 years. I find that a dynamic intertemporal liquidity network makes the liquidity interaction between firms possible. Of the firms in the sample, 84% (993 out of 1174) exhibited statistically significant connectivity in at least one direction during the sample period. Among 54,816,084 possible pairwise causality combinations, more than 12% of pairs have statistically significant relationships. Moreover, I find that firms are different in how they communicate liquidity; while some firms are more influential in the liquidity system, others tend to be influenced more. Furthermore, some firm-specific characteristics explain the cross-sectional differences in the firms' network structure. Specifically, smaller, riskier firms (measured by market capitalization and return volatility) with lower liquidity and a greater change in liquidity tend to be more influential in sending liquidity to others and explaining the network structure.

My second study provides evidence that shock transmission depends on the level of firm size. The greater intensity shocks influence transmission more through larger firms than small firms. This relationship holds for the subsamples of positive and negative shocks, suggesting that the way liquidity shock propagates into the system is independent of its sign. My outcome is in line with Chordia et al. (2014), who observe that shock in order flow is reflected in large stock prices within a month, while the smaller, less visible firms take over 6 months to reflect the effect entirely. I also find that with one unit increase in the size differences between firms, the odds of firms not being connected in the network increases by 2.5%, suggesting similar-size firms tend to have more connectivity. My size-based portfolio analysis shows that most portfolios tend to have higher explanatory power (measured by beta coefficients) when transmitting the shock to the next larger size quantile or the quantile nearest to them. I overall conclude that diversification against liquidity shock transmission is possible through the traditional approach of including different firm sizes.

Lastly, my third essay shows that liquidity interconnectedness varied across industries before the COVID-19 pandemic. However, when COVID-19 hit the stock market, virtually all the industry groups in the S&P500 experienced a uniform increase in connectedness. More specifically, there was an increase in the mean of interconnectedness from 40.1% to 62.7%. As a result of higher interconnectedness, liquidity risk became harder to diversify. Some earlier work (e.g., Driessen & Laeven, 2007) shows that the benefits of international diversification have been declining over the past decades. My findings suggest that the benefits of cross-industry diversification have also declined, potentially exposing investors to further market downturns.

5.2 Limitations of the Study and Future Research

I have undertaken three studies on liquidity networks. As any other studies, my work is subject to some limitations. Although S&P500 is one of the most popular indexes that reflects the U.S. economy, investigating other indexes or none-index securities would provide additional insight into the existence and structure of a liquidity network.

Identifying the existence of the liquidity network opens up a new path for future research. For example, a cross-country examination of potential country-specific regulations that might influence the existence of a liquidity network could improve our knowledge in this area even further. Moreover, recognizing firm-specific attributes that explain the liquidity network is a first step to look into other probable determinants of the network. There is a negative relationship between transparency and several measures of liquidity uncertainty, such as liquidity volatility, a reaction to extreme liquidity events, and correlations between firm liquidity and market liquidity (Lang & Maffett, 2011). Therefore, firms' information environment might be a potential determinant for explaining the cross-sectional differences in firms' network structure.

Another critical research issue open for investigation is whether the liquidity network is priced. There is already evidence that illiquid firms get a higher expected return (Amihud & Mendelson, 1986; Jacoby et al., 2000). Given the liquidity/illiquidity spillovers through the liquidity connections, an important question is whether the most connected firms in the network receive higher expected returns.

The more we understand financial asset interdependence, the more power we have to use these ties to control the damage or benefit of these interrelations. Therefore, an interesting line of research is to see if there is a liquidity network in different asset classes or across different exchanges and what factors determine such networks.

References

Acemoglu, D., Ozdaglar, A., & ParandehGheibi, A. (2010). Spread of (mis) information in social networks. *Games and Economic Behavior, 70*(2), 194–227.

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics, 77*(2), 375–410.

Akhtaruzzaman, M., Boubaker, S., & Sensoy, A. (2020). Financial contagion during COVID–19 crisis. *Finance Research Letters*, 101604.

Allen, F., Babus, A., & Carletti, E. (2012). Asset commonality, debt maturity and systemic risk. *Journal of Financial Economics, 104*(3), 519–534.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31–56.

Amihud, Y., & Mendelson, H. (1986). Liquidity and stock returns. *Financial Analysts Journal, 42*(3), 43–48.

Anderson, R. G., & Gascon, C. S. (2009). The commercial paper market, the Fed, and the 2007–2009 financial crisis. *Federal Reserve Bank of St. Louis Rev, 91*(6), 589–612.

Ang, A., Papanikolaou, D., & Westerfield, M. M. (2014). Portfolio choice with illiquid assets. *Management Science, 60*(11), 2737–2761.

Angelidis, T., & Andrikopoulos, A. (2010). Idiosyncratic risk, returns and liquidity in the London Stock Exchange: A spillover approach. *International Review of Financial Analysis, 19*(3), 214–221.

Asness, C., Frazzini, A., Israel, R., Moskowitz, T. J., & Pedersen, L. H. (2018). Size matters, if you control your junk. *Journal of Financial Economics, 129*(3), 479–509.

Atilgan, Y., Bali, T. G., Demirtas, K. O., & Gunaydin, A. D. (2020). Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. *Journal of Financial Economics, 135*(3), 725–753.

Avramov, D., Chordia, T., & Goyal, A. (2006). Liquidity and autocorrelations in individual stock returns. *The Journal of Finance, 61*(5), 2365–2394.

Bali, T. G., Peng, L., Shen, Y., & Tang, Y. (2014). Liquidity shocks and stock market reactions. *The Review of Financial Studies, 27*(5), 1434–1485.

Banz, R. W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics, 9*(1), 3–18.

Barberis, N., Shleifer, A., & Wurgler, J. (2005). Comovement. *Journal of Financial Economics*, *75*(2), 283–317.

Ben-Rephael, A. (2017). Flight-to-liquidity, market uncertainty, and the actions of mutual fund investors. *Journal of Financial Intermediation, 31*, 30–44.

Berger, D. (2017). *Total U.S. stock market Vs. the S&P 500 index: An investor's guide.* Forbes. https://www.forbes.com/sites/robertberger/2017/06/01/total-u-s-stock-market-vs-the-sp-500-index-an-investors-guide/

Billio, M., Getmansky, M., Lo, A., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559.

Brennan, M. J., & Subrahmanyam, A. (1996). Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of financial economics*, *41*(*3*), 44–464.

Brockman, P., & Chung, D. Y. (2002). Commonality in liquidity: Evidence from an order-driven market structure. *Journal of Financial Research, 25*(4), 521–539.

Brockman, P., Chung, D. Y., & Pérignon, C. (2009). Commonality in liquidity: A global perspective. *Financial and Quantitative Analysis, 44*, 851–882.

Brunetti, C., Harris, J. H., & Mankad, S. (2021). *Liquidity networks, interconnectedness, and interbank information asymmetry*. Finance and Economics Discussion Series 2021–017. Board of Governors of the Federal Reserve System.

Brunetti, C., Harris, J. H., Mankad, S., & Michailidis, G. (2019). Interconnectedness in the interbank market. *Journal of Financial Economics, 133*(2), 520–538.

Brunnermeier, M. K., & Pedersen, L. H. (2008). Market liquidity and funding liquidity. *The Review of Financial Studies, 22*(6), 2201–2238.

Cespa, G., & Foucault, T. (2014). Illiquidity contagion and liquidity crashes. *The Review of Financial Studies, 27*(6), 1615–1660.

Chaieb, I., Errunza, V., & Langlois, H. (2021). How is liquidity priced in global markets? *The Review of Financial Studies, 34*(9), 4216–4268.

Choi, T. Y., & Liker, J. K. (1995). Bringing Japanese continuous improvement approaches to US manufacturing: The roles of process orientation and communications. *Decision Sciences, 26*(5), 589–620.

Choi, T. Y., Dooley, K. J., & Rungtusanatham, M. (2001). Supply networks and complex adaptive systems: control versus emergence. *Journal of operations management, 19(3),* 351–366.

Chordia, T., Hu, J., Subrahmanyam, A., & Tong, Q. (2014). Shocks to order flow volatility and stock returns. *SSRN Electronic Journal*. https://dx.doi.org/10.2139/ssrn.2517219

Chordia, T., Roll, R., & Subrahmanyam, A. (2000). Commonality in liquidity. *Journal of Financial Economics*, *56*(1), 3–28.

Chordia, T., Roll, R., & Subrahmanyam, A. (2001). Market liquidity and trading activity. The *Journal of Finance, 56*(2), 501–530.

Chordia, T., Roll, R., & Subrahmanyam, A. (2005). Evidence on the speed of convergence to market efficiency. *Journal of Financial Economics, 76*(2), 271–292.

Chordia, T., Roll, R., & Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics, 87*(2), 249–268.

Chordia, T., Sarkar, A., & Subrahmanyam, A. (2011). Liquidity dynamics and cross autocorrelations. *Journal of Financial and Quantitative Analysis, 46*(3), 709–736.

Chordia, T., Subrahmanyam, A., & Anshuman, V. R. (2001). Trading activity and expected stock returns. *Journal of Financial Economics, 59*(1), 3–32.

Chung, D., & Hrazdil, K. (2010). Liquidity and market efficiency: A large sample study. *Journal of Banking & Finance, 34*(10), 2346–2357.

Chung, K. H., & Chuwonganant, C. (2018). Market volatility and stock returns: The role of liquidity providers. *Journal of Financial Markets*, *37*, 17–34.

Corwin, S. A., & Lipson, M. L. (2011). Order characteristics and the sources of commonality in prices and liquidity. *Journal of Financial Markets, 14*(1), 47–81.

Coughenour, J. F., & Saad, M. M. (2004). Common market makers and commonality in liquidity. *Journal of Financial Economics, 73*(1), 37–69.

Coval, J., & Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, *86*(2), 479–512.

Cushing, D., & Madhavan, A. (2000). Stock returns and trading at the close. *Journal of Financial Markets, 3*(1), 45–67.

Datar, V. T., Naik, N. Y., & Radcliffe, R. (1998). Liquidity and stock returns: An alternative test. *Journal of Financial Markets, 1*(2), 203–219.

Deng, X., Hung, S., & Qiao, Z. (2018). Mutual fund herding and stock price crashes. *Journal of Banking & Finance, 94*, 166–184.

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics, 182*(1), 119–134.

Driessen, J., & Laeven, L. (2007). International portfolio diversification benefits: Cross-country evidence from a local perspective. *Journal of Banking & Finance*, *31*(6), 1693–1712.

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance*, *47*(2), 427–465.

Fang, V. W., Noe, T. H., & Tice, S. (2009). Stock market liquidity and firm value. *Journal of Financial Economics, 94*(1), 150–169.

Farzami, Y., Gregory-Allen, R., Molchanov, A., & Sehrish, S. (2021). COVID-19 and the liquidity network. *Finance Research Letters*, 101937.

Fernando, C. S. (2003). Commonality in liquidity: Transmission of liquidity shocks across investors and securities. *Journal of Financial Intermediation*, *12*(3), 233–254.

Foley, S., Kwan, A., Philip, R., & Ødegaard, B. A. (2020). Contagious margin calls: How COVID-19 threatened global stock market liquidity. *SSRN Electronic Journal*. http://dx.doi.org/10.2139/ssrn.3646431

Foucault, T., Pagano, M., & Röell, A. (2013). *Market liquidity: Theory, evidence, and policy*. Oxford University Press.

Ghabri, Y., Guesmi, K., & Zantour, A. (2021). Bitcoin and liquidity risk diversification. *Finance Research Letters*, *40*, 101679.

Gromb, D., & Vayanos, D. (2002). Equilibrium and welfare in markets with financially constrained arbitrageurs. *Journal of Financial Economics, 66*(2–3) 361–407.

Hameed, A., Wenjin, K., & Viswanathan, S. (2010). Stock market declines and liquidity. *The Journal of Finance, 65*(1), 257–293.

Harford, J., & Kaul, A. (2005). Correlated order flow: Pervasiveness, sources, and pricing effects. *Journal of Financial and Quantitative Analysis*, *40*(1), 29–55.

Hasbrouck, J., & Seppi, D. (2001). Common factors in prices, order flows, and liquidity. *Journal of Financial Economics*, *59*(3), 383–411.

Hirshleifer, D., Hsu, P. H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, *107*(3), 632–654.

Holden, C. W., & Subrahmanyam, A. (2002). News events, information acquisition, and serial correlation. *The Journal of Business, 75*(1), 1–32.

Holland, P. R. (1995). *The quantum theory of motion: An account of the de Broglie-Bohm causal interpretation of quantum mechanics*. Cambridge University Press.

Hong, H., & Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance, 54*(6), 2143-2184.

Hou, K., & Moskowitz, T. J. (2005). Market frictions, price delay, and the cross-section of expected returns. *The Review of Financial Studies*, *18*(3), 981–1020.

Huberman, G., & Halka, D. (2001). Systematic liquidity. *Journal of Financial Research, 24*(2), 161–178.

Jacoby, G., Fowler, D. J., & Gottesman, A. A. (2000). The capital asset pricing model and the liquidity effect: A theoretical approach. *Journal of Financial Markets*, *3*(1), 69–81.

Jones, C. M. (2002). A century of stock market liquidity and trading costs. *Available at SSRN 313681*.

Kacperczyk, M., Nieuwerburgh, S. V., & Veldkamp, L. (2014). Time varying fund manager skill. *The Journal of Finance*, *69*(4), 1455–1484.

Kamara, A., Lou, X., & Sadka, R. (2008). The divergence of liquidity commonality in the cross-section of stocks. *Journal of Financial Economics, 89*(3), 444–466.

Karolyi, A. G., Lee, K.-H., & Van Dijk, M. A. (2012). Understanding commonality in liquidity around the world. *Journal of Financial Economics*, *105*(1), 82–112.

Karpoff, J. M. (1986). A theory of trading volume. *The Journal of Finance, 41*(5), 1069–1087.

Keim, D. B., & Ananth, M. (1995). The anatomy of the trading process. *Journal of Financial Economics, 37*(3), 371–398.

Kinlaw, W., Kritzman, M., & Turkington, D. (2013). Liquidity and portfolio choice: A unified approach. *The Journal of Portfolio Management, 39*(2), 19–27.

Knez, P. J., & Ready, M. J. (1996). Estimating the profits from trading strategies. *The Review of Financial Studies, 9*(4), 1121–1163.

Koch, A., Ruenzi, S., & Starks, L. (2016). Commonality in liquidity: A demand-side explanation. *The Review of Financial Studies, 29*(8), 1943–1974.

Kyle, A. S., & Wei, X. (2001). Contagion as a wealth effect. *The Journal of Finance, 56*(4), 1401–1440.

Lang, M., & Maffett, M. (2011). Transparency and liquidity uncertainty in crisis periods. *Journal of accounting and economics, 52*(2-3), 101-125.

Lee, H. C., Tseng, Y. C., & Yang, C. J. (2014). Commonality in liquidity, liquidity distribution, and financial crisis: evidence from country ETFs. *Pacific-Basin Finance Journal, 29*, 35–58.

Lee, K. H. (2011). The world price of liquidity risk. *Journal of Financial Economics, 99*(1), 136–161.

Lesmond, D. A., Schill, M. J., & Zhou, C. (2004). The illusory nature of momentum profits. *Journal of Financial Economics, 71*(2), 349–380.

Lim, D. (2019, September 18). Index funds are the new kings of Wall Street. *The Wall Street Journal*. https:// www.wsj.com/articles/index-funds-are-the-new-kings-of-wall-street-11568799004.

Liu, H., & Wang, Y. (2013). *A theory of correlated-demand driven liquidity commonality*. SSRN Working Paper. https://dx.doi.org/10.2139/ssrn.2024403

Liu, W. (2006). A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, *82*(3), 631–671.

Lo, A. W., Petrov, C., & Wierzbicki, M. (2003). It's 11 pm—Do you know where your liquidity is? The mean-variance–liquidity frontier. *The Journal of Investment Management*, *1,* 55–93.

Longstaff, F. A. (2001). Optimal portfolio choice and the valuation of illiquid securities. *The Review of Financial Studies*, *14*(2), 407–431.

Longstaff, F. A. (2009). Portfolio claustrophobia: Asset pricing in markets with illiquid assets. *American Economic Review, 99*(4), 1119–1144.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies*, *25*(12), 3457–3489.

Lowe, A. (2014). The demand-side explanation for commonality in liquidity: the role of institutional ownership in the Taiwan Stock Exchange. *Pacific-Basin Finance Journal, 29*, 59–85.

Mancini, L., Ranaldo, A., & Wrampelmeyer, J. (2013). Liquidity in the foreign exchange market: measurement, commonality, and risk premiums. *The Journal of Finance, 68*(5), 1805–1841.

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, *7*, 77–91.

Marshall, B. R., Nguyen, N. H., & Visaltanachoti, N. (2013). Liquidity commonality in commodities. *Journal of Banking & Finance, 37*(1), 11–20.

Martınez, M. A., Nieto, B., Rubio, G., & Tapia, M. (2005). Asset pricing and systematic liquidity risk: An empirical investigation of the Spanish stock market. *International Review of Economics & Finance*, *14*(1), 81–103.

Mazur, M., Dang, M., & Vega, M. (2020). COVID-19 and the March 2020 stock market crash: Evidence from S&P1500. *Finance Research Letters*, 101690.

Merton, R. C. (1969). Lifetime portfolio selection under uncertainty: The continuous-time case. *The Review of Economics and Statistics*, 247–257.

Michaely, R., & Vila, J. L. (1995). Investors' heterogeneity, prices, and volume around the ex-dividend day. *Journal of Financial and Quantitative Analysis, 30*(2), 171–198.

Michaely, R., & Vila, J. L. (1996). Trading volume with private valuation: Evidence from the ex-dividend day. *The Review of Financial Studies, 9*(2), 471–509.

Mitchell, M., Pulvino, T., & Stafford, E. (2002). Limited arbitrage in equity markets. *The Journal of Finance, 57*(2), 551–584.

Mittal, H., Saraiya, N., & Berkow, K. (2020, April 8). *US equity liquidity in the COVID-19 crisis*. https://www.marketsmedia.com/u-s-equity-liquidity-in-the-covid-19-crisis.

Moshirian, F., Qian, X., Wee, C. K., & Zhang, B. (2017). The determinants and pricing of liquidity commonality around the world. *Journal of Financial Markets, 33*, 22–41.

Næs, R., Skjeltorp, J. A., & Ødegaard, B. A. (2011). Stock market liquidity and the business cycle. *The Journal of Finance*, *66*(1), 139–176.

Nagel, S. (2005). Short sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics*, *78*(2), 277–309.

Newey, W., & West, K. (1987). A simple positive definite, heteroscedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*, 703–705.

Ozili, P. K., & Arun, T. (2020). Spillover of COVID-19: Impact on the global economy. *SSRN Electronic Journal*. https://dx.doi.org/10.2139/ssrn.3562570

Pástor, Ľ., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(3), 642–685.

Peng, L., & Xiong, W. (2006). Investor attention, overconfidence and category learning. *Journal of Financial Economics, 80*(3), 563–602. https://doi.org/10.1016/j.jfineco.2005.05.003

Ramelli, S., & Wagner, A. F. (2020). Feverish stock price reactions to COVID-19. CEPR Discussion Paper No. DP14511. https://ssrn.com/abstract=3560319

Reinganum, M. R. (1981). Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. *Journal of Financial Economics, 9*(1), 19–46.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: the role of liquidity risk. *Journal of Financial Economics, 80*(2), 309–349.

Sadka, R., & Scherbina, A. (2007). Analyst disagreement, mispricing, and liquidity. *The Journal of Finance, 62*(5), 2367–2403.

Samuelson, P. A. (1975). Lifetime portfolio selection by dynamic stochastic programming. In W. T. Ziemba & R. G. Vickson (Eds.), *Stochastic optimization models in finance* (pp. 517–524). Elsevier.

Schwarz, G. (1978). Estimating the dimension of a model. *The Annals of Statistics,* 461–464.

Selmi, R., & Bouoiyour, J. (2020). Global market's diagnosis on coronavirus: A tug of war between hope and fear. *Hal Open Science*, Hal-02514428.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance, 52*(1), 35–55.

Sias, R. W. (2004). Institutional herding. *The Review of Financial Studies, 17*(1), 165–206.

Vayanos, D. (2004). *Flight to quality, flight to liquidity, and the pricing of risk* (No. w10327). National Bureau of Economic Research.

Wasserman, S., & Faust, K. (1994). Social network analysis: Methods and applications. Cambridge University Press.

Yan, X., & Zhang, Z. (2007). Institutional investors and equity returns: Are short-term institutions better informed? *The Review of Financial Studies, 22*(2), 893–924.

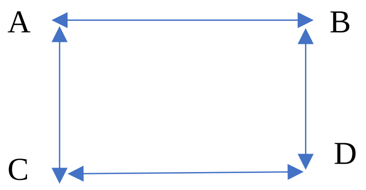
Yarovaya, L., Matkovskyy, R., & Jalan, A. (2020, May 27). The COVID-19 black swan crisis: Reaction and recovery of various financial markets. *SSRN Electronic Journal*. https://dx.doi.org/10.2139/ssrn.3611587

Appendices

Appendix A: *Eigenvector Centrality Calculation*

The following illustrates manual Eigenvector centrality calculation for a small directional network.

For the simplicity of manual computation, I use a simple directional network consisting of four firms where all the firms are connected. Each connection is equal to 1; therefore, they are equally important in the network.



As the first step to solve the Eigenvector centrality formula below, I first create the matrix of α, which is the adjacency matrix of the directional network

Eigenvector centrality formula: $\alpha * X = \beta * X$

Matrix α=

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

In the next step, I sum up the rows of the matrix α and get another 1×1 matrix called X:

$$X = \begin{bmatrix} 3 \\ 3 \\ 3 \\ 3 \end{bmatrix}$$

Now I should achieve an answer for the following formula to find the Eigenvector of our α matrix. The first number in our 1×1 matrix is associated with firm A, and β is the largest Eigenvalue associated with the Eigenvector.

$$A^* \ X=\begin{bmatrix}9\\9\\9\\9\end{bmatrix}$$

Now the question is, can we find a β value (Eigenvalue) so that α* X=β*X holds?

Yes, we can. Looking at the following $\beta(\text{Eigenvalue}) = 3$

$$\begin{bmatrix}9\\9\\9\\9\end{bmatrix} = \beta \times \begin{bmatrix}3\\3\\3\\3\end{bmatrix}$$

Given that $\begin{bmatrix}9\\9\\9\\9\end{bmatrix}$ is the $principal\ Eigenvector$. Now we need to normalize it.

The common way of normalizing Eigenvector is by dividing Eigenvector components to their squared roots. The formula is as follows:

$$\frac{1}{\sqrt{A^2 + B^2 + C^2 + D^2}} =$$

$$\frac{1}{\sqrt{9^2 + 9^2 + 9^2 + 9^2}} = \frac{1}{\sqrt{324}} = \frac{1}{18}$$

$$\begin{bmatrix}9/18\\9/18\\9/18\\9/18\end{bmatrix} = \begin{bmatrix}0.5\\0.5\\0.5\\0.5\end{bmatrix}$$

Appendix B: *Spearman Correlation of the Network Measures and Firm-Specific Characteristics*

	Out	In	In&out	Clos	Eig	AveAliq	AveΔAliq	Mcap	σRet	DE	BM	ROE
Out	1											
In	-0.058***	1										
In&Out	0.653***	0.607***	1									
Clos	-0.866***	0.013***	-0.598***	1								
Eig	0.868***	-0.149***	0.491***	-0.753***	1							
AveAliq	-0.020***	-0.001	0.035***	0.069***	-0.128***	1						
AveΔAliq	0.044***	-0.005*	-0.008***	-0.087***	0.101***	-0.384***	1					
Mcap	-0.034***	-0.022***	-0.012***	0.074***	-0.077***	0.863***	-0.201***	1				
σRet	0.035***	0.008**	0.023***	0.011***	0.077***	-0.197***	-0.171***	-0.223***	1			
DE	-0.008	-0.030***	-0.030***	0.019***	0.007**	0.007**	0.015***	0.068***	-0.087***	1		
BM	0.031***	0.019	0.039***	- 0.042***	- 0.002	-0.205***	-0.063***	-0.288***	0.024***	0.138***	1	
ROE	-0.019***	0.014***	-0.009***	0.027***	-0.010	0.209***	0.099***	0.290***	-0.103***	0.000	-0.659***	1

Note: Spearman correlation among firm-level network measures and firm-specific characteristics for 993 firms from January 1990 to December 2019. Each network metric contains 132588 observations. I source firm-specific variables from CRSP and WRDS Beta databases. *Out, In, In&Out, Clos and Eig* are network measures calculated from 36-month rolling-window Granger-causality outcomes with statistical significance at 5%. Liquidity average *AveAliq* is the monthly liquidity averaged over 36-month multiplied by 1000. Average change in liquidity *AveΔAliq* refers to the monthly change in liquidity averaged over 36-month multiplied by 1000. Firm size (*Mcap*) is the monthly market capitalization in logarithm where market capitalization= (daily absolute price × share outstanding). Return Volatility (*σRet*) is the concurrent monthly standard deviation of daily return. Debt-to-Equity Ratio (*DE*) is the monthly total liabilities to shareholders' equity winsorized at 1st and 99th Percentile. Book-to-Market Ratio (*BM*) refers to the monthly book value of equity as a fraction of the market value of equity in logarithm. Return-on-Equity ratio (*ROE*) is the monthly net income as a fraction of average book equity based on most recent two periods, where book equity is defined as the sum of total parent stockholders' equity and deferred taxes and investment-tax credit.

*, ** and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Appendix C: *Pearson Correlation of the Network Measures and Firm-Specific Characteristics*

	Out	In	In&out	Clos	Eig	AveAliq	AveΔAliq	Mcap	σRet	DE	BM	ROE
Out	1											
In	-0.023***	1										
In&Out	0.726***	0.671***	1									
Clos	-0.441***	-0.023***	-0.342***	1								
Eig	0.818***	-0.149***	0.504***	-0.371***	1							
AveAliq	0.0144***	0.026***	0.029***	0.024***	-0.014***	1						
AveΔAliq	0.014***	-0.005*	0.006**	-0.021***	0.036***	-0.095***	1					
Mcap	0.018***	0.042***	0.043***	0.056***	-0.041***	0.027***	-0.053***	1				
σRet	0.062***	0.053***	0.083***	0.046***	0.065***	-0.047***	-0.021***	-0.184***	1			
DE	-0.011***	-0.030***	-0.029***	0.008**	0.000	0.037***	0.000	0.083***	0.030***	1		
BM	0.066***	0.006	-0.005	- 0.041***	-0.041***	-0.080***	-0.003	-0.286***	0.065***	-0.033***	1	
ROE	-0.005*	-0.001	-0.005	0.011***	0.10***	0.02***	0.000	0.058***	-0.043***	0.055***	-0.170***	1

Note: Pearson correlation among firm-level network measures and firm-specific characteristics for 993 firms from January 1990 to December 2019. Each network metric contains 132588 observations. I source firm-specific variables from CRSP and WRDS Beta databases. *Out, In, In&Out, Clos and Eig* are network

measures calculated from 36-month rolling-window Granger-causality outcomes with statistical significance at 5%. Liquidity average *AveAliq* is the monthly liquidity averaged over 36-month multiplied by 1000. Average change in liquidity *AveΔAliq* refers to the monthly change in liquidity averaged over 36-month multiplied by 1000. Firm size (*Mcap*) is the monthly market capitalization in logarithm, where market capitalization= (daily absolute price × share outstanding). Return Volatility (*σRet*) is the concurrent monthly standard deviation of daily return. Debt-to-Equity Ratio (*DE*) is the monthly total liabilities to shareholders' equity winsorized at 1st and 99th Percentile. Book-to-Market Ratio (*BM*) refers to the monthly book value of equity as a fraction of the market value of equity in logarithm. Return-on-Equity ratio (*ROE*) is the monthly net income as a fraction of average book equity based on most recent two periods, where book value of quity is defined as the sum of total parent stockholders' equity and deferred taxes and investment-tax credit.

, * and *** denote statistical significance at the 10%, 5%, and 1%, respectively.

Appendix D: *Fixed-effect Regression of Firm-level Negative/Positive Liquidity Shock, Size and Liquidity Transmission*

PanelA_ Positive shock and transmission			
Variables	$(LIQU > 0)$	MCAP	(LIQU >0)× MCAP
Out	-0.0068 (-3.19)*** 0.162	-0.0012 (-3.75)*** 0.162	0.0006 (3.52)*** 0.162
Year Fixed effect	Yes	Yes	Yes
Industry Fixed effect	Yes	Yes	Yes
Number of observations	78590	78590	78590
PanelB_ Negative shock and transmission			
Independent variable	$-1(LIQU < 0)$	MCAP	$-1(LIQU < 0) \times$ MCAP
Out	-0.0044 (-3.54)*** 0.150	-0.0004 (-4.68) 0.150	0.0004 (3.57)*** 0.150
Year Fixed effect	Yes	Yes	Yes
Industry Fixed effect	Yes	Yes	Yes
Number of observations	47340	47340	47340

Note: Regression coefficients, *t*-statistics, and adjusted *R*-square come from the following general model:

$$Out_{jt}=\alpha+\beta_1\ LIQU_{j,t-1}+\beta_2\ Mcap_{j,t-1}+\beta_3\ LIQU_{j,t-1}\times Mcap_{j,t-1}\ +\vartheta_I+\eth_T+\varepsilon_{j,t}$$

The sample includes S&P500 constituents spanning from January 1990 to December 2019. Where *Uliq* is the monthly firm-level liquidity shock measured as the negative difference between *ILLIQ* and its past 12-month average, at time *t-1*. *(LIQU >0)* is the positive liquidity shock scaled by 1000 at time *t-1*. *-1(LIQU<0)* is the increasing function of the negative shock of liquidity scaled by 1000 at time *t-1*. *Mcap* is the lagged monthly market capitalization in logarithm. $LIQU \times Mcap$ is the interaction term between the firm-level liquidity shock (+/-) and market capitalization, and *Out* is the monthly firm-level measure of liquidity transmission.

The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West's (1987) standard errors. The first number in the table presents the coefficient of the fix effect model, the second value in the parenthesis is the t-statistics, and the third value is adjusted R-square.

*, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix E: *Summary Statistic of Firm-Level Negative and Positive Liquidity Shock Subsamples*

Descriptive statistics

Variable	Mean	Median	SD	5th	95th	N
$(LIQU > 0)$	0.5480	0.0559	4.0626	0.0023	1.9315	78590
$-1(LIQU < 0)$	0.6615	0.0504	7.5716	0.0015	2.1443	47340

Note: The summary statistic of the monthly firm-level positive and negative shocks subsamples. The firms are S&P500 constituents from January 1990 to December 2019. *LIQU* is the liquidity shock measured as the negative difference between *ILLIQ* and its past 12-month average. *(LIQU >0)* is the positive shock of liquidity scaled by 1000 at *time t-1*. *(-1(LIQU<0)* is the increasing function of the negative shock of liquidity scaled by 1000 at time *t-1*.

Appendix F: *Pairwise Size-Sorted Portfolio Liquidity Shock Transmission*

Quantile	Out-Q	Liquidity shock		
		B Coefficient	T-value	Adj R^2
1 (Smallest)	**Q1 to Q2**	**0.3791**	3.44***	0.1688
	Q1 to Q3	0.3748	3.83***	0.1503
	Q1 to Q4	0.3524	3.48***	0.1465
	Q1 to Q5	0.3456	3.30***	0.0916
2	Q2 to Q1	3.3990	10.23***	0.1483
	Q2 to Q3	**4.3072**	12.60***	0.1431
	Q2 to Q4	3.6308	11.07***	0.1372
	Q2 to Q5	3.7599	9.55***	0.0852
3	Q3 to Q1	3.8919	4.52***	0.1969
	Q3 to Q2	3.8876	4.81***	0.2035
	Q3 to Q4	**3.9948**	4.80***	0.1761
	Q3 to Q5	3.8756	4.36***	0.1116
4	Q4 to Q1	4.0549	4.85***	0.2247
	Q4 to Q2	4.0610	3.91***	0.2368
	Q4 to Q3	**4.3055**	4.43***	0.2117
	Q4 to Q5	**4.2989**	4.42***	0.1236
5 (Largest)	Q5to Q1	34.9735	7.61***	0.2321
	Q5 to Q2	33.5731	7.22***	0.2278
	Q5 to Q3	**39.7034**	9.01***	0.2128
	Q5 to Q4	**37.2066**	8.09***	0.2159

Note: Regression coefficients, t-statistics, and adjusted R-square for the following linear regression:

$$\left((j \mid \alpha_r) \to (i \mid \alpha_s)\right) = \beta_{0_{\alpha,t}} + \beta_1 \, LIQU\_Abs_{j,\alpha_r,t-1} + \vartheta_I + \eth_T + \epsilon_{\alpha,t}$$

The sample includes S&P500 constituents spanning from January 1990 to December 2019. Where the dependent variable of *Out-Q* is computed as the total sum of the liquidity connection that firm *j* from α_r sends out to α_s (with $r, s \in \{1, .., 5\}$ and $r \neq s$) divided by the number of firms in the α_r . *LIQU-Abs* is the monthly firm *j* liquidity shock in absolute value indexed in α_r at time *t-1* scaled by 1000. ϑ_I and $\eth_T$ are industry and year fixed-effect.

The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) standard errors. The first number in the table presents the coefficient of the fix effect model, the second value in the parenthesis is the t-statistics, and the third value is adjusted R-square.

*, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix G: *Summary Statistics of Firm Size and Liquidity Shock*

Panel A: *Mcap* summary statistics per quantile					
Quantiles	No. Obs	Min	Mean	Max	STD
Smallest Q1	26,189	10.6758	14.7204	16.3505	0.8757
Q2	26,376	13.9916	15.5662	16.8519	0.6515
Q3	26,388	14.6746	16.1359	17.3684	0.5945
Q4	26,376	15.2481	16.7292	18.0262	0.5954
Largest Q5	26,265	15.9039	17.9239	20.8772	0.8427
Panel B: *Uliq-abs* summary statistics per quantile					
Quantiles	No. Obs	Min	Mean	Max	STD
Smallest Q1	26,189	0.000	0.0019	0.7917	0.0124
Q2	26,376	0.000	0.0006	0.0606	0.0017
Q3	26,388	0.000	0.0003	0.0640	0.0010
Q4	26,376	0.000	0.0002	0.1756	0.0012
Largest Q5	26,265	0.000	0.0001	0.0054	0.0002

Note: Panel A reports the monthly firm-level market capitalization (*Mcap*) summary statistics per quantile. Panel B presents the summary statistics of the monthly firm-level liquidity shock in absolute value (*Uliq-abs*) at time *t-1* (multiplied to 1000). Sample includes S&P500 constituents from January 1990 to December 2019. Where *Uliq* is the monthly firm-level liquidity shock measured as the negative difference between *ILLIQ* and its past 12-month average, at time *t-1*. Mcap is then the monthly market capitalization in logarithm. *Mcap* is calculated as the daily Abs(price)× Share outstanding$_t$ averaged into monthly. The Daily data is acquired from The Center of Research in Security Prices (CRSP).

Appendix H: *Pairwise Size-Sorted Portfolios Negative Shock Transmission*

Quantile	Out-Q	Negative Liquidity shock		
		B Coefficient	T-value	Adj R^2
1 (smallest)	**Q1 to Q2**	**0.3099**	5.02***	0.1902
	Q1 to Q3	**0.3226**	5.24***	0.1677
	Q1 to Q4	0.2823	4.78***	0.1600
	Q1 to Q5	0.2754	4.64***	0.1068
2	Q2 to Q1	3.5486	6.80***	0.1403
	Q2 to Q3	**4.3289**	8.54***	0.1275
	Q2 to Q4	3.5290	7.27***	0.1389
	Q2 to Q5	3.4629	7.05***	0.0977
3	Q3 to Q1	3.7229	4.24***	0.1774
	Q3 to Q2	3.1411	3.62***	0.1889
	Q3 to Q4	3.1339	3.84***	0.1673
	Q3 to Q5	3.9293	4.75***	0.1192
4	Q4 to Q1	7.7482	3.81***	0.2292
	Q4 to Q2	9.1304	4.49***	0.2382
	Q4 to Q3	**10.3570**	5.21***	0.2132
	Q4 to Q5	8.9470	4.79***	0.1423
5 (Largest)	Q5to Q1	39.2199	6.04***	0.1963
	Q5 to Q2	24.6423	3.95***	0.2010
	Q5 to Q3	**41.5719**	6.71***	0.1758
	Q5 to Q4	**39.3731**	6.85***	0.1971

Note: Regression coefficients, t-statistics, and adjusted R-square for the general following linear regression:

$$\big((\mathrm{j}\,|\alpha_\mathrm{r}) \rightarrow (\mathrm{i}\,|\alpha_s)\big) = \beta_{0_{\alpha,t}} + \beta_1\, LIQU\_Neg_{j,\alpha_r,t-1} + \vartheta_I + \delta_T + \epsilon_{\alpha,t}$$

The sample spans from January 1990 to December 2019. The dependent variable of *Out-Q* is computed as the total sum of the liquidity connection that firm j from α_r sends out to α_s (with $r, s \in \{1,..,5\}$ $and\ r \neq s$) divided by the number of firms in the α_r. $LIQU$ is the monthly firm-level liquidity shock measured as the negative difference between *ILLIQ* and its past 12-month average at time *t-1*. $LIQU\_Neg$ *(-1(*$LIQU$ *<0)* is the increasing function of the negative liquidity shock of firm *j* indexed in α_r at *t-1* scaled by 1000 .

The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West's (1987) standard errors. The first number in the table presents the coefficient of the fix effect model, the second value in the parenthesis is the t-statistics, and the third value is adjusted R-square.

*, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix I: *Descriptive Statistics in Pre-and Post-COVID Periods.*

Pre-COVID period

Panel A: Descriptive Statistics							
	Mean	Median	SD	Min	Max	P25	P75
Out	20.1%	20.2%	4.4%	12.1%	34.1%	16.6%	22.6%
In	20.5%	20.6%	5.0%	6.9%	33.4%	17.8%	23.5%
In+out	40.6%	40.8%	4.9%	24.6%	50.2%	37.9%	43.9%

COVID period

Panel B: Descriptive Statistics							
	Mean	Median	SD	Min	Max	P25	P75
Out	40.2%	39.1%	9.2%	15.3%	65.8%	34.5%	44.8%
In	38.5%	38.4%	8.2%	11.5%	63.2%	33.5%	44.7%
In+out	78.7%	78.9%	13.3%	44.3%	118.3%	70.7%	85.8%

Note: Panel A presents the *s*ummary statistics of linear Granger-causality relationships (at the 5% level of statistical significance) among the weekly proportional quoted spread of all the firms included in *S&P500* during the in pre-COVID period. The Pre- COVID subsample spans from March 2019 to Jun 2019.

Panel B reports the *s*ummary statistics of the linear Granger-causality relationships (at the 5% level of statistical significance) among the weekly proportional proportional quoted spread of all the firms included in *S&P500* during the impact period. The impact period subsample spans from March 2020 to Jun 2020.

Proportional quoted spread is calculated as $\frac{AskPrice_{t-1} - BidPrice_{t-1}}{MidPrice_{t-1}} * 100$. *Out*, *In*, and *In+Out variables* are the average percentage of other industry groups in the system that are significantly Granger-caused by an industry group *j*, the average percentage of other industry groups in the system that significantly Granger-cause industry group *j*, and the summation of the two, respectively. All the measures are winsorised at the 5th and 95th percentile.