Commonality in liquidity:
A demand-side explanation

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JEL Classification: G10, G14
Keywords: Liquidity, Commonality, Mutual Funds

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Abstract

We hypothesize that a source of commonality in a stock's liquidity arises from correlated trading among the stock's investors. Focusing on correlated trading of mutual funds, we find that stocks with high mutual fund ownership have comovements in liquidity that are about twice as large as those for stocks with low mutual fund ownership. We also find that stocks owned by mutual funds with higher turnover have higher commonality in liquidity and that the impact of ownership on commonality is stronger when funds experience liquidity shocks themselves. These results suggest an important role for the demand side of liquidity in explaining commonality.

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1. Introduction

A stock's liquidity and the risks that may arise from potential illiquidity are important factors for many investors in their investment decisions. Liquidity has been shown to not only affect stock returns, but to also covary strongly across stocks, i.e. there is commonality in liquidity.[1] This commonality in liquidity can arise from both supply-side and demand-side sources. While studies have found support for supply-side sources (e.g., Coughenour and Saad, 2004; Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes, 2010), other studies indicate that these supply-side explanations cannot drive all of the observed commonality in liquidity (e.g., Brockman and Chung, 2002; Bauer, 2004).[2] In this paper we propose that mutual funds should be large contributors to the demand-side source of commonality in liquidity.

The intuition for our argument is as follows. If a group of investors is subject to similar liquidity shocks or changes in their information set, the trades of these investors will likely be in the same direction (within a given stock) and occur with similar timing. If these investors hold a similar group of stocks, then the stocks comprising their portfolios are likely to experience large trade imbalances at the same points in time. It follows that stocks held to a large extent by a group of investors that tend to trade in the same direction and at the same time should be characterized by strong comovements in their liquidity.

Mutual funds are a prime example of an investor group that could give rise to such an effect.[3] Mutual funds generally hold large, well-diversified portfolios and

[1] See, for example, Amihud and Mendelson (1986) and (1989), Brennan and Subrahmanyam (1996) Brennan, Chordia and Subrahmanyam (1998), Jacoby, Fowler and Gottesman (2000), Amihud (2002), Longstaff (2009), and Hasbrouck (2009) regarding liquidity and returns and Chordia, Roll and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), Brockman, Chung and Pérignon (2009), and Karolyi, Lee and van Dijk (2011) regarding commonality in liquidity.

[2] These papers find strong commonality in liquidity in pure limit order markets, while the explanation suggested in Coughenour and Saad (2004) is based on common market makers.

[3] There are other groups of investors, e.g. hedge funds, for which we might expect a similar effect. However, mutual funds offer the advantage that we have comprehensive holdings data and can thus conduct a detailed cross-sectional analysis on the stock level.

regularly face liquidity shocks in the form of positive or negative net-flows. These net-flows are typically highly correlated across funds, i.e., if one fund faces outflows (inflows), many others face outflows (inflows) at the same time. Furthermore, previous research provides evidence of herding and correlated trading by mutual funds as well as other institutional investors.[4] Consequently, we hypothesize that stocks with high mutual fund ownership should exhibit strong commonality in liquidity.

We test this basic hypothesis using a two-step process in which we first measure a stock's liquidity commonality and then estimate the relationship of that commonality to the stock's mutual fund ownership. Specifically, using data on mutual fund ownership and measures of stock liquidity for NYSE and AMEX stocks, we estimate the covariance between a stock's liquidity and the liquidity of a portfolio of stocks with high mutual fund ownership, where we define liquidity by the Amihud (2002) measure of daily stock liquidity. For the sake of brevity we label the regression coefficient on the high mutual fund ownership portfolio, β_{HI}, the mutual fund liquidity beta.

Our hypothesis implies a positive relation between β_{HI} and mutual fund ownership. To test this hypothesis, in each quarterly cross section we relate the stock's commonality in liquidity with the degree to which the stock is owned by mutual funds. We find that the liquidity of stocks with high mutual fund ownership covaries about twice as strongly with the liquidity of other high mutual fund ownership stocks than with the liquidity of stocks with low mutual fund ownership, controlling for other factors.

An alternative explanation for our findings is that mutual funds hold stocks with specific characteristics that explain commonality. That is, our results could be driven by individual stock characteristics such as firm size or level of liquidity that might jointly determine systematic liquidity and mutual fund ownership.[5] To test this alternative

[4] See, for example, Kraus and Stoll (1972), Lakonishok, Shleifer and Vishny (1992), Grinblatt, Titman and Wermers (1995), Sias and Starks (1997), Wermers (1999), Sias (2004), Coval and Stafford (2007), Anton and Polk (2010), and Greenwood and Thesmar (2011),

[5] See, for example, Del Guercio (1996), Falkenstein (1996), Gompers and Metrick (2001), Bennett, Sias and Starks (2003), and Massa and Phalippou (2005).

hypothesis, we conduct several refinements of our analysis. We examine the relationship between the mutual fund liquidity beta and mutual fund ownership within size and liquidity level quartiles. The positive relationship between these variables is strongest among large and liquid stocks, which tend to be the stocks most favored by mutual funds. However, the result also generally holds within all subsets except for the very smallest or most illiquid stocks, which is not surprising because mutual funds typically are not the dominant holders (or traders) of these types of stocks. Further, we also find that the positive relation between the mutual fund liquidity beta and mutual fund ownership continues to hold in a multivariate setting while controlling for the effects of a set of individual stock characteristics and even after including firm-fixed effects.

If the impact of ownership on commonality is driven by the trading activity of mutual funds, as we hypothesize, then one would expect the ownership-commonality relationship to be stronger under conditions in which ownership is a better proxy for correlated trading. To examine this hypothesis, we consider the following two types of mutual fund trading: voluntary trading (often associated with information-based investment strategies) and involuntary trading (typically caused by liquidity shocks from fund flows).

A mutual fund's level of voluntary trading is reflected in the fund's turnover ratio after controlling for the fund's flow-induced trading. If a high proportion of the mutual funds' voluntary trading is due to correlations in information-based trading across funds, then we would expect a relation between the level of such trading and commonality in liquidity. Consistent with this hypothesis, we find that mutual fund liquidity betas are greater for stocks that are owned by mutual funds with high turnover ratios than for stocks that are owned by mutual funds that do not trade a lot.

A mutual fund's involuntary or forced trading will be observed when the fund experiences liquidity shocks in its inflows or outflows. This creates buying or selling pressure for those stocks typically owned and traded by mutual funds (Coval and

Stafford, 2007, Khan, Kogan, and Serafeim, 2011, and Ben-Rephael, Kandel, and Wohl, 2011). Furthermore, the effects of inflows and outflows should differ because funds can accumulate cash or buy futures before they have to trade based on inflows, but outflows can force the fund to trade in order to meet redemptions (e.g., Edelen and Warther, 2001). In the latter case, mutual funds are clearly demanding liquidity which allows us to identify whether it is really the liquidity demand that drives commonality here. We find strong evidence that suggests flow-driven liquidity shocks are an important driver of the effects of the mutual fund ownership results that we document. The impact of mutual fund ownership on a firm's mutual fund liquidity beta, β_{HI}, is about 50% greater in quarters with high absolute aggregate flows as compared to quarters with low absolute aggregate flows. The effect is particularly pronounced for negative flow quarters; the impact of ownership on commonality is roughly 75% stronger in quarters with highly negative net flows. This evidence supports the hypothesis that liquidity shocks that mutual funds face propagate through to the commonality in liquidity among the stocks they hold. These results also support the hypothesis that liquidity demand of mutual funds contributes to commonality in liquidity.

Finally, rather than examining the propensity for correlated trading based on the stock's level of mutual fund ownership, we also examine actual trading through the change in mutual fund ownership obtained from quarterly SEC filings. Consistent with our hypothesis, we find a strong positive relation between changes in a stock's aggregate mutual fund ownership and its mutual fund liquidity beta. Overall, our results suggest an important role for mutual fund ownership and eventually liquidity demand in explaining commonality in liquidity across stocks.

Our results are stable over time and hold over different subsamples. They are also not driven by the definition of the Amihud (2002) illiquidity ratio, which we use as our primary illiquidity measure. One concern might be that changes in this measure are driven by changes in returns rather than changes in liquidity. However, we show that our results hold after controlling for return comovements among stocks with high mutual fund ownership. They also hold if we control for volatility comovements or if we use a stock's turnover ratio as alternative liquidity measure.

Our paper contributes to several main lines of research. It contributes to the broad empirical literature on liquidity in common stocks. A number of papers have documented the impact of liquidity on expected returns.[6] More recently, several studies document the existence of commonality in liquidity, in the U.S. as well as internationally.[7] Further the relevance of commonality for asset pricing is highlighted in both theoretical and empirical work.[8] The literature on commonality in liquidity has mainly focused on the supply side provision of liquidity. Coughenour and Saar (2004) show that commonality in liquidity can arise from the same NYSE specialist providing liquidity for many stocks. Consistent with this idea, Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) provide evidence that the aggregate inventory of all NYSE specialists is an important determinant of aggregate market liquidity. We contribute to this strand of the literature by showing the role of mutual funds in explaining commonality via the demand side.

The importance of the demand side of liquidity in explaining liquidity levels is suggested in Chordia, Roll, and Subrahmanyam (2002) who find that aggregate order imbalance – which is a measure for liquidity demand – reduces liquidity. However, their focus is on liquidity levels, while our contribution is to show that liquidity demand has an impact on liquidity covariances. While generally focusing on liquidity supply, Hameed, Kang, and Viswanathan (2010) also analyze the impact of correlated liquidity demand. Consistent with our results, they find that comovements in stock-level order imbalance

[6] See, for example, Amihud and Mendelson (1986), Brennan, Chordia and Subrahmanyam (1998), Jacoby, Fowler and Gottesman (2000), Amihud (2002), and Hasbrouck (2009).
[7] See, for example, Chordia, Roll and Subrahmanyam, (2000), Hasbrouck and Seppi (2001), Karolyi, Lee and van Dijk (2011), and Brockman, Chung and Pérignon (2009).
[8] See, for example, Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), Korajczyk and Sadka (2008), and Lee (2011).

measures help to explain commonality. Massa (2004) and Massa and Phalippou (2005) examine the relation between institutional investor ownership and the level of stock liquidity. The impact of liquidity demanding trades on movements in market prices is also examined in Hendershott and Seasholes (2009). We add to this literature by identifying a primary source of the comovements.

In particular, our findings compliment and extend the literature connecting institutional ownership with commonality in liquidity. This connection was first suggested by Chordia, Roll and Subrahmanyam (2002). Evidence consistent with this explanation is provided by Kamara, Lou, and Sadka (2008). Kamara et al. find that the liquidity of large (small) firms has become more (less) systematic over time, and that there is a corresponding change in institutional ownership. Furthermore, they segregate institutional ownership and find no significant relationship between common liquidity and ownership by banks and insurance companies, which are likely long-term investors.

These papers do not, however, conduct direct tests of the connection between the common trading of investors – and the resulting demand for liquidity – with commonality in liquidity, which is what we do in this paper. Using detailed data not just on ownership, but also on portfolio turnover and fund flows, we are able to document a connection between common trading, both voluntary and 'forced', and common liquidity. Furthermore, we show that this resulting common liquidity exists precisely within the set of stocks subject to common trading. In other words, controlling for market-wide common liquidity, we find that the liquidity of stocks subject to the common trading of mutual fund managers co-moves *with each other*.

The importance of the correlated trading explanation of commonality that we test in this paper is also highlighted in a recent paper by Karolyi, Lee, and van Dijk (2011). They use international data to run a horse race between several supply-side and demand-side explanations. The authors find the most reliable explanation for commonality in liquidity to be correlated trading, which they proxy for with commonality in stock turnover and interpret as evidence for liquidity demand explaining commonality. Our paper provides a different analysis from theirs, but we also conduct a complementary detailed analysis of the correlated trading explanation, in particular, our results on the role of flow-induced forced trading is consistent with their analysis and provides additional evidence in support of their hypothesis regarding correlated trading.

Our findings also contribute to the literature on the influence of investors, particularly institutional investors, on stock returns.[9] In terms of the impact of investors' correlated trading on returns, Greenwood (2009) shows that common trading patterns of index investors can give rise to substantial excess comovement of stock returns. Pirinsky and Wang (2004) and Kumar and Lee (2006) find that correlated trading among institutional and retail investors, respectively, gives rise to return comovement.[10] More closely related to our paper are Greenwood and Thesmar (2011) and Anton and Polk (2010). Greenwood and Thesmar also use mutual fund ownership and mutual fund flows to get a proxy for correlated trading. They show that stocks owned by mutual funds with correlated inflows exhibit larger return comovements. Anton and Polk provide evidence that common covariation in stock returns is associated with common ownership by mutual funds. We contribute to their findings by showing the channels through which institutional investors can give rise to commonality in returns. However none of these papers investigate the link between correlated trading and comovement in liquidity.

The remainder of this paper is organized as follows. In Section 2 we describe our data and the construction of our main variables. Our empirical analysis regarding commonality in liquidity and mutual fund ownership is presented in Section 3 and in Section 4 we consider proxies for mutual fund trading. We provide results from robustness tests in Section 5 and our conclusions in Section 6.

[9] See, for example, Sias and Starks (1997), Gompers and Metricks (2001), Sias, Starks, and Titman (2006).
[10] Evidence suggesting that investor clienteles might lead to return comovement is also provided in Barberis, Shleifer, and Wurgler (2005), Pirinsky and Wang (2006), and Green and Hwang (2009).

2. Data and variable construction

Our initial sample is based on mutual fund holdings from the CDA/Spectrum database over the 1980-2008 period. We match the holdings of these mutual funds to other fund variables in the CRSP mutual fund database using MFLinks. We also match these data to characteristics of the underlying stocks obtained from the CRSP stock database.

2.1. Variable definitions

We create a stock-level proxy for the likelihood of correlated trading based on the percentage of shares outstanding held by mutual funds. Specifically, for each stock we construct a quarterly measure of aggregate mutual fund ownership.[11] The fraction of ownership $mfown_{i,t}$, in stock i owned by J mutual funds at the end of quarter t, is

$$mfown_{i,t} = \frac{\sum_{j=1}^{J} sharesowned_{i,j,t}}{shrout_{i,t}},$$

where $sharesowned_{i,j,t}$ is the number of shares in stock i owned by mutual fund j at quarter t and $shrout_{i,t}$ is the total number of shares outstanding for stock i at time t.

In later analysis we use a turnover-weighted measure of mutual fund ownership. When summing ownership across funds within a stock, we weight ownership by turnover,

[11] To obtain quarterly stock level measures of aggregate mutual fund ownership using March, June, September, and December as quarter end dates we carry forward each fund's quarterly holdings for two months. Then, following the literature, we carry holdings forward an additional quarter if the fund appears to have missed a report date (see, e.g., Frazzini and Lamont, 2008). This is done for a maximum of a 6 month gap in report dates. Holdings are adjusted for splits that occur between the reporting and filing dates. We set holdings equal to zero if the report date is subsequent to the file date, if CRSP reports zero shares outstanding, or if the total mutual fund ownership exceeds the shares outstanding.

$$twmfown_{i,t} = \frac{\sum_{j=1}^{J}\left(turnover_{j,t} \cdot sharesowned_{i,j,t}\right)}{shrout_{i,t}}$$

where $turnover_{j,t}$ equals the turnover as reported in CRSP for fund *j* during quarter *t.*

We measure liquidity using the Amihud (2002) measure of daily stock illiquidity, which equals the absolute value of return for stock *i* on day *d* divided by the dollar volume of trading for stock *i* on day *d.* The Amihud measure is ideal for our research because it is based on widely available data and can be calculated for a large number of stocks at a daily frequency. Evidence also supports the use of the Amihud measure as a reliable proxy for a stock's liquidity with strong correlations between it and alternative liquidity measures based on intraday microstructure measures (e.g., Koraczyk and Sadka (2008) and Hasbrouck (2009)). More recently Goyenko, Holden, and Trzcinka (2009) show that the Amihud (2002) measure is a good proxy for price impact.

The Amihud (2002) measure comes into our analysis in two ways. First, we use the quarterly average of the daily Amihud illiquidity measure as a control variable in many of the regressions to take into account the potential impact of the level of stock liquidity. Second, for our primary variable we employ the change in the Amihud (2002) illiquidity measure. Specifically, we compute the change in the daily measure of stock illiquidity using volume and return data from CRSP,

$$\Delta illiq_{i,d} = \ln\left[\frac{illiq_{i,d}}{illiq_{i,d-1}}\right] = \ln\left[\frac{\dfrac{|\ r_{i,d}\ |}{|\ dvol_{i,d}\ |}}{\dfrac{|\ r_{i,d-1}\ |}{|\ dvol_{i,d-1}\ |}}\right],$$

where $r_{i,d}$ is the return on stock *i* for day *d* and $dvol_{i,d}$ is the dollar volume for stock *i* on day *d.*[12] We calculate the daily change in stock illiquidity for all common stocks on the NYSE and AMEX that are not penny stocks (i.e., price is above $2 per share), that trade on day *d* and *d-1*, and that have at least 40 return observations in a quarter. [13] To prevent outliers from affecting our analysis, we eliminate the top and bottom 1% of observations of our measure.

2.2. Summary statistics

Table 1 reports statistics on the sample stocks' market values, illiquidity measures, mutual fund ownership, and mutual fund ownership weighted by fund turnover. The table also reports statistics for aggregate quarterly mutual fund flows. Panel A shows the statistics across all stocks and quarters for which we have data. The final sample consists of 120,413 stock-quarters with both mutual fund ownership data and stock price data sufficient to calculate liquidity betas. Using the turnover-weighted mutual fund ownership reduces the sample to 66,598 stock-quarters because quarterly turnover data is only available beginning in 1999. The median firm has $897 million in market equity and 10% of its shares are owned by mutual funds. The mean turnover-weighted mutual fund ownership is slightly smaller than un-weighted mutual fund ownership, reflecting a typical annual fund turnover ratio of less than one (in our sample the average fund turnover is 0.83). In the last row we report summary statistics on aggregate quarterly net-flows into or out of the equity mutual fund industry. Over our sample period (1980-2008) mutual funds generally experience inflows, however,

[12] By taking the difference of the logs of Amihud's illiquidity measure we follow Kamara, Lou, and Sadka (2008). This is done to reduce effects of non-stationarity. However, in light of concerns of over-differencing, we also replicate the main results using the difference in Amihud's illiquidity measure from its five day moving average (see Section 5). Furthermore, the above definition shows that changes in liquidity could just be capturing changes in returns when trading volume remains constant. Thus, to make sure that our later analysis is not driven by return co-movements rather than liquidity co-movements, we will explicitly control for return (and volatility) co-movements in our robustness tests in Section 5.

[13] Results are similar requiring a minimum of 30 or 50 observations .

aggregate flows are negative in 17 of the quarters with the largest aggregate quarterly outflow equaling 3.05% of the NYSE and AMEX market capitalization, compared to the largest aggregate quarterly inflow of 2.83%.

Panel B of Table 1 shows the summary statistics by quartile of mutual fund ownership. In each quarter we rank stocks by *mfown* and report means, standard deviations, and medians of the selected variables. Typical stock size is about $3 billion in the lowest and highest quartiles of *mfown* compared to $7 and $4 billion for the second and third quartiles, respectively. There is, however, a monotonic relationship between mutual fund ownership and average liquidity, where average liquidity, *illiq(avg)*, is defined as the average daily Amihud measure over the quarter. Moving from the lowest to highest quartile of *mfown*, *illiq(avg)* drops from 0.19 to 0.04.

3. Commonality in liquidity and mutual fund ownership

In order to examine the extent to which mutual fund ownership is related to comovements in liquidity, we employ a two-step process. In the first step we estimate how individual stock liquidity co-moves with the liquidity of a portfolio of high mutual fund ownership stocks after controlling for comovement with market liquidity and additional variables (Section 3.1). In the second step we investigate whether comovement between individual stocks and the high *mfown* portfolio is stronger among firms with high mutual fund ownership (Section 3.2).[14]

3.1. Estimating liquidity covariances

For each firm-quarter we estimate the covariance between the daily changes in a stock's illiquidity and changes in the illiquidity of a portfolio of stocks with high mutual fund ownership. We control for the widely documented comovement in individual

[14] This process is along the same lines as that employed by Coughener and Saad (2004) in their examination of the role of market makers in commonality of liquidity.

illiquidity with market illiquidity (Chordia, Roll and Subrahmanyam, 2000). Thus, for each trading day in the quarter we compute changes in the value-weighted illiquidity of two portfolios: a market portfolio containing all stocks and a high mutual fund ownership portfolio comprised of the stocks in the top quartile of mutual fund ownership as ranked at the end of the previous quarter. [15]

For each firm, we run quarterly time series regressions of the firm's daily change in illiquidity, $\Delta illiq_{i,t}$, on changes in the high mutual fund ownership portfolios' illiquidity, $\Delta illiq_{mfown,t}$, and changes in the market illiquidity, $\Delta illiq_{mkt,t}$, as well as control variables:

$$\Delta illiq_{i,t} = \alpha + \beta_{HI} \Delta illiq_{mfown,t} + \beta_{mkt} \Delta illiq_{mkt,t} + \delta controls + \varepsilon_{i,t}. \qquad (1)$$

We focus on changes, or to be precise changes in logs, because we want to investigate the similarity in movements in liquidity. Furthermore, this approach helps to avoid econometric problems due to the potential nonstationarity of the liquidity measure. For each regression, the firm of interest is removed from the market portfolio as well as the high mutual fund ownership portfolio (when applicable). We follow the approach taken by Chordia, Roll, and Subrahmanyam (2000) and include lead, lag and contemporaneous market returns, contemporaneous firm return squared, and lead and lag changes in the two portfolio illiquidity measures. The latter controls are designed to capture lagged adjustments in liquidity, while the market returns are included to control for possible correlations between returns and our illiquidity measure. The squared stock returns are included to capture volatility which may related to liquidity. We show later in robustness tests (Section 5) that this particular specification of the first stage time series regressions is not crucial to our main results.

[15] Results using equal-weighted portfolios are very similar (see Section 5).

Table 2 presents sample statistics on the market and high mutual fund ownership portfolios used in the time series regressions as well as coefficients of interest from the regressions. In Panel A we summarize output for a set of representative quarters from the beginning (1980), the middle (1995), and the end (2008) of our sample. In Panel B we summarize by 5 year periods as well as the full sample.

The left-hand side of each panel reports the average of the mutual fund liquidity beta coefficients across all firms in that quarter, the percentage of beta coefficients that are positive and the percentage that are significant, as well as a t-statistic on the sample of beta coefficients in that quarter. The table also reports the number of stocks in the portfolio and the average firm size and illiquidity.

Relatively few of the individual beta estimates from the quarterly regressions are significantly different from zero at the 5%-level based on two-sided t-tests.[16] However, the mean of the distribution of quarterly beta estimates is different from zero with a high degree of significance as indicated by the t-statistic shown in Table 2 on the sample of estimates. The right-hand side of the table summarizes the same variables for the market liquidity beta coefficients. The bottom panel summarizes the time series regression output by 5 year periods. Overall, the positive average and the similar magnitude of the two beta coefficients, β_{HI} and β_{mkt}, clearly shows that individual stock liquidity on average co-moves positively with both the liquidity of the market portfolio as well as the liquidity of a high mutual fund ownership portfolio. In the next section we test our main hypothesis: that β_{HI} is higher among shares with high mutual fund ownership.

[16] In unreported tests, using the full available time series for each stock we find that 71% of the market liquidity betas and 77% of mutual fund liquidity betas are positive, with 24% and 28% significantly different from zero at the 5 % level, respectively.

3.2. Mutual fund ownership and commonality

Our central hypothesis is that the liquidity of stocks with high levels of mutual fund ownership will covary strongly with other stocks also owned to a high degree by mutual funds. Table 3 provides results from a first set of tests of our central hypothesis using one dimensional and dependent sorts based on quarterly rankings of mutual fund ownership. In this and all future tests, β_{HI} and β_{mkt} are estimated over quarter t, while mutual fund ownership is measured at the end of quarter t-1.

Panel A shows that the average β_{HI} is monotonically increasing in mutual fund ownership as predicted by the hypothesis. The lowest ownership quartile has an average β_{HI} of 0.20 compared to 0.40 for the highest quartile. The difference is economically and statistically significant, providing evidence that the liquidity of stocks owned to a high degree by mutual funds strongly covary together. Further, the results for β_{HI} in Panel A can be contrasted with those for β_{mkt} reported on the right hand side of Panel A. There is no significant difference between the comovement of stocks' liquidity with the overall market liquidity in the highest and lowest mutual fund ownership quartiles.[17]

We also report averages for β_{HI} and β_{mkt} from sorts based on firm size and liquidity. Our results show that large and liquid stocks co-move more heavily with both market as well high mutual fund ownership portfolio liquidity compared to small and illiquid stocks.

Next we extend these univariate results to a multivariate setting. Mutual funds do not randomly select stocks but have preferences for certain stock characteristics. Importantly, in aggregate they prefer large and liquid stocks (see, e.g., Del Guercio, 1996; Falkenstein, 1996). Since the results in Panel A of Table 3 suggest that these

[17] In unreported tests, we also replace the change in portfolio liquidity of the stocks with high mutual fund ownership in our regression equation (1) with the change in portfolio liquidity of the stocks with low mutual fund ownership, i.e. those within the lowest quartile of *mfown*. The respective regression coefficient is labeled as $\beta_{LO.}$ The average β_{LO} is -0.01. Among stocks with low *mfown*, average β_{LO} is 0.01 and among high *mfown* stocks, average β_{LO} is -0.02.

characteristics are also related to β_{HI}, in Panel B we present average liquidity betas after double sorts based on size or illiquidity and mutual fund ownership. Specifically, in each quarter we first sort on size or illiquidity and then within each quartile we sort on mutual fund ownership. The results show that the positive relation between β_{HI} and mutual fund ownership is robust to subsets by firm size and illiquidity. In all cases the average β_{HI} is increasing in mutual fund ownership although the effect is insignificant among the most illiquid stocks. The latter are the stocks that are least held by mutual funds, which we would not expect to be much affected by correlated mutual fund stock trading.

In a second test of our central hypothesis we control for stock characteristics in a multivariate regression. We regress β_{HI} against the previous quarter's mutual fund ownership, controlling for firm size and average illiquidity. We include time dummies and cluster the standard errors at the firm level in order to account for time series and cross sectional dependence.[18] The specification is

$$\beta_{HI,i,t} = a + b_1\, mfown_{i,t-1} + b_2\, ln(size_{i,t-1}) + b_3\, illiq(avg)_{i,t-1} + time\ dummies + \varepsilon_{i,t}. \qquad (2)$$

The results of this regression are presented in Panel A of Table 4. The first column of the table shows the results for the full sample for the regression of β_{HI} against mutual fund ownership and time dummies only. Consistent with our central hypothesis, we find that stocks with high mutual fund ownership exhibit strong comovement, evidenced by the significant coefficient estimate of 0.896. As this regression includes time fixed effects, the higher β_{HI} should not be caused by a possible common time trend in mutual fund ownership levels and liquidity comovements.

In Model (2) we control for the stock's size and average liquidity. Again the coefficient on mutual fund ownership is positive and highly significant, and is similar in magnitude

[18] If the time effect is fixed, then indicator variables for each cross section and clustered standard errors at the fund level will account for time series and cross sectional dependence (Petersen (2009)).

to the coefficient estimated in the absence of controls. The result is also economically significant – a one standard deviation increase (0.10) in mutual fund ownership is associated with a 0.08 increase in β_{HI}, which equates to a 27% increase from its mean. A possible alternative explanation for our results is that mutual fund managers have preferences for stock characteristics (other than size and liquidity) that are correlated with β_{HI}. Although it is not clear what the source of any unobserved heterogeneity and correlation might be, in Model (3) we include firm fixed effects to address this concern. We continue to include time dummies and cluster standard errors at the firm level. The results show that time invariant unobservable heterogeneity is not driving our results.

The last two models in Table 4 use corrections for different assumptions on the structure of the error term. Model (4) employs standard errors with two dimensional clustering, and Model (5) uses a Fama and MacBeth (1973) specification. In both alternative models we find a positive relationship between the mutual fund liquidity beta and mutual fund ownership that is both economically and statistically significant.

Overall, these results provide considerable evidence that the liquidity of stocks with high mutual fund ownership strongly co-move. The effect is robust to various assumptions regarding unobserved heterogeneity, independence of observations, and functional form, as well as a variety of subsamples. [19]

4. Commonality in liquidity and mutual fund trading

In the previous section we provide evidence that commonality in a stock's liquidity is strongly associated with the level of mutual fund ownership in the stock. We claim that this relationship exists because mutual fund ownership proxies for the likelihood that trading in these stocks will be correlated. That is, it is not the level of ownership that matters per se, but the extent to which it reflects future correlated trading.

[19] In the Appendix we conduct several additional tests for alternative explanations of our results.

In this section we examine the relation between commonality in liquidity and three measures of mutual fund trading that are designed to capture different aspects of mutual fund demand for liquidity: voluntary correlated trading, forced correlated trading, and overall correlated trading.

4.1. Voluntary correlated trading

The first measure allows for differential trading among mutual funds by incorporating the fund's turnover ratio into the ownership measure. When summing ownership across funds within a stock, we weight mutual fund ownership by the holding fund's turnover. From this we get a turnover-weighted mutual fund ownership, $twmfown_{i,t}$ as defined in Section 2.1. Thus, we treat ownership by high turnover funds as a better proxy for the likelihood of correlated trading than the same level of ownership by funds with low turnover. Because the turnover ratio as reported in CRSP is corrected for trading due to flows, it reflects voluntary trading.

Our hypothesis implies that the turnover-weighted measure, to the extent that it is a better proxy for correlated liquidity demand, is more strongly associated with high commonality in liquidity than an unconditional measure of mutual fund ownership.[20] The results are reported in Table 5. Since CRSP does not report quarterly fund turnover prior to 1999, the sample period for this analysis is 1999 to 2008. The first model includes *twmfown* only. For comparison, the second column repeats the evaluation of our baseline model using *mfown* as the primary independent variable for the 1999 to 2008 period. It should be noted that the results for *mfown* in this shorter time period are consistent with the results for the full sample period reported in Table 4. The model reported in the third column includes both *twmfown* and *mfown.*[21] The coefficient on the

[20] Importantly, this would not be case if there exists a negative relationship between correlated trading and fund turnover strong enough to outweigh the high levels of trading reflected by high fund turnover.

[21] The correlation between *mfown* and *twmfown* is 0.78, which might hint at multicollinearity in the model including both variables. However, the significant impact of *twmfown* we find as well as the relatively low

turnover-weighted mutual fund ownership variable is strongly significant in all three models irrespective of the inclusion of un-weighted mutual fund ownership.

The summary statistics reported in Table 1 show sufficient similarity in the means and standard deviations of the weighted and unweighted mutual fund ownership measures, which suggests that we can roughly compare the coefficients of the two measures. Such a comparison shows that the coefficient for the turnover-weighted mutual fund ownership measure in Column 3 is 1.152, which is clearly larger than the coefficient for the unweighted mutual fund ownership, which is 0.185 and not statistically distinguishable from zero. To provide a more precise comparison in the last three models of the table we use standardized independent variables. Again the results indicate that ownership by mutual funds with greater portfolio turnover is associated with higher commonality in liquidity than simply ownership by mutual funds in general. Further, Column 6 shows that a one standard deviation increase in *twmfown* is associated with a 0.09 increase in β_{HI}. Thus, consistent with our hypothesis, stocks held by mutual funds that trade more frequently have stronger commonality in their liquidity.

Voluntary trading is often information-based trading. Thus, the strong impact of voluntary mutual fund trading on commonality suggests that the trading of individual mutual funds does not cancel out. This is consistent with the view that mutual funds tend to trade on the same information in the same direction, which eventually leads to correlated liquidity demand and thus commonality in liquidity.

An alternative story to explain these results is that voluntary trading is not information driven (and thus a sign of liquidity demand), but that mutual funds also act as liquidity suppliers in some cases (Da, Gao, and Jagannathan, 2011). Therfore, in the following section we focus on the impact of liquidity shocks mutual funds face

variance inflation factors of 3.68 and 2.97 for *mfown* and *twmfown*, respectively, suggest that this is not a concern here.

themselves. This allows us to isolate cases in which any potential effects arise via a demand-side channel.

4.2. Involuntary correlated trading

In this section we estimate the relation between β_{HI} and involuntary correlated trading. We infer differences in trading intensities by conditioning mutual fund ownership on aggregate fund flows.[22] Flows can lead to buying or selling pressure of mutual funds, i.e. liquidity demand. According to our hypothesis, the impact of mutual fund ownership should be greater in periods with high absolute flows. This effect should be particularly strong for outflows as suggested by the results of Coval and Stafford (2007). The reason we expect a stronger impact of outflows is that inflows can first be used to accumulate cash or buy futures and could also be more easily spread across stocks, but fund outflows, if met through stock sales, must be met by eventually selling the stocks currently held by the mutual funds.[23]

To examine the impact of flow levels, in each quarter we aggregate fund flows to compute a net dollar flow into or out of equity mutual funds. We then scale this amount by the dollar value of the total market at the beginning of the quarter. From the flow data we calculate two dummy variables; *hiabsflow* equals one if aggregate flows in a quarter are in the top or bottom 10% of all quarters, and zero otherwise and *negnetflow* equals one if aggregate flows are negative, and zero otherwise. Net flows are signed, so the bottom (top) 10% is comprised of the largest net outflow (inflow) quarters. Each of these dummy variables is interacted with *mfown* in the previously described regression

[22] Chordia, Roll, and Subrahmanyam (2011) find that fund flows are partially responsible for the increased turnover in equity markets over recent years. Furthermore, mutual funds tend to scale up their existing holdings if they face inflows of new money (Pollet and Wilson, 2008), i.e. inflows should lead to liquidity demand for those stocks with high previous mutual fund ownership.
[23] That high negative mutual fund flows lead to correlated liquidity demand is also suggested by the findings of Hameed, Kang, and Viswanathan (2010) who document a negative relation between commonality in order imbalances and aggregate net fund flows.

specifications used in Table 4. We continue to use time dummies to pick up general increases or decreases in systematic liquidity during periods of extreme flows.

The results of these regressions are reported in Table 6. The results of Model (1) show that the impact of ownership on commonality is much stronger during periods of high absolute net flows. Specifically, the coefficient on *mfown* is 0.765 in 80% of the quarters, compared to 0.765 + 0.395 = 1.160 in the top and bottom 10% of flows (strong inflows and outflows). In Column 2 the relation between β_{HI} and *mfown* is 0.575 larger when the mutual fund industry experiences net outflows relative to the quarters with net inflows. This effect is highly significant both economically and statistically. These results are consistent with the hypothesis that fund flows lead to correlated liquidity demand by mutual funds and that this effect is more pronounced for outflows. These results are also consistent with those of Coval and Stafford (2007) regarding mutual fund fire sales.

Columns 3 through 6 show the results from our base regression from equation (2) within subsamples of quarters split by the level of aggregate funds flows. The strong relation between commonality in liquidity and mutual fund ownership holds in each of the subsamples. There is some evidence of a U-shaped relationship between the magnitude of liquidity commonality and aggregate net flows, as would be expected if mutual fund ownership has a larger impact during periods of extreme flows. However, consistent with results from the interactions in Columns 1 and 2, this seems primarily driven by negative flow quarters. In Panel B of Table 6 we test specifically for a U-shaped conditional relationship. First, we run 114 quarterly cross sectional regressions based on equation (2), regressing commonality on ownership and controls. Then we use the time series of coefficients on *mfown* as the dependent variable in a regression with aggregate net flows and squared aggregate net flows as independent variables. We find that the impact of ownership on commonality is strongest in periods of high inflows and outflows as evidenced by the positive coefficient on aggregate flows squared, and that the effect of outflows dominates the effect of inflows, as evidenced by the negative coefficient on aggregate flows.

Overall, the findings from this section show that, in addition to voluntary information-based trading, flow induced liquidity demanding trades give rise to commonality in liquidity.

4.3. Actual Mutual Fund Trading

Finally we use changes in mutual fund ownership of individual stocks to capture a lower bound on actual mutual fund trading. Specifically, we compute the absolute value of the change in $mfown_i$ from $t\text{-}1$ to t, and denote this variable $|\Delta mfown_{i,t}|$.

We measure the change contemporaneously with the estimation of β_{HI} to determine whether higher sensitivity to aggregate mutual fund liquidity occurs in the same period as greater mutual fund trading, which would be consistent with correlated trading by mutual funds contributing to commonality in liquidity. We employ the following specification for this test:

$$\beta_{HI,i,t,} = a + b_1 |\Delta mfown_{i,t}| + b_2 \, ln(size_{i,t-1}) + b_3 \, avgilliq_{i,t-1} + time\ dummies + \varepsilon_{i,t}. \qquad (3)$$

A positive and significant b_1 would support our hypothesis.

The results of this regression are provided in Table 7. We use the absolute value of the change in *mfown* in the first model, and a dummy variable equal to one if the absolute change is in the top quartile that quarter, and zero otherwise, in the second model. In both cases the coefficient on the change measure is positive and significant at the 1% level, consistent with our hypothesis that mutual fund trading in a stock as reflected by changes in a stock's mutual fund ownership increases systematic liquidity.

Overall, the results of Tables 5, 6, and 7 clearly support our hypothesis that the relation between commonality in liquidity and mutual fund ownership is due to correlations in the trading by mutual funds.

5. Robustness tests

In this section we address possible concerns arising from our first stage estimate of common liquidity, and in particular our use of the Amihud illiquidity ratio as the measure of liquidity. For example, the commonality that we document may be driven by common (absolute) returns, not necessarily common movements in the ratio of returns to volume. In this section we first demonstrate that our results are not driven by common returns or common volatility, and then show that our results are not specific to the structure of our first stage estimation.

We address a potential impact of common returns and common volatility in three ways. First, we add beta estimates between the firm return and the value-weighted return of the high mutual fund ownership portfolio (estimated contemporaneously with the liquidity beta) as an additional control variable in our base regression equation (2). We call this variable mutual fund return beta. Adding this variable controls for the impact of common information – that has a joint impact on the returns of the stocks with high mutual fund ownership – on the comovements in liquidity. Results are presented in the first column of Panel A in Table 8. The significantly positive coefficient on the mutual fund return beta shows that common return effects (as a proxy for information affecting the returns of high mutual fund ownership stocks) also impacts commonality in liquidity among these stocks. While interesting in itself, in our context it is more important that the positive impact of mutual fund ownership on β_{HI} still remains highly significant and is only slightly reduced after inclusion of the mutual fund return beta as compared to the results reported in Table 4. Second, to capture any potential non-linear relationship between β_{HI} and return comovements, we run our base regression (2) on subsamples based on mutual fund return beta quartiles. Results reported in Columns 2 through 5 show that our main finding holds in all subsamples as indicated by a highly significant positive estimate for the impact of *mfown* on β_{HI} in each case. Third, we modify the first stage regression (1) in order to capture the impact of a potential comovement between individual stock liquidity and the return of the portfolio of high mutual fund ownership stocks. Thus, we include the return of a portfolio of high mutual fund ownership stocks as additional control variable in (1). Results from equation (2) using the β_{HI} from this modified first stage model as dependent variable are presented in Column 6 in Panel A of Table 8.[24] We still find a highly significant positive impact of *mfown* on $\beta_{HI.}$

An additional concern is that our results may be driven by comovements in volatility among stocks with high mutual fund ownership which might be caused by joint changes in the riskiness of the stocks owned by mutual funds. To address this concern we conduct the same battery of tests as above, but now replace the return by the return squared (for both the individual stock and the high mutual fund ownership portfolio), i.e. we use squared returns as volatility proxy. Results in Panel B of Table 8 show that our earlier results hold: the positive relationship between *mfown* and β_{HI} is highly significant also after controlling for comovements in volatility (mutual fund return^2 beta; Panel B, Columns 1 through 5). Adding the squared return of the high mutual fund ownership portfolio in the first stage regression (to control for the impact of the comovement of individual liquidity and high mutual fund ownership portfolio volatility) does not change the results obtained from the standard second stage regression (Panel B, Column 6).

Finally, in the Appendix, we repeat the entire two-step procedure using stock turnover instead of the Amihud illiquidity ratio as an alternative liquidity measureand

[24] We find similar results if we include market returns instead of or additionally in Model (1).

find that there continues to be a strong positive relationship between ownership and commonality using the alternative liquidity proxy. [25]

Overall, these findings show that our previous results are not driven by return or volatility comovements among stocks with high mutual fund ownership or some other mechanical effect which might arise due to the definition of the Amihud liquidity measure. In the Appendix we show that our results are not dependent on the specification of the first stage liquidity covariance estimation procedure.

6. Conclusion

We hypothesize that correlated trading among investors in a stock is an important explanation for commonality in liquidity across stocks. Using data on mutual fund ownership and stock liquidity from NYSE and AMEX stocks for the period 1980 to 2008, we find evidence that suggests mutual fund trading is an important factor in explaining commonality in liquidity. We use a two-step process and first regress a stock's liquidity on the liquidity of two portfolios: a market portfolio and a portfolio consisting of stocks with high mutual fund ownership. This regression results in two liquidity betas: a high mutual fund ownership portfolio liquidity beta and a market portfolio liquidity beta. In the second step, we examine the relation between the high mutual fund ownership liquidity beta and the extent to which a stock is owned by mutual funds. We find that mutual fund liquidity betas are about twice as large for stocks with high mutual fund ownership as for those with low mutual fund ownership. We also find that this result is not only driven by common time trends in commonality and mutual fund ownership, thereby complementing the time series evidence presented in Kamara, Lou, and Sadka (2008). Our results are also not driven by stock characteristics such as firm size, liquidity

[25] We use the Amihud measure in our main examination, because stock turnover is only a weak proxy for liquidity and is also mechanically related to our measure of turnover-weighted mutual fund ownership, because trading of mutual funds is directly linked to turnover on the stock level.

levels, or other unobservable stock characteristics that might jointly determine systematic liquidity and mutual fund ownership.

We also expect the relation between commonality in liquidity and mutual fund ownership to be stronger in circumstances with greater mutual fund trading and our results support that hypothesis. We find that the commonality in liquidity is stronger in stocks that are owned by mutual funds with high turnover ratios. We also find that the commonality is greater during periods of negative or extreme aggregate mutual fund flows. Further, we find a strong positive relation between actual trading by mutual funds, i.e., changes in aggregate mutual fund ownership, and a stock's mutual fund liquidity beta.

Overall our results suggest that – in addition to the supply-side explanations for commonality in liquidity found in earlier studies (e.g., Coughenour and Saad, 2004; Comerton-Forde, Hendershott, Jones, Moulton and Seasholes, 2010) – demand-side factors, i.e., mutual fund ownership and particularly flow-induced trading, are important explanations as well. Thus, liquidity risk arises not only from the actions of market specialists, but also the investors in the stock. These results suggest that mutual fund trading may add to the risk of a stock, consistent with the findings of Sias (1996) that institutional investors contribute to a stock’s volatility. Mutual fund managers might consider avoiding stocks with higher systematic liquidity risk, i.e., stocks whose ownership is dominated by other mutual funds, particularly if they are concerned about the effects of liquidity shocks hitting themselves in the form of investor flows. However, our results also suggest that this – at least in aggregate – is not possible, because mutual funds themselves give rise to much of the commonality in liquidity we observe.

In this paper we have selected mutual funds as a group of investors to examine for correlated trading and resulting commonality. Of course, this does not preclude the possibility that the correlated trading of other groups of investors such as hedge funds or other institutional investors might also give rise to commonality.

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Appendix
Robustness tests

A.1. Alternative explanations and specifications for determinants of β_{HI}

In our regressions of β_{HI} against the previous quarter's mutual fund ownership, controlling for firm size and average illiquidity (the results of which are shown in Table 4), we have no direct prediction on the functional form of the relationship between ownership and commonality. For further robustness we conduct several additional tests. First we repeat our tests using an indicator variable for high mutual fund ownership rather than a continuous variable. We replace $mfown_{i,t-1}$ in equation (2) by $mfown(dummy)_{i,t-1}$, which is equal to one if mutual fund ownership is in the top quartile in quarter *t-1*, and zero otherwise. These results are reported in Table A-1. The use of this variable provides a natural economic interpretation. From Column 2 in the table, stocks in the highest mutual fund ownership quartile have a β_{HI} in the next quarter that is 0.12 higher than those outside the top quartile. This is a large economic effect given the unconditional mean β_{HI} of 0.31. The coefficient on this dummy variable is positive and statistically significant in all other specifications as well.

The sorts in Table 3 indicate a possible non-linear relation between β_{HI} and firm size or illiquidity. Thus, we rerun our primary multivariate specification (quarter fixed effects and firm clusters) for samples divided by size quartiles, additionally controlling for size and liquidity within each subsample. We also conduct this test for subsamples divided by liquidity, time (5 year subperiods), and whether the quarter has a positive or negative market return. Table A-2 reports these results again for a linear impact of *mfown* (Panels A and B) as well as for the impact of the high mutual fund ownership dummy (Panels C and D).

In Panels A and C, the first four columns split the sample into size quartiles (ranked quarterly) and show that a significantly positive relation between β_{HI} and mutual fund ownership exists in all but one of the subsamples, the quartile of stocks with the smallest market capitalization. The next four columns report the results from the sample divided into liquidity quartiles and show a significantly positive relationship between β_{HI} and mutual fund ownership in all but the most illiquid stocks. This result is consistent with our results using dependent sorts in Panel B of Table 3.

When we divide our sample into approximate 5-year subsamples from 1980 to 2008 (with the last subperiod containing almost 8 years) in Panels B and D, we find that the effect exists in all subperiods, but the magnitude of the coefficient for the relation between β_{HI} and mutual fund ownership varies over time.

Motivated by results of magnified liquidity effects in down markets in Chordia, Roll, and Subrahmanyam (2002) and Hameed, Kang, and Viswanathan (2010), we also look at subsamples of up as well as down market quarters. We find a strong effect in both cases. The coefficient on *mfown* is larger in quarters with negative market returns, however the difference between the coefficients is not significant. While previous research documents higher commonality in liquidity in down markets, we find no significant variation in the impact of mutual fund ownership in explaining liquidity. Rather, results are fairly stable across market regimes.[26]

A.2.Alternative specifications of liquidity covariances

In this section we show that our results are not dependent on the specification of the first stage liquidity covariance estimation procedure. We re-estimate β_{HI} in a variety of ways and report the results of second-stage tests of our main hypothesis [equation (2)] using the variety of first-stage β_{HI} estimates. These results are reported in Columns 2 through 9 of Table A-3. In the first approach, instead of using value-weighted portfolio

[26] In unreported results we examine differences between the levels of market-wide commonality in up and down markets and confirm the results of Chordia, Roll, and Subrahmanyam (2002) and Hameed, Kang, and Viswanathan (2010) in our sample.

liquidity to determine β_{HI}, we regress the individual stock liquidity measure on equal-weighted market and high mutual fund ownership portfolio liquidity after including the standard controls. Consistent with our results using value weighted portfolio liquidity, we find a very strong positive relation between the high mutual fund liquidity beta and mutual fund ownership. In this case, the coefficient is more than twice as large as the coefficient using value-weighted portfolio liquidity (2.063 in Table A-3, Column 2, compared to 0.838 in Column 2 of Table 4). In the second approach, we employ our standard time series estimation procedure similar to equation (1) but now follow Chordia, Roll, and Subrahmanyam (2000) and also use sum betas in the second stage, which equal β_{HI} plus the betas on the lead and lag values of the high mutual fund ownership (and similarly for the market beta). The results, reported in Column 3 of Table A-3, are consistent with our previous results. Next, the liquidity of stocks belonging to the same industry would be expected to comove more strongly with each other than with stocks not in the industry. Thus, in our third approach we include industry-level measures in the first stage liquidity covariance estimation in two ways. The results in the fourth and fifth columns of Table A-3 use β_{HI} estimated after controlling for the covariation between the firm's liquidity and that of a portfolio of stocks in its industry (identified by two-digit SIC code). In Column 4 we use β_{HI} on the typical high *mfown* portfolio, but we also control for liquidity covariation with stocks in the same industry by including lead, lag, and contemporaneous changes in the value-weighted industry portfolio liquidity. In Column 5, we use a similar β_{HI} but additionally add the lead, lag, and contemporaneous *return* of the value weighted industry portfolio. In both cases, our measure of commonality in liquidity in high mutual fund ownership stocks, β_{HI}, has a positive and significant relationship with *mfown.* In Columns 6 and 7 we use only one liquidity portfolio in the time series estimation. First, we remove the high mutual fund ownership portfolio (and its returns) and estimate a covariance with only the market portfolio. In Column 7 we do the same using only a high mutual fund ownership portfolio. Not surprisingly, we find a positive relationship in the second stage between *mfown* and β_{mkt}, and a positive but much stronger relationship between *mfown* and β_{HI}. In Column 8 we revert to the standard first stage portfolios and control variables used in the earlier tables. However, we now employ a different liquidity calculation to address the concern that changes in illiquidity might be over-differenced: as suggested by Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010), we use a quasi-differencing method. Instead of using differences in logs of Amihud's illiquidity ratio we use the difference from a 5 day moving average. We find results that are similar to those from our main specification.

Finally, we generate a portfolio of randomly selected stocks and include it instead of the portfolio of high mutual fund ownership stocks. Specifically, we randomly choose 25% of the stocks in each quarter and compute a value-weighted change in daily liquidity for this portfolio. We then use liquidity betas on this portfolio as the independent variable in our regression models. As expected, results in Column 9 show that the liquidity beta on randomly selected stocks' liquidity in this placebo regression is not related to mutual fund ownership.

Table 1
Summary statistics.
This table reports summary statistics for select variables. Panel A reports statistics for the full sample of stock-quarters over the 1980-2008 period. *mfown* is the number of shares owned by mutual funds scaled by shares outstanding. *firm size* is the market value of the stock at the end of the quarter. *illiq(avg)* is the average over the quarter of the absolute value return scaled by dollar volume (in millions). *twmfown* is the total shares owned by mutual funds weighted by each fund's turnover, scaled by shares outstanding. Aggregate flows are the net dollar flows to or from all mutual funds in a quarter scaled by beginning of quarter total market value. Panel B reports means, standard deviations, and medians for subsamples of firms by *mfown* quartile ranked quarterly.

Panel A: Full Sample	N	Mean	Std Dev	Min	Max	Median
firm size (millions)	120,413	4270	16052	2	571197	897
illiq(avg)	120,413	0.08	0.3	< 0.001	215.74	0.008
mfown	120,413	0.13	0.1	0	0.88	0.10
twmfown	66,598	0.10	0.08	0	0.78	0.08
aggregate flows (% of mkt cap)	114	0.65%	0.73%	-3.05%	2.83%	0.65%

	mfown (ranked quarterly)			
Panel B: By mfown quartile	LO	2	3	HI
	Mean, (Std dev), Median			
firm size (millions)	3168	6686	4400	2821
	(14938)	(22869)	(11802)	(6487)
	401	1079	1199	1044
illiq(avg)	0.19	0.06	0.04	0.04
	(0.54)	(0.22)	(0.15)	(0.14)
	0.04	0.006	0.004	0.004
mfown	0.04	0.10	0.15	0.23
	(0.03)	(0.06)	(0.07)	(0.11)
	0.03	0.10	0.16	0.24
twmfown	0.03	0.08	0.12	0.19
	(0.03)	(0.04)	(0.06)	(0.10)
	0.02	0.07	0.11	0.17

Table 2
Time series estimates of liquidity betas.
This table reports summary statistics on liquidity betas with respect to a high mutual fund ownership portfolio and a market portfolio of NYSE and AMEX stocks. Panel A reports these statistics for representative quarters in the sample. In each quarter and for each firm, the daily change in the firm's illiquidity (Amihud measure) is regressed on the daily changes in the illiquidity measure for a portfolio of high mutual fund ownership stocks and a market portfolio as well as control variables.

$$\Delta illiq_{i,t} = \alpha_i + \beta_{mfown} * \Delta illiq_{mfown,t} + \beta_{mkt} * \Delta illiq_{mkt,t} + controls$$

where $\Delta illiq_{i,t} = log\left[\frac{illiq_{i,t}}{illiq_{i,t-q}}\right] = log\left[\frac{\frac{|r_{i,t}|}{vold_{i,t}}}{\frac{|r_{i,t-1}|}{vold_{i,t-1}}}\right]$. In each time series regression the stock's individual measure is removed from the market portfolio and the high *mfown* portfolio (when applicable). The left columns summarize the coefficient estimates for the high *mfown* liquidity portfolio, and the right columns summarize the market liquidity portfolio. In each quarter we record the average beta, the percent positive and percent significant at the 5% level, and we compute a t-statistic on the sample of beta estimates in that quarter. Panel A reports averages for representative quarters and Panel B reports averages over 5 year periods and the full sample.

Panel A: Representative quarters

		HI *mfown* portfolio								Market portfolio							
	R^2	β_{HI}	% pos	% sig	tstat	size	mfown	illiq(avg)	# stocks	β_{mkt}	% pos	% sig	tstat	size	mfown	illiq(avg)	# stocks
19802	0.30	0.22	54%	6%	3.39	543	0.09	0.083	301	0.20	56%	6%	3.86	878	0.04	0.126	999
19803	0.29	0.27	58%	6%	5.96	565	0.09	0.093	293	0.32	58%	8%	7.39	982	0.04	0.129	973
19804	0.30	0.57	67%	9%	11.97	637	0.09	0.084	275	0.15	54%	8%	3.19	1008	0.04	0.121	938
.																	
19951	0.29	0.31	62%	6%	6.50	2753	0.22	0.010	333	0.23	54%	8%	3.92	3973	0.13	0.038	898
19952	0.29	0.10	51%	6%	1.89	2865	0.23	0.010	333	0.37	59%	8%	7.14	4108	0.14	0.036	930
19953	0.29	0.42	58%	9%	7.08	2945	0.22	0.012	340	0.31	59%	8%	5.68	4236	0.14	0.040	961
19954	0.31	0.51	64%	9%	10.20	3096	0.23	0.012	364	0.30	59%	7%	6.47	4353	0.14	0.042	1063
.																	
20081	0.32	0.29	60%	8%	8.02	3764	0.36	0.016	317	0.36	63%	12%	10.95	7869	0.22	0.091	1142
20082	0.31	0.40	60%	10%	9.47	3060	0.36	0.010	309	0.38	62%	9%	9.55	7465	0.23	0.090	1106
20083	0.31	0.19	55%	8%	5.20	1872	0.37	0.019	282	0.47	63%	13%	12.36	5807	0.24	0.138	1009

Panel B: Five-year quarterly averages and full sample

1980-1985	0.29	0.32	58%	7%	6.18	714	0.09	0.091	283	0.23	56%	7%	4.46	1201	0.05	0.120	916
1986-1990	0.31	0.34	59%	8%	6.35	1670	0.11	0.046	254	0.22	57%	7%	4.46	2509	0.06	0.063	794
1991-1995	0.30	0.30	58%	7%	5.44	2267	0.18	0.022	311	0.31	58%	8%	5.73	3487	0.11	0.045	884
1996-2000	0.28	0.26	57%	6%	5.68	4953	0.26	0.018	410	0.24	56%	7%	5.55	5874	0.15	0.054	1329
2001+	0.29	0.33	60%	8%	8.91	4023	0.33	0.012	341	0.33	61%	9%	9.14	6831	0.20	0.074	1228
Full sample	0.29	0.31	58%	7%	6.66	2813	0.20	0.036	321	0.27	58%	8%	6.17	4204	0.12	0.073	1048

Table 3
Liquidity betas sorted by firm characteristics.
Panel A presents mutual fund and market liquidity betas sorted by firm characteristics. At the end of each quarter we sort stocks into quartiles based on *mfown*, *firm size*, or *illiq(avg)*. For each quartile we report the average β_{HI} and β_{mkt} measured over the subsequent quarter. Panel B presents dependent sorts. First we sort on *firm size* or *illiq(avg)* each quarter, then within each bin we sort on *mfown*. All t-statistics are on the difference in sample averages paired by quarter.

Panel A: One way sorts

Sort		Average β_{HI}: Lo	2	3	Hi	Hi - Lo	H-L tstat	Average β_{mkt}: Lo	2	3	Hi	Hi - Lo	H-L tstat
mfown		0.20	0.28	0.35	0.40	0.20	(12.22)	0.24	0.33	0.29	0.24	0.00	(-0.49)
firm size		0.23	0.33	0.38	0.29	0.06	(3.47)	0.09	0.20	0.27	0.53	0.44	(24.45)
illiq(avg)		0.31	0.37	0.34	0.21	-0.09	(-5.90)	0.51	0.29	0.19	0.10	-0.41	(-22.97)

Panel B: Dependent sorts - First on size or illiq(avg) then on mfown

		Average β_{HI} (mfown): Lo	2	3	Hi	Hi - Lo	H-L tstat	Average β_{mkt} (mfown): Lo	2	3	Hi	Hi - Lo	H-L tstat
firm size	Small	0.18	0.28	0.26	0.27	0.09	(2.33)	0.09	0.06	0.10	0.12	0.03	(1.02)
	2	0.22	0.27	0.36	0.42	0.20	(6.63)	0.23	0.22	0.20	0.18	-0.05	(-2.68)
	3	0.27	0.33	0.41	0.45	0.18	(6.46)	0.28	0.32	0.24	0.26	-0.02	(-0.98)
	Big	0.16	0.24	0.33	0.41	0.25	(9.48)	0.61	0.61	0.50	0.40	-0.21	(-6.79)
illiq(avg)	Lo	0.14	0.24	0.33	0.43	0.29	(12.07)	0.68	0.61	0.48	0.37	-0.31	(-9.78)
	2	0.27	0.31	0.40	0.44	0.17	(5.92)	0.35	0.35	0.25	0.25	-0.10	(-4.30)
	3	0.27	0.31	0.37	0.42	0.15	(4.91)	0.20	0.20	0.18	0.17	-0.03	(-2.67)
	Hi	0.17	0.26	0.24	0.24	0.07	(1.65)	0.11	0.06	0.12	0.13	0.02	(0.85)

Table 4
Relation between liquidity commonality and mutual fund ownership.
This table reports results from the following Pooled OLS regression using alternate specifications:

$$\beta_{HI,i,t} = a + b_1 * mfown_{i,t-1} + b_2 * ln(firmsize_{i,t-1}) + b_3 * illiq(avg)_{i,t-1} + \varepsilon_{i,t}$$

where β_{HI} is estimated as in equation (1). *mfown* and *ln(firm size)* are measured at the end of the previous quarter. *illiq(avg)* is the firm's average daily Amihud (2002) illiquidity measure over the previous quarter. Quarter dummies are included in all regressions. Standard errors are clustered by stock.

Panel A	(1)	(2)	(3)	(4)	(5)
mfown	0.896***	0.838***	0.457***	0.557***	1.009***
	(14.73)	(13.12)	(4.58)	(5.33)	(9.23)
ln(firm size)		-0.0021	0.0187**	-0.0053	1.75e-05
		(-0.56)	(1.97)	(-1.10)	(0.00)
illiq(avg)		-0.0890***	-0.0529**	-0.1030***	-0.0954***
		(-4.75)	(-2.23)	(-5.50)	(-2.78)
Observations	120413	120413	120413	120413	120413
R^2	0.012	0.012	0.055	0.002	0.002

Table 5
Relation between liquidity commonality and turnover-weighted mutual fund ownership.
This table reports results from a pooled OLS regression using a turnover weighted measure of mutual fund ownership. Specifically we compute for each stock i at quarter t,

$$twmfown_{i,t} = \frac{\sum_{j=1}^{J} sharesowned_{j,i,t} * turnover_{j,t}}{shrout_{i,t}}$$

where $sharesowned_{j,i,t}$ is the ownership of fund j in stock i at end of quarter t from CDA/Spectrum and $turnover_{j,t}$ is the turnover reported by CRSP for fund j over quarter t. Results are reported for the following regression using the subsample in which the turnover variable is available quarterly from CRSP (1999+):

$$\beta_{HI,i,t} = a + b_1 * twmfown_{i,t-1} + b_2 * mfown_{i,t-1} + b_3 * ln(firmsize_{i,t-1}) + b_4 * illiq(avg)_{i,t-1} + \varepsilon_{i,t}.$$

Model (1) includes *twmfown* and for comparison model (2) includes the standard (unweighted) *mfown* over the same sample for which turnover is available (1999+), and model (3) includes both variables. To facilitate comparison of coefficients, the last three models repeat the first three but use standardized values of *twmfown* and *mfown*. Quarter dummies are included but not reported. Standard errors are clustered by stock.

				standardized variables		
	(1)	(2)	(3)	(4)	(5)	(6)
twmfown	1.331***		1.152***	0.112***		0.0972***
	(15.45)		(8.31)	(15.45)		(8.31)
mfown		0.925***	0.185		0.0935***	0.0188
		(12.65)	(1.60)		(12.65)	(1.60)
ln(firm size)	-0.0026	-0.0031	-0.0035	-0.0026	-0.0031	-0.0035
	(-0.54)	(-0.60)	(-0.72)	(-0.54)	(-0.60)	(-0.72)
illiq(avg)	-0.0750***	-0.0787***	-0.0733***	-0.0750***	-0.0787***	-0.0733***
	(-3.39)	(-3.55)	(-3.31)	(-3.39)	(-3.55)	(-3.31)
Observations	48907	48907	48907	48907	48907	48907
R^2	0.021	0.020	0.021	0.021	0.020	0.021

Table 6
Relation between liquidity commonality and mutual fund ownership conditional on flows.
This table reports results from a Pooled OLS regression of β_{HI} on *mfown* conditional on fund flows. We define dummy variables based on one of three measures of flows; aggregate net flows, aggregate inflows, or aggregate outflows in each quarter. All aggregate flows are scaled by total US market capitalization. Flows are measured contemporaneously with β_{HI}. The dummy variable *hiabsflow* equals one if aggregate net flows are in either the highest 10% or lowest 10%, zero otherwise. *negnetflow* equals one if aggregate net flows are negative (outflows) for that quarter and zero otherwise. We then define two dummy variables using inflows and outflows aggregated separately in each quarter. *hiinflow* equals one for the top 25% of quarters of inflows scaled by market cap, and *hioutflow* equals one for the top 25% of quarters of outflows scaled by market cap. Models (1)-(4) use the full sample. Models (5)-(8) show the effect of *mfown* within subsamples defined by aggregate net flows. Quarter dummies are included but not reported. Standard errors are clustered by stock. In Panel B we first run 115 cross sectional regressions of β_{HI} on *mfown* and control for size and liquidity. Then we regress the time series of *mfown* coefficients on aggregate flows and the square of aggregate flows in order to test for a U-shaped relationship.

	Full sample		Subsamples:Agg flows as % of US mkt cap			
Panel A			$< 0\%$	0 to 0.5%	0.5 to 1%	$> 1\%$
	(1)	(2)	(3)	(4)	(5)	(6)
mfown	0.765***	0.762***	1.174***	0.852***	0.710***	0.935***
	(11.13)	(11.33)	(7.97)	(7.04)	(8.01)	(7.14)
hiabsflow * mfown	0.395***					
	(3.12)					
negnetflow * mfown		0.575***				
		(3.91)				
ln(firm size)	-0.002	-0.002	-0.001	-0.008	-0.002	0.004
	(-0.50)	(-0.47)	(-0.062)	(-1.23)	(-0.47)	(0.52)
illiq(avg)	-0.088***	-0.088***	-0.106**	-0.135***	-0.096***	-0.016
	(-4.70)	(-4.70)	(-2.14)	(-3.62)	(-3.53)	(-0.54)
Observations	120413	120413	16873	23900	53604	26036
R^2	0.012	0.012	0.012	0.012	0.013	0.008

Panel B

Dependent variable: Coefficient on *mfown*	
aggflows	-1.04**
	(-2.09)
aggflows^2	0.57***
	(3.07)
Constant	1.28***
	(4.95)
Observations	115
R-squared	0.11

Table 7
Relation between liquidity commonality and changes in mutual fund ownership.
This table reports results of a Pooled OLS regression of β_{HI} at time t on the absolute value of the change in *mfown* from $t-1$ to t, lagged firm size and lagged average illiquidity:

$$\beta_{HI,i,t} = a + b_1 * |\Delta_{t-1,t} mfown_i| + b_2 * ln(firmsize_{i,t-1}) + b_3 * illiq(avg)_{i,t-1} + \varepsilon_{i,t}.$$

In model (2) we replace the absolute change in mutual fund ownership with a dummy variable set to one if the absolute change is in the top quartile in that quarter. Quarter dummies are included but not reported. Standard errors are clustered by stock.

	(1)	(2)
$\lvert\Delta_{t-1,t} mfown\rvert$	1.029***	
	(4.620)	
$\lvert\Delta_{t-1,t} mfown\rvert$ (dummy)		0.0399***
		(9.265)
ln(firm size)	0.0002	0.0016
	(0.047)	(0.378)
illiq(avg)	-0.137***	-0.116***
	(-4.412)	(-3.779)
Observations	105312	105312
R^2	0.011	0.011

Table 8

Robustness tests: controlling for return and volatility covariation.

This table reports results from Pooled OLS regressions of β_{HI} on *mfown* with additional controls. Panel A reports results controlling for commonality in returns and Panel B reports results controlling for commonality in volatility. The first model repeats the standard regression of β_{HI} on mutual fund ownership (as in models (1) and (2) of Table IV) and includes as a control variable the beta estimate between the firm return and the value-weighted return on the high mutual fund ownership portfolio estimated contemporaneously with the liquidity beta. Models (2)-(5) run the standard regression on cross-sectional subsamples sorted by the return beta. Model (6) runs the standard regression, but controls for return covariation in the first stage. Specifically, the dependent variable is a liquidity beta estimated in a time series regression that controls for firm returns and the return on the high mutual fund ownership portfolio. We repeat this analysis in Panel B, substituting returns-squared for returns, as a proxy for volatility.

Panel A: Controlling for covariation in returns

		mutual fund return beta subsamples				1st stage control
	full	Lo	2	3	Hi	for returns
	(1)	(2)	(3)	(4)	(5)	(6)
mfown	0.706***	0.619***	0.716***	0.516***	0.620***	0.806***
	(11.25)	(5.34)	(5.89)	(4.45)	(5.44)	(12.08)
ln(firm size)	0.0009	-0.0260***	-0.0126*	0.0174**	0.0468***	0.00125
	(0.25)	(-4.67)	(-1.91)	(2.54)	(6.73)	(0.32)
illiq(avg)	-0.0807***	-0.0641***	-0.121***	-0.0950	-0.0709**	-0.0707***
	(-4.33)	(-2.64)	(-3.06)	(-1.63)	(-2.09)	(-3.33)
mutual fund	0.051***					
return beta	(17.42)					
Observations	120413	30057	30120	30150	30086	120413
R^2	0.015	0.016	0.015	0.016	0.021	0.011

Panel B: Controlling for covariation in returns-squared

		mutual fund return^2 beta subsamples				1st stage control
	full	Lo	2	3	Hi	for ret squared
	(1)	(2)	(3)	(4)	(5)	(6)
mfown	0.830***	0.673***	0.839***	0.638***	0.671***	0.800***
	(13.01)	(6.16)	(7.07)	(5.32)	(5.64)	(11.93)
ln(firm size)	-0.0020	-0.0145**	-0.0230***	0.0117*	0.0352***	0.00174
	(-0.52)	(-2.32)	(-3.48)	(1.87)	(5.22)	(0.44)
illiq(avg)	-0.0876***	-0.0663***	-0.139**	-0.157***	-0.0627*	-0.0948***
	(-4.69)	(-2.72)	(-2.27)	(-3.95)	(-1.88)	(-4.56)
mutual fund	0.0022***					
return^2 beta	(4.84)					
Observations	120413	30057	30120	30150	30086	120413
R^2	0.012	0.014	0.015	0.015	0.022	0.012