Liquidity Commonality and its Pricing: Evidence from Firms in Supply Chain Networks

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Abstract

This paper investigates how economic links from customer-supplier relationships affect liquidity commonality and its pricing. I show that a stock's liquidity co-moves with liquidity of its economically linked stocks and this liquidity commonality decreases with the level of information asymmetry on the stock. A long-short portfolio from the high-minus-low liquidity commonality with economically linked firms yields economically and statistically significant average returns, and these returns cannot be explained by majorly known systematic risk factors. The results imply that supply-chain networks are another important channel for liquidity risk.

JEL Classification: G10, G12, L14

Keywords: Liquidity synchronization; Liquidity risk premium; Economic linkage

It is well documented that liquidity co-moves across stocks.[1] Such systematic movement in liquidity is important, because it is a source of liquidity risk which influences asset prices (Pástor and Stambaugh 2003; Acharya and Pedersen 2005; Sadka 2006; Lee 2011). Therefore, understanding liquidity commonality is important in that it may shed light on how and why asset liquidity fluctuates, and ultimately, how liquidity risk possibly affects investors' wealth and investment decision.

There are two major lines of studies on what drives liquidity commonality. Supply-side theory suggests that liquidity commonality arises from correlated changes in the liquidity provisions of market makers or liquidity providers (Coughenour and Saad 2004; Chordia, Sarkar, and Subrahmanyam 2005; Brunnermeier and Pedersen 2009; Hameed, Kang, and Viswanathan 2010), while demand-side theory suggests that correlated trading by investors drives liquidity commonality (Kamara, Lou, and Sadka 2008; Karolyi, Lee, and van Dijk 2012; Koch, Ruenzi, and Starks 2016). Although these studies disagree on the origin of the correlated trading activity, they agree that correlated trading induces liquidity co-movement.

While previous literature has examined the link between correlated trading and liquidity commonality, it remains unclear what drives such correlated trading despite the importance of liquidity risk.[2] In this paper, I provide evidence that economic linkage among firms is an important source of liquidity commonality. I show that supply-chain networks play a significant role in understanding systematic movement in liquidity and pricing of liquidity risk. I label this liquidity

[1] Prior research provides evidence that liquidity co-moves. Chordia, Roll, and Subrahmanyam (2000) have first documented that individual stock liquidity is correlated with industry and market liquidity. Hasbrouck and Seppi (2001), and Huberman and Halka (2001) support this finding by providing similar evidence with different methodologies and samples. Karolyi, Lee, and van Dijk (2012) also find that liquidity commonality presents in the international stock markets.

[2] Since Chordia, Roll, and Subrahmanyam (2000) found the liquidity of the market and industry portfolio could partially explain the liquidity of individual stocks, most researches have been based on a stock's liquidity commonality with the market portfolio. Only few researches have tried to find a new source of liquidity commonality. For example, Chung and Chuwonganant (2014) show that market volatility is another source of liquidity commonality.

commonality from supply-chain networks as "economic linkage liquidity commonality" (ELC, hereafter).

Supply-chain networks are a natural channel that induces investors to trade some stocks simultaneously. Given that firms share risk through supply-chain networks and this economic channel systematically affects stock prices (Cohen and Frazzini 2008; Menzly and Ozbas 2010; Shahrur, Becker, and Rosenfeld 2010; Acemoglu et al. 2012; Ahern 2013; Aobdia, Caskey, and Ozel 2014), it may be natural to think that investors consider the information on this economic linkage when they trade and price economically-linked stocks.[3] Such investors' reliance of the information on the network possibly results in their correlated demand for these stocks and ELC.

One may think that liquidity co-movement is just a "mirror image" that reflects return co-movement in liquidity and thus it might be trivial to examine liquidity commonality, because systematic risks of stocks are strongly associated with investors' common supply and demand for stocks. However, liquidity commonality moves quite differently in complicated economic relationships including the supply-chain relationship where stocks are allowed to have different signs of exposure to a systematic risk.

Suppose that there are two firms called "Customer" and "Supplier." "Customer" firm may experience a negative shock to its operating profit. Then, "Supplier" firm could be affected by this negative shock because "Customer" firm would increase (decrease) the product orders from "Supplier" firm by trying to win the product market shares from its competitors (by acclimating to the worsened funding constraints by the bad performance). Since these two firms are exposed to the

[3] Recent literature demonstrates that supply-chain networks are one of the systematic channels for explaining cross-sectional variations of expected returns. For instance, Acemoglu et al. (2012) theoretically show that inter-industry relationships allow an idiosyncratic shock arising from an industry to have systematic impact on the market. Ahern (2013) supports this study by showing that risk-adjusted returns are greater for firms with higher exposure to their supply chain networks.

same risk with the opposite (same) direction, investors would trade "Customer" and "Supplier" stocks with similar timing and these stocks should show similar trade imbalances in absolute terms. This implies that, unlike return commonality between the two stocks, ELC is independent of the signs of stocks' exposure to the network risk. Therefore, in some cases, the price impact of the network risk (i.e., the average of return commonality across stocks) might be indistinguishable from zero, but the impact of liquidity risk stemming from ELC (i.e., the estimate of ELC across stocks) can be significant. This difference indicates that it is important to look into both liquidity and return commonality in order to correctly understand an economic linkage and its impact.

To formulate testable hypotheses, I devise a one-period equilibrium model with asymmetric information and imperfect competition of market makers. The model is built on Liu and Wang (2013, 2016) because it allows me to obtain an analytic solution for liquidity covariance of stocks by using equilibrium bid and ask prices. For the purpose of the paper, the model is extended with the following modifications. First, my model allows risky assets to share a supply-chain network risk. Second, the informed investors only receive a private signal on the supply-chain network risk with uncertainty. Third, I assume that liquidity demands of the informed are independent. These modifications help to concentrate on the effect of correlated demand for stocks arising from the economic network, not on the simple transmission effect of correlated liquidity demand for stocks, to liquidity commonality.

My model delivers several testable predictions for ELC. First, investors' reliance on the information on the supply-chain network leads to ELC. Second, an increase in the level of information asymmetry on the supply-chain network diminishes ELC due to the increased investors' hedging demand against adverse selection. Lastly, stocks with a higher degree of ELC are associated with higher average returns since these stocks are more exposed to liquidity risk. All these predictions point to the fact that supply-chain networks are another important source of liquidity risk.

To test these predictions, I use data on the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) stocks from July 1997 to June 2018. I compute and use different daily liquidity measures proposed by Amihud (2002), and Chung and Zhang (2014). For the customer-supplier networks, I compute the liquidity and return of a customer or supplier portfolio for each stock based on the inter-industry trade flows in the Input-Output (IO) tables by the US Bureau of Economic Analysis (BEA), which is the same method applied by Menzly and Ozbas (2010), and Shahrur, Becker, and Rosenfeld (2010).[4,5]

I first estimate ELC by running the panel regressions of a stock's liquidity on its customer or supplier portfolio's liquidity. Consistent with the first model prediction, I show that ELC is statistically significant and positive even after controlling for previously studied determinants of liquidity commonality including market and industry liquidity commonality (Chordia, Roll, and Subrahmanyam 2000), and the Chicago Board Options Exchange Market Volatility Index (VIX) (Chung and Chuwonganant 2014). Surprisingly, economic significance of ELC is about four times larger than that of industry liquidity commonality at most. This suggests that economic linkage among firms is important in understanding systematic variations of liquidity.

Next, I investigate the relation between ELC and information asymmetry. I first obtain the

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[4] Although some of the previous studies regarding supply chains have used the Form 10K to define economic linkage, the sample using the customer data published in the 10K reports is likely biased for the following reasons. First, firms are only required to report their major customers which account for more than 10 percent of their sales. This requirement might make most of the firms in the sample have only large-sized customers which are able to purchase a lot of goods from suppliers at one time. Second, the number of available supply chain pairs from the 10K reports is not enough for the results with this sample to be generalized. In some years, the number of the available pairs after filtration is less than 40.

[5] I also provide some results with the 10K-defined economic linkage on the Appendix. Overall, the results with the 10K-defined linkage still support the same conclusions drawn by the results with the IO tables, although the results have weaker statistical significance than those with the IO tables.

stock-year estimates for ELC from the time-series regression with daily data for each stock and year. Then, I run the panel regressions of these estimated ELCs on a proxy for the level of information asymmetry on the supply-chain network of each stock and other possible explanatory variables in the prior literature. I use analyst coverage and blockholder ownership per entity as proxies for the level of information asymmetry on the supply-chain network.[6] Consistent with the second model prediction, the results show that ELC increases (decreases) with analyst coverage (blockholder ownership per entity). This implies that a stock's ELC is greater when there are investors who have more incentives to exploit public information on the supply-chain relationship for trading, supporting the demand-side theory of liquidity commonality.

Lastly, I analyze the pricing effect of ELC. To understand the relationship between asset returns and ELC, I assign stocks to different portfolios based on the previous year's ELC. Such sorting shows a linear increase in average returns with ELC. The long-short strategy between the highest and the lowest ELC quintile portfolio produces statistically significant average returns and yields up to 7.92% per annum. The risk-adjusted returns of the long-short strategy are also sizable and statistically significant. For example, the risk-adjusted returns controlling for the model with the Fama-French (2015) five factors, Carhart (1997) momentum factor, and Pástor-Stambaugh (2003) factor are estimated as up to 4.16% annually. These results imply that the liquidity risk associated with ELC is priced and cannot be explained by known factors.

I also investigate the explanatory power of ELC in cross-sections of expected returns. I conduct the Fama-MacBeth (1973) regressions with ELC and other predictors such as size, book-to-market ratio, asset growth, book leverage, investment intensity, R&D intensity, and return on

[6] Since the degree of information asymmetry on the supply-chain network of a stock is unobservable, I assume that it is positively related to the level of information asymmetry on the stock.

equity. I show that ELC is an economically and statistically significant predictor for stock returns. Following Petersen (2009), I run the panel regressions with fixed effects and use firm and time clustered standard errors. The results are qualitatively and quantitatively similar to those with the Fama-MacBeth regressions.

Additionally, I estimate the risk premium of ELC. Following standard practice in the asset pricing literature, I run the two-stage cross-sectional regressions of test portfolios on the long-short portfolio based on ELC and other known factors including the Fama-French five factors, Carhart (1997) momentum factor, and Pástor-Stambaugh (2003) liquidity factor. I use the Fama-French (1997, 2015) 48 industry portfolios and 75 factor portfolios (i.e., 25 size and book-to-market, 25 size and operating profitability, and 25 size and investment portfolios) as test portfolios. I find a positive and significant risk premium for ELC. The liquidity risk premium associated with ELC is estimated as up to 6.44% per annum. These results not only reconcile with the evidence of risk premium of liquidity commonality provided by the prior literature (Pástor and Stambaugh 2003; Acharya and Pedersen 2005; Sadka 2006; Lee 2011), but also suggest the importance of the pricing effect of the economic network on liquidity risk.

The major contribution of the paper is threefold. First, it contributes to the literature on the systematic factors of stock liquidity. Since Chordia, Roll, and Subrahmanyam (2000) found that market and industry portfolio's liquidity have explanatory power for an individual stock's liquidity, several important factors have been documented. For instance, Chung and Chuwonganant (2014) find that market volatility measured by VIX is a strong predictor for liquidity. Li and Wang (2019) also provides evidence that geographical proximity of firms can partially explain liquidity. This paper adds to this strand of literature by emphasizing the importance of supply-chain networks in explaining stock liquidity.

The paper also contributes to the studies on the explanation of liquidity commonality. Many papers document that supply-side is a main driver of liquidity commonality. For example, Coughenour and Saad (2004) argue that liquidity commonality is driven by correlated adjustments in liquidity provisions from specialists and such common changes in liquidity provisions depend on their shared capital constraints and information. Hameed, Kang, and Viswanathan (2010) find that liquidity commonality increases during times when there is a lack of funding liquidity. On the other hand, some papers argue that demand-side is a critical driver of liquidity commonality. Koch, Ruenzi, and Starks (2016) show that stocks with higher mutual fund ownership have greater liquidity commonality and this tendency becomes prominent when stocks are owned by mutual funds with a high turnover ratio. This paper adds to this line of the literature by providing evidence that investors' correlated trading on stocks in the supply-chain network plays an important role in liquidity commonality.

Lastly, the paper contributes to the growing body of literature on supply-chain networks of firms. Cohen and Frazzini (2008), Menzly and Ozbas (2010), and Shahrur, Becker, and Rosenfeld (2010) find that returns are predictable by using economically related firms' returns. Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) put an emphasis on the importance on the pricing effect of supply-chain networks with their theoretical model. Ahern (2013) and Aobdia, Caskey, and Ozel (2014) provide evidence that firms with higher centrality in the supply-chain network tend to have greater stock returns. While these studies have only focused on asset returns, this is, to the best of my knowledge, the first paper to document economic links among firms affect liquidity risk and its pricing.

The rest of the paper is presented as follows. Section 1 develops testable hypotheses from the model predictions. Section 2 discusses the data and variables. Section 3 studies the relationship between liquidity commonality and economic linkage among firms. Section 4 examines the pricing effect of ELC. Section 5 concludes. Additional test results and the detail on the model are provided on the Appendix.

1. Development of Hypotheses

In this section, I develop testable hypotheses to examine how supply-chain networks shape liquidity commonality and its pricing. I conjecture that supply-chain networks are another important source of liquidity risk due to investors' correlated demands for stocks in supply-chain networks. Validating this conjecture entails answering the following questions: (i) does a supply-chain channel lead to ELC? (ii) how does information asymmetry on the supply-chain network change ELC? (iii) how does ELC affect asset prices? To answer these questions, I introduce the basic setup of an equilibrium model with two assets and asymmetric information. Then, I discuss the basic intuition of the model and develop hypotheses based on the insights from the model.

1.1. The Model Setup

I consider a one-period ($t = 1, 2$) economy with asymmetric information. There are two equity-financed firms ($k = 1{,}2$) that share a supply chain network. The payoff of risky asset k at time 2 is given by

$$V_k = \bar{V}_k + \delta_k c + \epsilon_k, \tag{1}$$

where $\bar{V}_k$ is the initial value of risky asset k at time 1; c is the output related to the supply chain risk and follows $N(0,\sigma_c^2)$; δ_k is the sensitivity of stock k to the network risk; ϵ_k is the value created from the individual risk of asset k which follows $N(0,\sigma_\epsilon^2)$ and uncorrelated between stocks.[7] Notice that one of δ_ks can take a negative value unlike other systematic risks in practice. This is due to the fact that firms in the same supply chain network are not always exposed to the network risk with the same sign.[8] Since I restrict firms under a supply-chain network, I assume that the overall exposure of stocks to the supply chain risk is positive: $\delta_1 + \delta_2 > 0$.[9] There is also a risk-free asset which has zero-net supply, and it is used as the numeraire.[10]

There are three types of agents: informed (I), uninformed investors (U), and market makers (M). The total number of agents is N which is equal to the sum of numbers of three different market participants: $N = N_I + N_U + N_M$. I require the number of each group of agents to be strictly positive: $N_I, N_U, N_M > 0$. Each agent is endowed with $\bar{\theta}$ shares of stock k and thus the total supply for stock k is $\bar{\theta}(N_I + N_U + N_M)$ shares. Investors must trade with market makers at the quote bid and ask prices and are assumed to be price takers.

The informed investors have access to a signal, s, on the payoff for c with the uncertainty of $\sigma_{\epsilon_s}^2$: $s = c + \epsilon_s$, $\epsilon_s \sim N(0,\sigma_{\epsilon_s}^2)$. On the other hand, the uninformed investors can guess signals for both stocks by observing the expected prices by the informed investors: $\hat{s}_1$, $\hat{s}_2$. As argued in Wang (1994), Vayanos and Wang (2012), and Liu and Wang (2016), the informed also

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7 For simplicity of the model, I exclude other systematic risks. Incorporating other systematic risks does not change the results of the model qualitatively.

8 Suppose that firm 1 purchases goods from firm 2 and c is the output from the network shock stemming from firm 1 (i.e., $\delta_1 = 1$). Then, δ_2 can take either a positive or negative value for various reasons. For example, if a new competitor against firm 1 appears and competes for the existing market share, such event is realized as a negative value of c. In case firm 1 decides to do a "Chicken" game, δ_2 will be negative since firm 1 is likely to order more goods from firm 2 to increase the supply and expel the new competitors out of the product market. On the other hand, firm 1 could adapt to its shrunken market share and decrease orders from firm 2, which is the case of a positive δ_2.

9 The overall exposure could be negative temporarily, but on average, it should be positive. If the overall exposure is negative in the long run, firms are likely under a rivalry. Relaxing this condition does not affect the results of the model.

10 As a result, the risk-free rate is normalized to 0.

demand liquidity for each stock and it follows a normal distribution with zero mean and the variance of σ_l^2: $l_k \sim N(0, \sigma_l^2)$. The realizations of l_1 and l_2 are known to the informed investors at time 1. I assume that liquidity demands for stocks are independent. This independent assumption on liquidity demands for stocks is appropriate to understand the relation between liquidity comovement and supplier-customer networks, since it helps focus only on the effect of correlated demand for stocks arising from economic networks, not on the transmission effect of correlated liquidity demand for stocks, to liquidity commonality.

I assume that all investors try to maximize their expected constant absolute risk aversion utility for the final wealth at time 2 by trading assets at time 1 and 2. Given the bid and ask prices for stocks, the maximization problem of investor $i \in \{I, U\}$ is

$$\max_{\theta_{i1},\theta_{i2}} E[-e^{-\gamma w_i}|\mathcal{I}_i] \;\; s.t. \; w_i = \sum_{k=1,2} \theta_{ik}^{-} B_k - \theta_{ik}^{+} A_k + (\bar{\theta} + \theta_{ik} + l_{ik}) V_k, \tag{2}$$

where $\gamma > 0$ is the absolute risk aversion parameter; $\mathcal{I}_i$ is the information set of investor i at time 1; θ_{ik} is the signed order size of investor i for stock k at time 1; B_k is the bid price for stock k at time 1; A_k is the ask price for stock k at time 1; l_{ik} is the liquidity demand of investor i for stock k and takes zero for the uninformed; $x^+ \equiv max\,(0, x)$ and $x^- \equiv max\,(0, -x)$.

Similarly, for $j = 1, 2, \cdots, N_M$, the maximization problem of the market maker j is

$$\max_{\alpha_{jk}\geq 0, \beta_{jk}\geq 0} E[-e^{-\gamma w_j}|\mathcal{I}_M] \;\; s.t. \; w_j = \sum_{k=1,2} \alpha_{jk} A_k - \beta_{jk} B_k + \left(\bar{\theta} + \beta_{jk} - \alpha_{jk}\right) V_k, \tag{3}$$

where α_{jk} is the number of shares of stock k that the market maker j sells at the ask price A_k; β_{jk} is the number of shares of stock k that the market maker j buys at the bid price B_k.[11]

Finally, the market clearing condition is to match supply and demand from investors and market makers. That is,

$$\alpha_k = \sum_{i=I,U} N_i \theta^{*+}_{ik}, \qquad \beta_k = \sum_{i=I,U} N_i \theta^{*-}_{ik}, \tag{4}$$

where α_k is the total sales by market makers; β_k is the total purchases by market makers; θ^*_{ik} is the demand schedule of investor i for stock k.

1.2. The Model Predictions

1.2.1. Liquidity Commonality and Information Asymmetry

Since ELC is the co-movement of bid-ask spreads of stocks, it is necessary to obtain the equilibrium bid and ask prices for each stock: A^*_k, B^*_k. To this end, I first compute the optimal orders for investors $(\theta^*_{Ik}, \theta^*_{Uk})$ from the first-order condition of investors (i.e., the maximization problem of equation (2)), and then calculate the optimal total sales and purchases for market makers (α^*_k, β^*_k) by using the first-order condition of market makers (i.e., the maximization problem of equation (3)). Finally, using the market clearing condition (4), I can obtain the equilibrium bid and ask prices. Detail on the derivation of the model is provided in the Appendix A.1. The following proposition can be obtained for ELC.

[11] Market makers know that their trades affect A_k and B_k.

Proposition. *Liquidity commonality as measured by the covariance of bid-ask spreads is:*

$$Cov(A_1^* - B_1^*, A_2^* - B_2^*) = |\delta_1||\delta_2| f\left(\sigma_{\epsilon_s}^2\right), \tag{5}$$

where $f\left(\sigma_{\epsilon_s}^2\right)$ *is a monotonically increasing function of* $\sigma_{\epsilon_s}^2$ *(i.e.,* $\frac{\partial f(\sigma_{\epsilon_s}^2)}{\partial \sigma_{\epsilon_s}^2} > 0$*), and independent of the signs of* δ_1 *and* δ_2*.*[12]

Proposition entails several important interpretations for ELC. First, unlike the covariance between asset returns, ELC is independent of the signs of the exposure of each firm to the network risk. This is simply due to the fact that ELC is driven by the absolute magnitudes of the exposures, not the signs. Such sign independency is a key reason to examine liquidity commonality in a complex network in practice. Because some economic relationships including supply-chain networks are conceptually intertwined with positive and negative feedbacks ($\delta_1\delta_2 > 0$ and $\delta_1\delta_2 < 0$, respectively), the sign-dependent feature of return co-movement helps to identify which feedback dominates in an economic relationship. If positive and negative feedbacks are similarly distributed in an economic relationship, the estimate of return co-movement will be indistinguishable from zero. On the other hand, as implied by the Proposition, such sign effect does not affect liquidity commonality and this helps to understand the true economic relationship among firms.[13]

[12] $f\left(\sigma_{\epsilon_s}^2\right)$ also includes other exogenous variables such as σ_c^2, σ_ϵ^2, and σ_l^2. However, I only denote $\sigma_{\epsilon_s}^2$ since the informational environment is of the interest for this study and $\sigma_{\epsilon_s}^2$ is the only exogenous variable related to the information asymmetry in the model.

[13] Suppose that there are n supply-chain networks, the half of the networks are positive feedbacks ($\delta_1\delta_2 > 0$), and the rest are negative feedbacks ($\delta_1\delta_2 < 0$). Denote σ_{R_n} and σ_{L_n} as the return and liquidity covariance of the assets of the nth network, respectively. If the magnitude of δ_k is same across firms, the estimate of return commonality is

Therefore, it is necessary to look into both liquidity and return commonality for a clear understanding of the relationship among firms and its impacts.

Second, the Proposition implies that ELC arises only if these assets are economically linked (i.e., $\delta_k \neq 0$). Intuitively, since firms share risk through the supply-chain network, in equilibrium, investors will trade both stocks together in order to take a proper amount of the network risk (c). One might think that investors can achieve the optimal exposure to the network risk by trading only one stock. However, they are not likely to use this one stock strategy for the utility maximization, because they also want an optimal exposure to each individual risk (ϵ_1, ϵ_2). Therefore, demands for both stocks will be partially correlated and this induces ELC. This leads to the first hypothesis.

Hypothesis 1. *A stock's liquidity co-moves with the liquidity of economically related stocks.*

Third, the Proposition shows that ELC is an increasing function of the uncertainty of the private signal of the informed investors. Intuitively, correlated trading of investors decreases with the level of information asymmetry because overall investors rely more on the public information on the network and concern less about adverse selection when the private signal becomes less certain. This can be summarized as the second hypothesis.

Hypothesis 2. *A stock's liquidity commonality with its economically related stocks decreases with the level of information asymmetry on the economic linkage.*

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exactly zero: $\overline{\sigma_{R_n}} = \sum \sigma_{R_n}/n = 0$. On the other hand, the estimate of liquidity commonality ($\overline{\sigma_{L_n}}$) is $\sum \sigma_{L_n}/n = \sigma_{L_n}$. Therefore, the estimate of return commonality possibly underestimates or even misses the true economic relationship, while the estimate of liquidity commonality does not.

1.2.2. Expected Returns and Liquidity Commonality

To understand the link between asset returns and ELC, I have the following corollary for liquidity risk from the Proposition.

Corollary 1. *The liquidity risk from the supply-chain network for stock* k *is:*

$$\beta_{ELC_k} \equiv \frac{Cov(A_1^* - B_1^*, A_2^* - B_2^*)}{Var\left(A_{k'}^* - B_{k'}^*\right)} = |\delta_1||\delta_2| g_k\left(\sigma_{\epsilon_s}^2\right), \tag{6}$$

where k' *denotes the other stock against stock* k *in the supply-chain network (e.g., if* $k = 1$*, then* $k' = 2$ *and vice versa);* g_k *is a monotonically increasing function with respect to* $\sigma_{\epsilon_s}^2$*, and independent of the signs of* δ_1 *and* δ_2*.*

Corollary 1 shows that, other things being equal, liquidity risk from the supply-chain network for both stocks increases with liquidity commonality. This suggests that liquidity risk is different from the network risk since it is independent to the sign of exposure of each firm to the network risk. With the equation (6), I can deduce the following corollary.

Corollary 2. *The equilibrium bid-ask spread for stock* k *can be decomposed as follows:*

$$A_k^* - B_k^* = a_k + \beta_{ELC_k}\left(A_{k'}^* - B_{k'}^*\right) + e_k, \tag{7}$$

where a_k *is a constant for stock* k*;* e_k *is a realization of a random variable which follows the normal distribution with zero mean and is not correlated with* $A^*_{k'} - B^*_{k'}$.

Corollary 2 illustrates that the equilibrium bid-ask spreads are positively associated with liquidity risk. Since equilibrium bid-ask spreads are considered as the cost that overall investors have to pay when trading, an increase in equilibrium bid-ask spreads possibly forces the prices to decline and thus the asset returns to increase. Combined with Corollary 1, Corollary 2 implies that an increased degree of liquidity commonality makes it costly for investors to change their position of both stocks. Consequently, the stock prices are changed toward reflecting the increased liquidity risk. This consideration allows for positing the last testable hypothesis.

Hypothesis 3. *Stocks with a higher degree of liquidity sensitivity to their economically linked stocks have higher asset returns.*

2. Data and Variable Construction

2.1. Data

I obtain daily data of NYSE and AMEX stocks from the Center of Research in Security Prices (CRSP).[14] The dataset includes prices, returns, trading volumes, closing bid and ask prices, shares outstanding, Standard Industrial Classification (SIC) codes, and North American Industry Classification System (NAICS) codes. I also merge the CRSP data with the Compustat database

[14] According to Chordia, Subrahmanyam, and Anshuman (2001), and Karolyi, Lee, and van Dijk (2012), NASDAQ volume reports differently from NYSE and AMEX volume, and tends to be overstated.

for firm characteristics. I set the observations with negative book value as missing. I preferentially use SIC and NAICS codes from the Compustat database and use these codes from the CRSP database only if they are not available in the Compustat database. The sample period of data is from July 1997 to June 2018. Following Chordia, Roll, and Subrahmanyam (2000) and Kamara, Lou, and Sadka (2008), I include only common stocks which are restricted by the CRSP share code 10 or 11 because other types of stocks such as REITs, ADRs, and so forth might have different liquidity properties. I also exclude stocks if their prices are less than a dollar at the start of fiscal year so that asset liquidity is not mainly driven by changes in tick size or any other possible noises.[15] By using the liquidity measures proposed by Amihud (2002), and Chung and Zhang (2014), I calculate daily liquidity estimates. I discard if the number of daily observations in each fiscal year is less than 120.

I download the institutional blockholder ownership and the number of institutional from Thomson Reuters, and the number of analysts from the Institutional Brokers' Estimate System (IBES).[16] As in Chung and Chuwonganant (2014), I assign zero for the number of analysts following a firm if there is no data of the firm in the IBES database. I download the daily VIX data from the Federal Reserve Economic Data.

I also obtain the annual IO tables from the US BEA. I utilize the use tables valued at producers' prices because purchasers' prices tend to underestimate the trade flows of transportation industries. Although the IO tables are available from 1947, I use the IO tables from 1997 to 2017 since these tables use the identical industry classifications based on the NAICS code and

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[15] Similar filtrations have been applied to prior literature. For example, Amihud (2002) have used five-dollar criteria to restrict stocks. Koch, Ruenzi, and Starks (2016) have excluded stocks less than four dollars.

[16] The variable names for institutional blockholder ownership, the number of blockholders, and the number of analysts are INSTBLOCKOWN, NUMINSTBLOCKOWNERS, and NUMREC, respectively. For the institutional blockholder ownership, I use the ratio of INSTBLOCKOWN over share outstanding for each stock and quarter. Blockholders are the shareholders with ownership greater than or equal to 5%.

redefinition for secondary products is only available for these periods. The IO tables include 71 different accounts. I exclude Federal general government (defense), Federal general government (nondefense), Federal government enterprises, State and local general government, and State and local government enterprises because there are no available NYSE or AMEX stocks in these accounts. I also merge Housing and Other real estates because the NAICS codes for these accounts are identical in the BEA-NAICS concordance table. Thus, I have a total of 65 different industries. At the end of June of each year, I assign the IO table for that year to stocks and use the same table over the next twelve months.[17] As the CRSP database provides the NAICS codes for firms from June 10, 2004, I use the SIC-NAICS concordance tables to assign the NAICS codes for the data before June 10, 2004. The SIC-NAICS concordance tables are obtained from the U.S. Census Bureau.

2.2. Liquidity measures

2.2.1. Amihud (2002) Liquidity Measure

Due to its availability and reliability, the Amihud (2002) liquidity measure is widely used in the prior literature. For instance, Goyenko, Holden, and Trzcinka (2009) show that the Amihud measure is highly correlated with the intraday microstructure variables. Acharya and Pedersen (2005), Watanabe and Watanabe (2008), Karolyi, Lee, and van Dijk (2012), and Koch, Ruenzi, and Starks (2016) have applied the Amihud measure to investigate liquidity risk and liquidity commonality. In line with this literature, I employ the Amihud measure as a main liquidity measure. In this paper, I define the Amihud liquidity measure as

[17] For example, the IO table for 1997 is used for July 1997 to June 1998.

$$Amihud_{it} = -\log\left(\frac{|R_{it}|}{Price_{it} \times Vol_{it}}\right), \tag{8}$$

where $|\boldsymbol{R_{it}}|$ is the absolute value of daily return of stock $\boldsymbol{i}$ on day $\boldsymbol{t}$; $\boldsymbol{Price_{it}}$ is the closing price of stock $\boldsymbol{i}$ on day $\boldsymbol{t}$; $\boldsymbol{Vol_{it}}$ is the trading volume of stock $\boldsymbol{i}$ on day $\boldsymbol{t}$. I use the negative value of logarithm of Amihud illiquidity measure to make the measure have a greater value when stock $\boldsymbol{i}$ is more liquid on day $\boldsymbol{t}$.

2.2.2. Chung and Zhang (2014) CRSP effective spreads

Chung and Zhang (2014) investigates the relation between the bid-ask spread from the CRSP data and the counterpart from the Trade and Quote data. By using the sample from 1993 to 2009, the authors find the high correlation between the CRSP spread and the Trade and Quote spread. Especially, the CRSP effective spreads outperform other low-frequency liquidity measures in cross-sectional environments.

For consistency, I use the negative logarithm of the CRSP bid-ask spread that Chung and Zhang (2014) define. For stock i on day t, the CRSP effective spread is

$$CRSP_{it} = -log\left(\frac{Ask_{it} - Bid_{it}}{M_{it}}\right), \tag{9}$$

where Ask_{it} is the ask price of stock i on day t from the CRSP daily data; Bid_{it} is the bid price of stock i on day t from the CRSP daily data; M_{it} is the mid-price of Ask_{it} and Bid_{it}

defined as $\frac{Ask_{it}+Bid_{it}}{2}$. Following Chung and Zhang (2014), I set all the CRSP effective spreads that are greater than 50% of the quote midpoint as missing.

2.3. Variable definitions

Following the previous convention, for market liquidity of stock i on day t, MKT_{it}, I create the value-weighted market portfolio's liquidity except for the asset liquidity of stock i. The weight is based on market capitalization on the previous month and monthly updated. Similarly, I create the value-weighted industry liquidity except for the asset liquidity of stock i on day t, IND_{it}. For the industry liquidity, I discard an industry if the number of stocks in the industry is less than three.[18] I use the industry classifications of the IO tables to classify industries. Unlike the market and industry liquidity, the market ($MKTR_t$) and industry ($INDR_{it}$) portfolio's returns are value-weighted including stocks themselves, resulting in no differences across firms and within an industry, respectively.

Similar to Menzly and Ozbas (2010), and Shahrur, Becker, and Rosenfeld (2010), I define the customer liquidity of stock i in industry j on day t as

$$CUS_{it} = \sum_{\substack{k=1 \\ k \neq j}}^{N_t} \frac{TF_{j,k,t}}{\sum_{\substack{k=1 \\ k \neq j}}^{N_t} TF_{j,k,t}} \times IND_{kt,}^{+} \tag{10}$$

[18] This is the minimum requirement such that IND_{it} differs depending on different weighting schemes (i.e., value-weighting or equal-weighting).

where, in Equation (10), N_t is the number of customer industries for supplier industry j on day t; $TF_{j,k,t}$ is the trade flow from industry j (supplier) to k (customer) on day t based on the annual IO table; IND_{kt}^{+} is the liquidity of the value-weighted portfolio of stocks in industry k on day t.[19] A customer portfolio's return, $CUSR_{it}$, is formed in the same method, using the value-weighted industry portfolios' returns.

I also define the supplier liquidity of stock i in industry k on day t as follows.

$$SUP_{it} = \sum_{\substack{j=1 \\ j \neq k}}^{N_t} \frac{TF_{k,j,t}}{\sum_{\substack{j=1 \\ j \neq k}}^{N_t} TF_{k,j,t}} \times IND_{jt,}^{+} \tag{11}$$

where N_t is the number of supplier industries for customer industry k on day t; $TF_{k,j,t}$ is the trade flow from industry k (customer) to j (supplier) on day t based on the annual IO table; IND_{jt}^{+} is the liquidity of the value-weighted portfolio of stocks in industry j on day t. A supplier portfolio's return, $SUPR_{it}$, is also created in the same way, using the value-weighted industry portfolios' returns.

Throughout the paper, I use the daily difference of the liquidity variables as primary variables. As discussed in Chordia, Roll, and Subrahmanyam (2000), Chung and Chuwonganant (2014), and Koch, Ruenzi, and Starks (2016), the time-series level variables of liquidity are likely to entail econometric issues because of their non-stationary characteristics. Therefore, I consider daily changes of liquidity variables as valid variables in order to shun the possible non-stationary

[19] I put the positive sign on the variable to distinguish it from the industry liquidity, IND_{it}. The difference of the two variables is that IND_{it} excludes liquidity of stock i itself, but IND_{kt}^{+} does not. This is due to the fact that IND_{kt}^{+} does not include stock i.

problems.

2.4. *Summary statistics*

Table 1 contains the descriptive statistics of liquidity measures and other major variables. It summarizes the statistics for full sample firm-day observations. The average liquidity measures (i.e., $Amihud$, and $CRSP$) of individual stocks have lower values than those of their customer, supplier, market, and industry portfolios ($CUS\ (Amihud)$, $SUP\ (Amihud)$, $MKT\ (Amihud)$, $IND\ (Amihud)$, $CUS\ (CRSP)$, $SUP\ (CRSP)$, $MKT\ (CRSP)$, and $IND\ (CRSP)$) because the average liquidity measures of customer, supplier, market, and industry stocks have higher weights on stocks with bigger market capitalization. On the other hand, the standard deviations of individual stock liquidity measures are higher than those of customer, supplier, market, and industry liquidity measures since these portfolio liquidity measures do not have much variation within the same economic network, market, or industry. The means and standard deviations of returns follow the similar patterns as liquidity measures (i.e., higher averages and standard deviations for individual stock returns and lower for portfolios' returns).

3. Liquidity Commonality and Economic Linkage

3.1. Liquidity commonality among firms in supply chain

In Hypothesis 1, I expect liquidity commonality with economically linked stocks to exist due to correlated trading on these stocks. In order to examine this hypothesis, I first focus on the relation between a supplier stock's liquidity and its customer stocks' liquidity and run the following panel regression with daily variables.

$$dLIQ_{it} = \beta_0 + \beta_{CUS} dCUS_{it} + \beta_{MKT} dMKT_{it} + \beta_{IND} dIND_{it} + \beta_{VIX} dVIX_t + \beta_{CUSR} CUSR_{it} + \beta_{MKTR} MKTR_t + \beta_{INDR} INDR_{it} + \beta_R R_{it} + FE + \epsilon_{it}, \tag{12}$$

where dx is the time difference of variable x ($dx \equiv x_t - x_{t-1}$); LIQ_{it} in the regression (12) is one of the liquidity measures (i.e., $Amihud_{it}$, or $CRSP_{\mathrm{it}}$) of stock i on day t; CUS_{it} is the customer liquidity for stock i on day t; MKT_{it} is the market liquidity for stock i on day t; IND_{it} is the industry liquidity for stock i on day t; VIX_t is VIX on day t; $CUSR_{it}$ is the daily return of the customer portfolio for stock i on day t; $MKTR_t$ is the daily market portfolio's return on day t; $INDR_{it}$ is the daily industry portfolio's return for stock i on day t; R_{it} is the daily return of stock i on day t; FE is the fixed effects.

I include VIX to control for the market-wide effect of uncertainty studied by Chung and Chuwonganant (2014). I control the market and industry liquidity, and the market and industry return. These variables have been known to have significant effects on the stock liquidity.[20] I include the customer portfolio's return to control for its possible effect to the stock liquidity. I include the return of stock i and fixed effects to capture possibly missing factors. Depending on the specifications, industry-time, firm, time, or firm and time fixed effects is used. I choose monthly frequency for time fixed effects.[21] Standard errors are clustered at the firm and daily level.

Table 2 shows the results of panel regressions with different liquidity measures based on the regression (12). Panel A reports the estimates with Amihud liquidity. In Model (A), the estimated coefficient of the customer portfolio's liquidity, β_{CUS}, is 0.543 and its t-statistic is 43.15. This implies that ELC exists and is positive. Moreover, CUS_{it} has its own explanatory power

[20] See, for instance, Chordia, Roll, and Subrahmanyam (2000), and Chordia, Sarkar, and Subrahmanyam (2005).

[21] This is mainly due to some control variables that have only time-variations (i.e., VIX_t and $MKTR_t$). With day fixed effects, the results remain unchanged (unreported).

different from customers' return, $CUSR_{it}$, implying that the economic and statistical significance of β_{CUS} is not simply a by-product of its return counterpart. In Model (B), the market and industry liquidity have strong explanatory power and positive values as reported in the previous literature. Consistent with Chung and Chuwonganant (2014), β_{VIX} is also significant and negative. β_{CUS}s are all positively estimated and statistically significant even after controlling for variables in Model (B). In Model (C), β_{CUS} is estimated as 0.166 at the 0.01 significant level and is almost twice bigger than the estimate of β_{IND}. This pattern does not change with different fixed effects as confirmed from Model (D) to Model (F). Panel B reports the results with CRSP effective spreads. All the results remain qualitatively the same. Economic magnitude and statistical significance become even bigger. For instance, in Model (C), β_{CUS} is estimated as 0.261 and is almost four times greater than the estimate of β_{IND}.

I also run the following panel regression to study the relation between a customer stock's liquidity and its supplier stocks' liquidity.

$$\begin{aligned} dLIQ_{it} = \beta_0 + \beta_{SUP} dSUP_{it} + \beta_{MKT} dMKT_{it} + \beta_{IND} dIND_{it} + \beta_{VIX} dVIX_t \\ + \beta_{SUPR} SUPR_{it} + \beta_{MKTR} MKTR_t + \beta_{INDR} INDR_{it} + \beta_R R_{it} + FE + \epsilon_{it}, \end{aligned} \tag{13}$$

where SUP_{it} is the supplier liquidity for stock i on day t; $SUPR_{it}$ is the daily return of the supplier portfolio for stock i on day t.

Table 3 summarizes the results of panel regression with different liquidity measures based on the regression (13). Panel A contains the panel regression results with Amihud liquidity. The coefficients for the supplier liquidity, β_{SUP}, are all positively estimated and statistically significant at the 0.01 level. The economic significance is also sizable. SUP_{it} seems to have its own explanatory power differing from the supplier portfolio's return, $SUPR_{it}$. For example, in Model (C) which controls for other variables including $SUPR_{it}$, β_{SUP} is estimated as 0.235 which is almost four times bigger than the estimate of β_{IND}. The results are not changed from Model (D) to (F), implying that the effect of β_{SUP} is pervasive. Panel B reports the results with CRSP effective spreads. All the estimates remain qualitatively similar, and their significance becomes even bigger. For instance, in Model (C), β_{SUP} is estimated as 0.391 and is almost eight times greater than the estimate of β_{IND} and even slightly greater than β_{MKT}. Consistent with Hypothesis 1, the empirical evidence suggests that economic linkage plays a pivotal role to liquidity commonality by showing the economic and statistical significance of β_{CUS} and β_{SUP} even after controlling for known factors for asset liquidity.[22]

3.2. Economic linkage liquidity commonality and information asymmetry

In Hypothesis 2, I expect firms with a less level of information asymmetry on their economic linkage to show a higher degree of ELC. To proxy for the level of information asymmetry on the economic linkage of a stock, I use analyst coverage and blockholder ownership per entity. The data for the number of analysts following stock is obtained from IBES. For the blockholder ownership per entity, I first obtain institutional blockholder ownership and the number of institutional blockholders from Thomson Reuters, and then calculate the percentage ownership per blockholder for each stock. The purpose of averaging out is to precisely measure the level of information asymmetry on the stock.[23]

---

[22] I also provide the supporting evidence with the 10K-based sample in Table A.1. Overall, the results remain qualitatively unchanged.
[23] Using either ownership or the number of blockholders only might poorly proxy the level of information asymmetry. For example, if blockholder ownerships are identical across stocks, to what extent there is information asymmetry in each stock will be very different depending on the number of blockholders.

I first obtain the firm-year liquidity commonality of a stock to its related stocks by running the following time-series regression for firm i and fiscal year y. For the customer liquidity commonality,

$$
\begin{aligned}
dLIQ_{it} = \beta_{iy} + \beta_{cus,iy} dCUS_{it} + \beta_{mkt,iy} dMKT_{it} + \beta_{ind,iy} dIND_{it} + \beta_{vix,iy} dVIX_t \\
+ \beta_{cusr,iy} CUSR_{it} + \beta_{mktr,iy} MKTR_t + \beta_{indr,iy} INDR_{it} + \beta_{r,iy} R_{it} \\
+ \gamma_{ym} + \epsilon_{i,t},
\end{aligned}
\tag{14}
$$

where γ_{ym} denotes the time fixed effect at monthly frequency.

Similarly, for the supplier liquidity commonality,

$$
\begin{aligned}
dLIQ_{it} = \beta_{iy} + \beta_{sup,iy} dSUP_{it} + \beta_{mkt,iy} dMKT_{it} + \beta_{ind,iy} dIND_{it} + \beta_{vix,iy} dVIX_t \\
+ \beta_{supr,iy} SUPR_{it} + \beta_{mktr,iy} MKTR_t + \beta_{indr,iy} INDR_{it} + \beta_{r,iy} R_{it} \\
+ \gamma_{ym} + \epsilon_{i,t}.
\end{aligned}
\tag{15}
$$

Finally, to test the hypothesis, I run the panel regressions of the estimated customer ($\hat{\beta}_{cus,iy}$) or supplier ($\hat{\beta}_{sup,iy}$) liquidity commonality as follows.

$$
\begin{aligned}
&\hat{\beta}_{cus,iy} \text{ or } \hat{\beta}_{sup,iy} \\
&\quad = \gamma_0 + \gamma_{AC} Analyst\ Coverage_{iy} + \gamma_{BO} Blockholder\ Ownership_{iy} \\
&\quad + \gamma_{MR} Market\ Return_y + \gamma_{MS} Market\ Size_y + \gamma_{VIX} VIX_y \\
&\quad + \gamma_{RET} Retrun_{iy} + \gamma_{SZ} Size_{iy} + \gamma_{BM} B/M_{iy} + \gamma_{AG} AG_{iy} \\
&\quad + \gamma_L Leverage_{iy} + \gamma_{IA} I/A_{iy} + \gamma_{RD} R\&D_{iy} + \gamma_{ROE} ROE_{iy} + \gamma_j + \epsilon_{i,t}.
\end{aligned} \tag{16}
$$

where $Analyst\ Coverage_{iy}$ is the time-series average of quarterly updated number of analysts following the stock i for year y; $Blockholder\ Ownership_{iy}$ denotes the time-series averages of quarterly reported percentage ownership per blockholder for stock i and fiscal year y; $Market\ Return_y$ is the time-series mean of daily value-weighted stock market returns for fiscal year y; $Market\ Size_y$ is the mean of daily market capitalizations during year y; $Retrun_{iy}$ is the average of daily stock returns for stock i and fiscal year y; $Size_{iy}$ is defined as the market capitalization of stock i at the end of each June in year y; B/M_{iy} is the book-to-market ratio of stock i defined as book equity of fiscal year ending in year $y-1$ to market capitalization at the end of year $y-1$; AG_{iy} is the asset growth of stock i calculated as total asset in fiscal year $y-1$ divided by total asset in fiscal year $y-2$. $Leverage_{iy}$ is defined as debt in year $y-1$ divided by total asset in year $y-2$ for stock i; I/A_{iy} is the investment rate of stock i, which is the ratio of capital expenditure in year $y-1$ over lagged total asset; $R\&D_{iy}$ is the R&D expenses of stock i scaled by its total asset in year $y-1$; ROE_{iy} is the return on equity for stock i defined as income before extraordinary items plus depreciation expenses in fiscal year $y-1$ scaled by book equity in year $y-2$; All the independent variables are standardized with zero mean and unit standard deviation.

Table 4 has the regression results based on the model specification (16) with customer liquidity commonality. Panel A summarizes the estimates with customer liquidity commonality based on Amihud liquidity. From Model (A) to (B), the coefficient estimates from the univariate regressions with the proxies for information asymmetry are reported. The results show that analyst coverage for a stock have a positive relationship with ELC, while ELC decreases with blockholder ownership per entity. All these relations are statistically significant. Overall, this finding suggests that information asymmetry prevents correlated trading among investors from happening. From Model (C) to (E), I control for other possible explanatory variables and firm characteristics. Particularly, I include market returns, market capitalizations, and VIX, and these variables are known to be relevant to the liquidity demand of financial intermediaries or investors (Coughenour and Saad 2004; Brunnermeier and Pedersen 2009; Hameed, Kang, and Viswanathan 2010; Karolyi, Lee, and van Dijk 2012). The results show that the coefficient estimates for the proxies for information asymmetry remain statistically important or even stronger in explaining customer liquidity commonality, and they are more crucial than other possible candidates. For example, Model (C) shows that the coefficient for analyst coverage is estimated as 0.041 and this is about 1.6 times greater than the coefficient estimate for market size. Panel B reports the estimates with customer liquidity commonality based on CRSP effective spreads. From Model (A) to (B), all the coefficient estimates for the information asymmetry proxies are as expected, but only the estimates for analyst coverage are statistically significant. After controlling for other variables, the results are quantitatively and qualitatively similar.

Table 5 contains the regression results based on the regression (16) with supplier liquidity commonality. Panel A reports the results based on Amihud liquidity. From Model (A) to (B), the coefficient estimates from the univariate regressions with the proxies for information asymmetry are reported. Similar to the results in Table 4, the results show that the estimates for the two proxies for information asymmetry are statistically significant, and analyst coverage (blockholder ownership per entity) has a positive (negative) relationship with ELC. From Model (C) to Model (E), I report the estimates with other possible explanatory variables and firm characteristics. The proxies for information asymmetry remain qualitatively unchanged. Panel B reports the estimates with supplier liquidity commonality based on CRSP effective spreads. From Model (A) to (B), all the signs of the coefficient estimates for the information asymmetry proxies are as expected and statistically significant. Controlling other variables, the explanatory power of the proxies for information asymmetry becomes relatively weak. While blockholder ownership per entity remains qualitatively unchanged, analyst coverage loses its statistical significance. Overall, the results in Table 4 and Table 5 accord with Hypothesis 2 and support the demand-side explanation for liquidity commonality by showing that an increase in the likelihood of trading on the private information leads to a decrease in ELC.[24]

4. Economic Linkage Liquidity Commonality and Expected Returns

4.1. Risk premium of economic linkage liquidity commonality

In Hypothesis 3, I conjecture that investors should require higher risk premiums for stocks with a higher degree of ELC. To test this logic, I create five portfolios sorted on ELC. I first obtain the estimated ELC by running the time-series regression with daily data for each stock and fiscal year based on the regression (14) for customers and (15) for suppliers. At the end of June of each year, I rank stocks into quintiles by the estimates of ELC. As a result, the lowest (highest) portfolio

[24] I also report some results with the 10K-based sample in Table A.2. The overall results imply that information asymmetry decreases ELC.

consists of stocks with the lowest (highest) ELC and the sample period is from July 1998 to June 2018. Then, I create the equally weighted monthly returns on these quintile portfolios for the next twelve months.

Table 6 reports firm characteristics of ELC-sorted portfolios. Panel A contains averages of firm characteristics by quintile portfolios sorted on customer liquidity commonality. From the lowest to highest quintile portfolio, the average sizes show an inverted U-shaped trend with Amihud liquidity, while the ones with CRSP effective spreads show a small increase. For quintile portfolios with both liquidity measures, I observe a downward slope and an upward trend for book-to-market and return on equity, respectively. Especially, return on equity shows a noticeable difference between the lowest and highest quintile portfolio. From the lowest to highest quintile, return on equity increases by 116% (63%) for Amihud liquidity (CRSP effective spreads). The rest of the firm characteristics seem to have no patterns and almost same across portfolios. Panel B has average firm characteristics by quintile portfolios based on supplier liquidity commonality. I observe similar patterns as seen in Panel A: an inverted U-shaped tendency of size with Amihud liquidity, an upward trend of size with CRSP effective spreads, a downward slope for book-to-market, and a considerable increase for return on equity from the lowest to highest quintile portfolios.

Table 7 reports estimated alphas of customer-based portfolios from time-series regressions with various models. The first row in Panel A contains average excess returns of quintile portfolios. In both portfolios based on Amihud liquidity and CRSP effective spreads, expected excess returns linearly increase with customer liquidity commonality. The long-short portfolios yield economically and statistically significant average returns. The long-short strategy based on Amihud liquidity (CRSP effective spreads) produces 7.08% (5.09%) per annum. Panel A also reports various risk-adjusted abnormal returns of these quintile portfolios by using the market model (α_{CAPM}), Fama-French (1993) three factor model (α_{FF3}), Carhart (1997) four factor model (α_{C4}), and Fama-French (2015) five factor model (α_{FF5}). In any case, the linear trend of expected returns across quintile portfolios as well as significant return spreads of the long-short strategy remain. Panel B shows factor sensitivities of quintile portfolios based on customer liquidity commonality. I include all the factors that appear in Panel A: the Fama-French (2015) five factors (the market factor, $R_m - R_f$; the size factor, SMB; the value factor, HML; the profitability factor, RMW; the investment factor, CMA), Carhart (1997) momentum factor (UMD), and Pástor-Stambaugh (2003) liquidity factor (LIQ).[25] The risk-adjusted alphas linearly rise from the lowest to highest quintile portfolios. The risk-adjusted returns on the long-short strategy are economically sizable and statistically significant. The annualized expected return spread is 4.16% (3.83%) with Amihud liquidity (CRSP effective spreads). Exposures to known factors with Amihud liquidity-based quintile portfolios relatively have small dispersions. From the lowest to highest quintile, sensitivities to $R_m - R_f$, HML, CMA, and LIQ do not show statistically meaningful differences, while exposure to SMB, RMW, and UMD have upward patterns. Especially, RMW has a strong predictive power for the long-short portfolios. This is not surprising because, consistent with the results in Table 6, return on equity varies a lot across the quintiles. However, the explanatory power of known factors is not sufficiently enough to explain the abnormal returns of the liquidity risk associated with customer-supplier relationships.

Table 8 summarizes the estimated alphas and factor sensitivity of five portfolios sorted on supplier liquidity commonality. The first row in Panel A reports average excess returns of quintile portfolios. Regardless of liquidity measures, average excess returns linearly rise across quintiles

[25] For a fair comparison with other studies, I obtain these factors from Kenneth French's and Lubos Pastor's website.

and the long-short strategies produce substantial average returns (7.92% for Amihud liquidity, and 4.33% for CRSP effective spreads). Panel A also reports the estimated alphas from popular asset pricing models. From the lowest to highest quintile, all the alphas show linearly upward patterns and their long-short strategies yield economically and statistically significant returns. Panel B reports factor sensitivity of quintile portfolios based on supplier liquidity commonality. The risk-adjusted alphas linearly increase across quintile portfolios. The risk-adjusted returns on the long-short strategy are positive and economically significant. The annualized estimated return is 4.62% (2.09%) with Amihud liquidity (CRSP effective spreads). From the lowest to highest quintile portfolio with Amihud liquidity (CRSP effective spreads), sensitivities to SMB, HML, RMW, UMD, and LIQ ($R_m - R_f$, SMB, and RMW) show statistically meaningful differences. Consistent with the results in Table 6 and Table 7, RMW is the strongest predictor for the long-short portfolios. However, the predictive power of known factors is not enough to explain the abnormal returns of the liquidity risk associated with economic networks. Overall, all the results in Table 7 and Table 8 suggest that ELC is priced and common risk factors cannot explain the abnormal returns arising from ELC.

4.2. Robustness tests

4.2.1. Asset pricing tests with firm characteristics

For robustness, I examine the explanatory ability of ELC for cross-sectional stock returns by using the Fama-MacBeth (1973) regressions. I run standard Fama-MacBeth regressions of monthly excess stock returns on the estimated ELC and other firm characteristic variables. That is,

$$Return_{it} = \beta_0 + \beta_1 Sensitivity_{iy} + \beta_2 Log(Size)_{iy} + \beta_3 Log(B/M)_{iy} + \beta_4 AG_{iy} + \beta_5 Leverage_{iy} + \beta_6 I/A_{iy} + \beta_7 R\&D_{iy} + \beta_7 ROE_{iy} + \epsilon_{it}, \quad (17)$$

where $Return_{it}$ is the monthly excess return of stock i on month t; $Sensitivity_{iy}$ is the previous fiscal year's estimate for customer or supplier liquidity using the regression (14) or (15), respectively; all the independent variables are normalized to zero mean and one standard deviation.

Table 9 reports the results from the Fama-MacBeth regressions with ELC and various firm characteristics. The results from the Fama-MacBeth regressions are consistent with the ones with quintile portfolios sorted on ELC. The univariate results (Model (A), (C), (E), and (H)) show ELC is positively priced. For example, Model (A) reports that one standard deviation increase in customer liquidity commonality leads to a considerable increase of 2.78% in the annualized stock returns. After controlling for various firm characteristics (Model (B), (D), (F), and (H)), these estimates remain almost the same. For instance, Model (B), which is a controlled version of Model (A), shows only a decrease of 0.002 in the slope for customer liquidity commonality, while its statistical significance slightly increases. For a comparison, I also report the panel regressions with ELC and firm characteristics in Table 10. Following Petersen (2009), I include monthly time fixed effects and t-statistics are calculated based on the clustered standard errors at the firm and monthly level. Regardless of liquidity measures and types of economic network, the estimated slopes are similar to the ones in Table 9. In summary, empirical evidence in Table 9 and Table 10 implies that the positive abnormal returns due to ELC cannot be ascribed to other predictors.[26]

[26] Table A.3 also shows the consistent results with the 10k-based data.

4.2.2. Cross-sectional regressions with test portfolios

To study the predictive ability of liquidity risk from economic networks for the cross-sectional returns, I conduct the standard two-stage cross-sectional regressions with several test portfolios. For brevity, I call the long-short portfolio based on customer (supplier) liquidity commonality as CLC (SLC). In the first stage, I run the following time-series regression for each test portfolio.

$$
\begin{aligned}
R_{it} - R_{ft} = \beta_0 &+ \beta_{CLC,i} CLC_t \ (or\ \beta_{SLC,i} SLC_t) + \beta_{R_m - R_f,i}\left(R_{mt} - R_{ft}\right) + \beta_{SMB,i} SMB_t \\
&+ \beta_{HML,i} HML_t + \beta_{RMW,i} RMW_t + \beta_{CMA,i} CMA_t + \beta_{UMD,i} UMD_t \\
&+ \beta_{LIQ,i} LIQ_t + e_{it},
\end{aligned}
\tag{18}
$$

where $R_{it} - R_{ft}$ denotes the excess return of the Fama-French 48 industry portfolios (FF48) or 75 test (25 size and book-to-market, 25 size and operating profitability, and 25 size and investment) portfolios (FF75) i on month t; CLC_t (SLC_t) is the factor portfolio based on customer (supplier) liquidity commonality on month t.

In the second stage, I run the cross-sectional regression of excess returns on factors estimated in the first stage regression. That is,

$$
\begin{aligned}
R_i - R_f = \lambda_0 &+ \lambda_{CLC} \beta_{CLC,i} \ (or\ \lambda_{SLC} \beta_{SLC,i}) + \lambda_{R_m - R_f} \beta_{R_m - R_f,i} + \lambda_{SMB} \beta_{SMB,i} \\
&+ \lambda_{HML} \beta_{HML,i} + \lambda_{RMW} \beta_{RMW,i} + \lambda_{CMA} \beta_{CMA,i} + \lambda_{UMD} \beta_{UMD,i} \\
&+ \lambda_{LIQ} \beta_{LIQ,i} + v_i.
\end{aligned}
\tag{19}
$$

Table 11 summarizes the two-stage cross-sectional regressions of excess returns of test portfolios on factors. Panel A reports the results with FF48 portfolios. Model (A) and (B) are introduced as the benchmark models. Any of the Fama-French five factors (Model (A)) do not have explanatory power for FF48 portfolios in the sample period. In Model (B), the value, profitability, and liquidity factors are priced but the estimated value premium is negative in the sample. From Model (C) to (F), CLC and SLC based on Amihud liquidity are included. The estimated risk premium for customer liquidity commonality with the Fama-French five factor model (Model (C)) is economically and statistically significant estimated as 4.70% per annum. Although its significance decreases after additionally controlling for UMD and LIQ, the premium is still statistically significant and sizable (3.83% per annum). The estimated SLCs also show similar patterns. SLC is estimated as 4.30% (4.02%) per annum with the Fama-French five factor model (the full model). From Model (G) to (J), I report the results based on CRSP effective spreads. In Model (G) and (H), CLCs are statistically insignificant, while the signs of the estimates are positive. On the other hand, SLCs are statistically significant and estimated as larger than with Amihud liquidity. The estimated risk premium with the five factor model (the full model) is 6.44% (5.93%) per annum. Panel B contains the results with FF75 portfolios. Unlike the results in Panel B, the Fama-French five factor model (Model (A)) has some predictive power for FF75 portfolios. SMB, RMW, and CMA are positively estimated and statistically significant. Similarly, some factors of the full model (Model (B)) also have explanatory ability for FF75 portfolios. In addition to SMB, RMW, and CMA, the estimated UMD is economically and statistically significant. In both Model (C) and (D), the risk premiums of customer liquidity commonality are positively estimated but statistically insignificant. In Model (E) and (F), SLCs are economically substantial and statistically significant but their statistical significance becomes less than those of the counterparts in Panel A. However, Model (G) and (H) show that CLCs become strongly significant, compared to the counterparts in Panel A. For example, CLC in Model (G) is estimated as 4.88% per annum with a t-statistic of 2.61, while CLC with the same specification in Panel A is reported as 1.75% annually with a t-statistic of 0.75. The estimated SLCs in Model (I) and (J) remain qualitatively and quantitatively similar, compared with the counterparts in Panel A. In summary, Table 11 shows that liquidity risk associated with economic networks is pervasive and priced.

5. Conclusion

I have explored the relation between supply-chain networks and liquidity commonality, and carried out some analyses on how ELC varies with the degree of information asymmetry between investors. Therefore, my study helps to shed light on our understanding of what drives liquidity commonality by emphasizing the demand-side role. Taking it one step further, I connect ELC with average returns, which adds to our knowledge on the channels for liquidity risk.

Findings in the paper can be summarized as follows. First, I show that supply-chain networks play a critical role in explaining liquidity commonality. With the customer-supplier relationships defined by the IO tables, I find that ELC is pervasively observed on the stock market. Second, I provide some evidence that a stock's ELC decreases with the level of information asymmetry on its supply-chain network proxied by analyst coverage, or blockholder ownership per entity. This result implies that investors' consideration of the information on supply-chain networks drives ELC which supports the demand-side theory of liquidity commonality. Lastly, I show that ELC is priced and its risk premium is economically and statistically substantial. The long-short strategy based on ELC produces annualized expected returns of 7.92% at most. The risk-adjusted premiums with various asset pricing models are also economically and statistically significant. Furthermore, all the estimates from the Fama-MacBeth, panel, and two-stage cross-sectional regressions show consistent results. This consistent pattern of abnormal returns suggests that the liquidity risk arising from economic networks is important in investors' wealth and investment decisions.

This study hints at many potential directions for research. One example might be to examine whether the effect of correlated trading on liquidity commonality is effective in other asset classes. Moreover, the theoretical model that encompasses the demand- and supply-side together could be an interesting research topic to promote a better understanding of liquidity commonality.

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Table 1. Descriptive Statistics

Variables	Obs.	Mean	SD	p1	p25	p50	p75	p99
Amihud	7,768,044	15.267	3.200	6.890	13.312	15.718	17.547	21.370
CUS (Amihud)	7,682,724	17.261	1.543	13.507	16.263	17.514	18.293	20.870
SUP (Amihud)	7,440,656	17.257	1.320	13.922	16.316	17.485	18.261	19.615
MKT (Amihud)	7,768,044	18.691	0.963	16.030	18.072	18.903	19.467	20.117
IND (Amihud)	7,767,522	17.863	1.885	12.080	16.944	18.105	19.121	21.116
CRSP	7,914,416	6.047	1.886	2.050	4.450	6.282	7.657	9.272
CUS (CRSP)	7,682,724	6.573	1.780	1.289	5.021	7.201	8.069	8.886
SUP (CRSP)	7,440,656	6.623	1.750	1.297	5.142	7.228	8.066	8.677
MKT (CRSP)	7,914,416	6.963	1.546	2.844	5.427	7.466	8.374	8.843
IND (CRSP)	7,913,881	6.821	1.680	2.375	5.296	7.399	8.182	9.111
VIX	8,292,500	2.961	0.360	2.306	2.671	2.972	3.193	3.906
CUSR (%)	7,682,724	0.038	1.317	-3.671	-0.575	0.071	0.680	3.630
SUPR (%)	7,440,656	0.036	1.328	-3.765	-0.568	0.074	0.673	3.661
MKTR (%)	8,296,198	0.038	1.165	-3.235	-0.480	0.065	0.597	3.234
INDR (%)	8,296,198	0.041	1.623	-4.460	-0.701	0.058	0.794	4.480
R (%)	8,296,198	0.053	3.421	-8.602	-1.148	0.000	1.157	9.560
Institutional Blockholder Ownership	8,296,198	0.148	0.154	0	0	0.118	0.246	0.611
Number of Institutional Blockholders	8,296,198	1.770	1.747	0	0	1	3	6
Analyst Coverage	8,296,198	8.456	7.922	0	2	6	13	32
Size (in millions)	8,296,198	6,865	21,958	9	263	1,186	4,204	107,930

This table reports the summary statistics for firm-day observations of major variables for the sample period of July 1997 to June 2018. *Amihud*, and *CRSP* are the negative logarithm of daily liquidity estimates proposed by Amihud (2002), and Chung and Zhang (2014), respectively. *CUS* is the customer portfolio's liquidity. *SUP* is the supplier portfolio's liquidity. *MKT* is the market portfolio's liquidity. *IND* is the industry portfolio's liquidity. *VIX* is the logarithm of Chicago Board Options Exchange Volatility Index. *CUSR*, *SUPR*, *MKTR*, and *INDR* are the daily customer, supplier, market, and industry portfolio's returns, respectively. *R* is the daily stock's returns. *Institutional Blockholder Ownership* and *Number of Institutional Blockholders* denote, respectively, institutional blockholder ownership and the number of institutional blockholders from Thomson Reuters for every quarter. Blockholders are the shareholders with ownership greater than or equal to 5%. *Analyst Coverage* is the number of analysts following a firm from the Institutional Brokers' Estimate System database for every quarter. *Size* is defined as the multiplication between monthly stock price and shares outstanding from the Center of Research in Security Prices. Following the previous research, I exclude a stock itself in creating the market and industry liquidity for the stock. All the portfolios except for the customer and supplier portfolio are value-weighted by using market capitalizations of firms on the previous month. I use the industry classifications used in the Input-Output tables by the U.S. Bureau of Economic Analysis. For the customer (supplier) portfolio, I use the trade flows among industries to weight the customer (supplier) industries and, for each industry, I use value-weighted industry portfolio. Following Menzly and Ozbas (2010), and Shahrur, Becker, and Rosenfeld (2010), when I create a customer or supplier portfolio for a stock, I exclude the industry portfolio to which the stock belongs. Obs. is the number of observations. SD is the standard deviation. p1, p25, p50, p75, and p99 denote the 1st, the 25th, the 50th, the 75th, and the 99th percentiles of the distribution, respectively.

Table 2. Effect of Customer Linkage on Liquidity

Panel A: Panel Regressions with Amihud Liquidity

Model	(A)	(B)	(C)	(D)	(E)	(F)
$dCUS_{it}$	0.543***		0.166***	0.192***	0.158***	0.151***
	(43.15)		(21.04)	(18.95)	(17.21)	(16.81)
$dMKT_{it}$		0.679***	0.529***	0.483***	0.521***	0.511***
		(48.66)	(35.22)	(26.66)	(30.71)	(31.82)
$dIND_{it}$		0.086***	0.087***	0.114***	0.108***	0.107***
		(20.03)	(18.44)	(18.49)	(17.82)	(17.71)
$dVIX_t$		-0.751***	-0.665***	-0.660***	-0.664***	-0.664***
		(-45.65)	(-38.24)	(-33.68)	(-37.96)	(-39.29)
$CUSR_{it}$	0.007***		0.006***	-0.005	0.004*	0.004*
	(3.55)		(2.71)	(-1.37)	(1.77)	(1.81)
$MKTR_t$		-0.008***	-0.011***	-0.001	-0.008**	-0.009**
		(-2.92)	(-3.21)	(-0.25)	(-2.26)	(-2.30)
$INDR_{it}$		0.001	-0.000	-0.002	-0.001	-0.001
		(0.54)	(-0.43)	(-1.14)	(-1.00)	(-0.98)
R_{it}		-0.003**	-0.003***	-0.004***	-0.003***	-0.003***
		(-2.50)	(-2.80)	(-3.02)	(-2.63)	(-2.60)
$Constant$	-0.000	0.001	0.000	0.001	0.000	0.000
	(-0.08)	(0.18)	(0.16)	(0.17)	(0.19)	(0.21)
Obs.	6,566,041	7,336,724	6,562,747	6,562,739	6,562,747	6,562,739
R-squared	0.216	0.258	0.259	0.235	0.242	0.243
Firm FE				Yes		Yes
YM FE					Yes	Yes
Industry-YM FE	Yes	Yes	Yes			
Clustering			Firm & Time			

Table 2 (continued)

Panel B: Panel Regressions with CRSP Effective Spreads

Model	(A)	(B)	(C)	(D)	(E)	(F)
$dCUS_{it}$	0.745^{***}		0.261^{***}	0.274^{***}	0.242^{***}	0.232^{***}
	(114.00)		(18.24)	(17.99)	(17.55)	(17.24)
$dMKT_{it}$		0.730^{***}	0.453^{***}	0.423^{***}	0.454^{***}	0.447^{***}
		(74.56)	(25.28)	(22.75)	(26.01)	(26.09)
$dIND_{it}$		0.073^{***}	0.064^{***}	0.080^{***}	0.083^{***}	0.082^{***}
		(13.26)	(11.84)	(11.14)	(12.68)	(12.56)
$dVIX_{t}$		-0.083^{***}	-0.122^{***}	-0.118^{***}	-0.120^{***}	-0.136^{***}
		(-7.62)	(-10.87)	(-9.89)	(-10.67)	(-12.53)
$CUSR_{it}$	-0.003^{**}		-0.001	0.007^{**}	-0.001	-0.002
	(-2.36)		(-0.47)	(2.25)	(-0.84)	(-0.88)
$MKTR_{t}$		-0.009^{***}	-0.008^{***}	-0.017^{***}	-0.007^{**}	-0.007^{**}
		(-3.33)	(-2.89)	(-3.49)	(-2.46)	(-2.54)
$INDR_{it}$		-0.001^{**}	-0.001^{*}	-0.001	-0.001	-0.001
		(-1.98)	(-1.83)	(-1.59)	(-1.57)	(-1.56)
R_{it}		0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}	0.001^{***}
		(3.65)	(3.32)	(3.70)	(3.30)	(3.26)
$Constant$	-0.000	0.000	0.000	0.000	0.000	0.000
	(-0.01)	(0.09)	(0.07)	(0.06)	(0.08)	(0.09)
Obs.	6,742,532	7,587,608	6,738,921	6,738,913	6,738,921	6,738,913
R-squared	0.582	0.601	0.594	0.573	0.586	0.588
Firm FE				Yes		Yes
YM FE					Yes	Yes
Industry-YM FE	Yes	Yes	Yes			
Clustering			Firm & Time			

Table 2 (continued)

This table reports panel regression coefficients and t-statistics in parentheses. The sample has the period from July 1997 to June 2018 at daily frequency. dx is the time difference of variable x. That is, $dx \equiv x_t - x_{t-1}$. The dependent variable is $dAmihud_{it}$ (Panel A) or $dCRSP_{it}$ (Panel B) for stock i on day t. $Amihud_{it}$, and $CRSP_{it}$ are the negative logarithm of daily liquidity estimates proposed by Amihud (2002), and Chung and Zhang (2014), respectively. CUS_{it} is the customer portfolio's liquidity for stock i on day t. MKT_{it} is the market liquidity for stock i on day t. IND_{it} is the industry liquidity for stock i on day t. VIX_t is the logarithm of Chicago Board Options Exchange Volatility Index on day t. $CUSR_{it}$ is the customer portfolio's return for stock i on day t. $MKTR_{it}$ is the market return for stock i on day t. $INDR_{it}$ is the daily industry return for stock i on day t. R_{it} is the return of stock i on day t. Following the previous research, I exclude a stock itself in creating the market and industry liquidity for the stock. All the portfolios except for the customer portfolio are value-weighted by using market capitalizations of firms on the previous month. I use the industry classifications used in the Input-Output tables by the U.S. Bureau of Economic Analysis. For the customer portfolios, I use the trade flows among industries to weight the customer industries and, for each industry, I use value-weighted industry portfolio. Following Menzly and Ozbas (2010), and Shahrur, Becker, and Rosenfeld (2010), when I create a customer portfolio for a stock, I exclude the industry portfolio to which the stock belongs. YM FE denotes time fixed effects at monthly frequency. Industry-YM FE is the interaction between of industry and time fixed effects at monthly frequency. The standard errors are clustered at the firm and daily level. The table also reports the number of observations and the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 3. Effect of Supplier Linkage on Liquidity

Panel A: Panel Regressions with Amihud Liquidity						
Model	(A)	(B)	(C)	(D)	(E)	(F)
$dSUP_{it}$	0.635***		0.235***	0.264***	0.215***	0.205***
	(56.13)		(24.07)	(21.94)	(18.49)	(17.79)
$dMKT_{it}$		0.679***	0.456***	0.405***	0.460***	0.454***
		(48.66)	(30.26)	(22.17)	(26.13)	(26.86)
$dIND_{it}$		0.086***	0.084***	0.110***	0.105***	0.104***
		(20.03)	(19.02)	(19.13)	(18.53)	(18.43)
$dVIX_t$		-0.751***	-0.668***	-0.668***	-0.668***	-0.668***
		(-45.65)	(-39.00)	(-34.73)	(-38.74)	(-40.10)
$SUPR_{it}$	0.007***		0.001	-0.010**	-0.000	0.000
	(3.70)		(0.28)	(-2.44)	(-0.05)	(0.01)
$MKTR_t$		-0.008***	-0.007*	0.004	-0.005	-0.005
		(-2.92)	(-1.88)	(0.71)	(-1.24)	(-1.29)
$INDR_{it}$		0.001	0.001	-0.001	-0.000	-0.000
		(0.54)	(0.97)	(-0.52)	(-0.11)	(-0.12)
R_{it}		-0.003**	-0.003***	-0.004***	-0.003***	-0.003***
		(-2.50)	(-2.87)	(-3.08)	(-2.70)	(-2.68)
$Constant$	-0.000	0.001	0.000	0.000	0.000	0.000
	(-0.09)	(0.18)	(0.14)	(0.15)	(0.18)	(0.19)
Obs.	6,772,731	7,336,724	6,769,235	6,769,227	6,769,235	6,769,227
R-squared	0.230	0.258	0.262	0.237	0.243	0.244
Firm FE				Yes		Yes
YM FE					Yes	Yes
Industry-YM FE	Yes	Yes	Yes			
Clustering			Firm & Time			

Table 3 (continued)

Panel B: Panel Regressions with CRSP Effective Spreads						
Model	(A)	(B)	(C)	(D)	(E)	(F)
$dSUP_{it}$	0.761***		0.391***	0.372***	0.362***	0.349***
	(119.50)		(23.28)	(19.45)	(21.32)	(21.04)
$dMKT_{it}$		0.730***	0.324***	0.326***	0.335***	0.329***
		(74.56)	(15.57)	(14.42)	(16.12)	(16.15)
$dIND_{it}$		0.073***	0.057***	0.074***	0.078***	0.077***
		(13.26)	(11.54)	(10.98)	(12.62)	(12.50)
$dVIX_t$		-0.083***	-0.131***	-0.128***	-0.129***	-0.144***
		(-7.62)	(-11.94)	(-10.91)	(-11.63)	(-13.49)
$SUPR_{it}$	-0.002		-0.000	0.009**	-0.001	-0.001
	(-1.45)		(-0.23)	(2.06)	(-0.47)	(-0.49)
$MKTR_t$		-0.009***	-0.007**	-0.019***	-0.006**	-0.006**
		(-3.33)	(-2.52)	(-3.13)	(-2.15)	(-2.25)
$INDR_{it}$		-0.001**	-0.001**	-0.001	-0.001*	-0.001*
		(-1.98)	(-2.26)	(-1.30)	(-1.82)	(-1.79)
R_{it}		0.001***	0.001***	0.001***	0.001***	0.001***
		(3.65)	(3.10)	(3.49)	(3.08)	(3.04)
$Constant$	-0.000	0.000	0.000	0.000	0.000	0.000
	(-0.03)	(0.09)	(0.06)	(0.06)	(0.07)	(0.08)
Obs.	6,950,032	7,587,608	6,946,216	6,946,208	6,946,216	6,946,208
R-squared	0.593	0.601	0.597	0.576	0.589	0.591
Firm FE				Yes		Yes
YM FE					Yes	Yes
Industry-YM FE	Yes	Yes	Yes			
Clustering			Firm & Time			

Table 3 (continued)

This table reports panel regression coefficients and t-statistics in parentheses. The sample has the period from July 1997 to June 2018 at daily frequency. dx is the time difference of variable x. That is, $dx \equiv x_t - x_{t-1}$. The dependent variable is $dAmihud_{it}$ (Panel A) or $dCRSP_{it}$ (Panel B) for stock i on day t. $Amihud_{it}$, and $CRSP_{it}$ are the negative logarithm of daily liquidity estimates proposed by Amihud (2002), and Chung and Zhang (2014), respectively. CUS_{it} is the supplier portfolio's liquidity for stock i on day t. MKT_{it} is the market liquidity for stock i on day t. IND_{it} is the industry liquidity for stock i on day t. VIX_t is the logarithm of Chicago Board Options Exchange Volatility Index on day t. $CUSR_{it}$ is the supplier portfolio's return for stock i on day t. $MKTR_{it}$ is the market return for stock i on day t. $INDR_{it}$ is the daily industry return for stock i on day t. $R_{i,t}$ is the return of stock i on day t. Following the previous research, I exclude a stock itself in creating the market and industry liquidity for the stock. All the portfolios except for the supplier portfolio are value-weighted by using market capitalizations of firms on the previous month. I use the industry classifications used in the Input-Output tables by the U.S. Bureau of Economic Analysis. For the supplier portfolios, I use the trade flows among industries to weight the supplier industries and, for each industry, I use value-weighted industry portfolio. Following Menzly and Ozbas (2010), and Shahrur, Becker, and Rosenfeld (2010), when I create a supplier portfolio for a stock, I exclude the industry portfolio to which the stock belongs. YM FE denotes time fixed effects at monthly frequency. Industry-YM FE is the interaction between of industry and time fixed effects at monthly frequency. The standard errors are clustered at the firm and daily level. The table also reports the number of observations and the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 4. The Determinants of Customer Liquidity Commonality

Panel A: Panel Regressions of Customer Liquidity Commonality based on Amihud Measure

Model	(A)	(B)	(C)	(D)	(E)
$Analyst\ Coverage_{iy}$	0.030***		0.041***		0.038***
	(4.93)		(5.49)		(4.98)
$Blockholder\ Ownership_{iy}$		-0.007*		-0.010***	-0.007**
		(-1.89)		(-3.08)	(-2.41)
$Market\ Return_{y}$			-0.016	-0.012	-0.015
			(-0.80)	(-0.52)	(-0.65)
$Market\ Size_{y}$			0.025*	0.024	0.020
			(1.80)	(1.56)	(1.36)
VIX_{y}			0.011	0.016	0.015
			(0.80)	(1.05)	(1.00)
$Return_{iy}$			0.005	0.006	0.006
			(1.35)	(1.29)	(1.31)
$Size_{iy}$			-0.014***	0.001	-0.015***
			(-4.13)	(0.31)	(-3.82)
B/M_{iy}			-0.005	-0.022**	-0.014
			(-1.24)	(-2.37)	(-1.67)
AG_{iy}			-0.005**	-0.006	-0.004
			(-2.32)	(-0.86)	(-0.60)
$Leverage_{iy}$			-0.000	0.003	0.000
			(-0.07)	(0.56)	(0.08)
I/A_{iy}			-0.004	-0.019**	-0.018**
			(-1.27)	(-2.43)	(-2.37)
$R\&D_{iy}$			-0.010**	-0.023***	-0.025***
			(-2.49)	(-2.94)	(-3.03)
ROE_{iy}			0.002	0.014**	0.012*
			(0.56)	(2.15)	(1.87)
Constant	0.150***	0.174***	0.152***	0.171***	0.170***
	(97.98)	(90.08)	(8.62)	(8.51)	(8.83)
Obs.	29,034	19,334	27,427	18,453	18,453
R-squared	0.140	0.161	0.086	0.094	0.103
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes			
Clustering			Firm & Year		

Table 4 (continued)

Panel B: Panel Regressions of Customer Liquidity Commonality based on CRSP Effective Spreads					
Model	(A)	(B)	(C)	(D)	(E)
$Analyst\ Coverage_{iy}$	0.018**		0.020***		0.014**
	(2.60)		(2.98)		(2.17)
$Blockholder\ Ownership_{iy}$		-0.002		-0.003	-0.002
		(-0.39)		(-0.76)	(-0.47)
$Market\ Return_{y}$			-0.029**	-0.033***	-0.035***
			(-2.62)	(-3.12)	(-3.09)
$Market\ Size_{y}$			0.010	0.019***	0.017**
			(1.50)	(2.91)	(2.76)
VIX_{y}			0.001	0.001	0.001
			(0.15)	(0.18)	(0.10)
$Return_{iy}$			0.001	0.004	0.004
			(0.18)	(0.78)	(0.79)
$Size_{iy}$			-0.008*	-0.007*	-0.013***
			(-2.05)	(-1.77)	(-3.89)
B/M_{iy}			-0.011***	-0.015**	-0.013**
			(-3.03)	(-2.33)	(-2.29)
AG_{iy}			0.007*	0.009	0.009
			(1.82)	(1.54)	(1.65)
$Leverage_{iy}$			-0.001	-0.000	-0.001
			(-0.45)	(-0.08)	(-0.24)
I/A_{iy}			-0.006**	-0.008*	-0.008*
			(-2.77)	(-2.07)	(-2.01)
$R\&D_{iy}$			-0.004	-0.010	-0.010
			(-1.39)	(-1.17)	(-1.25)
ROE_{iy}			0.004**	0.001	0.002
			(2.26)	(0.83)	(0.83)
Constant	0.098***	0.103***	0.098***	0.100***	0.099***
	(97.07)	(82.29)	(12.68)	(12.26)	(12.31)
Obs.	29,226	19,354	27,535	18,454	18,454
R-squared	0.027	0.031	0.023	0.026	0.026
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes			
Clustering			Firm & Year		

Table 4 (continued)

This table reports panel regression coefficients and t-statistics in parentheses. The sample has the period from July 1997 to June 2018 and yearly frequency. Panel A is based on Amihud (2002) liquidity measure. Panel B is based on the effective spreads proposed by Chung and Zhang (2014). The dependent variable is a stock's liquidity sensitivity to its customer portfolio's liquidity, $\beta_{cus,iy}$, obtained from running the following time-series regression for each firm i and year y:

$$dLIQ_{it} = \beta_{iy} + \beta_{cus,iy} dCUS_{it} + \beta_{mkt,iy} dMKT_{it} + \beta_{ind,iy} dIND_{it} + \beta_{vix,iy} dVIX_t + \beta_{cusr,iy} CUSR_{it} + \beta_{mktr,iy} MKTR_t + \beta_{indr,iy} INDR_{it} + \beta_{r,iy} R_{it} + \gamma_m + \epsilon_{i,t},$$

where γ_m is the time fixed effects at monthly frequency; the rest variables are defined in Table 2. For independent variables, *Analyst Coverage* is the number of analysts following a firm from the Institutional Brokers' Estimate System database for every quarter. *Blcokholder Ownership* is defined as institutional blockholder ownership divided by the number of institutional blockholders from Thomson Reuters for every quarter. Blockholders are the shareholders with ownership greater than or equal to 5%. *Return* is the daily stock return. *Market Return* is the daily value-weighted stock market return. *Market Size* is the sum of daily market capitalizations of stocks in the firm. *Size* is defined as the market capitalization at the end of each June. *B/M* is the book-to-market ratio defined as book equity of fiscal year ending in year t-1 to market capitalization at the end of year t-1. *AG* is the asset growth calculated as total asset in fiscal year t-1 divided by total asset in fiscal year t-2. *Leverage* is defined as debt in fiscal year t-1 divided by total asset in fiscal year t-2. *I/A* is the investment rate, which is the ratio of capital expenditure in fiscal year t-1 over lagged total asset. *R&D* is the R&D expenses scaled by total asset in fiscal year t-1. *ROE* is the return on equity defined as income before extraordinary items plus depreciation expenses in fiscal year t-1 scaled by book equity in fiscal year t-2. All the quarterly-defined independent variables are averaged out for each stock and fiscal year and standardized with zero mean and unit standard deviation. The standard errors are clustered by firm and year. The table also reports the number of observations and the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5. The Determinants of Supplier Liquidity Commonality

Panel A: Panel Regressions of Supplier Liquidity Commonality based on Amihud Measure

Model	(A)	(B)	(C)	(D)	(E)
$Analyst\ Coverage_{iy}$	0.035***		0.043***		0.037***
	(5.10)		(5.71)		(4.61)
$Blockholder\ Ownership_{iy}$		-0.008**		-0.012***	-0.010***
		(-2.67)		(-3.57)	(-3.05)
$Market\ Return_{y}$			-0.016	-0.014	-0.016
			(-0.80)	(-0.60)	(-0.73)
$Market\ Size_{y}$			0.039***	0.040***	0.037**
			(3.17)	(3.00)	(2.79)
VIX_{y}			0.019	0.021	0.019
			(1.37)	(1.37)	(1.34)
$Return_{iy}$			0.008	0.007	0.006
			(1.50)	(1.02)	(1.03)
$Size_{iy}$			-0.008**	0.011**	-0.004
			(-2.19)	(2.77)	(-1.17)
B/M_{iy}			-0.007	-0.021**	-0.014
			(-1.65)	(-2.18)	(-1.62)
AG_{iy}			-0.003	-0.002	-0.000
			(-1.17)	(-0.29)	(-0.03)
$Leverage_{iy}$			-0.006	-0.005	-0.007
			(-1.71)	(-0.95)	(-1.38)
I/A_{iy}			0.000	-0.010*	-0.009
			(0.05)	(-1.78)	(-1.62)
$R\&D_{iy}$			-0.010*	-0.034***	-0.035***
			(-1.96)	(-5.05)	(-5.13)
ROE_{iy}			-0.001	0.011	0.009
			(-0.54)	(1.45)	(1.12)
Constant	0.158***	0.181***	0.161***	0.177***	0.175***
	(95.10)	(87.58)	(9.26)	(8.76)	(9.07)
Obs.	29,034	19,365	27,425	18,482	18,482
R-squared	0.131	0.147	0.083	0.089	0.097
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes			
Clustering			Firm & Year		

Table 5 (continued)

Panel B: Panel Regressions of Supplier Liquidity Commonality based on CRSP Effective Spreads					
Model	(A)	(B)	(C)	(D)	(E)
$Analyst\ Coverage_{iy}$	0.012*		0.011		0.004
	(1.76)		(1.56)		(0.52)
$Blockholder\ Ownership_{iy}$		-0.004**		-0.005**	-0.004**
		(-2.27)		(-2.32)	(-2.17)
$Market\ Return_{y}$			-0.025**	-0.032**	-0.032**
			(-2.31)	(-2.82)	(-2.78)
$Market\ Size_{y}$			0.017	0.023*	0.023*
			(1.43)	(1.79)	(1.73)
VIX_{y}			0.004	0.001	0.001
			(0.49)	(0.14)	(0.12)
$Return_{iy}$			-0.002	0.002	0.002
			(-0.45)	(0.37)	(0.37)
$Size_{iy}$			-0.005	-0.002	-0.004
			(-1.51)	(-0.51)	(-0.91)
B/M_{iy}			-0.013***	-0.018**	-0.017**
			(-2.96)	(-2.81)	(-2.78)
AG_{iy}			0.001	-0.001	-0.000
			(0.17)	(-0.10)	(-0.08)
$Leverage_{iy}$			0.004	0.002	0.002
			(1.16)	(0.40)	(0.35)
I/A_{iy}			0.001	0.002	0.002
			(0.15)	(0.12)	(0.13)
$R\&D_{iy}$			-0.009*	-0.020**	-0.020**
			(-1.96)	(-2.18)	(-2.19)
ROE_{iy}			0.004***	0.013	0.013
			(2.91)	(0.78)	(0.76)
Constant	0.103***	0.113***	0.103***	0.109***	0.109***
	(91.30)	(84.06)	(11.86)	(11.61)	(11.71)
Obs.	29,226	19,321	27,535	18,432	18,482
R-squared	0.024	0.030	0.018	0.023	0.023
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes			
Clustering			Firm & Year		

Table 5 (continued)

This table reports panel regression coefficients and t-statistics in parentheses. The sample has the period from July 1997 to June 2018 and yearly frequency. Panel A is based on Amihud (2002) liquidity measure. Panel B is based on the effective spreads proposed by Chung and Zhang (2014). The dependent variable is a stock's liquidity sensitivity to its supplier portfolio's liquidity, $\beta_{sup,iy}$, obtained from running the following time-series regression for each firm i and year y:

$$dLIQ_{it} = \beta_{iy} + \beta_{sup,iy} dSUP_{it} + \beta_{mkt,iy} dMKT_{it} + \beta_{ind,iy} dIND_{it} + \beta_{vix,iy} dVIX_t + \beta_{supr,iy} SUPR_{it} + \beta_{mktr,iy} MKTR_t + \beta_{indr,iy} INDR_{it} + \beta_{r,iy} R_{it} + \gamma_m + \epsilon_{i,t},$$

where γ_m is the time fixed effects at monthly frequency; the rest variables are defined in Table 3. For independent variables, *Analyst Coverage* is the number of analysts following a firm from the Institutional Brokers' Estimate System database for every quarter. *Blcokholder Ownership* is defined as institutional blockholder ownership divided by the number of institutional blockholders from Thomson Reuters for every quarter. Blockholders are the shareholders with ownership greater than or equal to 5%. *Return* is the daily stock return. *Market Return* is the daily value-weighted stock market return. *Market Size* is the sum of daily market capitalizations of stocks in the firm. *Size* is defined as the market capitalization at the end of each June. *B/M* is the book-to-market ratio defined as book equity of fiscal year ending in year t-1 to market capitalization at the end of year t-1. *AG* is the asset growth calculated as total asset in fiscal year t-1 divided by total asset in fiscal year t-2. *Leverage* is defined as debt in fiscal year t-1 divided by total asset in fiscal year t-2. *I/A* is the investment rate, which is the ratio of capital expenditure in fiscal year t-1 over lagged total asset. *R&D* is the R&D expenses scaled by total asset in fiscal year t-1. *ROE* is the return on equity defined as income before extraordinary items plus depreciation expenses in fiscal year t-1 scaled by book equity in fiscal year t-2. All the quarterly-defined independent variables are averaged out for each stock and fiscal year and standardized with zero mean and unit standard deviation. The standard errors are clustered by firm and year. The table also reports the number of observations and the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 6. Firm Characteristics of Liquidity Commonality-Sorted Portfolios

Panel A: Customer Liquidity Commonality

	Amihud Liquidity					CRSP Effective Spreads				
	L	2	3	4	H	L	2	3	4	H
Sensitivity	-0.26	0.04	0.19	0.39	0.84	-0.21	0.15	0.40	0.70	1.22
Log(Size)	13.66	14.55	14.51	14.21	13.72	13.74	14.01	14.08	14.11	14.17
Log(B/M)	-0.56	-0.68	-0.68	-0.64	-0.63	-0.61	-0.62	-0.60	-0.61	-0.67
AG	1.10	1.12	1.11	1.12	1.16	1.15	1.11	1.11	1.11	1.12
Leverage	0.27	0.28	0.28	0.28	0.30	0.29	0.28	0.28	0.27	0.28
I/A	0.06	0.08	0.06	0.05	0.05	0.09	0.07	0.05	0.05	0.05
R&D	0.02	0.01	0.02	0.02	0.02	0.02	0.01	0.02	0.02	0.01
ROE	0.06	0.11	0.12	0.14	0.13	0.08	0.09	0.11	0.15	0.13
N	253	256	256	258	257	254	256	258	259	258

Panel B: Supplier Liquidity Commonality

	Amihud Liquidity					CRSP Effective Spreads				
	L	2	3	4	H	L	2	3	4	H
Sensitivity	-0.24	0.07	0.24	0.43	0.84	-0.27	0.14	0.39	0.67	1.14
Log(Size)	13.82	14.60	14.44	14.18	13.61	13.73	14.04	14.04	14.08	14.22
Log(B/M)	-0.59	-0.67	-0.65	-0.65	-0.63	-0.58	-0.58	-0.56	-0.65	-0.74
AG	1.13	1.11	1.11	1.11	1.16	1.13	1.11	1.11	1.12	1.14
Leverage	0.27	0.28	0.28	0.28	0.28	0.29	0.30	0.27	0.27	0.26
I/A	0.06	0.06	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.07
R&D	0.03	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0.01	0.02
ROE	0.07	0.13	0.13	0.12	0.12	0.06	0.10	0.13	0.11	0.14
N	253	256	257	257	257	253	257	258	259	258

This table reports the time-series averages of yearly firm characteristics for liquidity commonality-sorted portfolios. The sample period is July 1998 to June 2018. Panel A has the results with five portfolios sorted by customer liquidity commonality and Panel B contains the estimates with five portfolios sorted by supplier liquidity commonality. Customer (supplier) liquidity commonality is estimated from the regression in Table 4 (Table 5) for each firm i and year y. Estimates for customer or supplier liquidity commonality in fiscal year y are used to sort stocks and create portfolios in the following fiscal year $y + 1$. *Sensitivity* is the estimates for customer or supplier liquidity commonality in the previous fiscal year. *N* is the number of firms in each portfolio. The rest of variables in this table are also defined in Table 4 and 5.

Table 7. Abnormal Returns of Customer Liquidity Commonality-Sorted Portfolios

Panel A: Estimated Alphas from Various Models

	Amihud Liquidity						CRSP Effective Spreads					
	(L)	(2)	(3)	(4)	(H)	(H-L)	(L)	(2)	(3)	(4)	(H)	(H-L)
$E[R]$	0.600	0.701*	0.940***	0.927***	1.189***	0.590***	0.652*	0.819**	0.866**	0.983***	1.076***	0.424***
	(1.49)	(1.96)	(2.78)	(2.81)	(3.41)	(3.68)	(1.82)	(2.26)	(2.42)	(2.77)	(3.37)	(3.39)
α_{CAPM}	-0.035	0.154	0.420**	0.425**	0.681***	0.716***	0.115	0.273	0.317*	0.438**	0.592***	0.478***
	(-0.18)	(0.78)	(2.25)	(2.28)	(3.11)	(4.58)	(0.55)	(1.29)	(1.67)	(2.31)	(3.16)	(3.77)
α_{FF3}	-0.216	-0.015	0.255**	0.252**	0.474***	0.691***	-0.063	0.093	0.126	0.255**	0.423***	0.486***
	(-1.51)	(-0.12)	(2.21)	(2.32)	(3.34)	(4.57)	(-0.42)	(0.67)	(1.23)	(2.26)	(3.40)	(3.84)
α_{C4}	-0.074	0.078	0.333***	0.324***	0.558***	0.632***	0.028	0.221*	0.219**	0.343***	0.481***	0.453***
	(-0.56)	(0.66)	(3.09)	(3.24)	(4.01)	(4.18)	(0.19)	(1.75)	(2.17)	(3.33)	(3.93)	(3.50)
α_{FF5}	-0.168	-0.150	0.088	0.059	0.223*	0.390***	-0.131	-0.011	-0.026	0.068	0.180*	0.312**
	(-1.05)	(-1.14)	(0.79)	(0.55)	(1.67)	(2.65)	(-0.80)	(-0.08)	(-0.27)	(0.62)	(1.66)	(2.45)

Table 7 (continued)

Panel B: Full Model	Amihud Liquidity						CRSP Effective Spreads					
	(L)	(2)	(3)	(4)	(H)	(H-L)	(L)	(2)	(3)	(4)	(H)	(H-L)
α	-0.115	-0.122	0.097	0.082	0.232*	0.347**	-0.128	0.021	0.011	0.100	0.192**	0.319**
	(-0.83)	(-1.06)	(1.06)	(0.93)	(1.96)	(2.38)	(-0.83)	(0.18)	(0.13)	(1.09)	(1.99)	(2.33)
$R_m - R_f$	1.064***	1.058***	1.026***	1.005***	0.997***	-0.067	0.980***	1.003***	1.053***	1.070***	0.985***	0.005
	(24.80)	(31.63)	(31.79)	(37.43)	(27.19)	(-1.59)	(21.67)	(32.62)	(38.16)	(35.05)	(29.23)	(0.13)
SMB	0.574***	0.472***	0.443***	0.514***	0.715***	0.141**	0.496***	0.533***	0.586***	0.544***	0.562***	0.065
	(11.31)	(8.32)	(10.32)	(13.49)	(13.96)	(2.50)	(9.00)	(11.76)	(10.59)	(12.26)	(11.55)	(1.36)
HML	0.261***	0.381***	0.359***	0.337***	0.257***	-0.004	0.380***	0.375***	0.342***	0.307***	0.214***	-0.166**
	(3.59)	(6.17)	(6.64)	(6.85)	(4.24)	(-0.07)	(4.06)	(5.53)	(7.37)	(5.88)	(3.82)	(-2.28)
RMW	0.005	0.306***	0.320***	0.377***	0.498***	0.493***	0.178***	0.297***	0.328***	0.350***	0.436***	0.258***
	(0.07)	(4.73)	(7.12)	(7.59)	(8.34)	(8.20)	(2.68)	(4.66)	(4.98)	(6.82)	(8.04)	(4.88)
CMA	0.030	0.067	0.138**	0.123*	0.119*	0.089	0.043	0.013	0.096	0.185***	0.177***	0.134
	(0.37)	(0.81)	(2.13)	(1.92)	(1.73)	(1.14)	(0.42)	(0.16)	(1.47)	(2.95)	(3.03)	(1.62)
UMD	-0.266***	-0.191***	-0.169***	-0.158***	-0.187***	0.078**	-0.184***	-0.255***	-0.192***	-0.187***	-0.137***	0.047**
	(-6.79)	(-7.27)	(-6.45)	(-6.74)	(-5.52)	(2.01)	(-5.66)	(-8.50)	(-4.73)	(-8.46)	(-5.68)	(2.09)
LIQ	0.077*	0.082***	0.113***	0.066**	0.127***	0.051	0.140***	0.122***	0.059**	0.069**	0.081**	-0.058
	(1.87)	(2.81)	(4.46)	(2.30)	(3.39)	(1.28)	(2.68)	(3.45)	(2.14)	(2.50)	(2.57)	(-1.19)
Obs.	240	240	240	240	240	240	240	240	240	240	240	240

This table reports the estimated alphas for five portfolios sorted on customer liquidity commonality. The sample period is July 1998 to June 2018. (L) is the lowest quintile portfolio based on the estimates of customer liquidity commonality in the previous fiscal year. (H) is the highest quintile portfolio based on the estimates of customer liquidity commonality in the previous fiscal year. Customer liquidity commonality is estimated from the regression in Table 4 for each firm i and year y. Panel A contains estimated alphas from various model and Panel B reports the estimates for alphas and betas for the full model that include all the factors used in Panel A. $E[R]$ is the time-series average of excess returns. α_{CAPM}, α_{FF3}, α_{C4}, and α_{FF5} are obtained from the market, Fama-French (1993) three factor, Carhart (1997) four factor, and Fama-French (2015) five factor models, respectively. For fair comparisons, I download and use the Fama-French five factors and the Carhart (1997) momentum factor from Kenneth French's website. LIQ is the liquidity risk factor by Pástor and Stambaugh (2003) and downloaded from Lubos Pastor's website. t-statistics are calculated by using the Newey-West (1987) standard error estimates. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Table 8. Abnormal Returns of Supplier Liquidity Commonality-Sorted Portfolios

Panel A: Estimated Alphas from Various Models

	Amihud Liquidity						CRSP Effective Spreads					
	(L)	(2)	(3)	(4)	(H)	(H-L)	(L)	(2)	(3)	(4)	(H)	(H-L)
$E[R]$	0.537	0.820**	0.880***	0.929***	1.197***	0.660***	0.650*	0.865**	0.904***	0.967***	1.012***	0.361***
	(1.39)	(2.46)	(2.62)	(2.63)	(3.26)	(4.00)	(1.91)	(2.57)	(2.62)	(2.62)	(2.87)	(3.41)
α_{CAPM}	-0.076	0.295*	0.364*	0.401*	0.667***	0.743***	0.131	0.350*	0.372*	0.405**	0.479**	0.347***
	(-0.42)	(1.74)	(1.89)	(1.92)	(2.80)	(4.11)	(0.68)	(1.85)	(1.95)	(2.00)	(2.33)	(3.14)
α_{FF3}	-0.229	0.147	0.199*	0.202*	0.438***	0.668***	-0.033	0.183	0.195*	0.206*	0.287**	0.320***
	(-1.61)	(1.34)	(1.74)	(1.66)	(2.95)	(4.06)	(-0.24)	(1.59)	(1.78)	(1.76)	(2.11)	(2.84)
α_{C4}	-0.085	0.239**	0.267**	0.288**	0.519***	0.605***	0.070	0.281**	0.277***	0.301***	0.365***	0.295***
	(-0.65)	(2.38)	(2.43)	(2.51)	(3.64)	(3.73)	(0.54)	(2.55)	(2.74)	(2.71)	(2.79)	(2.60)
α_{FF5}	-0.218	0.028	0.014	0.004	0.229	0.447***	-0.116	0.049	0.031	0.046	0.071	0.187*
	(-1.45)	(0.27)	(0.13)	(0.03)	(1.50)	(2.79)	(-0.78)	(0.42)	(0.29)	(0.39)	(0.57)	(1.73)

Table 8 (continued)

Panel B: Full Model

	Amihud Liquidity						CRSP Effective Spreads					
	(L)	(2)	(3)	(4)	(H)	(H-L)	(L)	(2)	(3)	(4)	(H)	(H-L)
α	-0.161	0.064	0.032	0.020	0.225*	0.386**	-0.098	0.082	0.053	0.083	0.076	0.174
	(-1.28)	(0.75)	(0.32)	(0.20)	(1.70)	(2.43)	(-0.74)	(0.82)	(0.63)	(0.81)	(0.72)	(1.61)
$R_m - R_f$	1.054***	1.009***	1.039***	1.034***	1.015***	-0.039	0.949***	0.985***	1.037***	1.082***	1.038***	0.089***
	(24.70)	(34.47)	(31.57)	(33.08)	(27.68)	(-0.88)	(23.57)	(32.38)	(38.51)	(31.69)	(28.71)	(2.87)
SMB	0.488***	0.423***	0.452***	0.609***	0.740***	0.251***	0.463***	0.491***	0.520***	0.601***	0.645***	0.182***
	(7.69)	(8.38)	(11.70)	(14.96)	(15.48)	(3.69)	(10.91)	(10.27)	(12.13)	(11.82)	(11.17)	(3.73)
HML	0.186***	0.299***	0.348***	0.389***	0.376***	0.189***	0.275***	0.334***	0.352***	0.386***	0.267***	-0.008
	(2.65)	(5.23)	(6.01)	(8.38)	(5.61)	(3.08)	(3.54)	(6.02)	(6.76)	(6.97)	(4.40)	(-0.15)
RMW	0.054	0.262***	0.342***	0.419***	0.434***	0.380***	0.167***	0.302***	0.338***	0.350***	0.434***	0.267***
	(0.72)	(5.02)	(6.47)	(8.39)	(6.77)	(5.36)	(3.69)	(4.49)	(6.55)	(5.19)	(6.88)	(5.30)
CMA	0.085	0.096	0.155**	0.070	0.067	-0.017	0.159*	0.082	0.099	0.084	0.095	-0.064
	(1.03)	(1.34)	(2.32)	(1.10)	(0.83)	(-0.22)	(1.94)	(1.12)	(1.50)	(1.27)	(1.25)	(-0.96)
UMD	-0.272***	-0.187***	-0.150***	-0.185***	-0.179***	0.093**	-0.208***	-0.201***	-0.173***	-0.197***	-0.173***	0.035
	(-6.53)	(-5.87)	(-5.89)	(-6.54)	(-6.98)	(2.09)	(-7.56)	(-5.74)	(-7.30)	(-5.40)	(-8.10)	(1.49)
LIQ	0.071**	0.056**	0.077**	0.107***	0.155***	0.083**	0.121***	0.076**	0.084***	0.064**	0.127***	0.006
	(2.04)	(2.34)	(2.47)	(3.63)	(3.80)	(2.34)	(2.93)	(2.52)	(2.92)	(2.22)	(3.74)	(0.18)
Obs.	240	240	240	240	240	240	240	240	240	240	240	240

This table reports the estimated alphas for five portfolios sorted on supplier liquidity commonality. The sample period is July 1998 to June 2018. (L) is the lowest quintile portfolio based on the estimates of supplier liquidity commonality in the previous fiscal year. (H) is the highest quintile portfolio based on the estimates of supplier liquidity commonality in the previous fiscal year. Supplier liquidity commonality is estimated from the regression in Table 5 for each firm i and year y. Panel A contains estimated alphas from various model and Panel B reports the estimates for alphas and betas for the full model that include all the factors used in Panel A. $E[R]$ is the time-series average of excess returns. α_{CAPM}, α_{FF3}, α_{C4}, and α_{FF5} are obtained from the market, Fama-French (1993) three factor, Carhart (1997) four factor, and Fama-French (2015) five factor models, respectively. For fair comparisons, I download and use the Fama-French five factors and the Carhart (1997) momentum factor from Kenneth French's website. LIQ is the liquidity risk factor by Pástor and Stambaugh (2003) and downloaded from Lubos Pastor's website. t-statistics are calculated by using the Newey-West (1987) standard error estimates. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Table 9. Fama-MacBeth Regressions with Firm Characteristics

	Customer Liquidity Commonality				Supplier Liquidity Commonality			
	Amihud Liquidity		CRSP Effective Spreads		Amihud Liquidity		CRSP Effective Spreads	
	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)
Sensitivity	0.232***	0.230***	0.167***	0.193***	0.233***	0.232***	0.162***	0.181***
	(3.51)	(3.65)	(3.68)	(4.93)	(3.20)	(3.29)	(4.21)	(4.64)
Log(Size)		-0.104		-0.125		-0.099		-0.125
		(-1.01)		(-1.32)		(-0.96)		(-1.30)
Log(B/M)		0.086		0.082		0.079		0.087
		(1.26)		(1.19)		(1.15)		(1.25)
AG		-0.177		-0.156		-0.179		-0.164
		(-1.49)		(-1.29)		(-1.50)		(-1.35)
Leverage		-0.028		-0.010		0.001		0.013
		(-0.37)		(-0.13)		(0.01)		(0.17)
I/A		0.063		0.100		0.023		0.051
		(0.38)		(0.61)		(0.14)		(0.31)
R&D		0.145		0.098		0.156		0.102
		(1.47)		(0.87)		(1.58)		(0.91)
ROE		-0.049		-0.018		-0.095		-0.027
		(-0.15)		(-0.05)		(-0.29)		(-0.07)
Constant	0.853**	0.809**	0.882**	0.813**	0.857**	0.810**	0.888**	0.814**
	(2.25)	(2.11)	(2.34)	(2.14)	(2.26)	(2.12)	(2.36)	(2.15)
Obs.	240	240	240	240	240	240	240	240

This table reports the results of Fama-MacBeth (1973) regressions of monthly stock excess returns against their sensitivity to customer or supplier liquidity and other firm characteristics. The sample ranges from July 1998 to June 2018. *Sensitivity* of stock i and year y is the estimate for customer (supplier) liquidity commonality obtained from the regression in Table 4 (Table 5) for each firm i and year $y-1$. The rest of the variables in this table are identically defined as in Table 4 and 5 and normalized to mean zero and one standard deviation. t-statistics are calculated by using the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard error estimates. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Table 10. Panel Regressions with Firm Characteristics

	Customer		Supplier	
	Amihud	CRSP	Amihud	CRSP
Model	(A)	(B)	(C)	(D)
Sensitivity	0.273***	0.162***	0.270***	0.151***
	(5.46)	(4.42)	(5.02)	(3.65)
Log(Size)	-0.118	0.104	-0.110	-0.131
	(-1.24)	(1.09)	(-1.15)	(-1.49)
Log(B/M)	0.104	0.030*	0.101	0.096
	(1.47)	(1.66)	(1.42)	(1.36)
AG	-0.121	-0.104	-0.118	-0.106
	(-1.54)	(-1.35)	(-1.47)	(-1.37)
Leverage	-0.055	-0.035	-0.039	-0.011
	(-0.84)	(-0.18)	(-0.59)	(-0.16)
I/A	-0.061	-0.022	-0.099	-0.076
	(-0.31)	(-0.33)	(-0.51)	(-0.39)
R&D	0.085	-0.135	0.092	0.105
	(0.98)	(-1.55)	(1.06)	(1.10)
ROE	0.038*	0.090	0.039*	0.029*
	(1.69)	(1.29)	(1.71)	(1.66)
Constant	0.823***	0.834***	0.824***	0.832***
	(77.37)	(116.55)	(77.46)	(115.08)
Obs.	288,779	287,604	288,779	287,604
R-squared	0.158	0.155	0.158	0.155
YM FE	Yes	Yes	Yes	Yes
Clustering	Firm & Month			

This table reports the results of panel regressions of monthly stock excess returns against their sensitivity to customer or supplier liquidity and other firm characteristics. The sample ranges from July 1998 to June 2018. *Sensitivity* of stock i and year y is the estimate for customer (supplier) liquidity commonality obtained from the regression in Table 4 (Table 5) for each firm i and year $y-1$. The rest of the variables in this table are identically defined as in Table 4 and 5 and normalized to mean zero and one standard deviation. The standard errors are clustered at the firm and monthly level. The table also reports the number of observations and the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 11. Cross Sectional Regressions with Test Portfolios

Panel A: Cross Sectional Regressions with Fama-French 48 Industries

			Amihud Liquidity				CRSP Effective Spreads			
Model	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
$\beta_{CLC,i}$			0.392***	0.319*			0.146	0.287		
			(2.72)	(1.84)			(0.75)	(1.68)		
$\beta_{SLC,i}$					0.358***	0.335**			0.537***	0.494***
					(2.78)	(2.08)			(3.91)	(3.13)
$\beta_{R_m-R_f,i}$	0.258	0.320	0.298*	0.345	0.330*	0.378	0.282	0.278	0.192	0.243
	(1.27)	(1.35)	(1.76)	(1.59)	(1.87)	(1.64)	(1.52)	(1.26)	(1.27)	(1.14)
$\beta_{SMB,i}$	-0.041	-0.086	-0.094	-0.115	-0.185	-0.169	-0.010	-0.192	-0.418**	-0.390**
	(-0.25)	(-0.61)	(-0.60)	(-0.83)	(-1.38)	(-1.19)	(-0.05)	(-1.36)	(-2.61)	(-2.22)
$\beta_{HML,i}$	-0.056	-0.182*	-0.191*	-0.190*	-0.275**	-0.262**	-0.203	-0.280**	-0.436***	-0.407***
	(-0.39)	(-1.81)	(-1.76)	(-1.80)	(-2.63)	(-2.59)	(-1.58)	(-2.62)	(-3.14)	(-2.97)
$\beta_{RMW,i}$	0.069	0.221*	0.089	0.156	0.204	0.214*	0.118	0.192	0.296**	0.305**
	(0.40)	(1.83)	(0.61)	(1.17)	(1.67)	(1.74)	(0.85)	(1.63)	(2.60)	(2.62)
$\beta_{CMA,i}$	0.108	-0.015	0.010	-0.025	-0.100	-0.096	0.074	-0.049	-0.089	-0.095
	(0.52)	(-0.09)	(0.06)	(-0.15)	(-0.56)	(-0.52)	(0.36)	(-0.28)	(-0.56)	(-0.58)
$\beta_{UMD,i}$		0.458		0.358		0.316		0.475		0.356
		(0.94)		(0.77)		(0.69)		(0.99)		(0.82)
$\beta_{LIQ,i}$		0.410***		0.302		0.241		0.477***		0.265*
		(2.80)		(1.54)		(1.10)		(2.94)		(1.76)
α_i	0.384*	0.324	0.301	0.279	0.274	0.241	0.332	0.332	0.380**	0.346
	(1.76)	(1.34)	(1.63)	(1.25)	(1.40)	(1.01)	(1.67)	(1.52)	(2.25)	(1.62)
Obs.	48	48	48	48	48	48	48	48	48	48
R-Squared	0.051	0.220	0.232	0.270	0.264	0.270	0.102	0.277	0.341	0.351

Table 11 (continued)

Panel B: Cross Sectional Regressions with Fama-French 75 Portfolios (SIZE – B/M, SIZE – OP, and SIZE - INV)

			Amihud Liquidity				CRSP Effective Spreads			
Model	(A)	(B)	(C)	(D)	(E)	(F)	(G)	(H)	(I)	(J)
$\beta_{CLC,i}$			0.294	0.294			0.406**	0.376**		
			(1.26)	(1.21)			(2.61)	(2.47)		
$\beta_{SLC,i}$					0.339*	0.311**			0.426***	0.493***
					(1.99)	(2.00)			(2.79)	(2.99)
$\beta_{R_m-R_f,i}$	0.009	0.287	-0.096	0.251	-0.154	0.229	-0.208	0.172	-0.362	-0.012
	(0.05)	(1.32)	(-0.52)	(1.04)	(-0.77)	(0.95)	(-1.03)	(0.66)	(-1.55)	(-0.04)
$\beta_{SMB,i}$	0.332***	0.334***	0.330***	0.334***	0.334***	0.336***	0.337***	0.339***	0.338***	0.341***
	(8.79)	(9.27)	(8.82)	(9.29)	(9.13)	(9.56)	(9.04)	(9.60)	(9.07)	(9.64)
$\beta_{HML,i}$	0.035	0.088	0.030	0.089	0.037	0.090	0.040	0.092	0.047	0.096
	(0.40)	(1.04)	(0.36)	(1.09)	(0.43)	(1.06)	(0.47)	(1.08)	(0.59)	(1.22)
$\beta_{RMW,i}$	0.248***	0.225***	0.243***	0.221***	0.229***	0.217***	0.215***	0.205***	0.214***	0.201***
	(4.42)	(4.15)	(3.93)	(3.83)	(4.08)	(3.86)	(3.56)	(3.40)	(3.52)	(3.36)
$\beta_{CMA,i}$	0.279***	0.270***	0.280***	0.271***	0.278***	0.272***	0.275***	0.269***	0.268***	0.270***
	(3.94)	(4.29)	(3.87)	(4.30)	(3.76)	(4.23)	(3.55)	(4.02)	(3.52)	(4.09)
$\beta_{UMD,i}$		1.369***		1.342***		1.295***		1.264***		1.162***
		(3.74)		(3.43)		(3.62)		(3.40)		(3.21)
$\beta_{LIQ,i}$		0.041		-0.014		-0.069		-0.112		-0.332
		(0.14)		(-0.04)		(-0.18)		(-0.36)		(-0.96)
α_i	0.548***	0.293	0.653***	0.325	0.708***	0.348	0.754***	0.397	0.896***	0.567**
	(3.18)	(1.35)	(3.54)	(1.36)	(3.54)	(1.45)	(3.76)	(1.55)	(3.91)	(2.07)
Obs.	75	75	75	75	75	75	75	75	75	75
R-Squared	0.693	0.744	0.709	0.745	0.711	0.745	0.716	0.749	0.724	0.759

Table 11 (continued)

This table presents the results of two-stage monthly cross-sectional regressions on factor betas. The sample period is from July 1998 to June 2018. For the dependent variables, I use monthly value-weighted Fama-French (1997, 2015) 48 industry portfolios (Panel A), or monthly value-weighted 25 size and book-to-market, 25 size and operating profitability, and 25 size and investment portfolios (Panel B). For fair comparisons with other studies, all the test portfolios data are downloaded from Kenneth French's website. CLC is the risk factor based on customer liquidity commonality from the time-series regression for each stock and fiscal year. Similarly, SLC is the risk factor based on supplier liquidity commonality from the time-series regression for each stock and fiscal year. CLC and SLC are calculated as the highest- minus the lowest-quintile portfolio based on the previous fiscal year estimates of customer and supplier liquidity commonality, respectively. LIQ is the liquidity risk factor by Pástor and Stambaugh (2003). All the factors except for CLC and SLC are downloaded from Kenneth French's or Lubos Pastor's website. Factor betas are estimated from time-series regressions of the test portfolio returns on factors. Heteroskedasticity-robust t-statistics are reported in parentheses. The table also reports the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% level, respectively.

Appendix

A.1. Overview of The Model

In this section, I discuss the process of finding the equilibrium of the model. In order to obtain the equilibrium, I first solve the maximization problems for investors, and then obtain the optimal total sales and purchases for market makers.

First order conditions for investors

Equation (2) can have four different variations with respect to the ranges of variables θ_{i1}, θ_{i2}. To explain the derivation of liquidity commonality, I consider the two cases: Case 1 ($\theta_{i1} \geq 0$ and $\theta_{i2} \geq 0$) and Case 2 ($\theta_{i1} < 0$ and $\theta_{i2} < 0$).

For Case 1, the budget constraint in equation (2) can be rewritten as

$$w_i = -\theta_{i1}A_1 - \theta_{i2}A_2 + (\bar{\theta} + \theta_{i1} + l_1)V_1 + (\bar{\theta} + \theta_{i2} + l_2)V_2. \tag{A.1}$$

Then, the optimal signed orders for investor i can be obtained from the first order condition of equation (A.1) as follows.

$$\begin{pmatrix} \theta_{i1}^* \\ \theta_{i2}^* \end{pmatrix} = \frac{1}{\gamma} \begin{pmatrix} Var[V_1|\mathcal{I}_i] & Cov[V_1, V_2|\mathcal{I}_i] \\ Cov[V_1, V_2|\mathcal{I}_i] & Var[V_2|\mathcal{I}_i] \end{pmatrix}^{-1} \begin{pmatrix} P_{i1} - A_1 \\ P_{i1} - A_2 \end{pmatrix}, \tag{A.2}$$

where $P_{i1} \equiv E[V_1|\mathcal{I}_i] - \gamma(\bar{\theta} + l_{i1})Var[V_1|\mathcal{I}_i] - \gamma(\bar{\theta} + l_{i2})Cov[V_1, V_2|\mathcal{I}_i]$; $P_{i2} \equiv E[V_2|\mathcal{I}_i] - \gamma(\bar{\theta} + l_{i1})Cov[V_1, V_2|\mathcal{I}_i] - \gamma(\bar{\theta} + l_{i2})Var[V_2|\mathcal{I}_i]$.

Similarly, for Case 2, the budget constraint in equation (2) can be rewritten as

$$w_i = \theta_{i1}B_1 + \theta_{i2}B_2 + (\bar{\theta} + \theta_{i1} + l_1)V_1 + (\bar{\theta} + \theta_{i2} + l_2)V_2, \tag{A.3}$$

and the optimal signed orders are

$$\begin{pmatrix} \theta_{i1}^* \\ \theta_{i2}^* \end{pmatrix} = \frac{1}{\gamma}\begin{pmatrix} Var[V_1|\mathcal{I}_i] & Cov[V_1, V_2|\mathcal{I}_i] \\ Cov[V_1, V_2|\mathcal{I}_i] & Var[V_2|\mathcal{I}_i] \end{pmatrix}^{-1} \begin{pmatrix} P_{i1}^R - B_1 \\ P_{i2}^R - B_2 \end{pmatrix}. \tag{A.4}$$

Notice that P_{i1} and P_{i2} are the reservations prices of investor i for stock 1 and 2, respectively. (A.2) and (A.4) suggest that the reservation price of stock k for investor i is the expected price to which the investor refers when they trade. That is, the investor purchases (sell) stock k if and only if the ask (bid) price is lower (higher) than the reservation price.

Conditional expectations and variances for informed investors

As assumed in the paper, the informed investors know the public information on V_1 and V_2, and the signal on c, s. Therefore, the conditional expectations are

$$\begin{pmatrix} E[V_1|\mathcal{I}_I] \\ E[V_1|\mathcal{I}_I] \end{pmatrix} = \begin{pmatrix} \bar{V}_1 \\ \bar{V}_2 \end{pmatrix} + \begin{pmatrix} \delta_1\sigma_c^2 \\ \delta_2\sigma_c^2 \end{pmatrix} \frac{1}{\sigma_c^2 + \sigma_{\epsilon_s}^2} s. \tag{A.5}$$

The conditional variances are

$$\begin{pmatrix} Var[V_1|\mathcal{J}_I] & Cov[V_1,V_2|\mathcal{J}_I] \\ Cov[V_1,V_2|\mathcal{J}_I] & Var[V_2|\mathcal{J}_I] \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix} - \frac{1}{\sigma_c^2+\sigma_{\epsilon_s}^2} \begin{pmatrix} \delta_1\sigma_c^2 \\ \delta_2\sigma_c^2 \end{pmatrix} (\delta_1\sigma_c^2 \quad \delta_2\sigma_c^2). \tag{A.6}$$

With (A.2) and (A.4), the reservation price of informed investors for stock k is

$$P_{Ik} = E[V_k|\mathcal{J}_I] - \gamma(\bar{\theta}+l_{Ik})\sigma_{Ik}^2 - \gamma(\bar{\theta}+l_{Ik'})\sigma_{I12} = \bar{V}_k - \gamma\bar{\theta}(\sigma_k^2+\sigma_{12}) + \hat{s}_k, \tag{A.7}$$

where k' refers to the other stock – if $k=1$, then $k'=2$ and vice versa; σ_{Ik}^2 and σ_{I12} are $Var[V_k|\mathcal{J}_I]$ and $Cov[V_1,V_2|\mathcal{J}_I]$, respectively ; $\hat{s}_1 \equiv \frac{\delta_1\sigma_c^2}{\sigma_c^2+\sigma_{\epsilon_c}^2}s - \gamma l_1\sigma_{I1}^2 - \gamma l_2\sigma_{I12}$; $\hat{s}_2 \equiv \frac{\delta_2\sigma_c^2}{\sigma_c^2+\sigma_{\epsilon_c}^2}s - \gamma l_1\sigma_{I12} - \gamma l_2\sigma_{I2}^2$.

Note that $\hat{s}_1$ and $\hat{s}_2$ are the uninformed signals which the uninformed investors guess based on the reservation prices of the informed. (A.13) shows that the estimated signal of stock k consists of three different random variables: the informed signal and liquidity demands for both stocks. Since there are two linear equations with three unknown variables, the uninformed investors are not able to identify the informed signal perfectly.

Conditional expectations and variances for uninformed investors

The uninformed investors know the public information on V_1 and V_2, and the guess information from observing the reservation prices of informed investors, $\hat{s}_1$ and $\hat{s}_2$. Thus, the conditional expectations are

$$\begin{pmatrix} E[V_1|\mathcal{I}_U] \\ E[V_1|\mathcal{I}_U] \end{pmatrix} = \begin{pmatrix} \bar{V}_1 \\ \bar{V}_2 \end{pmatrix} + \begin{pmatrix} \sigma_{1\hat{s}_1} & \sigma_{1\hat{s}_2} \\ \sigma_{2\hat{s}_1} & \sigma_{2\hat{s}_2} \end{pmatrix} \begin{pmatrix} \sigma_{\hat{s}_1}^2 & \sigma_{\hat{s}_1\hat{s}_2} \\ \sigma_{\hat{s}_1\hat{s}_2} & \sigma_{\hat{s}_2}^2 \end{pmatrix}^{-1} \begin{pmatrix} \hat{s}_1 \\ \hat{s}_2 \end{pmatrix}$$

$$= \begin{pmatrix} \bar{V}_1 \\ \bar{V}_2 \end{pmatrix} + \begin{pmatrix} \dfrac{\sigma_{1\hat{s}_1}\sigma_{\hat{s}_2}^2 - \sigma_{1\hat{s}_2}\sigma_{\hat{s}_1\hat{s}_2}}{\sigma_{\hat{s}_1}^2\sigma_{\hat{s}_2}^2 - \sigma_{\hat{s}_1\hat{s}_2}^2} & \dfrac{\sigma_{1\hat{s}_2}\sigma_{\hat{s}_1}^2 - \sigma_{1\hat{s}_1}\sigma_{\hat{s}_1\hat{s}_2}}{\sigma_{\hat{s}_1}^2\sigma_{\hat{s}_2}^2 - \sigma_{\hat{s}_1\hat{s}_2}^2} \\ \dfrac{\sigma_{2\hat{s}_1}\sigma_{\hat{s}_2}^2 - \sigma_{2\hat{s}_2}\sigma_{\hat{s}_1\hat{s}_2}}{\sigma_{\hat{s}_1}^2\sigma_{\hat{s}_2}^2 - \sigma_{\hat{s}_1\hat{s}_2}^2} & \dfrac{\sigma_{2\hat{s}_2}\sigma_{\hat{s}_1}^2 - \sigma_{2\hat{s}_1}\sigma_{\hat{s}_1\hat{s}_2}}{\sigma_{\hat{s}_1}^2\sigma_{\hat{s}_2}^2 - \sigma_{\hat{s}_1\hat{s}_2}^2} \end{pmatrix} \begin{pmatrix} \hat{s}_1 \\ \hat{s}_2 \end{pmatrix} \tag{A.8}$$

$$\equiv \begin{pmatrix} \bar{V}_1 \\ \bar{V}_2 \end{pmatrix} + \begin{pmatrix} D_1 & D_2 \\ D_3 & D_4 \end{pmatrix} \begin{pmatrix} \hat{s}_1 \\ \hat{s}_2 \end{pmatrix},$$

and the conditional variances are

$$\begin{pmatrix} Var[V_1|\mathcal{I}_U] & Cov[V_1, V_2|\mathcal{I}_U] \\ Cov[V_1, V_2|\mathcal{I}_U] & Var[V_2|\mathcal{I}_U] \end{pmatrix}$$

$$= \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix} + \begin{pmatrix} \sigma_{1\hat{s}_1} & \sigma_{1\hat{s}_2} \\ \sigma_{2\hat{s}_1} & \sigma_{2\hat{s}_2} \end{pmatrix} \begin{pmatrix} \sigma_{\hat{s}_1}^2 & \sigma_{\hat{s}_1\hat{s}_2} \\ \sigma_{\hat{s}_1\hat{s}_2} & \sigma_{\hat{s}_2}^2 \end{pmatrix}^{-1} \begin{pmatrix} \sigma_{1\hat{s}_1} & \sigma_{1\hat{s}_2} \\ \sigma_{2\hat{s}_1} & \sigma_{2\hat{s}_2} \end{pmatrix} \tag{A.9}$$

$$= \begin{pmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{12} & \sigma_2^2 \end{pmatrix} + \begin{pmatrix} D_1 & D_2 \\ D_3 & D_4 \end{pmatrix} \begin{pmatrix} \sigma_{1\hat{s}_1} & \sigma_{1\hat{s}_2} \\ \sigma_{2\hat{s}_1} & \sigma_{2\hat{s}_2} \end{pmatrix},$$

where $\sigma_{1\hat{s}_1} = Cov(V_1, \hat{s}_1) = \delta_1^2 \frac{\sigma_c^2}{\sigma_c^2 + \sigma_{\epsilon_c}^2} \sigma_c^2$;

$\sigma_{1\hat{s}_2} = Cov(V_1, \hat{s}_2) = \delta_1\delta_2 \frac{\sigma_c^2}{\sigma_c^2 + \sigma_{\epsilon_c}^2} \sigma_c^2$;

$\sigma_{2\hat{s}_1} = Cov(V_2, \hat{s}_1) = \sigma_{1\hat{s}_2}$;

$\sigma_{2\hat{s}_2} = Cov(V_2, \hat{s}_2) = \delta_2^2 \frac{\sigma_c^2}{\sigma_c^2 + \sigma_{\epsilon_c}^2} \sigma_c^2$;

$$\sigma_{\hat{s}_1}^2 = Var(\hat{s}_1) = \delta_1^2 \left(\frac{\sigma_c^2}{\sigma_c^2+\sigma_{\epsilon_c}^2}\right)^2 (\sigma_c^2 + \sigma_{\epsilon_s}^2) + \gamma^2\sigma_{I1}^4\sigma_l^2 + \gamma^2\sigma_{I12}^2\sigma_l^2;$$

$$\sigma_{\hat{s}_1\hat{s}_2} = Cov(\hat{s}_1, \hat{s}_2) = \delta_1\delta_2 \frac{\sigma_c^2}{\sigma_c^2+\sigma_{\epsilon_c}^2} (\sigma_c^2 + \sigma_{\epsilon_s}^2) + \gamma^2\sigma_{I1}^2\sigma_{I12}\sigma_l^2 + \gamma^2\sigma_{I12}\sigma_{I2}^2\sigma_l^2;$$

$$\sigma_{\hat{s}_2}^2 = Var(\hat{s}_2) = \delta_2^2 \left(\frac{\sigma_c^2}{\sigma_c^2+\sigma_{\epsilon_c}^2}\right)^2 (\sigma_c^2 + \sigma_{\epsilon_s}^2) + \gamma^2\sigma_{I12}^2\sigma_l^2 + \gamma^2\sigma_{I2}^4\sigma_l^2.$$

Market clearing

For an illustration, I only consider the case where the informed and uninformed are respectively net-buyers and net-sellers for stocks.[28] Then, (A.2) and (A.4) can be rewritten as

$$\begin{aligned}
\begin{pmatrix}\theta_{I1}^* \\ \theta_{I2}^*\end{pmatrix} &= \frac{1}{\gamma}\begin{pmatrix} Var[V_1|\mathcal{I}_I] & Cov[V_1,V_2|\mathcal{I}_I] \\ Cov[V_1,V_2|\mathcal{I}_I] & Var[V_2|\mathcal{I}_I]\end{pmatrix}^{-1}\begin{pmatrix}P_{I1} - A_1 \\ P_{I2} - A_2\end{pmatrix} \\
&= \begin{pmatrix} \dfrac{1}{\gamma}\dfrac{Var[V_2|\mathcal{I}_I](P_{I1} - A_1) - Cov[V_1,V_2|\mathcal{I}_I](P_{I2} - A_2)}{Var[V_1|\mathcal{I}_I]Var[V_2|\mathcal{I}_I] - Cov^2[V_1,V_2|\mathcal{I}_I]} \\ \dfrac{1}{\gamma}\dfrac{Var[V_1|\mathcal{I}_I](P_{I2} - A_2) - Cov[V_1,V_2|\mathcal{I}_I](P_{I1} - A_1)}{Var[V_1|\mathcal{I}_I]Var[V_2|\mathcal{I}_I] - Cov^2[V_1,V_2|\mathcal{I}_I]} \end{pmatrix} \qquad \text{(A.10)} \\
&\equiv \begin{pmatrix} E_{I2}(P_{I1} - A_1) - E_{I12}(P_{I2} - A_2) \\ E_{I1}(P_{I2} - A_2) - E_{I12}(P_{I1} - A_1)\end{pmatrix},
\end{aligned}$$

and

[28] The three other cases follow the same procedure as the case that I explain here.

$$\begin{pmatrix}\theta_{U1}^{*}\\ \theta_{U2}^{*}\end{pmatrix}=\frac{1}{\gamma}\begin{pmatrix}Var[V_1|\mathcal{I}_U] & Cov[V_1,V_2|\mathcal{I}_U]\\ Cov[V_1,V_2|\mathcal{I}_U] & Var[V_2|\mathcal{I}_U]\end{pmatrix}^{-1}\begin{pmatrix}P_{U1}-B_1\\ P_{U2}-B_2\end{pmatrix}$$

$$=\begin{pmatrix}\frac{1}{\gamma}\frac{Var[V_2|\mathcal{I}_U](P_{U1}-B_1)-Cov[V_1,V_2|\mathcal{I}_U](P_{U2}-B_2)}{Var[V_1|\mathcal{I}_U]Var[V_2|\mathcal{I}_U]-Cov^2[V_1,V_2|\mathcal{I}_U]}\\ \frac{1}{\gamma}\frac{Var[V_1|\mathcal{I}_U](P_{U2}-B_2)-Cov[V_1,V_2|\mathcal{I}_U](P_{U1}-B_1)}{Var[V_1|\mathcal{I}_U]Var[V_2|\mathcal{I}_U]-Cov^2[V_1,V_2|\mathcal{I}_U]}\end{pmatrix} \tag{A.11}$$

$$\equiv\begin{pmatrix}E_{U2}(P_{U1}-B_1)-E_{U12}(P_{U2}-B_2)\\ E_{U1}(P_{U2}-B_2)-E_{U12}(P_{U1}-B_1)\end{pmatrix}.$$

Then, from the market clearing condition (4), the equilibrium bid and ask prices can be derived in terms of the total sales and purchases. That is,

$$\begin{pmatrix}A_1\\ A_2\\ B_1\\ B_2\end{pmatrix}=\begin{pmatrix}P_{I1}\\ P_{I2}\\ P_{U1}\\ P_{U2}\end{pmatrix}+F\times\begin{pmatrix}\alpha_1\\ \alpha_2\\ \beta_1\\ \beta_2\end{pmatrix}, \tag{A.12}$$

where $F=\begin{pmatrix}-F_{U1} & -F_{U12} & 0 & 0\\ -F_{U12} & -F_{U2} & 0 & 0\\ 0 & 0 & F_{I1} & F_{I12}\\ 0 & 0 & F_{I12} & F_{I}\end{pmatrix}$;

$F_{U1}=\frac{E_{U1}}{(E_{U1}E_{U2}-E_{U12}^2)N_U}$;

$F_{U12}=\frac{E_{U12}}{(E_{U1}E_{U2}-E_{U12}^2)N_U}$;

$F_{U2}=\frac{E_{U2}}{(E_{U1}E_{U2}-E_{U12}^2)N_U}$;

$F_{I1}=\frac{E_{I1}}{(E_{I1}E_{I2}-E_{I12}^2)N_I}$;

$F_{I12}=\frac{E_{I12}}{(E_{I1}E_{I2}-E_{I12}^2)N_I}$;

$F_{I2} = \frac{E_{I2}}{(E_{I1}E_{I2} - E_{I12}^2)N_I}$.

First order conditions for market makers

From (3), the first order conditions for market makers are

$$0 = \begin{pmatrix} A_1 + \alpha_{j1}\frac{\partial A_1}{\partial \alpha_{j1}} - E[V_1|\mathcal{I}_U] + \gamma(\bar{\theta} + \beta_{j1} - \alpha_{j1})Var[V_1|\mathcal{I}_U] \\ A_2 + \alpha_{j2}\frac{\partial A_2}{\partial \alpha_{j2}} - E[V_2|\mathcal{I}_U] + \gamma(\bar{\theta} + \beta_{j2} - \alpha_{j2})Var[V_2|\mathcal{I}_U] \\ B_1 + \beta_{j1}\frac{\partial B_1}{\partial \beta_{j1}} - E[V_1|\mathcal{I}_U] + \gamma(\bar{\theta} + \beta_{j1} - \alpha_{j1})Var[V_1|\mathcal{I}_U] \\ B_2 + \beta_{j2}\frac{\partial B_2}{\partial \beta_{j2}} - E[V_2|\mathcal{I}_U] + \gamma(\bar{\theta} + \beta_{j2} - \alpha_{j2})Var[V_2|\mathcal{I}_U] \end{pmatrix}, \quad (A.13)$$

and using (4), (A.10), and (A.11), I can rearrange (A.13) as follows.

$$G = H \times \begin{pmatrix} \alpha_1^* \\ \alpha_2^* \\ \beta_1^* \\ \beta_2^* \end{pmatrix}, \quad (A.14)$$

where $G = \begin{pmatrix} N_M\left[P_{I1} - E[V_1|\mathcal{I}_U] + \gamma\bar{\theta}_1 Var[V_1|\mathcal{I}_U]\right] \\ N_M\left[P_{I2} - E[V_2|\mathcal{I}_U] + \gamma\bar{\theta}_2 Var[V_2|\mathcal{I}_U]\right] \\ N_M\left[P_{U1} - E[V_1|\mathcal{I}_U] + \gamma\bar{\theta}_1 Var[V_1|\mathcal{I}_U]\right] \\ N_M\left[P_{U2} - E[V_2|\mathcal{I}_U] + \gamma\bar{\theta}_2 Var[V_2|\mathcal{I}_U]\right] \end{pmatrix}$;

H is a 4 by 4 matrix defined as

$$\begin{pmatrix} (N_M+1)F_{I1}+\gamma Var[V_1|\mathcal{I}_U] & (N_M+1)F_{I12}+\gamma Cov[V_1,V_2|\mathcal{I}_U] & \cdots \\ (N_M+1)F_{I12}+\gamma Cov[V_1,V_2|\mathcal{I}_U] & (N_M+1)F_{I2}+\gamma Var[V_2|\mathcal{I}_U] & \\ \gamma Var[V_1|\mathcal{I}_U] & \gamma Cov[V_1,V_2|\mathcal{I}_U] & \\ \gamma Cov[V_1,V_2|\mathcal{I}_U] & \gamma Var[V_2|\mathcal{I}_U] & \end{pmatrix}$$

$$\begin{pmatrix} \cdots & -\gamma Var[V_1|\mathcal{I}_U] & -\gamma Cov[V_1,V_2|\mathcal{I}_U] \\ & -\gamma Cov[V_1,V_2|\mathcal{I}_U] & -\gamma Var[V_2|\mathcal{I}_U] \\ & -(N_M+1)F_{U1}-\gamma Var[V_1|\mathcal{I}_U] & -(N_M+1)F_{U12}-\gamma Cov[V_1,V_2|\mathcal{I}_U] \\ & -(N_M+1)F_{U12}-\gamma Cov[V_1,V_2|\mathcal{I}_U] & -(N_M+1)F_{U2}-\gamma Var[V_2|\mathcal{I}_U] \end{pmatrix}.$$

Finally, with (A.12) and (A.14), the equilibrium bid and ask prices are

$$\begin{pmatrix} A_1^* \\ A_2^* \\ B_1^* \\ B_2^* \end{pmatrix} = P + F \times H^{-1} \times G. \tag{A.15}$$

A.2. Proof of Proposition

Using (A.12) and (A.15), the covariance between the equilibrium bid-ask spreads is

$$Cov(A_1^*-B_1^*, A_2^*-B_2^*)$$

$$= Cov(\Delta_1 - (F_{U1}\alpha_1^* + F_{U12}\alpha_2^* + F_{I1}\beta_1^* + F_{I12}\beta_2^*), \Delta_2 - (F_{U12}\alpha_1^* \tag{A.16}$$

$$+ F_{U2}\alpha_2^* + F_{I12}\beta_1^* + F_{I2}\beta_2^*)),$$

where $\Delta_1 = P_{I1}^R - P_{U1}^R$; $\Delta_2 = P_{I2}^R - P_{U2}^R$.

If G and H^{-1} are respectively denoted as $\begin{pmatrix} g_1 \\ \vdots \\ g_4 \end{pmatrix}$ and $\begin{pmatrix} h_{11} & \cdots & h_{14} \\ \vdots & \ddots & \vdots \\ h_{41} & \cdots & h_{44} \end{pmatrix}$, then (A.14) can be expressed as

$$\begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \beta_1 \\ \beta_2 \end{pmatrix} = \begin{pmatrix} h_{11}g_1 + h_{12}g_2 + h_{13}g_3 + h_{14}g_4 \\ h_{21}g_1 + h_{22}g_2 + h_{23}g_3 + h_{24}g_4 \\ h_{31}g_1 + h_{32}g_2 + h_{33}g_3 + h_{34}g_4 \\ h_{41}g_1 + h_{42}g_2 + h_{43}g_3 + h_{44}g_4 \end{pmatrix}, \tag{A.17}$$

and specifically,

$$g_1 = N_M\left[P_{I1}^R - E[V_1|\mathcal{J}_U] + \gamma\bar{\theta}Var[V_1|\mathcal{J}_U]\right] = N_M[\hat{s}_1 - D_1\hat{s}_1 - D_2\hat{s}_2] + \cdots,$$

$$g_2 = N_M\left[P_{I2}^R - E[V_2|\mathcal{J}_U] + \gamma\bar{\theta}Var[V_2|\mathcal{J}_U]\right] = N_M[\hat{s}_2 - D_3\hat{s}_1 - D_4\hat{s}_2] + \cdots,$$

$$g_3 = N_M\left[P_{U1}^R - E[V_1|\mathcal{J}_U] + \gamma\bar{\theta}Var[V_1|\mathcal{J}_U]\right] = -N_M\gamma\bar{\theta}Cov[V_1, V_2|\mathcal{J}_U],$$

$$g_4 = N_M\left[P_{U2}^R - E[V_2|\mathcal{J}_U] + \gamma\bar{\theta}Var[V_2|\mathcal{J}_U]\right] = -N_M\gamma\bar{\theta}Cov[V_1, V_2|\mathcal{J}_U].$$

Since g_3 and g_4 are constant, but g_1 and g_2 are the functions of random variables $\hat{s}_1$ and $\hat{s}_2$, $A_1^* - B_1^*$ can be rewritten as

$$
\begin{aligned}
A_1^* - B_1^* &= \Delta_1 - (F_{U1}\alpha_1^* + F_{U12}\alpha_2^* + F_{I1}\beta_1^* + F_{I12}\beta_2^*) \\
&= (\hat{s}_1 - D_1\hat{s}_1 - D_2\hat{s}_2) \\
&- N_M(F_{U1}h_{11} + F_{U12}h_{21} + F_{I1}h_{31} + F_{I12}h_{41})(\hat{s}_1 - D_1\hat{s}_1 - D_2\hat{s}_2) \\
&- N_M(F_{U1}h_{12} + F_{U12}h_{22} + F_{I1}h_{32} + F_{I12}h_{42})(\hat{s}_2 - D_3\hat{s}_1 - D_4\hat{s}_2) + \cdots \\
&\equiv (\hat{s}_1 - D_1\hat{s}_1 - D_2\hat{s}_2) - m_1(\hat{s}_1 - D_1\hat{s}_1 - D_2\hat{s}_2) \\
&- m_2(\hat{s}_2 - D_3\hat{s}_1 - D_4\hat{s}_2) + \cdots.
\end{aligned} \tag{A.18}
$$

and similarly, $A_2^* - B_2^*$ can be expressed as

$$
\begin{aligned}
A_2^* - B_2^* &= (\hat{s}_2 - D_3\hat{s}_1 - D_4\hat{s}_2) \\
&- N_M(F_{U12}h_{11} + F_{U2}h_{21} + F_{I12}h_{31} + F_{I2}h_{41})(\hat{s}_1 - D_1\hat{s}_1 - D_2\hat{s}_2) \\
&- N_M(F_{U12}h_{12} + F_{U2}h_{22} + F_{I12}h_{32} + F_{I2}h_{42})(\hat{s}_2 - D_3\hat{s}_1 - D_4\hat{s}_2) + \cdots \\
&\equiv (\hat{s}_2 - D_3\hat{s}_1 - D_4\hat{s}_2) - m_3(\hat{s}_1 - D_1\hat{s}_1 - D_2\hat{s}_2) \\
&- m_4(\hat{s}_2 - D_3\hat{s}_1 - D_4\hat{s}_2) + \cdots,
\end{aligned} \tag{A.19}
$$

Therefore, liquidity commonality is

$$
\begin{aligned}
&Cov(A_1^* - B_1^*, A_2^* - B_2^*) \\
&= \{(1 - m_1)(1 - D_1) + m_2D_3\}\{-m_3(1 - D_1) - (m_4 - 1)D_3\}\sigma_{\hat{s}_1}^2 \\
&+ \{-(m_1 - 1)D_2 - m_2(1 - D_4)\}\{m_3D_2 + (1 - m_4)(1 - D_4)\}\sigma_{\hat{s}_2}^2 \\
&+ [\{(1 - m_1)(1 - D_1) + m_2D_3\}\{m_3D_2 + (1 - m_4)(1 - D_4)\} \\
&+ \{-m_3(1 - D_1) - (m_4 - 1)D_3\}\{-(m_1 - 1)D_2 - m_2(1 - D_4)\}]\sigma_{\hat{s}_1\hat{s}_2}.
\end{aligned} \tag{A.20}
$$

Considering other cases including Case 2, and substituting (A.8), (A.9), and (A.12) into (A.20), I can obtain the Proposition.

$$Cov(A_1^* - B_1^*, A_2^* - B_2^*) = |\delta_1||\delta_2| f\left(\sigma_{\epsilon_s}^2\right), \tag{A.21}$$

where

$$f\left(\sigma_{\epsilon_s}^2\right) = \left(\gamma^2 \sigma_c^2 \sigma_l^2 \left[\sigma_\epsilon^2 \{2\sigma_c^2 \sigma_\epsilon^2 + (\delta_1^2 + \delta_2^2)\sigma_c^2 \sigma_{\epsilon_s}^2 + 2\sigma_\epsilon^2 \sigma_{\epsilon_s}^2\} \gamma^2 \{\sigma_c^2 \sigma_\epsilon^2 + \left((\delta_1^2 + \delta_2^2)\sigma_c^2 + \sigma_\epsilon^2\right)\sigma_{\epsilon_s}^2\}^2 \sigma_l^2 - \sigma_c^2 \sigma_\epsilon^4 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right)^3\right]\right) / \left((1 + N_M)^2 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right)^2 \left[(\delta_1^2 + \delta_2^2)\sigma_c^4 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right) + \gamma^2 \{\sigma_c^2 \sigma_\epsilon^2 + \left((\delta_1^2 + \delta_2^2)\sigma_c^2 + \sigma_\epsilon^2\right)\sigma_{\epsilon_s}^2\}^2 \sigma_l^2\right]\right);$$

$$\frac{\partial f}{\partial \sigma_{\epsilon_s}^2} = \left(\gamma^4 \sigma_c^4 \left[\sigma_\epsilon^2 \sigma_{\epsilon_s}^2 + \sigma_c^2 \{\sigma_\epsilon^2 + (\delta_1^2 + \delta_2^2)\sigma_{\epsilon_s}^2\}\right]^3 + \sigma_l^4 \left[\left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right)\{\sigma_\epsilon^2 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right) + (\delta_1^2 + \delta_2^2)\sigma_c^2 \left(4\sigma_c^2 + \sigma_{\epsilon_s}^2\right)\} + 2\gamma^2 \{\sigma_c^2 \sigma_\epsilon^2 + \left((\delta_1^2 + \delta_2^2)\sigma_c^2 + \sigma_\epsilon^2\right)\}^2 \sigma_l^2\right]\right) / \left((1 + N_M)^2 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right)^3 \left[(\delta_1^2 + \delta_2^2)\sigma_c^4 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right) + \gamma^2 \{\sigma_c^2 \sigma_\epsilon^2 + \left((\delta_1^2 + \delta_2^2)\sigma_c^2 + \sigma_\epsilon^2\right)\sigma_{\epsilon_s}^2\}^2 \sigma_l^2\right]^2\right)$$

and is strictly positive if $\delta_k \neq 0$. $Q.E.D.$

A.3. Proof of Corollary 1

By using (A.18), (A.19), and (A.21), $g_k\left(\sigma_{\epsilon_s}^2\right)$ is:

$$g_k\left(\sigma_{\epsilon_s}^2\right) = \left(\sigma_c^2 \left[\sigma_\epsilon^2 \{2\sigma_c^2 \sigma_\epsilon^2 + \left(\delta_1^2 + \delta_2^2\right)\sigma_c^2 \sigma_{\epsilon_s}^2 + 2\sigma_\epsilon^2 \sigma_{\epsilon_s}^2\} \left\{\gamma^2 \sigma_c^2 \sigma_\epsilon^2 + \gamma \left(\left(\delta_1^2 + \delta_2^2\right)\sigma_c^2 + \sigma_\epsilon^2\right) \sigma_{\epsilon_s}^2\right\}^2 \sigma_l^2 - \sigma_c^2 \sigma_\epsilon^4 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right)^3\right]\right) / \left(\delta_k^2 \sigma_c^4 \sigma_\epsilon^4 \left(\sigma_c^2 + \sigma_{\epsilon_s}^2\right)^3 + \gamma^2 \left\{\sigma_c^2 \sigma_\epsilon^2 + \left(\left(\delta_1^2 + \delta_2^2\right)\sigma_c^2 + \sigma_\epsilon^2\right) \sigma_{\epsilon_s}^2\right\}^2 \sigma_l^2 \left[\sigma_c^4 \sigma_\epsilon^4 + \right.\right.$$

$2\sigma_c^2\sigma_\epsilon^2\left(\delta_{k'}^2\sigma_c^2+\sigma_\epsilon^2\right)\sigma_{\epsilon_s}^2+\left\{\delta_1^2\delta_2^2\sigma_c^4+\left(\delta_k'^2\sigma_c^2+\sigma_\epsilon^2\right)^2\right\}\sigma_{\epsilon_s}^4\Big]\Big)$.

Also, the partial derivative with respect to $\sigma_{\epsilon_s}^2$ is positive as follows.

$\frac{\partial g_k}{\partial\sigma_{\epsilon_s}^2}=\Big(\gamma^4\sigma_c^4\sigma_\epsilon^4\sigma_l^4\left(\sigma_c^2+\sigma_{\epsilon_s}^2\right)\left\{\sigma_\epsilon^2\sigma_{\epsilon_s}^2+\sigma_c^2\left(\sigma_\epsilon^2+(\delta_1^2+\delta_2^2)\sigma_{\epsilon_s}^2\right)\right\}^3\sigma_l^2\left\{\left(\sigma_c^2+\sigma_{\epsilon_s}^2\right)\left(\sigma_\epsilon^2\left(\sigma_c^2+\right.\right.\right.$

$\left.\left.\left.\sigma_{\epsilon_s}^2\right)+(\delta_1^2+\delta_2^2)\sigma_c^2\left(4\sigma_c^2+\sigma_{\epsilon_s}^2\right)\right)\right\}+2\gamma^2\left\{\sigma_c^2\sigma_\epsilon^2+\left((\delta_1^2+\delta_2^2)\sigma_c^2+\sigma_\epsilon^2\right)\sigma_{\epsilon_s}^2\right\}^2\sigma_l^2\Big)\,/$

$\Big[\delta_1^2\sigma_c^4\sigma_\epsilon^4\left(\sigma_c^2+\sigma_{\epsilon_s}^2\right)^3+\gamma^2\left\{\sigma_c^2\sigma_\epsilon^2+\left((\delta_1^2+\delta_2^2)\sigma_c^2+\sigma_\epsilon^2\right)\sigma_{\epsilon_s}^2\right\}^2\sigma_l^2\left\{\sigma_c^4\sigma_\epsilon^4+2\sigma_c^2\sigma_\epsilon^2\left(\delta_{k'}^2\sigma_c^2+\right.\right.$

$\left.\left.\sigma_\epsilon^2\right)\sigma_{\epsilon_s}^2+(\delta_1^2\delta_2^2\sigma_c^4+(\delta_k'^2\sigma_c^2+\sigma_\epsilon^2)^2)\sigma_{\epsilon_s}^4\right\}\Big]^2$. $Q.E.D.$

A.4. Proof of Corollary 2

Because (A.18) and (A.19) follows a joint normal distribution, each equilibrium bid-ask spread can be decomposed into the explainable part with the other spread and the part that is not correlated with the other spread as in Corollary 2. $Q.E.D.$

Table A.1. Effect of Customer Linkage on Liquidity (10k Linkage)

Panel A: Panel Regressions with Amihud Liquidity						
Model	(A)	(B)	(C)	(D)	(E)	(F)
$dCUS_{ijt}$	0.100***		0.057***	0.057***	0.057***	0.057***
	(22.09)		(15.61)	(15.65)	(15.64)	(15.64)
$dMKT_{it}$		0.378***	0.444***	0.444***	0.444***	0.444***
		(18.71)	(28.05)	(28.11)	(28.10)	(28.10)
$dIND_{it}$		0.094***	0.056***	0.056***	0.056***	0.056***
		(15.81)	(13.34)	(13.39)	(13.38)	(13.38)
$dVIX_t$		-0.529***	-0.458***	-0.452***	-0.459***	-0.459***
		(-9.02)	(-5.89)	(-5.88)	(-5.92)	(-5.91)
$CUSR_{ijt}$	0.009***		0.001*	0.001	0.001*	0.001*
	(4.93)		(1.65)	(1.64)	(1.67)	(1.67)
$MKTR_t$		0.001	-0.005	-0.005	-0.005	-0.005
		(0.85)	(-1.01)	(-1.05)	(-1.08)	(-1.08)
$INDR_{it}$		-0.000	0.005***	0.006***	0.006***	0.006***
		(-0.30)	(2.71)	(2.92)	(2.86)	(2.87)
R_{it}		-0.001	-0.001	-0.001	-0.001	-0.001
		(-1.09)	(-1.04)	(-0.92)	(-0.92)	(-0.95)
$Constant$	0.001	0.001	0.001	0.001	0.001	0.001
	(0.31)	(0.02)	(0.50)	(0.49)	(0.50)	(0.50)
Obs.	2,109,414	8,418,938	2,108,284	2,108,300	2,108,301	2,108,300
R-squared	0.011	0.044	0.036	0.035	0.035	0.035
Firm FE				Yes		Yes
YM FE					Yes	Yes
Industry-YM FE	Yes	Yes	Yes			
Clustering			Firm & Time			

Table A.1 (continued)

Panel B: Panel Regressions with CRSP Effective Spreads						
Model	(A)	(B)	(C)	(D)	(E)	(F)
$dCUS_{ijt}$	0.020***		0.016***	0.016***	0.016***	0.016***
	(6.28)		(5.14)	(5.17)	(5.16)	(5.16)
$dMKT_{it}$		0.017	0.089***	0.089***	0.089***	0.089***
		(1.55)	(7.53)	(7.53)	(7.55)	(7.55)
$dIND_{it}$		0.047***	0.011***	0.011***	0.011***	0.011***
		(10.78)	(4.27)	(4.33)	(4.33)	(4.33)
$dVIX_t$		-0.118***	0.039	0.035	0.040	0.040
		(-4.47)	(1.20)	(1.10)	(1.21)	(1.21)
$CUSR_{ijt}$	0.004***		0.000	0.000	0.000	0.000
	(6.96)		(0.98)	(1.03)	(1.02)	(1.02)
$MKTR_t$		0.001*	0.009***	0.009***	0.009***	0.009***
		(1.80)	(2.84)	(2.76)	(2.82)	(2.82)
$INDR_{it}$		-0.001*	0.001	0.001	0.001	0.001
		(-1.78)	(0.91)	(1.09)	(1.03)	(1.04)
R_{it}		0.002***	0.002**	0.002**	0.002**	0.002**
		(4.31)	(2.32)	(2.36)	(2.34)	(2.35)
$Constant$	0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.27)	(-0.00)	(-0.05)	(-0.04)	(-0.05)	(-0.05)
Obs.	2,191,219	8,856,942	2,189,429	2,189,443	2,189,443	2,189,443
R-squared	0.001	0.036	0.003	0.002	0.002	0.002
Firm FE				Yes		Yes
YM FE					Yes	Yes
Industry-YM FE	Yes	Yes	Yes			
Clustering	Firm & Time					

Table A.1 (continued)

This table reports panel regression coefficients and t-statistics in parentheses. The sample has the period from July 1997 to June 2018 at daily frequency. dx is the time difference of variable x. That is, $dx \equiv x_t - x_{t-1}$. The dependent variable is $dAmihud_{it}$ (Panel A) or $dCRSP_{it}$ (Panel B) for stock i on day t. $Amihud_{i,t}$, and $CRSP_{i,t}$ are the negative logarithm of daily liquidity estimates proposed by Amihud (2002), and Chung and Zhang (2014), respectively. CUS_{ijt} is the j-th customer's liquidity for stock i on day t. MKT_{it} is the market liquidity for stock i on day t. $IND_{i,t}$ is the industry liquidity for stock i on day t. VIX_t is the logarithm of Chicago Board Options Exchange Volatility Index on day t. $CUSR_{ijt}$ is the j-th customer's return for stock i on day t. $MKTR_{it}$ is the market return for stock i on day t. $INDR_{it}$ is the daily industry return for stock i on day t. R_{it} is the return of stock i on day t. Following the previous research, I exclude a stock itself in creating the market and industry liquidity for the stock. All the portfolios except for the customer portfolio are value-weighted by using market capitalizations of firms on the previous month. I classify industries based on the first two digit Standard Industrial Classification code. For the customers, I use customer firms reported in the Form 10K for each firm. YM FE denotes time fixed effects at monthly frequency. Industry-YM FE is the interaction between of industry and time fixed effects at monthly frequency. The standard errors are clustered at the firm and daily level. The table also reports the number of observations and the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table A.2. The Determinants of Customer Liquidity Commonality (10k Linkage)

Panel A: Panel Regressions of Customer Liquidity Commonality based on Amihud Measure					
Model	(A)	(B)	(C)	(D)	(E)
$Analyst\ Coverage_{iy}$	0.016***		0.016***		0.014***
	(9.30)		(6.23)		(4.66)
$Blockholder\ Ownership_{iy}$		-0.001		-0.000	0.000
		(-0.38)		(-0.08)	(0.08)
$Market\ Return_{y}$			-0.001	0.001	0.000
			(-0.54)	(0.25)	(0.03)
$Market\ Size_{y}$			0.001	0.004	0.004
			(0.48)	(1.42)	(1.36)
VIX_{y}			0.003	0.006*	0.006*
			(0.97)	(1.74)	(1.85)
$Return_{iy}$			0.002	0.005	0.003
			(0.94)	(1.44)	(1.04)
$Size_{iy}$			0.011	0.032***	0.011*
			(1.51)	(7.69)	(1.77)
B/M_{iy}			-0.001	-0.006	-0.003
			(-0.32)	(-1.36)	(-0.68)
AG_{iy}			0.002	0.001	-0.002
			(0.26)	(0.15)	(-0.30)
$Leverage_{iy}$			-1.839	-1.524	-1.898
			(-1.56)	(-1.01)	(-1.25)
I/A_{iy}			0.002	0.009	0.012
			(0.25)	(0.85)	(1.01)
$R\&D_{iy}$			-0.004	-0.008	-0.009
			(-0.54)	(-1.10)	(-1.15)
ROE_{iy}			-0.089	-0.100	-0.092
			(-1.10)	(-0.97)	(-0.85)
Constant	0.040***	0.040***	0.002	0.013	0.002
	(35.23)	(23.23)	(0.07)	(0.36)	(0.06)
Obs.	8,221	5,905	6,218	4,533	4,360
R-squared	0.059	0.050	0.059	0.058	0.067
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes			
Clustering			Firm & Year		

Table A.2 (continued)

Panel B: Panel Regressions of Customer Liquidity Commonality based on CRSP Effective Spreads					
Model	(A)	(B)	(C)	(D)	(E)
$Analyst\ Coverage_{iy}$	0.017		0.017		0.003
	(1.05)		(0.66)		(0.10)
$Blockholder\ Ownership_{iy}$		-0.026		-0.019	-0.020
		(-1.07)		(-0.95)	(-0.99)
$Market\ Return_{y}$			0.002	-0.016	-0.014
			(0.19)	(-1.28)	(-1.16)
$Market\ Size_{y}$			0.007	0.012	0.010
			(0.79)	(1.53)	(1.17)
VIX_{y}			0.008	0.006	0.005
			(0.70)	(0.30)	(0.25)
$Return_{iy}$			0.010	0.037	0.044
			(0.53)	(1.36)	(1.59)
$Size_{iy}$			-0.013	0.018	-0.009
			(-0.37)	(0.44)	(-0.22)
B/M_{iy}			-0.011	-0.031	-0.034
			(-0.29)	(-0.46)	(-0.51)
AG_{iy}			0.044	-0.002	-0.007
			(0.81)	(-0.04)	(-0.13)
$Leverage_{iy}$			0.864	4.700	4.765
			(0.09)	(0.40)	(0.42)
I/A_{iy}			0.053	0.101	0.118
			(1.16)	(1.31)	(1.43)
$R\&D_{iy}$			0.064	0.064	0.073
			(1.32)	(1.08)	(1.14)
ROE_{iy}			-0.385	-0.800	-0.789
			(-0.62)	(-1.00)	(-0.96)
Constant	0.026***	0.025***	0.058	0.155	0.154
	(5.95)	(7.42)	(0.28)	(0.60)	(0.62)
Obs.	8,755	6,211	7,050	5,026	4,800
R-squared	0.015	0.014	0.015	0.011	0.011
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes			
Clustering			Firm & Year		

Table A.2 (continued)

This table reports panel regression coefficients and t-statistics in parentheses. The sample has the period from July 1997 to June 2018 and yearly frequency. Panel A is based on Amihud (2002) liquidity measure. Panel B is based on the effective spreads proposed by Chung and Zhang (2014). The dependent variable is a stock's liquidity sensitivity to its customer portfolio's liquidity, $\beta_{cus,ijy}$, obtained from running the following time-series regression for firm i, customer j, and year y:

$$dLIQ_{it} = \beta_{ijy} + \beta_{cus,ijy}dCUS_{ijt} + \beta_{mkt,ijy}dMKT_{it} + \beta_{ind,ijy}dIND_{it} + \beta_{vix,ijy}dVIX_t + \beta_{cusr,ijy}CUSR_{ijt} + \beta_{mktr,ijy}MKTR_t + \beta_{indr,ijy}INDR_{it} + \beta_{r,ijy}R_{it} + \gamma_{mj} + \epsilon_{ijt},$$

where γ_m is the time fixed effects at monthly frequency; the rest variables are defined in Table 2. For independent variables, *Analyst Coverage* is the number of analysts following a firm from the Institutional Brokers' Estimate System database for every quarter. *Blcokholder Ownership* is defined institutional blockholder ownership divided by the number of institutional blockholders from Thomson Reuters for every quarter. Blockholders are the shareholders with ownership greater than or equal to 5%. *Return* is the daily stock return. *Market Return* is the daily value-weighted stock market return. *Market Size* is the sum of daily market capitalizations of stocks in the firm. *Size* is defined as the market capitalization at the end of each June. *B/M* is the book-to-market ratio defined as book equity of fiscal year ending in year t-1 to market capitalization at the end of year t-1. *AG* is the asset growth calculated as total asset in fiscal year t-1 divided by total asset in fiscal year t-2. *Leverage* is defined as debt in fiscal year t-1 divided by total asset in fiscal year t-2. *I/A* is the investment rate, which is the ratio of capital expenditure in fiscal year t-1 over lagged total asset. *R&D* is the R&D expenses scaled by total asset in fiscal year t-1. *ROE* is the return on equity defined as income before extraordinary items plus depreciation expenses in fiscal year t-1 scaled by book equity in fiscal year t-2. All the quarterly-defined independent variables are trimmed at 2.5% and 97.5% and standardized. The standard errors are clustered by firm and year. The table also reports the number of observations and the adjusted R-squared. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table A.3. Asset Pricing Tests with Firm Characteristics (10k Linkage)

	Fama-MacBeth		Panel	
	Amihud	CRSP	Amihud	CRSP
Model	(A)	(B)	(C)	(D)
Sensitivity	0.093*	0.127*	0.112**	0.029
	(1.77)	(1.71)	(2.25)	(0.79)
Log(Size)	-0.081	-0.110	-0.118	-0.113
	(-0.57)	(-0.80)	(-0.89)	(-0.84)
Log(B/M)	0.036	0.010	0.013	-0.037
	(0.29)	(0.07)	(0.10)	(-0.26)
AG	-0.248**	-0.273**	-0.268**	-0.255**
	(-2.39)	(-2.53)	(-2.33)	(-2.16)
Leverage	0.057	0.037	0.120	0.073
	(0.66)	(0.42)	(1.45)	(0.81)
I/A	0.101	0.108	0.011	0.023
	(0.76)	(0.80)	(0.07)	(0.15)
R&D	0.167**	0.164*	0.173**	0.175**
	(2.13)	(1.93)	(2.21)	(2.05)
ROE	0.054	0.049	0.034	-0.011
	(0.46)	(0.40)	(0.31)	(-0.09)
Constant	0.715*	0.660	0.763***	0.768***
	(1.82)	(1.63)	(24.28)	(22.39)
Obs.	240	240	66,204	65,781

This table reports the results of panel regressions of monthly stock excess returns against their sensitivity to customer liquidity and other firm characteristics. The sample ranges from July 1998 to June 2018. *Sensitivity* of stock i and year y is the estimate for customer liquidity commonality obtained from the regression in Table A.2 for each firm i and year $y-1$. The rest of the variables in this table are identically defined as in Table A.2. All the independent variables are trimmed at 2.5% and 97.5% and standardized. For the Fama-MacBeth regressions, t-statistics are calculated by using the heteroskedasticity and autocorrelation consistent Newey-West (1987) standard error estimates. For the Panel regressions, the year-month fixed effects are used and the standard errors are clustered at the firm and monthly level. The table also reports the number of observations. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.