The Divergence of Liquidity Commonality in the Cross-Section of Stocks *

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Abstract

This paper demonstrates that the cross-sectional variation of liquidity commonality has increased over the period 1963-2005. The divergence of systematic liquidity can be explained by patterns in institutional ownership over the sample period. We document that our findings are associated with similar patterns in systematic risk. Our analysis also indicates that the ability to diversify systematic risk and aggregate liquidity shocks by holding large-cap stocks has declined. The evidence suggests that the fragility of the US equity market to unanticipated events has increased over the past few decades.

The literature on asset liquidity has received much attention in recent years. It is now widely accepted that the liquidity of financial assets changes over time, and that these time variations are governed by a significant common component in the liquidity across assets (see, e.g., Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Amihud (2002), and Korajczyk and Sadka (2007)). Current literature focuses on either the cross-sectional differences in asset liquidity or the existence of commonality. This paper studies the evolution of systematic liquidity in the cross-section of US stocks from 1963 through 2005, and the implications for asset returns.

Following Chordia, Roll, and Subrahmanyam (2000) we use the market model of liquidity to estimate the sensitivity of each firm's liquidity to variations in market liquidity. To proxy for the changes in liquidity we use the daily change in (the log of) Amihud's (2002) measure of firm's illiquidity. To the extent that the sensitivity to market liquidity is an indicator of systematic liquidity risk, we find that systematic liquidity, which we define as the sensitivity of the stock's liquidity to market liquidity, has decreased significantly for small-cap firms, but increased significantly for large-cap firms (size quintiles 1 and 5, respectively). We show that this increased divergence of systematic liquidity in the cross-section of firms can be explained by the patterns of institutional ownership over the sample period. Moreover, the temporal patterns of systematic liquidity have important implications for asset prices.

One of the key developments in the US equity market over our sample period is the substantial increase in institutional investing and index trading. The estimated percent of US shares held by institutional investors rose from 21% in 1965 to 35% in 1980 and 50% in 2002 (source: NYSE). It is well known that increases in institutional investing and index trading have played a key role in the increases of trading volume and liquidity levels of US equity markets.[1] What is less known is how they have affected the commonality in liquidity. We investigate the effects of the increased institutionalization of the US equity markets on the

[1]Exchange Traded Funds (ETFs) represent the fastest growing recent financial innovation. The first ETF, called SPDR (symbol: SPY), which was initiated in 1993, replicates the S&P500 portfolio. By March 2006 there were some 150 domestic equity ETFs, with SPDR representing one-third of the total market value of domestic equity ETFs, and other large-cap ETFs representing almost another one-third of the total market value (source: AMEX). SPDR and the NASDAQ 100 index tracking stock (QQQQ) are also typically the two most actively traded securities on AMEX. For example, in February 2005 these two basket securities accounted for more than half of the total trading volume on AMEX (source: AMEX).

systematic liquidity of stocks. We use the CDA/Spectrum data on institutional ownership of common stocks from January 1981 until December 2005. We find that, in the cross-section of firms, the sensitivity of the stock's liquidity to aggregate liquidity shocks increases with institutional ownership. These results support the argument in Chordia, Roll, and Subrahmanyam (2000) that institutional trading is a significant source of commonality of liquidity among stocks. Furthermore, examining institutional ownership by type of institution, we find that liquidity betas increase with ownership by investment companies and investment advisors, but not with ownership by other types of institutions.

Moreover, the increases in institutional ownership over time can explain the divergence of liquidity commonality. Institutional investing and index trading have been more concentrated in large-cap stocks than in small-cap stocks. Institutional herding is also more prevalent in large-cap stocks, especially those included in the S&P500 index. Some institutions are required to satisfy the "prudent man" rule, which may lead them to under-invest in small-cap stocks that are viewed as less prudent (see Del Guercio (1996)). Moreover, since the S&P500 is the most widely followed index by index funds and index arbitrageurs, index trading, especially trading related to stock index-derivative contracts, is also much more prevalent in large-caps stocks than in small-cap stocks. Consequently, indexation and institutionalization often have different effects on the behavior of large firms' shares than on the behavior of small firms' shares.[2] Gompers and Metrick (2001) find that institutional investors tend to increase demand for large-cap stocks and decrease demand for small-cap stocks, and that these demand shifts can explain part of the decline in the small-firm premium embedded in equity returns. We find that differences between the percentages of institutional ownership (especially ownership of investment companies and investment advisors) of large and small stocks cause differences in their sensitivities to aggregate liquidity. This can explain why large firms' stocks have become more sensitive to market liquidity shocks relative to small firms' stocks.[3]

[2]Kamara (1997) finds that institutionalization and index derivatives had significantly different effects on the negative Monday seasonal in daily returns of large and small firms over 1963-1993. They led to a decline in the Monday seasonal of S&P500 returns, and subsequent to the inception of S&P500 futures in 1982, S&P500 returns no longer exhibited the seasonal. In contrast, small-cap firm returns continued to display the negative seasonal, and if anything, the seasonal even became more negative over the 1963-1993 period.

[3]Harford and Kaul (2005) examine order flows in 1986 and in 1996. They find significant common effects

Another feature of institutional and index trading is the use of security baskets as possible means of trading.[4,5] The model of Gorton and Pennacchi (1993) predicts that equity basket trading increases the commonality in liquidity for the constitute stocks in the basket, but reduces liquidity commonality for individually traded stocks. Since they are a dominant fraction of institutional and index trading, large-cap stocks are more likely to be a part of basket trading than small-cap stocks. Thus, Gorton and Pennacchi (1993) can explain why we find that the sensitivity of large-cap stocks to systematic liquidity shocks has increased over our sample period, while the sensitivity of small-cap stocks' liquidity to systematic liquidity has declined. Further supporting their model, we find that the liquidity betas of S&P500 stocks have increased significantly relative to the liquidity betas of non-S&P500 stocks, over our sample period.

We also study the implications of the time patterns in systematic liquidity for asset returns. It is widely accepted that trading activity affects prices. If the factor causing the trading activity and its price impact is market-wide, then trading activity could also affect the systematic risk of firms' returns. There is a growing body of literature which predicts that aggregate variables can affect both firm systematic liquidity (liquidity beta) and firm systematic return (return beta). For example, Chordia, Roll, and Subrahmanyam (2000), Coughenour and Saad (2004) and Vayanos (2004) suggest that changes in market volatility affect systematic liquidity by creating correlated trading patterns among investors and affecting the supply of liquidity by market makers, across many stocks. Since trading activity affects stock prices, this can increase the comovement of stock returns. In addition, the models of Kyle and Xiong (2001), Vayanos (2004), and Brunnermeier and Pedersen (2007), as well as the empirical findings of Ang and Chen (2002) and Hameed, Kang, and Viswanathan (2006), suggest that market return affects both systematic liquidity and systematic return.

for S&P500 stocks, but weak effect for other stocks.

[4]Kavajecz and Keim (2005) study the recent innovation of blind-auction trading of equity baskets and show that they substantially improve liquidity.

[5]The NYSE, for example, has recently begun reporting program trading statistics, where program trading is defined as trading a basket of at least 15 stocks with a total value of $1 million or more. In 2005, the weekly ratio of program trades to trading volume on the NYSE was between 50% to 76%. These percentages (which are only published as market aggregates and are not available at the firm level) are for total (buy plus sell) program trades, and thus, double count sell programs that fully transact with buy programs.

The underlying idea is that market declines reduce the capital available to money managers and market makers and force them to reduce their stocks holdings in a manner that increases commonality in liquidity as well as the correlations in asset returns. In these studies, market volatility and market return typically affect liquidity betas and return betas by affecting the liquidity in the market, which suggests that market illiquidity may be another potential determinant of liquidity commonality and return commonality. Consistent with the studies above, we find that market volatility, market return, and market liquidity affect both firms' systematic liquidity and firms' systematic return.

In light of the common market determinants of systematic liquidity and systematic return, we conjecture that the divergence in liquidity commonality would translate to similar divergence in return commonality. Indeed, we show that return commonality exhibits a similar divergence: The systematic risk of different size groups estimated by using a market model of stock returns exhibit similar time trends to their respective systematic liquidity. We also find that time variations in systematic risk are significantly (positively) related to time variations in systematic liquidity. This relation is significantly stronger for large firms than for small firms.

Our results about systematic risk complement the work of Campbell, Lettau, Malkiel, and Xu (2001) that documents an increasing trend in idiosyncratic return volatility over the period 1962-1997. There are two main differences. First, focusing on the cross-section of firms, we show different size groups can have different patterns of systematic risk. Second, while Campbell, Lettau, Malkiel, and Xu (2001) essentially assume a beta of one for all stocks, we allow beta to vary across firms and over time, e.g. we use a market model for stock returns. This enables us to discuss time patterns in systematic risk (beta) as well as the idiosyncratic component. We find that idiosyncratic risk has increased for the small firms but has declined for the large firms. Most importantly, we show that the patterns of systematic risk that we have uncovered in the cross-section are highly related to systematic liquidity.

The increased divergence of liquidity in the cross-section of firms has important implications for the ability to diversify return volatility and aggregate liquidity shocks across firms.

We find that the ability to diversify risk and liquidity shocks by holding relatively liquid, large-cap, stocks has declined over the sample period of 1963-2005, both in absolute terms and relative to the diversification benefits of small-cap stocks. Our evidence suggests that the ability to diversify risk and liquidity shocks by holding an otherwise well-diversified, value-weighted portfolio has declined over time. In contrast, we find that the ability to diversify risk and liquidity shocks by holding shares of small firms has improved over time. This is particularly noteworthy because of the "flight to quality" in turbulent times from small-cap stocks to large-cap stocks.[6] We also show that liquidity sensitivity to extreme market illiquidity events has diverged over time across large and small firms. This suggests that the fragility of the US equity market to unanticipated events has increased over the past few decades.

There are several additional reasons why the evolution of systematic liquidity across firms is an interesting topic of financial research. First, the evolution of liquidity across firms has implications for the efficient functioning of financial markets: Amihud, Mendelson, and Wood (1990) find that sudden unanticipated declines in liquidity have played a key role in the stock market crash of October 1987. Second, variations in (systematic and total) liquidity volatility affect the ability of arbitrageurs and derivative traders to exploit and eliminate "mispricing" (see, e.g., Kamara (1988), Amihud and Mendelson (1991), Pontiff (1996), Mitchell and Pulvino (2001), Lesmond, Schill, and Zhou (2004), Korajczyk and Sadka (2004), and Sadka and Scherbina (2006)). Third, Longstaff (2001) and Longstaff (2005) show that asset illiquidity has a significant effect on the optimal portfolio choices of investors, leading them to abandon diversification as a strategy. Thus, our results are also imperative for active investment managers who rebalance their portfolios frequently. Last, since liquidity is associated with the price discovery process and, can thus, affect the systematic and idiosyncratic volatility of stock returns (O'Hara (2003)), our study may also have implications for the recently documented pricing of idiosyncratic return volatility (Goyal and Santa-Clara (2003), Ghysels, Santa-Clara, and Valkanov (2005), and Ang, Hodrick, Xing, and Zhang (2006)).

[6] Amihud, Mendelson, and Wood (1990) report that the October 1987 crash was accompanied by a flight to quality from low-liquidity stocks to high-liquidity, large-cap stocks.

The remainder of the paper is organized as follows. Section 1 describes the data. Section 2 describes the evolution of systematic liquidity over the sample period of 1963-2005. In particular, Subsection 2.2 investigates the evolution of systematic liquidity for firms in the smallest and largest size quintiles. We then discuss some explanations for, and implications of, the cross-sectional divergence of systematic liquidity. In Section 3 we investigate the relation between institutional ownership of a firm's equity and its exposure to systematic liquidity. In Section 4 we study the relation between time variations in systematic liquidity and time variations in systematic risk. Section 5 analyzes the implications for the ability to diversify liquidity risk using small and large stocks. In Section 6 we examine the robustness of our results. Section 7 concludes.

1 Data

We obtain daily data of stock prices, returns, volume, shares outstanding, and Standard Industrial Classification (SIC) codes from CRSP. We utilize only common stocks (CRSP share code 10 and 11) listed on NYSE/AMEX over our sample period, December 31, 1962, through December 31, 2005. Because the liquidity characteristics of securities such as American depository receipts, closed end funds, etc. might differ from common equities, we follow Chordia, Roll, and Subrahmanyam (2000) and utilize only common stocks.

We obtain institutional ownership data of firms' common stocks from the CDA/Spectrum database provided by Thomson Financial. The data are derived from institutional investors' quarterly filings of SEC Form 13F. A 1978 amendment to the Securities and Exchange Act of 1934 requires institutions with more than $100 million of securities under management to report all equity positions that are greater than 10,000 shares or $200,000 in value. Our data include quarterly holdings for each stock for each quarter between December 1980 and December 2005.

2 Systematic Liquidity Over Time

Illiquidity is not a simple concept that can be directly observable, yet it is generally associated with the price impact induced by trades. Our daily liquidity measure is based on Amihud (2002) measure of firm's stock illiquidity, which is calculated as the ratio of the absolute value of daily return over the dollar volume, a measure that corresponds to the notion of price impact. There are other measures of illiquidity, such as bid-ask spreads or the price-impact measures used in Brennan and Subrahmanyam (1996) and Sadka (2006), that require intraday data.[7] We choose the Amihud measure because it can be computed using daily data and, therefore, allows us to study a much longer time period.[8] Nevertheless, recent studies (see, e.g., Hasbrouck (2005) and Korajczyk and Sadka (2007)) find that many measures of liquidity, especially the Amihud measure, are highly correlated and driven by a common systematic component.

Due to the nonstationary nature of the time series of Amihud's measure, we use the change in Amihud's measure (in logs) as our daily liquidity measure. Specifically, for each firm i and day d, we define $\Delta ILLIQ_{i,d}$, the change in the firm's illiquidity, as

$$\Delta ILLIQ_{i,d} \equiv \log \left[\frac{|r_{i,d}|}{dvol_{i,d}} / \frac{|r_{i,d-1}|}{dvol_{i,d-1}} \right]. \tag{1}$$

In addition, following Chordia, Roll, and Subrahmanyam (2000) and Amihud (2002), we apply the following data filters. First, $\Delta ILLIQ_{i,d}$ is defined only for positive values of $dvol_{i,d}$ and $dvol_{i,d-1}$, and non-missing non-zero values of $r_{i,d}$ and $r_{i,d-1}$. Second, for a daily observation to be included in our sample, the stock's price at the end of the previous trading day has to be at least \$2. Third, we discard firm-days outliers with $\Delta ILLIQ_{i,d}$ in the lowest and highest 1% percentiles of the sample remaining after applying the first two filters. Finally, we retain a stock in a given year only if the stock has at least 100 valid observations after applying the previous filters. There are 73,933 firm-year observations. The number of

[7] Note that measures based on the bid-ask spread typically represent the cost of executing an average-size transaction, which involves a small number of shares, and is less appropriate for large-size transactions.

[8] Acharya and Pedersen (2005), for example, use the Amihud (2002) measure of firm's stock illiquidity to test and estimate their liquidity-adjusted CAPM.

firms in each year over our sample period ranges from 1,267 to 2,154.

2.1 The Evolution of Market Liquidity Variation

Since our study focuses on systematic liquidity, we begin our empirical analysis with an investigation of the time series of the market's change in liquidity. We define the market's change in illiquidity, $\Delta ILLIQ_{m,d}$, as the daily cross-sectional, value-weighted, average of $\Delta ILLIQ_{i,d}$ (value weights are calculated as market capitalizations as of the previous trading day). This is similar to the definition in Chordia, Roll, and Subrahmanyam (2000).

Figure 1(a) plots the time series of $\Delta ILLIQ_{m,d}$. The graph clearly shows there is no particular time trend in the market's change in liquidity. This is particularly noteworthy because it helps to alleviate any concern that our subsequent results about time-series trends in systematic liquidity may be a direct result of a time trend in our measure of change in liquidity. Therefore, although it is well known that market liquidity has substantially improved over our sample period, the rate of change in market liquidity remains stationary.

The graph also reveals occasional spikes in illiquidity that seem to correspond to recognizable events. For example, three of the biggest declines in liquidity have occurred in October 1989, October 1997, and July 2002. The first two events were accompanied by market-wide trading halts. Consistent with our thesis, in two of these cases, an event in one large-cap firm triggered trading and large price swings in other large firms. For example, on Friday, October 13, 1989, the Dow Jones Industrial Average lost about 7% in late selling. "Most of the loss occurred in the last hour of trading, following news reports that the pending takeover of UAL Corp., parent of United Airlines, was in jeopardy because of financing problems. Chaos reigned on the floor of the New York Stock Exchange, as trading in stock after stock had to be halted due to a shortage of buyers." (David A. Vise, "Stock Market Takes Steepest Dive Since '87," *The Washington Post*, October 14, 1989.) The October 1997 spike represents another market-wide plunge and trading halts. Following a more than 500-point drop in the Dow Jones Industrial Average on October 27, 1997, which was caused by the economic crisis in Asia, officials at the Exchange for the first time invoked the "circuit breaker" rule to stop trading. Lastly, the spike during July 2002 appears related to the large market-wide price fluctuations upon the collapse of WorldCom, which formally filed for bankruptcy on July 22, 2002.

In subsequent sections we examine the time series of the sensitivities (betas) of individual firms' changes in liquidity to the market's change in liquidity. We document that the cross-sectional dispersion of these betas has increased over time. One concern is that this may be a reflection of a decline in the volatility of $\Delta ILLIQ_{m,d}$ rather than an increase in the dispersion of the covariances of individual firms liquidity with market liquidity. To further investigate this issue, we calculate the standard deviation of $\Delta ILLIQ_{m,d}$ in each year and present the results in Figure 1(b). The plot suggests that the volatility of the market's change in liquidity has generally increased over the sample period, especially since 2000. We conclude that the volatility of the market's change in liquidity has certainly not declined over time. The plot, thus, eliminates any concern that a time trend in market volatility explains our cross-section findings below, because an increase in market volatility would generate a cross-sectional convergence of liquidity betas, which is contrary to our findings below.

2.2 The Evolution of Systematic Liquidity

In this section, we employ a market model of liquidity to formally examine the time series of the commonality of liquidity, and in particular, to investigate the evolution of the systematic liquidity of the firms in the smallest and largest size quintiles (Quintiles 1 and 5), respectively. We henceforth use "small" and "large" to refer to the firms in the smallest and largest size quintiles.

Following Chordia, Roll, and Subrahmanyam (2000), each year, we run the following time-series regression for each firm i:

$$\Delta ILLIQ_{i,d} = a + \beta_i \Delta ILLIQ_{m,d} + \varepsilon_{i,d}, \tag{2}$$

where β_i measures the sensitivity of changes in firm i's liquidity to changes in aggregate liquidity. We henceforth refer to β_i as liquidity beta.[9] It is important to note that we exclude the firm from the market portfolio when we calculate its liquidity beta. After obtaining the estimate of the liquidity beta per firm per year, we calculate equal-weighted averages of liquidity beta for all the firms in each size quintile, and for the entire market.

Table 1 reports the cross-sectional average liquidity beta every year during the sample period, as well as the fraction of firms with a positive beta and also a statistically positive significant beta. Similar diagnostics are reported for the small and large firms. Studying the commonality in liquidity in the year 1992, Chordia, Roll, and Subrahmanyam (2000) find that large firms are more sensitive than small firms to market-wide liquidity variations. We find that this is true for almost the entire period of 1963-2005. The last column of the table reports the p-values for the null hypothesis that the liquidity beta of large firms is not bigger than that of small firms, and the null hypothesis is rejected in almost every year (except for year 1967), with p-values less than 0.05. More interestingly for our purposes, two different time trends emerge when we separate the firms in the small and large size quintiles. In general, the betas have decreased for small firms and increased for large firms. Therefore, the differences in betas between large and small firms have also increased. To see the trends more clearly, we plot the two time series of the betas, as well as their difference, in Figure 2. The results suggest that small-cap firms have become less sensitive to market-wide liquidity variations, and large-cap firms have become more sensitive to market-wide liquidity variations.

The results reported above use a value-weighted market portfolio, and each firm is excluded from the market portfolio when calculating its liquidity beta. It is important to note that in Section 6 we show that the results are robust to the definition of the market portfolio and to the calculation of liquidity beta.

[9]Our notion of liquidity beta as the sensitivity of stock liquidity to market liquidity is based on Chordia, Roll, and Subrahmanyam (2000), and it differs from the notion of liquidity beta as the sensitivity of stock returns to market liquidity, as in Pástor and Stambaugh (2003). It is important to note that the reason for using a market model of liquidity stems from our hypothesis that increases in correlated trading activity over time are the underline of the patterns of liquidity commonality. Using a market model of liquidity to estimate liquidity betas provides a simple way of gauging liquidity commonality and it also allows us to investigate the effects in the cross-section of firms. In contrast, Pástor and Stambaugh (2003) are interested in testing whether changes in market liquidity are a priced systematic risk factor, which is not the goal of this paper.

To formally test whether the time series of betas exhibit any time trend, we first test the possibility of a stochastic time trend in the time series by conducting the Dickey and Fuller (1981) unit-root test with a time trend and a drift. Formally, for each size quintile, as well as for the difference between Quintiles 1 and 5, we run the following regression:

$$\beta_t = a + \delta t + \gamma \beta_{t-1} + \epsilon_t. \tag{3}$$

The null hypothesis is that there is a unit-root, i.e., $\gamma = 1$. Panel A of Table 2 reports the test results for all the size quintiles. The hypothesis of a unit root is rejected at conventional levels for the size quintiles of interest (Quintiles 1 and 5), and Quintiles 2 and 4, while for firms in Quintile 3, we cannot reject a stochastic time trend. Furthermore, the hypothesis of a unit root is rejected at conventional levels for the time series of the differences between the liquidity betas of the large and small size quintiles.

Following our rejections of stochastic time trends for the small and large size quintiles, we test the existence of a deterministic time trend in the time series of average betas. Panel B of Table 2 reports the results for all the size quintiles. The time series of average β of Quintile 1 has a statistically significant negative time trend (with a p-value of 0.005). In contrast, the corresponding time series of Quintile 5 has a statistically significant positive time trend (with a p-value of less than 0.001). The time series of average β of the second largest size quintile (Quintile 4) also has a statistically significant positive time trend (with a p-value of 0.002). In addition, the time trends of average β increase monotonically across the size quintiles, from -3.668 for the smallest quintile to 9.406 for the largest quintile. Lastly, the time trend for large minus small is also significantly positive.

It is imperative to remember that "small" and "large" in our paper refer to stocks in the smallest and largest quintiles. Small stocks are not the complementary set of large stocks; there are three more quintiles in the sample. Consequently, the positive time trend of the beta of large firms does not mechanically induce a negative time trend for small firms. Since we examine five size portfolios, we could have, for example, found a U-shape relation between the time trend of beta and size. The monotonic relation between the time trend of beta and size is therefore an additional independent finding.

Additionally, we investigate the divergence of liquidity commonality conditional on extreme declines in market liquidity. Figure 3 plots the difference of liquidity beta between large and small stocks where the liquidity beta is estimated using observations in days with extreme values of $\Delta ILLIQ_{m,d}$, i.e. days that correspond to extreme increase in market illiquidity. In Panel (a), extreme days are classified as days when $\Delta ILLIQ_{m,d}$ are in the top 5, 10, or 25 percentile of the entire sample period 1963 through 2005. To ensure sensible estimation of liquidity beta, years are divided into several non-overlapping bins of 5, 3, or 2 years, for the top 5, 10, or 25 percentiles, respectively. The market model of liquidity is estimated per firm per bin using values in extreme days. Only firms with at least 25 valid observations used for the estimation are included. In Panel (b), extreme values are defined as those in the top 5, 10, or 25 percentiles in every 3, 2, or 1 years, respectively. All panels exhibit an upward trend in the difference between the liquidity beta of large and small firms over the sample period.

Amihud, Mendelson, and Wood (1990) find that sudden unanticipated declines in liquidity have played a critical role in the stock market crash of October 1987. Our evidence in Figure 3 suggests that the vulnerability of US equity markets to unanticipated liquidity events has increased over 1963-2005. This is particularly troublesome because of the "flight to quality" from small-cap stocks to large-cap stocks in turbulent times, which Amihud, Mendelson, and Wood (1990) document for the October 1987 crash.

The opposite time trends in the systematic liquidity of the small and large size quintiles are consistent with the conjecture in Chordia, Roll, and Subrahmanyam (2000) that correlated trading of multiple stocks by institutions with similar investment styles is an important reason for commonality in liquidity. The opposite time trends also support the predictions of the model of Gorton and Pennacchi (1993) that security basket trading increases the commonality in liquidity for the constitute stocks in the basket, and reduces liquidity commonality for individually traded securities. Index-based trading and program trading have increased substantially over the sample period. Since they are much more prevalent in large-cap stocks than in small-cap stocks, they should lead to an increase in liquidity commonality for large firms and a reduction in liquidity commonality for small firms. The different patterns are also consistent with studies, such as Kamara (1997), Gompers and Metrick (2001), and Harford and Kaul (2005), who find that institutionalization and indexation have had different, and sometimes opposite, effects on the temporal behavior of large-cap and small-cap stock returns and their order flows. We now formally test the relation between the growth in institutional investing and systematic liquidity.

3 Systematic Liquidity and Institutional Ownership

In this section we test the relation between sensitivity to aggregate liquidity shocks (liquidity beta) and institutional ownership both in the cross-section of firms and over time. Regrettably, because the institutional ownership data start in 1981 we cannot examine the effects of the substantial growth in institutional ownership before 1981, which has resulted, for example, in the abolition in 1975 of the almost-monopolistic policies of the NYSE's regarding pricing and membership.

For the analysis, we use the total amount of institutional ownership, but we also investigate its decomposition into several types of institutions. Thomson Financial provides five classification codes: banks, insurance companies, investment companies, independent investment advisors, and others. Yet, it is important to note that the type codes have serious classification errors in recent years. Thomson Financial explains that a mapping error occurred when integrating data from another source, regrets that the problem occurred, but has no plans to fix the problem. For example, in the first quarter of 1999, the number of independent investment advisors drops from over 1200 to about 200, while the Other group jumps from roughly 100 to over 1300. Therefore, when we decompose the different types of institutional investors, we limit the sample to 1981 through 1998. To increase the power of our tests, we group banks with insurance companies, and investment companies with independent investment advisors. As our hypothesis links the divergence in liquidity beta to institutional ownership through correlated trading patterns and indexation, we expect that ownership by investment companies and independent investment advisors will explain the divergence.

To examine the cross-sectional relation between liquidity beta and institutional ownership, each year t, we estimate the following cross-sectional regression

$$\beta_{i,t} = a_t + \lambda_t \cdot IO_{i,t-1} + \nu_{i,t} \tag{4}$$

where $\beta_{i,t}$ is the liquidity beta for firm i in year t, $IO_{i,t-1}$ measures firm $i's$ market cap owned by institutions (either total or by type) as the percentage of total market capitalization at the end of year $t-1$. When we decompose institutional ownership into the three types, we use a multiple regression of liquidity beta on all three types. Because firm's institutional ownership and size are highly positively correlated, we also repeat the regressions above including firm size as an additional variable. This should alleviate any concerns that the institutional ownership coefficients may be capturing a pure size effect.

Table 3 Panel A reports the results of the time-series averages of the coefficients in the regressions and their t-statistics using the Fama and MacBeth (1973) methodology, with a Newey and West (1987) correction. Our results indicate that liquidity betas are significantly positively associated with the fraction of institutional ownership across all size quintiles. That is, an increase in the fraction of institutional ownership at the end of the previous year is associated with a greater sensitivity to market-wide liquidity shocks in the current year. Our findings support the hypothesis of Chordia, Roll, and Subrahmanyam (2000) that institutional investing is a significant reason for commonality in liquidity. We also find that the value of the coefficient on the fraction of institutional ownership decreases monotonically with size. The results continue to hold when we add the firm's market value at the end of the previous year as an additional explanatory variable. The coefficient on the firm's market value is significantly positive at conventional levels in the regressions of Quintiles 3 and 5, but not in any of the other regressions.

In Panel B of Table 3, we show that stock ownership by different institutional investors has a different impact on liquidity commonality. We segregate institutional investors into three groups: insurance companies and banks, investment companies and independent investment advisors, and other. We group insurance companies and banks together, and as a separate group, because they often seek business relations with the firms in which they invest through their trust departments (Brickley, Lease, and Smith (1988)). Consequently, they tend to be long-term investors with less frequent trading than investment companies and independent investment advisors, who typically do not seek such business relations with the firms in which they invest. Therefore, we expect insurance companies and banks to have a smaller impact on liquidity beta, and investment companies and independent investment advisors to have a larger impact on liquidity beta, as they tend to trade more often. The results in Panel B show that stock ownership by investment companies and investment advisors indeed has a significant impact on liquidity beta, even after controlling for size. Ownership by banks and insurance companies, however, does not impact liquidity beta during this period. Ownership by other institutions also affects liquidity beta, but their impact, after controlling for size, is only significant for Quintiles 3 and 4. These results are consistent with our hypothesis that liquidity commonality is partly driven by institutional trading and indexation.

We also examine whether the cross-sectional divergence of systematic liquidity over time is associated with the growth in institutional investing. Since we find above that liquidity betas are significantly positively associated with the fraction of institutional ownership across all size quintiles, a proper test should investigate the effects of institutional ownership on the difference between the liquidity commonality of large firms and the liquidity commonality of small firms, over time. Formally, we estimate the following regression:

$$\beta_{large,t} - \beta_{small,t} = a + \delta \cdot t + \gamma \cdot (IO_{large,t-1} - IO_{small,t-1}) + \varsigma \cdot (Size_{large,t-1} - Size_{small,t-1}) + \omega_t \quad (5)$$

where the subscripts “large” and “small” represent the average variable for the firms in size quintiles 5 and 1, respectively. The hypothesis that the divergence of systematic liquidity over time is associated with the growth in institutional investing predicts that γ is positive

Table 4 reports the results of annual regressions during 1981-2005. Because we have only 25 years of data when we use the total institutional ownership and 18 years of data when we use the different types of institutions, the regressions should be interpreted with caution. Nevertheless, the results are consistent with our predictions. The first regression, which includes only the time trend as an explanatory variable, confirms our findings above that there is a significant divergence in the liquidity betas of large and small firms over 1981-2005. The second regression adds the lagged difference in average institutional ownership of stocks in the large and small size quintiles. The coefficient of the difference in institutional ownership is positive and statistically significant. Moreover, the coefficient of the time trend is no longer significant at conventional levels. To address any concerns that the difference in institutional ownership variable above may capture a size effect rather than an institutional ownership effect, we repeat the second regression while including the difference in market values (in logs) of large and small stocks measured at the end of year $t-1$, as an additional variable. The coefficient on the size variable is insignificant and all the results of the second regression remain the same. In particular, the coefficient of the difference in institutional ownership variable remains significantly positive with a t-statistic of 2.41.

The next sets of regressions in Table 4 report the results of the analyses of the different types of institutions. Our hypothesis that the divergence in liquidity beta is related to institutional ownership through correlated trading patterns and indexation, postulates that the coefficient on ownership by investment companies and independent investment will be positive. The tests show that only ownership by investment companies and independent investment advisors has a statistically significant coefficient and the effect is positive. It also eliminates the significance of the time trend. In addition, using investment companies and independent investment advisors as an explanatory variable produces the highest adjusted R-square values; even greater than using aggregate institutional ownership as an explanatory variable. Hence, the results in Table 4 strengthen the support for the hypothesis that the cross-sectional divergence of systematic liquidity is associated with the growth in institutional investing and indexation.

Another test that supports an indexation explanation for liquidity commonality divergence is shown in Figure 4. This figure plots the time series of the average liquidity beta of stocks in our sample that are included in the S&P500 index and stocks that are not included in the index. The figure shows that the commonality of S&P500 stocks has significantly increased over the sample period relative to the commonality of non-S&P500 stocks.

Therefore, though we do not have data that will allow us to directly test the effects of basket trading and indexation, given the dominant role of investment companies and investment advisors in trading baskets of securities and indexation activity, and the divergence of commonality between S&P500 versus non-S&P500 stocks, our evidence thus far also supports the hypothesis of Gorton and Pennacchi (1993) that security-basket trading increases the commonality in liquidity for the constitute stocks but decreases the commonality in liquidity for the non-constitute stocks.

4 Systematic Liquidity and Systematic Risk

In the previous sections we study temporal patterns in systematic liquidity, and find that they can be explained by the growth in institutional ownership. In this section, we investigate the relation between temporal patterns in the systematic liquidity and systematic risk of asset returns. We begin our analysis by investigating possible reasons for an association between the liquidity betas and return betas (systematic risk). We continue by investigating the temporal patterns in the betas of firm returns and documenting a positive relation between firms' liquidity betas and return betas.

4.1 Common Aggregate Determinants of Liquidity Beta and Return Beta

One of the fundamental insights from the market microstructure literature is that trading activity and order flows affect prices. But, this does not imply that trading activity affects the systematic risk of firms' returns. It depends on whether the factor causing the trading activity and its price impact is firm-specific or market-wide. A growing body of literature suggests that market volatility, market return, and market liquidity can affect both liquidity beta and return beta by producing correlated trading patterns of investors and affecting the supply of liquidity by market makers across many stocks.

First, changes in market volatility can cause changes in inventories and create institutional trading that are correlated across many stocks, therefore, they are likely to affect systematic liquidity. Market volatility is a common determinant of the risk to market makers of maintaining inventories of their securities (Chordia, Roll, and Subrahmanyam (2000)). In addition, as shown in Coughenour and Saad (2004), the fact that each NYSE specialist firm provides liquidity for many stocks creates commonality in the supply of liquidity. Hence, changes in market volatility are likely to affect the optimal levels of inventories that specialists maintain to accommodate trading, across many stocks. Changes in volatility often also cause correlated trading by institutions. For example, Vayanos (2004) advances that a greater market volatility increases the likelihood that fund managers will perform below their threshold and are consequently forced to liquidate their positions in many securities. Correlated trading by institutions is therefore likely to affect the demand for liquidity, as well as exert pressures on market makers' inventories, across many stocks.

Because trading activity affects stock prices, then the correlated trading due to the change in market volatility will increase the comovement of stock returns. Changes in market volatility can therefore affect systematic risks of asset returns. In addition, Vayanos (2004) argues that investors' risk aversion is positively related to the volatility of the stock market. He advances that this introduces a new source of commonality in asset returns and increases the correlations between assets returns.

Second, recent studies (e.g., Kyle and Xiong (2001), Vayanos (2004), and Brunnermeier and Pedersen (2007)) have developed models advancing that market return can affect systematic liquidity and systematic return. In Vayanos (2004), market declines increase the likelihood that the performance of fund managers falls below an exogenously determined target. This causes investors to withdraw their investments in mutual funds and forces fund mangers to liquidate their positions in many stocks, therefore increasing both liquidity commonality and return commonality. Brunnermeier and Pedersen (2007) advance that market return affects funding constraints faced by both fund managers and market makers, and therefore affects the demand of, and supply for, liquidity across securities, leading to commonality in liquidity. In Kyle and Xiong (2001), negative economy-wide shocks cause wealth effects, which force traders to liquidate their assets in a manner that increases correlations in asset returns.

Moreover, these models predict asymmetric effects of market return on systematic liquidity and systematic return, since fund managers and market makers are more likely to be capital constrained when prices fall. Ang and Chen (2002) and Hameed, Kang, and Viswanathan (2006) find evidence supporting the asymmetric effect predicted by these models. Ang and Chen (2002) find that correlations between US stocks and the aggregate US market are much greater for downside market moves than for upside market moves. Hameed, Kang, and Viswanathan (2006) find that liquidity commonality increases following relatively large negative market returns.

These studies also suggest that market illiquidity has an indirect impact on liquidity betas and return betas. In these models, market volatility and market return typically affect liquidity betas and return betas by affecting the trading patterns of investors and the supply of liquidity by market makers. That is, they affect liquidity betas and return betas through affecting the market's illiquidity.

To summarize, studies discussed above suggest that liquidity betas and return betas of individual firms have common aggregate determinants, including market volatility, market return, and market illiquidity. We next adopt a methodology in the spirit of vector autoregressions to empirically examine the effects of these aggregate variables on liquidity betas and return betas of individual firms. Formally, we estimate the following system of equations for each firm i in year t:

$$\Delta ILLIQ_{i,d} = a_1 + \beta_1 \cdot \Delta ILLIQ_{m,d} + \left(s_1 \cdot \sigma_{m,d-1} + r_1 \cdot Ret_{m,d-1} + q_1 \cdot \Delta ILLIQ_{m,d-1}\right) \times \Delta ILLIQ_{m,d} + v_{1,i,d} \quad (6)$$

$$Ret_{i,d} = a_2 + \beta_2 \cdot Ret_{m,d} + \left(s_2 \cdot \sigma_{m,d-1} + r_2 \cdot Ret_{m,d-1} + q_2 \cdot \Delta ILLIQ_{m,d-1}\right) \times Ret_{m,d} + v_{2,i,d} \quad (7)$$

where d denotes days, and m denotes value-weighted market variables. Each of the two equations includes the respective market variable ($\Delta ILLIQ_{m,d}$ and $Ret_{m,d}$) and the product of that market variable with lagged market volatility ($\sigma_{m,d-1}$), lagged market return ($Ret_{m,d-1}$), and lagged market illiquidity ($\Delta ILLIQ_{m,d-1}$). The studies above suggest that market volatility affects positively both liquidity betas and return betas. This implies that coefficients (s_1 and s_2) of the products of the market variables with lagged market volatility should be positive. The studies above also suggest that market return affects both liquidity betas and return betas, and in particular, market declines lead to increases in both liquidity betas and return betas, therefore implying negative signs for both coefficients r_1 and r_2. We also include lagged market illiquidity in the analysis because the models above suggest that one channel for market volatility and return to affect liquidity betas and return betas is by impacting the market liquidity. We expect coefficients q_1 and q_2 to have positive signs.

The daily market volatility shock, $\sigma_{m,d}$, is obtained following Schwert (1990). First, $ret_{m,d}$ is regressed on an intercept, four weekday dummies, and its 22 lags. The residual is $u_{m,d}$. Next, $|u_{m,d}|$ is regressed on an intercept and its own 22 lags and the residual is $\sigma_{m,d}$. The systems of equations are estimated for each firm i and year t. The estimated coefficients are then averaged across firms and years, and the t-statistics of the coefficients are calculated using clustered (by firm) standard errors. Before we continue, it is important to emphasize that our results below are not a manifest of our measure of illiquidity: the daily average of the cross-sectional correlation of Ret and $\Delta ILLIQ$ (across 25 size portfolios) is -0.03.

Table 5 reports the results. The first group of tests examines each effect separately. It shows that both liquidity betas and return betas change depending on what happened to lagged market illiquidity, lagged market returns, and lagged market volatility. The first pair of equations shows that the coefficients on the interactions of both, market illiquidity and market return, with market volatility are both significantly positive. Hence, an increase in market volatility is followed by statistically significant increases in both liquidity betas and return betas, which is consistent with the studies above, and in particular, Vayanos (2004).

The second and third pairs of equations examine the effects of lagged market returns. The second pair show that increases in market returns are followed by statistically significant increases in liquidity betas and statistically significant declines in return betas. The theories above predict, however, that the effect of market return should be asymmetric, and in particular, that both liquidity betas and return betas should increase with market declines. The third pair of equations looks separately at market declines and rises. Consistent with the theories above, the coefficients on the interactions of both, market illiquidity and market return, with market declines are both negative. Because the values of this explanatory variable are negative, a negative coefficient implies that greater lagged market declines are followed by greater increases in liquidity betas and return betas. The regressions also show that return betas do not change significantly following positive market returns, but liquidity betas increase significantly following positive market returns. Our finding that liquidity betas are also affected by positive lagged market returns lends further support to Chordia, Roll, and Subrahmanyam (2002). They find that investors are contrarian, on aggregate: Buying activity is more pronounced following market declines, and selling activity is more pronounced following market rises. Both positive and negative lagged market returns thus lead to aggregate order imbalances. They further find that order imbalances affect the inventories of market makers and the liquidity not just of individual securities, but of the aggregate market as well. We find that both larger market declines and larger market rises are followed by higher liquidity betas.

The fourth pair of equations shows that an increase in lagged market illiquidity is followed by statistically significant increases in both liquidity betas and return betas. Since greater market illiquidity increases the cost of holding inventories to market makers and the risk of delayed liquidation to fund managers, the positive effects on liquidity betas and return betas are consistent with the theories above.

The fifth and sixth pairs of equations include all three conditioning variables together. The results regarding lagged market returns continue to hold. The effect of lagged market illiquidity on liquidity betas remains positive, but its effect on return betas becomes significantly negative. That is, after controlling for the effects of lagged market returns and lagged market volatility, increases in market illiquidity are followed by declines in return betas.

The effects of lagged market volatility depends on whether or not we include positive and negative lagged market returns as separate explanatory variables. When we do not separate the effects of positive and negative market returns, lagged market volatility continues to have a significantly positive effect on both liquidity betas and return betas. But, when we allow for positive and negative lagged market returns to have different effects, the effect of lagged market volatility on liquidity betas becomes significantly negative, and its effect on return betas becomes statistically insignificant.

The reversing of signs when the regressions include all three effects may, at least partially, reflect multicollinearity. French, Schwert, and Stambaugh (1987) document a significant negative relation between returns and volatility.[10] In addition, splitting the market return variable into positive and negative returns also induces collinearity since both large positive and negative returns are likely to be associated with greater volatility. Indeed, in our sample, the correlation coefficient between market volatility and market return is -0.08, whereas the correlations of market volatility with positive and negative market returns are 0.89 and -0.91, respectively. There is also evidence (see Chordia, Roll, and Subrahmanyam (2002), Hameed, Kang, and Viswanathan (2006), and Henderson, Moulton, and Seaholes (2006)) that negative market returns and higher market volatility also tend to be associated with greater market illiquidity. This is because inventory holding costs, which arise from risk and financing constraints, appear to be particularly high in down markets. In our sample, the correlation coefficient between market illiquidity and market volatility is 0.45, and the correlations of market illiquidity with positive and negative market returns are 0.34 and -0.43, respectively. Lastly, for each pair of equations, we also calculate the average correlations of residuals of the two equations. They range between -0.0125 and -0.0134 and are all statistically significant, which suggests that there are other factors, beyond those suggested by the studies above, that simultaneously affect a firm's liquidity innovation and return.

To summarize, in this section we point out aggregate factors that can create a linkage between liquidity commonality and return commonality. We also find clear evidence that negative lagged market returns increase both liquidity betas and return betas.

4.2 Divergence of Liquidity Beta and Return Beta

The previous subsection advocates a possible correlation between liquidity beta and return beta as both have common aggregate determinants. Therefore, we conjecture that the divergence in liquidity commonality across large and small firms would transcribe to a similar

[10] They suggest that it reflects mainly two factors (see also Bekaert and Wu (2000) for summary or recent evidence): First, many firms are levered. A decline in equity value relative to debt value increases leverage, and increases the variance of the stocks' return. Second, a positive relation between the market's risk and expected return implies that increases in market volatility are associated with declines in stock prices.

divergence in return commonality. In what follows, we show that return beta exhibits a similar divergence. We use regression analysis to show that the divergences of liquidity beta and return beta are positively correlated over and beyond their common time trend.

For this analysis, we estimate the beta of firm returns, each year, similar to our estimation of firm's liquidity beta in Regression (2), but replacing log of daily change in firm liquidity with daily firm return and log of daily change in market liquidity with daily (value-weighted) market return (excluding own stock). Similar to our systematic liquidity analysis, we calculate the average return beta for five size quintiles. Table 6 Panel A presents the time-trend tests. There are two notable findings. First, the return betas of all size quintiles, except for Quintile 5, have declined over time, and, in particular, the coefficients for the time trend are significantly negative for Quintiles 1 and 2. These findings are consistent with the finding of Campbell, Lettau, Malkiel, and Xu (2001) that the idiosyncratic risk of the typical stock in the US market has increased over time. Second, the systematic return beta of Quintile 5 has increased and the trend is positively significant. That is, there is a divergence in return betas between large and small stocks. In addition, the time trend is the most negative for the small firms and increases monotonically with size.

To assess the relation between systematic liquidity and systematic risk, we run the following regressions:

$$\beta_{ret,t} = a_b + \delta_b t + \theta_b \beta_{liq,t} + e_{b,t}. \tag{8}$$

These regressions provide some insight as to whether the observed patterns in systematic risk are correlated with the patterns in systematic liquidity. Since the time series of liquidity beta and return beta both exhibit a significant time trend, the regressions also include a deterministic time trend which enables us to test whether the correlation between the two time series is over and beyond their common time trend.

Table 6 Panel B presents the results. The coefficients of liquidity beta across all size quintiles are always positive and statistically significant (the lowest t-statistic is 4.16). Since the regressions above include liquidity betas as independent variables, they suffer from an errors-in-variable problem. Yet, in our specific case of a multiple regression (the independent variables are the time trend and beta) where only a single variable (liquidity beta) is measured with error, the coefficient on this error prone variable is biased toward zero (see Greene (2003), Pages 85-86). Consequently, although there is no standard way of fixing the problem, the error-in-variable problem works against finding a positive coefficient for liquidity beta, which we find in all the regressions. It should be noted, however, that the coefficients for the time trend are also biased, and in unknown directions. A comparison of the two panels of Table 6 reveals that the inclusion of systematic liquidity in the regressions reverses the sign of the time trend for large firms from positive to negative. Yet, the difference between large and small continues to have a positive and significant time trend, although the coefficient is reduced by almost one-half. By comparing the regression R^2 of the two panels of Table 6 one can also calculate the marginal increase in R^2 of each regression from the addition of the corresponding systematic liquidity variable to the regression with the time trend only (i.e., the difference in estimating the regression with and without the systematic liquidity variable). The marginal variation in return beta explained by variation in liquidity beta is 7% for the small quintile and 26% for the large quintile. These results suggest that there are positive correlations between the time patterns in systematic risk and the time patterns in systematic liquidity over and above the general time trend, especially for large firms.

It is important to emphasize that a positive association between time patterns in systematic risk and time patterns in systematic liquidity does not suggest a causal relation, i.e., liquidity beta affects return beta or vice versa. Moreover, the frequency in which betas are estimated may also be important. For example, return betas calculated using quarterly or annual data are more likely to reflect a firm's fundamental risk, such as the sensitivity of its stock returns to business cycles. This is less likely to show up in our return betas, which are estimated using daily stock information. We therefore expect that the association between liquidity betas and return betas in the longer frequencies will be weaker. If a positive relation between liquidity beta and return beta exists in longer frequencies, it would suggest that microstructure considerations have a long lasting effect or that liquidity betas are influenced by return betas, or both. Although these are interesting questions, they cannot be satisfactorily answered with the framework of our paper.

5 Implications for the Diversification of Systematic Risk and Systematic Liquidity

Our findings about the divergence of liquidity betas and return betas have implications for the ability to diversify both liquidity volatility and return volatility. In this section we study the degree to which the benefits of diversification of return volatility and liquidity volatility have changed over time for different size portfolios.

Our empirical methodology follows Campbell, Lettau, Malkiel, and Xu (2001), and we employ it for both liquidity volatility and return volatility. For each of the large and small quintiles, we construct, each year, equally weighted portfolios containing different numbers (5 through 50) of randomly selected stocks (without replication). Using daily data we then calculate the annual excess liquidity (or return) volatility of each portfolio relative to the market, which we define as the difference between the standard deviation of liquidity (or return) of the portfolio and the standard deviation of liquidity (or return) of a value-weighted portfolio of all the stocks in the sample. (We continue to measure the liquidity of each stock by $\Delta ILLIQ_{i,d}$.) To examine changes over time, we divide our sample into two halves: 1963-1984 and 1985-2005. For each subperiod we calculate the average annual excess volatility of each of the portfolios.

Panel (a) of Figure 5 shows the average annual excess liquidity volatilities of portfolios with different numbers of stocks. Panel (b) of Figure 5 shows the average annual excess return volatilities of the portfolios. There are four curves in each panel: two representing portfolios constructed using only stocks in the large size quintile over the periods 1963-1984 and 1985-2005; and two representing portfolios constructed using only stocks in the small size quintile over the same periods. Each curve plots the annual excess volatility versus the number of stocks in the portfolio. Because the results regarding the ability to diversify aggregate return and liquidity shocks are similar, we will discuss them together.

In both panels the excess volatilities of portfolios with only a few stocks are lower for portfolios of large stocks than for portfolios of small stocks. This reflects the fact that small stocks have higher idiosyncratic volatilities than large stocks. However, as we add stocks to the portfolios, a clear difference emerges between the relative benefits of diversification in the first and the second subperiod. In 1963-1984, the excess return volatility of small stocks portfolios is always substantially higher than the excess return volatility of the corresponding portfolios of large stocks. In contrast, in 1985-2005, the excess return volatility of small-stock portfolios remains higher than the excess volatility of the corresponding portfolios of large stocks only until each portfolio has about 27 stocks. Then, as we add stocks, the excess volatility of small-stock portfolios clearly falls below the excess volatility of the corresponding large-stock portfolios. The excess liquidity volatility of small-stock portfolios in 1963-1984 is higher than the excess volatility of the corresponding large-stock portfolios until each portfolio has more than 35. When the portfolios have more than 40 stocks, the excess liquidity volatility of small-stock portfolios falls slightly below the excess volatility of the corresponding large-stock portfolios. In contrast, in 1985-2005, the excess liquidity volatility of small-stock portfolios remains higher than the excess volatility of the corresponding portfolios of large stocks only until each portfolio has about 20 stocks. Then, as we add stocks, the excess liquidity volatility of small-stock portfolios falls substantially below the excess liquidity volatility of the corresponding large-stock portfolios. Unlike the 1963-1984 subperiod, in 1985-2005 there is a clear advantage to diversify return and liquidity volatility using small quintile stocks rather than large quintile stocks. In 1985-2005 investors who used portfolios of at least 27 stocks to diversify return volatility and liquidity volatility achieved much lower excess volatility by using small stocks rather than large stocks.

The changes over time in the benefits of diversifications are also evident when we compare the excess volatility of the portfolios from the same size quintile in 1963-1984 and 1985-2005, respectively. As the curves demonstrate, the benefits from diversification using portfolios of small stocks have increased from 1963-1984 to 1985-2005. The curve describing the excess volatility in 1985-2005 lies below the curve describing 1963-1984: over the entire graph for excess return volatility, and when we hold portfolios of 10 stocks for excess liquidity volatility. In contrast, the curves that chart the excess volatility of large stocks portfolios in 1963-1984 and 1985-2005, suggest exactly the opposite pattern. The curve describing the excess volatility in 1985-2005 lies above the curve describing 1963-1984: over the entire graph for excess return volatility, and when we hold portfolios of 25 stocks for excess liquidity volatility. These curves demonstrate that the diversification benefits of portfolios of large stocks have declined from 1963-1984 to 1985-2005. Hence, the curves of small-stock portfolios and large-stock portfolios exhibit opposite changes over time. The diversification benefits of small-stock portfolios have increased over time, whereas, the diversification benefits of large-stock portfolios have declined over time.

6 Robustness tests

6.1 Different Measures of Market-Wide Liquidity

The liquidity commonality in this paper is based on beta coefficient generated by a market model for liquidity, where the market is a value-weighted average and each firm is excluded from the market portfolio when calculating its liquidity beta. It is important to note that our results are robust to the definition of the market portfolio and the calculation of liquidity beta. Specifically, we repeat the calculations in Figure 6, which shows the divergence of liquidity commonality between large and small firms, in four different ways: (1) using an equal-weighted market portfolio, (2) using an equal-weighted market portfolio and excluding each firm when calculating its liquidity beta, (3) using a value-weighted market portfolio (but without excluding each firm when calculating its liquidity beta), and (4) using an equal-weighted market portfolio with the Dimson (1979) correction to account for the effect of non-synchronous trading, which can be important when using an equal-weighted market portfolio. All the four panels in Figure 6 exhibit a clear time trend in the divergence of liquidity commonality.

6.2 Systematic Component Measured as R^2

So far we have estimated systematic liquidity as the beta generated by a market model. However, given the evidence in Campbell, Lettau, Malkiel, and Xu (2001) that idiosyncratic return volatility has increased significantly over the period 1962-1997, it is perhaps informative to also study the time trends of the R^2 generated by the market model of liquidity (i.e., Regression (2)) and their implications to possible trends in R^2 generated by a market model of returns.

Table 7 reports the results of this analysis. Panel A of the table shows that similar to our findings for liquidity betas, the liquidity R^2 are decreasing for small firms and increasing for large firms (each of the time trends is statistically significant with p-value of less than 0.01). In addition, the time trends in average R^2 increase monotonically across the size quintiles, and the time trend of liquidity R^2 for Quintile 5 minus Quintile 1 is also significantly positive.

The results for the trends in R^2 generated by the market model of returns are reported in Panel B of Table 7. The results are similar to those reported in Panel A. The time trend of small firms is significantly negative, whereas for large firms the time trend is positive and significant.

To study the relation between liquidity R^2 and return R^2 we run the following regressions (in analogy to Regression (8)):

$$R^2_{ret,t} = a_r + \delta_r t + \theta_r R^2_{liq,t} + e_{r,t}. \tag{9}$$

The results reported in Panel C of Table 7 indicate that the coefficient on liquidity R^2 is statistically positive for all size quintiles. Interestingly, the time trends shown in Panel B are no longer statistically significant (the time trend of large firms even reverses) once liquidity R^2 is added to the regressions. The t-statistic of the time trend of large-minus-small drops from 4.46 to 0.12. [11]

[11] Note that the errors-in-variable problem due to using liquidity R^2 as an independent variable biases the tests against finding a positive coefficient for liquidity R^2. Yet, we caution that the coefficients for the time trend may be biased in unknown directions.

Since the difference between 1 and the R^2 of the market model of returns can be interpreted as idiosyncratic risk, this section presents new results in relation to those presented in Campbell, Lettau, Malkiel, and Xu (2001): even though idiosyncratic risk has increased over the sample period for the average firm, the pattern differs across size groups. In particular, idiosyncratic risk has increased for small firms but has declined for large firms; the change in idiosyncratic risk has a monotonic negative relation with firm size; and the time trends in idiosyncratic liquidity in the cross-section of stocks explain a substantial fraction in the the time trends in idiosyncratic risk. These results provide further support that institutional trading and index/basket trading, which are both more prevalent in large stocks than in small stocks, create a significant linkage between systematic risk and systematic liquidity.

6.3 Robustness to Distribution of Firm Age and Size

Our analysis demonstrates different time trends of liquidity beta for different size groups over the period 1963-2005. Yet, one may argue that the cross-sectional distribution of firm size may have changed over the sample period, for example, a small firm in 1963 may not have similar characteristics to a small firm in 2005. Therefore, one interesting question concerning the interpretation of the results is whether our results about time trends of systematic liquidity are driven by changes in beta for the same firms or by changes in the universe of firms.

Unfortunately, this question is quite difficult to answer because a firm might change its assigned quintile either because the firm has changed in value or because the size distribution in the cross-section has changed. The size distribution can change (and thus the quintile break points) either because all firms shift in value in different ways or because firms enter/exit the sample.

To shed more light on this issue we provide three graphs in Figure 7. In Panel (a), we repeat the analysis for Figure 2, with the exception that the average liquidity beta for each quintile each year is calculated using only the firms that exist over the entire sample period; there are 292 such firms. Due to our data filters, some firms drop from the sample in some years, therefore the median number of firms in the cross-section each year is 246 (ranging from 221 to 262). Note that the size break points each year are kept at the same levels as in Figure 2, which are determined using the entire sample of NYSE/AMEX-listed firms. The results suggest that even if we only use firms that exist for the entire sample period, we still observe the divergence in liquidity beta of small versus large firms.

Another test is provided in Panel (b). In contrast to Panel (a), here we study the entire sample of firms, but rebalance the size quintiles once every ten years instead of every year. That is, we rebalance at the beginning of 1963, 1973, 1983, and 1993, using the market values at the end of the 1962, 1972, 1982, and 1992, respectively, of all the firms that exist on the rebalancing date. Therefore, the size quintiles remain fixed for periods of ten consecutive years, and although firms may drop due to delisting, we do not add new firms, except when we rebalance the portfolios. This way we control for the potential change in the cross-section of firm size (every ten years), but we note that a firm may change it's actual relative size ranking during the ten-year holding period although it is held fixed in it's original size quintile at the beginning of the period. The figure in Panel (b) shows the results in Figure 2 are robust to this kind of procedure. This suggests that the potential change of size distribution over time is not driving our results, but rather, firms' liquidity betas have changed over time.

Finally, we also examine the possibility that the divergence in liquidity betas could simply stem from newly listed firms, which may have lower commonality in the initial years of their trading. In Panel (c) only firms that have been publicly traded for at least three years (as of the beginning of the year in which their liquidity betas are calculated) are included in the calculation of the average liquidity beta of the size quintile. The divergence in liquidity commonality remains apparent, which alleviates the concern that the divergence is driven by new listings.

6.4 Industry Effects

Following Chordia, Roll, and Subrahmanyam (2000), we also test the robustness of our results above by repeating Regression (2) with both market and industry liquidity measures.

That is, we estimate the regression

$$\Delta ILLIQ_{i,d} = a + \beta_{i,m}\Delta ILLIQ_{m,d} + \beta_{i,ind}\Delta ILLIQ_{ind,d} + \varepsilon_{i,d}, \tag{10}$$

where $\Delta ILLIQ_{ind,d}$ is value-weighted average of $\Delta ILLIQ_{i,d}$ of the industry portfolio to which firm i belongs, and $\beta_{i,m}$ and $\beta_{i,ind}$ measure the sensitivity of a firm's liquidity to the market liquidity and industry liquidity. Similar to the previous method, note that when running the regression for firm i, the firm is excluded from its industry portfolio and the market portfolio. We use 20 industry portfolios, which are constructed using the Moskowitz and Grinblatt (1999) industry classification.

The results are presented in Table 8. The industry betas are low relative to the market betas, which suggests that liquidity commonality is mostly a market-wide effect, not industry specific. Nevertheless, it seems that both market and industry liquidity beta exhibit similar time series patterns: they decrease for small firms, while increase for large firms. Examining the time series of R^2, Table 8 shows that the average R^2 of small firms continues to experience a downward trend while that of large firms continues to exhibit an upward trend. Our conclusions, that small firms' liquidity has become less common and that large firms' liquidity has become more common, are unchanged by the inclusion of industry liquidity.

6.5 Additional Robustness Tests

We also test the robustness of our results by expanding the sample to the pre-1963 period. Though, for brevity, we do not report the results in additional tables, we discuss them below.

CRSP has recently extended its daily data for NYSE firms back to 1926. We repeat our tests for the entire period from 1946 (after the end of the second world war) through 2005. Our results continue to hold. In particular, the time series of average liquidity β of Quintile 1 has a statistically significant negative time trend of -4.893 (multiplied by 10^3) with a t-statistic of -6.45. In contrast, the corresponding time series of Quintile 5 has a statistically significant positive time trend of 3.679 (multiplied by 10^3) with a t-statistic of 3.19. In addition, the time trend for large-minus-small is positive with a t-statistic of 11.21.

The data suggest that the time trends begin around the late 1950s to early 1960s, which coincides with the emergence of institutional investing.

7 Conclusions

We study the evolution of liquidity commonality across common shares of US firms from 1963 through 2005. We find that the commonality in liquidity has increased significantly for large firms, but declined significantly for small firms. Many developments have affected the liquidity of US equity markets over the sample period of 1963-2005. Among them are the fundamental change in the composition of equity investors due to the substantial increase in institutional investing, and the introduction of, and considerable growth in, index-based financial products and basket trading strategies. Using data on institutional ownership of common stocks from January 1981 until December 2005, we find that increases in institutional ownership are associated with increases in the stock's sensitivity to systematic liquidity shocks. Institutional investing and index trading are much more prevalent in large stocks than in small stock. We also find that differences between the percentages of institutional ownership of large and small stocks can explain the differences in their liquidity betas. Our results therefore suggest that these changes in the structure of the equity market have caused an increase in the exposure of large stocks to common liquidity shocks, both in absolute terms and relative to the exposure of small stocks to common liquidity shocks.

We study the implications of the cross-sectional divergence of systematic liquidity for asset returns. We find that market volatility, market return, and market liquidity affect both firm systematic liquidity and firm systematic return. In particular, we find that negative lagged market returns increase both liquidity betas and return betas. This supports the predictions of recent models (Kyle and Xiong (2001), Vayanos (2004), and Brunnermeier and Pedersen (2007)) in which market declines reduce capital availability to fund managers and market makers, and forces them to liquidate their assets in a manner that increases both firms' liquidity betas and firms' return betas. We also find that time variations in systematic risk are significantly (positively) related to time variations in systematic liquidity, even after accounting for the time trends in systematic risk. This relation is significantly stronger for large firms than for small firms. Our results complement those of Campbell, Lettau, Malkiel, and Xu (2001) that documents an increasing trend in idiosyncratic return volatility over the period 1962-1997. We provide two additional insights. First, focusing on the cross-section of firms, we find that even though idiosyncratic risk has increased over the sample period for the typical firm, there is a monotonic negative size effect. In particular, idiosyncratic risk has increased for small firms but has declined for the large firms. Second, the patterns of systematic risk in the cross-section of stocks are highly related to systematic liquidity.

The cross-sectional divergence of systematic liquidity also has strategic implications for the ability to diversify systematic risk and aggregate illiquidity shocks. We find that the ability to diversify systematic risk and aggregate illiquidity shocks by holding relatively liquid, large, stocks has declined over the sample period of 1963-2005, both in absolute terms and relative to the diversification benefits of small stocks. This implies that benefits from the tendency of investor to flee to quality in turbulent times by holding relatively liquid, large-cap, stocks have declined over 1963-2005. Indeed, we find that liquidity sensitivity to extreme market illiquidity events across large and small firms has also diverged over time. Our evidence therefore suggests that the vulnerability of US equity markets to unanticipated events has increased over 1963-2005.

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Table 1: Summary of Systematic Liquidity

For each firm i in year t, we run the time-series regression, $\Delta ILLIQ_{i,d} = a + \beta_i \Delta ILLIQ_{m,d} + \epsilon_{i,d}$, where $\Delta ILLIQ_{i,d}$ is the first difference of the logarithm of daily Amihud (2002) measure of firm i in day d, and $\Delta ILLIQ_{m,d}$ is the value-weighted market average of $\Delta ILLIQ_{j,d}$ for all $j \neq i$. Each year t, firms are assigned into five size groups based on the market capitalization at the end of year $t-1$. The table reports the annual cross-sectional average of β_i of all stocks as well as stocks in the smallest and largest size quintiles. The last three columns present the difference between large and small stocks and the T-stat and P-value of the null hypothesis that $H_0 : \beta_{large} - \beta_{small} \leq 0$. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1963 through December 2005.

	All				Small				Large				Large Minus Small		
			%	%			%	%			%	%			
Year	Mean	T-stat	Pos	Sig	Mean	T-stat	Pos	Sig	Mean	T-stat	Pos	Sig	Mean	T-stat	P-value
1963	0.334	[27.76]	80	32	0.247	[9.19]	75	20	0.460	[16.69]	86	46	0.213	[5.52]	< .0001
1964	0.203	[15.07]	68	21	0.162	[5.03]	67	17	0.252	[8.31]	70	28	0.090	[2.04]	0.021
1965	0.483	[38.52]	85	40	0.409	[13.94]	81	29	0.502	[18.75]	86	43	0.092	[2.33]	< .0001
1966	0.461	[37.02]	81	45	0.309	[12.29]	74	33	0.589	[20.39]	87	58	0.280	[7.31]	< .0001
1967	0.534	[42.13]	83	37	0.474	[15.84]	80	34	0.488	[17.14]	80	37	0.015	[0.35]	0.362
1968	0.512	[49.37]	86	45	0.363	[15.81]	79	33	0.615	[27.71]	92	55	0.251	[7.87]	< .0001
1969	0.502	[47.72]	86	43	0.416	[17.98]	83	34	0.584	[24.36]	89	50	0.167	[5.02]	< .0001
1970	0.500	[51.86]	88	51	0.375	[18.31]	84	36	0.583	[28.53]	93	61	0.209	[7.21]	< .0001
1971	0.489	[49.96]	86	46	0.401	[19.08]	83	34	0.596	[28.03]	91	58	0.195	[6.52]	< .0001
1972	0.471	[42.13]	82	37	0.387	[14.90]	78	30	0.551	[23.98]	88	43	0.164	[4.74]	< .0001
1973	0.389	[42.37]	84	44	0.252	[14.26]	76	27	0.597	[28.08]	94	66	0.345	[12.48]	< .0001
1974	0.377	[38.68]	85	47	0.230	[12.70]	76	27	0.656	[27.74]	95	78	0.426	[14.31]	< .0001
1975	0.451	[44.34]	88	49	0.336	[16.03]	81	32	0.668	[27.99]	95	73	0.332	[10.47]	< .0001
1976	0.402	[39.26]	85	43	0.251	[11.81]	76	25	0.615	[26.76]	97	63	0.364	[11.64]	< .0001
1977	0.295	[23.88]	73	30	0.121	[4.63]	62	18	0.603	[21.45]	90	54	0.482	[12.56]	< .0001
1978	0.443	[46.78]	88	48	0.281	[15.11]	79	31	0.673	[28.66]	94	70	0.392	[13.09]	< .0001
1979	0.443	[38.35]	83	43	0.289	[11.16]	72	31	0.697	[25.57]	93	61	0.408	[10.87]	< .0001
1980	0.472	[47.36]	88	50	0.279	[15.50]	81	29	0.742	[31.90]	97	75	0.463	[15.75]	< .0001
1981	0.436	[37.20]	82	39	0.270	[11.19]	72	23	0.754	[28.91]	94	68	0.484	[13.61]	< .0001
1982	0.497	[50.96]	91	55	0.298	[16.87]	82	34	0.803	[36.27]	99	85	0.506	[17.86]	< .0001
1983	0.367	[32.53]	77	33	0.238	[10.55]	71	20	0.681	[26.83]	92	60	0.443	[13.04]	< .0001
1984	0.481	[39.56]	84	44	0.254	[9.74]	70	27	0.769	[29.39]	95	73	0.515	[13.93]	< .0001
1985	0.447	[37.19]	84	36	0.267	[10.85]	73	17	0.718	[27.66]	95	64	0.451	[12.60]	< .0001
1986	0.416	[37.02]	83	44	0.181	[8.44]	71	20	0.842	[35.95]	97	83	0.661	[20.83]	< .0001
1987	0.446	[49.53]	90	56	0.248	[14.58]	80	33	0.844	[45.17]	99	93	0.597	[23.61]	< .0001
1988	0.456	[42.60]	88	54	0.229	[11.59]	77	27	0.895	[45.90]	100	95	0.666	[24.00]	< .0001
1989	0.478	[40.77]	86	53	0.220	[9.76]	73	23	0.891	[45.04]	100	93	0.672	[22.41]	< .0001
1990	0.446	[40.42]	88	51	0.264	[12.33]	76	25	0.841	[39.08]	100	92	0.577	[19.02]	< .0001
1991	0.420	[36.56]	83	46	0.204	[8.86]	70	21	0.797	[34.26]	97	85	0.593	[18.14]	< .0001
1992	0.467	[36.27]	82	39	0.302	[9.81]	70	24	0.756	[28.75]	95	70	0.454	[11.23]	< .0001
1993	0.482	[36.12]	82	40	0.240	[7.88]	69	19	0.800	[32.09]	96	70	0.559	[14.21]	< .0001
1994	0.525	[45.17]	86	47	0.340	[11.88]	73	29	0.819	[40.29]	99	81	0.479	[13.65]	< .0001
1995	0.524	[44.69]	86	43	0.383	[13.76]	75	27	0.799	[35.86]	97	72	0.416	[11.66]	< .0001
1996	0.522	[53.49]	90	57	0.300	[14.13]	81	31	0.872	[45.30]	99	91	0.572	[19.95]	< .0001
1997	0.457	[52.76]	89	53	0.190	[11.32]	72	21	0.851	[45.17]	99	91	0.661	[26.24]	< .0001
1998	0.463	[47.34]	86	44	0.221	[10.55]	72	21	0.842	[38.28]	98	78	0.621	[20.45]	< .0001
1999	0.339	[31.43]	76	32	0.148	[5.46]	61	22	0.646	[26.09]	93	59	0.498	[13.59]	< .0001
2000	0.470	[42.22]	85	42	0.248	[9.47]	69	21	0.738	[32.56]	96	68	0.490	[14.14]	< .0001
2001	0.545	[47.91]	88	54	0.241	[9.91]	71	26	0.791	[30.01]	96	73	0.551	[15.36]	< .0001
2002	0.524	[53.63]	92	67	0.143	[8.37]	69	24	0.858	[39.09]	100	92	0.715	[25.70]	< .0001
2003	0.552	[53.82]	92	69	0.163	[9.68]	72	25	0.924	[41.30]	99	95	0.760	[27.13]	< .0001
2004	0.606	[55.72]	90	67	0.148	[7.88]	67	19	0.852	[36.76]	98	85	0.704	[23.62]	< .0001
2005	0.592	[51.78]	89	63	0.136	[6.30]	65	20	0.844	[37.49]	99	86	0.708	[22.69]	< .0001

Table 2: Time-Trend Tests

Panel A of the table presents the results of Dickey-Fuller (1981) unit-root tests for average liquidity betas of firms in each of the five size quintiles. Formally, we regress each time series on its first lag, a drift, and a time trend, i.e., $\beta_t = a + \delta t + \gamma\beta_{t-1} + \epsilon_t$. The table presents the estimate of γ, test statistic $T(\gamma - 1)$, where T = 42, and the p-value for the null hypothesis $\gamma = 1$. Panel B of the table presents the deterministic time-trend test results for average liquidity betas of firms in each of the five size quintiles. Formally, we regress the beta series on a constant and a time trend, i.e., $\beta_t = a + \delta t + \epsilon_t$. The table reports the coefficient estimate of the time-trend, its t-statistic, and the corresponding p-value. The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) standard errors. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1963 through December 2005.

Panel A : Stochastic Time Trend: $\beta_t = a + \delta t + \gamma\beta_{t-1} + \epsilon_t$

Firms	γ		
	Estimate	$T(\gamma - 1)$	P-value
1 (small)	0.275	-30.43	0.001
2	0.513	-20.46	0.033
3	0.622	-15.87	0.109
4	0.362	-26.81	0.005
5 (large)	0.470	-22.27	0.020
5 minus 1	0.404	-25.04	0.009

Panel B: Deterministic Time Trend: $\beta_t = a + \delta t + \epsilon_t$

Firms	a			$\delta(\times 10^3)$		
	Estimate	T-statistic	P-value	Estimate	T-statistic	P-value
1 (small)	0.347	10.32	$< .001$	-3.668	-2.99	0.005
2	0.367	7.46	$< .001$	0.084	0.04	0.968
3	0.362	6.20	$< .001$	3.168	1.25	0.217
4	0.410	10.56	$< .001$	4.957	3.26	0.002
5 (large)	0.507	15.02	$< .001$	9.406	6.66	$< .001$
5 minus 1	0.160	4.88	$< .001$	13.07	9.53	$< .001$

Table 3: Systematic Liquidity and Institutional Ownership in the Cross-Section

This table presents the results of Fama and MacBeth (1973) regressions of annual liquidity beta on institutional ownership and size. Institutional ownership is a firm's market value owned by institutions as the percentage of capitalization of the entire market. Size is the logarithm of firm's market capitalization (in millions). Both variables are measured at the end of the prior year. In Panel B, we decompose institutional investors into three groups: (1) bank and insurance company; (2) investment company and independent investment advisors; and (3) other. The table presents the time-series averages and t-statistics (in brackets) of the coefficient estimates. The t-statistics are adjusted for heteroskedasticity and autocorrelation using Newey and West (1987) standard errors. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1981 through December 2005 (1998 for Panel B).

Panel A: All Types of IO			Panel B: Decomposition of IO Type			
	IO	Size	Bank + Insurance	Investment Company + Independent Advisors	Other	Size
1 (small)	77.35		-553.2	106.2	798.1	
	[3.03]		[-1.09]	[1.38]	[2.00]	
	57.58	0.018	-562.4	188.6	497.5	-0.072
	[2.04]	[0.19]	[-1.10]	[1.97]	[1.46]	[-1.00]
2	36.09		9.164	19.09	48.6	
	[6.96]		[0.70]	[2.09]	[1.56]	
	32.12	0.020	12.85	23.47	51.69	-0.047
	[7.88]	[0.77]	[1.08]	[2.42]	[1.63]	[-1.08]
3	12.26		2.603	17.76	35.35	
	[8.00]		[0.44]	[4.04]	[2.64]	
	10.99	0.026	0.983	16.30	33.21	0.035
	[6.59]	[2.36]	[0.17]	[3.64]	[2.52]	[1.90]
4	6.697		2.845	9.716	25.85	
	[7.38]		[1.28]	[4.56]	[4.24]	
	6.148	0.019	2.799	9.734	26.01	-0.001
	[5.12]	[1.01]	[1.15]	[4.52]	[4.05]	[-0.05]
5 (large)	0.731		0.029	2.490	1.206	
	[6.82]		[0.10]	[3.63]	[2.80]	
	0.150	0.142	-0.555	1.789	-0.008	0.174
	[2.30]	[7.58]	[-1.90]	[2.54]	[-0.01]	[17.50]

Table 4: Divergence of Systematic Liquidity and Difference in Institutional Ownership

This table presents the results for time-series regressions with the following specification: Formally, we estimate the following regression:

$$\beta_{large,t} - \beta_{small,t} = a + \delta \cdot t + \gamma \cdot (IO_{large,t-1} - IO_{small,t-1}) + \varsigma \cdot (Size_{large,t-1} - Size_{small,t-1}) + \omega_t$$

where $\beta_{large,t}$ is the average systematic liquidity across the largest size quintile, $IO_{i,t-1}$ measures firm $i's$ market cap owned by institutions as the percentage of total market capitalization at the end of year $t-1$, and $IO_{large,t-1}$ is the average $IO_{i,t-1}$ across all firms in the largest size quintile. The table presents the coefficient estimates and the corresponding t-statistics (in brackets). T-statistics are calculated using heteroskedasticity and autocorrelation corrected (Newey-West) standard errors. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1981 through December 2005.

	Intercept	Trend ($\delta \times 10^3$)	IO (γ)	Size (ς)	$AdjR^2$
Trend Only	0.492	6.337			0.187
	[12.62]	[2.25]			
All IO Types (1981-2005)	0.218	0.812	2.765		0.297
	[1.88]	[0.21]	[2.22]		
All IO Types (1981-2005)	0.358	2.338	2.857	-0.035	0.268
	[0.77]	[0.38]	[2.41]	[-0.35]	
All IO Types (1981-1998)	0.261	0.238	2.459		0.130
	[2.35]	[0.05]	[2.05]		
Bank and Insurance Company	0.159	8.970	6.144		0.090
	[0.86]	[2.52]	[1.80]		
Investment Company and	0.327	-11.18	6.293		0.159
Independent Investment Advisors	[4.22]	[-1.30]	[2.19]		
	0.372	4.656	9.275		0.106
Other	[5.84]	[1.36]	[1.87]		
All IO Types (1981-1998)	0.143	-0.630	2.445	0.027	0.070
	[0.34]	[-0.11]	[1.96]	[0.29]	
Bank and Insurance Company	-0.034	7.554	6.160	0.044	0.032
	[-0.07]	[1.47]	[1.71]	[0.46]	
Investment Company and	0.274	-11.51	6.264	0.012	0.099
Independent Investment Advisors	[0.65]	[-1.20]	[2.11]	[0.13]	
	0.253	3.756	9.214	0.027	0.044
Other	[0.63]	[0.76]	[1.77]	[0.29]	

Table 5: Common Aggregate Determinants of Liquidity Beta and Return Beta

For each firm i in year t, vector regressions with two equations are estimated with the main specification as follows:

$$\Delta ILLIQ_{i,d} = a_1 + \beta_1 \cdot \Delta ILLIQ_{m,d} + (s_1 \cdot \sigma_{m,d-1} + r_1 \cdot Ret_{m,d-1} + q_1 \cdot \Delta ILLIQ_{m,d-1}) \times \Delta ILLIQ_{m,d} + v_{1,i,d}$$
$$Ret_{i,d} = a_2 + \beta_2 \cdot Ret_{m,d} + (s_2 \cdot \sigma_{m,d-1} + r_2 \cdot Ret_{m,d-1} + q_2 \cdot \Delta ILLIQ_{m,d-1}) \times Ret_{m,d} + v_{2,i,d}$$

where d denotes days, and m denotes value-weighted market variable. For example, $ret_{m,d}$ is the value-weighted average of $ret_{i,d}$. The variable $\sigma_{m,d}$ is daily market volatility shock obtained following Schwert (1990). First, $ret_{m,d}$ is regressed on an intercept, four weekday dummies, and its 22 lags. The residual is $u_{m,d}$. Next, $|u_{m,d}|$ is regressed on an intercept and its own 22 lags. The residual is $\sigma_{m,d}$. We also consider additional models where positive return and negative return days are separated. The coefficient r_- is for the interaction between negative $Ret_{m,d-1}$ and $\Delta ILLIQ_{m,d}$ (or $Ret_{m,d}$), while r_+ is the coefficient for the interaction term with positive $Ret_{m,d-1}$. The table presents the average coefficient estimates and the corresponding t-statistics (in brackets) of the vector regressions. T-statistics are calculated using clustered (by firm) standard errors. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1963 through December 2005.

Equation		a	β	s	r	r_-	r_+	q
$\Delta ILLIQ$	Estimate	-0.003	0.466	0.026				
	T-stat	[-11.78]	[109.4]	[10.48]				
Ret	Estimate	0.062	1.046	0.061				
	T-stat	[69.99]	[162.5]	[18.82]				
$\Delta ILLIQ$	Estimate	-0.004	0.469		0.004			
	T-stat	[-22.99]	[108.4]		[2.79]			
Ret	Estimate	0.064	1.045		-0.049			
	T-stat	[69.39]	[163.8]		[-22.14]			
$\Delta ILLIQ$	Estimate	-0.003	0.453			-0.012	0.025	
	T-stat	[-13.10]	[104.2]			[-3.54]	[7.75]	
Ret	Estimate	0.066	1.013			-0.110	-0.006	
	T-stat	[69.33]	[147.7]			[-28.62]	[-1.30]	
$\Delta ILLIQ$	Estimate	-0.003	0.468					0.050
	T-stat	[-12.01]	[108.7]					[11.63]
Ret	Estimate	0.062	1.045					0.019
	T-stat	[70.30]	[162.7]					[3.98]
$\Delta ILLIQ$	Estimate	-0.003	0.459	0.017	0.005			0.023
	T-stat	[-10.56]	[106.1]	[5.08]	[2.61]			[4.28]
Ret	Estimate	0.067	1.043	0.055	-0.058			-0.043
	T-stat	[70.47]	[162.9]	[14.74]	[-23.34]			[-7.88]
$\Delta ILLIQ$	Estimate	-0.003	0.424	-0.038		-0.047	0.056	0.022
	T-stat	[-10.76]	[64.25]	[-3.91]		[-4.65]	[6.07]	[4.11]
Ret	Estimate	0.067	1.001	-0.010		-0.126	0.009	-0.035
	T-stat	[69.82]	[131.9]	[-0.97]		[-11.89]	[0.93]	[-6.37]

Table 6: Systematic Liquidity and Systematic Risk

Panel A estimates the time-series regression $\beta_{ret,t} = a_b + \delta_b t + e_{b,t}$, and Panel B estimates the time-series regression $\beta_{ret,t} = a_b + \delta_b t + \theta_b \beta_{liq,t} + e_{b,t}$ where $\beta_{liq,t}$ and $\beta_{ret,t}$ are the average $\beta_{liq,i}$ and $\beta_{ret,i}$ across firms in each of the five size quintiles, and $\beta_{liq,i}$ and $\beta_{ret,i}$ are estimated from market models for firm i in year t: $\Delta ILLIQ_{i,d} = a + \beta_{liq,i} \Delta ILLIQ_{m,d} + \varepsilon_{i,d}$ and $ret_{i,d} = a + \beta_{ret,i} ret_{m,d} + \varepsilon_{i,d}$. Market variables in each firm-year regression are value-weighted average excluding the firm's own value. The table presents coefficient estimates, corresponding t-statistics, and R^2 for the regressions. T-statistics are calculated using heteroskedasticity and autocorrelation corrected (Newey-West) standard errors. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than \$2 for the period January 1963 through December 2005.

Panel A: $\beta_{ret,t} = a_b + \delta_b t + e_{b,t}$

Firms	$\delta(\times 10^3)$		R^2
	Estimate	T-statistic	
1 (small)	-22.377	[-10.33]	0.81
2	-12.596	[-2.58]	0.31
3	-7.478	[-1.77]	0.18
4	-3.821	[-1.71]	0.15
5 (large)	1.653	[2.50]	0.19
5 minus 1	24.030	[12.79]	0.82

Panel B: $\beta_{ret,t} = a_b + \delta_b t + \theta_b \beta_{liq,t} + e_{b,t}$

Firms	$\delta(\times 10^3)$		θ		R^2
	Estimate	T-statistic	Estimate	T-statistic	
1 (small)	-18.126	[-10.35]	1.159	[4.76]	0.88
2	-12.745	[-5.07]	1.772	[4.83]	0.72
3	-12.120	[-8.41]	1.466	[6.91]	0.75
4	-9.099	[-5.85]	1.065	[5.58]	0.58
5 (large)	-1.263	[-1.27]	0.310	[4.16]	0.45
5 minus 1	13.602	[4.19]	0.798	[4.46]	0.88

Table 7: Systematic Components Measured by R^2

Panel A presents the results of the time-series regression: $R^2_{liq,t} = a + \delta t + e_t$. Panel B estimates the time-series regression $R^2_{ret,t} = a_r + \delta_r t + e_{r,t}$, and Panel C estimates the time-series regression $R^2_{ret,t} = a_r + \delta_r t + \theta_r \beta_{liq,t} + e_{r,t}$ where $R^2_{liq,t}$ and $R^2_{ret,t}$ are the average $R^2_{liq,i}$ and $R^2_{ret,i}$ across firms in each of the five size quintiles, and $R^2_{liq,i}$ and $R^2_{ret,i}$ are estimated from market models for firm i in year t: $\Delta ILLIQ_{i,d} = a + \beta_{liq,i} \Delta ILLIQ_{m,d} + \varepsilon_{i,d}$ and $ret_{i,d} = a + \beta_{ret,i} ret_{m,d} + \varepsilon_{i,d}$. Market variables in each firm-year regression are value-weighted average excluding the firm's own value. The table presents coefficient estimates, corresponding t-statistics, and R^2 for the regressions. T-statistics are calculated using heteroskedasticity and autocorrelation corrected (Newey-West) standard errors. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than \$2 for the period January 1963 through December 2005.

Panel A: $R^2_{liq,t} = a + \delta t + e_t$

Firms	$\delta(\times 10^3)$		R^2
	Estimate	T-statistic	
1 (small)	-0.136	[-3.21]	0.30
2	-0.002	[-0.02]	< 0.01
3	0.289	[1.57]	0.15
4	0.488	[2.57]	0.25
5 (large)	1.116	[3.62]	0.29
5 minus 1	1.252	[4.11]	0.36

Panel B: $R^2_{ret,t} = a_r + \delta_r t + e_{r,t}$

Firms	$\delta(\times 10^3)$		R^2
	Estimate	T-statistic	
1 (small)	-1.141	[-3.44]	0.25
2	0.101	[0.13]	< 0.01
3	1.037	[1.10]	0.06
4	1.558	[1.85]	0.10
5 (large)	2.465	[2.44]	0.13
5 minus 1	3.606	[4.46]	0.34

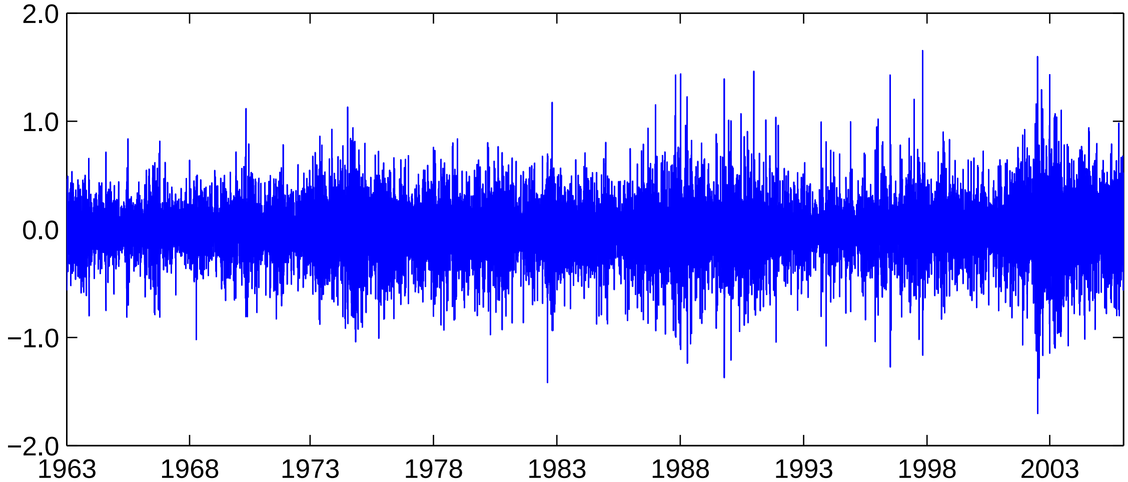
Panel C: $R^2_{ret,t} = a_r + \delta_r t + \theta_r R^2_{liq,t} + e_{r,t}$

Firms	$\delta(\times 10^3)$		θ		R^2
	Estimate	T-statistic	Estimate	T-statistic	
1 (small)	-0.426	[-1.02]	5.253	[2.94]	0.47
2	0.113	[0.33]	6.143	[11.97]	0.56
3	-0.345	[-0.90]	4.788	[9.86]	0.64
4	-0.572	[-1.44]	4.366	[7.24]	0.66
5 (large)	-1.256	[-2.13]	3.335	[8.84]	0.82
5 minus 1	0.046	[0.12]	2.844	[12.82]	0.93

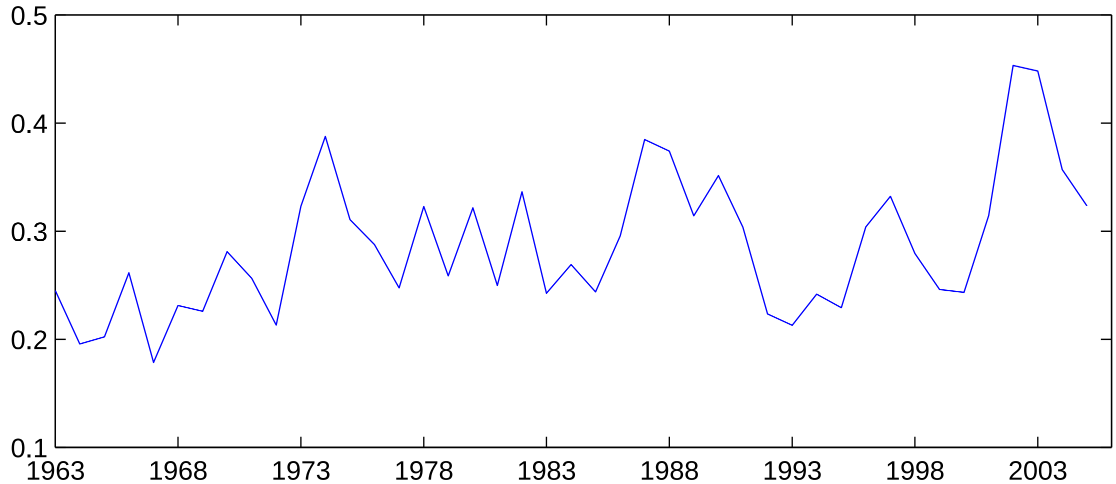
Table 8: Industry Effects

For firm i in year t, the time-series regression, $\Delta ILLIQ_{i,d} = a + \beta_{i,m}\Delta ILLIQ_{m,d} + \beta_{i,ind}\Delta ILLIQ_{ind,d} + \varepsilon_{i,d}$, is estimated, where $\Delta ILLIQ_{i,d}$ is the first difference of the logarithm of daily Amihud measure of firm i in day d, $\Delta ILLIQ_{m,d}$ is the value-weighted market average of $\Delta ILLIQ_{j,d}$ for all $j \neq i$, and $\Delta ILLIQ_{ind,d}$ is the value-weighted industry average of $\Delta ILLIQ_{k,d}$ for all $k \neq i$ in the same industry. We obtain estimates of $\beta_{i,m}$, $\beta_{i,ind}$, and the regression R^2 for each firm i in year t. The table reports the time-series means of the annual cross-sectional average of the market betas, industry betas, and regression's R^2 for all the firms in the sample, as well as for firms in the smallest and largest size quintiles for nine sub-periods. Each sub-period includes five years except the last sub-period (2003-2005). Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than \$2 for the period January 1963 through December 2005.

Firms	Sub-period	β_m	β_{ind}	R^2
All	1963-1967	0.370	0.065	0.027
	1968-1972	0.452	0.081	0.031
	1973-1977	0.336	0.090	0.035
	1978-1982	0.380	0.112	0.038
	1983-1987	0.361	0.103	0.035
	1988-1992	0.382	0.094	0.042
	1993-1997	0.407	0.121	0.038
	1998-2002	0.340	0.163	0.042
	2003-2005	0.405	0.223	0.061
Small	1963-1967	0.297	0.043	0.025
	1968-1972	0.350	0.064	0.027
	1973-1977	0.215	0.048	0.026
	1978-1982	0.238	0.068	0.027
	1983-1987	0.209	0.045	0.024
	1988-1992	0.225	0.029	0.025
	1993-1997	0.261	0.044	0.025
	1998-2002	0.176	0.032	0.021
	2003-2005	0.148	0.008	0.017
Large	1963-1967	0.387	0.122	0.031
	1968-1972	0.531	0.100	0.033
	1973-1977	0.540	0.143	0.054
	1978-1982	0.589	0.190	0.063
	1983-1987	0.620	0.195	0.066
	1988-1992	0.667	0.202	0.086
	1993-1997	0.572	0.284	0.069
	1998-2002	0.440	0.385	0.081
	2003-2005	0.501	0.400	0.106



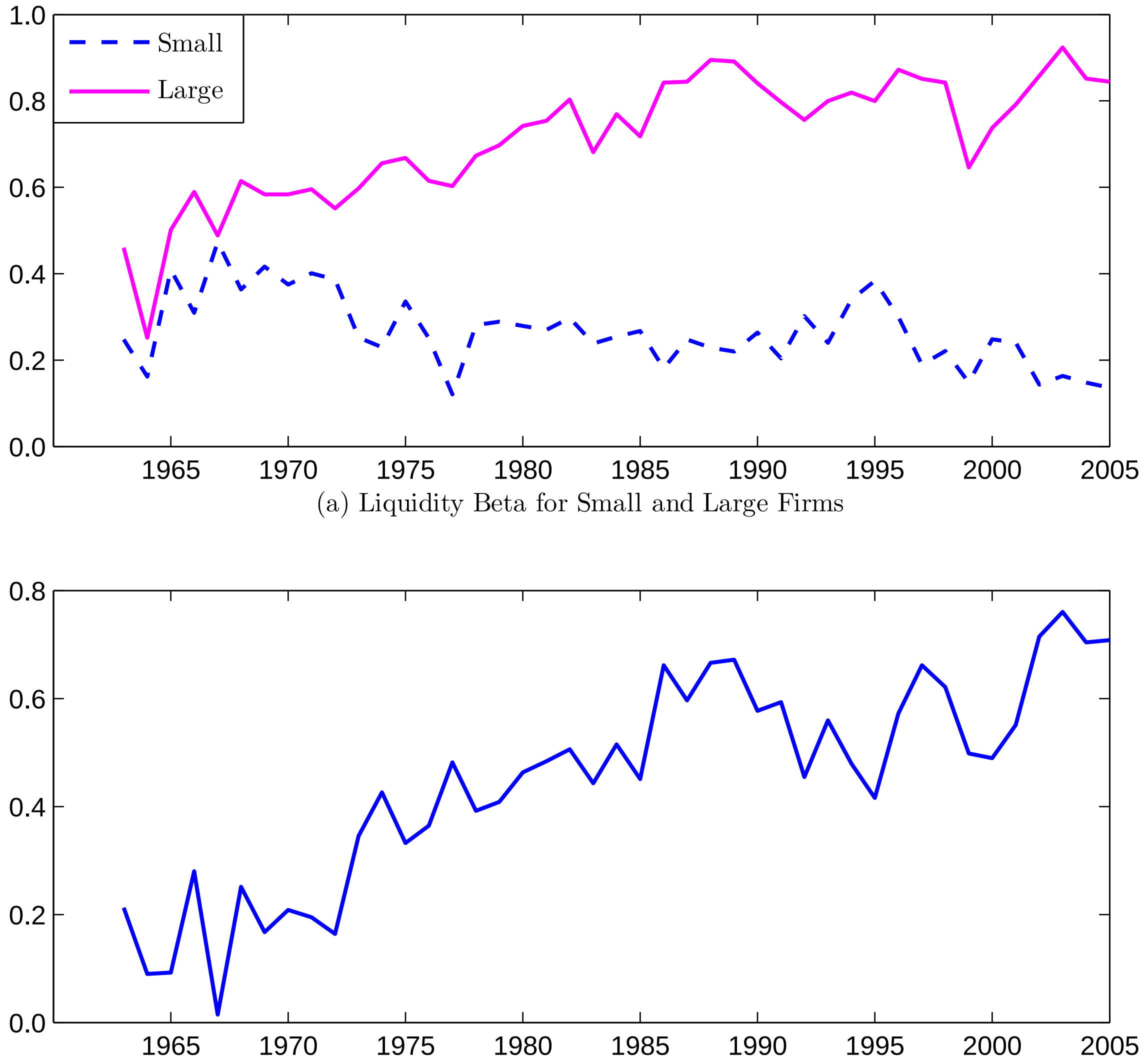
(a) Market Liquidity Variation: $\Delta ILLIQ_{m,d}$



(b) Volatility of $\Delta ILLIQ_{m,d}$

Figure 1: Time Series and Volatility of $\Delta ILLIQ_{m,d}$

$\Delta ILLIQ_{i,d}$ is the daily change in the logarithm of Amihud (2002) illiquidity measure from day $d-1$ to day d for firm i. $\Delta ILLIQ_{m,d}$ is the cross-sectional value-weight average of $\Delta ILLIQ_{i,d}$ over all the stocks in our sample, which includes all NYSE/AMEX-listed firms with beginning-of-day price of no less than \$2 for the period January 1963 through December 2005. Panel (a) presents the time-series plot of $\Delta ILLIQ_{m,d}$. Panel (b) shows the annual standard deviation of $\Delta ILLIQ_{m,d}$.

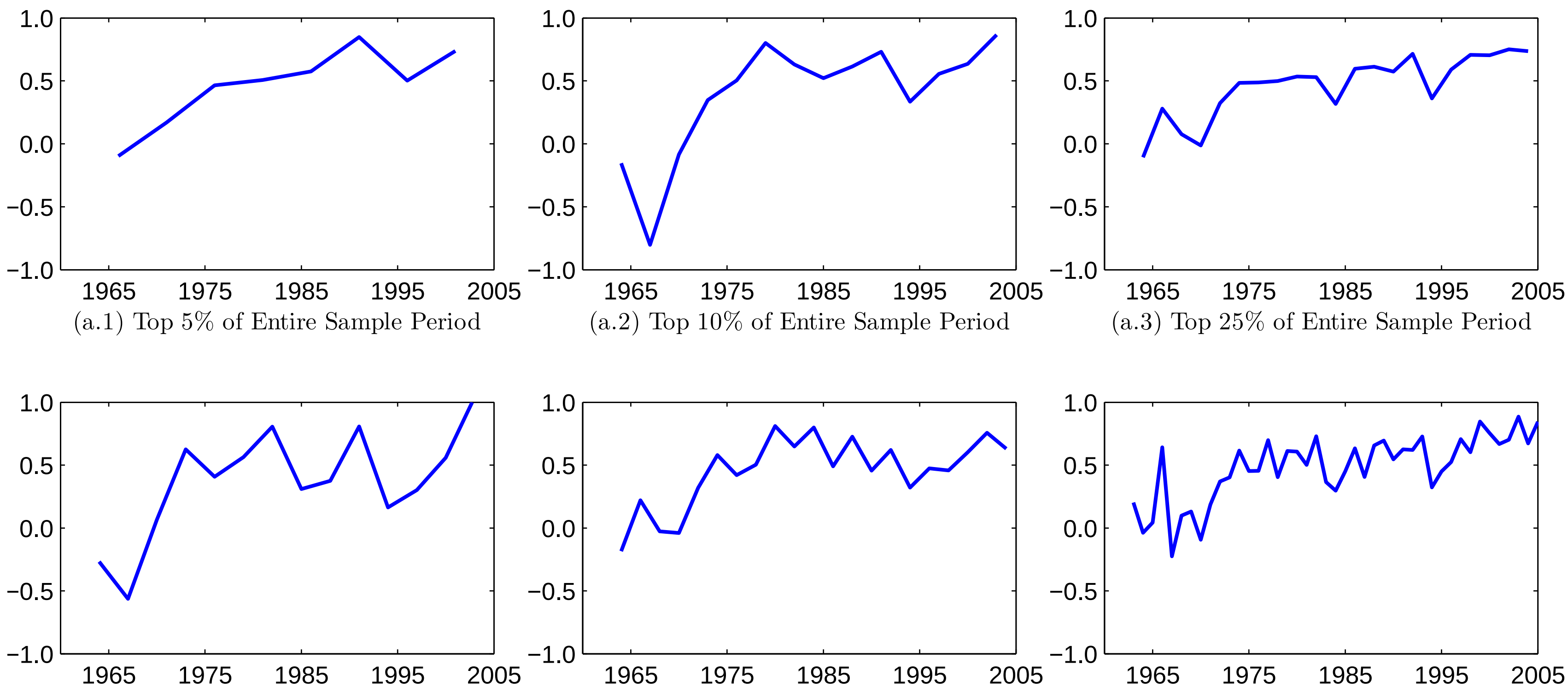


(a) Liquidity Beta for Small and Large Firms

(b) Difference in Liquidity Beta Between Large and Small Firms

Figure 2: Times Series of Liquidity Beta (market model)

For each firm i and year t, we run the following time-series regressions: $\Delta ILLIQ_{i,d} = a + \beta_i \Delta ILLIQ_{m,d} + \varepsilon_{i,d}$, where d denotes the days in year t, $\Delta ILLIQ_{i,d}$ is the change in the logarithm of daily Amihud (2002) illiquidity measure, and $\Delta ILLIQ_{m,d}$ is the value-weight average of $\Delta ILLIQ_{j,d}$ for all $j \neq i$. Each year, only firms with at least one hundred valid observations are retained. Firms are sorted into five size groups each year based on the market capitalization at the end of the prior year. Small and large firms are firms in the smallest and largest size quintile, respectively. We calculate the annual cross-sectional mean of β across each size quintile. Panel (a) plots the average β for small and large firms, while Panel (b) shows the difference in liquidity beta between large and small firms. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than \$2 for the period January 1963 through December 2005.



(a.1) Top 5% of Entire Sample Period

(a.2) Top 10% of Entire Sample Period

(a.3) Top 25% of Entire Sample Period

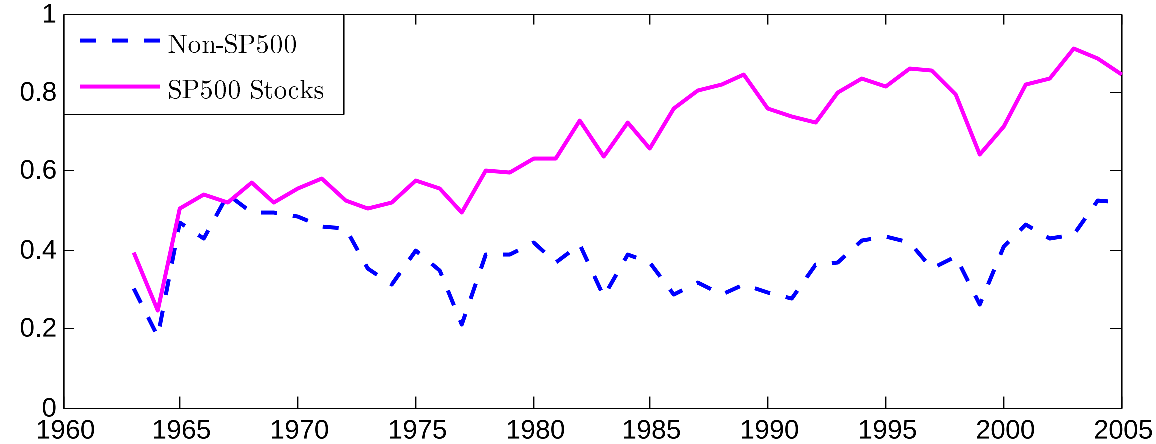
(b.1) Top 5% in Every Three Years

(b.2) Top 10% in Every Two Years

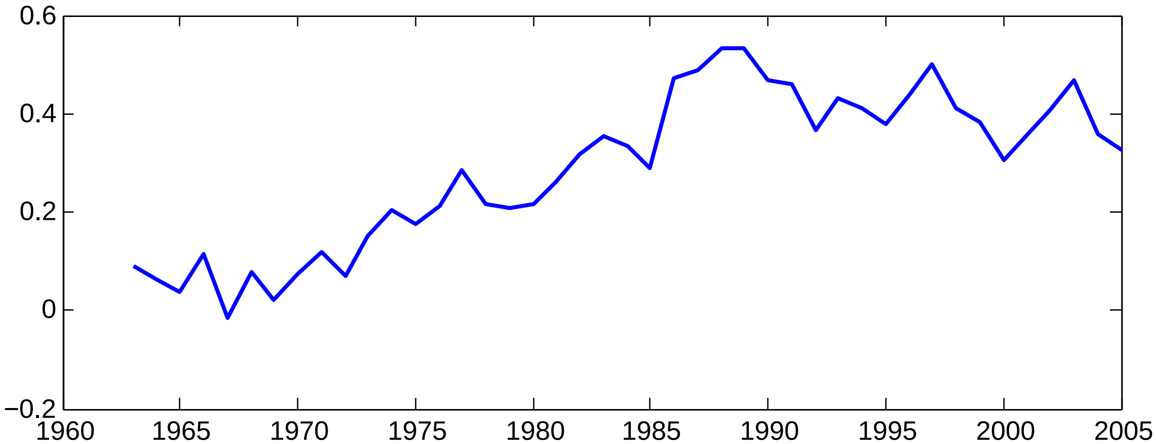
(b.3) Top 25% in Every Year

Figure 3: Divergence of Liquidity Beta in Days with Extreme Values of $\Delta ILLIQ_{m,d}$

The figure plots the difference of liquidity beta between large and small stocks where the liquidity beta is estimated using observations in days with extreme values of $ILLIQ_{m,d}$. $ILLIQ_{m,d}$ is the value-weighted average of $ILLIQ_{i,d}$ for all i in the sample. In the three figures in Panel (a), extreme days are those when $ILLIQ_{m,d}$ are in the top five (or 10 or 25) percentile of the entire sample period 1963 through 2005. Years are divided into several bins without overlap: every five years for Panel (a.1), every three years for Panel (a.2), and every two years in Panel (a.3). Market model is estimated using values in extreme days for each firm-bin. Only firms with at least 25 observations used in the estimation are included. In Panel (b), extreme values are defined as those in the top five (or 10 or 25) percentile in every three (or two or one) years.



(a) Liquidity Beta of SP500 and Non-SP500 Stocks



(b) Difference in Liquidity Beta Between SP500 and Non-SP500 Stocks

Figure 4: Divergence of Liquidity Beta Between S&P500 Stocks and Non-S&P500 Stocks

Each year, a firm in the sample is assigned into the S&P 500 portfolio if it is included in the S&P500 index throughout the year. Panel (a) plots the annual liquidity beta averaged across all firms in the S&P 500 portfolio as well as the average liquidity beta for the rest of the stocks. Panel (b) plots the difference of liquidity beta between stocks in the S&P 500 portfolio and those not in the S&P 500 portfolio. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1963 through December 2005.

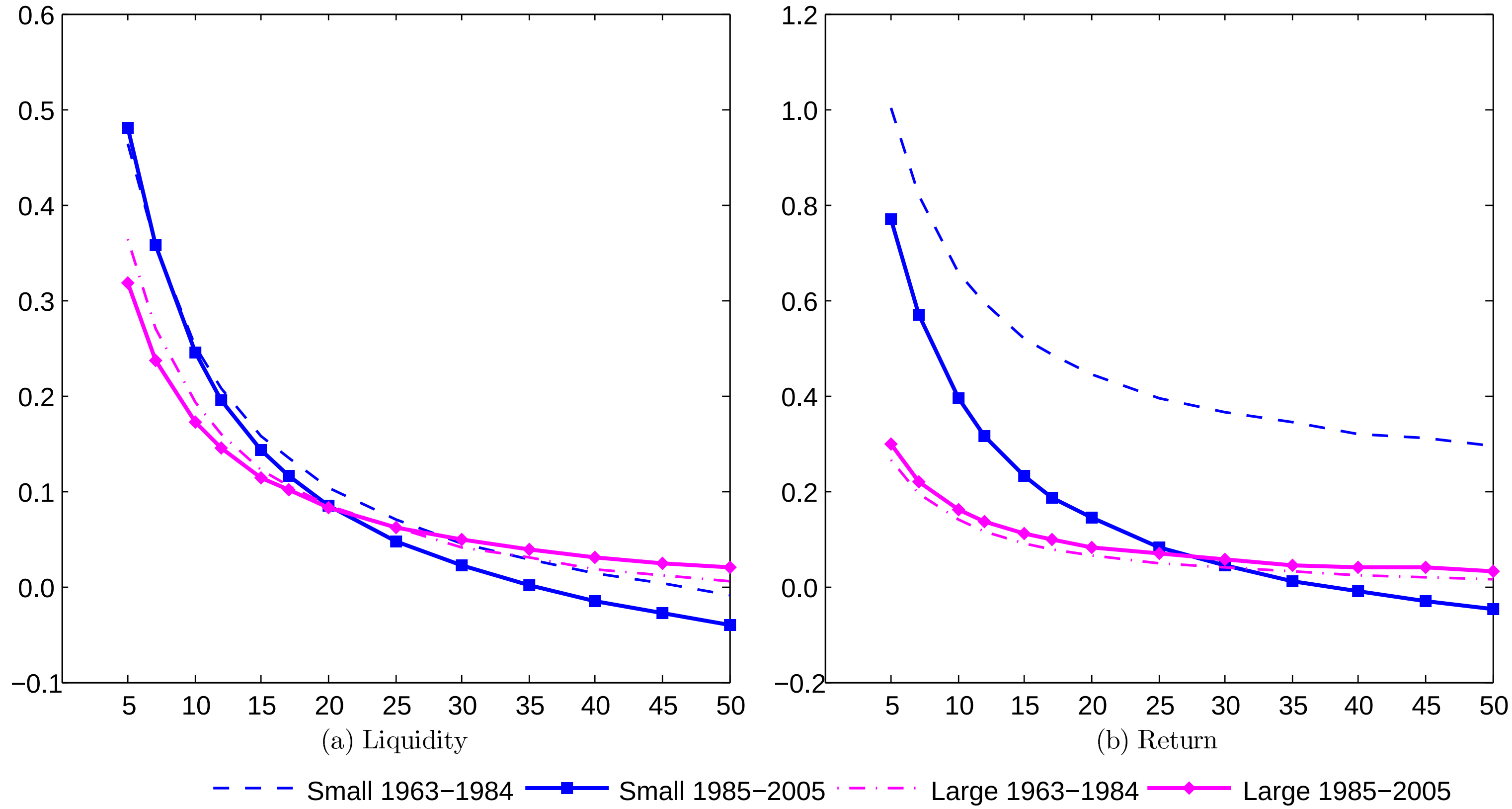
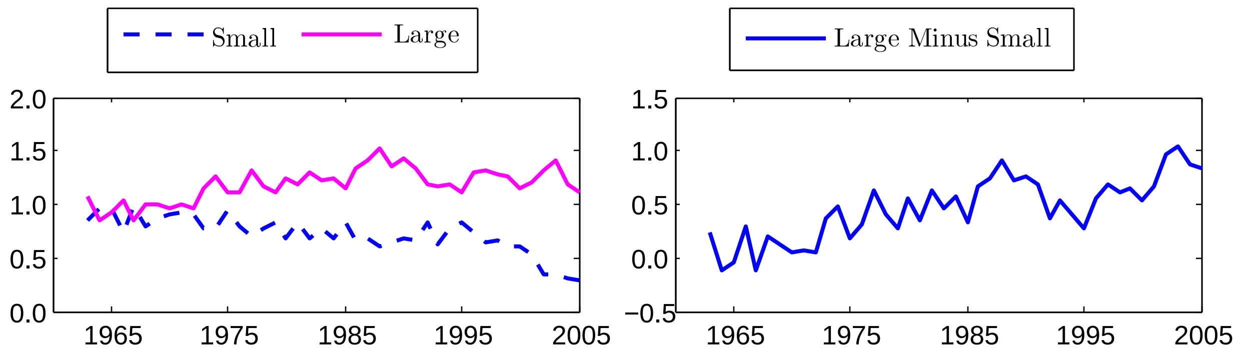
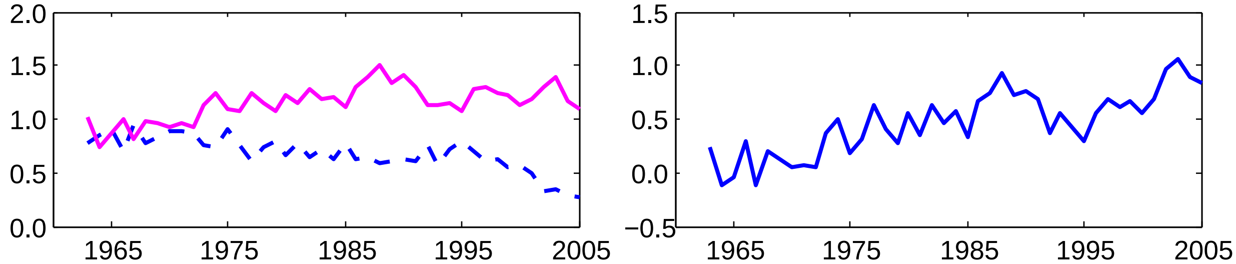


Figure 5: Diversification of Small and Large Firms over Time

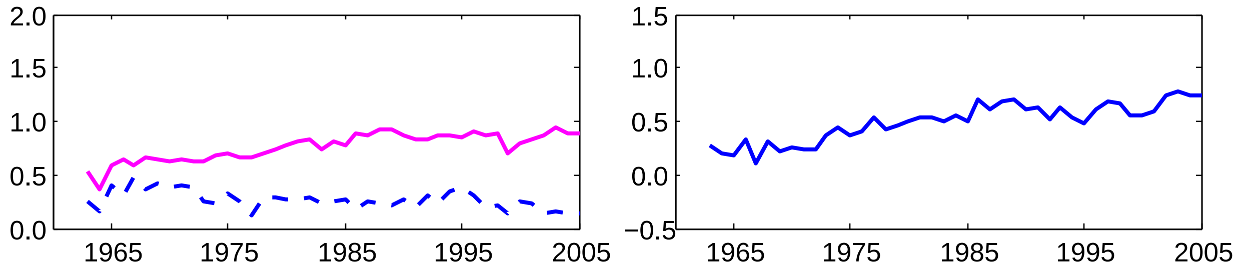
Panel (a) plots the volatility of liquidity of portfolios composed of stocks of small (only) and large (only) firms in excess of the volatility of market liquidity over two subperiods: 1963-1984 and 1985 - 2005. Small and large firms are firms in the smallest and largest size quintile, respectively. The excess liquidity volatility of the portfolio is on the vertical axis. The number of stocks in the portfolio is on the horizontal axis. Each year stocks in each size quintile are randomly assigned to portfolios. The liquidity volatility of portfolios in year t are calculated, and the average annual liquidity volatility is then calculated over two subperiods: 1963-1984 and 1985-2005. Panel (b) plots the return volatilities of portfolios in excess of the market return volatility following the similar procedure in Panel (a). Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1963 through December 2005.



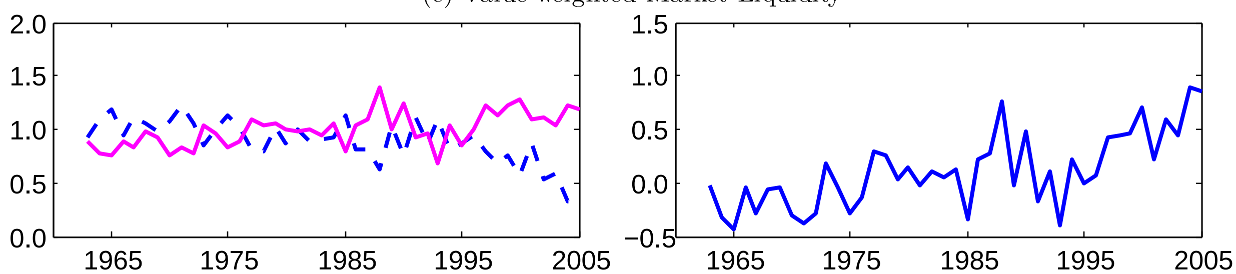
(a) Equal-weighted Market Liquidity



(b) Equal-weighted Market Liquidity Without Its Own Value



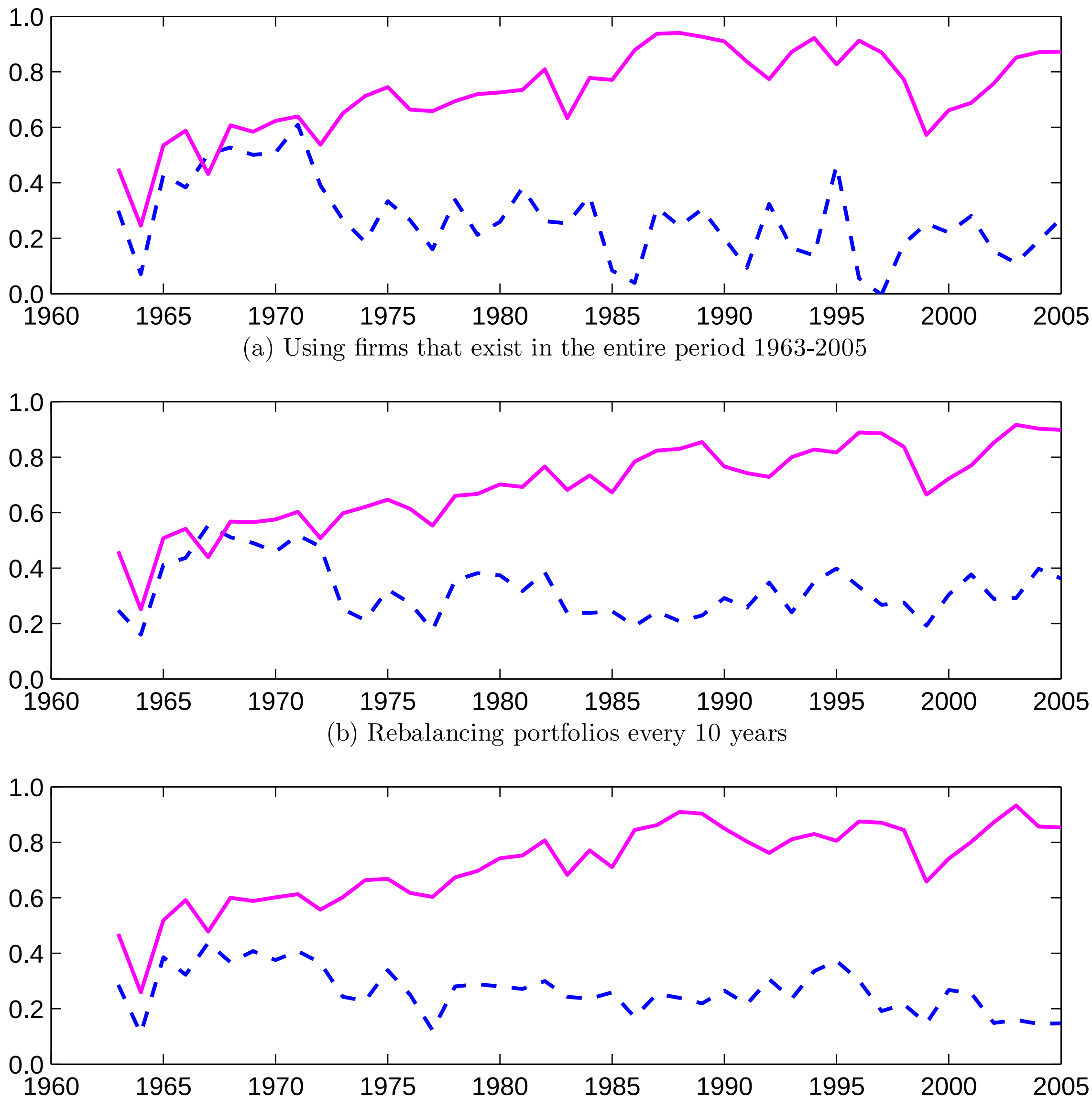
(c) Value-weighted Market Liquidity



(d) Equal-weighted Market Liquidity with Dimson Correction

Figure 6: Times Series of Liquidity Beta (Other Models)

The figure plots the average liquidity beta of small and large stocks, as well as the difference between large and small stocks for four market models. In Panel (a), $\Delta ILLIQ_{m,d}$ is the equal-weight average of $\Delta ILLIQ_{j,d}$ for all j. In Panel (b), $\Delta ILLIQ_{m,d}$ is the equal-weight average of $\Delta ILLIQ_{j,d}$ for all $j \neq i$. In Panel (c), $\Delta ILLIQ_{m,d}$ is the value-weight average of $\Delta ILLIQ_{j,d}$ for all j. In Panel (d), the liquidity beta is $\beta_{i,-1}+\beta_{i,0}+\beta_{i,1}$ from $\Delta ILLIQ_{i,d} = a+\beta_{i,-1}\Delta ILLIQ_{m,d-1}+\beta_{i,0}\Delta ILLIQ_{m,d}+\beta_{i,1}\Delta ILLIQ_{m,d+1}+\varepsilon_{i,d}$, where $\Delta ILLIQ_{m,d}$ is the equal-weight average of $\Delta ILLIQ_{j,d}$ for all j. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1963 through December 2005.



(a) Using firms that exist in the entire period 1963-2005

(b) Rebalancing portfolios every 10 years

(c) Using firms that have been publicly traded for at least three years

Figure 7: Robustness to Distribution of Firm Age and Size

For each firm i and year t, we run the following time-series regressions: $\Delta ILLIQ_{i,d} = a + \beta_i \Delta ILLIQ_{m,d} + \varepsilon_{i,d}$, where d denotes the days in year t, $\Delta ILLIQ_{i,d}$ is the change in the logarithm of daily Amihud (2002) illiquidity measure, and $\Delta ILLIQ_{m,d}$ is the value-weight average of $\Delta ILLIQ_{j,d}$ for all firms $jnei$. In Panel (a), average liquidity beta for each size quintile each year is calculated using only the firms that exist over the entire sample period, and the size break points each year are determined using the entire sample of NYSE-listed firms. In Panel (b), the size quintile is determined once every ten years (1963, 1973, 1983, 1993), and average beta for each quintile and each year is calculated using all firms in the size quintile. In Panel (c), only firms that have been publicly traded for at least three years (as of the beginning of the year in which their liquidity betas are estimated) are included in calculating the average beta of the size quintile. Our sample includes daily data for NYSE/AMEX-listed firms with beginning-of-day price of no less than $2 for the period January 1963 through December 2005.