INSTITUTIONAL OWNERSHIP, LIQUIDITY AND LIQUIDITY RISK

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INSTITUTIONAL OWNERSHIP, LIQUIDITY AND LIQUIDITY RISK

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In this dissertation, I focus on examining the effects of institutional ownership on stocks' liquidity and liquidity risk using a sample of firms listed on the NYSE and the AMEX over the period 1980–2005. The first chapter provides a brief introduction to liquidity and emphasizes the role of institutional ownership in financial markets.

In the second chapter, I examine the relationship between institutional ownership and liquidity of stocks, focusing on the effect of institutions' relative information advantage. The information advantage of institutions can affect liquidity through two channels: decreasing liquidity resulting from increasing information asymmetry *(adverse selection effect)* and increasing liquidity resulting from increasing price discovery due to competition among institutions' *information efficiency effect*.

My evidence indicates a non-monotonic (U-shaped) relationship between the level of institutional ownership and stock liquidity. The two effects vary with the amount of publicly available information and asset risk. I also find that institutional ownership *(Granger)* causes liquidity, allaying concerns that the findings result from institutions' preference for liquid stocks. Lastly, I document that liquidity decreases with increasing diversification of the portfolio of institutional investors and the fraction of equity held by long-term investors.

In the third chapter, I examine the effects of institutional ownership on stocks' time variation in liquidity. It helps advance an understanding of the sources of commonality in liquidity and the determinants of the sensitivity of an asset's liquidity to changes in marketwide liquidity (systematic liquidity risk) and the total variance of liquidity of a firm over time. I interpret my findings in the context of correlated trading by institutions resulting either from their tendency to herd or to trade on common information and signals.

I find that systematic liquidity risk increases with the level of institutional ownership, homogeneity and investment-horizon of the institutional investor base, while it decreases with ownership concentration and increase in blockholdings. However, the variance of liquidity decreases with the level of institutional ownership, homogeneity of the investor base and ownership concentration. Overall, the findings indicate that the ownership structure of stocks affects both the systematic liquidity risk and the variation in their liquidity over time.

BIOGRAPHICAL SKETCH

Prasun Agarwal was born 16 November 1976 in Jaipur, India. He holds a Bachelor of Technology (Mechanical Engineering) degree from Indian Institute of Technology Bombay, (Mumbai) India, a Master of Business Administration degree from the Cox School of Business at Southern Methodist University, Dallas, TX, and a Master of Science (Finance) degree and a Ph.D. in Management from Cornell University, Ithaca, NY.

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CHAPTER 1: INTRODUCTION

Financial markets facilitate the mobilization of capital needed to fund growth. By identifying and funding those entrepreneurs with the best chances of successfully implementing innovative products and production processes and allocating capital efficiently they spur technological innovation. Ross Levine (1997) states "that the development of financial markets and institutions is a critical and inextricable part of the growth process."

One of the most important roles of financial markets is that they ease trading of assets and thus help in sharing and diversifying risk. By providing claims on physical assets—like equity, bonds and demand deposits—that an investor can buy or sell easily, they encourage long-term capital investment in longer term production processes. Liquidity refers to the ease with which assets or claims on the assets can be transacted and converted into cash or another medium of exchange. A reduction in the costs associated with transacting these claims could therefore encourage greater long-term investment.

In general, the classical asset pricing models assume perfect financial markets without frictions and ignore both the effects of trading costs and the diverse features of liquidity. Increase in liquidity should improve sharing of financial risks by influencing investors' trading decisions because a reduction in transaction costs eases making changes to portfolio and holding diversified portfolios (Domowitz and Wang (2002), Harford and Kaul (2005)). Furthermore, a growing body of asset pricing literature examines how liquidity and its time variation affects the required returns of traded assets. Current theories predict that both the level of liquidity and the liquidity risk are priced, while existing empirical studies find that the effects of liquidity on asset prices are both statistically and economically significant.[1] Existing empirical evidence indicates that an asset's liquidity and systematic liquidity risk are priced.

Liquidity, by its very nature, is a difficult construct and has multiple dimensions. Kyle (1985) writes that "liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets." It tries to capture the notion that there are costs associated with searching for counterparty, risk of adverse selection when trading with an informed counterparty, inventory risk due to delays incurred in transacting, and other costs due to imperfect competition in asset markets. Liquidity of assets is also a dynamic concept as liquidity exhibits a time varying nature. Changes in liquidity at the market level have been associated with various puzzling episodes like the stock market crash of 1987, the global liquidity crisis of 1998, and the financial crisis of 2007–2009. This nature of liquidity both as a priced characteristic and as a factor in asset returns, and its role in economic growth makes for understanding its determinants important.

Another key element in modern financial markets is the interplay between firms that increasingly raise capital in public markets, and institutional investors that are managing a growing pool of assets. Most individual investors select mutual funds, pension funds, or retirement products offered by insurance companies and banks, as their primary investment vehicle, to ameliorate the problems created by information and other frictions. Within the U.S., the average institutional ownership of equity in firms, listed on the NYSE and the AMEX, has increased from 15% in 1983 to 60% in 2005, reflecting a growth rate of 6.3% over the 25 year period. The fact that

[1] For recent surveys refer to Amihud, Mendelson, and Pedersen (2005); Easley and O'Hara (2003); and O'Hara (2003).

institutions are managing such a sizable share of the wealth invested in the U.S. equity markets indicates their increasingly important role in financial markets.

In this dissertation, I therefore focus on examining the effects of institutional ownership on stocks' liquidity and its variation over time. While liquidity and liquidity risk are important, it is not clear whether institutional ownership should affect them. Yet, institutions could clearly play a very important role. Institutions due to their scale have an inherent advantage in producing and processing information about a firm, and thus are better informed than other investors. Their information advantage can therefore affect liquidity. Furthermore, by acting as pooling vehicles, they can diversify individual liquidity needs, and thereby enhance overall liquidity and reduce variation of liquidity over time. However, a concern is raised that the herding behavior exhibited by institutions, acts as a force that destabilizes markets by exacerbating volatility. Xu and Malkiel (2003) attribute the increasing volatility in financial markets over time to an increase in institutional ownership. Even though institutions may diversify away the liquidity needs of individuals, their correlated trading behavior can still increase episodic demand for liquidity and cause a greater variation in liquidity over time.

There is an extensive literature in finance examining the growth in institutional ownership, the role they play in financial markets and their effects on firm policies. Khorana, Servaes, and Tufano (2005) study the large growth in institutional ownership among equity markets. Preferences of institutions and effects of these preference on equity prices is examined in Lakonishok, Shleifer and Vishny (1992), Falkenstein (1996), Gompers and Metrick (2001), Dahlquist and Robertsson (2001), Bennett, Sias, and Starks (2003), and Ferreira and Matos (2008). Additionally significant attention is given to analyze the performance of mutual funds and pension funds [Grinblatt and Titman (1992, 1993), Hendricks, Patel, Zeckhauser (1993), Coggin, Fabozzi and Rahman (1993), Goetzmann and Ibbotson (1994), Brown and Goetzmann (1995), Grinblatt, Titman and Wermers (1995), Wermers (1996), Carhart (1997), Blake, Lehmann, and Timmermann (1999)]. Institutional investors also play an important role in corporate governance by monitoring and disciplining managers through explicit actions or "voting with their feet." A series of papers examines the effect of institutions on corporate governance [Smith (1996), Wahal (1996), Bushee (2001), Abarbanell, Bushee, and Raedy (2003), Gillan and Starks (2003), Hartzell and Starks (2003), Parrino, Sias and Starks (2003), Almazaan, Hartzell and Starks (2005), Chen, Harford and Li (2007), etc.].

Both the importance of the liquidity of assets in facilitating trading and helping share and diversify risks and the growing role of institutions in financial markets, motivates this dissertation. I focus on empirically examining the effects of institutional ownership on stocks' liquidity and time variation in liquidity using a large sample of firms listed on NYSE and AMEX over the period 1980–2005.

In the second chapter, I examine the relationship between institutional ownership and liquidity of stocks, focusing on the effect of institutions' relative information advantage. I derive implications using microstructure theories that relate investors' characteristics to liquidity and examine how aggregate institutional holdings influence stocks' liquidity level. I also address concerns related to the direction of causality that arise from institutions' preference for liquid stocks. I test for the direction of causality in a time series context, and find strong evidence indicating that institutional ownership *(Granger)* causes liquidity and only weak evidence indicating that liquid stocks attract institutions. My findings strongly suggest that information advantage of institutions affects liquidity and that changes in institutional ownership help predict changes in liquidity.

In the second chapter, I further examine the effects of heterogeneity among institutions on liquidity. First, I find strong evidence indicating that liquidity declines with an increase in investment horizon and only weak evidence that liquidity of stocks affects the investment horizon of institutions. Second, I examine the effect of the diversification of the portfolios of institutions holding the stocks on liquidity, considering institutions with more diverse portfolios as more risk averse. I find strong evidence that increased risk aversion of investors, results in a decline in liquidity consistent with a reduction in information efficiency effect.

The determinants of the levels of liquidity have received sizable attention in existing empirical studies in microstructure. In the third chapter, I focus on the time variation in liquidity of assets and the sources of commonality in liquidity. Commonality in liquidity refers to the existence of systematic factors that commonly affect the liquidity of individual securities in financial markets. I aim at gaining an understanding of the determinants of the sensitivity of an asset's liquidity to the changes in marketwide liquidity (systematic liquidity risk) and the total variance of liquidity of a firm over time. I examine the effects of both aggregate institutional holdings and other characteristics of the institutions holding the stocks on their liquidity variation over time. I derive implications using the literature on herding and interpret my findings in the context of correlated trading by institutions resulting from their tendency to either herd or trade on common information.

I find strong evidence that the ownership structure of an asset affects both the sensitivity of an asset's liquidity to changes in marketwide liquidity (systematic liquidity risk) and the variation in its liquidity over time. I find that the level of institutional ownership, investment horizon of the institutional investor base, concentration of ownership, and homogeneity of the investor base are important determinants of both systematic liquidity risk and total liquidity variance. Systematic liquidity risk increases with institutional ownership, increase in investor horizon, and increasing homogeneity of the investor base, while it decreases as ownership gets concentrated and block-holdings increase. The total liquidity variance however reacts to institutional ownership measures differently. The variance of liquidity decreases with level of institutional ownership, homogeneity of the investor base and increasing ownership concentration. With increasing information asymmetry among investors, systematic liquidity risk decreases while the total liquidity variance increases.

Overall, the evidence indicates that ownership by institutions affects both liquidity and its variation over time for the U.S. equities. Characteristics of the institutional investor base such as their investment horizon, diversification of their respective portfolio holdings, concentration of ownership among institutions holding the stock, and the homogeneity of the institutional investor base are important determinants of liquidity and its time variation.

CHAPTER 2: INSTITUTIONAL OWNERSHIP AND LIQUIDITY

INTRODUCTION

Institutional ownership is a growing characteristic of U.S. capital markets. As such, the role institutions play in financial markets is becoming increasingly important. This chapter examines the effects of institutional ownership on stocks' liquidity. I derive implications using microstructure theories that relate investors' characteristics to liquidity and examine how aggregate institutional holdings influence stocks' liquidity level and whether these effects vary with institution type.

Why is liquidity important? The topic of liquidity has received substantial attention from both academics and popular press. Increase in liquidity can lead to improved sharing of financial risks by influencing investors' trading decisions due to reduction in transaction costs associated with making portfolio changes. Trading costs are large and economically significant (~1%) for large stocks in comparison to expected returns on stocks.[2] Liquidity also plays a critical role in the price discovery process. A growing body of literature examines how liquidity affects the required returns of traded assets.[3] Current theories predict that both the level of liquidity and liquidity risk are priced, while existing empirical studies find that effects of liquidity on asset prices are both statistically and economically significant.

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[2] In addition, institutions and asset management firms are concerned about minimizing transaction costs, therefore creating a demand for firms that help them in trade execution and reducing trading costs. They also care about liquidity of their portfolios, due to concerns of liquidation risk, while determining investments.

[3] For recent surveys refer to Amihud, Mendelson, and Pedersen (2005); Easley and O'Hara (2003); and O'Hara (2003).

While liquidity and liquidity risk are important, it is not clear whether institutional ownership should affect them. Yet, institutions could clearly play a very important role. Large institutions have an inherent advantage in producing and processing information about a firm, and thus are better informed than other investors.[4] In this chapter, I primarily focus on the effect of institutions' information advantage on liquidity.

Much has been written in the field of microstructure that examines the effect of informed traders on liquidity. However, underlying differences in modeling the trading behavior of informed investors, the trading motivations of uninformed investors, and information structure results in different predictions for stocks' liquidity in the presence of multiple informed traders. I maintain that the presence of informed institutions imposes adverse selection costs on uninformed investors and market makers, resulting in higher bid-ask spread (transactions cost) and lower liquidity levels of a firm's stock [Glosten and Milgrom (1985), Easley and O'Hara (1987)]. I also assert that informed institutions could play another role. In the presence of multiple informed institutions competing among themselves, the rate at which information is incorporated into prices increases, leading to lower uncertainty about the true value of the asset [Subrahmanyam (1991), Holden and Subrahmanyam (1992), Spiegel and Subrahmanyam (1992), Wang (1993), and Easley and O'Hara (2004)]. With stock prices becoming more informationally efficient, traders increase their willingness to accommodate supply shocks, given reduction in their trading losses, resulting in improved liquidity levels [Madhavan (1992) and Mendelson and Tunca (2004)]. The net effect of informed institutional holdings on a stocks' liquidity level is thus unclear

[4] Yan and Zhang (2007) find that trading by short-term institutions forecasts stock returns while Aslan et al. (2007) find strong evidence that firms with higher institutional ownership have a higher probability of informed trading.

and will depend on both the impact of *adverse selection* and *information efficiency (price discovery)*. In this chapter, I focus on this tradeoff in order to determine whether institutional ownership is associated with cross-sectional differences in liquidity levels. I further examine whether differences in characteristics of institutions holding the stocks affect their liquidity, mainly focusing on their investment horizon and diversification of their portfolio holdings.

My first finding indicates a non-monotonic (U-shaped) relationship between spreads (a measure of liquidity) and fraction of shares held by institutions. The non-monotonic relationship supports the existence of effects from both *adverse selection* and *information efficiency* on liquidity, that arise from institutions' information advantage. Growth in institutional ownership is associated with both improved price discovery and a simultaneous increase in information asymmetry between informed institutions and uninformed investors. The effect of improved price discovery dominates the adverse selection effect at lower levels of institutional ownership, resulting in lower spreads and increased liquidity. However, at higher levels of institutional ownership the adverse selection effect tends to dominate the information efficiency effect associated with price discovery, resulting in higher spreads and lower liquidity. The non-monotonic relationship between institutional ownership and liquidity can be attributed to the consequences of adverse selection and information efficiency effects. The marginal effect of increasing institutional ownership on increasing information efficiency (price discovery) will be higher at low levels of institutional ownership. At higher levels of institutional ownership, the marginal price discovery effect will be limited. This gives rise to a non-monotonic effect. The two effects of institutions on liquidity are fairly robust, and they vary with the available public information and asset risk.[5]

Second, I find strong evidence that growth in competition among informed investors increases the rate at which information is incorporated into prices. I examine intraday pattern in spreads across firms with different institutional ownership levels and find that spreads decline more during the day for firms with greater number of informed investors. The finding suggests that the role informed institutions play in price discovery has a significant effect on improving liquidity, a notion that is consistent with the theoretical findings of Holden and Subrahmanyam (1992), and Mendelson and Tunca (2004).[6]

Third, I attempt to address concerns related to direction of causality. Falkenstein (1996) and others state that institutions exhibit a preference for large liquid stocks.[7] This preference for liquid securities or a joint determination of both liquidity and institutional ownership can affect the relationship I observe in data. However, the non-monotonic relationship between institutional holdings and stock liquidity partly alleviates this concern. For example, if institutions exhibit a preference for liquid stocks, stocks that are more liquid will have higher institutional holdings, thus suggesting a monotonically increasing relationship. I test for direction of causality in a time series context, and find strong evidence indicating that institutional ownership

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[5] This dual effect of institutional ownership on liquidity is robust when using different measures for liquidity, controlling for various known determinants of liquidity, and across subsamples based on different firm characteristics. The findings are also robust when attempting to control for endogeneity.

[6] Boehmer and Kelley (2007) also find that stocks with greater institutional ownership and trading are priced more efficiently, in the sense that their transaction prices follow a random walk more closely.

[7] Falkenstein (1996) analyses mutual fund portfolios and tests their preference for liquidity using share turnover. In the cross-sectional analysis, he assumes that share turnover is an exogenous variable. My findings indicate that institutional ownership *(Granger)* causes share turnover. The portfolio turnover measure of institutions is highly persistent over time.

(Granger) causes liquidity and only weak evidence indicating that liquid stocks attract institutions. These findings strongly suggest that information advantage of institutions affects liquidity and that changes in institutional ownership help predict changes in liquidity.

For the three findings reported above, I view institutions as a homogeneous group. However, institutions exhibit different characteristics. I therefore examine whether heterogeneity among their characteristics—such as investment horizon and portfolio diversification—also affect the liquidity of stocks they hold.

My fourth finding relates to the effect of institutions' investment horizon on liquidity. Amihud and Mendelson (1986) indicate that investors select securities based on anticipated liquidity needs. I use turnover measures of institutions' portfolios to classify institutions into groups based on their investment horizon. After controlling for the level of institutional ownership, I find that liquidity increases with a shift in holdings from long-term to short-term investors. This finding is also robust in tests of causality in the time series context, indicating that changes in investment horizon of institutions affect changes in liquidity.

My fifth finding relates the diversification of institutions' portfolio holdings to liquidity. Investors' risk aversion can affect liquidity through various channels depending on the investor's information set, trading motives, and the competition faced. For lack of a better measure for risk-aversion, I create a proxy for institutions' risk aversion using the concentration of their portfolio holdings. I assume that institutions having more diversified portfolio holdings are likely to exhibit greater risk aversion, and therefore consider institutions with diversified portfolios as more risk averse. After controlling for ownership level and other known determinants of liquidity, I find that liquidity decreases with risk aversion of institutions. The marginal effect of institutions' risk aversion on spreads increases with the number of institutions, a finding suggesting that risk aversion of informed investors weakens the information efficiency effect on liquidity.

Prior empirical work on ownership and liquidity has examined effects of dispersion of ownership [Kothare (1997); Amihud, Mendelson, and Uno (1999); Chiang and Venkatesh (1988)] and presence of informed traders on liquidity [Heflin and Shaw (2000); Sarin, Shastri, and Shastri (2000); Dennis and Weston (2001); and Rubin (2007)].[8] Sarin, Shastri, and Shastri (2000), as well as Dennis and Weston (2001), use cross-sectional analysis to examine the effect of institutions' information advantage on both spreads posted by the market maker and the adverse selection component of spreads. Sarin, Shastri, and Shastri find that higher fractional ownership of stocks by both institutions and firm managers (insiders) increases the spread and reduces quoted depth after controlling for the endogeneity between ownership and liquidity. However, the authors also find that higher institutional ownership does not affect adverse selection component of spreads. On the other hand, Dennis and Weston find that spreads decrease with institutional ownership, while the adverse selection component increases. Rubin (2007) finds that liquidity increases with the level of institutional holdings, due to higher trading activity, and decreases with institutions' block holdings

[8] Both Kothare (1997) and Amihud, Mendelson, and Uno (1999) find that liquidity improves with dispersion of ownership. Chiang and Venkatesh (1988) use concentration of insider holdings as a measure of information asymmetry and find that bid-ask spreads increase with fraction of insider holdings. More recently, Heflin and Shaw (2000) look at 260 firms trading on NYSE/AMEX during the year 1988 and find that firms with greater block-holder ownership by either managers or external entities have larger quoted and effective spreads, higher adverse selection spread components, and smaller quoted depths. The authors conclude that the presence of blockholders reduces liquidity but do not find support that liquidity plays a significant role in determining block holdings.

due to higher adverse selection. To summarize, the existing findings on effect of institutional ownership on liquidity provide mixed evidence.[9]

When examining the effect of institutions on liquidity, all the studies previously mentioned assume institutions have a relative information advantage. However, the studies focus only on the adverse selection effect resulting from the information advantage and test for a linear relationship between institutional ownership and liquidity. Unlike these papers, I take a broader approach, from both theoretical and empirical standpoints. Theoretically, I consider an additional aspect, the potential effect of institutional ownership on information efficiency, which can cause an increase in liquidity. Empirically, I test for both the adverse selection and information efficiency effects, and I allow for the presence of a non-monotonic relationship between institutional holdings and liquidity. I further examine the variation in effects of institutional ownership on liquidity depending on both asset risk and information availability and also examine effects of differences in institution type on liquidity.

Another limitation of existing studies is the use of cross-sectional analysis based on data over a short time interval. The shorter time frame in the existing studies makes it harder to effectively control for unobserved firm-specific effects that simultaneously influence institutional ownership and liquidity and the potentially endogenous relation between the two.[10] To test the relationship between institutional ownership and

[9] Glosten and Harris (1988) also find an insignificant relationship between spreads and insider holdings for 250 firms belonging to NYSE over the period 1981–1983. It is thus possible that insiders also have two effects on liquidity due to increases in information efficiency and adverse selection.

[10] In their simultaneous equation systems for the purpose of identification, Dennis and Weston (2001) exclude size and 1/Price from the liquidity equation, while Sarin, Shastri, and Shastri (2000) exclude size, age of the firm, and R&D to sales from the liquidity equation. Size can influence liquidity independent of ownership structure because it affects the amount of information available about the firm. These studies do not report tests of validity of exclusions. Dennis and Weston also use pooled regressions. Their findings could therefore be biased, given persistence in both ownership and liquidity measures over time, resulting in a lack of independence across periods. Refer to Petersen (2007).

liquidity, I use both annual and quarterly data for the period 1980 to 2005 on institutional holdings and various liquidity measures. The panel comprising of 4,578 firms and spanning 26 years allows me to not only examine variation in liquidity across firms, but also, follow firms over time and examine the relationship between changes in institutional holdings and changes in liquidity at firm level.

I provide a number of new results on the relationship between institutional holdings and liquidity, and by implication, on the validity of some of the theories related to the effects of informed trading on liquidity. To an extent, I reconcile the differences in findings across existing studies. Besides the sample differences, the more likely explanation for the differences is the existence of a non-monotonic relationship between institutional ownership and liquidity. Ignoring the effect of information efficiency on liquidity, which also results from institutions' information advantage, and trying to estimate the relationship using a linear specification can bias the results.

The remainder of this chapter is organized as follows. Section 1 presents the main hypotheses relating the effects of informed traders on liquidity by reviewing the microstructure literature to develop the hypothesis. Section 2 introduces data focusing on the measures of liquidity and institutional holdings, while briefly introducing other control variables. Section 3 presents the findings from tests on effects of institutional ownership on liquidity and summarizes the robustness checks. Section 4 tests the effect of competition among informed investors on information efficiency and intraday patterns in spreads. Section 5 addresses the endogeneity concerns and presents findings from *Granger* causality tests. Section 6 examines the effect of institutional characteristics such as investor horizon and risk aversion on liquidity. I present conclusions on the effects of institutional ownership on liquidity in Section 7.

SECTION 1: THEORIES AND HYPOTHESIS DEVELOPMENT

Large institutions have an inherent advantage with respect to producing and processing information compared to other investors. They devote resources to gathering information and sometimes are privy to corporate information that individual investors do not have. However, some institutions follow passive indexing strategies and refrain from investing effort in collecting firm-specific information. Nevertheless, institutions generally tend to have an information advantage over other investors.

The effect of informed traders on liquidity and price efficiency is an actively researched topic. Glosten and Milgrom (1985) and Easley and O'Hara (1987) indicate that in the presence of informed investors acting nonstrategically, the adverse selection risk faced by the risk-neutral market maker gives rise to spreads, even in the absence of any fixed costs. With an increase in the number of informed institutions, a risk-neutral market maker widens the spreads to set regret-free prices due to the higher adverse selection risk. Thus, firms with a higher fraction of informed traders will have higher spreads. This is because both the probability of a trade arising from an informed trader and the amount of information represented in the order flow are higher. Therefore, spreads should increase and liquidity decline with increases in the number of institutions or the fraction of equity held by institutions.[11] Hypothesis 1 summarizes the prediction relating the effect of adverse selection arising from institutions' information advantage to liquidity.

[11] In addition, institutions' propensity to herd and trade in the same direction can force specialists to maintain larger inventories to provide liquidity. This can result in higher spreads or trading costs with an increase in institutional ownership due to increased inventory holding costs. The effect of institutional herding on time variation in liquidity is explored in Chapter 2 of the dissertation.

Hypothesis 1 [Adverse selection hypothesis]: All else being equal, firms with greater institutional holdings or held by larger numbers of institutions will have *lower* liquidity (*higher* spreads).

My second hypothesis relates to the information efficiency effect that also results from information advantage of institutions. Kyle (1985) framework is used extensively to study the effect of informed traders and their information advantage on liquidity and price efficiency. Mendelson and Tunca (2004) consider a variation of Kyle's model with a single informed investor in a multi-period model and endogenized liquidity trading. The authors indicate that as prices reflect more information about the security's value, the reduction in risk of trading the security results in an increase in liquidity trading, which provides a greater opportunity for the informed investors to hide in the order flow. The increased trading of informed investors' result in prices reflecting more information, an effect I call as information efficiency.

Subrahmanyam (1991), Holden and Subrahmanyam (1992), and Spiegel and Subrahmanyam (1992) show that information efficiency effect is enhanced by competition among informed investors. Subrahmanyam (1991) considers a risk-averse market maker and multiple informed investors observing a noisy signal of the value of the asset. His model suggests that sensitivity of price to order flow (*lambda*) is monotonically decreasing with respect to the number of informed traders, if they are risk neutral, and indicates that even in the presence of strategic behavior, increasing competition among the informed investors results in higher liquidity. Spiegel and Subrahmanyam (1992) extend Subrahmanyam (1991) and allow the liquidity trades to be endogenous by motivating them based on hedging needs. The authors also indicate that with an increase in the number of risk-neutral informed investors, the greater competition results in higher liquidity.[12]

Holden and Subrahmanyam (1992), Foster and Viswanathan (1996), and Back, Cao, and Willard (2000) further investigate the effect of multiple informed traders acting strategically on liquidity. They analyze the effects of informed traders in multi-period models with exogenous liquidity trading. Holden and Subrahmanyam find that in the presence of a large number of informed investors with *perfectly* correlated signals, the increased competition among risk-neutral informed investors increases the information efficiency of prices. Markets become infinitely deep and almost infinitely tight in no time (i.e., there is a low cost to turning around a position). Foster and Viswanathan, and Back, Cao, and Willard also suggest that an increase in the correlation among signals of the informed investors can enhance the competition among them, resulting in a faster incorporation of information into prices.

These theoretical findings suggest that, in the presence of risk-neutral informed investors, the growth in competition among them causes prices to incorporate information faster and become more information efficient. This results in reduced uncertainty about the value of the stock. As a result, in the presence of informed institutions, the price impact of order flow will decrease and uninformed traders will be more likely to invest in the stock, further increasing liquidity.[13] Hypothesis 2

[12] The strategic-trader models also indicate that with an increase in informed traders the amount of information represented in the order flow increases, thereby increasing the adverse selection effect as suggested in sequential trade models by Glosten and Milgrom (1985) and Easley and O'Hara (1987).

[13] Madhavan (1992) demonstrates that, for infrequently traded stocks, the lack of continuous prices impedes the price discovery process. As a result, prices are less efficient and information gathering becomes more expensive, further reducing liquidity. This may suggest that the presence of institutions with a relative information advantage will lead to price discovery and improve liquidity. On the other hand, increased liquidity can result in more uninformed trading, resulting in a slower adjustment of prices. Admati and Pfleiderer (1988) also indicate that an increase in the number of informed traders

summarizes the prediction relating information efficiency effect of institutions on liquidity.

Hypothesis 2 [Information efficiency hypothesis]: All else being equal, firms with greater institutional holdings or held by larger numbers of institutions will have *higher* liquidity (*lower* spreads).

Wang (1993) models the two implications of informed trading on asset prices by incorporating both aspects of information structure: asymmetric information and imperfect information. All traders in the model are risk averse and informed traders act competitively. Uninformed investors face an adverse selection problem, in the presence of the informed, while trying to meet their liquidity needs by trading in the market. Informed investors bring more information into prices thus reducing the perceived uncertainty about future cash flows and risk of investing in the stock. In this setting, the sensitivity of stock price to supply shocks depends on the net effect of the two offsetting forces, imperfect information effect and information asymmetry effect and can be non-monotonic.[14]

The strategic-trader models of Subrahmanyam (1991), Holden and Subrahmanyam (1992), etc., also predict a non-monotonic relationship between the number of informed investors and liquidity in the presence of risk-averse informed traders. The presence of informed investors thus results in both the effects of adverse selection and information efficiency. The observed relationship between liquidity and institutional

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can lead to improvement in terms of trade for uninformed traders. Another argument is that increase in information efficiency will reduce the risk of holding on to inventory.

[14] Wang indicates that instabilities become important in the presence of an endogenous information structure. Thus, the effects of multiple informed traders in case of costly information acquisition are unclear.

ownership will therefore depend on the net effect. Based on these theoretical papers, the predicted relationship is highly sensitive to the assumptions of their models. I therefore examine the possibility that the net effect of institutions on liquidity resulting from both adverse selection and information efficiency effects is *non-monotonic*.[15]

The information efficiency hypothesis has an additional implication for the intraday variation in liquidity measures.[16] In both sequential trade models and multi-period strategic-trader models, prices incorporate more information as trading progresses after arrival of information. The rate at which prices converge to their true value increases with trading intensity of informed investors. With improvement in information efficiency of prices, the risk faced by market maker and uninformed investors decreases, resulting in higher liquidity. At the start of trading, both the likelihood of existence and the magnitude of private information are higher due to information accumulation after the end of trading on the previous day. A market maker should therefore post higher spreads at the beginning of trading to reduce the adverse selection costs. With progress in trading over the day, prices become more information efficient and the market maker lowers spreads.

Holden and Subrahmanyam (1992) use a multi-period model to capture the effect of multiple informed traders acting strategically on liquidity. The authors find that soon after the *start of trading,* both market depth and tightness (i.e., cost to turn around a position) increase. The rate of decline in spreads increases with the number of

[15] Similarly, in Watanabe (2008) in a multi-period model with persistence of information shocks, the market maker worsens the terms of trade due to adverse selection. At the same time, the higher competition among informed traders allows him to improve the liquidity because each of the informed traders makes less profit.

[16] Intra-day spreads for stocks listed on NYSE typically exhibit an inverse J shaped pattern (McInish and Wood, (1992)). Spreads decline after opening and exhibit a small spike just prior to close.

informed traders. The net effect is that for firms with larger numbers of informed traders, spreads start out higher and exhibit a larger decline during the day, relative to firms with fewer informed traders. Hypothesis 3 summarizes this prediction with respect to information efficiency effect on intraday patterns in spreads.[17]

Hypothesis 3: Spreads of firms with higher institutional ownership and held by larger numbers of institutions will decline more during the day.

The three hypotheses rely on the assumption that institutions are both informed and homogeneous. In reality, institutions are not completely homogeneous and differ widely with respect to various attributes. Institutional investors differ according to their incentive structures and fiduciary duties, and even have different investment horizons [Bushee (1998), Bushee and Noe (2000)].[18] Gammill and Marsh (1988) document that pension funds, individual investors, and corporations repurchasing their own shares were the biggest providers of liquidity on October 20, 1987, a day after "Black Monday." Dennis and Strickland (2005) also find strong evidence that banks tend to provide liquidity while mutual funds and investment advisors tend to demand liquidity on days with large abnormal returns. I therefore examine the effect of institutional characteristics such as investment horizon and portfolio diversification on liquidity, with the objective of gaining insight into how holdings by different types of institutions affect stocks liquidity.

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[17] I only test the relationship between the decline in spreads during the day and institutional ownership, as NYSE opens with a call auction which makes it harder to estimate liquidity in the first period.

[18] Institutions differ in their preference for assets since their objectives and constraints vary widely. For example: insurance companies are less concerned about liquidity as opposed to investment companies which may face large fund outflows at short notice in response to poor performance or other shocks.

SECTION 2: DATA AND DESCRIPTIVE STATISTICS

SECTION 2.1: LIQUIDITY MEASURES

Liquidity is a difficult construct. It captures the notion that there are costs associated with transacting. These costs are associated with exogenous transaction costs, search costs, asymmetric information, inventory risk, and imperfect competition in asset markets. In addition, liquidity of an asset also indicates the speed and ease with which it can be transacted. The unobservable nature of liquidity and its multiple facets make it difficult for a single measure to capture its various dimensions. For lack of better measures, most studies use the bid-ask spreads posted by a dealer or estimates of the price impact of a trade, based on structural models, to quantify liquidity. The empirically derived measures of liquidity of stocks that are based on both high frequency and daily returns are noisy estimates of the true parameter(s). However, most of the measures used in the existing literature are highly correlated. I rely on the following four measures to ensure robustness of results: Gibbs estimate *(c_BMA)* proposed by Hasbrouck (2004, 2006), *ILLIQ* proposed by Amihud (2002), Quoted Spread measure divided by price (*RELQSPR*) and Effective Spread measure divided by price *(RELESPR)*.[19]

Gibbs estimate (*c_BMA*) for liquidity is obtained using a variant of Roll's model (1984) and daily closing prices. Underlying it is the square root of the negative of the serial covariance of daily price changes. The estimated annual measure for the effective cost of trading is highly correlated with effective spread measures based on intraday trading data both in cross-section and in time series.[20] Amihud's measure of

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[19] I include only common equity (CRSP share codes 10 or 11) in calculating the liquidity measures as trading characteristics of other assets (such as: certificates, ADRs, shares of beneficial interest, units, companies incorporated outside U.S., closed end funds, American trust components, preferred stocks, and REITs) may differ from that of common equity.

[20] The Bayesian approach proposed by Hasbrouck (2006) has various advantages. The primary advantage is that it overcomes estimation errors in the first-order auto-covariance of changes in prices.

liquidity *ILLIQ* is related to Kyle's lambda (1985) and is defined as |R|/(P*Vol), where R is daily return, P is the closing daily price, and Vol is the number of shares traded during the day. To obtain an annual measure, I take the average of the daily values over the year and use the square-root transform to reduce skewness. One obvious problem with *ILLIQ* is its estimation on days with no trading.

I estimate two other measures of liquidity using the intra-day data from ISSM and TAQ for NYSE and AMEX firms. The ISSM database includes trades and quotes data for NYSE- and AMEX-listed firms for the period January 1983 through December 1992, while TAQ database includes similar information for NYSE/AMEX- and NASDAQ-listed stocks for the period January 1993 through December 2005. *RELQSPR* is defined as the difference between ask and bid, scaled by the midpoint of the prevailing quote.[21] *RELESPR* is defined as the absolute value of the difference between the transaction price and the quote midpoint, scaled by the midpoint of the quote. I compute these measures of liquidity by first averaging them over the trading day and then using the mean of the daily values for the year. Both *c_BMA* and *ILLIQ* are available for the entire period 1980–2005, while *RELQSPR* and *RELESPR* are available for years 1983–2005.[22] I also estimate *RELQSPR* and *RELESPR* on a

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The correlation of the measure with various other liquidity measures in my sample is very high. (Please refer to Table 2.3.)

[21] I calculate the spread measures for firms using quotes only from NYSE and AMEX because the autoquotes from other exchanges tend to inflate the quoted spreads. I also kept quotes where the Mode field was equal to 1, 3, 6, 10, or 12 and eliminate quotes with non-positive bid or ask price, quotes where bid was greater than ask, and in cases in which the quoted spread and effective spread either exceeded 25% of the quote midpoint or were greater than $5. I use trades that are coded as regular and eliminate trades with non-positive prices or sizes, where the price of the trade was either less than 50%, or more than 150%, of the price of the previous trade. I also eliminate opening trades to avoid after-hour liquidity effects [Barclay and Hendershott, (2004)] and eliminate quotes established before the opening of the market.

[22] All findings are robust to using these measures of liquidity. For the sake of brevity, I report findings using *c_BMA* for most tests and summarize findings using the other measures.

quarterly basis to conduct *Granger* causality tests. All the measures indicate illiquidity for the stocks and an *increase* in these measures indicates a *decline* in liquidity.

SECTION 2.2: INSTITUTIONAL OWNERSHIP MEASURES

I obtain institutional holdings data from Thomson Financial (previously known as CDA Spectrum) database, consisting of 13F filings reported quarterly to the Securities and Exchange Commission (SEC) for the period 1980–2005.[23] Institutional investment managers are supposed to report their holdings—number of shares and fair market value as of the last day of the calendar quarter as required by Section 13(f)(1) and Rule 13f-1. The 13F reporting requirements apply regardless of whether an institution is regulated by the SEC or not. They also apply to foreign institutions if they "use any means or instrumentality of United States interstate commerce in the course of their business."[24] I simply sum up the holdings at the end of each quarter, for all institutions in the sample, to obtain total institutional holdings of the security at the end of the quarter. I divide the total institutional holdings by the shares outstanding obtained from CRSP at end of each quarter and then take the yearly average of the proportion

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[23] All institutional managers who exercise investment discretion over 13F securities with a market value over $100 million are required to report their holdings within 45 days after the close of the quarter, according to the 1978 amendment to the Securities and Exchange Act of 1934. Institutions are required to report all equity positions greater than 10,000 shares or $200,000 in market value. In two respects, 13F data is incomplete: (1) institutions may be granted exception from filing these reports when they request confidential treatment to prevent disclosure of their proprietary trading strategies and (2) institutions have to disclose only their long positions, and the 13F filings do not contain information on short positions or options written. Given that a majority of institutional investors (pension funds, mutual funds, insurance companies) have mandates preventing them from short sales, and, on average short interest in most securities is around 2%, this factor should not materially affect the holdings data. In addition, CDA-Spectrum classifies each institutional investor as one of five types: bank trust departments, insurance companies, mutual funds, independent investment advisors, and unclassified institutions.

[24] The filing requirements also apply to hedge funds, if their holdings of U.S. stocks exceed the specified thresholds. Hedge funds may be able to mask their holdings from the SEC and, given that a large fraction of hedge funds invest in long/short equity strategy, the holdings data will not be accurate. Identifying the holdings by hedge fund managers is difficult as the reporting entity is the institution and not the fund. An institution can have other funds besides hedge funds, like mutual funds, and the disclosed holdings to SEC are at the aggregate level.

of the holdings to obtain an annual measure of institutional holdings referred to as *fracinst*.

SECTION 2.3: CONTROL VARIABLES

High-price volatility and low trading volume increase the inventory risk faced by market makers [Amihud and Mendelson (1980), Ho and Stoll (1983), and O'Hara and Oldfield (1986)]. Further, higher residual uncertainty about stock prices results in reduced liquidity trading and thinner markets. Benston and Hagerman (1974) find that higher individual stock volatility is cross-sectionally associated with higher spreads. I therefore include stock-return volatility (*volatility*) as a control variable calculated using the standard deviation of the daily stock returns, excluding dividends, over a one year period.

With increases in institutional holdings in a stock, the incidence of large blocks is likely to increase. To control for the effect of block ownership on spreads and associated reductions in trading, I include the variable number of blocks (*NumBlocks*), where a block exists if an institution holds more than 5% of outstanding equity in the firm. I obtain the fraction of shares held by insiders (*fracinsider*) from Disclosure Incorporated's Compact D database and match the data to CRSP and TAQ using the firm's CUSIP. Insider ownership can result in lower liquidity through two means: by reducing free float of outstanding shares and by aggravating the information asymmetry problems. Increasing insider ownership could increase information efficiency.

I include additional control variables: log of market capitalization (*LnSize*), which captures size of the firm, and share turnover (*turnover*) measured as total trading volume scaled by total shares outstanding.[25] Stoll and Whaley (1983) indicate that it is less expensive to trade stocks of larger firms as there is more information available about them due to greater media and analyst coverage. Size also influences liquidity by influencing the breadth of ownership of the stock. The payout policy of a firm may also influence trading behavior in the firm's equity, as investors may not need to liquidate their holdings to realize gains for a firm paying dividends. Payout policy is also associated with clientele of the firm (Grinstein and Michaely, 2005) and may thus be associated with liquidity. I therefore include an indicator variable (*DivDummy*), for firms paying dividends, and an additional variable dividend yield (*DivYld*) calculated as annual dividends divided by share price.

Capital structure of a firm can affect information disclosure as suggested in security design literature. Diamond and Verrecchia (1991) indicate that increased disclosure by a firm leads to a reduction in information asymmetry between the firm and the investors, resulting in improved liquidity. Brennan and Subrahmanyam (1995); and Easley, O'Hara, and Paperman (1998) also indicate that an increase in the number of investment analysts following a firm, which proxies for the number of individuals producing information, reduces adverse selection costs of trading in the stock and improves liquidity. Hence I include both leverage (*MktLev*) measured as long-term debt by market value of total assets (market value of equity plus book value of debt and preferred stock) and the log of number of equity analysts following the firm (*LnNumest*) defined as log of (1 + Number of Analysts). High-growth firms tend to attract more attention from both media and investors, hence, I include book to market ratio (*BookToMkt)* and R&D to sales ratio (*RDbySales*) as additional control variables.

[25] Turnover is used as a proxy for a variety of effects and, so, interpretation may be difficult. High share turnover may indicate a higher dispersion in beliefs of investors arising from differences in information, while it can also indicate a measure of liquidity. My findings are robust to excluding turnover as a control variable. The findings on using turnover as a measure for liquidity are similar.

I include inverse of share price (*InvPrice*) since spread measures exhibit a nonlinear relationship with share prices [Chordia, Roll, and Subrahmanyam (2001)].[26]

Liquidity measures may be sensitive to changes in stock price of the firm during the year. Hence, I include annual returns (*annret*) during the year to control for any related effects. Including contemporaneous returns controls for both inventory-related effects resulting from financial constraints of market makers, herding behavior of institutions and effects related to investors funding status on liquidity. Since institutions also respond to past performance by chasing trends and exhibiting herding behavior, I include lagged annual returns (*lagannret*) as another control variable to isolate the effect of the herding behavior from information-related effects.[27]

Presence of credit ratings may suggest lower uncertainty about a firm and indicate that the investment is prudent. To control for effect of credit ratings and the associated information effects, I include an additional indicator variable *CredRatDummy* equal to 1 for firms that have available credit ratings and equal to 0 otherwise.[28] I also include profit margin (*profitability*), defined as net income divided by sales, and an additional indicator variable for positive cash flows (*CashFlowDummy*) to capture effects associated with financial distress risk on liquidity.

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[26] To capture any potential nonlinearity due to the minimum tick size and fixed components in the spread measures, I also include log of share price (*LnPrice*). All findings are robust to using either *LnPrice or InvPrice* or both of the measures.

[27] I take log of (1+return), as a measure of annual return, to reduce skewness in the returns.

[28] The credit rating used is Standard & Poor's Long-Term Domestic Issuer Credit Rating (Compustat data item 280). This rating is the firm's "corporate credit rating," which is a "current opinion on an issuer's overall capacity to pay its financial obligations" (Standard and Poor's (2001b, p. 61) "SP"). 1985 is the first year for which this rating is available in Compustat.

Hypotheses 1 through 3 rely on the premise that institutions have an information advantage over other investors. However, many institutions tend to follow passive investing strategies and are uninformed. Over time, indexing has become more popular as a low cost alternative to active investing. Current estimates suggest that roughly 20% of the outstanding equity of various firms held by institutions is managed passively through index funds and ETF's tracking popular benchmarks.[29] The presence of index funds acting as a pooling vehicle can reduce trading volume and change the information environment of firms included in the indices. To control for the effect of being included in leading stock indices on liquidity, I create two additional indicator variables for firms belonging to the S&P 500 (*SP500Dummy*) and the Dow Jones Industrial Index (*DJDummy*).[30]

I include industry fixed effects to control for differences in liquidity using Fama-French 12 classification. I also include time fixed effects to control for the effects of general market conditions such as interest rates—which affects costs of margin trading and short selling—default spreads, market volatility, and other macroeconomic conditions on liquidity. Time fixed effects also help control for time trends in measures of liquidity, resulting from changes in minimum tick sizes and other changes in technology.

SECTION 2.4: SAMPLE DESCRIPTION

Data on CRSP is available for 80,022 firm years over the period 1980–2005 for firms listed on NYSE and AMEX, with 8,558 unique firms. I retain firms listed on NYSE

[29] March 4, 2009, The Wall Street Journal, Active vs. Passive: Indexing Wins '08, Benchmarked Mutual Funds Pick Up Share

[30] Hegde and McDermott (2003) find that spreads decline when firms are included in the S&P 500 index, while they increase on their deletion from the index. Liquidity for stocks included among index can also increase due to index arbitrage activities.

and AMEX for the entire year and securities designated as ordinary common shares (share codes 10 and 11), resulting in 57,242 firm-year observations. After merging with Gibbs sampler estimate from Hasbrouck and accounting data from CRSP/Compustat merged database, 49,190 firm-years remain. After including control variables from other data sources and eliminating observations with missing values of dividend yield, book to market ratio, last periods' annual returns, profit margin, leverage ratio, and earnings to price ratio, 46,696 observations remain.

The data specified previously is matched to ownership data from Thomson Financial using CUSIP's. The matching procedure results in 42,931 firm-years. I further eliminate firms with stock prices less than $5 and stock prices greater than $1000, resulting in 39,701 firm-years, with 4,578 unique firms with an average of 1,525 firms each year. Overall, the distribution of firms is uniform over the 26-year sample period.[31] Of the 39,701 firm-years remaining, institutional ownership data exists for 31,388 firm-years. For firms with missing ownership data, I assume that institutional ownership is zero.[32] On merging with liquidity measures estimated using intraday data from ISSM and TAQ (over the period 1983–2005), 34,575 observations remain. I report results based on a full sample of 39,701 firms when using liquidity measures *c_BMA* and *ILLIQ,* and based on 34,575 firms when using the liquidity measures *RELESPR* and *RELQSPR* obtained from intraday trade data. To remove the effect of outliers, I also winsorize at 1% level and 99% level, the following variables: volatility,

[31] Of the 4,578 firms, 3,116 firms are listed on NYSE (31,701 firm-years), with the remaining 1,462 on AMEX (8,000 firm years). There are 722 observations for firms belonging to the Dow Jones Industrial Index and 7,771 observations for firms belonging to the S&P 500 Index. The sample size is very similar to that in Boehmer and Kelley (2007) who look at effect of institutional holdings on price efficiency.

[32] All findings in this chapter are robust to excluding these firms from the analysis. The findings are almost identical when retaining firms with stock prices greater than $1 instead of $5.

book to market, share turnover, market leverage, profitability, dividend yield, R&D by sales, and annual returns.

SECTION 2.5: SUMMARY STATISTICS

Table 2.1 presents the summary statistics of the various measures of liquidity over the sample period. The measures are comparable to liquidity measures used in other studies. The mean of *c_BMA* is 0.0046, indicating trading costs of 46 basis points on average. The relative effective spread *RELESPR* (0.0075) is smaller than the relative quoted spread *RELQSPR* (0.0106), indicating that transactions often take place within the quotes. These measures are similar to those reported in existing studies [Chordia, Roll, and Subrahmanyam (2000), etc.].

Table 2.2 presents summary statistics for other variables. The mean of equity holdings by institutions is 35.4%, for firms in the sample. The average number of institutions holding securities is 155, for firms with institutional ownership data available. The average market capitalization of firms is $3.1 B with total assets of $6.8 B and a mean book to market ratio of 0.70, indicating a bias toward larger firms with lower growth, typical for a sample restricted to NYSE/AMEX firms. Approximately 71% of firm-years have dividend payments with the average dividend yield of 5.1%, again indicating the presence of larger and more mature firms. For the 28,455 firm-years with analyst following greater than zero, the median number of analysts is 9.6, while for the whole sample, the median number of analysts is 6.9. The average stock price is $28. Figure 2.1 plots the average illiquidity measures for NYSE/AMEX firms and fraction of equity of the firm held by institutions over time. Average institutional ownership of equity in firms belonging to NYSE/AMEX has increased from 15% in

1983 to 60% in 2005 reflecting a growth rate of 6.3% over the last 25 years. The illiquidity measures have declined over the period indicating an increase in liquidity.

SECTION 3: INSTITUTIONAL OWNERSHIP AND LIQUIDITY RESULTS

The analysis of the effect of institutional ownership on liquidity measures follows the exposition of the arguments in the introduction. First, I present univariate results followed by those from multivariate analysis. Multivariate analysis not only helps control for correlation among various variables and liquidity measures, but also helps test the result of interaction between the adverse selection and information efficiency effects.

SECTION 3.1: UNIVARIATE RESULTS

Panel A of Table 2.3 presents correlations between various liquidity measures for firms listed on NYSE and AMEX, while Panel B presents the correlation of Hasbrouck's measure of liquidity (*c_BMA*) with other variables of interest. The lower triangles present Pearson correlations and the upper triangles present Spearman rank correlations, as some variables exhibit skewness. The correlations are first calculated on an annual basis and the time series means are presented. The variable *c_BMA* exhibits strong positive correlations with other measures of illiquidity *(ILLIQ, RELQSPR* and *RELESPR)*. The correlation between *RELESPR* and *RELQSPR* is 0.943. The quoted depth (*QuotedDepth*) measure exhibits a marginally negative correlation with the spread-based measures of liquidity.

Table 2.1: Summary statistics: Liquidity measures. This table presents summary statistics for liquidity measures. Summary statistics represent observations pooled over the entire sample period 1980–2005 for the following measures: Gibbs Sample and Amihud's illiquidity measure. The summary statistics for remaining liquidity measures obtained using intraday trading data are for the period 1983–2005. The liquidity measures are *c_BMA*, the Gibbs sampler estimate obtained from Joel Hasbrouck; *ILLIQ*, square root of the Amihud's measure of illiquidity [Absolute(ret)/Volume]; *QSPR*, the quoted spread (bid-ask); *ESPR*, the effective spread, equal to [transaction price - (bid+ask)/2]; *RELQSPR*, relative quoted spread [QSPR/Price]; *RELESPR*, relative effective spread [ESPR/Price]; *FracAS_GH*, the adverse selection component of the spread estimated using the Glosten and Harris approach.

Variable	**N**	**Mean**	**Median**	**Minimum**	**P1**	**P99**	**Maximum**	**Std Dev**	**Skewness**	**Kurtosis**
c_BMA	39701	0.0046	0.0036	0.0008	0.0011	0.0161	0.0631	0.0033	2.18	9.49
Amihud (ILLIQ)	39701	0.2738	0.1257	0.0027	0.0086	1.7699	6.0511	0.3718	2.81	11.60
RELQSPR	34575	0.0106	0.0085	0.0003	0.0005	0.0376	0.1319	0.0086	1.57	4.80
RELESPR	34575	0.0075	0.0056	0.0003	0.0004	0.0286	0.1557	0.0067	2.70	22.15
FracAS_GH	33957	0.5195	0.5089	-1.0868	0.1776	0.9344	1.7743	0.1551	0.41	1.35

Table 2.2: Summary statistics: Other variables. Summary statistics of institutional ownership measures and other control variables, representing pooled observations over the entire sample period of 1980–2005 for the following measures: *fracinst*, amount of shares held by institutions that have reported that they held long positions in the security of interest in 13F filings divided by shares outstanding; *sqfracinst*, *fracinst*fracinst*; *fracinsider*, fraction of shares held by insiders in the firm; *InstDummy*, an indicator variable and is equal to 1 for firms with fracinst greater than 0, and 0 otherwise; *NumInst*, average number of institutions that have reported having held long positions in the security of interest in 13F filings; *MktCap*, the total market capitalization of the firm calculated at beginning of the year (shares outstanding * Price); *Price*, average monthly closing share price of the firm over the year; *Profitability*, net income divided by total sales; *CashFlowDummy*, an indicator variable equal to 1 for firms with positive cash flow per share and 0 otherwise; *SPRatDummy*, an indicator variable equal to 1 if the firm has a rating available from S&P 500 and 0 otherwise; *BookToMkt*, book value of equity at previous fiscal year ending divided by market value of equity at end of last calendar year; *MktLev*, total debt outstanding divided by sum of total assets and market value of equity less book value of equity; *Volatility*; standard deviation of daily returns over the calendar year; *turnover*, total trading volume divided by shares outstanding; *annret*, the annual returns including dividends; *lagannret*, annual returns from last year; *DivDummy*, an indicator variable equal to 1 for firms that have positive dividend payout and 0 otherwise; *DivYld*, total dividends paid divided by book value of equity; *RDD*, an indicator variable and is equal to 1 for firms reporting positive R&D expenses and 0 otherwise; *RDbySales*, equal to R&D expenses divided by total sales and is zero for firms when RDD=0; *NumEst*, average number of analysts following the firm; *LnNumEst*, natural log of (1+NumEst); *ForecastDev*, dispersion in the analyst forecast; *LnSize*, the natural log of the market capitalization of the firm.

Variable	N	Mean	Median	Minimum	P1	P99	Maximum	StdDev	Skewness	Kurtosis
fracinst	39701	0.3543	0.3492	0.0000	0.0000	0.9452	0.9500	0.2768	0.23	-1.12
InstDummy	39701	0.8204	1.0000	0.0000	0.0000	1.0000	1.0000	0.3838	-1.67	0.79
sqfracinst	39701	0.2022	0.1219	0.0000	0.0000	0.8935	0.9025	0.2246	1.14	0.51
NumInst	31388	155	98	1	2	885	1636	181	2.49	8.97
fracinsider	39701	0.0573	0.0035	0.0000	0.0000	0.6916	0.9499	0.1344	3.45	13.13
Sales	39701	6836	772	1	14	104741	1494037	37126	18.13	459.95
MktCap	39701	3159	497	2	9	49846	507217	13353	14.14	296.50
Price	39701	28.17	23.00	5.00	5.25	103.00	998.00	26.36	9.84	226.03
profitability	39701	0.0443	0.0472	-5.6818	-0.3607	0.2814	0.3983	0.1522	-14.44	377.27
CashFlowDummy	39701	0.3736	0.0000	0.0000	0.0000	1.0000	1.0000	0.4838	0.52	-1.73
SPRatDummy	39701	0.6137	1.0000	0.0000	0.0000	1.0000	1.0000	0.4869	-0.47	-1.78
BookToMkt	39701	0.7043	0.6095	-8.6534	-0.1196	2.4831	9.9317	0.5226	1.25	16.05
MktLev	39701	0.1840	0.1560	0.0000	0.0000	0.6287	0.7822	0.1530	0.85	0.27
volatility	39701	0.0227	0.0209	0.0068	0.0088	0.0526	0.1132	0.0095	1.46	4.40
turnover	39701	0.7667	0.5715	0.0355	0.0629	3.4738	6.3541	0.6913	2.62	10.73
annret	39701	0.1919	0.1303	-0.9227	-0.5786	1.8088	5.1696	0.4500	1.94	9.10
DivDummy	39701	0.7098	1.0000	0.0000	0.0000	1.0000	1.0000	0.4539	-0.92	-1.15
DivYld	39701	0.0367	0.0275	0.0000	0.0000	0.1922	0.3912	0.0415	2.04	7.43
RDD	39701	0.3523	0.0000	0.0000	0.0000	1.0000	1.0000	0.4777	0.62	-1.62
RDbySales	39701	0.0136	0.0000	0.0000	0.0000	0.1600	1.2552	0.0373	9.58	211.25
NumEst	39701	6.9158	3.9167	0.0000	0.0000	32.1667	47.8333	8.1022	1.37	1.42
ForecastDev	25975	0.1159	0.0542	0.0000	0.0000	0.8760	34.2300	0.3857	54.16	4241.02
LnNumEst	39701	1.4787	1.5926	0.0000	0.0000	3.5015	3.8884	1.1551	0.00	-1.37
LnSize	39701	6.1793	6.2093	0.5625	2.1673	10.8167	13.1367	1.9274	0.12	-0.28

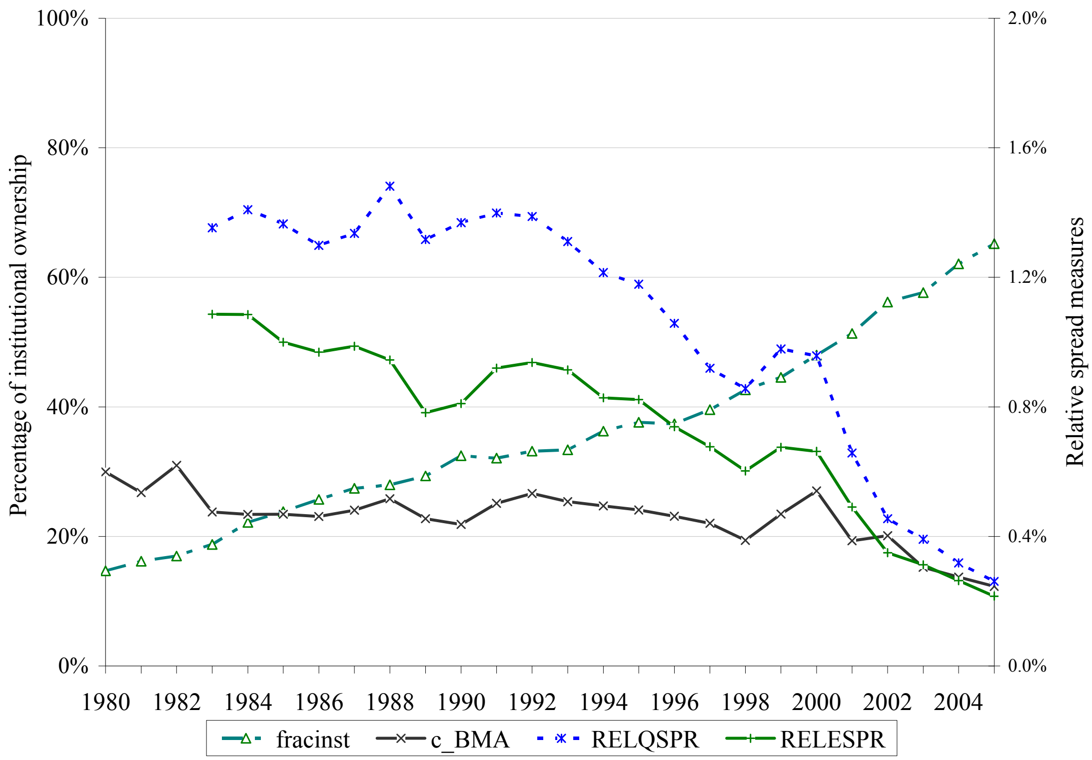

Figure 2.1: Time trend, liquidity measures, and institutional ownership

Table 2.3: Correlation measures. Correlations across variables of interest for firms listed on NYSE and AMEX during the sample period 1980–2005. The bottom triangle presents the Pearson correlations, while the upper triangle presents the Spearman rank correlations. The correlations are estimated by pooling all observations over the sample period. Panel A presents correlations between various liquidity measures. Panel B presents the correlations between Hasbrouck's effective spread measure (*c_BMA*), institutional ownership (*fracinst*) and among various other variables.

Panel A

Variable	*c_BMA*	*Amihud (ILLIQ)*	*RELQSPR*	*RELESPR*	*fracAS_GH*
c_BMA		0.516	0.581	0.579	-0.027
Amihud (ILLIQ)	0.582		0.828	0.841	0.474
RELQSPR	0.690	0.723		0.985	0.264
RELESPR	0.664	0.737	0.943		0.284
FracAS_GH	-0.008	0.472	0.226	0.258	

Note. Panel A variables: The liquidity measures are *c_BMA*, the Gibbs sampler estimate obtained from Joel Hasbrouck; *ILLIQ*, square root of the Amihud's measure of illiquidity [Absolute(ret)/Volume]; *QSPR*, the quoted spread (bid-ask); *ESPR*, the effective spread, equal to [transaction price - (bid+ask)/2]; *RELQSPR*, relative quoted spread [QSPR/Price]; *RELESPR*, relative effective spread [ESPR/Price]; *FracAS_GH*, the adverse selection component of the spread estimated using the Glosten and Harris approach.

Table 2.3 (Continued)

Panel B

Variable	*c_BMA*	*fracinst*	*fracinsider*	*NumInst*	*Price*	*profitability*	*BookToMkt*	*MktLev*	*volatility*	*turnover*	*annret*	*DivYld*	*RDbySales*	*NumEst*	*LnSize*
c_BMA		-0.282	-0.011	-0.462	-0.670	-0.260	0.173	0.085	0.515	-0.144	-0.023	-0.298	-0.017	-0.297	-0.517
fracinst	-0.305		0.247	0.726	0.314	0.053	-0.226	-0.100	-0.037	0.442	-0.037	-0.060	0.101	0.696	0.434
fracinsider	0.063	-0.049		0.031	-0.053	0.021	-0.209	-0.105	0.060	0.103	-0.031	-0.205	-0.021	0.045	0.047
NumInst	-0.333	0.494	-0.143		0.612	0.234	-0.389	-0.072	-0.180	0.557	-0.012	0.249	0.099	0.817	0.952
Price	-0.385	0.238	-0.073	0.382		0.398	-0.368	-0.220	-0.488	0.175	0.280	0.369	0.059	0.402	0.706
profitability	-0.149	0.061	-0.050	0.114	0.150		-0.273	-0.273	-0.294	-0.041	0.152	0.273	-0.060	0.134	0.313
BookToMkt	0.175	-0.192	-0.048	-0.281	-0.224	-0.028		0.287	-0.026	-0.246	-0.250	-0.065	-0.153	-0.250	-0.424
MktLev	0.110	-0.103	-0.022	-0.127	-0.192	-0.090	0.235		0.049	0.023	-0.118	-0.044	-0.168	-0.086	-0.102
volatility	0.476	-0.063	0.093	-0.153	-0.298	-0.238	-0.012	0.077		0.352	-0.067	-0.518	0.109	-0.095	-0.287
turnover	-0.114	0.437	-0.058	0.303	0.092	-0.056	-0.163	-0.005	0.358		-0.007	-0.226	0.129	0.350	0.401
annret	0.079	-0.054	0.016	-0.044	0.148	0.035	-0.219	-0.116	0.107	0.048		0.000	-0.034	-0.047	0.075
DivYld	-0.242	-0.045	-0.135	0.282	0.166	0.156	-0.147	-0.065	-0.392	-0.189	-0.061		-0.032	0.159	0.318
RDbySales	0.002	0.071	0.018	0.119	0.018	-0.349	-0.131	-0.177	0.169	0.159	-0.012	-0.056		0.092	0.060
NumEst	-0.288	0.531	-0.102	0.722	0.305	0.089	-0.195	-0.123	-0.136	0.226	-0.061	0.194	0.116		0.604
LnSize	-0.511	0.452	-0.102	0.852	0.498	0.155	-0.378	-0.143	-0.264	0.294	0.022	0.315	0.070	0.643	

Note. Panel B variables: *fracinst*, amount of shares held by institutions that have reported that they held long positions in the security of interest in 13F filings divided by shares outstanding; *sqfracinst*, *fracinst***fracinst*; *fracinsider*, fraction of shares held by insiders in the firm; *InstDummy*, an indicator variable and is equal to 1 for firms with fracinst greater than 0, and 0 otherwise; *NumInst*, average number of institutions that have reported having held long positions in the security of interest in 13F filings; *MktCap*, the total market capitalization of the firm calculated at beginning of the year (shares outstanding * Price); *Price*, average monthly closing share price of the firm over the year; *Profitability*, net income divided by total sales; *CashFlowDummy*, an indicator variable equal to 1 for firms with positive cash flow per share and 0 otherwise; *SPRatDummy*, an indicator variable equal to 1 if the firm has a rating available from S&P 500 and 0 otherwise; *BookToMkt*, book value of equity at previous fiscal year ending divided by market value of equity at end of last calendar year; *MktLev*, total debt outstanding divided by sum of total assets and market value of equity less book value of equity; *Volatility*; standard deviation of daily returns over the calendar year; *turnover*, total trading volume divided by shares outstanding; *annret*, the annual returns including dividends; *lagannret*, annual returns from last year; *DivDummy*, an indicator variable equal to 1 for firms that have positive dividend payout and 0 otherwise; *DivYld*, total dividends paid divided by book value of equity; *RDD*, an indicator variable and is equal to 1 for firms reporting positive R&D expenses and 0 otherwise; *RDbySales*, equal to R&D expenses divided by total sales and is zero for firms when RDD=0; *NumEst*, average number of analysts following the firm; *LnNumEst*, natural log of (1+NumEst); *ForecastDev*, dispersion in the analyst forecast; *LnSize*, the natural log of the market capitalization of the firm.

Panel B indicates that *c_BMA* exhibits a strong negative correlation with fraction of institutional ownership *(fracinst)*, number of institutional investors *(NumInst)*, size of the firm *(LnSize)*, number of analysts following the firm *(NumEst)*, profit margin *(Profitability)*, share price *(Price)*, dividend yield *(DivYld),* and share turnover *(Turnover)*. The illiquidity measures decrease if last years' returns are higher, while the relationship with contemporaneous returns is not strong. Firms with higher leverage *(MktLev)*, value firms with higher book-to-market ratio *(BookToMkt),* and firms with higher stock return volatility *(Volatility)* exhibit higher illiquidity.

Table 2.4 presents summary statistics for firms grouped on the basis of their level of institutional ownership *(fracinst)* each year by first forming a separate group for firms with missing institutional ownership data. Liquidity monotonically increases with *fracinst* across firms. However, the rate at which it increases with *fracinst* appears to be diminishing. I similarly find that size of the firms *(LnSize)*, share price, dividend yield, and profit margin increase monotonically, while return volatility exhibits a slight decrease with *fracinst*. Since these other variables also affect liquidity due to changes in asset risk and information availability, I use multivariate analysis to test the relationship between *fracinst* and liquidity.[33] In the multivariate analysis, I emphasize results that are consistent and stable across a variety of specifications to ensure that multicollinearity issues are not influencing any inferences.

[33] Nonparametric results in Table 2.4 fail to control for the high correlation across various control variables. However, a fully nonparametric approach suffers from the curse of dimensionality due to the large number of control variables.

Table 2.4: Parametric analysis: Groups based on level of institutional ownership. The univariate relationship between level of institutional ownership and various measures of liquidity is presented. Ten groups are formed each year by ranking firms based on fraction of institutional ownership, after excluding firms having no reported institutional ownership. Measures for firms with no reported institutional ownership are presented separately in group 0. Other variables of interest are also presented.

Group no.	No. Of firms	Percent	*fracinst*	*NumInst*	*c_BMA*	*RELESPR*	*RELQSPR*	*ILLIQ*	*TWQuotedDepth*	*LnSize*	*Price*	*turnover*	*volatility*	*MktLev*	*NumEst*	*DivYld*	*BookToMkt*
0	7129	18.0	0.000	0	0.48%	0.74%	1.05%	0.264	42.6	6.3	26.8	0.78	2.28%	0.22	0.26	0.04	0.76
1	3245	8.2	0.071	19	0.73%	1.51%	1.99%	0.778	15.4	4.2	15.4	0.39	2.63%	0.18	1.35	0.02	0.76
2	3260	8.2	0.176	52	0.58%	1.10%	1.52%	0.487	19.6	4.9	18.8	0.47	2.38%	0.19	3.07	0.03	0.77
3	3259	8.2	0.262	94	0.53%	0.93%	1.32%	0.355	30.9	5.5	21.2	0.59	2.35%	0.19	5.21	0.03	0.76
4	3261	8.2	0.338	136	0.48%	0.79%	1.13%	0.280	33.7	5.9	24.2	0.68	2.29%	0.19	6.85	0.04	0.74
5	3256	8.2	0.404	166	0.44%	0.69%	0.99%	0.225	34.1	6.3	27.5	0.76	2.25%	0.18	8.26	0.04	0.70
6	3262	8.2	0.466	187	0.41%	0.61%	0.89%	0.178	39.1	6.6	30.1	0.83	2.23%	0.18	10.01	0.04	0.67
7	3262	8.2	0.525	205	0.38%	0.52%	0.78%	0.136	37.8	6.9	34.3	0.85	2.16%	0.17	11.31	0.04	0.63
8	3258	8.2	0.586	205	0.37%	0.51%	0.76%	0.121	39.1	7.0	33.4	0.94	2.18%	0.17	11.94	0.04	0.64
9	3261	8.2	0.652	217	0.34%	0.44%	0.67%	0.093	37.0	7.1	36.7	1.04	2.15%	0.16	13.47	0.04	0.62
10	3248	8.2	0.752	200	0.32%	0.43%	0.65%	0.099	32.7	7.1	41.3	1.16	2.13%	0.17	12.73	0.03	0.66

Section 3.2: Multivariate results

3.2.1: Pooled time series and cross-sectional regressions

I study the relationship between liquidity and institutional ownership in a multivariate framework by estimating the following regression:

$$Liq_{it} = \alpha_t + \beta_1 fracinst_{it} + \beta_2 sqfracinst_{it} + \sum_{j=1}^{J} \delta_j X_{ij,t} + \sum_{k=1}^{12} \gamma_k Industry_k * [I_{i \in k}] + \varepsilon_{it} \ldots.(1)$$

Due to the inherently unbalanced nature of the data, I rely on pooled regressions with year and industry fixed effects. The year fixed effects take into account the time trends of the variables and thus avoid spurious relationships. Due to persistence in measures of liquidity for a firm over time, I estimate the standard errors by clustering them both on firm and time dimensions. Clustering ensures that the inference is based on standard errors robust to correlation across residuals within a firm over time and across firms in the same year.[34]

Table 2.5 presents the findings from the pooled regressions. Spec 1 tests for a linear relationship between liquidity and *fracinst* without any additional control variables. The coefficient on *fracinst* is negative and significant (-0.0037) indicating that spreads decrease with institutional ownership. A one standard deviation increase in *fracinst* (0.2768) leads to a 22% decline in proportional spreads. Spec 2 controls for insider ownership, analyst following, size of the firm, and share price, along with time and industry fixed effects. The coefficient on *fracinst* stays negative and significant, though the effect has a much smaller magnitude of -0.0006. An adjusted R^2 of 46.5% indicates that the additional variables and the time and industry fixed effects explain a sizable variation in liquidity in the sample. The coefficients on both *fracinst* and

[34] I also use Fama-Macbeth approach to check robustness and stability of parameter estimates over time.

fracinsider are negative and significant, a finding that is inconsistent with the adverse selection hypothesis. The negative coefficient on *fracinst* supports the information efficiency hypothesis as well as the role of institutions in information production and dissemination. Larger firms and firms with higher share prices are more liquid.

Spec 3 adds return volatility and share turnover as additional control variables with similar findings. Spreads increase with *volatility* while decreasing with *turnover*. In Spec 4, I add various firm characteristics that are associated with the firm's financial performance and capital structure. In Table 2.4, a difference in liquidity and other control variables was evident between firms with zero institutional ownership and remaining firms in the sample. I therefore include an indicator variable for firms with zero reported institutional ownership. I also control for effect of inclusion in indices and holdings of index funds by including two indicator variables *SP500Dummy* and *DJDummy*. I further include number of blocks (*NumBlocks*) held by institutions, as institutions holding large positions may not trade frequently. These variables are associated with the amount of free float of the securities in the market.[35] The coefficient on *fracinst* becomes positive, indicating adverse selection effects of institutional ownership on liquidity. The small magnitude of the coefficient and changes in sign suggest the possibility of a non-monotonic relationship between institutional ownership and liquidity.

[35] Findings indicate that firms included in indices have lower liquidity. Firms with more block holders (*NumBlocks*) tend to have higher liquidity, while firms with no institutional ownership have lower liquidity. On using relative quoted spread as a measure of liquidity the sign on *NumBlocks* flips, while the coefficients for inclusion in indices are not robust across other specifications. Hence, I avoid drawing inferences from these findings.

Table 2.5: Cross-sectional results: Determinants of liquidity. Cross-sectional results for effects of institutional ownership on liquidity for stocks listed on NYSE and AMEX are presented. The dependent variable is the annual measure of liquidity *c_BMA* obtained from Joel Hasbrouck. The period of study is 1980–2005 and includes 39,701 firm years in the sample. Specification 1 excludes year and industry fixed effects, while the remaining specifications include both year and industry fixed effects. The coefficient on constant term is suppressed. Pooled regression is run using year and industry fixed effects due to inherently unbalanced nature of the panel. The standard errors are estimated by clustering on year and firm and are presented in italics below the estimates.

Variable	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5	Spec 6
fracinst	-0.00366***	-0.00057***	-0.00029**	0.00092***	-0.00464***	-0.00264***
	0.00036	*0.00015*	*0.00014*	*0.00024*	*0.00045*	*0.00039*
sqfracinst					0.00602***	0.00385***
					0.00048	*0.00044*
fracinsider		-0.0004**	-0.00075***	-0.00024***	-0.00059***	-0.00039***
		0.00018	*0.00019*	*0.00017*	*0.00015*	*0.00013*
LnNumEst		-0.00004	-0.00005*	-0.00007*	0.00006	0.00002
		0.00003	*0.00003*	*0.00004*	*0.00004*	*0.00003*
volatility			0.1076***	0.08832***	0.09029***	0.06377***
			0.00761	*0.00605*	*0.00587*	*0.00501*
turnover			-0.00043***	-0.00034***	-0.00045***	-0.00019***
			0.00015	*0.00012*	*0.00012*	*0.00007*
annret				0.00105***	0.00106***	0.00114***
				0.00022	*0.00022*	*0.0002*
lagannret				-0.00018**	-0.00016**	-0.00012**
				0.00008	*0.00007*	*0.00006*
RDD				-0.00004	-0.00003	-0.00006
				0.00005	*0.00005*	*0.00004*
RDBySales				-0.00106*	-0.00114**	-0.00113*
				0.00063	*0.00061*	*0.00062*
DivDummy				-0.00015*	-0.00011	0.00021***
				0.00008	*0.00008*	*0.00005*
DivYld				-0.00019	-0.00007	-0.00206***
				0.00061	*0.00059*	*0.0005*
LnPrice		-0.00272***	-0.00201***	-0.0024***	-0.0024***	-0.00025
		0.00025	*0.00023*	*0.00029*	*0.00029*	*0.00017*
InvPrice						0.04312***
						0.00421
LnSize		-0.00007*	-0.0001**	-0.00018***	-0.00016***	-0.00108***
		0.00004	*0.00004*	*0.00005*	*0.00005*	*0.00015*
SqLnSize						0.00008***
						0.00001
BookToMkt				-0.00003	0	-0.00026***
				0.00007	*0.00006*	*0.00005*
MktLev				-0.00058***	-0.00062***	-0.00078***
				0.0002	*0.0002*	*0.00016*
profitability				0.00047***	0.00041***	0.00055***
				0.00015	*0.00014*	*0.00013*
NumBlocks				-0.00025***	-0.00022***	-0.00012***
				0.00003	*0.00003*	*0.00002*
InstDummy				-0.00008	0.0006***	0.00026***
				0.00012	*0.00016*	*0.0001*
CashFlowDummy				0.00009**	0.00009**	0.00003
				0.00004	*0.00004*	*0.00003*
SPRatDummy				0.00036***	0.00041***	0.00022***
				0.00008	*0.00008*	*0.00006*
DJDummy				0.0004***	0.00043***	-0.00076***
				0.00012	*0.00012*	*0.00014*
SP500Dummy				0.00045***	0.00042***	-0.0001**
				0.00006	*0.00005*	*0.00005*
Adj. R2	9.3%	46.5%	50.6%	53.2%	54.0%	59.9%
No. of parameters	1	40	42	57	58	60
F-Value	4077.1	458.5	500.7	409.9	412.2	562.4

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

The coefficient on number of analysts is negative and significant, indicating that increasing analyst coverage increases liquidity. Liquidity is higher for dividend-paying firms and increases with dividend yield. Surprisingly, I find that value firms (higher book to market) have higher liquidity, while firms with higher debt-to-equity ratio have higher liquidity.[36] Liquidity declines for firms with higher contemporaneous annual returns and increases for firms with large returns in the past.

In Spec 5, I therefore include a second-order term for *fracinst*, designated *sqfracinst,* to test the existence of a non-monotonic relationship between institutional ownership and stock liquidity. The remaining control variables are from Spec 4. The coefficient on *fracinst* is negative and strongly significant (-0.0046) while coefficient on *sqfracinst* is positive and strongly significant (0.0060). The increase in adjusted R^2 from 53.2% to 54.0% along with large reductions in both AIC and BIC indicate the better fit of the model with the quadratic term. I do not find any support for the existence of other higher-order terms.[37]

Spec 6 addresses the possibility that the nonlinearity we observe in Spec 6 could result from the nonlinear relationship between liquidity measures and firm size or result from the scaling of the liquidity measures by share price. I therefore include square of log size and inverse of share price to control for potential nonlinear effects due to size and price. The inclusion of these variables improves the fit of the model but the estimates of *fracinst* and *sqfracinst* remain similar and statistically significant. Spec 6

[36] The coefficient on market leverage is not significant when using other measures of liquidity.

[37] Easley, O'Hara and Srinivas (1998) indicate that informed traders find it more profitable to trade in options and thus tend to migrate to options. I therefore include an indicator variable for firms that have equity options traded to control for the effect of options on reducing adverse selection risk faced by market makers. All findings are robust to inclusion of option dummy. Data on traded options was obtained from Optionmetrics, starting January 1996.

indicates that the findings are robust to controlling for nonlinear relationship with other variables where a potential nonlinear relationship may exist. The negative effect on liquidity at higher levels of *fracinst* observed even after controlling for *turnover*, *NumBlocks* and inclusion in indices, allays concerns that the increase in spreads is associated with reduction in float and trading volume.[38]

I interpret the findings of the non-monotonic relationship between institutional ownership and stock liquidity as support for both the *information efficiency* and *adverse selection* effect arising from institutions relative information advantage. With an increase in institutional ownership, the marginal effect of their information advantage on price discovery and increasing information efficiency will progressively decline. On the other hand, the marginal adverse selection effect is more likely to exhibit an increase as market makers will have fewer uninformed investors to recoup their losses to the informed investors. For a market maker supplying liquidity, as the fraction of informed investors trading the stock increase, the adverse selection risk keeps increasing. The observed relationship between liquidity and the fraction of informed traders is therefore non-monotonic due to the combination of the two effects.

3.2.2: Alternate measures for institutional ownership

The non-monotonic relationship between *fracinst* and liquidity measures indicates two effects of institutions' information advantage on liquidity. I use two additional variables that capture the degree of competition among institutions in order to further test the effect of information efficiency on liquidity. First, I use the natural log of the average number of institutions holding the security in a year *(lnnuminst)* as a measure of competition. Second, using the Herfindahl-Hirschman Index, I measure

[38] These findings are also robust to including either of square of log size and inverse of share price. All findings are robust to controlling for effects of share price using *InvPrice* instead of *LnPrice*.

concentration of institutional ownership in a firm, defining it as the sum of the squares of the ownership of each institution in the firm, where the ownership is expressed as a percentage of outstanding shares. Due to the positive skewness of the variable, I take its natural logarithm to obtain a measure of ownership concentration *(lnhhi_inst).* An increase in ownership concentration also implies a decrease in ownership dispersion. The two variables have a correlation of 0.45 in the sample while they exhibit correlations of 0.73 and 0.75 with *fracinst* respectively.

Table 2.6 summarizes findings from the effects of competition among institutions and dispersion in their ownership on liquidity. The control variables used in these tests are identical to those used in Spec 6, Table 2.5, and estimates of the control variables have been suppressed for sake of brevity. Each specification is estimated using Spec 6 from Table 2.5 after excluding *fracinst* and *sqfracinst* and adding the variable listed here. Spec 7 in this table is thus equivalent to Spec 6 in Table 2.5 for the variable *c_BMA*. Spec 1 presents findings for effect of *fracinst* on liquidity and indicates that the effect of increased institutional holdings on liquidity is not consistent across the various liquidity measures. This inconsistency across the liquidity measures primarily results because of the non-monotonic relationship between *c_BMA* and *fracinst* found earlier. In Spec 2, I include *lnnuminst* and find strong evidence that liquidity increases with the number of institutions. The finding supports the effect of greater competition on liquidity and hints at the role institutions play in increasing information efficiency.[39] Spec 3 tests the effect of institutional ownership concentration. Again, the findings are not consistent across the various liquidity measures and tend to indicate that liquidity increases with institutional ownership concentration, a surprising finding. This

[39] I take the natural log transformation of the number of institutions (*LnNumInst*) and Herfindahl Index, and also use a log transformation for the Herfindahl Index (*LnHHI_Inst*) to reduce skewness. *ResidFracinst* is obtained by orthogonalizing *fracinst* with *LnNumInst* to make interpretation of the estimates easier.

situation can result because of the strong positive correlation between ownership concentration and institutional holdings.[40]

Table 2.6: Cross-sectional results: Determinants of liquidity—Alternate measures of institutional holdings. Findings from cross-sectional regressions using other measures of institutional holdings are summarized. Findings are presented using institutional holdings, with number of institutions holding equity positions in the firm, and ownership concentration of institutions measured using a Herfindahl Index. Findings for other liquidity measures are presented. Estimates for other variables are suppressed to conserve space. Standard errors are clustered at the level of firm and time and presented below the estimates in italics.

		Dependent variable				
Additional variable		*c_BMA*	*ILLIQ*	*RELESPR*	*RELQSPR*	*FracAS_GH*
Spec 1	*fracinst*	0.0009***	0.1009**	-0.0006*	-0.00043	0.0589***
		0.00017	*0.03855*	*0.00033*	*0.00045*	*0.01018*
Spec 2	*LnNumInst*	-0.0004***	-0.1139***	-0.0020***	-0.0018***	-0.0257***
		0.00009	*0.01762*	*0.00025*	*0.00037*	*0.00629*
Spec 3	*LnHHI_Inst*	-0.00006**	-0.0214***	-0.00015***	-0.00001	0.00180
		0.00003	*0.00375*	*0.00004*	*0.00006*	*0.00201*
Spec 4	*fracinst*	0.0013***	0.2284***	0.0011***	0.00115**	0.0921***
		0.00021	*0.02985*	*0.00033*	*0.00051*	*0.01235*
	LnNumInst	-0.0005***	-0.14537***	-0.00213***	-0.00198***	-0.04027***
		0.00010	*0.01865*	*0.00026*	*0.00039*	*0.00772*
Spec 5	*ResidFracinst*	0.00097***	0.24325***	0.00103***	0.00102**	0.08081***
		0.00021	*0.03012*	*0.00033*	*0.00048*	*0.01059*
	LnNumInst	-0.00041***	-0.12132***	-0.002***	-0.00184***	-0.0291***
		0.00010	*0.01848*	*0.00025*	*0.00037*	*0.00660*
Spec 6	*LnNumInst*	-0.0004***	-0.1060***	-0.0021***	-0.0021***	-0.03181***
		0.00010	*0.01727*	*0.00026*	*0.00038*	*0.00767*
	LnHHI_Inst	-0.00001	-0.0066**	0.0001**	0.0003**	0.0059**
		0.00003	*0.00320*	*0.00005*	*0.00006*	*0.00252*
Spec 7	*fracinst*	-0.0026***	-0.465***	-0.00667***	-0.00566***	-0.0816***
		0.00039	*0.09764*	*0.00105*	*0.00162*	*0.02875*
	sqfracinst	0.0039***	0.6108***	0.00637***	0.00545***	0.1467***
		0.00044	*0.06756*	*0.00082*	*0.00133*	*0.02659*

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

[40] I do not find a significant relationship when including a square root transformation of the Herfindahl Index.

Table 2.7: Cross-sectional results: Determinants of liquidity—Other liquidity measures and testing methods. Findings across different testing methods and using different measures of liquidity are summarized. Control variables from Spec 6 in Table 2.5 are used. Standard errors from pooled regression and with firm fixed estimates are clustered at level of firm and year. Both methods include year and industry fixed effects. Fama-Macbeth regression includes industry fixed effects and presents the time series mean of the coefficient estimates. The between-firm estimates are obtained from running a cross-sectional regression for mean values of the dependent and independent variables over time at firm level. White standard errors are reported in case of between-firm estimates. Estimates for other variables are suppressed for the sake of brevity. The standard errors are presented in italics below the estimates.

	c_BMA	*ILLIQ*	*RELESPR*	*RELQSPR*
Panel A: Pooled				
fracinst	-0.0026***	-0.465***	-0.0067***	-0.0057***
	0.0004	*0.0976*	*0.0011*	*0.0016*
sqfracinst	0.0038***	0.6108***	0.0064***	0.0055***
	0.0004	*0.0676*	*0.0008*	*0.0013*
Adj. R2	59.92%	80.77%	74.18%	80.86%
Minimum point	34.3%	38.1%	52.4%	51.9%
Panel B: Firm fixed estimates				
fracinst	-0.0032***	-0.1945***	-0.0067***	-0.0060***
	0.0004	*0.0571*	*0.0012*	*0.0021*
sqfracinst	0.0034***	0.3299***	0.0053***	0.004**
	0.0005	*0.0457*	*0.0011*	*0.0018*
Adj. R2	38.73%	55.27%	46.11%	59.76%
Minimum point	45.9%	29.5%	63.1%	75.3%
Panel C: Fama-Macbeth approach				
fracinst	-0.0009*	-0.6005***	-0.0061***	-0.0055***
	0.0005	*0.0768*	*0.0009*	*0.0013*
	Neg (15 /Sig 7)	Neg (23 /Sig 22)	Neg (23 /Sig 15)	Neg (16 /Sig 13)
sqfracinst	0.0014***	0.7197***	0.0062***	0.0057***
	0.0005	*0.0657*	*0.0007*	*0.0009*
	Pos (17 /Sig 7)	Pos (24 /Sig 23)	Pos (22 /Sig 16)	Pos (20 /Sig 14)
Adj. R2	56.10%	77.59%	67.94%	72.63%
No. of years	26	26	23	23
Minimum point	32.1%	41.7%	49.2%	48.2%
No. of observations	**39701**	**39701**	**34575**	**34575**

Panel D: Between firm estimates				
fracinst	-0.0021***	-0.44055***	-0.0058***	-0.0035**
	0.0007	*0.0588*	*0.0013*	*0.0017*
sqfracinst	0.0034***	0.75489***	0.0038***	0.00023
	0.0007	*0.0599*	*0.0011*	*0.0016*
Adj. R2	66.28%	83.31%	76.77%	76.92%
Minimum point	30.9%	29.2%	75.2%	775.3%
No. of observations	**4578**	**4578**	**4287**	**4287**

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

Spec 4 includes both *fracinst* and *lnnuminst* to capture the effect of an increase in the level of institutional holdings and number of institutions. Both coefficients are significant at 1% level across all liquidity measures and indicate that liquidity declines with institutional holdings but increases with number of institutions. These findings are consistent with those from Spec 1 and Spec 2, indicating that multicollinearity is not an issue. The positive coefficient on *fracinst* supports the adverse selection hypothesis, indicating that liquidity declines with an increase in the level of institutional holdings. The negative coefficient on *lnnuminst* supports the information efficiency hypothesis, indicating that liquidity increases with growth in competition among institutions. In Spec 5, I address concern related to the correlation among institutional holdings and number of institutions by using the residual obtained from orthogonalizing *fracinst (residfracinst)* to *lnnuminst*. Similar findings confirm that liquidity increases with number of institutions, while it decreases with institutional holdings, keeping the number of institutions constant. Spec 6 includes both *lnnuminst* and *lnhhi_inst*. Liquidity increases with number of institutions but tends to decline with institutional ownership concentration, though the effect of ownership concentration is not consistent across measures. These findings are consistent with those of Amihud, Mendelson, and Uno (1999), where liquidity increases with ownership dispersion due to increased trading demand. However, since I obtain these findings after controlling for share turnover, I interpret the increase in liquidity associated with number of institutions as support for the information efficiency effect. Overall, these findings lend support to both adverse selection and information efficiency effects arising from institutions' information advantage on liquidity.

3.2.3: Institutional ownership and adverse selection

The previous subsections present evidence on adverse selection effect using measures of liquidity. The spread measures used to proxy liquidity also have components associated with order processing and maintaining inventory. These components do vary across firms but should be independent of the presence of informed investors. I therefore decompose bid-ask spreads and estimate the adverse selection component using a trade indicator model following the approach of Glosten and Harris (1988). The last column of Table 2.6 presents findings from cross-sectional regressions of the fraction of spread associated with adverse selection *(fracas_gh)* and firm characteristics using control variables as in Spec 6 of Table 2.5. The variable *fracas_gh* increases with institutional holdings, while it decreases with number of institutions holding the stock. This finding suggests that with an increase in institutional ownership a higher fraction of the spread is associated with adverse selection. However, growth in competition among the institutions increases the information efficiency effect, resulting in lowering of the adverse selection component. The finding indicates that the two effects of adverse selection and information efficiency effects are related and is consistent with the prediction in Mendelson and Tunca (2004) where they indicate that an increase in information efficiency can result in a lowering of adverse selection effect.

3.2.4: Other findings

The estimates on control variables are broadly consistent with earlier findings in the literature and across different measures of liquidity. Spreads increase with volatility and contemporaneous returns, while they decrease with share turnover, dividend yield, share price, number of blocks, and inclusion in major indices. The significant positive coefficient on volatility indicates that spreads increase and liquidity declines with an increase in asset risk. Larger firms are more liquid, consistent with their having more visibility among investors, greater analyst and media coverage, and greater breadth of ownership. Firms with higher past returns have higher liquidity or lower spreads subsequently, while firms with higher returns contemporaneously seem to have higher spreads. Liquidity is lower for high-growth firms, an effect perhaps resulting from higher information uncertainty about them. The effect of inclusion of firms in the Dow Jones Index or the S&P 500 Index on liquidity varies across specification, and is sensitive to inclusion of other control variables. Similarly, the evidence on effect of analyst coverage on liquidity is not robust and therefore I refrain from drawing any inferences.

SECTION 3.3: ROBUSTNESS TESTS

3.3.1: Additional testing methods

I test robustness of the results obtained in Section 3.2.1 using alternative estimation methods and other liquidity measures. The control variables are identical to those used in Spec 6 of Table 2.5. I summarize findings in Table 2.7 by reporting the coefficients for variables of interest (*fracinst* and *sqfracinst*), number of firms in the subgroups and adjusted R^2. The estimates based on within-firm variation obtained using firm fixed effects, estimates obtained using between firm variation, and those obtained from the Fama-Macbeth approach are very similar. The minimum point of liquidity across different measures and estimation techniques is around institutional ownership levels of 35%–50%. The consistency in results across other liquidity measures (*ILLIQ, RELQSPR* and *RELESPR*) and estimation techniques indicates both robustness of findings and suggests that unobserved firm-specific effects are not biasing the main conclusions.[41]

Depth conveys another dimension of liquidity and refers to shares that an investor can buy and sell at the quoted prices. An increase in depth is associated with improvement in liquidity. I test the relationship between depth posted by the market maker and *fracinst* and find that the coefficient on *fracinst* is significantly positive while that of *sqfracinst* is significantly negative, suggesting that depth initially increases with *fracinst* and subsequently starts declining.

3.3.2: Testing for non-monotonicity

I use four additional estimation methods to allay three concerns related to the non-monotonic relationship between *fracinst* and measures of liquidity. The first concern is that the relationship is convex instead of U-shaped, while the second arises due to a lower bound of zero on the illiquidity measures. The third concern exists from collinearity among various independent variables.

The first two methods use slope dummies and the piecewise linear regression approach from Morck, Shleifer, and Vishny (1988). The findings from the slope dummies approach indicate that the slope coefficient monotonically increases from a significantly negative value for firms with low institutional ownership to a significantly positive value for firms with high institutional ownership. The results are further robust to changing the number of groups, using different measures of liquidity,

[41] I also estimate the firm fixed effects regression after eliminating firms with less than 10 years of data. Similar findings indicate that dynamic panel data bias is not influencing the results. On regressing changes in liquidity on changes in the level of ownership *(delfracinst)* and an interaction term of *delfracinst* and *fracinst*, I find that the coefficient on *delfracinst* was negative and significant while that on the interaction term was positive and significant. These results further confirm the non-monotonic effect found earlier.

and forming a separate group for firms with no institutional ownership. The findings from piecewise linear regression approach are very similar to findings from the slope dummies approach.

To address the second concern of a lower bound of zero on the illiquidity measures, I take the natural log of the illiquidity measures and carry out the tests using the transformed measures. Similar findings indicate that the non-monotonic relationship is not an artifact of the lower bound on the spread measures and the relationship is, in fact, U shaped.

To address the third concern and ensure the robustness of results to correlation among various independent variables and a naturally strong correlation among *fracinst* and *sqfracinst*, I use a semiparametric approach. I first estimate the residuals from the regression of liquidity measure against other control variables using a linear model (by excluding *fracinst* and *sqfracinst* and other potentially endogenous variables *volatility, turnover,* and *annret*). I subsequently test the relationship between the estimated residuals and *fracinst* nonparametrically. I divide firms into 15 groups based on the fraction of institutional ownership and calculate both the mean value of residuals for firms in each group and *fracinst*.[42]

Figure 2.2 plots the mean value of residuals for firms in each group and the 95% confidence interval for the residuals against both mean value of *fracinst* and rank for the respective group (group number). The first two groups have zero institutional ownership, and I therefore combine the two groups. Since I include an indicator

[42] A fully nonparametric approach is not feasible due to the curse of dimensionality as there are a large number of control variables and time fixed effects. The approach used here is similar to a partial linear model.

variable for presence of institutions, the mean value of the residuals for the first two groups is zero. We can observe a significant U-shaped relationship between the mean value of the residuals and mean values of *fracinst*, and also observe a minimum point in a similar range as found earlier. The left axis indicates the mean value of the residuals for the groups. The right axis indicates the mean value of the residuals scaled by average *c_BMA* measure for the entire sample, thus indicating the economic effect in percentage terms. The figure allays concerns related to multicollinearity and indicates that the mean residuals are significantly positive for firms with high institutional ownership.[43]

3.3.3: Sub-sample tests

I further test robustness of results by partitioning the sample into groups based on firm characteristics and carry out the tests using Spec 6 from Table 2.5. This approach assists in checking stability of parameters and existence of significant interaction effects that may influence the main results.

The results are robust to splitting the sample into equal subperiods 1980–1992 and 1993–2005 and are further robust to analyzing data prior to reduction of tick size, from 1/8th to 1/16th, in 1997 and after the reduction. Consistent findings across these sub-periods and findings from the Fama-Macbeth approach indicate stability of estimates over time and further suggest that an increase in assets under management with hedge funds and/or increase in assets with passively managed index funds are not influencing

[43] The plot is very similar when residuals from a regression of logarithmic transformation of *c_BMA* are used, indicating that the results are not an artifact of having a lower bound of zero on the illiquidity measures. Findings from varying the number of groups and using other measures of liquidity are also similar. If I plot the residuals for liquidity measure against residuals from ownership obtained from regressing both on other control variables, as in a partitioned regression, no significant pattern emerges, indicating that non-monotonicity tends to mask the relationship. The findings are similar when controlling for *volatility, turnover,* and *annret* and when using other specifications for estimating residuals.

the results. The findings are very similar when analyzing separately the firms from NYSE and AMEX, when excluding firms with missing institutional ownership, and when excluding firms belonging to the financial and utilities sector (SIC codes belonging to 6000–6999 and 4900–4949, respectively).[44]

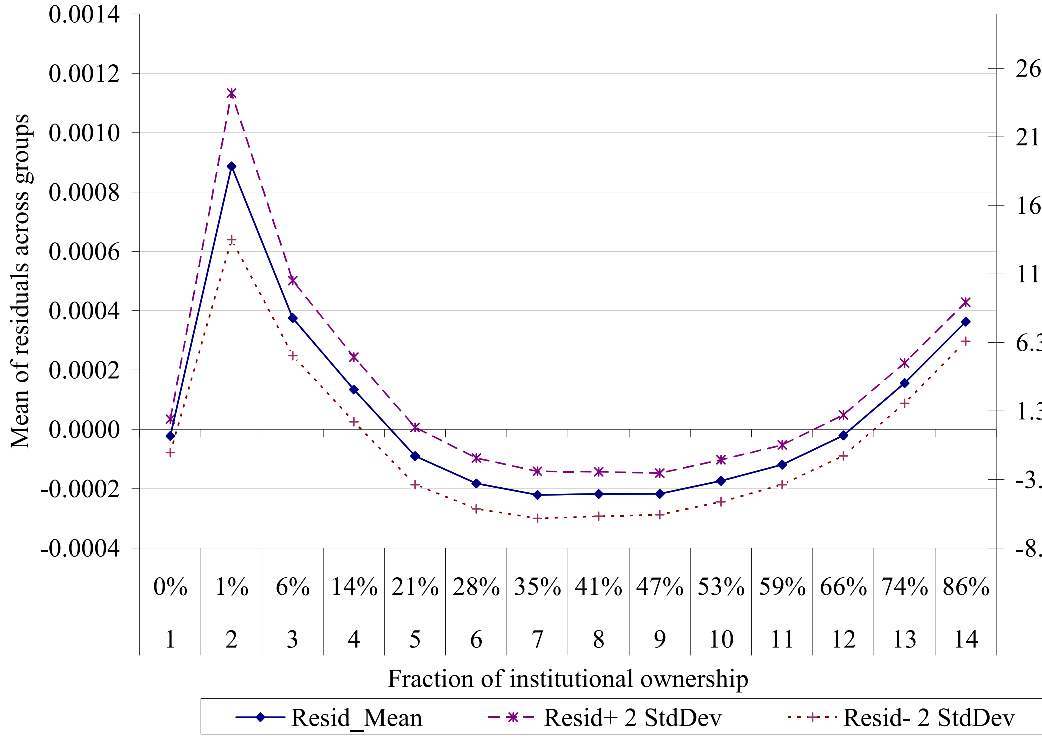

Figure 2.2: Residuals from *c_BMA* against level of institutional ownership (*fracinst*)

In addition, I group firms based on various characteristics, which institutions consider attractive when making investment decisions, and test whether the effect of institutional ownership on liquidity is consistent across these groups. I form groups based on the following firm characteristics: size, dividend yield, analyst coverage, positive cash flows, stock price, volatility, turnover, number of analysts, and existence of common stock ranking and credit rating. The non-monotonic relationship is evident

[44] In addition, I looked at different industry classifications based on 1-digit and 2-digit SIC codes. The findings are not affected by the classification choice.

across all subsamples, further reducing some concern that the relationship between liquidity and institutional holdings results from institutional preferences for certain stock characteristics. Some differences in parameter estimates across groups based on size and volatility are evident, suggesting that the effect of institutional ownership on liquidity varies with the amount of publicly available information and asset risk. I explore these interaction effects in more detail in the next section.

SECTION 3.4: INTERACTION EFFECT OF PUBLIC INFORMATION AND ASSET RISK ON LIQUIDITY

The amount of public information available and asset risk can influence trading decisions of investors and thereby affect liquidity. I explore this possibility by examining the differences in effects of institutional ownership on liquidity across firms with varying amounts of public information and asset risk. For the sake of conciseness, I present the findings using only two measures of liquidity. I selected *c_BMA* and *ILLIQ* as they are available for the longest duration.

3.4.1: Effect of publicly available information

Information advantage of institutions can vary with public information availability. I therefore contend that with increases in available public information, the effect of institutions on liquidity through the two channels of increasing information efficiency and adverse selection will be attenuated. The resulting prediction is that with an increase in public information, the relationship between institutional ownership and liquidity will become less convex. I examine this interaction effect using two variables that proxy for increase in public information about the firm: analyst following and firm size. I create interaction terms of the two variables with institutional ownership variables *fracinst* and *lnnuminst* and their squared terms, respectively. I then add the interacted variables to the pooled regression (Spec 6, Table 2.5) for testing the effect of public information availability on the relationship between institutional ownership and liquidity.

Panel A of Table 2.8 indicates that the coefficient on *lnnuminst*Size* is positive and significant while that on *sqlnnuminst*Size* is negative and significant. The findings are similar when using number of analysts to measure information availability and are robust across other measures of liquidity. Results from the interaction of these variables with institutional ownership level, *fracinst*, tend to be somewhat consistent but are not statistically significant. Overall, the findings support that an increase in public information attenuates both the information efficiency and adverse selection effects and, in addition, reduces the effect of information advantage of institutions on liquidity.[45]

3.4.2: Effect of asset risk

Mendelson and Tunca (2004) indicate that in the presence of a single informed trader, the effect of adverse selection on liquidity is enhanced with greater risk and uncertainty about firm value. In the presence of multiple informed traders acting strategically, the findings are not entirely obvious. It seems reasonable to expect that the role informed investors will play in reducing uncertainty will be larger when the asset is more risky. I therefore argue that both adverse selection and information

[45] On partitioning the firms into groups based on size of the firm and number of analysts I find that the coefficient on *fracinst* is negative and larger in magnitude for smaller firms and fewer analysts compared to those for larger firms and more analysts. In unreported results, on forming five groups based on size of the firm each year and estimating the coefficients on *fracinst* and *sqfracinst* separately for each size group, the coefficients on *fracinst* are negative and significant and those on *sqfracinst* are positive and significant for all the size groups. The coefficient on *fracinst* decreases in magnitude with size of the group, while that on *sqfracinst* has similar magnitude across the groups. The findings are identical when using natural log of sales as a measure for size of the firm and are qualitatively similar when using age of the firm as a measure of information availability.

efficiency effects on liquidity arising from an institution's information advantage will be enhanced for firms with higher risk. The resulting prediction is that with increase in firm risk, the relationship between institutional ownership and liquidity will become more convex. To examine this interaction effect, I use two variables that are associated with increases in asset risk and uncertainty about firm value: return volatility and analyst forecast dispersion. As in the previous subsection, I test the effect of asset risk on the relationship between institutional ownership and liquidity using the interaction terms in the pooled regression.

Panel B of Table 2.8 indicates that the coefficient of *fracinst*Volatility* is negative and significant while that on *sqfracinst*Volatility* is positive and significant. The findings are similar when using analyst forecast dispersion to measure uncertainty about firm value. However, the coefficients on the main effects *lnnuminst* and *sqlnnuminst* lose significance when interaction terms with volatility are included, while the interaction terms with analyst forecast dispersion are not statistically significant. Overall, these findings support that an increase in asset risk enhances both information efficiency and adverse selection effects and increases the effect of information advantage of institutions on liquidity.[46]

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[46] These findings are largely consistent with findings in the robustness section in which I estimated coefficients on *fracinst* and *sqfracinst* separately for groups based on volatility. I found that for firms with higher volatility, the adverse selection effect on liquidity tends to be higher, as indicated by a larger coefficient on *sqfracinst*. The coefficient on *fracinst* was slightly more negative.

Table 2.8: Interaction effect with available public information and asset risk. Findings to test for the differential effects of institutional ownership on liquidity across firms with varying public information availability and asset risk are presented. Panel A presents the effect of public information availability. Panel B presents the effects of asset risk. The tests are carried out using Spec 6 from Table 2.5. Estimates for other variables are suppressed for the sake of conciseness. The variable *c_BMA* is the Gibbs sampler estimate obtained from Joel Hasbrouck; *ILLIQ*, square root of the Amihud's measure of illiquidity [Absolute(ret)/Volume]; *LnNumInst* is defined as log (number of institutions); *SqLnNumInst*, square of *LnNumInst*; *NumEst*, number of analysts following the firm; *ForecastDev*, standard deviation of the analyst forecasts. Standard errors are clustered at the level of firm and time and presented below the estimates in italics.

Panel A: Differential effect of public information availability

Variable	*c_BMA*	*ILLIQ*		*c_BMA*	*ILLIQ*		*c_BMA*	*ILLIQ*
Spec 1			Spec 3			Spec 5		
LnNumInst	-0.0028***	-0.6920***	*LnNumInst*	-0.0021***	-0.3552***	*LnNumInst*	-0.00166	-0.4258***
	0.00047	*0.04318*		*0.00037*	*0.04457*		*0.00030*	*0.05362*
SqLnNumInst	-0.0002**	0.01615*	*SqLnNumInst*	0.00028***	0.03116***	*SqLnNumInst*	0.00021	0.0496***
	0.00009	*0.00944*		*0.00005*	*0.00487*		*0.00004*	*0.00493*
*LnNumInst*LnSize*	0.00104***	0.1633***	*LnNumInst*NumEst*	0.0005***	0.19335***	*LnNumInst*log(1+Age)*	0.00010	0.0121***
	0.00011	*0.01312*		*0.00016*	*0.01361*		*0.00003*	*0.00258*
*SqLnNumInst*LnSize*	-0.00004***	-0.00945***	*SqLnNumInst*NumEst*	-0.0001***	-0.0184***	*SqLnNumInst*log(1+Age)*	-0.00002	-0.0024***
	0.00001	*0.00088*		*0.00002*	*0.00164*		*0.00001*	*0.00049*
Spec 2			Spec 4			Spec 6		
fracinst	-0.0055***	-1.2899***	*fracinst*	-0.0026***	-0.8823***	*fracinst*	-0.0031***	-0.5059***
	0.0017	*0.1414*		*0.0007*	*0.1212*		*0.0005*	*0.1092*
sqfracinst	0.0029	1.4123***	*sqfracinst*	0.00343***	0.9024***	*sqfracinst*	0.0042***	0.6361***
	0.0021	*0.1995*		*0.0009*	*0.1100*		*0.0005*	*0.0818*
*fracinst*LnSize*	0.0006***	0.1355***	*fracinst*NumEst*	0.0001	0.3419***	*fracinst*log(1+Age)*	0.0002	0.0138
	0.0002	*0.0174*		*0.0003*	*0.0415*		*0.0001*	*0.0122*
*sqfracinst*LnSize*	-0.0001	-0.1355***	*sqfracinst*NumEst*	0.0001	-0.2748***	*sqfracinst*log(1+Age)*	-0.0001	-0.0083
	0.0003	*0.0277*		*0.0004*	*0.0431*		*0.0002*	*0.0167*

Panel B: Differential effect of asset risk

Variable	*c_BMA*	*ILLIQ*		*c_BMA*	*ILLIQ*
Spec 1			Spec 3		
LnNumInst	0.00020	-0.2147***	*LnNumInst*	-0.0014***	-0.3707***
	0.00052	*0.04949*		*0.00029*	*0.05117*
SqLnNumInst	-0.00004	0.0204***	*SqLnNumInst*	0.00015***	0.0395***
	0.00006	*0.00558*		*0.00003*	*0.00459*
*LnNumInst*Volatility*	-0.0600***	-6.765***	*LnNumInst*ForecastDev*	-0.00005	-0.1054***
	0.01456	*2.07049*		*0.00014*	*0.01142*
*SqLnNumInst*Volatility*	0.0075***	0.8971***	*SqLnNumInst*ForecastDev*	-0.00001	0.0223***
	0.00194	*0.23978*		*0.00003*	*0.00245*
Spec 2			Spec 4		
fracinst	-0.0002	-0.2105*	*fracinst*	-0.0025***	-0.4372***
	0.0008	*0.1152*		*0.0004*	*0.0965*
sqfracinst	0.0013*	0.2311**	*sqfracinst*	0.0036***	0.5575***
	0.0008	*0.1039*		*0.0005*	*0.0665*
*fracinst*Volatility*	-0.1078***	-11.1983***	*fracinst*ForecastDev*	-0.0024***	-0.3373***
	0.0350	*3.5084*		*0.0009*	*0.0692*
*sqfracinst*Volatility*	0.1101***	16.7331***	*sqfracinst*ForecastDev*	0.0036**	0.7011***
	0.0374	*4.5244*		*0.0015*	*0.1106*

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

SECTION 4: INSTITUTIONAL OWNERSHIP AND INFORMATION EFFICIENCY

In this section, I test the implications arising from the effect of information efficiency on liquidity in an intraday context. In both sequential trade and multi-period strategic trader models, prices incorporate more information as trading progresses. Liquidity increases (spreads decline) with information efficiency of prices, while growth in competition among the informed traders enhances the rate at which spreads decline during the day. The net effect is that for firms with a greater number of informed traders, spreads should start out higher and exhibit a larger decline over the day, relative to firms with fewer informed traders holding everything else equal. I test this claim of Hypothesis 3 by looking at the intraday patterns in spreads and examine the relationship between changes in spreads and fraction of equity held by institutions.

Figure 2.3 presents a plot of changes in quoted spreads for five groups of firms based on their level of institutional ownership. I first calculate spreads for firms for each 10-minute interval starting at 9:30 AM (a total of 39 intervals).[47] I then calculate mean decline in spreads for firms in each group and plot it against time intervals. The plot indicates that across all groups spreads decline as trading progresses during the day; the decline is higher for firms with larger *fracinst*. The rate of decline in spreads is higher at the beginning of the day consistent with the claim that liquidity increases as prices become more informationally efficient. The familiar inverse J-shaped relationship for intraday spread measures, shown in McInish and Wood (1992) is

[47] I carry out the intraday analysis using data for four years at four-year intervals (1986, 1990, 1994, and 1998). Data for 1986 and 1990 come from ISSM database while that for 1994 and 1998 come from TAQ database. I selected only four years due to extensive computational requirements. The findings for individual years are similar.

evident, though the evidence on increase in spreads near the end of the trading day is not as strong.[48]

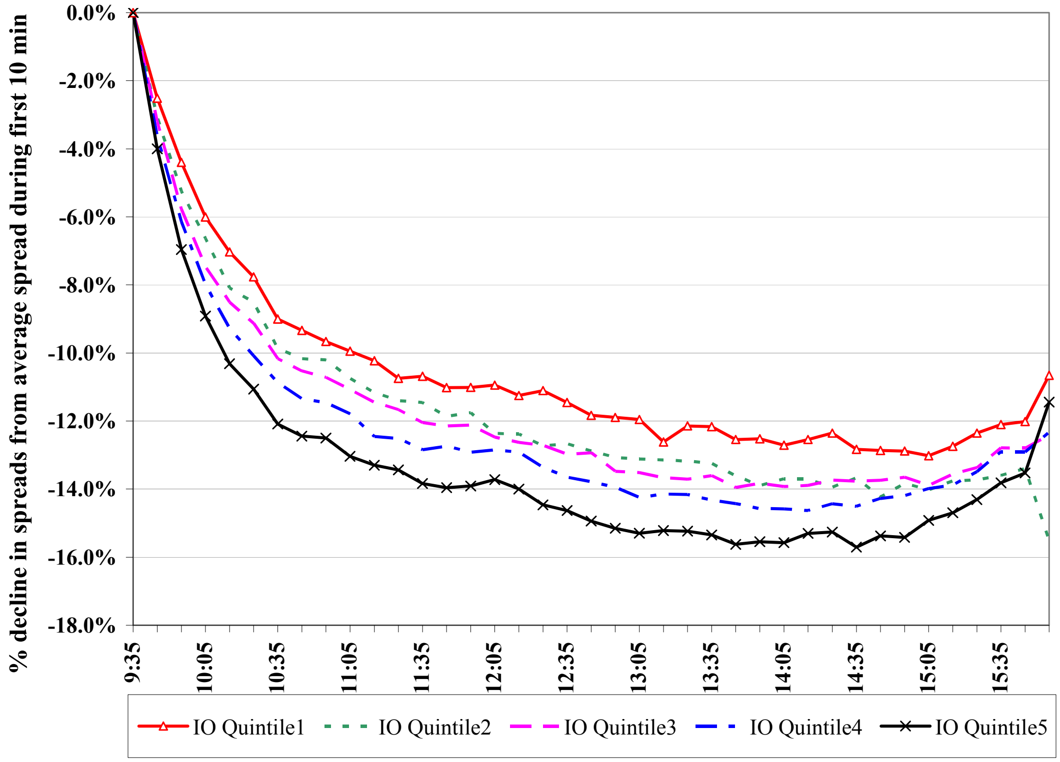

Figure 2.3: Intraday pattern–Decline in quoted spreads at different IO Levels

I obtain similar results when dividing the firms into five quintiles based on the number of institutions.[49] Figure 2.4 presents a similar plot, along with 95% confidence intervals for the percentage changes in quoted spreads, for firms belonging to the bottom and top quintiles. The plot indicates a statistically significant difference in the intraday decline across the two quintiles, with the decline being larger for firms with a greater number of institutions.

[48] These findings are robust to using other measures of liquidity (effective spread, time weighted quoted spreads, and their versions scaled by share prices).

[49] Number of institutions is a better measure to capture the degree of competition.

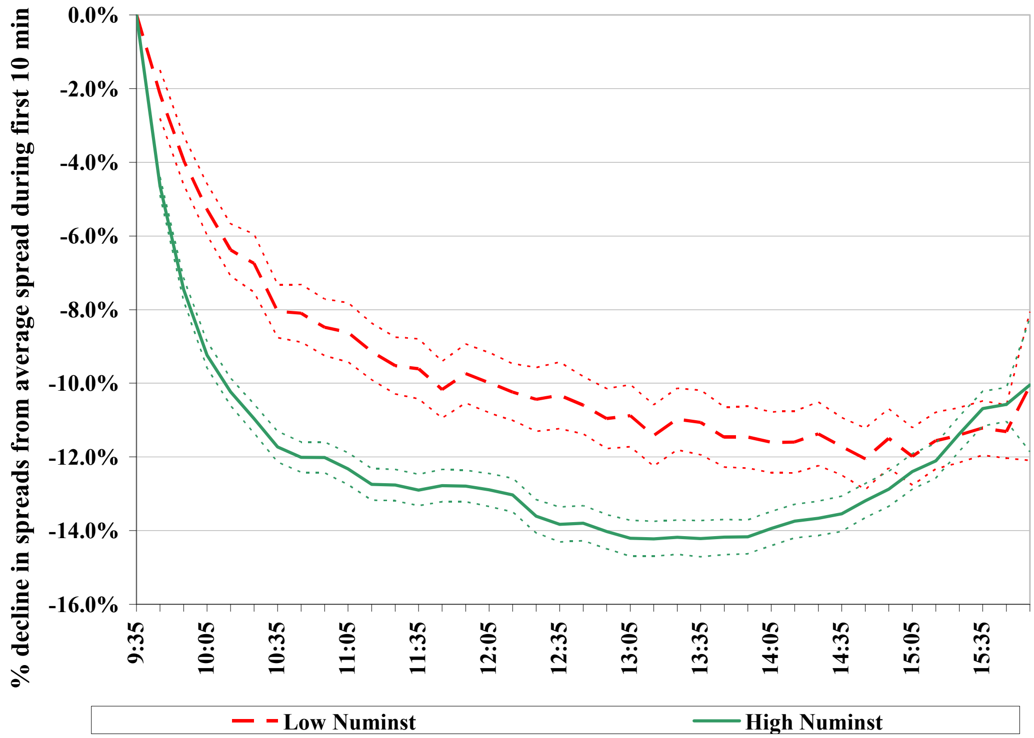

Figure 2.4: Intraday pattern–Decline in quoted spreads for different number of institutions

Table 2.9 presents findings from cross-sectional regressions between percentage change in liquidity measures and level of institutional ownership. I control for various firm characteristics that are associated with information environment of firm and asset risk. Intraday change in liquidity for firms is calculated by taking the percentage change in the average spreads from the first half hour of trading (9:30 AM to 10:00 AM) to the half hour of trading prior to noon (11:30 AM to 12:00 PM). The table also presents findings with respect to changes in spreads from the first 10-minute interval (9:30 AM to 9:40 AM) and spreads half an hour later (10:10 AM to 10:20 AM). The positive and significant coefficient of *fracinst* indicates that the percentage decline in spreads during the day increases with institutional ownership. Another interesting observation is that spreads decline more for high-growth firms. This suggests that there is greater private information for high-growth firms at start of trading. These findings are also robust to first calculating the percentage change every day and subsequently taking an average for the firm over the year. These findings indicate a reduction in spreads as trading progresses during the day, with larger declines observed for firms with higher institutional ownership and greater number of institutions. The result supports the role institutional investors' play in increasing information efficiency and suggests that competition among them can result in an increase in liquidity. The finding is consistent with the prediction of Holden and Subrahmanyam (1992), where informed traders have correlated signals about the value of the asset causing an increase in competition and faster incorporation of information into prices.[50] The findings are also consistent with those of Boehmer and Kelley (2007) who find that institutional holdings and institutional trading improve price efficiency using a different methodology.

SECTION 5: ENDOGENEITY OF INSTITUTIONAL OWNERSHIP AND CAUSALITY

So far in this chapter, I have assumed that the level of institutional holdings in a firm is exogenously set and independent of the liquidity of the firm's shares. Falkenstein (1996); Gompers and Metrick (2001); and Bennett, Sias, and Starks (2003) use cross-sectional analysis to show institutional preference for large liquid stocks. However, these studies view liquidity as exogenous. For example, Falkenstein (1996) uses monthly share turnover to measure liquidity and treats it as an exogenous variable when looking for preference of mutual funds.[51] Another possible concern is that

[50] In Back, Cao and Willard (2000) when informed investors have imperfectly correlated signals, competition does not necessarily improve information efficiency. A large amount of private information remains near the end of the trading day, and authors argue that market will learn more from a monopolist than competing informed traders.

[51] My findings presented later in this section suggest that turnover measure of institutional portfolios is a persistent characteristic and institutional ownership Granger causes share turnover measures.

institutions select stocks based on characteristics that are correlated with future liquidity. For example Chan and Lakonishok (1995) indicate that large institutions try to incorporate the price impact of their trades when selecting their trading strategy, thus implying that trade by institutions influences price impact measures, and hence liquidity. However, if institutional preference for liquid stocks were determining the earlier results, we would instead expect a negative linear relationship between *fracinst* and liquidity measures. The robust non-monotonic relationship therefore suggests that there exists more to the link between liquidity and institutional ownership and that the relationship could be jointly endogenous. Also, the robustness of findings to including firm fixed effects reduces the concern that effects associated with unobserved firm characteristics are biasing the relationship between liquidity and *fracinst*.

In this section, I test for causality in the time series context in an attempt to mitigate the concern related to institutional preference for liquid stocks. I explore the intertemporal association between stocks' liquidity and the fraction of shares held by institutions. Liquidity measures and institutional ownership of firms are highly persistent after accounting for time trends when examined using transition matrices. Controlling for endogeneity is a challenge due to difficulty in identifying exogenous changes in institutional ownership levels and finding valid external instruments. The strong persistence in the endogenous variables also result in weak internal instruments (lagged values of endogenous variables).[52] Following a firm over time and examining

[52] I used the system GMM estimator suggested by Arellano and Bover (1995) and by Blundell and Bond (1998) for panels with a large number of firms and a small time dimension as an additional robustness measure. The system GMM approach combines two approaches for handling the firm fixed effects and dealing with potentially endogenous variables, while avoiding the dynamic panel bias. It estimates a combination of two sets of equations, first in differences to remove the firm fixed effect and second in levels. For the difference equation, deeper lags of both dependent and endogenous variables are used as instruments. To expunge the fixed effects from the level equation, the system GMM also introduces differences in the endogenous variable as instruments, under the assumption that changes in the endogenous variables are uncorrelated with the firm fixed effect under suitable stationarity conditions [Anderson and Hsiao (1982)]. The instrument set is created following the procedure

the association between changes in institutional ownership and stocks' liquidity helps provide some evidence on the direction of causality in a time series context. I employ *Granger* causality tests to identify the lead-lag relationship between liquidity and institutional ownership, making use of quarterly data of institutional ownership available over the period 1983–2005.

For the *Granger* causality tests, I use the liquidity measures based on the intraday trading data from ISSM/TAQ (*RELESPR* and *RELQSPR*) and aggregate the data to a quarterly frequency, as institutional ownership data is available quarterly for each firm. Using quarterly data for the time series tests helps increase the number of observations in time series. Other data filters are similar to those reported in Section 2. The panel spans 1983–2005 and has data on 81,962 firm quarters for 3,055 firms after retaining firms with a minimum of ten quarters of consecutive data available. I refrain from making the panel balanced for most tests, as doing so leads to a sizable reduction in the number of firms. I first test whether the time series of institutional ownership and liquidity measures are *trend* stationary using various unit root tests available for panel data. I strongly reject the null hypothesis of nonstationarity in *fracinst* and both liquidity measures with P-values of less than 0.0001 across different tests.[53]

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suggested by Holtz-Eakin, Newey, and Rosen (1988), which increases number of available instruments. The system is then estimated as a single equation, under the assumption that the same functional relationship applies to both the transformed (differenced) and untransformed (level) variables. The findings from the system GMM approach using various specifications and both quoted and effective spreads are very similar to those obtained from the cross-sectional regressions earlier. However, the persistence in both liquidity and ownership variables results in weak instruments, making it difficult to address the endogeneity problem. These findings are available from the author.

[53] Similar results are obtained using a balanced panel.

Table 2.9: Intraday pattern in liquidity–Information efficiency effect. Cross-sectional results from regression of percentage decline in spreads against institutional ownership level are presented. Spec 1 and Spec 2 use percentage decline in spreads from first half hour of trading to half hour of trading prior to 12 PM as dependent variable. Spreads are first calculated for each firm over 30-minute intervals for each day in a year, and then taking an average of the spread measure is calculated over the year. Spec 3 and Spec 4 use percentage decline in spreads from first 10 minutes of trading to those prevailing half an hour after the end of the first 10 minutes. Percentage decline is calculated by measuring the change in the average spread (quoted spread and effective spread) measures over the year during those time intervals. Intraday data for four years (1986, 1990, 1994, and 1998) at intervals of four years are used in the analysis to reduce computational requirements. All specifications include year and industry fixed effects. Standard errors are clustered at the level of firm and time and presented below the estimates in italics.

Variable	Spec 1	Spec 2	Spec 3	Spec 4
Constant	0.00968	0.10208***	-0.05031***	0.02467
	0.0203	*0.0296*	*0.0051*	*0.0241*
fracinst	0.0153**	0.00955*	0.02454**	0.02847***
	0.0077	*0.0050*	*0.0107*	*0.0104*
price	0.00003	0.00045*	-0.00006	0.00023
	0.0001	*0.0002*	*0.0001*	*0.0002*
lnsize	0.00303	-0.00644	0.00998***	0.00157
	0.0023	*0.0045*	*0.0016*	*0.0031*
volatility	0.34972	0.02269	0.41441**	0.26455
	0.2805	*0.3239*	*0.1858*	*0.3795*
turnover	0.01383***	0.00551	0.02135***	0.01061*
	0.0012	*0.0060*	*0.0021*	*0.0059*
booktomkt	-0.00503***	-0.00955***	-0.00201	-0.01166**
	0.0024	*0.0024*	*0.0020*	*0.0053*
mktlev	0.01186***	-0.00317	0.01597	-0.01642
	0.0040	*0.0046*	*0.0106*	*0.0111*
numblocks	-0.00089	0.00228	-0.00175	-0.00093
	0.0009	*0.0024*	*0.0018*	*0.0038*
sp500dummy	-0.01456*	-0.01548***	-0.00708	-0.01063**
	0.0076	*0.0034*	*0.0069*	*0.0049*
djdummy	-0.03217***	-0.01179	-0.04511***	-0.02709*
	0.0096	*0.0112*	*0.0142*	*0.0147*

% decline measured over the periods	*(9:30 AM to 10:00 AM) - (11:30 AM to 12:00 PM)*		*(9:30 AM to 9:40 AM) - (10:10 AM to 10:20 AM)*	
Liquidity measure	QSPR	ESPR	QSPR	ESPR
Adj. R2	40.6%	20.5%	38.7%	14.7%
No. of observations	4729	4755	4729	4755
No. of parameters	23	23	23	23
F-Value	137.62	64.37	137.62	50.66

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

Having recognized that the time series are *trend* stationary, I test whether changes in *fracinst* lead to changes in liquidity, and vice versa, using the *Granger* causality tests. I estimate pooled regressions and include additional control variables from the cross-sectional study to control for effect of other time-varying variables on liquidity measures. I also include time fixed effects for each quarter to account for time trends in both liquidity measures and *fracinst* as well as to prevent structural changes from biasing the results. I test for *Granger* causality using the specifications given below.[54] To test if *fracinst (Granger)* causes *Liq* (liquidity measures), I test the joint hypothesis that $\delta_1 = \delta_2 = \delta_3 = \ldots\ldots = \delta_n$ are all equal to zero, by using both standard F test and Bayesian Information Criterion (BIC). To test if *Liq (Granger)* causes *fracinst*, I test the joint hypothesis that $\eta_1 = \eta_2 = \eta_3 = \ldots\ldots = \eta_n$ are all equal to zero. Since right-hand side variables in equations 2 and 3 are identical, I use OLS to estimate the equations separately.[55]

$$Liq_{it} = \alpha_0 + \sum_{l=1}^{m} \beta_l Liq_{i,t-l} + \sum_{k=1}^{n} \delta_k \, fracinst_{i,t-k} + \sum_{j=1}^{p} \gamma_j z_{ij} + u_{it} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

$$fracinst_{it} = \varphi_0 + \sum_{l=1}^{m} \eta_l Liq_{i,t-l} + \sum_{k=1}^{n} \kappa_k \, fracinst_{i,t-k} + \sum_{j=1}^{p} \lambda_j z_{ij} + \nu_{it} \ldots\ldots\ldots\ldots\ldots(3)$$

[54] To reduce the possible combinations to be estimated, I follow the standard practice of restricting the lag lengths of both *fracinst* and liquidity measures to be equal, and sufficient such that u_{it} is a white noise term. I test whether residuals are a white noise using the portmanteau statistic for a multivariate time series following Granger and Newbold (1986) and combine tests across firms following the approach of Fisher's test. Findings from the system GMM approach also indicate no second order autocorrelation among the first differenced residuals.

[55] OLS is efficient in this case. Only in case of Spec 3, when I include *sqfracinst* and its lagged values in equation 2, OLS will not be efficient, even though it will still be a consistent estimator. Since I include time fixed effects for each quarter in both the equations, the correlation between the error terms from the two equations should be small due to a well-specified model, suggesting that the loss in efficiency will be small.

Table 2.10 presents the findings from testing whether institutional ownership *(Granger)* causes liquidity using both relative quoted spread *(RELQSPR)* and relative effective spread *(RELESPR)* as liquidity measures, while Table 2.11 presents findings from reverse causality tests. Spec 1 includes lagged values of both returns and *volatility* and further includes other contemporaneous control variables used in the cross-sectional study.[56] Spec 2 modifies Spec 1 by including lagged values of *turnover* measured on a quarterly basis, while excluding the contemporaneous *turnover* measure; Spec 3 modifies Spec 2 by including the lagged values of *sqfracinst* in order to account for the nonlinear effects when testing effects of institutional ownership on illiquidity. I strongly reject the hypothesis that institutional ownership does not *(Granger)* cause liquidity when using lags of the orders of 1 to 10, using both F tests and likelihood ratio tests using BIC for comparing the fit between the unrestricted and restricted models. The test for incremental lag lengths indicates that five to six lags are sufficient to capture the dynamic behavior. In most cases, the P-values from F tests are less than 0.001. On including *sqfracinst* in Spec 3, I observe a significant improvement in model fit at all lag lengths, when comparing model fit with the unrestricted case of Spec 2. The findings are similar across the two measures of liquidity. Investors may use trading volume and *turnover* as a metric for liquidity and prefer stocks with high *turnover*. Therefore, I test robustness of the *Granger* causality tests using *turnover* as a measure of liquidity. I find strong evidence indicating that *fracinst* (*Granger*) causes *turnover*, while only weak evidence suggesting that *turnover (Granger)* causes *fracinst*. On testing whether measures of liquidity *RELQSPR* or *RELESPR (Granger)* causes *fracinst* (Table 2.11), I fail to reject the

[56] Number of analysts, size at end of quarter, share turnover in the quarter, both natural log and inverse of average share price during the quarter, book-to-market ratio, dividend yield during the year, market leverage, profitability, R&D by sales and indicator variables for positive dividend payout, R&D expenses, existence of S&P common stock rating, and inclusion in the Dow Jones Industrial Index and the S&P 500 Index.

hypothesis that liquidity does not *(Granger)* cause *fracinst* using the F test, but reject the hypothesis on using BIC as model selection criterion. Only weak evidence of reverse causality exists, and the evidence tends to weaken with inclusion of higher order lags.[57]

Overall, these findings indicate a strong effect of institutional ownership on future liquidity, robust to inclusion of higher-order lags of liquidity measures. Only weak evidence exists supporting the notion that liquidity affects future institutional ownership. Many other specifications give similar results—the qualitative results are not sensitive to the lag order and exclusion of variables that may be considered endogenous such as volatility, turnover, number of analysts, and dividend yields. These findings suggest that the relationship between institutional ownership and liquidity is not a result of institutional preference for liquid stocks. Ownership by institutions appears to have a direct effect on the information structure of the firm and thus appears to play a role in determining liquidity.

SECTION 6: INSTITUTIONAL OWNERSHIP TYPE AND LIQUIDITY

This section further examines the effect of heterogeneity among institutions on liquidity. Institutional investors have varying incentive structures and fiduciary duties, and even different investment horizons [Bushee (1998), Bushee and Noe (2000)]. To better understand the effect of institution type on liquidity, I classify institutions into groups based on portfolio holding and trading characteristics. I examine the effect of institutions' investment horizon and risk aversion measured using portfolio

[57] The findings in this section are also robust to using the F-M framework and running a VAR for each quarter using cross-sectional variation for identification of the parameters. I test model fit using F tests and find strong evidence that *fracinst (Granger)* causes liquidity. I only find weak evidence in favor of reverse causality. Also, on summing up the coefficients for lagged values of *fracinst* and *sqfracinst*, the sums are negative for *fracinst* and positive for *sqfracinst*. Results are also robust to excluding size of the firm, as institutions may use size of the firm as a proxy for liquidity.

concentration on liquidity. Ideally, I would like to classify the institutions at the fund level as each reporting institution may have different types of funds with different objectives; however, the reporting entity being the institution precludes this choice.

SECTION 6.1: INVESTOR HORIZON

I use institutional holdings data from CDA/Spectrum as of the end of the quarter and estimate measures of portfolio turnover for each institution. The rationale for using portfolio turnover as a means for classifying institutions is that short-term investors will buy and sell their investments frequently, while long-term investors will hold their positions unchanged for a considerable period. To implement this idea empirically, I follow the approach proposed by Gaspar, Massa, and Matos (2005) to estimate portfolio turnover measures of the institutions. Yan and Zhang (2009) also use this approach to classify institutions as short-term and long-term and, subsequently, show that trading by short-term institutions forecasts future stock returns. The turnover measures exhibit considerable persistence over time, indicating that institutions do not typically change their investment horizon and trading habits (Table 2.12).[58]

[58] I divide institutions into 3 groups based on the measure of their portfolio turnover, with group 1 having the lowest turnover and group 3 having the largest. Subsequently, I calculate transition probabilities for each group, i.e., the probability that next year the institutions would fall into the three turnover groups after conditioning on this year's rank. Finally, I take the time series average across all years. In Table 2.12, I find that one year onward the probability of staying in the same group remains considerably higher (60%–65%) than the probability of switching to one of the other two groups (unconditional probability should be 33%). Similar results are observed when dividing the institutions into more groups.

Table 2.10: Granger causality tests: Institutional ownership causes liquidity. Results from testing whether institutional ownership Granger causes liquidity measures are presented. Spec 1 includes lagged values of returns and volatility of returns and other contemporaneous control variables used in the cross-sectional study (Spec 6, Table 2.5). Spec 2 includes lagged values of share turnover measured on a quarterly basis and excludes the contemporaneous turnover measure, while Spec 3 includes both the lagged values of share turnover and squared term of the fraction of institutional ownership to account for the nonlinear effects when testing effects of institutional ownership on illiquidity. There are 81,962 firm quarters used in the estimation. Firms with data available for less than 10 consecutive quarters are eliminated from the study. Bayesian Information Criterion (BIC) is used for model selection as it penalizes free parameters more strongly than does Akaike Information Criterion (AIC).

		fracinst (Granger) causes ***RelQSPR***						*fracinst (Granger)* causes ***RelESPR***					
No. of Lags	No. of parameters	Unrestricted (includes Fracinstqtr and lagged values of it) BIC	Restricted (excludes Fracinstqtr and lagged values of it) BIC	F-Test	Rest versus Unrestricted	Decrease in LL/(Increase in DOF) (Spec 2 versus Spec 3) [Unrestricted]	Incremental lag length test	Unrestricted (includes Fracinstqtr and lagged values of it) BIC	Restricted (excludes Fracinstqtr and lagged values of it) BIC	F-Test	Rest versus Unrestricted	Decrease in LL/(Increase in DOF) (Spec 2 versus Spec 3) [Unrestricted]	Incremental lag length test
Spec 1													
1	102	629	717	106.40	87.97			3362	4016	674.99	654.28		
2	106	567	651	58.87	41.56		15	1561	2076	274.89	257.53		450
3	110	554	613	36.80	19.86		3	510	915	151.57	135.17		263
4	114	280	335	30.55	13.75		68	101	440	100.78	84.75		102
5	118	194	238	25.53	8.82		22	-105	178	72.30	56.47		52
6	122	125	146	20.18	3.54		17	-219	14	54.53	38.83		29
7	126	131	133	16.79	0.20		-2	-297	-106	42.86	27.25		19
8	130	151	139	15.04	-1.52		-5	-294	-136	35.44	19.87		-1
9	134	-80	-106	13.61	-2.92		58	-281	-150	30.10	14.59		-3
10	138	42	0	12.28	-4.21		-31	-113	0	26.77	11.30		-42
Spec 2													
1	102	531	743	230.67	211.83			3397	4069	692.72	671.86		
2	107	477	688	123.06	105.53		11	1618	2158	287.45	269.99		356
3	112	454	638	78.18	61.10		4	571	1009	162.58	146.11		210
4	117	156	339	62.73	45.82		60	162	538	110.14	94.06		82
5	122	109	278	50.64	33.85		9	-48	278	81.00	65.12		42
6	127	48	194	41.15	24.44		12	-180	101	62.58	46.84		26
7	132	67	193	34.65	18.00		-4	-262	-23	49.77	34.12		16
8	137	91	206	30.94	14.32		-5	-280	-67	42.22	26.62		4
9	142	-109	-11	27.40	10.83		40	-261	-74	36.27	20.73		-4
10	147	32	112	24.47	7.93		-28	-77	92	32.44	16.94		-37
Spec 3													
1	103	451	743	328.84	292.41	80.58		2991	4069	1120.49	1078.41	406.55	
2	109	353	688	202.36	167.49	61.96	16	1229	2158	500.37	464.77	194.78	294
3	115	351	638	130.36	95.67	34.57	0	250	1009	287.03	253.12	107.00	163
4	121	62	339	104.12	69.44	23.61	48	-119	538	197.57	164.25	70.19	61
5	127	24	278	85.38	50.72	16.87	6	-293	278	147.19	114.18	49.05	29
6	133	-23	194	70.84	36.21	11.78	8	-394	101	115.30	82.47	35.64	17
7	139	11	193	60.60	26.00	8.00	-6	-449	-23	93.59	60.88	26.76	9
8	145	47	206	54.40	19.80	5.48	-6	-444	-67	79.79	47.14	20.52	-1
9	151	-152	-11	50.05	15.63	4.80	33	-416	-74	70.45	38.01	17.28	-5
10	157	-6	112	46.06	11.77	3.83	-24	-224	92	63.88	31.60	14.65	-32

Table 2.11: Granger causality tests: Liquidity causes institutional ownership. Results from *Granger* causality tests for reverse causality (i.e., testing whether liquidity measures Granger cause institutional ownership) are presented. Spec 1 includes lagged values of returns and volatility of returns and other contemporaneous control variables used in the cross-sectional study (Spec 6 Table 2.5). Spec 2 includes lagged values of share turnover measured on a quarterly basis and excludes the contemporaneous turnover measure. There are 81,962 firm quarters used in the estimation. Firms with data available for less than 10 consecutive quarters are eliminated from the study. Bayesian information criterion (BIC) is used for model selection as it penalizes free parameters more strongly than does Akaike Information Criterion (AIC).

		RELQSPR (Granger)* causes *Fracinst					***RELESPR (Granger)* causes *Fracinst***				
		BIC					BIC				
No. of Lags	No. of parameters	Unrestricted (includes RelQSPR and lagged values of it)	Restricted (Excludes RelQSPR and lagged values of it)	F-Test	Rest versus Unrestricted	Incremental lag length test	Unrestricted (includes RelESPR and lagged values of it)	Restricted (excludes RelESPR and lagged values of it)	F-Test	Rest versus Unrestricted	Incremental lag length test
Spec 1											
1	102	8506	8506	3.69	-0.42		8503	8506	7.60	0.82	
2	106	1613	1607	0.97	-2.72	1723	1610	1607	3.15	-3.03	6892
3	110	618	619	3.76	0.21	249	625	619	2.49	-1.72	985
4	114	405	415	5.99	2.49	53	424	415	2.21	-1.64	201
5	118	317	326	5.44	1.96	22	338	326	2.32	-2.11	87
6	122	212	216	4.16	0.69	26	232	216	1.97	-3.76	106
7	126	126	124	3.14	-0.33	21	143	124	1.82	-6.07	88
8	130	81	77	3.04	-0.43	11	99	77	1.77	-7.23	44
9	134	34	25	2.38	-1.09	12	50	25	1.77	-10.55	50
10	138	11	0	2.40	-1.09	6	30	0	1.87	-12.47	20
Spec 2											
1	102	8659	8662	7.59	3.50		8656	8662	10.75	0.81	
2	107	1742	1741	3.27	-0.39	1383	1739	1741	5.46	0.52	6917
3	112	735	741	5.72	2.19	201	743	741	4.25	-0.20	997
4	117	534	550	7.55	4.06	40	554	550	3.61	-0.55	188
5	122	455	473	6.97	3.50	16	479	473	3.49	-0.80	76
6	127	362	373	5.39	1.94	19	382	373	3.07	-1.67	96
7	132	292	297	4.11	0.66	14	308	297	2.92	-2.76	74
8	137	251	253	3.64	0.19	8	266	253	2.91	-3.53	43
9	142	210	207	3.09	-0.35	8	221	207	2.93	-4.71	44
10	147	195	192	3.18	-0.28	3	210	192	3.10	-5.50	12

Table 2.12: Persistence in trading characteristics of institutions. A transition matrix is presented that is constructed based on classifying managers into groups based on their portfolio turnovers. Portfolio turnover of manager is estimated following the method proposed by Gaspar et al. (2005). Managers are ranked into three groups each year based on the estimated portfolio turnover measure. The transition matrix presents the likelihood that a manager will move from one group to another group in the subsequent year (t+1) or 3 years later (t+3). First row for each group presents number of managers belonging to the group at time t and their groups in subsequent year/three year later. Second row for each group presents the transition probabilities for managers starting in a group (from left-hand column) into a different group. Third row presents the transition probabilities based on the overall universe.

	Year t+1 (Ending group)			
Year t (Starting Group)	Low	Medium	High	Total
Low	7380 72.4% 24.1%	2265 22.2% 7.4%	555 5.4% 1.8%	10200
Medium	2411 23.3% 7.9%	5908 57.1% 19.3%	2024 19.6% 6.6%	10343
High	580 5.7% 1.9%	2259 22.4% 7.4%	7252 71.9% 23.7%	10091
Total	10371	10432	9831	30634

	Year t+3 (Ending group)			
Year t (Starting Group)	Low	Medium	High	Total
Low	5240 67.0% 22.1%	1979 25.3% 8.4%	603 7.7% 2.5%	7822
Medium	2257 27.8% 9.5%	4124 50.9% 17.4%	1726 21.3% 7.3%	8107
High	688 8.9% 2.9%	2172 28.1% 9.2%	4869 63.0% 20.6%	7729
Total	8185	8275	7198	23658

	After 1 year	After 3 years
Numbers that stay in same group	20540	14233
Fraction that stays in same group	67.0%	60.2%

Table 2.13: Investor horizon and liquidity. Findings on the differential effect of investor horizon on liquidity of stocks are presented. A summary of findings across different testing methods and using different measures of liquidity is presented. The variable *long_short* is difference between *fraclong* and *fracshort* (the difference between long-term ownership and short-term ownership). Control variables from Spec 6 in Table 2.5 are used. Turnover is excluded from the regression as it used to classify institutions into groups. Standard errors from pooled regression and with firm fixed estimates are clustered at level of firm and year. Both methods include year and industry fixed effects. Fama-Macbeth regression includes industry fixed effects and presents the time series mean of the coefficient estimates. Estimates for other variables are suppressed for the sake of brevity. The standard errors are presented in italics below the estimates.

	c_bma	Illiq	relespr	relqspr
Panel A: Pooled				
fracinst	-0.0027***	-0.5266***	-0.0075***	-0.0067***
	0.0005	*0.0647*	*0.0010*	*0.0016*
sqfracinst	0.0033***	0.4980***	0.0057***	0.0049***
	0.0004	*0.0534*	*0.0009*	*0.0014*
long_short	0.0003	0.03605**	0.0015***	0.0014***
	0.0002	*0.0177*	*0.0004*	*0.0003*
Adj. R2	58.00%	78.33%	75.77%	82.61%
Minimum Point	42%	53%	66%	68%
Panel B: Firm fixed estimates				
fracinst	-0.0030***	-0.2364***	-0.0066***	-0.0051***
	0.0004	*0.0260*	*0.0007*	*0.0008*
sqfracinst	0.0030***	0.2693***	0.0048***	0.0037***
	0.0004	*0.0212*	*0.0005*	*0.0006*
long_short	0.0007***	0.0224***	0.0014***	0.0015***
	0.0001	*0.0069*	*0.0003*	*0.0002*
Adj. R2	36.26%	51.52%	51.51%	67.19%
Minimum Point	51%	44%	68%	70%
Panel C: Fama-Macbeth approach				
fracinst	-0.0008*	-0.6701***	-0.0077***	-0.0071***
	0.0005	*0.0554*	*0.0008*	*0.0012*
sqfracinst	0.0009**	0.6764***	0.0066***	0.0061***
	0.0004	*0.0524*	*0.0006*	*0.0008*
long_short	0.0004***	0.045***	0.0016***	0.0015***
	0.0001	*0.0152*	*0.0002*	*0.0002*
	Pos (20/Sig 3)	Pos (20/Sig 4)	Pos (23/Sig 14)	Pos (22/Sig 12)
Adj. R2	49.67%	73.30%	65.05%	68.72%
No of years	25	25	23	23
Minimum Point	50%	50%	50%	58%
No. of Obs.	**29260**	**29260**	**27630**	**27630**

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

I form three groups of institutions each year based on their portfolio turnover, classifying them as having a short-term, medium-term or long-term investment horizon. Subsequently, I divide stock holdings of each firm into three categories based on the fraction of shares held by each type of institution. I form the three categories by using the investment horizon of institutions from the previous year, to reduce the contemporaneous effect of their turnover on liquidity. Fraction of shares held by low turnover institutions is referred to as *fraclong*. Buy and hold investors have low turnover. Similarly, *fracmedium* and *fracshort* represent shares held by medium-term investors and short-term *(high turnover)* investors, respectively.

Cross-sectional tests: I test for the effect of differences in investors' trading horizon on liquidity measures. I include the difference between shares held by long-term investors (*fraclong*) and short-term investors (*fracshort*)—represented as *long_short*—as an additional variable to Spec 6, Table 2.5. I do exclude turnover as a control variable since I partitioned institutions into groups based on their portfolio turnovers and evidence in the previous section indicated that *fracinst (Granger)* causes *turnover*. Table 2.13 presents the findings for various liquidity measures and estimation techniques. The coefficient on *long_short* is positive and significant, indicating that firms with higher long-term institutional ownership tend to be less liquid. An increase in investor horizon resulting from growth in long-term ownership by 1%, keeping total institutional ownership level constant, results in an increase of *RELQSPR* and *RELESPR* by about 13% to 20%. This finding indicates the sizable impact investor horizon and composition can have on liquidity measures.

Granger causality tests: Amihud and Mendelson (1986) suggest that investors with higher liquidity needs prefer more liquid securities. The effect of investor horizon on liquidity can therefore be a consequence of the matching of investors with firms, with short-term investors preferring more liquid firms. I therefore conduct *Granger* causality tests by breaking down the fraction of equity held in a firm by long-term (*fraclong*) and short-term (*fracshort*) investors, following the procedure described in Section 5.1, in order to identify whether investor horizon has an influence on measures of liquidity.

I reject the hypothesis that both *fraclong* and *fracshort* do not *(Granger)* cause liquidity measures *RELESPR* and *RELQSPR,* respectively, when including the squared terms of the ownership variables (*sqfraclong* and *sqfracshort*). Including the squared terms of ownership type improves the model fit significantly for both measures of liquidity, strongly suggesting the existence of the nonlinear effect. The findings from both F tests and comparing model fit using BIC are similar. The findings are also robust to various other specifications and to including *turnover* measure. Five to seven lags are usually sufficient to capture the dynamic behavior across different specifications.

However, I cannot reject the hypothesis that liquidity does not *(Granger)* cause levels of holdings by both long-term and short-term investors. There is only very weak evidence (unreported results) that *RELQSPR (Granger)* causes *fracshort*. The findings thus indicate that liquidity of the securities in the past has some influence on short-term ownership but not on long-term ownership. This finding is consistent with the claim by Amihud and Mendelson (1986) that investors with higher liquidity needs will invest in securities with greater liquidity. Overall, these findings also support that even after controlling for institutions preference for liquid securities, their investment horizon influences liquidity.

SECTION 6.2: RISK AVERSION

Risk aversion of investors can affect liquidity by influencing the trading intensity of informed investors and trading (portfolio rebalancing) needs of the uninformed investors. Pritsker (2005) also indicates that investors risk aversion is an important determinant of market liquidity, as it determines investors' willingness to pay to eliminate or take on additional risk for an additional period. Subrahmanyam (1991) models the effect of risk aversion of informed traders on liquidity in a single-period model and finds that liquidity could be decreasing, unimodal or increasing function of risk aversion depending on the number of informed investors. Liquidity increases with risk aversion for a smaller number of informed investors while it decreases with risk aversion as the number of informed investors increases. However in a multi-period model, as used by Holden and Subrahmanyam (1992), risk-averse informed investors trade more aggressively in the earlier periods (if their signals are perfectly correlated) resulting in faster incorporation of information into prices and increasing liquidity. However, if the signals of the informed are not perfectly correlated their trading intensity may decrease, resulting in reduced information efficiency and perhaps lower liquidity. The theoretical work therefore suggests that risk aversion of informed investors affects liquidity and the effect on liquidity varies with the degree of competition among the informed and the information structure.[59]

I try to empirically identify the effect of risk aversion of informed investors on liquidity. Risk aversion of investors is an unobserved characteristic and I therefore create a proxy for risk aversion using various measures of portfolio concentration of

[59] Spiegel and Subrahmanyam (1992), as well as Mendelson and Tunca (2004) investigate the effect of risk aversion of uninformed investors/liquidity traders on liquidity. Spiegel and Subrahmanyam find that liquidity increases with risk aversion of uninformed investors, if their trading is motivated by hedging needs, while Mendelson and Tunca indicate the opposite—that liquidity is a decreasing function of risk aversion of liquidity traders.

institution: size of the portfolio, Herfindahl Index for portfolio, number of industries the institution invests in, number of securities in the portfolio, and number of securities that comprise 50%, 75%, and 90% of the portfolio, respectively. I consider institutions with more concentrated portfolios and holding fewer securities as less risk averse, and institutions with less-concentrated portfolios and holding more securities as more risk averse.[60] As expected, Herfindahl Index for the portfolio exhibits a negative correlation with the other measures of portfolio concentration of institution and size of the portfolio. I subsequently take the first principal component of these measures and use it as a measure for risk aversion of each manager/institution.[61] The obtained risk aversion measure for each institution is then used to construct a weighted-average measure for each firm, with weights being the fraction of equity held by the institution in the firm. This weighted-average measure, called *Diverse,* indicates whether the investors owning the securities in the firm have concentrated portfolios or diverse portfolios. This measure for risk aversion of investors in a firm differs from both concentration in ownership (*lnhhi_inst*) and fraction of equity held by the institutions (*fracinst*), used earlier. *Diverse* exhibits a correlation of 0.75 with *fracinst* and a correlation of 0.52 with the concentration of institutional holdings *(lnhhi_inst)* in the firm, indicating that firms with higher institutional ownership tend to have more-diversified investors.

I test the effect of risk aversion of institutions on liquidity by using pooled regressions as described earlier. I present findings using *c_BMA* as the liquidity measure and add *Diverse* as an additional variable to Spec 6, Table 2.5. I exclude the indicator variable

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[60] One way to think of the argument is that not only the proportion of equity held by all institutions but also the characteristics of each institutions'overall portfolio has an affect on the liquidity of assets they hold.

[61] The first principal component by itself explained close to 61% of the total variance in the 7 variables.

InstDummy, as *Diverse* measure is available only for firms with institutional ownership data available. Table 2.14 presents the findings. Spec 1 controls for the non-monotonic relationship between liquidity and institutional ownership (*fracinst*) and indicates that spreads increase in risk aversion of investors.[62] Findings from Spec 2 and Spec 3 are similar after controlling for number of investors and concentration of institutional ownership. A one standard-deviation increase in *Diverse (1.613)*, holding the ownership level constant, is associated with an increase in the effective spread measure of *(0.0003)*, which is equivalent to almost a 0.1 standard-deviation decrease in liquidity measure. These findings indicate that, ceteris paribus, if investors in the firm are more risk averse and have more diversified portfolios then liquidity is lower. I include interaction term between *Diverse* and *fracinst* in Spec 4, and an interaction term between *Diverse* and *lnnuminst* in Spec 5. The positive and significant interaction term indicates that with growth in competition among institutions, the marginal effect of investor risk aversion on spreads becomes larger. I interpret these findings to indicate that increasing risk aversion of informed investors reduces the information efficiency effect, resulting in lower liquidity. This finding is consistent with the theoretical predictions in Subrahmanyam (1991), where liquidity decreases with investor risk aversion and the marginal effect of investor risk aversion on liquidity increases as the number of informed investors increase.

[62] The effect of investor risk aversion on liquidity is consistent with the claim in Brunnermeier and Pedersen (2007) where market liquidity is a function of funding liquidity and decreases with investor risk aversion.

Table 2.14: Investor risk-aversion (portfolio diversification of institutions) and liquidity. Cross-sectional results for effects of estimate of risk aversion of institutions on liquidity for stocks listed on NYSE and AMEX are presented. The dependent variable is the annual measure of liquidity *c_BMA* obtained from Joel Hasbrouck. The variable *Diverse* is a weighted-average measure trying to capturing how diverse the institutions holding equity in the firm are. For construction of *Diverse* please refer Section 6.2. The period of study is 1980–2005. Pooled regression is run using year and industry fixed effects due to the inherently unbalanced nature of the panel. The standard errors are estimated by clustering on year and firm and are presented in italics below the estimates. Control variables from Spec 6 in Table 2.5 are used and their coefficients are suppressed for sake of brevity.

Variable	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
fracinst	-0.0033***			-0.00268***	-0.00316***
	0.0005			*0.00057*	*0.00051*
sqfracinst	0.00369***			0.00232***	0.00305***
	0.00048			*0.0007*	*0.00046*
lnnuminst		-0.00123***			
		0.00027			
sqlnnuminst		0.00012***			
		0.00003			
lnhhi_inst			-0.00025**		
			0.00009		
sqlnhhi_inst			0.00002**		
			0.00001		
Diverse	0.00014***	0.00018***	0.00018***	0.00004	-0.00012**
	0.00004	*0.00003*	*0.00003*	*0.00006*	*0.00006*
*fracinst*Diverse*				0.00028***	
				0.0001	
*numinst*Diverse*					0.00008***
					0.00001
Adj. R2	58.3%	57.9%	57.6%	58.4%	58.1%
No. of Obs.	32373	31126	31126	32373	31063
No. of Parameters	61	61	61	62	62
F-Value	425.0	410.6	399.8	418.6	400.9

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

To summarize, the findings in this section show that both ownership structure of a firm and characteristics of the investors affect liquidity. Intrinsic differences among owners' characteristics can have a large effect on liquidity of the assets they hold, even after trying to account for preferences for certain security characteristics and controlling for known determinants of liquidity.

SECTION 7: CONCLUSION

An extensive literature in finance examines the effects of informed traders on liquidity and price efficiency of assets. Using a large sample of firms belonging to NYSE and AMEX over the period 1980–2005, I empirically examine the effect of institutional ownership on liquidity. Institutions are distinct from other investors due to their information advantage, providing an appropriate setting in which to test the theories relating effects of informed traders on liquidity. In this chapter, I examine two effects on liquidity that evolve from information advantage of institutions: *information efficiency effect* and *adverse selection effect*.

Increase in fraction of institutions among the population of investors is associated with more information gathering and informed trading, which reduces the perceived uncertainty about the terminal asset payoffs [Wang (1993), Easley and O'Hara (2004)]. The presence of institutions and competition among them increases the rate at which information is incorporated into prices. This makes prices more information efficient, helping to improve liquidity of stocks. Increase in fraction of institutions also results in greater information asymmetry and the adverse selection risk faced by uninformed traders and market makers, resulting in a decline in liquidity. The presence of informed traders on liquidity depends on the net of these two effects.

Taken as a whole, I find strong evidence that institutional ownership affects liquidity. Foremost, I obtain a robust nonlinear (U-shaped) relationship between various measures of liquidity and fraction of shares held by institutions after controlling for other known determinants of stock liquidity. As institutional ownership increases in cross-section, liquidity initially increases (spreads decrease). However, for ownership levels beyond 35%–40%, further increase in institutional ownership causes a decline in liquidity (spreads increase). I interpret these empirical findings as support for the hypotheses that the information advantage of institutions affects liquidity through two channels. The decline in spreads with number of institutions is consistent with the effect of information efficiency on liquidity. The evidence provides support for the strategic trader models by Kyle (1985), Subrahmanyam (1991), Holden and Subrahmanyam (1992), and Mendelson and Tunca (2004), where liquidity improves with increases in number of informed investors and competition among them. At higher levels of institutional holdings, the observed decline in liquidity is consistent with the asymmetric information models of Glosten and Milgrom (1985) and of Easley and O'Hara (1987). The adverse selection effect on liquidity gets further enhanced as the number of uninformed and liquidity motivated traders decline with growing institutional ownership.

The net effect on liquidity arising from the information advantage of institutions is an outcome of both the information efficiency and adverse selection effects. The marginal effect of increasing institutional ownership on information efficiency declines, resulting in a non-monotonic effect of institutional ownership level on liquidity. Both the effects arising from the information advantage of institutions also vary with the amount of public information availability and asset risk.

I further address the simultaneity problem due to joint determination of institutional ownership and liquidity, using *Granger* causality tests. I reject the hypothesis that institutional ownership does not *(Granger)* cause liquidity, indicating that changes in institutional ownership help forecast changes in liquidity. The non-monotonic effect along with *Granger* causality results strongly suggest that institutions have a causal effect on liquidity by influencing the information structure of the firm. It is interesting to note that only weak evidence exists in support of the reverse causality.

Further, I examine the effects of heterogeneity among institutions on liquidity. First, I find strong evidence indicating that liquidity declines with an increase in investment horizon and only weak evidence that liquidity of stocks affects the ownership type and investment horizon of institutions. Second, I examine the effect of diversification of the portfolios of institutions holding the stocks on liquidity, considering institutions with more diverse portfolios as more risk averse. I find strong evidence that increased risk aversion of investors results in a decline in liquidity consistent with a reduction in information efficiency effect.

Overall, the findings strongly suggest that ownership structure of an asset plays a significant role in determining its liquidity by affecting the information structure. The presence of informed investors not only increases the adverse selection risk faced by uniformed investors, but also helps to increase the information efficiency of prices reducing the uncertainty about future payoffs. The net effect on liquidity is a combined result of these two effects. Future research may benefit from treating liquidity of an asset as endogenous and incorporating the effects of ownership structure on liquidity for asset pricing implications.

CHAPTER 3: INSTITUTIONAL OWNERSHIP AND LIQUIDITY RISK

INTRODUCTION

A large increase in institutional ownership of stocks within the U.S. market has made it important to study their role in the functioning of financial markets. The effect of liquidity and its time variation on asset valuation and expected returns has received substantial attention from both academics and the popular press. There is growing empirical evidence that an asset's liquidity and systematic liquidity risk are priced.[63] Recent events in the financial markets also indicate the importance of considering both liquidity and its time variation in portfolio construction. Most studies of liquidity document that liquidity varies in cross-section and examine its determinants by analyzing this cross-sectional heterogeneity. In the second chapter, I studied the effects of institutional ownership on liquidity of stocks. In this chapter, I analyze the cross-sectional heterogeneity in the time-series variation of liquidity in equity markets. I try to answer the question why does the day-to-day variation in liquidity differ across firms. I mainly focus on the effects of institutional ownership and various other attributes of the institutional investor base holding common stock on the stocks' daily variation in liquidity. I also try to understand the mechanics by which the ownership structure affects the transmission of liquidity demand across securities.

Why should we care about time variation in liquidity? Most institutions and investors express concerns about liquidity and liquidity risk of the portfolio constituents when determining investments. Coffee (1991) and Bhide (1994) even make the case that

[63] For brief surveys please refer to Amihud, Mendelson, and Pedersen (2005); Easley and O'Hara (2003); and O'Hara (2003). Time variation in liquidity has been identified as a non-diversifiable priced risk in Acharya and Pedersen (2006); Pastor and Stambaugh (2003); and Koraczyk and Sadka (2008). More explicitly, liquidity risk of an asset has been identified as the sensitivity of an assets liquidity to changes in marketwide conditions, mainly marketwide liquidity and market returns.

institutions concern for liquidity of their investments deters them from building up the concentrated ownership that is required to have an influence on corporate decisions. Longstaff (2004) shows that illiquidity of assets can have a significant effect on the optimal portfolio choices of investors and can lead investors to abandon diversification as a strategy. I here argue that not only should an asset's liquidity but also the variation of an asset's liquidity over time matter to an investor's portfolio choices. Merton Miller (1991) said "Liquidity, according to Keynes, offers a classic example of the fallacy of composition: what is true for a part is not necessarily true for the whole. The ability to reverse positions and get out quickly vanishes when everyone tries to do it at once." So, under normal circumstances, investors can time their trades to take place when trading costs are low. However, if investors don't have the required discretion in the timing of their trades giving consideration to the time varying nature of liquidity becomes increasingly important. For example an investor trying to replicate or hedge an option, has much less discretion about when he can trade the underlying. This suggests that time variation in liquidity could play an important role in the area of derivative pricing. Stochastic liquidity will also affect the ability of arbitrageurs to eliminate mispricing. The capital constraints on arbitrageurs generally force them to hold undiversified portfolios, thus exposing them to total liquidity variation. This emphasizes the importance of being cognizant of the time variation in liquidity of an asset and identifying the determinants of both total and systematic liquidity variation of an asset over time.

Chordia, Roll, and Subrahmanyam ((2000), hereafter referred to as CRS), Huberman and Halka (2001), and Hasbrouck and Seppi (2001) were first to document comovement in liquidity indicating existence of a systematic component in the time variation of liquidity. O'Hara (2003), in her presidential address, points out that, not only is the issue of sources of commonality in trading costs (liquidity) unresolved, the impact of such commonality on asset returns is also contentious. Unless such commonality in driven by systematic factors and is undiversifiable, effect of liquidity on asset returns will be of second order. Thus, tracing commonality in liquidity to its sources is important. Also, while documenting commonality CRS find that changes in marketwide liquidity explain only a small fraction of the time-variation in liquidity of a firm, thereby indicating a large idiosyncratic component to liquidity variation. Chordia, Subrahmanyam, and Anshuman (2001) examine the effect of volatility of liquidity on expected returns, using trading activity as a measure of liquidity. They hypothesize that since investors care about transaction costs, risk-averse agents will desire compensation for fluctuations in trading cost which don't necessarily have to be systematic. However, they find that the second moment of liquidity has a significant negative impact on equity returns, a finding not only surprising but also contrary to their hypothesis.

The second chapter in the dissertation found that institutional ownership had a significant effect on liquidity. I found that the information advantage of institutions affects liquidity through two channels: *adverse selection* and *information efficiency*. The adverse-selection effect results from an increase in information asymmetry. The information-efficiency effect, however, results from an increase in competition among institutions. Competition promotes the rate at which private information is incorporated into prices, reducing uncertainty about future payoffs. I found evidence of a non-monotonic (U-shaped) relationship between the level of institutional ownership and various measures of stock liquidity. I also observed that institutional investor characteristics, such as investment horizon and risk aversion, affect liquidity.

This chapter goes a step further and examines time variation in liquidity and liquidity risk of assets. Sudden changes in marketwide liquidity have been associated with various puzzling episodes like the stock market crash of 1987, the global liquidity crisis of 1998, and the financial crisis of 2007–2009. Identifying factors and variables that determine liquidity risk of an asset will thus aid in both the portfolio construction process and risk management.[64] In spite of the growing evidence that liquidity risk is priced, the empirical evidence on what causes differences in the sensitivity of changes in an assets' liquidity to changes in marketwide liquidity is limited. Furthermore, our knowledge of what determines the cross-sectional variation in measures of volatility of liquidity is also very narrow.

In this chapter, I focus on determining whether ownership structure of an asset is an important determinant of both total and systematic liquidity variation over time. To the best of my knowledge, only Kamara, Lou, and Sadka (2008, hereafter referred to as KLS) attempts to identify sources of difference in sensitivity of an asset's liquidity to marketwide liquidity, the systematic component of liquidity variation. Their study examines the effect of firm size on commonality in liquidity and finds that larger stocks exhibit greater commonality in liquidity. They claim that the greater commonality in liquidity among stocks of the larger firms results from greater institutional holdings of those stocks and attribute it to the institutional herding behavior. Chordia, Shivkumar, and Subrahmanyam (2004) examine the cross-sectional heterogeneity in the time-series variation of liquidity in equity markets and find that smaller firms exhibit greater day to day variation in liquidity.[65] These studies help us

[64] Commonality in liquidity has implications for risk management by asset management firms as induced co-movement in returns caused by effects of current portfolio holdings of institutions on liquidity and returns may be independent of historical correlation of returns of the underlying stocks.

[65] The authors examine the comovement between liquidity and absolute returns and find that the institutional holdings influence the relationship negatively in large firms.

learn about the effect of level of institutional ownership but leave us without much understanding of the effect of different attributes of institutional ownership on time variation in liquidity.

In this chapter, I try to address some of these gaps in the literature and answer the following questions: Why does the day-to-day variation in liquidity of stocks differ across firms? Does ownership structure of the firm explain the liquidity variation in its equity over time? Does clientele and ownership structure of firms result in commonality in liquidity, and if so why? What are the attributes of the ownership structure that lead to meaningful differences in both time series variation of liquidity and sensitivity of a firm's liquidity to market liquidity across firms? What other firm characteristics influence an asset's liquidity risk?

I focus on the U.S. equity markets and examine the effects of equity ownership by institutions on a stock's sensitivity to marketwide liquidity and its liquidity variation over time. I focus mainly on institutions, because they hold a large fraction of outstanding equity in the U.S. firms. Since the information environment of a firm is also a very important determinant of its liquidity, as indicated in the second chapter, I further examine the effects of information environment of the firm on measures of its liquidity variation over time.

Institutions can clearly play an important role in an asset's time variation in liquidity. Increasing volatility in financial markets over time is often attributed to the increase in institutional ownership (Xu and Malkiel (2003), Dennis and Strickland (2005)). Institutions often follow similar investment strategies. As a result, their trading could be correlated. For example, many institutions follow passive indexing strategies, in which they make changes to their portfolios only in case of fund flows or changes to the index constituents. Others follow active trading strategies (like value or momentum) with relatively higher turnover.

The institutional ownership in U.S. equity markets has been increasing. The institutions exhibit similarity to each other and are therefore susceptible to shocks faced by other institutions. This susceptibility to common shock increases the likelihood that the effect of these common shocks will be transmitted to the assets they hold. For example, in presence of a sudden demand for liquidity a contagion effect can be initiated, having a significant effect on asset valuations and liquidity. Differentiating the underlying motivation for a trade driven by liquidity needs from one driven by information is not easy, making liquidity suppliers less willing to meet the sudden increased demand. This can enhance volatility of liquidity of an asset if its respective owners are more susceptible to liquidity shocks. Fernando, Herring, and Subrahmanyam (2008) provide evidence that the concentrated ownership of PERPS by Japanese banks was a primary cause for their sudden large decline in liquidity, even when it was evident that the liquidity demands of Japanese banks were not motivated by information. Another good example of correlated trading was the significant drawdown observed by institutions following similar quantitative equity strategies, in August 2007. Khandani and Lo (2007) find that the correlated trading resulted from a large number of levered long-short equity funds beginning to unwind their positions to reduce their leverage. Thus, increasing homogeneity of the investor composition can significantly increase liquidity risk, further indicating that increasing institutional ownership can enhance liquidity risk.

In this chapter, I focus on correlated trading by institutions as an underlying cause for commonality in liquidity. I rely on theories of herding, primarily ones related to information cascades, to come with various testable predictions. Correlated trading by institutions can result either from a tendency to herd or trade on common information and signals without relying on the actions of others. I examine whether measures of systematic liquidity risk and liquidity variation over time change with the ownership attributes of the firm and interpret the results in light of my predictions.

I first confirm the existence of commonality in liquidity, using a "market model" and various liquidity measures over a long sample period (1983–2005). Secondly, I examine the effect of institutional ownership attributes on measures of systematic liquidity risk. I find that systematic liquidity risk increases with the level of institutional ownership after controlling for the size of the firm. The finding indicates that stocks predominantly held by institutions exhibit greater commonality in liquidity and higher systematic liquidity risk, due to the greater homogeneity of institutional investors. This finding is inconsistent with the conjecture of Huberman and Halka (2001) who suggest that commonality in liquidity emerges due to noise traders, unless we are willing to reject the notion that institutions are informed traders in the financial markets.

After controlling for the level of institutional ownership and the size of the firm, I find that systematic liquidity risk increases with the homogeneity of the institutional investor base and the investor horizon, while it decreases with the concentration of ownership and an increase in the block-holdings. Increasing homogeneity of the investor base enhances the effect of a common liquidity shock faced by the owners of the assets. Furthermore, an increase in homogeneity of the institutional investor base will increase the likelihood of herding as each institution faces a similar decision problem and there is a reduction in dispersion of their private information. Homogeneity of the investor base thus becomes a source of commonality in liquidity and increased systematic liquidity risk. However, an increase in ownership concentration and block-holdings result in an opposite effect. Institutions holding larger stakes in a firm have greater incentives to collect information and act on their private information, and are less likely to rely on the inference drawn from the actions of others. As a result, with ownership getting concentrated among fewer institutions, the likelihood of correlated trading will reduce, thereby reducing commonality and systematic liquidity risk.

My third set of findings shows the effect of institutional ownership measures on time variation in firm-level liquidity. I find that a large component of variation in liquidity over time remains unexplained by market liquidity and market returns suggesting that firm-level liquidity variation is mostly idiosyncratic. However, the time variation in liquidity for a firm is highly persistent. It decreases with firm-size, institutional ownership, and homogeneity of the investor base, while increasing with concentration of ownership. The effect of investor horizon though wasn't consistent across measures.

Lastly, I find that the measures of information asymmetry play a useful role in determining the cross-sectional variation in both systematic liquidity risk and total liquidity variance. Systematic liquidity risk decreases while the total liquidity variance increases with increasing information asymmetry. Greater information asymmetry is associated with an increase in private information. Investors with private information are more likely to rely on their information in making decisions and, as a result, will not only exhibit a lower propensity to herd but would potentially act in a stabilizing manner. This stabilizing effect of the more informed institutions will reduce the likelihood of information cascades. Thus, increasing information asymmetry will be associated with reduced herding and correlated trading, resulting in a lower systematic liquidity risk. However, an increase in private information-based trading will result in idiosyncratic liquidity needs resulting in greater variation of liquidity over time. These findings provide a useful link between information asymmetry, one of the most important determinants of liquidity, and measures of changes in liquidity over time.

On the whole, the above findings point out the different effects of institutional ownership structure on variation of liquidity over time. KLS focus on examining the effect of fraction of equity held by institutions on the systematic liquidity risk, and exploring whether the effects vary across mutual funds, pension funds, investment advisors, etc. They did most of their analysis at portfolio level and find that the divergence in commonality in liquidity among the large and small U.S. stocks over time results from the growth in institutional ownership. In this study, I rely on the theoretical literature on herding behavior of agents and stochastic liquidity to formulate implications of a firm's ownership structure and information environment on correlated trading of the institutional investor base. Thereby, I find additional effects that arise from cross-sectional differences in institutional investor base—like homogeneity and investment-horizon of the institutional investor base, concentration in ownership among institutional investor base, and presence of blockholdings—on both systematic liquidity risk and the total variation in liquidity. I further examine the effects of information asymmetry and private information on time variation in liquidity and systematic liquidity risk, thereby establishing a link between information risk and stochastic liquidity.

There are some aspects of this study that should be interesting both from an academic and a practical point of view. First, it documents the sizable cross-sectional variation in time series behavior of liquidity and systematic liquidity risk. The time variation in liquidity has implications for portfolio managers following active strategies, and highlights the possibility that cost to liquidate a portfolio can vary significantly depending on market conditions. The results help shed light on the type of firms that are likely to become expensive to trade when market liquidity decreases. It also raises the possibility that portfolio managers following active investment strategies can reduce their execution costs by exploiting the time-series variation in liquidity and developing optimal execution strategies. Second, stochastic liquidity, a source of friction in asset markets, can have implications for asset pricing, especially for pricing derivative securities, where dynamic replication of portfolios leaves less discretion in terms of timing of trades. Considering the time variation in liquidity of the underlying assets, may therefore be important for market makers of options and other derivative instruments. Third, the study relates the time series variation in liquidity of an asset to its clientele. The findings point to the different effects of institutional ownership on systematic liquidity risk and total variation of liquidity and therefore could be useful for regulators to think of clientele effects on systemic risk. Furthermore, the causes of investor herding could be crucial for determining policy responses for mitigating herd behavior. Fourth, I find a link between measures of information asymmetry and time variation in liquidity, thereby establishing a link between information risk and liquidity risk. Various market microstructure models examine the effect of information asymmetry and probability of informed trading on liquidity levels. I indicate that private information by affecting the likelihood of correlated trading can increase the variation in liquidity over time while simultaneously decreasing the systematic liquidity risk. Fifth, in general there is a large focus on factors related to the supply of liquidity in the literature. I show that demand for liquidity also has a significant and varied impact than previously thought. Future empirical analysis can explore some of these demand effects.

This chapter also raises some additional interesting questions. First set of questions relate to the time series properties of liquidity. Does liquidity exhibit some sort of regimes with states of high and low liquidity? If so, what are some of the triggers of changes in liquidity and can we predict the duration of these different states of liquidity? Do changes in liquidity exhibit clustering similar to return volatility? Secondly, since many institutions and individual investors tend to follow "style investing" examining effect of ownership structure on commonality within the style buckets could also be interesting. In a similar line, examining commonality in liquidity among stocks predominantly held by institutions that belong to same location could provide further evidence on herding. Similarly, one could also examine the effect of uncertainties about firm and macro environment on the variation in stock liquidity. The finding on effect of lengthening investor-horizon on increasing liquidity risk remains a puzzle. Further examining the effect of investor horizon on liquidity risk in an equilibrium model and its effects on asset pricing could therefore be interesting. Lastly, another useful avenue of research could be to examine the effects of liquidity shocks and information shocks in the same equilibrium model. This can help understand the transmission of these shocks across assets and come up with additional empirical predictions on the joint dynamics of returns and liquidity.

The remaining chapter is broadly organized as follows. Section 1 presents related literature on commonality in liquidity and liquidity risk and develops hypotheses on effect of institutional ownership on commonality in liquidity. Section 2 describes the data and measures of systematic liquidity risk and liquidity variation over time. It also describes the measures of institutional ownership and characteristics. Section 3 presents the main findings on the effects of institutional ownership on liquidity risk and its time variation. I present my conclusions in Section 4.

SECTION 1: LIQUIDITY AND LIQUIDITY RISK

This section develops the study's hypotheses after briefly reviewing the literature on effect of liquidity risk on expected returns and commonality in liquidity.

SECTION 1.1: LIQUIDITY RISK AND EXPECTED RETURNS

Asset-pricing literature indicates the importance of both the effect of transaction costs and the sensitivity of an asset's liquidity to market returns and marketwide liquidity in determining its equilibrium expected returns. After controlling for various asset characteristics and risk measures, the influence of an assets' liquidity level and systematic liquidity risk on its prices appears to be both statistically and economically significant.[66] The findings indicate that the marketwide liquidity is a state variable that is important for asset pricing, and assets exhibiting a higher sensitivity to the state variable (facing higher liquidity risk) have higher expected returns. These studies also show that firms that are more illiquid seem to have higher liquidity risk measured in terms of their liquidity betas. The liquidity beta estimates the systematic liquidity risk of an asset by measuring the co-movement in the liquidity of the asset with that of the market liquidity. Most of these studies have examined market liquidity as a state variable but have not considered the total variation in liquidity of an asset. One

[66] For brief surveys please refer to Amihud, Mendelson, and Pedersen (2005); Easley and O'Hara (2003); and O'Hara (2003). For theoretical and empirical findings please refer to Amihud and Mendelson (1986); Brennan and Subrahmanyam (1996); Eleswarupu (1997); Chalmers and Kadlec (1998); Chordia, Subrahmanyam, and Anshuman (2001); Huang (2003); Pastor and Stambaugh (2003); Acharya and Pedersen (2005); Korajczyk and Sadka (2008); Bekaert, Harvey, and Lundblad (2007); etc.

exception is a study by Chordia, Subrahmanyam, and Anshuman (2001) which examines the effect of second moment of turnover on equity returns. The authors hypothesized that since investors care about transaction costs, risk-averse agents will desire compensation for fluctuations in trading cost. The effect will be more important if investors have less discretion in timing their trades. However, contrary to their hypothesis they find that the second moment of liquidity has a significant negative impact on equity returns. To summarize, these findings suggest that both the level of liquidity and its time variation, both systematic and unsystematic, should be related to expected returns.

SECTION 1.2: COMMONALITY IN LIQUIDITY AND SOURCES

Financial crises in the United States (1987), U.S./Iraq war (1990), South East Asia (1997), Russia (1997), LTCM collapse and bond market crisis (1998), and the sub-prime crisis (2007, 2008, 2009) indicate that credit and market conditions can tighten suddenly, leading to a large decline in marketwide liquidity. Various microstructure studies investigate factors that influence an asset's liquidity. Chapter 2 talks at length about the various determinants of asset liquidity. However, in general, theories don't explicitly state sources of time variation and commonality in liquidity.

Empirical studies first documented the existence of intertemporal changes in liquidity. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001) showed the existence of time variation and commonality in both measures of trading activity and liquidity in the equity markets. These papers suggest that commonality in liquidity arises due to the market makers' activity to preserve the inventory level, macro news announcements, and changes in other macro economic variables such as credit spreads and term spreads. Brockman, Chung, and

Perignon (2008) extended the evidence of commonality in liquidity across 46 exchanges. Subsequent studies tried to identify macroeconomic factors as a source of the time variation in liquidity. Chordia, Roll, and Subrahmanyam (2001) study the daily variation in aggregate market spreads, and the influence of market returns, volatility and interest rates on liquidity. Chordia, Sarkar, and Subrahmanyam (2005) indicate the presence of common factors that drive liquidity and volatility in stock and bond markets and establish a link between "macro" liquidity, or money flows, and "micro," or transactions, liquidity. In a vector autoregressive framework, they find that innovations to stock and bond market liquidity are correlated. Watanabe (2008), using data from 1965 to 2001, establishes a link between macroeconomic fundamentals and market liquidity and finds the effects to be stronger in the earlier part of the sample. Watanabe and Watanabe (2008) look at whether liquidity betas and liquidity risk premium vary across different economic states.

Recent theoretical work focuses on examining causes of commonality in liquidity. Various multi-security models of market microstructure have examined how the market-maker learns by observing signals and trading in other stocks. For example Caballe and Krishnan (1994), in a single period model, show that, due to correlated fundamentals, market makers learn from order flows of other stocks. This makes the security price determined not only by its own price or order flow but also by those of other stocks. Watanabe (2008) extends the multi-security model to a multi-period framework, and models the information arrival process explicitly as following a multi-variate GARCH process. He examines transmission of the information shocks across assets and their effect on asset liquidity and time variation in liquidity. The persistence and correlation in the information shocks, gives rise to commonality in liquidity by increasing return volatility. By examining Dow stocks Watanabe finds evidence that a

Dow stock's illiquidity exacerbates in the size of information about not only itself, but also about other Dow stocks, thus demonstrating a significant cross-sectional effect of information on liquidity. In contrast, Fernando (2003) examines transmission of liquidity shocks across assets. He decomposes liquidity shocks faced by investors into systematic and idiosyncratic components and models how heterogeneity in investors' sensitivity to the systematic shocks affects transmission of the liquidity shocks across assets. His model introduces liquidity shock as a change in investors' marginal valuation of risky assets without arrival of new information about the fundamental value of securities. He finds that common liquidity shocks do not give rise to commonality in liquidity demand. In contrast, idiosyncratic liquidity shocks create a demand for liquidity, which investors can then meet by trading in more liquid assets.

Other theoretical models have examined commonality in liquidity resulting from investor's time variation in their preference for liquidity and funding constraints on market-makers due to market fluctuations. Vayanos (2004) indicates that when fund flows to institutions are contingent on past performance, preference for liquidity can be time varying and increasing in return volatility. This can lead to a flight to quality and co-movement in returns and liquidity. Brunnermeier and Pedersen (2008) model the effects of availability of funds with traders on the liquidity of assets and find that funding liquidity and asset liquidity are mutually reinforcing. This mutual reinforcement can lead to sudden changes in market liquidity, commonality in liquidity, flight to liquidity and safety, etc.

Empirical studies have also tried to identify sources of commonality in liquidity. Coughenour and Saad (2004) discuss that commonality in liquidity can arise from common variation in either demand for liquidity or supply of liquidity or both. They look for the supplier effects and find evidence that the individual stock liquidity co-varies more with stocks that are handled by specialists belonging to the same company, apart from information reflected by market liquidity variation. They claim that this results from the shared capital and information among specialists within a firm. Brockman and Chung (2002) document the existence of liquidity commonality in purely order-driven settings of the Swiss Stock Exchange and Hong Kong Stock Exchange. Domowitz, Hansch, and Wang (2005), using ASX data, show that commonality in liquidity is driven by co-movement in supply and demand induced by cross-sectional correlation in order types. They indicate that order flow commonality is a source of return commonality while order type commonality is a source of liquidity commonality. The last two studies primarily indicate correlated trading as a source of liquidity commonality.

The above notion of commonality in liquidity closely relates to the effect of information environment of a firm and liquidity needs of investors on their trading and herding behavior. Herding is a result of an obvious intent by investors to copy the behavior of other investors or be influenced by others' actions and could be a rational behavior on part of financial market participants.[67] However, herding must be distinguished from "spurious herding" during which investors facing similar decision problems and information sets make similar decisions. In both cases, we will observe correlated trading (or similar decisions), but an observation of correlated trading does not necessarily indicate herding. Hong, Kubik and Stein (2005) document that the U.S. fund managers head-quartered in the same city exhibit similar portfolio choices. They argue that these correlated portfolio choices could arise (i) through peer to peer communication; or (ii) simply because fund managers in a given area commit

[67] For a brief survey on herding behavior in financial markets, please refer to Bikhchandani and Sharma (2001).

themselves to investment decisions based upon common sources of information—such as a local newspaper or TV station. The finding of Hong, Kubik and Stein suggests that interactions among institutions and access to common sources of fundamental information could result in herding and correlated trading.

The theoretical literature examining herding, indicates that herding can result from imperfect information, career and reputation concerns, and compensation structures. Banerjee (1992) proposes a herding model where the agents make their decisions sequentially. Each agent, to an extent, ignores his or her own private information and follows the decisions made previously by other agents. This behavior is rational since previously made decisions are based on important information that only those decision makers possessed. Such sequential decisions made by rational agents result in herding, where private information of agents deciding later stops playing a role in their decision making. Bikhchandani, Hirshleifer, and Welch (1992); Welch (1992); and Froot, Scharfstein, and Stein (1992) also examine herding that results from imperfect information leading to informational cascades. Scharfstein and Stein (1990) argue that in the presence of career and reputational concerns agents will herd together. Maug and Naik (1996) and Admati and Pfleiderer (1997) examine the effects of compensation structure and suggest that herding could also arise in the presence of benchmarking of performance as the incentives provided by the compensation scheme and terms of employment are such that imitation is rewarded. Herding can also result if agents imitate each other due to their intrinsic preference for conformity to others.

Concerns are raised that herding behavior by financial market participants could be a force that destabilizes markets by exacerbating volatility and, thus, also be a source for commonality in liquidity. By and large, the empirical studies that examine herding do not examine or test a particular model of herd behavior.[68] They generally use a purely statistical approach to gauge whether clustering of trading decisions, irrespective of the underlying reasons for such behavior, is taking place in certain securities markets. Due to the unobservability of the underlying motivation for trades, it is extremely difficult to identify whether the observed correlated trading is a result of herding behavior or a reaction to changes in underlying fundamentals.

However, on the whole the evidence suggests that correlated trading by institutions can be an underlying source of commonality in liquidity. These findings therefore suggest that institutional ownership can influence a stock's liquidity variation over time. Furthermore, depending on their underlying motivation for trading and propensity to herd, the observed variation in liquidity across groups of stocks could differ based on their ownership structure.

SECTION 1.3: HYPOTHESES

1.3.1: Ownership and liquidity risk

Chevalier and Ellison (1997), Sirri and Tufano (1998), and Bergstresser and Poterba (2002) find evidence that money flows to mutual funds depends on their past performance. Retail investors tend to chase winners, resulting in significant inflows to winners and outflows from losers. Del Guercio and Tkac (2002) on examining the flow-performance relationship for pension fund managers find that past winners do not attract large inflows, though the assets under management decline for the losers. They attribute this difference in flow-performance relationship between pension funds and

[68] Herding behavior among the U.S. pension funds is examined in Lakonishok, Shleifer, and Vishny (1992), while that among U.S. mutual funds is examined in Nofsinger and Sias (1999), Wermers (1995, 1999), Grinblatt, Titman, and Wermers (1995), Chevalier and Ellison (1999). Herding behavior in emerging markets is examined in Borensztein and Gelos (2000), Kim and Wei (1999), and Choe, Kho, and Stulz (1999), while that among security analysts is examined in Trueman (1994), Graham (1999), Hong, Kubik, and Solomon (2000), and Welch (2000).

mutual funds to their materially different clientele, possibly following different evaluation procedures and criteria. These fund flows can therefore induce demand for liquidity while differences in clientele in a stock can result in differences in systematic liquidity risk.

Barberis and Shleifer (2003) model the phenomenon of "style investing" as a source of commonality in returns. They argue that investors group assets into categories in order to simplify portfolio decisions and allocate funds at the level of these categories. If some of the investors using such categories are noise traders with correlated sentiment, then their allocation of funds can result in coordinated demand of assets. Teo and Woo (2003) find empirical support for "style investing." Barberis, Shleifer, and Wurgler (2005) further find that inclusion in the S&P 500 index results in an increasing co-movement (beta) of the stock with that of the index. The role of mutual funds and pension funds in the equity markets, along with the prevalence of "style investing," can therefore induce co-movement in returns and also be a source of commonality in liquidity.

The prevalence of herding behavior among the U.S. institutions (Nofsinger and Sias (1999), Lakonishok, Shleifer, and Vishny (1992), Wermers (1999)), correlated trading demands due to "style investing" (Barberis and Shleifer (2003)), dependence of fund flows on past performance resulting in time-varying liquidity needs (Vayanos (2004)), and effects of funding availability with traders on asset liquidity (Brunnermeier and Pedersen (2008)) suggest that institutional ownership level can influence the time variation in liquidity of stocks. The increasing likelihood of fund flows during volatile times due to flight to quality and safety can increase the demand for liquidity by institutions. Institutions are also relatively more homogeneous in nature than are the individual investors. Kelly (1995), Barber and Odean (2000), Goetzmann and Kumar (2001), find that households do not tend to diversify their account holdings. Households on average own three to four stocks in their brokerage account, while the median household portfolio includes only two stocks. One third of the households own only one stock. One can interpret these findings as reflecting a greater heterogeneity among individual holdings. Due to the greater homogeneity of institutions, the likelihood of them facing a common funding shock is higher. Susceptibility of institutions to funding shocks and their propensity to exhibit herding behavior can therefore induce correlated trading, causing both a time variation in market and asset liquidity. Furthermore, liquidity of firms with larger institutional ownership will exhibit higher commonality and also have greater measures of systematic liquidity risk. The above discussion sets the stage for the first hypothesis of this chapter.

Hypothesis 1: The sensitivity of a stock's liquidity to market liquidity will increase with an increase in the amount of outstanding equity held by institutions.

The above hypothesis assumes that institutions are more homogeneous in nature than are individual investors. Institutions do exhibit heterogeneity across various dimensions such as investment horizon, capital surplus requirements faced by them, accessibility to funding sources, investment styles they follow, etc. As ownership of an asset becomes more homogeneous, both the likelihood of owners facing a common liquidity shock and the effect of the liquidity shock on the asset will increase. Homogeneity of ownership also increases the likelihood of herding due to a reduction in the dispersion of the private information of institutions. Bikhchandani, Hirshleifer, and Welch (1992), Welch (1992), and Froot, Scharfstein, and Stein (1992) suggest that informational cascades begin when agents acting rationally start ignoring their private information and reach a decision based on observing the actions of others. With ownership becoming more homogeneous, the reduction in the dispersion in private information and an increase in the similarity of the decision problem increases the likelihood of herding. It also increases correlated trading arising from observation of common signals or following similar styles. Thus, for firms having similar levels of institutional ownership, increasing homogeneity of the investor base will increase the systematic liquidity risk. Fernando (2003) also finds that with increasing heterogeneity of investors exposure to systematic liquidity shocks, the impact of the liquidity shocks gets alleviated through partial risk-sharing by trading between high and low-exposure investors.

Hypothesis 2: The sensitivity of a stock's liquidity to market liquidity will increase with increasing homogeneity of investors, after controlling for the level of institutional ownership.

Liquidity risk may depend not just on the homogeneity of investor base but also on the concentration of ownership. If an institution holds concentrated or large positions in a firm, the institution will have a stronger incentive both to collect and act on its private information. So, for firms having ownership concentrated in fewer hands, its investors will have greater incentive to gather and act on their information. As ownership dispersion increases, this incentive to collect and act on private information reduces and investors may rely more on their inference of other's actions.[69] An increased reliance on the actions of others increases the likelihood of herding. As a result, for similar levels of institutional ownership, the likelihood of herding behavior and correlated trading will be lower when ownership is concentrated among fewer

[69] The free riding problem has been extensively discussed in Gromb (1993), Zingales (1995), Maug (1998), Bolton and Van Thadden (1998), Edmans and Manso (2008), etc.

institutions. Stocks having concentrated ownership or large block-holdings may therefore exhibit lower liquidity risk. In other words, ownership dispersion will be associated with increased herding behavior and correlated trading resulting in increased systematic liquidity risk.

Hypothesis 3: The sensitivity of a stock's liquidity to market liquidity will decrease with ownership concentration and block-holdings.

In the previous chapter, I examined the effect of differences in investment horizon of institutions holding the stock on its liquidity level. Investment horizon of an institution is determined by both its demand for liquidity and the likelihood of facing a liquidity shock. Constantinides (1986) argues that investors can alleviate the effects of transaction costs by investing for longer durations and reducing their trading activity. However, Huang (2003) shows that if investors are likely to face liquidity shocks and face borrowing constraints, they will invest in more liquid assets. In equilibrium, one would observe that institutions more likely to face liquidity shocks will have a short-term investment horizon and hold more liquid securities. Evidence in Chapter 2 showed that stocks held largely by institutions with short-term investment horizons were more liquid. I also found strong evidence that short-term institutional ownership *Granger* caused liquidity. This raises the possibility that liquidity risk of stocks will depend on investment horizon of the investors primarily holding those stocks. Investors with short horizon may be more likely to face liquidity shocks and demand liquidity during financial crisis when, in general, market liquidity is lower. As a result, sensitivity of an asset's liquidity to market liquidity will increase as the investment horizon of the investor base decreases.

Hypothesis 4: The sensitivity of a stock's liquidity to market liquidity will be a function of the investment horizon of investors holding the stock and should increase with shortening investor horizon.

Brunnermeier and Pedersen (2008) examine supplier effects as a source of commonality in liquidity and indicate that funding availability with traders should affect asset liquidity. Strength of balance sheet of financial intermediaries providing liquidity is dependent on market conditions and therefore should matter to asset liquidity. These financial intermediaries are more likely to face binding financial constraints precisely when it is most incumbent on them to provide liquidity. Market returns, by affecting financing constraints, affect the supply of liquidity; negative market returns decrease liquidity much more than positive returns increase liquidity. The asymmetric effect arises in their model as the providers of liquidity become demanders of liquidity after a large drop in asset prices, causing both an increase in liquidity demand as well as a reduction in the supply of liquidity. Hameed, Kang, and Viswanathan (2007) test these predictions and find that the impact of market returns on stocks' liquidity is asymmetric, with a larger decline in liquidity taking place in down markets in comparison to the increase in liquidity in up markets.

In hypothesis 4, I set out the role that investor horizon could have on systematic liquidity risk of stocks. I claimed that stocks held primarily by institutions having shorter-term investment horizons will exhibit greater liquidity risk. If there exists a common cause for liquidity shocks faced by short-term investors and other financial intermediaries supplying liquidity, then the asymmetric effect, noted by Brunnermeier and Pedersen (2008), could be aggravated with increase in short-term institutional ownership. This suggests that investor horizon will not only affect the systematic liquidity risk, but also help explain the asymmetric effect of market returns on liquidity of stocks. I use the following specification to estimate the asymmetric effect of market returns on liquidity of stocks.

$$\Delta Liq_{it} = \alpha_0 + \beta_{1+} * \Delta MktLiq_{+} + \beta_{1-} * \Delta MktLiq_{-} + \beta_{2+} * Mktret_{t+} + \beta_{2-} * Mktret_{t-} + \beta_3 * Sqret_{it} + \varepsilon_{it}$$

Hypothesis 5: The difference between the sensitivities **(β_{2+} - β_{2-})** of a stock's liquidity to positive market returns **(β_{2+})** and negative market returns **(β_{2-})** will be a function of investment horizon of institutions holding the stock and should increase with shortening investment horizon.

1.3.2: Information asymmetry and liquidity risk

The effect of increasing information asymmetry on liquidity measures is well documented in market microstructure literature. Glosten and Milgrom (1985) and Easley and O'Hara (1987) indicate that in the presence of informed investors acting non-strategically, the adverse-selection risk faced by the risk-neutral market maker gives rise to spreads, even in the absence of any fixed costs. With an increase in the number of informed institutions, a risk-neutral market maker widens the spreads to set regret-free prices due to the higher adverse selection risk. These theories however are not very explicit about the effect of information asymmetry on time variation of liquidity and systematic liquidity risk.

Hypothesis 1 set the role of institutions' herding behavior and correlated trading as a determinant of the systematic liquidity risk of assets. Correlated trading could result from both herding and investors acting on common signals about macroeconomic factors. However, as private information increases, those investors having more precise information may not join the herd and even act in a stabilizing manner. This would reduce the likelihood of herding resulting from information cascades (Bikhchandani, Hirshleifer, and Welch (1992); Welch (1992); Froot, Scharfstein, and Stein (1992)). Thus, in the presence of greater private information, both the likelihood of herd formation and correlated trading will reduce. One can make an opposite argument that if investors with private information know the same private signal, their trades will be correlated. The competition to exploit the information and resulting correlated trading will increase the demand for liquidity. However, if such private information originates in an idiosyncratic manner, then the resulting trades will be idiosyncratic. This will increase the total variation in liquidity and may not increase the systematic liquidity risk. This leads to the following hypothesis:

Hypothesis 6: Systematic liquidity risk of stocks will be smaller for firms with greater amounts of private information. Stated differently, systematic liquidity risk of stocks will decrease as information asymmetry among investors' increases.

All of the above hypotheses focused on understanding the determinants of commonality in liquidity and systematic liquidity risk. The second moment of liquidity has a significant negative impact on equity returns (Chordia, Subrahmanyam, and Anshuman (2001). I also claimed that time variation in asset liquidity should be important for derivative pricing and arbitrageurs trying to exploit and eliminate "mispricing." Because changes in market liquidity and returns explain a small part of the total liquidity variation over time, I further examine determinants of liquidity variance. I mainly examine the effects of institutional ownership and information asymmetry measures on liquidity variation.

As information becomes easily available and more dispersed, both ownership dispersion and liquidity increases. Reduction in information asymmetry makes investors more certain about the firm's expected cash flows, making it easier to infer the underlying motivation for a trade. As a result, liquidity suppliers will be more willing to meet sudden increased demands in case of idiosyncratic liquidity shocks. However, in presence of greater private information, the idiosyncratic liquidity shocks are likely to be associated with private information. The liquidity suppliers may therefore be less likely to meet these liquidity shocks, and as a result a greater time variation in liquidity may be observed. The spikes in demand for liquidity could also be greater in presence of private information. A cross-sectional implication of the information asymmetry argument is that stocks that are more likely to have greater information asymmetry, should not only have lower liquidity but also exhibit greater liquidity variation over time.

Hypothesis 7: Liquidity variation of stocks will be greater for firms with larger information asymmetry. Stated differently, liquidity variation of stocks will be greater for firms when the probability of information-based trading or adverse-selection component of spreads is larger.

SECTION 2: DATA AND METHODOLOGY

In this section, I first describe the data and measures of liquidity risk. I follow the approach of CRS to measure commonality in liquidity and liquidity risk. I use a much larger sample from 1983–2005 for firms listed on NYSE and AMEX in comparison to CRS, giving me the ability to explore the cross-sectional differences in sensitivity of a stocks liquidity to market liquidity (liquidity beta) in a panel setting. Following a firm over time provides the ability to associate changes in a firm's liquidity beta with changes in its ownership characteristics along with changes in other characteristics.

The rest of this section describes the data first, then summarizes the time variation in market liquidity, and later describes the firm level measures of liquidity risk and commonality in liquidity. Subsequently, I investigate whether differences in institutional ownership and investor type (holding periods of institutions) affect measures of liquidity risk, both the total time variation in liquidity of a firm's stock and liquidity beta a measure of systematic liquidity risk of a firm's stock and test the hypotheses.

SECTION 2.1: DATA DESCRIPTION:

I estimate daily liquidity measures for firms, as indicated in Section 2 of Chapter 2. I rely on the following four measures to ensure robustness of results: Quoted Spread (*QSPR*), Quoted Spread measure divided by price (*RELQSPR*), Effective Spread (*ESPR*), and Effective Spread measure divided by the midpoint of the quote *(RELESPR)*. *QSPR* is defined as the difference between ask and bid, while *ESPR* is defined as the absolute value of the difference between the transaction price and the quote midpoint. I estimate these four measures of liquidity using the intraday data obtained from ISSM and TAQ for NYSE and AMEX firms. The ISSM database includes trades and quotes data for NYSE- and AMEX-listed firms for the period January 1983 through December 1992, while TAQ database includes similar information for NYSE/AMEX- and NASDAQ-listed stocks for the period January 1993 through December 2005. I compute these four measures by first averaging them over the trading day. These measures are available on a daily basis for years 1983–

2005. All the measures indicate illiquidity for the stocks and an *increase* in these measures indicates a *decline* in liquidity.

I also filter stocks for the following additional criteria before including them in the analysis:

1) I exclude names belonging to the following categories: certificates, ADRs, shares of beneficial interests, units, companies incorporated outside the United States, Americus trust components, closed-end funds, and real estate investment trusts.
2) I exclude those names where the average price of the firm over the year is below \$2 and above \$200. This is important because daily variation in liquidity for firms outside these price ranges can be very high, due to either binding tick constraints, discreteness in price changes, or very low trading volume.

I map the liquidity data to data from CRSP/Compustat and institutional ownership data from 13-F filings using ticker and CUSIP combination resulting in 41,992 firm years. For the estimation of liquidity beta, I eliminate firms if daily return and liquidity measures are available for less than 100 days, resulting in 41,604 firm years in the sample, an average of 1808 firms each year. There are 4,914 unique firms over the period 1983–2005.

SECTION 2.2: MARKET LIQUIDITY AND MARKET RETURNS

I start with presenting summary statistics associated with the liquidity measures. Using the daily measures of liquidity for the firms in the sample, I estimate both an equal-weighted and a value-weighted measure of the marketwide liquidity. Subsequently, I calculate the percentage daily changes in the market liquidity.[70] Figure 3.1 presents the mean annual measures of marketwide liquidity over the sample period along with the bands that include 90% of the daily market liquidity values for each year. The chart indicates that the marketwide liquidity exhibits a sizable variation over time. The volatility of market liquidity measures also varies over time and is much higher in the years 1987, 1990, 1998, and 2001. The spread-based liquidity measures have clearly been trending down over time, indicating an increase in the market liquidity.

Table 3.1 presents the summary statistics of both equal-weighted and value-weighted marketwide liquidity measures. Since the liquidity measures increase with the size of the firm, the value-weighted measures of liquidity are smaller than the equal-weighted measures. The mean equal-weighted *RELQSPR* average is around 1.2% over the entire sample period, while the value-weighed measure is around 0.3%. The average *QSPR* is \$0.19 while average *ESPR* is \$0.15. Effective spread measures are lower than the quoted spreads, indicating existence of execution of trades within the quotes. The median spread measures are somewhat smaller than the means, suggesting existence of some positive skewness in the daily distribution of liquidity.

Figure 3.2 presents the daily value-weighted marketwide liquidity measures for *RELQSPR* and *RELESPR*, along with the value-weighted returns of the CRSP universe. This chart indicates the sizable variation in liquidity measures over time and the volatility in both the liquidity measures and market returns. Stochastic volatility is a well-known phenomena, and the chart indicates that the transaction costs increase with increasing volatility. The liquidity measures also exhibit a large decline around

[70] I further eliminate those days from the analysis when there were less than 200 securities for which liquidity measures were available, as changes in the composition of the index may inaccurately reflect changes in marketwide liquidity.

the reduction of minimum tick sizes in years 1997 (June 24th, 1997) and year 2001 (January 29th, 2001).[71] I observe large increases in spread measures around the 1987 crash, U.S./Iraq war (1990), LTCM crisis in 1998, Enron troubles in the later part of year 2001, and accounting fraud revelation at WorldCom in July 2002. There is evidence of the influence of business cycles on the liquidity measures as observed from increases in spreads in the early 1990s and early 2000s, when the economy was in a contraction phase.[72]

Table 3.2 presents summary statistics of the changes in daily marketwide liquidity measures. A prefix of Δ (or D1) on a measure indicates the daily percentage change in the measure. The changes in the daily market liquidity measures exhibit significant variation over time. The distribution of changes in market liquidity measures exhibits positive skewness and high kurtosis. This indicates that the spread-based measures of market liquidity vary over a wide range within short time periods. I also observe that the changes in value-weighted market liquidity measures (for *QSPR* and *RELQSPR*) tend to be larger than changes in the corresponding equal-weighted market liquidity measures. This finding can be considered consistent with larger firms exhibiting a higher liquidity commonality, while smaller firms exhibiting more variation in liquidity. Both the equal-weighted and value-weighted measures of market returns exhibit negative skewness and kurtosis.

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[71] In unreported results, the dollar depth measures indicate an upward trend indicating an increase in liquidity. Also, a large decline in quoted depth is observed around reduction in minimum tick sizes. The tick size changed from 1/8 to 1/16 of a dollar on 06/24/1997 and changed from 1/16 of a dollar to decimal system on 01/29/2001 respectively.

[72] http://www.nber.org/cycles.html

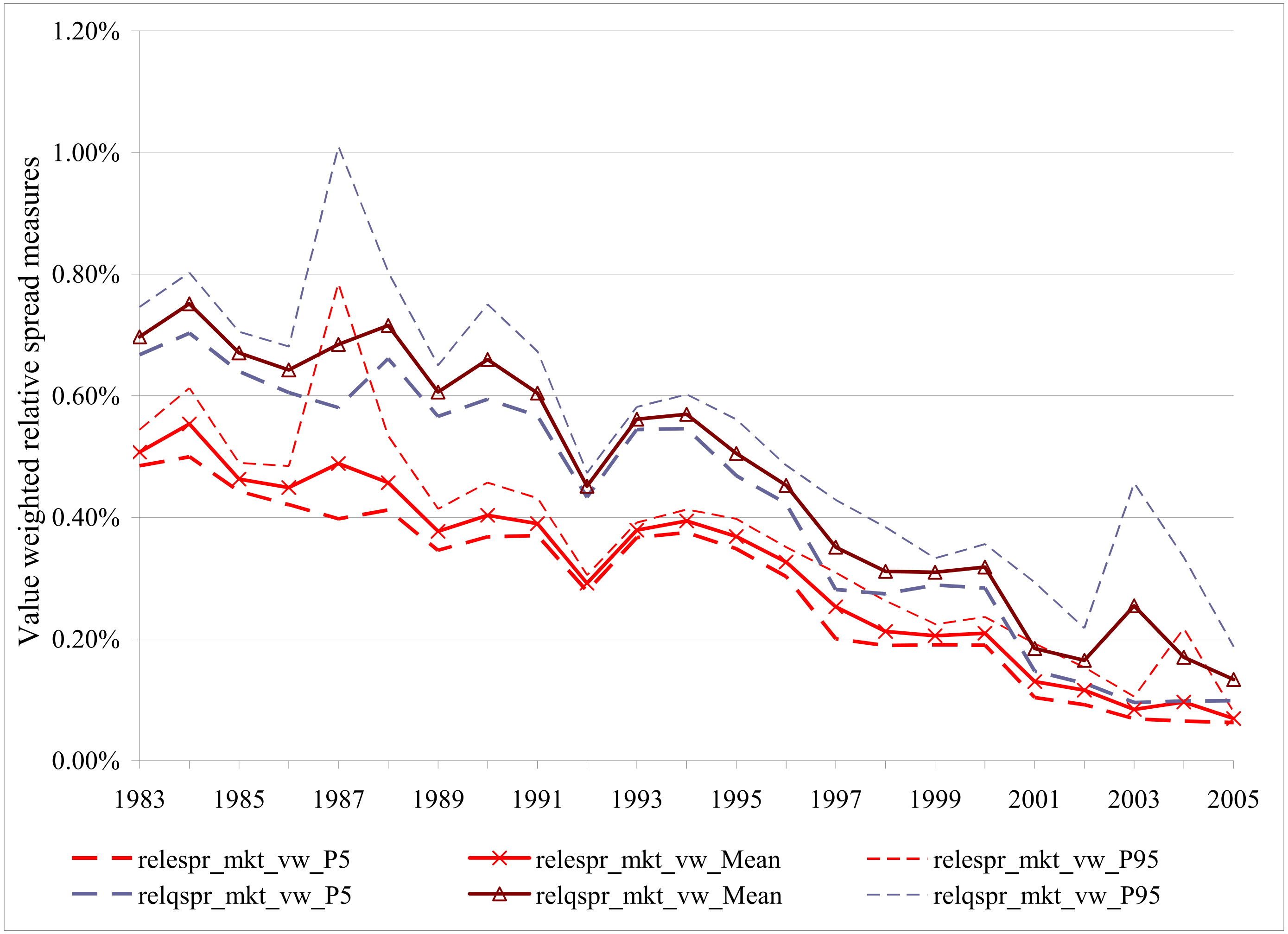

Figure 3.1: Market liquidity measures over time

Table 3.1: Summary statistics: Marketwide liquidity measures. Mean and median values of marketwide liquidity measures obtained using intra-day trading data for the period 1983–2005 are presented. Both equal weighted and value weighted marketwide liquidity measures are calculated based on firms included in the sample. The four liquidity measures calculated on a daily basis are *qspr*, which is the quoted spread (bid-ask); *espr*, which is the effective spread and is equal to [transaction price - (bid+ask)/2]; *relqspr*, which is proportional quoted spread [*qspr*/Price]; *relespr*, which is proportional effective spread [*espr*/Price]. Panel A presents the equal weighted measures. Panel B presents the value weighted measures.

Panel A	Equal Weighted (Mean)				Equal Weighted (Median)			
year	espr	qspr	relespr	relqspr	espr	qspr	relespr	relqspr
1983	0.2057	0.2629	0.0130	0.0159	0.2047	0.2619	0.0130	0.0159
1984	0.1889	0.2503	0.0154	0.0186	0.1881	0.2497	0.0156	0.0187
1985	0.1757	0.2414	0.0155	0.0190	0.1754	0.2411	0.0146	0.0188
1986	0.1871	0.2530	0.0158	0.0194	0.1863	0.2527	0.0153	0.0193
1987	0.1964	0.2627	0.0200	0.0208	0.1896	0.2574	0.0151	0.0187
1988	0.1590	0.2424	0.0182	0.0235	0.1523	0.2425	0.0170	0.0233
1989	0.1406	0.2293	0.0173	0.0224	0.1398	0.2285	0.0154	0.0221
1990	0.1409	0.2268	0.0217	0.0270	0.1395	0.2256	0.0179	0.0252
1991	0.1482	0.2210	0.0230	0.0269	0.1479	0.2204	0.0202	0.0264
1992	0.1406	0.2178	0.0129	0.0182	0.1401	0.2167	0.0129	0.0182
1993	0.2131	0.2123	0.0152	0.0193	0.2179	0.2118	0.0152	0.0192
1994	0.1754	0.2053	0.0143	0.0186	0.1673	0.2034	0.0142	0.0185
1995	0.2515	0.1940	0.0144	0.0175	0.2650	0.1939	0.0144	0.0174
1996	0.2133	0.1918	0.0127	0.0156	0.1381	0.1915	0.0121	0.0155
1997	0.1291	0.1771	0.0104	0.0136	0.1300	0.1795	0.0105	0.0138
1998	0.1216	0.1712	0.0108	0.0145	0.1212	0.1706	0.0099	0.0133
1999	0.1159	0.1666	0.0121	0.0166	0.1154	0.1657	0.0120	0.0165
2000	0.1194	0.1690	0.0131	0.0180	0.1179	0.1668	0.0126	0.0175
2001	0.0856	0.1147	0.0107	0.0142	0.0821	0.1094	0.0104	0.0138
2002	0.0688	0.0895	0.0092	0.0120	0.0691	0.0890	0.0091	0.0120
2003	0.0551	0.0783	0.0064	0.0088	0.0552	0.0763	0.0064	0.0089
2004	0.0550	0.0751	0.0047	0.0063	0.0546	0.0749	0.0048	0.0064
2005	0.0518	0.0678	0.0043	0.0057	0.0517	0.0673	0.0043	0.0057

Table 3.1 (Continued)

Panel B	Value Weighted (Mean)				Value Weighted (Median)			
year	espr	qspr	relespr	relqspr	espr	qspr	relespr	relqspr
1983	0.1829	0.2535	0.0051	0.0070	0.1828	0.2539	0.0050	0.0069
1984	0.1679	0.2394	0.0055	0.0075	0.1671	0.2387	0.0055	0.0075
1985	0.1568	0.2324	0.0046	0.0067	0.1559	0.2320	0.0046	0.0067
1986	0.1761	0.2559	0.0045	0.0064	0.1745	0.2544	0.0045	0.0064
1987	0.1839	0.2688	0.0049	0.0068	0.1785	0.2633	0.0044	0.0062
1988	0.1445	0.2342	0.0046	0.0072	0.1384	0.2331	0.0044	0.0071
1989	0.1285	0.2166	0.0038	0.0061	0.1275	0.2154	0.0037	0.0060
1990	0.1277	0.2188	0.0040	0.0066	0.1268	0.2173	0.0039	0.0065
1991	0.1293	0.2121	0.0039	0.0060	0.1287	0.2106	0.0038	0.0060
1992	0.1215	0.1924	0.0029	0.0045	0.1203	0.1891	0.0029	0.0045
1993	0.1319	0.1992	0.0038	0.0056	0.1322	0.1992	0.0038	0.0056
1994	0.1271	0.1871	0.0039	0.0057	0.1264	0.1843	0.0039	0.0057
1995	0.1322	0.1771	0.0037	0.0051	0.1356	0.1770	0.0037	0.0050
1996	0.1285	0.1776	0.0033	0.0045	0.1218	0.1771	0.0033	0.0045
1997	0.1092	0.1545	0.0025	0.0035	0.1060	0.1499	0.0023	0.0034
1998	0.0949	0.1404	0.0021	0.0031	0.0935	0.1390	0.0021	0.0030
1999	0.0920	0.1396	0.0021	0.0031	0.0907	0.1384	0.0020	0.0031
2000	0.0925	0.1413	0.0021	0.0032	0.0877	0.1348	0.0021	0.0032
2001	0.0479	0.0682	0.0013	0.0018	0.0436	0.0614	0.0012	0.0017
2002	0.0378	0.0526	0.0012	0.0016	0.0369	0.0507	0.0011	0.0016
2003	0.0265	0.0681	0.0008	0.0025	0.0259	0.0571	0.0008	0.0021
2004	0.0325	0.0565	0.0010	0.0017	0.0283	0.0520	0.0008	0.0015
2005	0.0277	0.0465	0.0007	0.0013	0.0276	0.0433	0.0007	0.0012

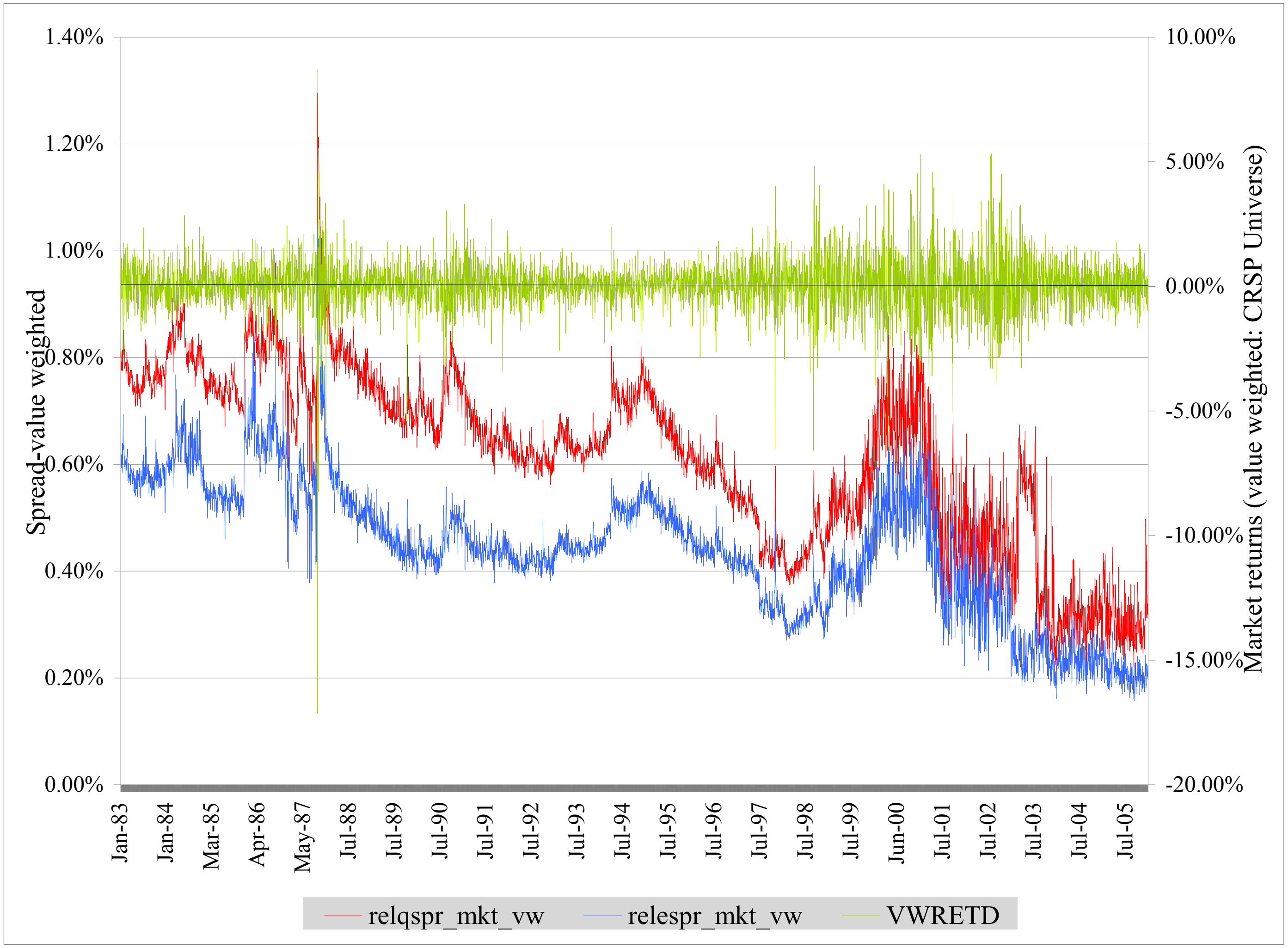

Figure 3.2: Daily time series of market liquidity and market returns

Table 3.2: Summary statistics: Changes in marketwide liquidity ad market returns. Summary statistics of daily percentage changes in marketwide liquidity measures using firms listed on NYSE and AMEX during the sample period 1983–2005 are presented. A prefix of D1 indicates the daily percentage change, for e.g. D1esprt =($espr_t$ - $espt_{t-1}$)/$espr_t$. Changes in both equal weighted and value weighted marketwide liquidity measures are calculated using firms in the sample. Also presented are the CRSP value weighted and equal weighted returns over the sample period.

	Min	P1	Mean	Median	P99	Max	Stddev	Kurt	Skew
Daily changes in equal weighted market wide liquidity measures									
D1espr	-0.5555	-0.2592	0.0025	-0.0010	0.3389	0.9895	0.0753	30.84	2.67
D1qspr	-0.2082	-0.0734	0.0001	-0.0006	0.0854	0.3836	0.0278	19.30	1.26
D1relespr	-0.8956	-0.4839	0.0140	-0.0002	0.9340	8.9047	0.2323	483.38	16.54
D1relqspr	-0.3641	-0.0635	0.0004	-0.0003	0.0731	0.5609	0.0280	40.93	1.79
Daily changes in value weighted market wide liquidity measures									
D1espr	-0.6816	-0.1548	0.0027	-0.0005	0.2083	2.0737	0.0856	156.93	7.99
D1qspr	-0.6823	-0.2788	0.0050	-0.0007	0.4044	2.2604	0.1165	114.76	7.31
D1relespr	-0.8009	-0.1816	0.0046	-0.0014	0.2411	3.5060	0.1174	279.55	12.29
D1relqspr	-0.7467	-0.3129	0.0073	-0.0011	0.4782	3.5323	0.1479	160.22	9.47
CRSP Returns									
EWRETD	-0.1039	-0.0192	0.0010	0.0015	0.0187	0.0693	0.0072	19.11	-1.32
VWRETD	-0.1714	-0.0251	0.0005	0.0008	0.0246	0.0866	0.0097	22.31	-1.13

Table 3.3: Correlation measures: Marketwide liquidity measures. Panel A presents correlations between the different marketwide liquidity measures, both equal weighted and value weighted. Panel B presents correlations between the changes in different marketwide liquidity measures and CRSP value weighted and index weighted returns. For both Panels A and B, the bottom triangle presents the Pearson correlations while the top triangle presents the Spearman rank correlations. Panel C presents the first and second order autocorrelation coefficients between the changes in value weighted marketwide liquidity measures. The suffix *_ew* indicates equal weighted measures of marketwide liquidity while the suffix *_vw* indicates value weighted measures of marketwide liquidity. A prefix of D1 indicates percentage daily change in the liquidity measures.

Panel A: Correlations between market wide liquidity measures

Variable	espr_ew	qspr_ew	relespr_ew	relqspr_ew	espr_vw	qspr_vw	relespr_vw	relqspr_vw
espr_ew	1.000	0.825	0.724	0.600	0.928	0.821	0.860	0.796
qspr_ew	0.741	1.000	0.780	0.739	0.944	0.989	0.950	0.946
relespr_ew	0.459	0.632	1.000	0.960	0.750	0.790	0.805	0.828
relqspr_ew	0.513	0.796	0.770	1.000	0.650	0.743	0.735	0.781
espr_vw	0.808	0.973	0.577	0.698	1.000	0.951	0.944	0.902
qspr_vw	0.730	0.985	0.624	0.774	0.973	1.000	0.948	0.954
relespr_vw	0.752	0.943	0.639	0.750	0.955	0.949	1.000	0.970
relqspr_vw	0.685	0.927	0.645	0.788	0.910	0.955	0.969	1.000

Table 3.3 (Continued)

Panel B: Correlations between changes in market wide liquidity measures and CRSP value weighted and equal weighted stock returns.

Variable	D1espr_ew	D1qspr_ew	D1relespr_ew	D1relqspr_ew	D1espr_vw	D1qspr_vw	D1relespr_vw	D1relqspr_vw	VWRETD	EWRETD
D1espr_ew	1.000	0.610	0.535	0.301	0.548	0.345	0.536	0.348	-0.047	-0.045
D1qspr_ew	0.252	1.000	0.277	0.469	0.462	0.591	0.452	0.600	-0.072	-0.057
D1relespr_ew	0.163	0.051	1.000	0.629	0.249	0.149	0.367	0.195	-0.072	-0.114
D1relqspr_ew	0.157	0.517	0.100	1.000	0.220	0.266	0.280	0.347	-0.121	-0.174
D1espr_vw	0.229	0.321	0.025	0.166	1.000	0.672	0.847	0.614	-0.103	-0.094
D1qspr_vw	0.082	0.612	0.013	0.255	0.639	1.000	0.588	0.908	-0.137	-0.109
D1relespr_vw	0.126	0.242	0.086	0.149	0.941	0.609	1.000	0.647	-0.196	-0.200
D1relqspr_vw	0.068	0.528	0.012	0.247	0.652	0.965	0.671	1.000	-0.257	-0.243
VWRETD	-0.048	-0.120	0.002	-0.173	-0.086	-0.068	-0.095	-0.083	1.000	0.795
EWRETD	-0.055	-0.128	-0.013	-0.241	-0.095	-0.064	-0.103	-0.083	0.838	1.000

Panel C: First and second order autocorrelations, pearson correlations.

Variable	Lag 1	Lag 2
D1espr_vw	-0.404	0.141
D1qspr_vw	-0.350	0.037
D1relespr_vw	-0.336	0.156
D1relqspr_vw	-0.302	0.034

Table 3.3 presents a summary of the correlations between both equal-weighted and value weighted measures of marketwide liquidity. In Panels A and B, I present both the Pearson correlations (bottom triangle) and Spearman rank correlations (top triangle) as the distributions of both the level and changes of marketwide liquidity measures exhibited positive skewness.

Panel A presents the correlations between the levels of different marketwide liquidity measures.[73] All four measures of marketwide liquidity measures exhibit strong positive correlation with each other indicating that they are capturing similar phenomenon. The correlations between *ESPR* and *QSPR* are 0.74 (equal-weighted series) and 0.97 (value-weighted series). Similarly, the correlations between *RELESPR* and *RELQSPR* are 0.77 (equal-weighted series) and 0.97 (value-weighted series). The correlations between the value-weighted and equal-weighted series for the four liquidity measures are also very high. Overall, the Spearman rank correlations tend to be higher than the Pearson ones.

Panel B of Table 3.3 presents the correlations between the daily changes in different marketwide liquidity measures and CRSP value-weighted and equal-weighted returns. The correlations between changes in different market liquidity measures are always positive and are, on average, around 0.4. However, those between the value-weighted measures tend to be higher and around 0.73, on average. The Spearman rank correlations tend to be higher than the Pearson correlations, similar to those obtained in Panel A. The correlations between market returns and changes in marketwide liquidity measures are negative and significant. There is a strong negative correlation

[73] As changes in tick sizes in 1997 and 2001 resulted in large declines in both spreads and market depths, I estimate the correlations between the marketwide liquidity measures over three subperiods (prior to 1997, between 1998 and the end of 2000, and after the beginning of 2002). I report the mean of the correlations for the three subperiods weighted by the number of observations in each period.

between market returns and changes in value-weighted market liquidity measures (-0.083 for *RELQSPR* and -0.095 for *RELESPR*). I observe similar negative correlations between market returns and unscaled versions of marketwide liquidity measures *QSPR* and *ESPR*. These correlations indicate that positive market returns are associated with an increase in market liquidity while negative market returns are associated with a decline in market liquidity, and the effects are not solely a result of changes in security prices. This finding is consistent with the prediction of Kyle and Xiong (2001) and Brunnermeier and Pedersen (2008), where the wealth effect of a marketwide drop in asset prices is associated with a fall in liquidity.

Panel C of Table 3.3 presents the autocorrelations between daily changes in market liquidity measures. I observe negative autocorrelation among the four market liquidity measures. The mean first order and second order auto-correlation coefficients for changes in the four marketwide liquidity measures are -0.35 and 0.09. The strong negative first order autocorrelation indicates that changes in market liquidity exhibit a strong reversal and the changes are not highly persistent. The negative autocorrelations among the unscaled measures *ESPR* and *QSPR* also shows that these autocorrelations are not solely an effect of security price changes.

SECTION 2.3: FIRM-LEVEL MEASURES OF LIQUIDITY RISK

To estimate systematic liquidity risk I follow the approach proposed by CRS (2000). I examine the relation between percentage changes in measures of firm liquidity and percentage changes in market liquidity to identify the degree of co-movement in liquidity. Following the process used for computing the changes in marketwide liquidity, I compute the changes in firm-level liquidity. Liquidity measures at firm level exhibit more extreme movements on a daily basis. I therefore winsorize the extreme observations of liquidity changes for a firm, at 5% and 95% level prior to running the regressions for estimating firm-level liquidity betas, to prevent the outliers from biasing the estimates.[74]

I run the following time-series regression for each firm, every year to estimate a simple "market model" for an individual stock regressed on market measures of liquidity and estimate the coefficients using Spec 1. I include market returns as an additional variable, to capture the effect of market returns on liquidity of stocks. Market returns will also remove any spurious dependence induced by an association between returns and spread measures, especially when they are functions of the transaction price. I include indicator variables for days of the week to prevent daily patterns observed in spreads from biasing the liquidity risk estimates. Existence of a regular pattern in spreads for securities during the week will induce a regular pattern in changes in spreads over time, subsequently inducing a positive correlation between market liquidity and stocks liquidity. Lastly, I include the squared returns to proxy for information flow. Both adverse selection risks and inventory risks faced by liquidity providers will increase with new information arrival, and thus impact measures of liquidity.

If liquidity measures for a firm are available for less than 100 trading days in a year, I eliminate the firm from subsequent analysis.

$$\Delta Liq_{it} = \alpha_0 + \beta_1 * \Delta MktLiq_t + \beta_2 * Mktret_t + \beta_3 * Sqret_{it} + \varepsilon_{it} \ldots Spec1$$

[74] The use of these regression helps curb the influence of the outliers, and the procedure results in more robust estimations of beta. The approach is discussed in details in Chan and Lakonishok (1992).

I run a modified version of the above regression, using Spec 2, to account for possible non-synchronicities in trading activities of the firms. The lead and lag terms for market liquidity and market returns are included to capture any lagged adjustments in commonality and account for the effects of return spillovers and liquidity spillovers. These terms could have more relevance for smaller stocks that happen to trade less frequently.

$$\Delta Liq_{it} = \alpha_0 + \beta_1 * \Delta MktLiq_t + \beta_2 * \Delta MktLiq_{t-1} + \beta_3 * \Delta MktLiq_{t+1} + \beta_4 * Mktret_t +$$
$$\beta_5 * Mktret_{t-1} + \beta_6 * Mktret_{t+1} + \beta_7 * ret_{it} + \beta_8 * Sqret_{it} + \varepsilon_{it} \ldots\ldots\ldots Spec\,2$$

While estimating these regressions for a firm to calculate its liquidity beta, I exclude that firm from the market portfolio in order to minimize the cross-sectional dependence in the estimated slope coefficients. I estimate these regressions using all four measures of liquidity (*ESPR*, *QSPR*, *RELQSPR*, and *RELESPR*) and both value-weighted and equal-weighted market liquidity measures. When estimating the coefficients using the value-weighted measure of market liquidity, I include the value-weighted market return. Similarly, when estimating the coefficients using the equal-weighted measure of market liquidity, I include the equal-weighted market return.

Table 3.4 presents a summary of the estimates of the beta coefficients: Panel A for those obtained using Spec 1 and Panel B for those obtained using Spec 2. I report the mean and median coefficients by first calculating the cross-sectional mean and median for the coefficients of interest each year and then taking the time-series mean over the period 1983–2005. I also present the fraction of market liquidity beta coefficients that are positive and the fraction that is positive and significant at 5% level each year. I similarly summarize the coefficients on the market return betas. I also present transition probabilities for the estimated beta coefficients in order to test the persistence of the measures of liquidity risk. To compute these transition probabilities, I rank the firms by their liquidity betas each year into 5 groups. By following the firms over time and examining their ranks in the subsequent year, I compute the fraction of firms for which the rank in subsequent year stayed the same, giving me an estimate for the transition probability. Transition probabilities indicate the probability that the firm will be staying in same group 1 year ahead. The last two columns present the R-square of the regressions. For Spec 2, I also present the sum of the liquidity beta coefficients β_1, β_2, and β_3, and the sum of the return beta coefficients β_4, β_5, and β_6 to examine the effects of non-synchronicities.

For the 41,604 firm years in the sample, when using Spec 1 and the value-weighted measures of market liquidity and returns, nearly 70% of firm years have a positive β_1 coefficient while 15% are positive and significant at 5% level. For the four liquidity measures, the mean (median) liquidity beta β_1 coefficients are approximately 0.24 (0.26), while the mean (median) return beta β_2 coefficients are approximately -0.13 (-0.15), respectively. The positive liquidity beta coefficients indicate that liquidity of individual stocks co-moves with market liquidity, confirming the existence of commonality in liquidity measures. The negative return beta β_2 coefficients indicate that stocks become more liquid when market returns are positive, while their liquidity decreases when market returns are negative. The finding suggests that as financing constraints of intermediaries providing liquidity relax, liquidity increases, consistent with the claims in Coughenour and Saad (2004) and Brunnermeier and Pedersen (2008). The mean and median coefficients obtained using the *RELQSPR* liquidity measure (0.290 and 0.313) are the largest among the four liquidity measures. Later, when examining cross-sectional variation in the systematic liquidity risk, I present findings using *RELQSPR* liquidity betas. I find a large positive-and-significant coefficient on squared returns, indicating that large price changes are associated with a decline in liquidity. This finding can easily result from market makers reducing liquidity provision at times of new information arrival. The findings from regressions using the equal-weighted market liquidity measures are mostly similar to those obtained using the value-weighted market liquidity measures. The unscaled measures, *QSPR* and *ESPR* appear to exhibit higher commonality than the scaled measures, *RELQSPR* and *RELESPR*. Also as noted previously, the quoted-spread measures exhibit higher commonality.

The findings from the modified regression presented in Panel B are almost identical to those of Panel A. The β_2 and β_3 coefficients for lagged and leading measures of market liquidity are very small, resulting in a sum of the liquidity beta coefficients almost identical to that of β_1 and also similar to those from Spec 1. Overall, these findings confirm the findings of CRS (2000) over a much longer sample period and indicate that liquidity at firm level exhibits commonality.[75] However, the average explanatory power of these regressions is around 4.3%, which suggests that market liquidity explains a very small part of the time variation in liquidity at firm level. Also, the transition probabilities based on forming 5 groups of firms indicates that the estimated liquidity beta coefficients at firm level are not persistent over time, which could be a result of errors in both estimation and time variation in liquidity risk. Pastor and Stambaugh (2003) also points out the difficulty in accurately estimating their measures of liquidity risk.

[75] On separately examining the findings for year 1992, without including the indicator variables for days of the week, I find that the results are similar to those of CRS (2000). The estimated mean and median liquidity beta coefficients for the four measures are in the range of 0.4–0.7. The fraction of the liquidity beta coefficients that are positive is around 75%, while the fraction of the liquidity beta coefficients that is positive and significant at 5% level is around 23%.

Table 3.4: Summary statistics: Firm-level systematic liquidity risk measures. The mean and median liquidity beta estimates for firms listed on NYSE and AMEX during the sample period 1983–2005 are calculated each year and then averaged over the sample period. Fraction of betas that are positive and positive and significant at 5% levels are also listed. Panel A presents estimates using Spec 1. Panel B presents findings using Spec 2.

	Liquidity beta					Return beta						
Panel A	Mean	Median	Fraction +	Fraction +/ Sig at 5%	Transition Probability	Mean	Median	Fraction -	Fraction -/ Sig at 5%	Transition Probability	R_square	Adj R_square
Spec 1 (Value weighted market portfolio)												
D1espr	0.211	0.227	68.4%	16.0%	25.2%	-0.121	-0.110	52.4%	3.0%	24.2%	4.37%	1.32%
D1qspr	0.221	0.238	67.2%	14.2%	24.4%	-0.072	-0.102	52.4%	2.9%	22.5%	4.30%	1.24%
D1relespr	0.249	0.258	69.6%	15.7%	24.4%	-0.226	-0.239	55.3%	3.9%	24.5%	4.26%	1.20%
D1relqspr	0.290	0.313	70.6%	16.3%	23.9%	-0.103	-0.149	53.7%	3.7%	22.7%	4.33%	1.27%
Spec 1 (Equal weighted market portfolio)												
D1espr	0.353	0.335	70.1%	15.4%	24.9%	-0.264	-0.253	54.4%	2.6%	24.4%	4.23%	1.17%
D1qspr	0.438	0.418	72.5%	14.3%	23.7%	-0.121	-0.182	53.2%	2.8%	23.0%	4.19%	1.12%
D1relespr	0.149	0.125	60.0%	7.5%	24.5%	-0.750	-0.770	63.6%	5.5%	24.4%	3.94%	0.87%
D1relqspr	0.225	0.202	64.7%	8.4%	23.2%	-0.527	-0.623	62.2%	5.5%	23.0%	4.02%	0.95%

Table 3.4 (Continued)

	Liquidity beta					Return beta						
Panel B	Mean	Median	Fraction +	Fraction +/ Sig at 5%	Transition Probability	Mean	Median	Fraction -	Fraction -/ Sig at 5%	Transition Probability	R_square	Adj R_square
Spec 2 (Value weighted market portfolio)												
D1espr	0.218	0.235	68.8%	11.1%	25.1%	-0.113	-0.106	52.1%	3.5%	24.3%	4.11%	1.02%
D1qspr	0.216	0.231	67.1%	9.8%	24.1%	-0.071	-0.099	52.0%	3.3%	22.8%	4.00%	0.91%
D1relespr	0.256	0.266	69.2%	10.3%	24.3%	-0.214	-0.225	54.9%	3.9%	24.6%	4.01%	0.92%
D1relqspr	0.293	0.314	70.3%	11.3%	23.7%	-0.101	-0.141	53.3%	3.6%	22.6%	4.04%	0.95%
Sum betas												
D1espr	0.222	0.236				-0.195	-0.144					
D1qspr	0.202	0.209				-0.172	-0.176					
D1relespr	0.248	0.252				-0.404	-0.372					
D1relqspr	0.279	0.293				-0.293	-0.324					
Spec 2 (Equal weighted market portfolio)												
D1espr	0.367	0.353	70.4%	9.4%	24.3%	-0.247	-0.251	53.4%	4.6%	24.5%	3.97%	0.88%
D1qspr	0.449	0.432	73.0%	9.4%	23.1%	-0.112	-0.164	52.6%	4.5%	23.2%	3.93%	0.83%
D1relespr	0.145	0.116	59.4%	4.0%	24.1%	-0.704	-0.736	61.1%	7.0%	24.5%	3.67%	0.57%
D1relqspr	0.240	0.203	64.6%	5.2%	23.1%	-0.439	-0.541	59.3%	6.7%	22.8%	3.72%	0.62%
Sum betas												
D1espr	0.386	0.376				-0.221	-0.150					
D1qspr	0.447	0.429				-0.154	-0.151					
D1relespr	0.151	0.118				-0.767	-0.701					
D1relqspr	0.277	0.236				-0.519	-0.586					

Table 3.5: Summary statistics: Firm-level total liquidity risk measures. Summary of firm-level standard deviation and coefficient of variation *[COV]* of liquidity measures. The *COV* is defined as the standard deviation of the daily liquidity measures scaled by the mean of the daily liquidity measures over the year.

	Min	P5	Mean	P95	Max	StdDev	Kurt	Skew	Transition probability Year 1	Year 3
Standard deviation of liquidity measures (calculated after winsorizing observations at 1% and 99% level)										
espr	0.000	0.005	0.042	0.079	3.681	0.127	183.23	18.65	64.4%	53.3%
qspr	0.000	0.006	0.040	0.074	2.011	0.062	139.01	9.00	58.9%	47.4%
relespr	0.000	0.000	0.006	0.020	0.174	0.049	14.92	6.81	72.2%	59.3%
relqspr	0.000	0.000	0.005	0.024	0.086	0.009	9.76	3.02	69.3%	57.6%
Coefficient of variation (defined as : Standard deviation/ Mean)										
espr	0.000	0.091	0.256	0.438	2.380	0.125	14.56	2.14	56.9%	48.4%
qspr	0.000	0.101	0.218	0.372	1.472	0.103	17.59	2.97	48.5%	39.9%
relespr	0.000	0.127	0.293	0.491	2.210	0.132	14.86	2.23	48.3%	41.8%
relqspr	0.000	0.127	0.256	0.434	1.497	0.114	13.36	2.62	41.1%	35.1%

The liquidity beta β_1 coefficients, the measure of systematic liquidity risk of a firm which captures the co-movement between liquidity of firm and market liquidity, also exhibits significant cross-sectional heterogeneity (not reported). I focus later on explaining whether firm-specific characteristics explain the cross-sectional variation in the measure of systematic liquidity risk. I specifically examine whether the ownership characteristics and measures of information asymmetry are important determinants of systematic liquidity risk. Given the low explanatory power of these "market model" regressions, I also examine the variance of liquidity of a firm.

SECTION 2.4: FIRM-LEVEL VARIATION IN LIQUIDITY/TOTAL LIQUIDITY RISK

Figure 3.2 illustrated the sizable time variation in market liquidity over the sample period. As expected, the total variation in liquidity at the firm level is much higher than that of the market. In Table 3.5, I present a summary of the variation in firm-level liquidity measures calculated over a one year period. Due to large outliers in liquidity measures, I winsorize the liquidity measures for a firm at 5% and 95% level and subsequently calculate their standard deviation. The standard deviation of the spread-based liquidity measures increases with the mean level of spreads of the firm and, therefore, I also examine the coefficient of variation (*COV*), a normalized measure of the standard deviation.[76] The *COV* measure is a dimensionless quantity. Both standard deviation and *COV* measures indicate a sizable variation in liquidity at firm level over time. To test whether the liquidity variation at firm level is persistent over time, I examine the transition probabilities for both the volatility and *COV* of the liquidity measures. To compute these transition probabilities, I rank the firms by their liquidity risk measures each year into 5 groups. By following the firms over time and examining their ranks in the subsequent year and three years ahead, I compute the

[76] *COV* is defined as Standard Deviation (*Liquidity*)/ Mean (*Liquidity*). I calculate the *COV* measures for each firm using daily measures of the liquidity of the firm over a 1 year period.

fraction of firms for which the rank in subsequent years stayed the same, giving me an estimate for the transition probability. The transition probabilities indicate a strong persistence in the measures of total variation of liquidity at firm level using all four measures of liquidity. The average probability of staying in the same ranked group one year ahead is 66.2%, while the average probability of staying in the same ranked group 3 years ahead is 54.4%, compared to the unconditional probabilities of 20%. I noted limited evidence of persistence in the systematic component of the liquidity risk measures in Section 2.3. The persistence in the liquidity variation over time and, to an extent, its effect on expected returns makes a case for examining its determinants.

SECTION 2.5: FIRM-LEVEL MEASURES OF INSTITUTIONAL OWNERSHIP

In this section, I briefly describe the institutional ownership data and my measures of ownership concentration, investor horizon, and investor homogeneity. I also briefly outline the variables used in existing microstructure literature for measuring information asymmetry and information risk.

I obtain institutional holdings data for the period 1980–2005 from Thomson Financial (previously known as CDA Spectrum) database, which consists of 13F filings reported quarterly to the Securities and Exchange Commission (SEC). Institutional investment managers are required to report their holdings—number of shares and fair market value—as of the last day of the calendar quarter according to Section 13(f)(1) and Rule 13f-1. The 13F reporting requirements apply regardless of whether an institution is regulated by the SEC or not. They also apply to foreign institutions if they “use any means or instrumentality of United States interstate commerce in the course of their business.” I simply sum up the holdings at the end of each quarter, for all institutions in the sample, to obtain total institutional holdings of the security at the end of the quarter. I divide the total institutional holdings by the shares outstanding obtained from CRSP at end of each quarter and then take the yearly average of the proportion of the holdings to obtain an annual measure of institutional holdings referred to as *fracinst*.[77] The mean level of institutional ownership for the sample is 40.1% while the median is 38.9%. In general, the level of institutional ownership in the sample has been increasing over time. The median institutional ownership in firms increased from 21.3% in 1983 to 66.7% in 2005.

2.5.1: Ownership concentration

I use three variables to test the effect of ownership concentration on liquidity risk. First, I create a measure of ownership dispersion by counting the average number of institutions holding equity in the firm over the four quarters. Due to the positive skewness of the variable in cross-section, I take its natural logarithm to obtain a measure of ownership dispersion, denoted as *lnnuminst*. Increase in the measure indicates an increase in ownership dispersion or reduction in concentration of holdings. Second, using the Herfindahl-Hirschman Index, I measure concentration of institutional ownership in a firm, defining it as the sum of the squares of the ownership

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[77] All institutional managers who exercise investment discretion over 13F securities with a market value over $100 million are required to report their holdings within 45 days after the close of the quarter, according to the 1978 amendment to the Securities and Exchange Act of 1934. Institutions are required to report all equity positions greater than 10,000 shares or $200,000 in market value. In two respects, 13F data is incomplete: (1) institutions may be granted exception from filing these reports when they request confidential treatment to prevent disclosure of their proprietary trading strategies, and (2) institutions have to disclose only their long positions and the 13F filings do not contain information on short positions or options written. Given that a majority of institutional investors (pension funds, mutual funds, insurance companies) have mandates preventing them from short sales, and, on average, short interest in most securities is around 2%, this factor should not materially affect the holdings data. In addition, CDA Spectrum classifies each institutional investor as one of five types: bank trust departments, insurance companies, mutual funds, independent investment advisors, and unclassified institutions. The filing requirements also apply to hedge funds, if their holdings of U.S. stocks exceed the specified thresholds. Hedge funds may be able to mask their holdings from the SEC and, given that a large fraction of hedge funds invest in long/short equity strategy, the holdings data will not be accurate. Identifying the holdings by hedge fund managers is difficult, as the reporting entity is the institution and not the fund. An institution can have other funds besides hedge funds, like mutual funds, and the disclosed holdings to the SEC are at the aggregate level.

of each institution in the firm, where the ownership is expressed as a percentage of outstanding shares. Again due to the positive skewness of the variable, I take its natural logarithm to obtain a measure of ownership concentration, denoted as *lnhhi_inst*. Increases in *lnhhi_inst* will indicate an increase in ownership concentration while a decrease will indicate the opposite. The two variables *lnnuminst* and *lnhhi_inst* exhibit correlations of 0.74 and 0.78 with *fracinst,* respectively, and a positive correlation of 0.475 with each other in sample. The findings indicate that with an increase in the number of institutions holding equity in a firm, the fraction of institutional ownership in the firm increases. The correlation coefficient between *lnhhi_inst* and *lnnuminst*, after partialing out the effect of level of institutional ownership (*fracinst*), is -0.21. As expected the finding indicates that for the same level of institutional ownership in a firm, ownership concentration decreases with an increase in the number of institutions holding equity in the firm. I also look at the effect of block ownership, as presence of blocks indicates concentrated ownership. I include the variable number of blocks (*NumBlocks*), where a block exists if an institution holds more than 5% of outstanding equity in the firm. The mean number of block-holdings in the sample is 1.23, while the median is 1. *NumBlocks* exhibits a high correlation of 0.70 with *lnhhi_inst* and 0.65 with *fracinst,* indicating that the incidence of large block-holdings will increase as the level of institutional holdings increases.

2.5.2: Investor horizon

Using institutional holdings data from CDA/Spectrum as of the end of each quarter in a year, I estimate measures of portfolio turnover for each institution. The rationale for using portfolio turnover as a means for classifying institutions, is that short-term investors will buy and sell their investments more frequently while long-term investors will hold their positions unchanged for a considerable period. Thus, greater differences in portfolio holdings will be observed over time for institutions with short-term investment horizon compared to those with long-term investment horizon. To implement this idea empirically, I follow the approach proposed by Gaspar, Massa, and Matos (2005) for estimating the portfolio turnover measures of the institutions. I measure an institution's portfolio turnover using all stocks held by the institution.[78]

The turnover measures exhibit considerable persistence over time, indicating that institutions do not typically change their investment horizon and trading habits.[79] I divide institutions into three groups based on the measure of their portfolio turnover, with group 1 having the lowest turnover and group 3 having the largest. The institutions that fall into group 1 are classified as having a long-term investment horizon, while those falling into group 3 are classified as having a short-term investment horizon. The remaining institutions that fell into group 2, are considered to be those having a medium-term investment horizon. Subsequently, I divide stock holdings of each firm into three categories based on the fraction of shares held by each type of institution: long-term (low turnover), medium-term (medium turnover) and short-term (high turnover). I form these three categories by using the investment horizon of institutions from the previous year, to reduce the contemporaneous effect of their turnover on measures of liquidity variation. Fraction of shares held by low-turnover institutions is referred to as *fraclong*. Buy and hold investors have low turnover. Similarly, *fracmedium* and *fracshort* represent shares held by medium-term investors and short-term (high turnover) investors, respectively. I examine the effect of

[78] Yan and Zhang (2009) use the approach by Gaspar et al. to classify institutions as short-term and long-term and, subsequently, show that trading by short-term institutions forecasts future stock returns.
[79] In unreported results, I again calculate transition probabilities for institutions by ranking them into three groups and following their ranks over time. I find that one year onward the probability of staying in the same ranked group remains considerably higher (60%–65%) than the probability of switching to one of the other two groups (unconditional probability should be 33%). Similar results are observed when dividing the institutions into more groups and examining over longer periods.

investor horizon by looking at the difference between long-term ownership and short-term ownership, designated as *long_short*.

The mean (median) level of *fraclong* for the sample is 11.9% (10.1%), while the mean (median) level of *fracshort* for the sample is 10.7% (8.7%). The difference between long-term and short-term institutional ownership (*long_short*) exhibits a sizable cross-sectional variation over the sample, with a standard deviation of 11.9%. The variable *long_short* exhibits a very small correlation of 0.02 with the level of institutional ownership, thus, allowing me to examine the difference in investment horizon of institutions holding equity in a firm on measures of time variation in liquidity.

2.5.3: Investor homogeneity

Using institutional holdings data from CDA/Spectrum and returns data from CRSP, I construct a measure to capture the homogeneity of the institutional investor base of a firm. The underlying idea is that two investors are considered alike if their observed portfolio holdings are similar. I consider a firm that has institutions exhibiting greater similarity in their portfolio holdings, as one with a more homogeneous investor base.

To implement this idea empirically, I first calculate the daily portfolio returns of all institutions in my sample using their portfolio holdings at the beginning of each quarter. Subsequently, I measure pair-wise correlations between the daily portfolio returns of all institutions every year. Suppose a firm *F* has *n* institutional investors that hold equity in it during a one year period. The correlation between the daily returns on portfolios held by two institutions "i" and "j" holding equity in firm *F* over a one year period is represented as $\rho_{i,jF}$. The fraction of equity held by the institution "i" in the firm *F* is denoted as v_{iF}. I then calculate the homogeneity measure hm_year_F of institutional investor base in a firm F as a weighted measure of the pair-wise correlations among portfolio returns of institutions having equity ownership in the firm as in Equation 1. The weight w_{iF} for an institution "i" in the firm F is calculated based on number of shares outstanding held by the institution in the firm as a fraction of total outstanding shares held by all institutions in the firm.

$$hm\_year_F = \sum_{i=1}^{n} w_{iF} * \left(\sum_{j=1}^{n} w_{jF} * \rho_{i,jF} \right) ......Equation..1$$

$$where..w_{iF} = v_{iF} / \sum_{i=1}^{n} v_{iF}$$

The measure hm_year_F will increase with an increase in the correlations of portfolio returns among investors holding equity in the firm. It will also increase with concentration of ownership in a firm assuming the correlations among investor base stay constant. Increases in hm_year_F will indicate an increase in investor homogeneity, while a decrease will indicate the opposite. If we represent the column vector of weights of holdings by institutions in firm F as $\mathbf{w}_F$ and the correlation matrix for institutions holding equity in firm F as $\boldsymbol{\rho}_F$ then an alternative representation for *hm_year* is in Equation 2.

$$hm\_year_F = w'_F * \rho_F * w_F ....Equation..2$$

This measure can therefore theoretically lie between 0 and 1, as correlation matrices are positive semi-definite. In the sample, the mean (median) homogeneity measure is 0.905 (0.917) with a standard deviation of 0.052. The measure ranges from 0.37 to 1.0, with 90% values lying between 0.79 and 0.97.

I present an example of the calculation of the homogeneity measure for illustration. Suppose a firm X has equity held by three institutions ‘a’, ‘b’ and ‘c’. The fraction of equity held by the three institutions are 25%, 15% and 10% respectively, therefore the total amount of equity held by the institutions in the firm X is 50%. As a result, the weights w_{aF}, w_{aF}, and w_{aF} of the institutions are 50%, 30% and 20% respectively. The vector of weights can be denoted as $\boldsymbol{w_X}$ (0.50, 0.30, 0.20). Let the correlation matrix of daily portfolio returns of the three institutions $\boldsymbol{\rho}_X$ be as following:

Institution	a	b	c
a	1	0.8	0.6
b	0.8	1	0.5
c	0.6	0.5	1

Then the homogeneity measure of the institutional investor base for firm X is $\boldsymbol{w_X}'\ \boldsymbol{\rho}_X\ \boldsymbol{w_X}$ and is equal to 0.8. Now, if the correlation between returns of institutions ‘a’ and ‘b’ increases from 0.8 to 0.9, keeping everything else constant, the homogeneity measure increases to 0.83. In essence, if portfolios of institutions ‘a’ and ‘b’ become similar, the homogeneity measure will increase.

SECTION 2.6: MEASURES OF ADVERSE-SELECTION COMPONENT OF SPREAD AND INFORMATION RISK

Measuring information asymmetry among the investors of a firm is extremely difficult, given the unobservability of private information. Over the years, market microstructure literature has come up with structural models to identify information asymmetry. I follow two approaches used in the literature to measure information asymmetry among the investors of a firm. One approach is to use a measure of the probability of informed trading (*PIN*) and the other is to use a measure of adverse-selection component of spread (*fracas_gh*).

In a series of papers (see Easley, Kiefer, and O'Hara (1996a, 1997); Easley et al. (1996b); and Easley, O'Hara, and Paperman (1998)), Easley and O'Hara provide a method to estimate the probability of information-based trading. Their method uses data on buys and sells to estimate the underlying parameters of the microstructure model and shows how to combine these parameters to find a single measure of the probability of information-based trading. *PIN* has been shown in previous work to explain a number of information-based regularities, providing me with the measure needed to examine the effect of information asymmetry on liquidity risk.

The second approach uses a measure based on the spread decomposition models. The spread posted by the market maker compensates him for the adverse selection risk he faces in trading with informed traders, inventory risk due to price volatility of the stock, and other fixed costs. Following the approach of Glosten and Harris (1988) and using the trade indicator model, I estimate the adverse selection component of spread (*fracas_gh*). The trade indicator model allows for decomposition of the spread posted by a market maker assuming that liquidity motivated trades have a temporary price impact, while information-motivated trades have a permanent impact.

SECTION 3: MAIN FINDINGS

I present results starting with the effect of institutional ownership on systematic liquidity risk measures. When examining the effect of institutional ownership and information asymmetry on systematic liquidity risk measures, hypotheses 1 through 6 provide the framework to interpret the findings. Given the low explanatory power of the "market model," for explaining the time variation in firm liquidity, I later examine the effect of institutional ownership on time variation and coefficient of variation

[COV] of liquidity measures. However, I don't have strong priors on the effect of institutional ownership on the total liquidity risk measures.

SECTION 3.1: INSTITUTIONAL OWNERSHIP AND SYSTEMATIC LIQUIDITY RISK

3.1.1: Portfolio results

In this section, I present the findings using the liquidity beta ($\boldsymbol{\beta_1}$) coefficients estimated with Spec 1 from Section 2.3. The liquidity beta coefficients measure the systematic liquidity risk of a stock resulting from the covariance of changes in the stocks liquidity with measures of changes in market liquidity. I start out by stratifying the sample into five quintiles each year, based on different firm and institutional investor characteristics. Table 3.6 presents some observations based on the variation of systematic liquidity risk measure across groups of firms formed on those firm characteristics. I present the mean liquidity beta coefficients for all four measures of liquidity (*ESPR, QSPR, RELESPR,* and *RELQSPR*) for groups formed based on size of the firm, liquidity level of the firm, institutional ownership of the firm, investor horizon, homogeneity of the investor base, and information risk measures. I quickly summarize findings from the portfolio results and defer a more detailed interpretation of the findings in the context of the hypotheses until I present the regression results.

Table 3.6 indicates that liquidity betas vary systematically across several firm characteristics. I find that systematic liquidity risk increases with size of the firm, as measured by both market capitalization of the firm and its revenues. It also increases with the level of institutional ownership and increasing homogeneity of the institutional investor base. Systematic liquidity risk also increases with increase in ownership by both short-term and long-term investors. On examining the difference between the long-term and short-term ownership (*long_short*), I find some evidence of a non-monotonic (U-shaped) relationship, with an overall trend indicating an increase in systematic liquidity risk measures with a shift in ownership towards long-term investors. On exploring the non-monotonic relationship further, I find that the systematic liquidity risk is higher when the magnitude of difference between holdings of long-term and short-term investors, an imbalance in ownership type, is high. A shift in holdings towards either short-term or long-term investors is associated with an increase in the homogeneity of the institutional investor base, which can result in an increase in liquidity risk. I also find that an increase in the measures of information asymmetry is associated with a reduction in the systematic liquidity risk.

Because both information risk and the level of institutional ownership measures exhibit a strong correlation with the firm size, and investor horizon, ownership concentration, and investor homogeneity measures exhibit a strong correlation with the level of institutional ownership, I also present findings by forming groups based on sequential sorts. In Panel A of Table 3.7, I present the findings by stratifying firms each year into five size-based quintiles and then, in turn, within each size-based quintile, into quintiles based on the characteristic of interest. This process of forming groups controls for the effect of size on systematic liquidity risk and produces variation in the liquidity betas related to the characteristic of interest. In a summary of the findings, I present the means of the liquidity betas for the characteristic-based quintiles across the different size categories.

After controlling for the effect of firm size, I find that the liquidity beta measures increase with *fracinst* and ownership dispersion (*lnnuminst*). Both increase in institutional ownership level and ownership dispersion can increase systematic liquidity risk, by increasing the likelihood of herd formation and correlated trading.

After controlling for size effect, I find that systematic liquidity risk decreases with both increases in spreads and with information asymmetry. The inverse relation between liquidity and systematic liquidity risk is consistent with a preference of investors to liquidate or trade in assets that are more liquid to save on transaction costs during declines in market liquidity. A decrease in liquidity risk with information asymmetry is consistent with the idea that, investors increase reliance on their private information in taking decisions, when the value of private information is higher. Herding is less likely to occur in such circumstances due to a reduced likelihood of information cascades.

In Panel B of Table 3.7, I present the findings by stratifying the firms into five *fracinst*-based quintiles for each year and then, in turn, within each *fracinst*-based quintile, into quintiles based on the characteristic of interest. This process of forming groups controls for the effect of the level of institutional ownership on systematic liquidity risk and relates the variation in the liquidity betas to other attributes of institutional ownership. In general, I find that the systematic liquidity risk increases with long-term ownership, while it decreases with short-term ownership. On examining the effect of the imbalance in ownership on liquidity risk, I find that liquidity risk increases with an increase in *long_short*, but at a decreasing rate suggesting that a shift towards longer term ownership results in increased systematic liquidity risk. This finding is inconsistent with Hypothesis 4 where I claimed that that liquidity risk of stocks will increase as ownership by short-term investors increases due to the greater likelihood of them facing liquidity shocks and demanding liquidity when market liquidity is low. A possible interpretation is that as the shares held by long-term investors in a firm increases, they get tied up for longer duration, and the fraction that remains exhibits more volatile trading.

Table 3.6: Parametric analysis: Systematic liquidity risk measures (single sorted). Liquidity beta estimates for firms listed on NYSE and AMEX during the sample period 1983–2005 are summarized. Each year firms are divided into five groups based on certain firm characteristics. Mean liquidity beta measures are presented for firms in the groups to examine the effect of variation in firm characteristic on the liquidity betas.

Characteristic	**Lowest**		**Medium**		**High**	**Characteristic**	**Lowest**		**Medium**		**High**
Market Capitalization *[lnSize]*						Short term institutional ownership *[fracshort]*					
espr	0.073	0.137	0.196	0.253	0.356	espr	0.093	0.178	0.242	0.280	0.280
qspr	0.072	0.114	0.170	0.259	0.453	qspr	0.098	0.197	0.272	0.297	0.274
relespr	0.123	0.201	0.253	0.278	0.328	relespr	0.152	0.220	0.271	0.292	0.300
relqspr	0.135	0.216	0.260	0.339	0.472	relqspr	0.174	0.279	0.342	0.366	0.355
Sales *[LnSales]*						Long term institutional ownership *[fraclong]*					
espr	0.092	0.155	0.200	0.248	0.348	espr	0.118	0.157	0.204	0.276	0.323
qspr	0.075	0.134	0.183	0.263	0.442	qspr	0.102	0.162	0.212	0.296	0.386
relespr	0.146	0.213	0.242	0.279	0.325	relespr	0.185	0.209	0.234	0.292	0.327
relqspr	0.154	0.228	0.276	0.330	0.461	relqspr	0.200	0.254	0.285	0.359	0.417
Liquidity measure *[c_BMA]*						Investor horizon *[long_short]*					
espr	0.326	0.271	0.241	0.182	0.081	espr	0.247	0.205	0.191	0.202	0.280
qspr	0.357	0.284	0.251	0.188	0.078	qspr	0.224	0.226	0.192	0.226	0.327
relespr	0.318	0.299	0.283	0.226	0.130	relespr	0.282	0.242	0.236	0.226	0.295
relqspr	0.399	0.351	0.325	0.275	0.152	relqspr	0.313	0.305	0.272	0.291	0.372
Institutional Ownership *[fracinst]*						Investor horizon *[abslong_short]*					
espr	0.087	0.157	0.217	0.282	0.322	espr	0.1784	0.192	0.2155	0.2559	0.2792
qspr	0.104	0.152	0.240	0.300	0.347	qspr	0.1869	0.2259	0.2384	0.2657	0.2776
relespr	0.150	0.205	0.246	0.301	0.327	relespr	0.2335	0.2254	0.2416	0.2806	0.297
relqspr	0.172	0.245	0.312	0.369	0.396	relqspr	0.2611	0.296	0.308	0.3403	0.3471
Homogeneity of investors *[hm_year]*						PIN					
espr	0.164	0.191	0.220	0.287	0.258	espr	0.290	0.253	0.216	0.191	0.088
qspr	0.173	0.175	0.220	0.314	0.299	qspr	0.362	0.305	0.234	0.172	0.093
relespr	0.209	0.234	0.259	0.295	0.280	relespr	0.292	0.284	0.258	0.256	0.128
relqspr	0.241	0.271	0.301	0.372	0.362	relqspr	0.417	0.379	0.323	0.263	0.162

Table 3.7: Parametric analysis: Systematic liquidity risk measures (double sorted). Liquidity beta measures of a firm each year by dividing the firms listed on NYSE and AMEX into groups each year are summarized. The portfolio sorts are carried out sequentially to identify the effect of the characteristic after controlling for the effect of control characteristics. The control characteristics are indicated in brackets and are either size or level of institutional ownership.

Characteristic	Lowest		Medium		High	Characteristic	Lowest		Medium		High
Panel A: Controlling for size of firm											
Institutional Ownership [fracinst] (Control: size)						PIN (Control: size)					
espr	0.150	0.198	0.212	0.231	0.247	espr	0.227	0.218	0.205	0.191	0.166
qspr	0.170	0.210	0.223	0.242	0.232	qspr	0.255	0.251	0.239	0.212	0.178
relespr	0.191	0.227	0.248	0.265	0.274	relespr	0.249	0.270	0.243	0.227	0.213
relqspr	0.247	0.281	0.289	0.314	0.308	relqspr	0.331	0.330	0.312	0.282	0.228
Ownership dispersion [lnnuminst] (Control: size)						Liquidity measure [c_BMA] (Control: size)					
espr	0.134	0.181	0.206	0.220	0.270	espr	0.260	0.249	0.224	0.192	0.130
qspr	0.133	0.197	0.197	0.252	0.295	qspr	0.253	0.236	0.238	0.217	0.152
relespr	0.183	0.223	0.237	0.262	0.279	relespr	0.291	0.277	0.248	0.226	0.177
relqspr	0.204	0.249	0.277	0.331	0.357	relqspr	0.310	0.305	0.310	0.293	0.229
Panel B: Controlling for institutional ownership (*fracinst*) of firm											
Long term institutional ownership [fraclong] (Control: fracinst)						Ownership concentration [lnhhi_inst] (Control: fracinst)					
espr	0.192	0.201	0.221	0.235	0.228	espr	0.273	0.222	0.205	0.190	0.151
qspr	0.156	0.205	0.245	0.267	0.264	qspr	0.327	0.233	0.200	0.187	0.145
relespr	0.240	0.244	0.254	0.256	0.244	relespr	0.285	0.238	0.250	0.242	0.208
relqspr	0.258	0.289	0.313	0.324	0.313	relqspr	0.376	0.314	0.291	0.259	0.220
Short term institutional ownership [fracshort] (Control: fracinst)						Ownership dispersion [lnnuminst] (Control: fracinst)					
espr	0.209	0.232	0.229	0.201	0.195	espr	0.144	0.157	0.194	0.238	0.281
qspr	0.228	0.274	0.232	0.219	0.180	qspr	0.102	0.151	0.183	0.257	0.369
relespr	0.241	0.251	0.252	0.241	0.236	relespr	0.195	0.229	0.233	0.264	0.288
relqspr	0.284	0.343	0.305	0.297	0.268	relqspr	0.185	0.222	0.267	0.334	0.414
Investor horizon [long_short] (Control: fracinst)						Homogeneity of investors [HM_year] (Control: fracinst)					
espr	0.199	0.203	0.217	0.229	0.229	espr	0.168	0.178	0.214	0.236	0.262
qspr	0.179	0.208	0.234	0.261	0.261	qspr	0.178	0.172	0.216	0.259	0.299
relespr	0.240	0.247	0.246	0.248	0.249	relespr	0.214	0.234	0.238	0.255	0.277
relqspr	0.270	0.289	0.305	0.322	0.313	relqspr	0.245	0.267	0.291	0.319	0.361

After controlling for the level of institutional ownership, I find that the liquidity beta measures decrease with ownership concentration (*lnhhi_inst*) while they increase with ownership dispersion. This finding is consistent with Hypothesis 3. The finding supports my claim that concentrated ownership will reduce the likelihood of herding due to greater incentives to collect and act on private information. Investors holding concentrated positions rely more on their private information and act less on the basis of their inference of others' actions. I also find strong evidence consistent with Hypothesis 2 that the liquidity risk measures increase with the homogeneity of investor base after controlling for the level of institutional ownership. The finding regarding effect of homogeneity of institutional investor base on liquidity risk supports my earlier claim that as ownership of an asset becomes more homogeneous, both the likelihood of owners facing a common liquidity shock and the effect of the liquidity shock on the asset increases. Homogeneity of ownership also increases the propensity to herd as it naturally results in a reduction in the dispersion of institutions' private information. This finding is consistent with that of Fernando et al. (2008), which found that the homogeneity in the investor base of PERPS, due to its concentrated ownership by Japanese banks, led to its sudden significant decline in liquidity.

3.1.2: Multivariate results

In this section, I examine the relationship between liquidity risk and the institutional ownership variables in a multivariate framework to control for other firm characteristics and test hypotheses 1 through 6. Due to the uneven number of firms in the panel each year, I rely on pooled regressions with year and industry fixed effects. I include industry fixed effects to control for the differences in liquidity risk across industries using the Fama-French 12 classification. The year fixed effects take into account the time trends of the variables and thus avoid spurious relationships. To ensure that standard errors are not biased, I estimate them by clustering them both on the firm and time dimensions. Clustering ensures that the inference is based on standard errors that are robust to correlation across residuals within a firm over time and across firms in the same year.[80] As the liquidity measures are noisy, there will be errors in the estimation of liquidity betas. However, there is no reason to believe that certain firm characteristics will influence the errors in the estimated liquidity betas, the dependent variables in the cross-sectional regression, and, thus, bias the inference drawn from studying the relationship between liquidity betas and firm characteristics. For the sake of brevity, I present the findings for liquidity betas for the *RELQSPR* measure. I present the results using value-weighted measures of market liquidity and returns using Spec 1 from Section 2.3, as these measures exhibited the greatest degree of commonality.

The primary variables of interest are the ones associated with ownership structure and information asymmetry. I also include additional control variables to capture those firm characteristics that I suspect could influence the time variation in a stock's liquidity and its liquidity risk. Investors in need of funds may prefer to liquidate assets that are more liquid, which can cause the liquidity demand for those assets to vary more over time. Watanabe and Watanabe (2008) also indicate the time-varying nature of the liquidity risk and use trading volume to identify the liquidity state. I, therefore, add the liquidity of a firm as an additional control variable. Benston and Hagerman (1974) find that higher individual stock volatility is cross-sectionally associated with higher spreads. Firms with higher volatility levels may exhibit greater time variation in volatility. For this reason, I include a lagged measure of the stock-return volatility (*lagvolatility*) as an additional control variable. Volatility is calculated using the

[80] Since the measured liquidity betas are not highly persistent over time, serial correlation among the residuals is not a concern.

standard deviation of the daily stock returns, excluding the dividends, over a one-year period. Grinblatt, Titman, and Wermers (1995) found greater herding behavior in past winners. They suggest that many mutual funds follow momentum strategies and, as a result, the herding behavior is likely to be more prominent in winner stocks. The researchers also observed that the growth-oriented funds exhibited a greater tendency to herd than the income-oriented funds. This could be because the growth-oriented funds trade and hold a larger proportion of growth stocks, many of which are small caps on whom public information is harder to obtain and analyze. As a result, there is a greater likelihood of the herding behavior in high-growth stocks. Nofsinger and Sias (1999) suggest that if institutional investors are better informed, they are more likely to herd in under-valued stocks. To control for the herding effects resulting from past returns and the growth prospects of a firm and style investing, I include the book-to-market ratio (*booktomkt*) and the last year's annual returns (*lagannret*).

Table 3.8 presents the findings from the pooled regressions. Spec 1 indicates that the systematic liquidity risk increases with the size and liquidity of the firm. As mentioned earlier, the inverse relation between liquidity and liquidity risk can result from a preference of investors to liquidate relatively liquid assets to save on the transaction costs during periods of low market liquidity. As a result, stocks that are more liquid may exhibit a greater reaction to aggregate liquidity changes given an increased liquidity demand for these stocks. This finding is consistent with the theoretical predictions of Fernando (2003) who find that investors facing liquidity shocks will trade in more liquid assets.

Table 3.8: Cross-sectional results: Determinants of systematic liquidity risk. Cross-sectional results for effects of institutional ownership on liquidity risk for stocks listed on NYSE and AMEX are presented. The dependent variable is the liquidity beta estimated from the regression of daily changes in relqspr on daily changes in a value weighted measure of market liquidity. *relqspr* measures are obtained using TAQ data. The period of study is 1983–2004 when using the PIN metric as an explanatory variable. Pooled regression is run using year and industry fixed effects due to inherently unbalanced nature of the panel. The standard errors are estimated by clustering on year and firm and are presented in italics below the estimates.

Variable	Spec 1	Spec 2	Spe c 3	Spec 4	Spec 5	Spec 6	Spec 7
Size	0.04***	0.04***	0.036***	0.033***	0.038***	0.039***	0.038***
	0.007	*0.007*	*0.006*	*0.006*	*0.007*	*0.007*	*0.007*
c_bma	-3.898***	-4.761***	-4.253***	-4.037***	-3.999***	-4.033***	-4.018***
	0.884	*0.872*	*0.880*	*0.877*	*0.875*	*0.876*	*0.869*
fracinst	0.033	0.05**	0.169***	0.173***		0.044*	0.042*
	0.022	*0.022*	*0.057*	*0.039*		*0.027*	*0.023*
PIN	-0.452***		-0.406***	-0.383***	-0.45***	-0.454***	-0.45***
	0.062		*0.063*	*0.064*	*0.062*	*0.062*	*0.063*
fracas_gh		-0.149***					
		0.034					
lnhhi_inst			-0.029***				
			0.008				
numblocks				-0.034***			
				0.006			
fraclong					0.222**		
					0.101		
fracshort					-0.035		
					0.050		
long_short						0.124*	
						0.063	
hm_year							0.275***
							0.105
lagvolatility	0.982**	0.824*	0.927**	1.018**	1.149**	1.15**	1**
	0.457	*0.426*	*0.457*	*0.452*	*0.495*	*0.497*	*0.454*
lagannret	0.028**	0.031**	0.022*	0.02	0.031**	0.032**	0.026**
	0.013	*0.012*	*0.013*	*0.013*	*0.013*	*0.013*	*0.013*
booktomkt	0.001	0**	0.001*	0.001	0.001	0.001	0.001
	0.001	*0.000*	*0.001*	*0.001*	*0.001*	*0.001*	*0.001*
Adj R2	5.29%	5.65%	5.40%	5.43%	5.33%	5.32%	5.32%
No. of obs.	38288	40472	38288	38288	38288	38288	38288
No. of parameters	39	40	40	40	40	40	40
F. Value	272.82	307.21	275.34	276.70	258.04	258.06	270.24

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

In the remaining specifications, where I control for other institutional characteristics, the coefficient on the level of institutional ownership is positive and significant. On the whole, I find that increasing institutional ownership results in an increasing commonality in liquidity and, in addition, is a source of systematic liquidity risk. These results lend support to Hypothesis 1 of this chapter. Stocks predominantly held by institutions could exhibit increased herding and correlated trading, due to the greater homogeneity of institutional investors, resulting in an increased liquidity risk and commonality in liquidity. This finding also relates to the evidence found by Barberis and Shleifer (2003) regarding the phenomenon of "style investing" as a source of commonality in returns.

After controlling for size and liquidity level, I find that an increase in information-asymmetry measures lead to a decline in the liquidity betas. Coefficient estimates of both the measures of information asymmetry, *PIN* (Spec 1) and *fracas_gh* (Spec 2), are negative and statistically significant (-0.452 and -0.149, respectively). The economic effects are not sizable, with a one standard deviation increase in these measures, leading to a decline in the systematic liquidity risk measure of ~0.06 standard deviation.[81] This finding lends additional support to both institutional herding and correlated trading as a source of commonality in liquidity and systematic liquidity risk. Correlated trading can be a result from herding or investors acting on common signals about macroeconomic factors. However, with the private information among investors increasing, investors having precise information are more likely to rely on their information in making decisions. Such investors are not only less likely to exhibit

[81] These findings are obtained after controlling for the effect of size of the firm. Size and the information asymmetry measures *PIN* and *fracas_gh* exhibit a strong negative correlation. Size is often considered as a proxy for the information environment of the firm, with larger firms having less private information. In light of the above, the effect of information asymmetry on systematic liquidity risk after controlling for the firm size, is a significant finding.

a herding tendency but also act in a stabilizing manner, thereby reducing the likelihood of information cascades. Another interpretation is that the informed investors in these firms are more likely to respond to sudden spikes in liquidity demand when there are changes in the market liquidity, thus reducing the systematic liquidity risk of these stocks. The above finding strongly supports the effect of information asymmetry on the liquidity risk and adds a potential link between the level of liquidity and the systematic liquidity risk.

In Spec 3 and Spec 4, I examine the effect of ownership concentration and block-holdings on the systematic liquidity risk after controlling for the level of ownership. Systematic liquidity risk decreases with both an increase in ownership concentration and an increase in block-holdings. These findings support the claim that concentrated ownership will reduce the likelihood of herding and correlated trading. When institutions hold larger stakes in a firm they have greater incentives to collect and act on their private information and are therefore less likely to rely on inferences drawn from the actions of others. As a result, for similar levels of institutional ownership, the likelihood of herding behavior and correlated trading is lower, when ownership is concentrated among fewer institutions, reducing the systematic liquidity risk. These findings are also consistent with the argument in Fernando (2003) where an increase in heterogeneity of investors exposure to systematic liquidity shocks alleviates the impact of the liquidity shocks thereby reducing commonality in liquidity.

In Spec 5 and Spec 6, I examine the effect of investor horizon on the systematic liquidity risk after controlling for the level of ownership. I find that the systematic liquidity risk increases with long-term institutional ownership (*fraclong* and *long_short*) indicating that the liquidity of firms having a larger fraction of shares held by long-term investors reacts more to changes in the marketwide liquidity. As mentioned earlier in the portfolio results, this finding is inconsistent with Hypothesis 3 that liquidity risk of stocks will increase as ownership by short-term investors increases. I had earlier proposed that the systematic liquidity risk should increase with increasing ownership by short-term investors due to their greater likelihood of facing liquidity shocks and demanding liquidity when market liquidity is low. This contrary finding is surprising and suggests that herding behavior by institutions with a short-term investment horizon may not be a primary cause for commonality in liquidity. An alternative interpretation of this finding is that the short-term investors are more likely to step in and provide liquidity to long-term investors when market liquidity is low. Long-term investors, however, may not step in and meet the liquidity needs of the short-term investors. Another possibility is that as the shares held by long-term investors in a firm increases, they get tied up for longer duration, and the fraction that remains exhibits more volatile trading.

In Spec 7, I find that the liquidity risk increases with investor homogeneity. The coefficient on *hm_year* (0.275) is positive and statistically significant. The economic effects though are not sizable, with a one standard deviation increase in these measures leading to an increase in the systematic liquidity risk measure of ~0.03 standard deviation. This finding supports my earlier claim that as the ownership of an asset becomes more homogeneous, both the likelihood of the owners facing a common liquidity shock and the effect of the liquidity shock on the asset will increase. The likelihood of herding increases with homogeneity of ownership as it naturally results in a reduction in the dispersion of the private information of institutions. This finding further confirms the claim that the tendency of institutions to herd and follow similar investment strategies can be a source of increased liquidity risk.

The average explanatory power of these cross-sectional regressions is low and around 5%. However, the findings examining the effect of institutional ownership on systematic liquidity risk highlight the role of ownership of assets as a source of commonality in liquidity and the liquidity risk. These findings from the equity markets provide a starting point to further examine the effects of the ownership attributes on the systematic liquidity risk in other asset markets.

3.1.3: Robustness tests

I first test robustness of the results obtained in Section 3.1.2 using alternative estimation methods. For sake of conciseness, I don't report results in this section and only present a summary of the various robustness tests. I obtain estimates consistent with those in Table 3.7 when using within-firm variation using firm fixed effects, estimates obtained using between firm variation, and those obtained using the Fama-Macbeth approach. I also estimate the cross-sectional regressions using other liquidity measures *QSPR, ESPR,* and *RELESPR*. Similarly, I redo the regressions to account for the effect of non-synchronicities, by using the sum of the liquidity beta coefficients β_1, β_2, and β_3, from Spec 2, in Section 2.3. The findings reported in Table 3.8 for determinants of the systematic liquidity risk measures using other liquidity measures and after accounting for non-synchronicities, remain qualitatively unaltered.

I test the robustness of the main results across two sub-periods and by dividing the sample into groups based on the following firm characteristics: size, volatility, book to market ratio and liquidity. I partition firms into equal sized groups using the median value of the characteristic over the sample period, and then test whether the effect of institutional ownership on systematic liquidity risk is consistent across these groups.

This approach assists in checking stability of parameters and existence of any interaction effects that may influence the main results.

I split the sample into the sub-periods 1983–1992 (ISSM data) and 1993–2005 (TAQ data) and also dividing them into equal periods 1983–1993 and 1994–2005. Consistent findings across these sub-periods and similar findings from the Fama-Macbeth approach indicate stability of estimates over time. On analyzing the firms from NYSE and AMEX separately, the findings are very similar. The findings are robust to excluding firms belonging to the financial and utilities sector (SIC codes belonging to 6000–6999 and 4900–4949, respectively). The findings are also very similar across equal sized groups of firms formed based on firm size, historical returns, liquidity and volatility. Overall, the findings indicate that both the effects of information asymmetry variables and institutional ownership variables—level of institutional ownership, concentration of institutional ownership, homogeneity of institutional investor base, investment horizon of the institutional investor base—are fairly robust though they tend to be relatively stronger for less liquid firms. Furthermore, on examining the effects of concentration of institutional ownership, homogeneity of institutional investor base, investment horizon of the institutional investor base across groups formed based on the level of institutional ownership the results are very consistent.

As mentioned in Chapter 2, over time, indexing has become more popular as a low cost alternative to active investing. Current estimates suggest that roughly 20% of the outstanding equity of various firms held by institutions is passively managed. Firms included in major stock indices can exhibit greater commonality in liquidity resulting from liquidity needs of passive indexers due to fund flows and active indexers trying to stay close to their respective benchmark weights. Harford and Kaul (2005) find that stocks listed in S&P 500 index are correlated more with other index components than with stocks that belong to the same industry, suggesting that basket trading by arbitrageurs of index components gives rise to correlated liquidity demands. I therefore test the robustness of results to including two indicator variables, first for inclusion of a firm in the Dow Jones Industrial Index and the other for inclusion of a firm in the S&P 500 index. I find evidence that systematic liquidity risk increases for firms that are included in these indices. The different effects of institutional ownership remain significant though their effects are marginally lower.

There is also a concern that lead-lag effects could drive some of the reported findings. Lo and MacKinlay (1990) show that small stocks react slowly compared to larger stocks to arrival of new information. This can result in systematic liquidity risk measures to increase with firm size when using value weighted measure of market liquidity. To address this concern, I redid my time-series regressions for estimating systematic liquidity risk with equal weighted measures of market liquidity and market returns and using Spec 1 from Section 2.3. While estimating these regressions for a firm to calculate its liquidity beta, I exclude that firm from the market portfolio in order to minimize the cross-sectional dependence in the estimated slope coefficients. I estimated the effect of institutional ownership variables on these new measures of liquidity beta. The cross-sectional regression results are qualitatively similar and indicate that the increase in systematic liquidity risk with firm size and level of institutional ownership is not an artifact of the lead-lag effects.

While examining the effect of investor horizon on measures of liquidity risk, I had classified the ownership by long-term and short-term institutions based on the portfolio turnover measures of institutions from the previous year. When reclassifying the institutions based on their contemporaneous portfolio turnover, the effect of investor horizon on liquidity risk measures remains practically identical.

The findings I have reported so far are based on following a two step procedure. In the first step, I measure systematic liquidity risk, and then in a subsequent step run the cross-sectional regression to determine the effects of ownership characteristics and information asymmetry on liquidity risk. I mentioned earlier that there could be a concern that some of these findings are biased due to the two-step procedure, if the estimation errors in first stage are related to firm characteristics. Nevertheless, I address this issue by estimating a single panel regression using both time-series as well as cross-sectional data. The panel regression allows me to estimate, the impact of the ownership characteristics on the measures of systematic liquidity risk in a single step. For purpose of illustration, I present the specification similar to Spec 1 of Table 3.7. I estimate the following regression across all firms and all days over the period 1983-2005.

$$
\begin{aligned}
\Delta Liq_{it} &= \alpha_0 + \beta_{10} * \Delta MktLiq_t * \sum_{k=1}^{12} \gamma_k Industry_k * [I_{i\in k}] + \beta_{10} * \Delta MktLiq_t * \sum_{n=1983}^{2004} \lambda_n Year_n * [I_{t\in n}] + \\
&\beta_{11} * \Delta MktLiq_t * Size_{it} + \beta_{12} * \Delta MktLiq_t * c\_BMA_{it} + \beta_{13} * \Delta MktLiq_t * fracinst_{it} + \\
&\beta_{14} * \Delta MktLiq_t * PIN_{it} + \beta_{15} * \Delta MktLiq_t * lagvolatility_{it} + \beta_{16} * \Delta MktLiq_t * lagannret_{it} \\
&+ \beta_{16} * \Delta MktLiq_t * booktomkt_{it} + \beta_2 * Mktret_t + \beta_3 * Sqret_{it} + \varepsilon_{it} .. Spec1
\end{aligned}
$$

In the above regression, the coefficients on the interaction terms capture the sensitivity of the co-movement of liquidity with market liquidity to the relevant cross-sectional variable. The coefficients of interest are β_{13} and β_{14}, which capture the effect of level of institutional ownership and information asymmetry on measures of systematic liquidity risk. The findings from following this one step procedure are qualitatively similar to those from the two step procedure presented in Table 3.7. For sake of conciseness, I don't present the specifications for the other cross-sectional regressions (Spec2–Spec7). Findings for these specifications using the one step procedure are consistent with those reported following the two step procedure.

In the measures of liquidity risk, using the market models, I winsorized the measures of liquidity at 5% and 95% level to remove the effect of outliers. This raises the concern that, I may not be capturing the large extreme changes in liquidity, the changes we should really be concerned about and are a significant component of liquidity risk. Therefore, to further test robustness of my results, I estimated measures of liquidity risk using the liquidity measures winsorized at 1% and 99% level. The findings are similar to those reported earlier. The effect of level of institutional ownership is somewhat stronger while the effect of ownership concentration is a little weak.

SECTION 3.2: INSTITUTIONAL OWNERSHIP AND TOTAL LIQUIDITY RISK

The previous section presented the effect of the institutional ownership measures on cross-sectional variation in the systematic liquidity risk. The average explanatory power of the "market model" regressions used to estimate the systematic liquidity risk was around 4.3%, which suggests that the changes in market liquidity explains a very small part of the time variation in the liquidity at the firm level. The estimated liquidity beta coefficients at firm level were also not persistent over time, indicating the difficulty in accurately estimating the measures of systematic liquidity risk. In Table 3.5, I showed that the time variation of the liquidity measures at the firm level were fairly persistent over time. I also claimed earlier that stochastic liquidity will be important for pricing derivatives, as investors trading derivatives may have less discretion in trading the underlying for replicating or hedging purposes. Similarly, stochastic liquidity will affect the ability of arbitrageurs to eliminate mispricing. The capital constraints on arbitrageurs generally force them to hold undiversified portfolios, thus exposing them not just to the systematic variation in liquidity but also to the total liquidity variation. I, therefore, turn to examining the effects of institutional ownership and information asymmetry at a firm level on the measures of total variation in liquidity.

3.2.1: PORTFOLIO RESULTS

As a precursor to the regressions, for each year, I stratify the sample into five quintiles based on different firm characteristics. Table 3.9 presents observations based on the standard deviation of firm level liquidity across the groups of firms formed on these firm characteristics. I find that the time variation of all four liquidity measures tends to decrease with the size of the firm as measured by the market capitalization or the annual sales of the firm. I also find that the total variation in liquidity measures tend to increase with the mean spreads of the firm and with an increase in both measures of information asymmetry, *PIN* and *fracas_gh*. These findings suggest that an increase in information asymmetry not only increases the measures of spreads but also increases their variation over time. With an increase in the level of institutional ownership *fracinst*, I find that the time variation in liquidity measures tend to decrease, indicating that the overall liquidity of firms held predominantly by institutions varies less over time. I find similar results when examining the ownership level by institutions having both long-term and short-term investment horizons. No clear pattern emerges from the effect of difference in investor horizon *(long_short)* and investor hormogeneity *(hm_year)* on time variation in liquidity.

Table 3.9: Parametric analysis: Total liquidity risk measures (single sorted). Total liquidity risk measures for firms listed on NYSE and AMEX during the sample period 1983–2005 are summarized. Each year firms are divided into five groups based on certain firm characteristics. Mean total liquidity risk measures are presented for firms in the groups to examine the effect of variation in firm characteristic on the liquidity betas.

Characteristic	**Lowest**		**Medium**		**High**
Sales *[lnSales]*					
espr	0.0888	0.0718	0.0719	0.0378	0.0517
qspr	0.0516	0.0489	0.0444	0.0398	0.0272
relespr	0.1127	0.0280	0.0412	0.0160	0.0010
relqspr	0.0145	0.0068	0.0039	0.0024	0.0011
Market Capitalization *[lnSize]*					
espr	0.1192	0.0692	0.0546	0.0337	0.0523
qspr	0.0511	0.0487	0.0453	0.0384	0.0286
relespr	0.1874	0.0220	0.0098	0.0016	0.0008
relqspr	0.0165	0.0063	0.0032	0.0018	0.0009
Liquidity measure *[c_BMA]*					
espr	0.0712	0.0389	0.0390	0.0655	0.1143
qspr	0.0426	0.0419	0.0421	0.0438	0.0415
relespr	0.0013	0.0030	0.0026	0.0119	0.2027
relqspr	0.0014	0.0021	0.0029	0.0050	0.0175
PIN					
espr	0.0384	0.0355	0.0554	0.0689	0.1115
qspr	0.0314	0.0342	0.0399	0.0485	0.0629
relespr	0.0325	0.0294	0.0461	0.0823	0.0434
relqspr	0.0035	0.0029	0.0043	0.0069	0.0120
Adverse selection component of Spread *[fracas_gh]*					
espr	0.0695	0.0385	0.0360	0.0700	0.1148
qspr	0.0284	0.0353	0.0395	0.0442	0.0646
relespr	0.1299	0.0226	0.0112	0.0164	0.0412
relqspr	0.0088	0.0048	0.0045	0.0046	0.0062

Characteristic	**Lowest**		**Medium**		**High**
Institutional Ownership *[fracinst]*					
espr	0.1121	0.0573	0.0413	0.0569	0.0613
qspr	0.0516	0.0460	0.0402	0.0371	0.0372
relespr	0.1690	0.0374	0.0110	0.0022	0.0019
relqspr	0.0148	0.0065	0.0036	0.0023	0.0017
Short term institutional ownership *[fracshort]*					
espr	0.1051	0.0580	0.0475	0.0621	0.0561
qspr	0.0546	0.0455	0.0384	0.0368	0.0367
relespr	0.1621	0.0332	0.0145	0.0038	0.0078
relqspr	0.0141	0.0059	0.0036	0.0028	0.0025
Long term institutional ownership *[fraclong]*					
espr	0.0983	0.0632	0.0552	0.0480	0.0641
qspr	0.0489	0.0471	0.0403	0.0369	0.0388
relespr	0.1498	0.0383	0.0193	0.0110	0.0029
relqspr	0.0131	0.0071	0.0041	0.0026	0.0020
Investor horizon *[long_short]*					
espr	0.0615	0.0550	0.0836	0.0530	0.0758
qspr	0.0394	0.0428	0.0433	0.0433	0.0433
relespr	0.0160	0.0344	0.1181	0.0320	0.0208
relqspr	0.0041	0.0071	0.0078	0.0063	0.0035
Homogeneity of investors *[hm_year]*					
espr	0.0623	0.0953	0.0489	0.0597	0.0626
qspr	0.0467	0.0437	0.0415	0.0379	0.0422
relespr	0.0563	0.0831	0.0329	0.0122	0.0367
relqspr	0.0068	0.0056	0.0047	0.0037	0.0082

3.2.2: MULTIVARIATE RESULTS

Because both the information risk and the level of institutional ownership measures exhibit a strong correlation with firm size, and investor horizon, ownership concentration, and investor homogeneity measures exhibit a strong correlation with the level of institutional ownership, in this section I present findings using multivariate analysis. I use pooled regressions including the time and the industry fixed effects. Due to the persistence in the variation of liquidity measures of a firm, I estimate the standard errors by clustering them on both firm and time dimensions. Clustering ensures that the inference is based on the standard errors robust to correlation across residuals within a firm over time and across firms in the same year. I also include additional control variables to capture those firm characteristics that I suspect could influence the time variation in a stock liquidity. Primarily, I include the size of the firm, liquidity, historical volatility, past returns, and the book-to-market ratio.

Table 3.10 presents the findings from the pooled regressions. For the sake of brevity, I present only the findings using the variation of *RELQSPR* measure. In Spec 1, I find that after controlling for the firm size and the liquidity measure, the liquidity variance over time increases with information asymmetry (*PIN*) while it decreases with the level of institutional ownership (*fracinst*). An increase in *PIN* is associated with an increase in private information-based trading, which can result in idiosyncratic liquidity needs causing a greater variation of liquidity over time. Institutions may be more willing to absorb idiosyncratic liquidity needs of other informed investors, and as a result, an increase in institutional ownership could decrease the liquidity variation over time.

Table 3.10: Cross-sectional results: Determinants of total liquidity risk. Cross-sectional results for effects of institutional ownership on liquidity risk for stocks listed on NYSE and AMEX are presented. The dependent variable is the standard-deviation of daily relative quoted spread [*relqspr*] using daily measures over a 1 year period. The period of study is 1983–2004. Pooled regression is run using year and industry fixed effects due to inherently unbalanced nature of the panel. The standard errors are estimated by clustering on year and firm and are presented in italics below the estimates.

Variable	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5	Spec 6
lnsize	-0.00104***	-0.00094***	-0.00096***	-0.00095***	-0.0009***	-0.00093***
	0.00008	*0.00007*	*0.00007*	*0.00007*	*0.00006*	*0.00006*
c_bma	0.53338***	0.46001***	0.46222***	0.46542***	0.4644***	0.46144***
	0.02522	*0.02371*	*0.02381*	*0.02400*	*0.02376*	*0.02310*
fracinst	-0.0037***	-0.00215***	-0.00248***		-0.00349***	-0.0033***
	0.00058	*0.00069*	*0.00063*		*0.00057*	*0.00056*
PIN	0.00302***	0.00506***	0.00506***	0.00505***	0.00494***	0.00481***
	0.00068	*0.00080*	*0.00079*	*0.00083*	*0.00079*	*0.00077*
lnhhi_inst		-0.00027***				
		0.00009				
numblocks			-0.00024***			
			0.00007			
fraclong				-0.00424***		
				0.00109		
fracshort				-0.00502***		
				0.00097		
long_short3					0.00023	
					0.00035	
hm_year						-0.00058***
						0.00013
lagvolatility		0.05631***	0.05693***	0.05944***	0.05783***	0.05759***
		0.00895	*0.00895*	*0.00901*	*0.00887*	*0.00894*
lagannret		-0.00143***	-0.00142***	-0.00134***	-0.00139***	-0.00142***
		0.00022	*0.00022*	*0.00023*	*0.00022*	*0.00022*
booktomkt		0.00001	0.00001	0	0.00001	0.00001
		0.00003	*0.00004*	*0.00000*	*0.00004*	*0.00005*
Adj R2	75.79%	77.45%	77.43%	77.20%	77.38%	77.49%
No. of obs	40785	39760	39760	39760	39760	39760
No. of parameters	36	40	40	40	40	40
F. Value	1280.97	1223.60	1231.72	1200.05	1196.72	1222.09

Note. *** indicates the result is significant at 1%, ** indicates the result is significant at 5%, and * indicates the result is significant at 10%. The significance is reported based on two-tailed tests.

Table 3.11: Cross-sectional results: Determinants of total liquidity risk across liquidity groups. Cross-sectional results for effects of institutional ownership on liquidity risk for stocks listed on NYSE and AMEX are presented. The dependent variable is the standard-deviation of daily relative quoted spread [*relqspr*] using daily measures over a 1 year period. The period of study is 1983–2004. Pooled regression is run using year and industry fixed effects due to inherently unbalanced nature of the panel. Cross-sectional regressions across groups formed by dividing firms based on their *RELQSPR* measure. Group 1 consists of the highest liquidity firms while Group 5 consists of lowest liquidity firms. The groups are formed each year.

	Group 1		**Group 2**		**Group 3**		**Group 4**		**Group 5**	
	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
Spec 1										
lnsize	-0.00012	-8.0979	-0.00021	-9.0121	-0.00021	-9.0121	-0.0005	-6.1545	-0.0015	-9.0287
c_bma	0.05171	3.6129	0.0372	2.7294	0.05124	2.9088	0.13754	4.7475	0.233	15.6911
fracinst	0.05171	-5.8295	-0.00031	-6.1523	-0.0004	-3.8893	-0.00094	-6.0077	-0.00256	-3.2382
adjpin	0.05171	10.1726	0.00122	5.4527	0.00168	4.7492	0.0014	3.1292	0.00001	0.0061
Spec 2: Additional control variables- lnsize, c_bma, fracinst, PIN, lagvolatility, lagannret, booktomkt.										
lnhhi_inst	0.00005	5.9901	0.00008	7.146	0.0001	3.7023	0.00015	2.4742	-0.00003	-0.343
Spec 3: Additional control variables- lnsize, c_bma, fracinst, PIN, lagvolatility, lagannret, booktomkt.										
numblocks	0.00002	4.898	0.00005	6.2705	0.00005	3.0966	0.00017	3.6981	-0.00032	-2.152
Spec 4: Additional control variables- lnsize, c_bma, PIN, lagvolatility, lagannret, booktomkt.										
fraclong	-0.00036	-4.1649	-0.00048	-4.4995	-0.00055	-2.6309	-0.00173	-3.0739	-0.00845	-6.4315
fracshort	-0.00051	-4.0085	-0.00044	-3.6006	-0.00063	-4.7073	-0.00168	-4.5406	-0.00198	-1.3477
Spec 5: Additional control variables- lnsize, c_bma, fracinst, PIN, lagvolatility, lagannret, booktomkt.										
long_short3	0.00005	0.6287	-0.00002	-0.2642	0.00005	0.3813	0.00005	0.1693	-0.00315	-3.8721
Spec 6: Additional control variables- lnsize,c_bma, fracinst, PIN, lagvolatility,lagannret, booktomkt.										
hm_year	-0.00058	-3.9989	-0.00096	-4.4897	-0.00022	-0.6183	-0.00138	-2.3898	0.00101	0.6217

The effect of increasing information asymmetry on increasing the total liquidity risk lends support to Hypothesis 7. For firms where there exists greater private information, the idiosyncratic liquidity demands will more likely be associated with private information. Liquidity suppliers will be less willing to meet sudden increased demands in liquidity in presence of greater information asymmetry. As a result, we observe a greater time variation in liquidity for firms with higher information asymmetry.

In Spec 2 and Spec 3, I examine the effect of ownership concentration. I find that with increases in ownership concentration measured by *lnhhi_inst* and *numblocks*, the variation in liquidity measures decrease. This finding is puzzling as I expected that the liquidity needs of large owners could cause a significant increase in the time variation in liquidity of assets they trade. With increasing ownership concentration, the idiosyncratic liquidity shocks faced by the owners may not get diversified and result in increasing liquidity variation of stocks having concentrated ownership. A possible interpretation could be that institutions having concentrated positions are sensitive to the effects of their trading on stocks mitigating the observed effects of concentrated ownership on time variation in liquidity. In Chapter 2, we observed a lower level of liquidity in case of concentrated ownership. Here, I find that concentrated ownership results in a reduced variation of liquidity over time. However, as observed earlier increase in concentration of institutional ownership does lower the systematic component of liquidity risk due to reduced herding risk.

In Spec 4 and Spec 5, I examine the effect of investor horizon. I find that with increases in both long-term and short-term institutional ownership the liquidity variation reduces. After controlling for the level of institutional ownership, I observe that a change in the mix of institutional ownership towards long-term investors leads to an increase in liquidity variation over time, though the finding is not statistically significant. When using the effective spread (*RELESPR*) measure of liquidity, the effect of *long_short* was opposite to that observed using *RELQSPR*, hence I avoid drawing a strong inference. Spec 6 presents the findings using the measure of investor homogeneity. I find that the overall time variation in liquidity decreases with investor homogeneity. Liquidity variation over time increases with historical volatility of returns while decreasing with historical returns.

In Table 3.11, I further examine the multivariate effects by partitioning the firms into five groups based on the level of liquidity measures. Consistent with earlier findings, I find that liquidity variation decreases with level of institutional ownership across all liquidity groups. Liquidity variation also increases with information risk across all liquidity groups though the effect is not significant for the least liquid firms in group 5. For the firms belonging to the four most liquid groups, liquidity variation increases with both ownership concentration measures *lnhhi_inst* and *numblocks*. This finding is consistent with my expectation that with an increase in ownership concentration, the idiosyncratic liquidity shocks faced by the owners may not get diversified and result in increasing liquidity variation of stocks having concentrated ownership, a finding that was not evident for the whole sample.[82] The findings of long-term and short-term institutional ownership across liquidity groups were similar to those for the whole sample while those for investor homogeneity were consistent with the earlier findings for firms in liquidity groups 1, 2 and 4.

[82] Another possibility is that when the tests on partitioned sample may reduce the ability to separate out the effects of ownwership concentration and level of institutional ownership due to the correlation between the measures.

Overall, the evidence suggests that the measures of institutional ownership and information asymmetry affect the variance of liquidity over time. These findings shed some additional light on the role of ownership of assets on variation of liquidity over time. Existing empirical studies in microstructure have emphasized the determinants of liquidity. I provide additional evidence on cross-sectional determinants of liquidity variation over time.

SECTION 3.3: LEVERAGE EFFECT

In this section, I test Hypothesis 5 and present the findings related to the asymmetric affect of the market returns on liquidity. Brunnermeier and Pedersen (2008) show that the funding available to traders affects asset liquidity and can result in commonality in liquidity. When the market returns are negative, asset liquidity declines as the suppliers are less willing to supply the liquidity due to a decline in value of their collateral. In their model, the providers of liquidity become demanders of liquidity after a large drop in asset prices. As a result, there is, not only a reduction in the liquidity the intermediaries could supply, but also an increase in the liquidity they demand. This results in an asymmetric effect of the market returns on asset liquidity. Hameed, Kang, and Viswanathan (2007) found that the impact of market returns on stocks' liquidity is asymmetric with a larger decline in liquidity taking place in down markets compared to the increase in liquidity in up markets. Earlier, I showed that the systematic liquidity risk of stocks increased with the investor horizon, with firms primarily held by long-term investors exhibiting greater systematic liquidity risk.

I, therefore, test for the effect of investor horizon on asymmetric liquidity risk. In this setting, the liquidity risk is measured as the covariance of the asset liquidity with the market returns. I use the following specification to obtain the effects of the positive and the negative market returns on changes in asset liquidity. The difference in the betas across up markets and down markets provides an estimate of the asymmetric impact of the market liquidity and market returns on firms' liquidity and allows for the quantification of the asymmetric effect. In general, liquidity increases with positive market returns and declines with negative market returns, indicating that both $\boldsymbol{\beta_{2+}}$ and $\boldsymbol{\beta_{2-}}$ coefficients will both be negative. Subsequently, I examine the cross-sectional variation of the difference between the sensitivities **($\boldsymbol{\beta_{2+}}$ - $\boldsymbol{\beta_{2-}}$)** of a stock's liquidity to positive market returns **($\boldsymbol{\beta_{2+}}$)** and negative market returns **($\boldsymbol{\beta_{2-}}$).**

$$\Delta Liq_{it} = \alpha_0 + \beta_{1+} * \Delta MktLiq_{+} + \beta_{1-} * \Delta MktLiq_{-} + \beta_{2+} * Mktret_{t+} + \beta_{2-} * Mktret_{t-} + \beta_3 * Sqret_{it} + \varepsilon_{it}$$

I regress the difference in the return betas $\boldsymbol{\beta_{2+}}$ **-** $\boldsymbol{\beta_{2-}}$ on both the level of institutional ownership and investor horizon (*long_short*), while including other control variables. The findings (not reported) indicate a strong and significant effect of investor horizon on the difference. The coefficient of *long_short* is negative and significant and confirms that the difference in sensitivity of an asset's liquidity to positive market returns and negative market returns is dependent on the investor horizon and increases with ownership by institutions having a short-term investment horizon. The finding confirms hypothesis 7 and suggests that the short-term investors tend to play a role in providing liquidity. However, the liquidity of a stock will become more sensitive to market returns, as short-term ownership of investors increases.

SECTION 4: CONCLUSION

An extensive literature in finance examines the effects of liquidity and liquidity risk on expected returns. Using a large sample of firms belonging to NYSE and AMEX over the period 1983–2005, I empirically examine the effect of institutional ownership on time variation in liquidity. I rely on theories of herding and stochastic liquidity, to guide my empirical work and interpret my findings in the context of correlated trading by institutions resulting from a tendency to either herd or trade on common information.

I find strong evidence that the ownership structure of an asset affects both the sensitivity of an asset's liquidity to changes in marketwide liquidity (systematic liquidity risk) and the variation in its liquidity over time. I find that level of institutional ownership, investment horizon of the institutional investor base, concentration of ownership, and homogeneity of the investor base are important determinants of both systematic liquidity risk and total liquidity variance. Systematic liquidity risk increases with institutional ownership, increase in investor horizon, and increasing homogeneity of the investor base, while it decreases as ownership gets concentrated and block-holdings increase. The total liquidity variance however reacts to institutional ownership differently. The variance of liquidity decreases with institutional ownership and concentration of institutional ownership, while increasing with increasing homogeneity of the institutional investor base for the more liquid firms. With increasing information asymmetry among investors, systematic liquidity risk decreases while the total liquidity variance increases. Future research may benefit from treating time variation in liquidity of an asset as endogenous and incorporating the effects of ownership structure on liquidity variation for asset pricing implications.

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