The Polarization of Systematic Liquidity 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. In particular, the sensitivity of large-cap firms' liquidity to market liquidity has increased, while that of small-cap firms has declined. This increased polarization of systematic liquidity can be explained by patterns in institutional ownership over the sample period. The analysis also indicates that the ability to diversify aggregate liquidity shocks by holding large-cap stocks has declined. The evidence, therefore, suggests that the fragility of the US equity market to unanticipated liquidity events has increased over the past few decades.

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The literature on asset liquidity has received much attention during recent years. It is now widely accepted that the liquidity of financial assets changes over time, and that this suggests the existence of commonality in liquidity across assets (see, e.g., Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Amihud (2002)). 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.

There are several reasons why the evolution of systematic liquidity across firms is an interesting topic of financial research. First, liquidity and trading costs affect expected returns simply because investors, who maximize expected returns net of trading costs, require a higher expected return to hold stocks with larger trading costs (Amihud and Mendelson (1986)). Second, recent studies document that liquidity risk is a priced risk factor (e.g., Pástor and Stambaugh (2003) and Acharya and Pedersen (2005)). Changes in systematic liquidity risk can thus have significant pricing implications. Third, 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. Fourth, 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)). Fifth, 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. 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)).

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 liquidity we use the daily change in (the log of) Amihud's (2002) measure of firm's illiquidity.[1] To the extent that the sensitivity to market liquidity is an indicator of systematic liquidity risk, we find that systematic liquidity has decreased significantly for smallest-cap firms, but increased significantly for largest-cap firms (size quintiles 1 and 5 respectively).[2] This increased polarization of liquidity in the cross-section of firms has important implications for the ability to diversify liquidity shocks across firms. We find that the ability to diversify aggregate 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. The evidence suggests that the ability to diversify aggregate liquidity shocks by holding an otherwise well-diversified, value-weighted portfolio has declined over time. In contrast, we find that the ability to diversify aggregate 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.[3] Our results are also imperative for active investment managers who rebalance their portfolios frequently.

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 to 50% in 2002 (source: NYSE). It is widely accepted 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.[4] What is less known is how they have affected the commonality in liquidity.

[1]There are other measures of liquidity, such as the price-impact measures used in Brennan and Subrahmanyam (1996) and Sadka (2006), that require intraday data. We choose the Amihud (2002) measure because it can be computed using daily data and, therefore, allows us to study a much longer time period. Moreover, recent studies (see, e.g., Hasbrouck (2005) and Korajczyk and Sadka (2006)) find that many measures of liquidity, especially the Amihud measure, are highly correlated and driven by a common systematic component. This suggests that our findings are not limited to a particular measure of liquidity.

[2]Our notion of systematic liquidity risk is based on the sensitivity of stock liquidity to market liquidity, as in Chordia, Roll, and Subrahmanyam (2000), rather than on the sensitivity of stock returns to market liquidity, as in Pástor and Stambaugh (2003).

[3]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.

[4]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

We investigate the effects of the increased institutionalization of the US equity markets on the 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 systematic liquidity shocks increases with institutional ownership.

Moreover, the increases in institutional ownership over time can explain the increased polarization 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.[5] 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 of large and small stocks Granger (1969) cause differences in their sensitivities to systematic liquidity. This can explain why large firms' stocks have become more sensitive to market liquidity shocks relative to small firms' stocks.[6]

Another feature of institutional and index trading is the use of security baskets as possible

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).

[5] 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.

[6] Harford and Kaul (2005) examine order flows in 1986 and in 1996. They find significant common effects for S&P500 stocks, but weak effect for other stocks.

means of trading.[7] 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%.[8] Chordia, Roll, and Subrahmanyam (2000) argue that institutional trading is a significant source of commonality of liquidity among stocks. 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.

Campbell, Lettau, Malkiel, and Xu (2001) document an increasing trend in idiosyncratic return volatility over the period 1962-1997. To the extent that price discovery affects asset prices, O'Hara (2003) argues that idiosyncratic volatility can be related to liquidity. In addition, Chordia, Roll, and Subrahmanyam (2000) advance that changes in systematic return volatility generate correlated trading by institutions with similar investment styles across many stocks, thereby creating a linkage between systematic return volatility and commonality in liquidity. It is, therefore, interesting to study the extent to which the evolution of systematic liquidity is related to the evolution of systematic return volatility. Our results support the thesis of Chordia, Roll, and Subrahmanyam (2000). We find that time variations in systematic liquidity are significantly (positively) related to time variations in systematic risk, even after accounting for the time trends in systematic liquidity. Moreover, this relation is significantly stronger for large firms than for small firms.

The remainder of the paper is organized as follows. Section 1 describes the data. Section

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

[8] 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.

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 polarization of systematic liquidity. In Section 3 we investigate the relation between institutional ownership of a firm's equity and its exposure to systematic liquidity, and 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 (on SEC Form 13F) 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, as reported on SEC Form 13F.

2 The Evolution of Systematic Liquidity

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.

Due to the nonstationary nature of the time series of Amihuds measure, we use the change in the Amihud's measure (in logs) as our daily liquidity measure.

Specifically, for each firm i and day d, we define $\Delta LIQ_{i,d}$, the change in the firm's liquidity, as

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

In addition, following Chordia, Roll, and Subrahmanyam (2000) and Amihud (2002), we apply the following three data filters. First, 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. Second, we discard firm-days outliers with $\Delta LIQ_{i,d}$ in the lowest and highest 1% percentiles of the sample remaining after applying the first filter. Finally, we retain a stock in a given year only if the stock has at least 100 valid observations after applying the first two filters. There are 73,933 firm-year observations. The number of 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 liquidity, $\Delta LIQ_{m,d}$, as the daily cross-sectional, equal-weighted, average of $\Delta LIQ_{i,d}$. This is similar to the definition in Chordia, Roll, and Subrahmanyam (2000), and its main purpose is to hold the average liquidity sensitivity in the liquidity market model studied in subsequent sections at a value of 1.

Figure 1(a) plots the time series of $\Delta LIQ_{m,d}$. 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.

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 $\Delta LIQ_{m,d}$ 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 $\Delta LIQ_{m,d}$ 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.

Using regression analysis, we estimate a market model of liquidity to estimate each firm's systematic liquidity. Specifically, following Chordia, Roll, and Subrahmanyam (2000), each year, we run the following time-series regression for each firm i:

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

where β_i measures the sensitivity of changes in firm i's liquidity to changes in aggregate liquidity.

After obtaining the estimate of liquidity beta (β_i) 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. The average liquidity beta for the entire market is always 1 or very close to 1 by construction (it is sometimes just below 1 because some firms are missing in some days).

Before we discuss the results we acknowledge the potential problem of nonsynchronous prices (see Scholes and Williams (1977) and Cohen, Hawawini, Maier, Schwartz, and Whitcomb (1983)). We will address this issue in Section 6, but would like to note that, as we will show later, our results in this section are robust to the effects of nonsynchronous trading.

Table 1 reports the averages of liquidity beta for different sub-periods over the sample period for the small and large firms. Two different time trends emerge when we separate the firms in the smallest and largest size quintiles. In general, the betas are decreasing for small firms and increasing for large firms. To see the trends more clearly, we plot the two time series of the betas, as well as their three-year moving average, in Figure 2. 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. More interestingly for our purposes, we find that, on average, over time, the betas of small firms have decreased, whereas, the betas of large firms have increased. That is, smallest-cap firms have become less sensitive to market-wide liquidity variations, and largest-cap firms have become more sensitive to market-wide liquidity variations.

It is important to note that the increase in the polarization of liquidity beta in the cross-section could occur if the volatility of market liquidity decreased. However, as discussed earlier and shown in Figure 1(b), the volatility of market liquidity has actually increased over our sample. This implies that the trend in the cross-sectional variation in individual stock's co-movement with the market is not an artifact of a change in the volatility of market liquidity.

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., $\gamma = 1$. 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 Quintile 4, while for firms in Quintiles 2 and 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 average liquidity betas of the largest and smallest firms (Quintile 5 minus Quintile 1).

Following our rejections of stochastic time trends for smallest and largest quintiles, we test the existence of a deterministic time trend in the time series of average betas. Table 3 reports the results for all the size quintiles. The time series of average β of the smallest size quintile has a statistically significant negative time trend (with a p-value of less than 0.001). In contrast, the corresponding time series of the largest size quintile has a statistically significant positive time trend (with a p-value of less than 0.005). 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 less than 0.001). In addition, the time trends of average β increase monotonically across the size quintiles, from -10.83 for the smallest quintile to 7.77 for the largest quintile. Lastly, the time trend for largest minus smallest (Quintile 5 minus Quintile 1) 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, coupled with a market average beta of one by construction, 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.

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 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.

Our findings have important implications for the ability to diversify liquidity shocks across firms. The evidence suggests that the ability to diversify aggregate liquidity shocks by holding well-diversified and value-weighted portfolios has declined over time, because these portfolios have become more common and more sensitive to systematic liquidity shocks. In contrast, the ability to diversify aggregate liquidity shocks by holding shares of small-cap firms has improved over time, since the liquidity of small-cap portfolios has become relatively more idiosyncratic and less sensitive to systematic liquidity variations. We will formally examine this issue in Section 5 below.

The opposite time trends in the systematic liquidity of the smallest and largest 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 behavior over time 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 systematic liquidity (liquidity beta) and the institutional ownership in the cross-section of firms. 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. Nor can we examine any additional effects from the introduction of stock index futures contracts on the S&P500 in 1982.

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 as the percentage of total market capitalization at the end of year $t-1$. 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 4 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. We also examine the robustness of the results reported in the table and found that they are robust to the possibility of a firm fixed effect. Specifically, we estimate the coefficients using pooled cross-sectional and time-series regressions with dummy variables for each year and calculated clustered standard errors by firm, and the results are as statistically significant as those using the Fama and MacBeth (1973) regressions.

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 size 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 the smallest and largest quintiles, but not in any of the other regressions.

We also examine whether the increased polarization 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 of the effects of institutional ownership on liquidity commonality over time should involve the difference between large and small firms. Specifically, we test whether the change over time in the difference between the average liquidity betas of the stocks in the largest and smallest size quintiles is associated with the change over time in the difference between the fractions of institutional ownership of stocks in the largest and smallest size quintiles. We will also address, again, any concerns that the difference in institutional ownership variable also captures a size effect rather than an institutional ownership effect.

Formally, we estimate the following regression:

$$\Delta\beta_{Size,t} = a + \delta \cdot t + \gamma \cdot \Delta IO_{Size,t-1} + \Delta\beta_{Size,t-1} + \omega_t \tag{5}$$

where $\Delta\beta_{Size,t}$ is the difference between the averages of $\beta_{i,t}$ across the largest and smallest quintiles, and $\Delta IO_{Size,t-1}$ is the difference between the averages of $IO_{i,t}$ across the largest and smallest quintiles.

This regression also tests whether the difference between the averages of the fractions of institutional ownership Granger (1969) causes the difference between the averages of liquidity betas. The difference in institutional ownership Granger causes the differences in liquidity betas if its coefficient is statistically significant, after including the own-lag of the difference in liquidity betas. In this case, the regression implies that the difference in average institutional ownership of largest and smallest stocks at the end of year $t-1$ helps predict the difference in average liquidity betas of largest and smallest stocks in year t.

Table 5 reports the results of annual regressions during 1981-2005. Because we have only 25 years of data, the regressions should be interpreted with caution. Nevertheless, the results are consistent with our findings above. The first regression, which includes only the time trend as an explanatory variable, confirms our findings above that there was a significant increase in the polarization of liquidity beta over 1981-2005. The second regression adds the lagged difference in the fractions of average institutional ownership of stocks in the largest and smallest size quintiles. These lagged fractions are measured at the end of the calendar year preceding the year during which the average differences in liquidity beta are measured. The coefficient of the difference in institutional ownership is positive and statistically significant at less than the 1% value. Moreover, the coefficient of the time trend is no longer significant at conventional levels.

The third regression allows us to test whether the difference in the fraction of institutional ownership Granger (1969) causes the difference in liquidity betas. Table 5 shows that the coefficient of the difference in institutional ownership remains statistically significant, and positive, at less than a 3% level, even after adding the (statistically significant positive) first-order own-lag of the differences in liquidity betas. Hence, we find that the difference in average fractions of institutional ownership of largest and smallest stocks Granger causes positively the difference in average liquidity betas of largest and smallest stocks. The results support our hypothesis that the growth in the institutionalization of the equity market is a significant reason for the increased polarization of systematic liquidity.

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 last regression while including the differences in market values of the firms in the size quintiles, measured at the end of year $t-1$, as an additional variable. Though not reported in the table for brevity, the coefficient on the size variable is insignificant at conventional levels and all the results of the third regression in Table 5 remain the same. In particular, the coefficient of the difference in institutional ownership variable remains significantly positive with an estimated value of 4.16 and a p-value of 0.019.

Though we do not have data that will allow us to directly test the effects of basket trading, given the dominant role of institutional investors in trading baskets of securities, 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. The evidence reported in the next section further supports this hypothesis.

4 Systematic Liquidity and Systematic Risk

Chordia, Roll, and Subrahmanyam (2000) argue that correlated institutional trading induce inventory pressure across many stocks, which creates a linkage between systematic risk (i.e., systematic return volatility) and commonality in liquidity. First, the risk (to dealers and market makers) of maintaining inventory depends on return volatility, which has a market component. In addition, as advanced in Coughenour and Saad (2004), commonality in the supply of liquidity can also arise from the fact that each NYSE specialist firm provides liquidity for many stocks. Hence, changes in systematic risk are likely to affect the optimal levels of inventories that specialists maintain to accommodate trading. Second, changes in systematic risk often also cause correlated trading by institutions, which is likely to exert pressures on dealer inventories across many stocks. If changes in systematic risk cause institutional trading and changes in specialists' inventories that are correlated across many stocks, they are also likely to affect systematic liquidity. In this section we study how much of the time series variation in systematic liquidity from 1963 to 2005 is associated with, or can be explained by, the time series variation in systematic risk for small and large firms.

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 relation between the time series of average liquidity R^2 and the time series of average return R^2 in addition to the relation between the time series of average liquidity and return betas.

Before we discuss our findings, let us describe very briefly the cross-sectional evolution of liquidity R^2 from 1963 to 2005, which we obtain using Regression (2). When we separate the firms in the smallest and largest size quintiles, two opposite time trends emerge. Similar to our findings for liquidity betas, the liquidity R^2 are decreasing for small firms and increasing for large firms. The R^2 for firms in the smallest quintile fell by more than half from 2.6% at the beginning of the sample period to 1.2% at the end of the sample period, whereas the average liquidity R^2 for firms in the largest quintile almost tripled from 2.7% to 7.5%. While one may debate the economic significance of a decline in R^2 from 2.6% to 1.2%, it is quite clear that the increase in R^2 from 2.7% to 7.5%, is economically significant. The formal tests of whether the liquidity R^2 series exhibit any time trend are also similar to those reported above for the liquidity betas. The time series of average liquidity R^2 of the smallest size quintile has a statistically significant negative time trend, whereas the corresponding time series of the largest size quintile has a statistically significant positive time trend (each with p-value of less than 0.01). In addition, the time trends in average R^2 increase monotonically across the size quintiles. Lastly, the time trend of liquidity R^2 for largest minus smallest quintiles (Quintile 5 minus Quintile 1) is also significantly negative.

For this analysis, we estimate the beta and R^2 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 (equal-weighted) market return .

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

$$\beta_{liq,t} = a_b + \delta_b t + \theta_b \beta_{ret,t} + e_{b,t}, \tag{6}$$

$$R^2_{liq,t} = a_r + \delta_r t + \theta_r R^2_{ret,t} + e_{r,t}. \tag{7}$$

These regressions provide some insight as to whether the patterns in systematic risk can explain the observed patterns in systematic liquidity. Because the time series of liquidity beta and liquidity R^2 exhibit a significant time trend, the regressions also include a deterministic time trend.

Table 6 presents our results of the relation between systematic liquidity and systematic risk over 1963-2005 for all size quintiles. The table also reports the marginal increase in R^2 of each regression from the addition of the corresponding systematic return variable to the regression with the time trend only (i.e., the difference in estimating the regression with and without the systematic return variable). In both regressions of liquidity β and liquidity R^2, and across all size quintiles, the coefficient of the respective systematic return variable is always positive and statistically significant (with p-values of less than 0.003). The marginal variation in liquidity beta explained by variation in return beta is 18% for the smallest quintile and 27% for the largest quintile. The marginal variation in liquidity R^2 explained by variation in return R^2 is 19% and 57%, respectively. A comparison of Tables 3 and 6 reveals that the inclusion of systematic risk in the regressions of the betas reduces the value of the estimated coefficient of the time trend, and the time trends for the smallest and largest quintiles are no longer significant at conventional levels. Nevertheless, the time trend in the regressions of liquidity R^2 on return R^2 remains statistically significant at conventional levels for both the regression of the smallest size quintile (in which the estimated coefficient is negative), and the regression of largest size quintile (in which the estimated coefficient is positive). These results suggest that although systematic risk cannot fully explain the pattern in systematic liquidity over and above the general time trend, it can explain a substantial fraction, especially for the largest firms. Note also that in the regression of liquidity R^2 on return R^2, both the magnitude of the coefficient on the systematic risk and its t-statistic increase with size. That is, the coefficients of the return R^2, exhibit a size effect, which is consistent with the view 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 return volatility and systematic liquidity.

5 Implications for the Diversification of Liquidity Risk

Our findings above that liquidity betas of the large stocks have increased over time, but those of the small stocks have declined over time, have implications for the ability diversify liquidity volatility. They suggest that the ability to diversify aggregate liquidity shocks by holding well-diversified and value-weighted portfolios has declined over time, because these portfolios have become more liquidity common and more sensitive to systematic liquidity shocks. In contrast, the ability to diversify aggregate liquidity shocks by holding shares of small-cap firms has improved over time, since the liquidity of small-cap portfolios has become relatively more idiosyncratic and less sensitive to systematic liquidity variations. In this section we study the degree to which the benefits of diversification have changed over time for different size portfolios.

Our empirical methodology follows Campbell, Lettau, Malkiel, and Xu (2001). For each of the largest and smallest 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 volatility of each portfolio relative to the market, which we define as the difference between the standard deviation of liquidity of the portfolio and the standard deviation of liquidity of an equally weighted portfolio of all the stocks in the sample. (We continue to measure the liquidity of each stock by $\Delta LIQ_{i,d}$.) 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.

Figure 3 shows the average annual excess liquidity volatility of portfolios with different numbers of stocks. The top panel of Figure 3 shows the average annual excess volatility of portfolios in 1963-1984, and the bottom panel shows the average annual excess volatility of portfolios in 1985-2005. There are two curves in each panel: one representing portfolios constructed using only stocks in the smallest size quintile and one representing portfolios constructed using only stocks in the largest size quintile. Each curve plots the annual excess volatility versus the number of stocks in the portfolio. 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 liquidity volatility 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 volatility of small stocks portfolios remains higher than the excess volatility of the corresponding portfolios of large stocks until each portfolio has more than 30 stocks. Then, when the portfolios have more than 40 stocks, the excess volatility of small stocks portfolios falls slightly below the excess volatility of the corresponding large stocks portfolios. In contrast, in 1985-2005, the excess volatility of small stocks portfolios remains higher than the excess volatility of the corresponding portfolios of large stocks only until each portfolio has about 22 stocks. Then, as we add stocks, the excess volatility of small stocks portfolios falls substantially below the excess volatility of the corresponding large stocks portfolios. Comparing portfolios of, say, 40 stocks or more, there is a small difference between the two curves in 1963-1984, but a much larger difference in 1985-2005. Unlike the 1963-1984 subperiod, in 1985-2005 there is a clear advantage to diversify liquidity volatility using smallest quintile stocks rather than largest quintile stocks. In 1985-2005 investors who used portfolios of at least 35 stocks to diversify liquidity risk 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 in Figure 4, which presents the same 4 curves above, but compares them differently. The two curves in the top panel of Figure 4 chart the excess volatility of portfolios of smallest stocks 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. When we hold portfolios of 30 stocks or more, the curve describing 1985-2005 lies below the curve describing 1963-1984. The two curves in the bottom panel of Figure 4 chart the excess volatility of large stocks portfolios in 1963-1984 and 1985-2005, respectively. These curves demonstrate that the diversification benefits of portfolios of large stocks have declined from 1963-1984 to 1985-2005. When we hold portfolios of 30 stocks or more, the curve describing 1985-2005 lies clearly above the curve describing 1963-1984. Hence, the curves of small stocks portfolios and large stocks portfolios exhibit opposite changes over time. The diversification benefits of small stocks portfolios have increased over time, whereas, the diversification benefits of large stocks portfolios have declined over time.

To summarize, we find that the increase over time in the liquidity betas of large-cap stocks is accompanied by a decline in the ability to diversify aggregate liquidity shocks by holding portfolios of large-cap stocks. In contrast, the decline over time in the liquidity betas of small-cap stocks is accompanied by an improvement in the ability to diversify aggregate liquidity shocks using portfolios of small-cap stocks.

6 Robustness tests

6.1 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

$$\Delta LIQ_{i,d} = a + \beta_{i,m}\Delta LIQ_{m,d} + \beta_{i,ind}\Delta LIQ_{ind,d} + \varepsilon_{i,d}, \tag{8}$$

where $\Delta LIQ_{ind,d}$ is equal-weighted average of $\Delta LIQ_{i,d}$ 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. We use 20 industry portfolios, which are constructed using the Moskowitz and Grinblatt (1999) industry classification.

The results are presented in Table 7. The market betas are low relative to the industry betas, which reflects the high correlation of some industries with the market portfolio. As a result, the regression R^2 provides better insight for the effects of including industry portfolios. Examining the time series of R^2, Table 7 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 large firms' liquidity has become more common are unchanged by the inclusion of industry liquidity.

6.2 Nonsynchronous Trading

As noted by Scholes and Williams (1977) and Cohen, Hawawini, Maier, Schwartz, and Whitcomb (1983), nonsynchronous trading may affect the estimation of β in regressions. We therefore re-run Regression (2) using current and lag market values as follows

$$\Delta LIQ_{i,d} = a + \beta_{i,m}\Delta LIQ_{m,d} + \beta_{i,m1}\Delta LIQ_{m,d-1} + \varepsilon_{i,d}. \tag{9}$$

Table 8 reports the time-series mean of the cross-sectional average of β_i, which is defined here as the sum of $\beta_{i,m}$ and $\beta_{i,m1}$, for the nine sub-periods between 1963 to 2005. Consistent with our previous findings, β_i decreases over time for small firms and increases over time for large firms. In fact, the cross-sectional averages of the β_i reported in Table 8 are only marginally different from those reported in Table 2. Therefore, it seems that nonsynchronous trading does not affect our results.

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 (size quintiles 1 and 5, respectively). In particular, we find that the sensitivity (beta) of the liquidity of large stocks to aggregate liquidity shocks has increased significantly over 1963-2005, whereas, the sensitivity of the liquidity of small stocks to aggregate liquidity shocks has declined significantly over that period.

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 Granger (1969) cause 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. In addition, we also find empirical evidence supporting the thesis of Chordia, Roll, and Subrahmanyam (2000) that correlated institutional trading creates a significant linkage between systematic returns volatility and commonality in liquidity.

The cross-sectional polarization of systematic liquidity has strategic implications for the ability to diversify aggregate liquidity shocks. We find that the ability to diversify aggregate liquidity 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. Amihud, Mendelson, and Wood (1990) find that sudden unanticipated declines in liquidity have played a crucial role in the stock market crash of October 1987. Our evidence suggests that the vulnerability of US equity markets to unanticipated liquidity 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, $\Delta LIQ_{i,d} = a + \beta_i \Delta LIQ_{m,d} + \epsilon_{i,d}$, where $\Delta LIQ_{i,d}$ is the first difference of the logarithm of daily Amihud (2002) measure of firm i in day d, and $\Delta LIQ_{m,d}$ is the equal-weighted market average of $\Delta LIQ_{i,d}$. 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 time-series means of the annual cross-sectional average of β_i for stocks 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.

Sub-period	Smallest	Largest
1963-1967	0.898	0.948
1968-1972	0.881	0.984
1973-1977	0.796	1.195
1978-1982	0.757	1.203
1983-1987	0.722	1.276
1988-1992	0.683	1.370
1993-1997	0.723	1.218
1998-2002	0.553	1.245
2003-2005	0.313	1.234

Table 2: Stochastic Time-Trend Tests

This table presents the results of Dickey-Fuller (1981) unit-root test 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 $\gamma = 1$. 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.

	$\beta_t = a + \delta t + \gamma\beta_{t-1} + \epsilon_t$		
Firms	γ	$T(\gamma - 1)$	P-value
1 (smallest)	0.39	-25.64	0.01
2	0.63	-15.53	0.12
3	0.86	-5.75	0.74
4	0.29	-29.76	$< .005$
5 (largest)	0.56	-18.68	0.05
5 minus 1	0.29	-29.88	$< .005$

Table 3: Deterministic Time-Trend Tests

This table presents the time-trend test results for average liquidity betas of firms in each of the five size quintiles. Formally, to test a deterministic trend in series, we regress the 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.

			$\beta_t = a + \delta t + \epsilon_t$			
Firms	Intercept ($a \times 10$)	T-statistic	P-value	Time trend ($\delta \times 10^3$)	T-statistic	P-value
1 (smallest)	9.59	30.90	$< .001$	-10.83	-5.21	$< .001$
2	9.62	31.37	$< .001$	-3.19	-2.09	0.04
3	9.25	20.33	$< .001$	2.21	1.01	0.32
4	9.30	73.15	$< .001$	4.89	7.59	$< .001$
5 (largest)	10.13	22.08	$< .001$	7.77	4.12	$< .005$
5 minus 1	0.53	1.16	0.25	18.59	8.23	$< .001$

Table 4: Systematic Liquidity and Institutional Ownership

This table presents the results for Fama and MacBeth (1973) regressions of liquidity beta on institutional ownership. Two models are estimated. One includes institutional ownership alone and the other adds size as well. Specifically, in each year t, the cross-sectional regressions estimated are: $\beta_{i,t} = a_t + \lambda_t \cdot IO_{i,t-1} + \nu_{i,t}$ and $\beta_{i,t} = a_t + \lambda_t \cdot IO_{i,t-1} + \varphi_t \cdot Size_{i,t-1} + \nu_{i,t}$, where $IO_{i,t-1}$ is firm i's market value owned by institutions as the percentage of capitalization of the entire market, measured at the end of year $t-1$, and $Size_{i,t-1}$ is the logarithm of firm i's market capitalization (in millions), also measured at the end of year $t-1$. The table presents the time-series averages and t-statistics (in brackets) of the coefficient estimates. 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.

Firms	$\beta_{i,t} = a_t + \lambda_t \cdot IO_{i,t} + \nu_{i,t}$	$\beta_{i,t} = a_t + \lambda_t \cdot IO_{i,t} + \varphi_t \cdot Size_{i,t} + \nu_{i,t}$	
	IO	IO	Size
1 (smallest)	190.9	140.9	0.041
	[4.74]	[3.97]	[3.21]
2	63.88	60.06	0.012
	[8.40]	[7.37]	[0.34]
3	16.30	15.98	0.004
	[5.76]	[4.70]	[0.15]
4	7.438	8.585	-0.058
	[6.66]	[5.23]	[-1.63]
5 (largest)	0.473	0.134	0.083
	[6.37]	[2.18]	[5.02]

Table 5: Polarization in Systematic Liquidity and Difference in Institutional Ownership

This table presents the results for time-series regressions with the following specification:

$$\Delta\beta_{Size,t} = a + \delta \cdot t + \gamma \cdot \Delta IO_{Size,t-1} + \Delta\beta_{Size,t-1} + \omega_t$$

where $\Delta\beta_{Size,t}$ is the difference of average systematic liquidity β across largest and smallest 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 $\Delta IO_{Size,t-1}$ is the difference of average IO across largest and smallest size quintile. The table presents the averages coefficient estimates, and the corresponding t-statistics and p-value (in brackets) of the coefficient estimates. T-statistics and p-values are calculated using heteroskedasticity and first-order 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.

	Time Trend	$\Delta IO_{Size,t-1}$	$\Delta\beta_{Size,t-1}$	R^2
Coefficient	0.013			0.209
T-stat	[2.35]			
P-value	[0.02]			
Coefficient	-0.001	6.851		0.409
T-stat	[-0.16]	[2.72]		
P-value	[0.87]	[0.01]		
Coefficient	-0.001	4.424	0.336	0.435
T-stat	[-0.21]	[2.21]	[3.38]	
P-value	[0.83]	[0.03]	[< 0.01]	

Table 6: Systematic Liquidity and Systematic Risk

Panel A estimates the time-series regression $\beta_{liq,t} = a_b + \delta_b t + \theta_b \beta_{ret,t} + e_{b,t}$, and Panel B estimates the time-series regression $R^2_{liq,t} = a_r + \delta_r t + \theta_r R^2_{ret,t} + e_{r,t}$, where $\beta_{liq,t}$ and $R^2_{liq,t}$ are the average β and R^2 from the liquidity market model estimated for firm i in year t, $\Delta LIQ_{i,d} = a + \beta_{liq,i}\Delta LIQ_{m,d} + \varepsilon_{i,d}$, while $\beta_{ret,t}$ and $R^2_{ret,t}$ are the average β and R^2 from the return market model estimated for firm i in year t, $ret_{i,d} = a + \beta_{ret,i} ret_{m,d} + \varepsilon_{i,d}$. The table presents coefficient estimates, corresponding t-statistics, and R^2 for the two regressions. The last column of both panels reports the change in R^2 between the regression with and without $\beta_{ret,t}$ and $R^2_{ret,t}$, respectively. 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	Time trend ($\delta \times 10^3$)	T-statistic	Return (θ)	T-statistic	R^2	Change in R^2
			Panel A: $\beta_{liq,t} = a_b + \delta_b t + \theta_b \beta_{ret,t} + e_{b,t}$			
1 (smallest)	-1.23	[-0.91]	0.66	[6.31]	0.82	0.18
2	-1.80	[-2.23]	0.56	[4.85]	0.55	0.38
3	-1.17	[-1.51]	1.12	[7.71]	0.73	0.66
4	2.80	[5.19]	0.37	[5.27]	0.72	0.06
5 (largest)	1.77	[1.39]	0.69	[6.06]	0.66	0.27
5 minus 1	5.82	[1.93]	0.55	[4.57]	0.75	0.11
			Panel B: $R^2_{liq,t} = a_r + \delta_r t + \theta_r R^2_{ret,t} + e_{r,t}$			
1 (smallest)	-0.26	[-3.75]	0.08	[3.21]	0.65	0.19
2	-0.13	[-1.54]	0.11	[3.44]	0.53	0.52
3	0.10	[0.83]	0.15	[3.81]	0.64	0.53
4	0.26	[2.37]	0.15	[4.03]	0.69	0.45
5 (largest)	0.45	[3.21]	0.23	[8.38]	0.81	0.57
5 minus 1	0.26	[2.06]	0.31	[11.64]	0.89	0.47

Table 7: Industry Effects

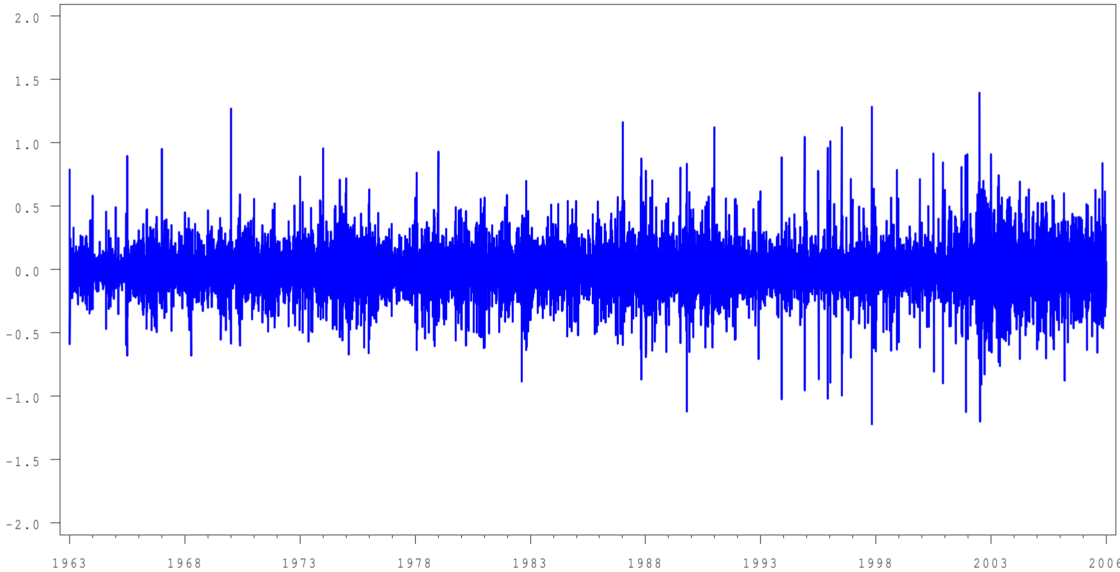
For firm i in year t, the time-series regression, $\Delta LIQ_{i,d} = a + \beta_{i,m}\Delta LIQ_{m,d} + \beta_{i,ind}\Delta LIQ_{ind,d} + \varepsilon_{i,d}$, is estimated, where $\Delta LIQ_{i,d}$ is the first difference of the logarithm of daily Amihud measure of firm i in day d, $\Delta LIQ_{m,d}$ is the equal-weighted market average of $\Delta LIQ_{i,d}$, and $\Delta LIQ_{ind,d}$ is the equal-weighted industry average of $\Delta LIQ_{i,d}$. 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	-0.016	0.988	0.057
	1968-1972	-0.014	0.989	0.054
	1973-1977	-0.029	0.990	0.063
	1978-1982	-0.027	0.995	0.063
	1983-1987	-0.023	0.991	0.058
	1988-1992	-0.050	1.006	0.068
	1993-1997	-0.013	0.987	0.060
	1998-2002	-0.011	0.979	0.064
	2003-2005	-0.019	0.991	0.086
Smallest	1963-1967	-0.042	0.932	0.053
	1968-1972	-0.046	0.908	0.050
	1973-1977	-0.188	0.979	0.055
	1978-1982	-0.228	1.003	0.053
	1983-1987	-0.201	0.931	0.047
	1988-1992	-0.348	1.043	0.052
	1993-1997	-0.243	0.985	0.045
	1998-2002	-0.202	0.774	0.034
	2003-2005	-0.312	0.643	0.028
Largest	1963-1967	-0.045	1.048	0.058
	1968-1972	-0.028	1.038	0.054
	1973-1977	0.162	1.024	0.074
	1978-1982	0.153	1.036	0.082
	1983-1987	0.262	1.008	0.081
	1988-1992	0.362	0.989	0.102
	1993-1997	0.067	1.118	0.083
	1998-2002	-0.171	1.381	0.102
	2003-2005	-0.091	1.284	0.127

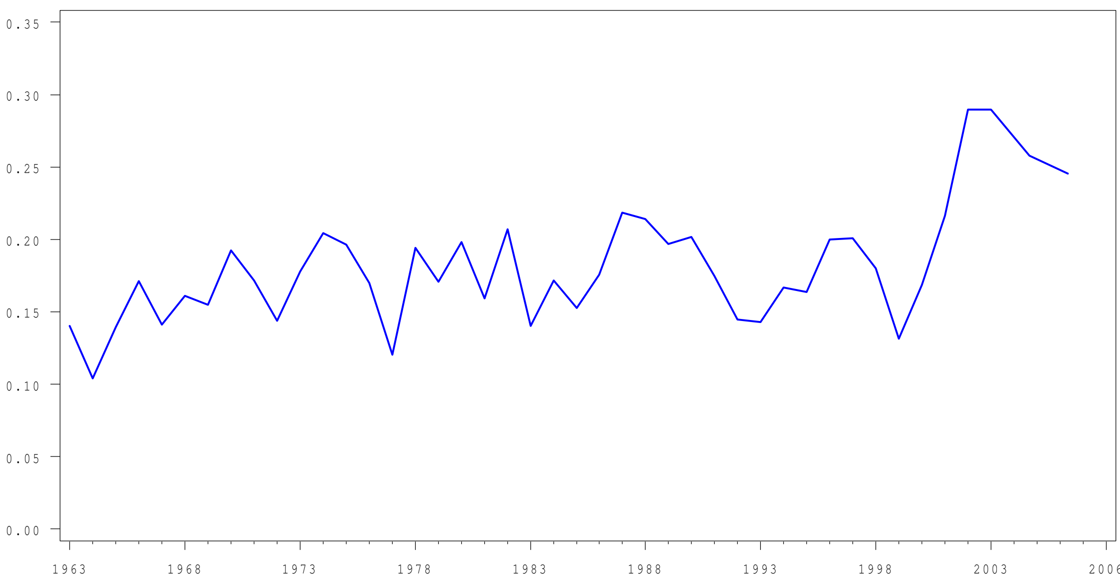
Table 8: Nonsynchronous Trading

For firm i in year t, the time-series regression, $\Delta LIQ_{i,d} = a + \beta_{i,m}\Delta LIQ_{m,d} + \beta_{i,m1}\Delta LIQ_{m,d-1} + \varepsilon_{i,d}$, is estimated, where $\Delta LIQ_{i,d}$ is the first difference of the logarithm of daily Amihud measure of firm i in day d, $\Delta LIQ_{m,d}$ is the equal-weighted market average of $\Delta LIQ_{i,d}$. We obtain estimates of $\beta_{i,m}$ and $\beta_{i,m1}$ for each firm i in year t, and β_i in year t is defined as the sum of $\beta_{i,m}$ and $\beta_{i,m1}$. The table reports the time-series means of the annual cross-sectional average of β_i 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.

Sub-period	Smallest	Largest
1963-1967	0.968	0.928
1968-1972	0.908	0.993
1973-1977	0.734	1.200
1978-1982	0.746	1.239
1983-1987	0.727	1.304
1988-1992	0.712	1.382
1993-1997	0.772	1.185
1998-2002	0.581	1.234
2003-2005	0.307	1.200



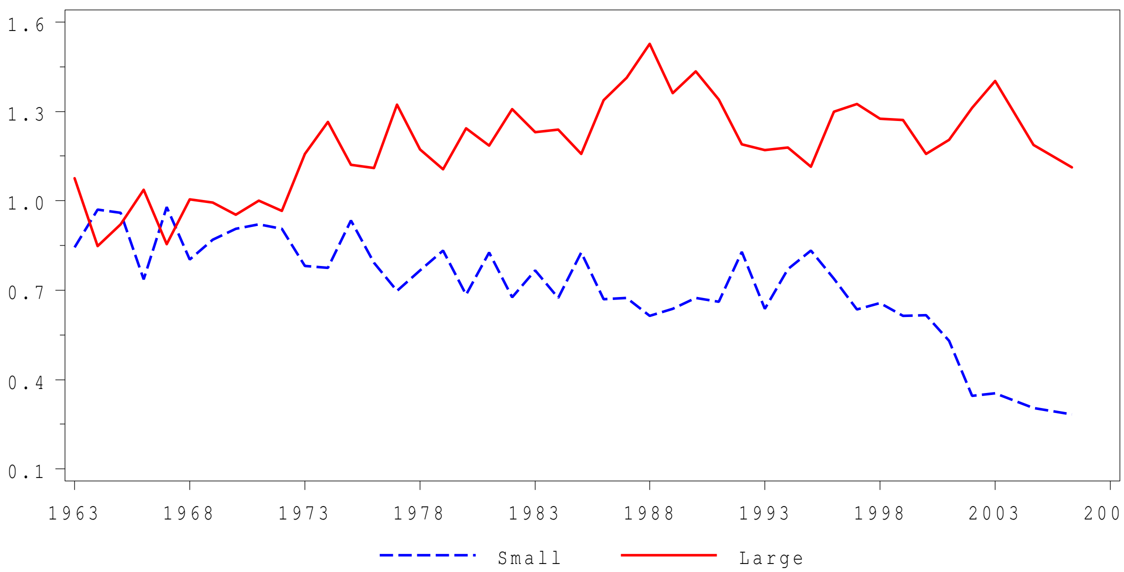
(a) Market Liquidity Variation: $\Delta LIQ_{m,d}$



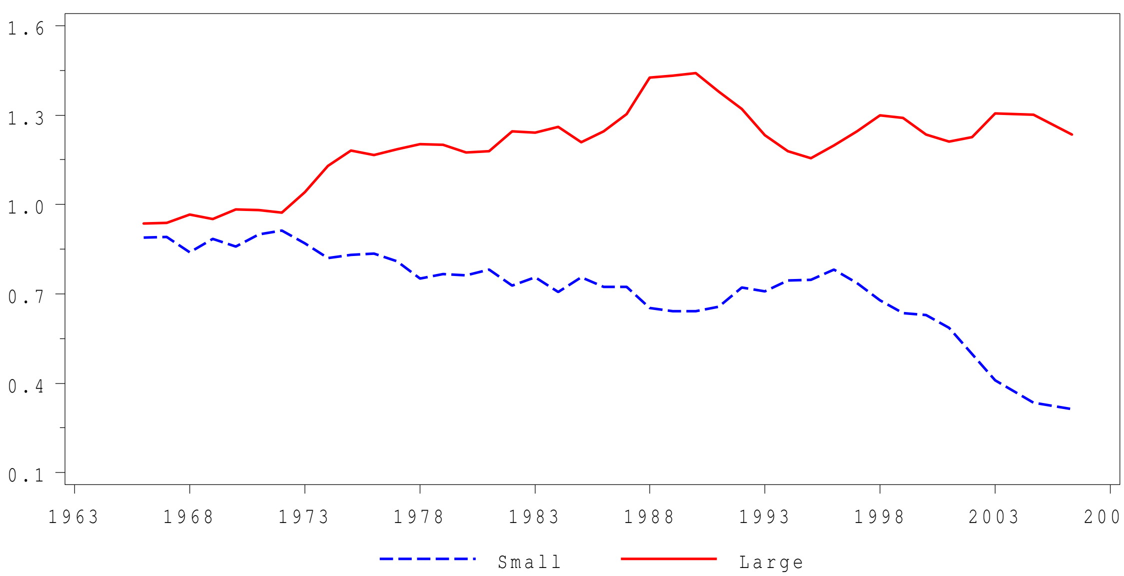
(b) Volatility of $\Delta LIQ_{m,d}$

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

$\Delta LIQ_{i,d}$ is the daily change in the logarithm of Amihud (2002) illiquidity measure from day $d-1$ to day d for firm i. $\Delta LIQ_{m,d}$ is the cross-sectional average of $\Delta LIQ_{i,d}$ 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. Figure 1(a) presents the time-series plot of $\Delta LIQ_{m,d}$. Figure 1(b) shows the annual standard deviation of $\Delta LIQ_{m,d}$.



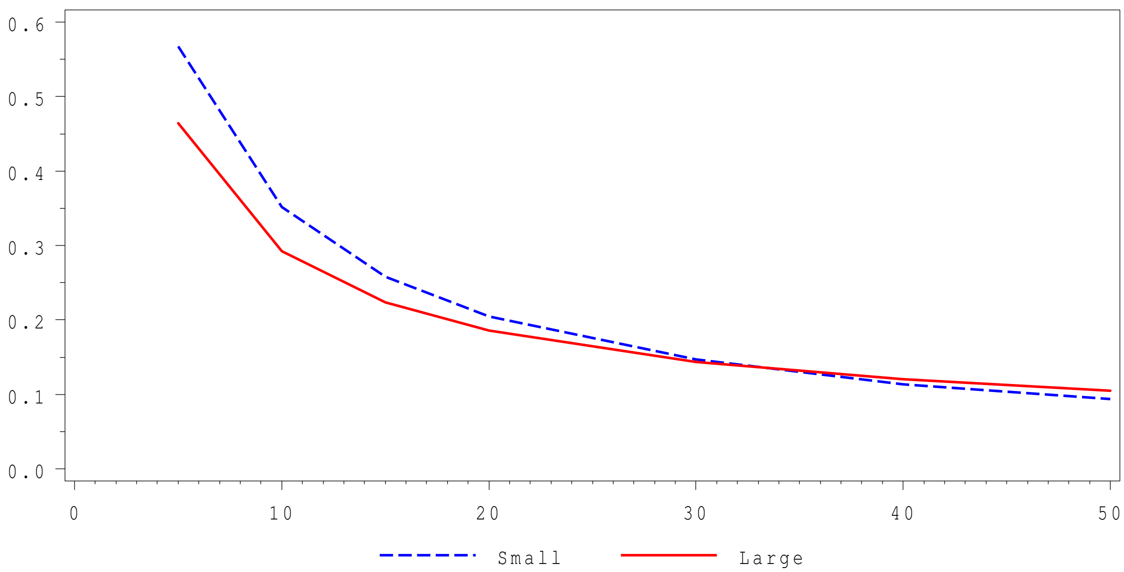
(a) Liquidity beta for small and large firms



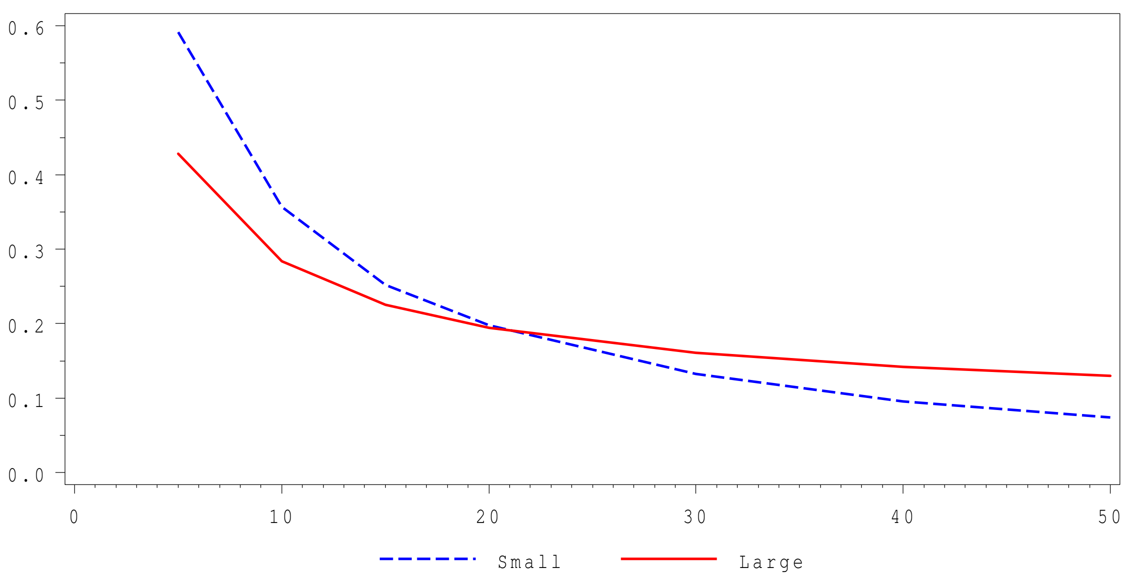
(b) Three-year moving average, MA(3), of liquidity beta

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

For each firm i and year t, we run the following time-series regressions: $\Delta LIQ_{i,d} = a + \beta_i \Delta LIQ_{m,d} + \varepsilon_{i,d}$, where d denotes the days in year t, $\Delta LIQ_{i,d}$ is the change in the logarithm of daily Amihud (2002) illiquidity measure, and $\Delta LIQ_{m,d}$ is the equally weighted average of $\Delta LIQ_{i,d}$ for all firms included in the sample. 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 the market and each size quintile. Panel A plots the average β for small and large firms, while Panel B shows the three-year moving average [MA(3)]. 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.



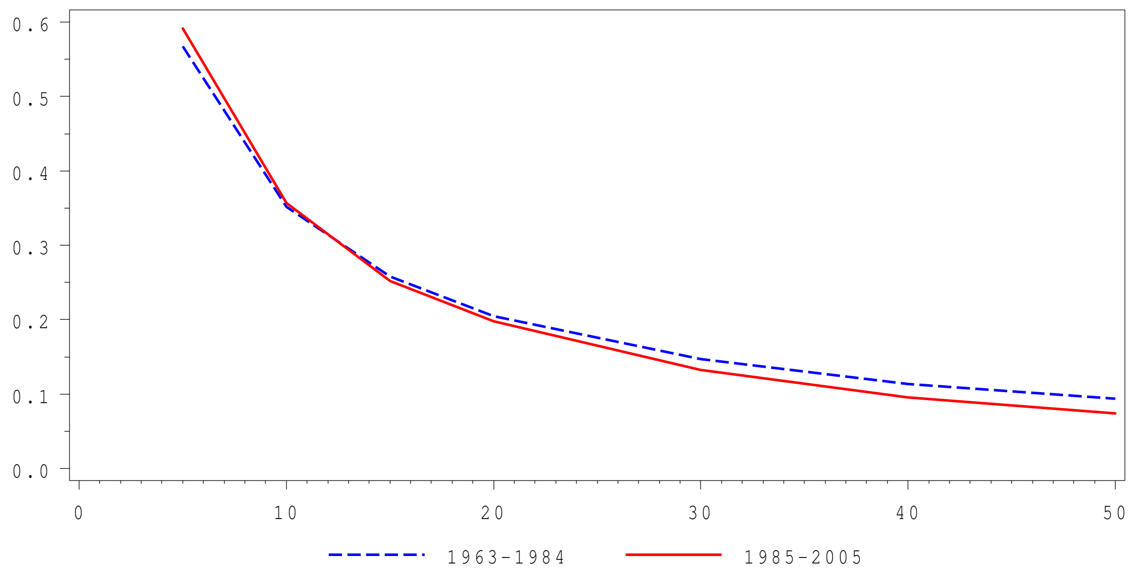
(a) 1963-1984



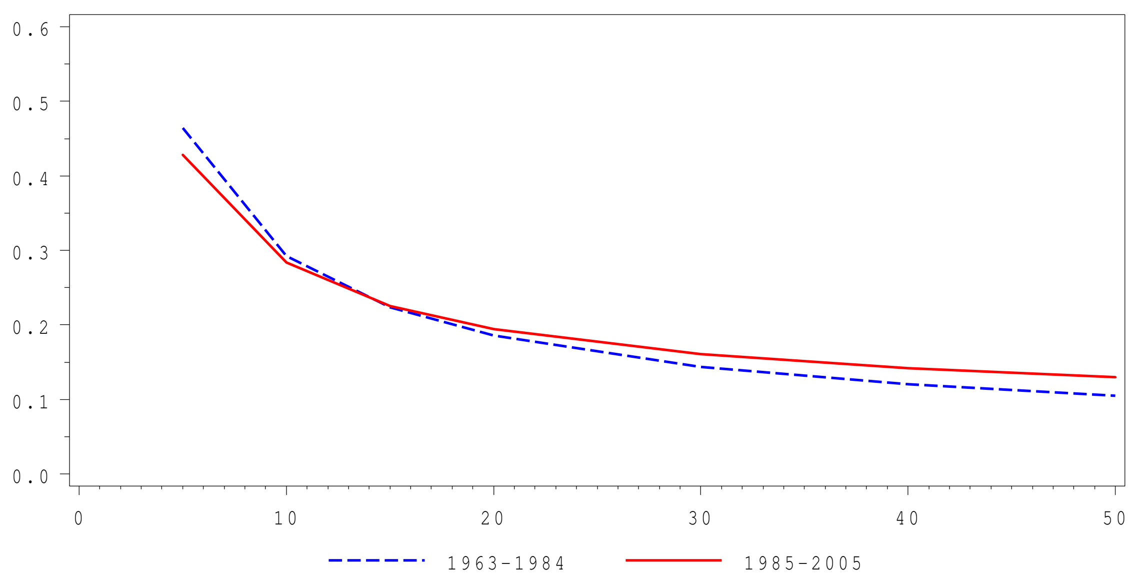
(b) 1985-2005

Figure 3: Diversification of Small and Large Firms

The graphs plot the volatility of liquidity of portfolios composed of stocks of small (only) and large (only) firms in excess of the volatility of market liquidity. 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 volatility of portfolios in year t are calculated, and average annual volatility is then calculated over two subperiods: 1963-1984 and 1985-2005. Panel A shows the excess volatility of portfolios in the first subperiod, and Panel B in the second subperiod. 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) Small



(b) Large

Figure 4: Diversification of Small and Large Firms over Time

The graphs plot the volatility of liquidity of portfolios composed of stocks of small (only) and large (only) firms in excess of the volatility of market liquidity. 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 volatility of portfolios in year t are calculated, and the average annual volatility is then calculated over two subperiods: 1963-1984 and 1985-2005. Panel A and Panel B show the excess volatility of portfolios of small and large firms, respectively, in each of the two subperiods. 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.