Commonality in Liquidity:
A Demand-Side Explanation

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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 and those owned by mutual funds that experience liquidity shocks themselves have higher commonality in liquidity. These results suggest an important role for the demand side of liquidity in explaining commonality.

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A stock's liquidity and the risks that may arise from potential illiquidity are important factors for many investors in their investment decisions. Chordia, Roll and Subrahmanyam (2000) document that liquidity strongly covaries across stocks, i.e. commonality in liquidity.[1] Thus, liquidity risk cannot be diversified away by investors. Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) show theoretically that returns of financial assets should depend on commonality, a prediction that has been supported by a number of empirical studies.[2]

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 the supply-side sources suggested in Cougehnor and Saad (2004) cannot explain all of the commonality in liquidity (e.g., Brockman and Chung, 2002; Bauer, 2004).[3]

In this paper we examine a demand-side source of commonality in liquidity, namely correlated trading among investors. Specifically, we examine the role of mutual funds as an investor group that can be a source of commonality in liquidity and show that mutual funds are an important factor in explaining commonality in liquidity.

We argue that the demand for liquidity of investors with similar holdings and trading patterns is relevant in determining commonality in liquidity. The intuition is as follows: The trades of certain groups of investors may exhibit similarity in both direction and timing. If a group of investors are 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 large group of

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[1] See also, Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Eckbo and Norli (2002).

[2] See, for example, Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), Korajczyk and Sadka (2008), and Lee (2010).

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

stocks, then the stocks comprising their holdings 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 co-movements in their liquidity.

Mutual funds managers are a prime example of an investor group that could give rise to such an effect. Previous research has provided evidence of correlated trading by mutual funds and other institutional investors.[4] Correlated trading emerges if these investors face correlated liquidity shocks themselves and if they trade in the same direction based on the same information. Mutual funds typically hold large, well-diversified portfolios and they regularly face liquidity shocks in the form of positive or negative net-flows. These net-flows that mutual funds experience are typically highly correlated across funds, i.e. if one fund faces outflows (inflows), many others face outflows (inflows) at the same time. Furthermore, evidence exists that institutional investors tend to trade in the same direction given a specific information environment, which will also lead to joint buying or selling pressure in stocks. Consequently, we hypothesize that the liquidity of stocks with high mutual fund ownership should exhibit strong commonality.

We test this basic hypothesis using a similar approach to the two-step method employed by Coughenour and Saad (2004) in their examination of the role of market makers in explaining commonality. Using data on mutual fund ownership and stock liquidity from NYSE and AMEX stocks for the period 1980 to 2008, we first estimate the covariance between a stock's liquidity and the liquidity of a portfolio of stocks with high mutual fund ownership, where liquidity is defined by the Amihud (2002) measure of

[4] See, for example, Wermers (1999), Sias and Starks (1997), or Sias (2004).

daily stock liquidity.[5] For the sake of brevity we label the beta on the high mutual fund ownership portfolio β_{HI}, or, the mutual fund liquidity beta.

The second stage of our analysis is the examination of the distribution of β_{HI}. In particular, in each cross section we relate the degree with which a stock is owned by mutual funds to the degree with which the stock's liquidity covaries with those of stocks owned to a high degree by mutual funds. We expect to find a positive relation between β_{HI} and mutual fund ownership. Confirming our main hypothesis, we find that stocks with high mutual fund ownership exhibit roughly twice the covariance with the high mutual fund ownership portfolio than stocks with low ownership.

An alternative explanation for these results 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 (e.g., Del Guercio, 1996; Falkenstein, 1996; Gompers and Metrick, 2001; Bennett, Sias and Starks, 2003; Massa and Phalippou, 2005). To test this alternative hypothesis, we conduct several refinements of our analysis. We examine the relationship between mutual fund ownership and the mutual fund liquidity beta within size and liquidity level quartiles. The positive relationship between mutual fund ownership and the mutual fund liquidity beta 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 the positive relation between mutual fund ownership and the mutual fund

[5] We control for market-wide commonality in liquidity when estimating the covariance by including the liquidity of the market portfolio in the time series regression. Coughenour and Saad (2004), in their analysis of the impact of common market makers on commonality, use the liquidity of a portfolio of shares that have the same market maker instead of the liquidity of a portfolio of high mutual fund ownership stocks as explanatory variable.

liquidity beta to continue 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 when ownership is a better proxy for correlated trading. To examine this, 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 when stocks are owned by mutual funds with high turnover ratios than for stocks that are owned by mutual funds that do not trade a lot.

Forced trading will be observed when mutual funds experience large inflows or outflows. This creates buying or selling pressure for those shares typically owned and traded by mutual funds (Coval and Stafford, 2007, Ben-Rephael, Kandel, and Wohl, 2009, and Khan, Kogan, and Serafeim, 2009). Furthermore, one would expect a difference between the effects of inflows and outflows as funds can accumulate cash before they have to trade based on inflows, but outflows can force the fund to eventually trade in order to meet redemptions (e.g., Edelen and Warther, 2001). 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 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 among the stocks they hold. These results also support the notion that liquidity demand of mutual funds contributes to commonality.

Last, in addition to using the level of ownership as a proxy for the likelihood of correlated trading we use the change in mutual fund ownership obtained from quarterly SEC filings. This is a lower bound of trading; it reflects the outcome of aggregate trading of mutual funds over the quarter but does not capture intra-quarter trading. This is the trade-off between using levels versus changes: we can be certain that changes in ownership measures trading but this measure is biased downward. 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.

Our results are stable over time, hold over different subsamples, and are not driven by return or volatility comovements among stocks with high mutual fund ownership. Overall, our results suggest an important role for mutual fund ownership and eventually liquidity demand in explaining commonality in liquidity across stocks. Thus, the main contribution of our paper is to show how commonality in liquidity is dependent on demand-side factors in addition to the supply-side factors shown in earlier research (Coughenour and Saad, 2004).

Our paper contributes to three main lines of research. First, it contributes to the broad empirical literature on liquidity. Many papers document 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 the theoretical work of Acharya and Pedersen (2005)

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[6] See, for example, Amihud and Mendelson (1986), Brennan, Chordia and Subrahmanyam (1998), Jacoby, Fowler and Gottesman (2000), Jones (2002), Amihud (2002), Chordia, Huh and Subrahmanyam (2007), and Hasbrouck (2009).

[7] See, for example, Chordia, Roll and Subrahmanyam, (2000), Hasbrouck and Seppi (2001), Brockman, Chung and Perignon (2007), and Karolyi, Lee and vanDijk (2008).

and Pastor and Stambaugh (2003). Some empirical evidence on commonality as a priced risk factor is provided in Pastor and Stambaugh (2003), Acharya and Pedersen (2005), Sadka (2006), Korajczyk and Sadka (2008), and Lee (2010). The literature trying to explain commonality in liquidity is primarily based on the supply side arguments put forward in Coughenour and Saar (2004), who propose that the commonality arises from the same NYSE specialist providing liquidity for many stocks. They show that stocks with the same specialist exhibit strong commonality in liquidity. 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 provided by 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 commonality of liquidity, too. 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 measures help to explain commonality. The impact of liquidity demanding trades on movements in market prices is also examined in Hendershott and Seasholes (2009).

Second, our findings complement the literature on the impact of correlated. Greenwood (2009) shows that common trading patterns of index investors can give rise to substantial excess co-movement 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.[8] More closely related to our

[8] 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).

paper, Greenwood and Thesmar (2009) also use mutual fund ownership and mutual fund flows to get a proxy for correlated trading. Looking at the 1990 to 2008 period they show that stocks owned by mutual funds with correlated inflows exhibit larger return comovement. However, none of these papers investigates the link between correlated trading and comovement in liquidity.

Finally, our study also contributes to the general literature on the influence of institutional investors on financial markets. Several studies examine the impact of institutional investors on corporate governance (e.g., Gillan and Starks, 2000, 2007), executive compensation (Hartzell and Starks, 2003), analyst recommendations (Ljungqvist, Marston, Starks, Wei and Yan, 2007), mergers (Chen, Harford and Li, 2007), and stock market returns (Sias and Starks, 1997; Sias, Starks and Titman, 2006). More closely related to our paper is the paper of Massa (2004), that shows that a large number of uninformed mutual funds can increase the level of liquidity of stocks. The interplay between liquidity levels, investment strategies, and the performance of mutual funds is examined in Massa and Phalippou (2005). While all of these studies focus on liquidity levels, Kamara, Lou and Sadka (2008) examine the impact of changing aggregate levels of institutional ownership on commonality. They find that commonality increases over time. Consistent with our results, they argue that this is driven by the increasing importance of institutional investors over time. We complement their findings by showing the channels through which institutional investments can give rise to commonality.

The remainder of this paper is organized as follows. In Section I 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 II and in Section III we consider proxies for mutual fund trading. Section IV provides the results from several robustness tests and Section V concludes.

I. Data and variable construction

Our initial sample is based on mutual funds with holdings in the CDA/Spectrum database over the period 1980 through 2008. 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 CRSP stock database.

A. Variable Definitions

Ideally we would be able to directly observe mutual fund trades in order to measure each stock's degree of correlated trading through time. Because we have quarterly snapshots of mutual fund ownership rather than trades, we create a stock-level proxy for the likelihood of correlated trading based on the percentage of shares outstanding held by mutual funds. Specifically, we construct a quarterly stock-level measure of aggregate mutual fund ownership.[9] The fraction of ownership $mfown_{i,t}$, in stock i owned by J mutual funds at 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. We use this variable as a proxy for the likelihood that, for a given stock, large order imbalances will occur.

In our later analysis, we also use a turnover-weighted version of $mfown_{i,t}$. When summing ownership across funds within a stock, we weight ownership by turnover,

[9] 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.*

Our primary measure of liquidity is 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.*[10] This measure is ideal for our research because it is based on widely available data and so can be calculated for a large number of stocks at a daily frequency. Hasbrouck (2005) finds the Amihud measure to be highly correlated with two measures of liquidity that are based on intraday TAQ microstructure data. Similar evidence for strong correlations between the Amihud (2002) measure and various microstructure measures is also provided in Koraczyk and Sadka (2008). More recently, Goyenko, Holden, and Trzcinka (2009) show that the Amihud (2002) measure is a good proxy for price impact. We use the average of the daily Amihud illiquidity measure throughout the quarter as a control variable in many of the regressions to take into account the potential impact of the level of stock liquidity.

For our primary variable, we employ the change in the Amihud illiquidity measure. Specifically, we compute the change in the daily measure of stock illiquidity using volume and return data from CRSP,

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

[10] We later replicate the main results using stock turnover as a proxy for liquidity (Section IV). Furthermore, concerns that commonality in liquidity determined based on the Amihud measure might partially capture return or volatility comovements (because the definition of that measure contains the absolute return in the nominator) are addressed in Section IV, too.

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.[11] 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) and that trade on day d and $d-1$. To prevent outliers from affecting our analysis, we eliminate the top and bottom 1% of observations of our measure.

B. Summary Statistics

Table 1 reports statistics on the sample stocks' market value, illiquidity measure, 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 sufficient data to calculate liquidity betas.[12] Using the turnover-weighted mutual fund ownership reduces the sample to 66,598 stock-quarters because 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 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%.

[11] 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 IV).

[12] We require at least 40 return observations per quarter to estimate our liquidity betas (Section II.A).

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; moving from the lowest to highest quartile of *mfown*, the *illiq(avg)* drop from 0.19 to 0.04.

II. Commonality in liquidity and mutual fund ownership

In order to examine the extent with which mutual fund ownership determines co-movement in liquidity, we follow an approach similar to that in Coughenour and Saad (2004). 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 II.A). In the second step we investigate whether co-movement between individual stocks and the high *mfown* portfolio is stronger among firms with high mutual fund ownership (Section II.B).

A. Estimating liquidity covariances

Our first step is to estimate for each firm-quarter 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 co-movement in individual 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:[13] a market portfolio containing all stocks and a high mutual

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

fund ownership portfolio comprised of the stocks in the top quartile of mutual fund ownership as ranked at the end of the previous quarter.

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 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 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. We include the latter controls to capture lagged adjustments, while the market returns are included to control for possible correlations between returns and our illiquidity measure. Squared stock returns are included to capture volatility which might be related to liquidity. We require a minimum of 40 observations for each firm-quarter.[14] We show later in robustness tests (Section IV) that this particular specification of the first stage time series regressions is not crucial to our main results.

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 and statistics on the coefficients. In the top panel we report a quarterly summary for quarters from the beginning (1980), the middle (1995) and the end (2008) of our sample. Below we summarize by 5 year periods as well as the full sample.

[14] Results are very similar if instead of requiring a minimum of 40 observations we require a minimum of 30 or 50 observations.

The left-hand side 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 beta estimates are significantly different from zero at the 5%-level based on two-sided t-tests. This is likely due to the large noise in the firm level regressions, which are conducted on a quarterly basis.[15] While few of the individual quarterly estimates are statistically significant, the mean of the distribution of estimates is different from zero with a high degree of significance as indicated by the t-statistic on the sample of estimates. The right-hand side of the table summarizes the same variables for the market liquidity beta coefficients. 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. However, the main hypothesis that we test in the next section is that β_{HI} is higher among shares with high mutual fund ownership.

The bottom panel summarizes the time series regression output by 5 year periods. We calculate summary variables and t-statistics for each quarter as above, and in this panel we report averages of these quarterly summary variables. For example, in the 1980-1985 period the typical quarter has a mean β_{HI} equal to 0.26 and the average t-statistic on each quarter's sample of estimates is 5.10.

The average size of firms in the high mutual fund ownership portfolio is smaller than the average size of the firms in the market portfolio. Average mutual fund ownership over the entire sample of stocks is increasing through time. The average

[15] 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.

mutual fund ownership in a stock is 4% in 1980 and this number increases to 24% in the third quarter of 2008. Among the stocks in the top quartile of mutual fund ownership, average ownership increases from 9% in 1980 to 37% in 2008. Stocks were less liquid in the 1980's relative to the later period. This finding is consistent with the results in Jones (2002). The decrease in illiquidity is most pronounced among the stocks in the highest quartile of mutual fund ownership. The average illiquidity among the stocks in this portfolio is lower than the average illiquidity of the stocks in the market portfolio in all quarters. This result shows that mutual funds prefer liquid stocks, which is also similar to results from earlier studies (e.g., Falkenstein, 1996).

B. 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 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. These findings provide first evidence for our central hypothesis.

The results for β_{HI} 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 market liquidity in the highest and lowest mutual fund ownership quartiles.

We also report averages for β_{HI} and β_{mkt} from sorts based on firm size and liquidity. For β_{HI}, the difference between the top and bottom quartiles is statistically significant in both cases. Large stocks have a significantly higher average β_{HI} of 0.29 compared to 0.23 among the smallest quartile. However, the relationship is non-monotonic. We find a similar non-monotonic relationship between average illiquidity and β_{HI}. There are also strongly significant differences between the comovement of a stock's liquidity with the market liquidity in the highest and lowest size and illiquidity, respectively, quartiles. Our results show that large and liquid stocks co-move more heavily with both market as well high mutual fund ownership portfolio liquidity as compared to small and illiquid stocks.

The results presented thus far are univariate in nature. However mutual funds do not randomly select stocks but have preferences for certain characteristics. Most importantly, in aggregate they prefer large and liquid stocks (see, e.g., Del Guercio, 1996; Falkenstein, 1996). Our previous results suggest that these characteristics are also related to β_{HI}. Thus, in Panel B of Table 4 we provide the results on the average liquidity betas for double sorts based on these variables and mutual fund ownership. The sorting is first done on size or illiquidity and then 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 barely held by mutual funds.

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. This accounts for all time series and cross sectional dependence as long as the time effect is fixed (Petersen (2009)). The specification is

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

Our main hypothesis predicts $b_1>0$. We do not have clear theoretical predictions on b_2 or b_3. However, given the results from Table 3, one might expect a positive relation between β_{HI} and firm size and a negative relation with illiquidity. 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. We affirm that stocks with high mutual fund ownership exhibit strong co-movement, evidenced by a b_1 estimate of 0.896 and a t-statistic of 14.73. 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 the second column we include *size* and *illiq(avg)* as controls. Again the coefficient on mutual fund ownership is positive and highly significant, and is similar in magnitude to the coefficient estimated in the absence of controls. In terms of economic significance, 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.

C. Potential Alternative Explanation and Some Robustness

Another potential explanation for our results is that mutual fund managers might have a preference for a stock characteristic (other than size and liquidity) that is correlated with β_{HI}. Although it is not clear what the source of the unobserved heterogeneity and correlation might be, in column 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 columns of the table use corrections for different assumptions on the structure of the error term. The fourth column reports results using standard errors with two dimensional clustering, and the last column uses a Fama-MacBeth specification. In both cases we find a positive relationship that is both economically and statistically significant.

We have no direct prediction on the functional form of the relationship between ownership and commonality, and so for further robustness 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 (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 Panel B of Table 4. The use of this variable provides a natural economic interpretation. From column 2 in Panel B, 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 an up or down market return. Table 5 reports these results again for a linear impact of *mfown* (Panel A) as well as for the impact of the high mutual fund ownership dummy (Panel B).

In both panels, 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), 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 in the up versus down market subsamples is not significant. This shows that while previous paper could document higher commonality in liquidity in down markets, up vs. down markets have no impact on the role of mutual fund ownership in explaining liquidity. Rather, results are fairly stable across market regimes.[16]

Overall, these results show 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.

III. Commonality in liquidity and mutual fund trading

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[16] 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.

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 will be correlated. Therefore, it is not the level of ownership that matters per se, but the extent to which it reflects future correlated trading. In the following section we offer a few possible alternative proxies for the probability of future correlated trading.

In the absence of directly observing trades, an ideal proxy would reflect two probabilities, i) the likelihood that a stock is traded and ii) conditional on being traded the likelihood that the trades are in the same direction. We refine $mfown_{i,t}$ in three ways to capture the likelihood of future correlated trading; a measure that reflects correlated voluntary trading, one that reflects correlated forced trading, and one that reflects overall correlated trading.

The first proxy incorporates a fund's turnover ratio. This takes into consideration that some funds trade more than others. 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. However, voluntary trading could reflect trading by mutual funds providing liquidity to other market participants as well as their information-based liquidity demanding trades (Da, Gao, and Jagannathan, 2008). While both cases could explain commonality, only the latter would be consistent with mutual funds demanding liquidity and eventually giving rise to commonality via this channel. Thus, to investigate whether the demand side channel plays any role, we include a second measure of future correlated trading which is designed to capture the effects of liquidity shocks to the fund itself due to inflows or outflows. Therefore our second refinement is to condition mutual fund ownership on aggregate fund flows. Because flows can lead to buying or selling pressure of mutual funds, i.e. liquidity demand, if commonality among mutual fund owned stocks is higher in periods of high absolute flows (and particularly in periods of high outflows), this is a clear indication that mutual funds have an impact on commonality via their liquidity demand.

Our final refinement is to use changes rather than levels of ownership. The change in ownership reflects actual trades in the same direction, thus capturing both the probability a stock is traded and the probability that trades are in the same direction. Therefore it should not be surprising that the change in ownership – at atomistic granularity – is the ideal measure. However data availability limits us to quarterly changes. Thus, using changes presents the tradeoff of measuring some fraction of trading with certainty, but also underestimating the amount of actual trading.

A. Mutual fund turnover

As a first approach to better capture the probability of correlated trading, we incorporate funds' turnover. When summing ownership across funds within a stock, we weight ownership by turnover (see Section I.A). In the following analysis we will then use turnover-weighted mutual fund ownership, $twmfown_{i,t}$.

Simply put, if we assume that every mutual fund trade is correlated, then a stock held by funds with high turnover is more likely to be traded in a correlated fashion than a stock with a similar mutual fund ownership level, but held by funds with low turnover. Clearly turnover-weighted mutual fund ownership will be larger for a stock predominantly held by funds with high turnover relative to a stock with the same level of ownership, but owned by funds with low turnover. The definition of the turnover ratio as reported in CRSP is already corrected for the impact of flows. Thus, turnover is capturing voluntary trading of the mutual fund.

We expect to find that the turnover-weighted measure, to the extent that it is a better proxy for correlated demand in liquidity, is more strongly associated with high commonality in liquidity than an unconditional measure of mutual fund ownership.[17] One clear drawback of this refinement is data limitation. CRSP does not report fund turnover prior to 1999 and so the sample period for these tests are from 1999 through 2008. The results are reported in Table 6. For comparison, the second column repeats the evaluation of our baseline model using *mfown* as the primary independent variable for the limited sample 1999 to 2008. Our previous results also strongly show up in this restricted time period. The first column uses *twmfown* only, and the third column includes both *twmfown* and *mfown.*[18] The coefficient on the turnover-weighted mutual fund ownership variable is strongly significant, whether un-weighted mutual fund ownership is included in the regression or not.

Table 1 shows large similarity in the means of the weighted and unweighted mutual fund ownership measures, which suggests that we can reasonably 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. In addition, we use standardized independent variables and report results in the last three columns. 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

[17] 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.

[18] 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 variance inflation factors of 3.68 and 2.97 for *mfown* and *twmfown*, respectively, clearly indicate that this is not a concern here.

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. Thus, in the following section we focus on the impact of liquidity shocks mutual funds face themselves. This will allow us to isolate cases in which any potential effect most likely works via a demand-side channel.

B. Aggregate fund flows

In Section A we investigate the relation between β_{HI} and a proxy for voluntary mutual fund trading. In this section we estimate the relation between β_{HI} and involuntary correlated trading. Thus, we infer differences in trading intensities using fund flows.[19] 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 why we expect a stronger impact of outflows is that inflows can be more easily spread across stocks, but fund outflows, if met through stock sales, must be met by selling the stocks currently held by the mutual funds.[20]

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 these flow data we calculate four dummy variables; *negnetflow* equals one if aggregate flows are

[19] Chordia, Roll, and Subrahmanyam (2009) find that fund flows can explain much of the increased turnover in equity markets over recent years. Furthermore, most mutual funds simply 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.

[20] That high negative mutual fund flows lead to correlated liquidity demand is also suggested by the finding of Hameed, Kang, and Viswanathan (2010) who document a negative relation between commonality in order imbalances and aggregate net fund flows.

negative, and zero otherwise, and *hiabsflow* equals one if aggregate flows in a quarter are in the top or bottom 10% of all quarters, and zero otherwise. Net flows are signed, so the bottom (top) 10% is comprised of the largest net outflow (inflow) quarters. We also aggregate inflows and outflows separately in each quarter. Then we set *hioutflow* (*hiinflow*) equal to one for the top 25% of quarters measured by outflows (inflows) scaled by market cap, and zero otherwise. Each of these dummy variables is interacted with *mfown* in the previously described regression 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 7. Column 1 shows that the impact of ownership on commonality is much stronger during periods of high positive or negative 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). Columns 2, 3 and 4 provide similar results. 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. Columns 3 and 4 show that we find similar results when aggregating inflows and outflows separately in each quarter. 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 5 through 8 show the results from our base regression (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 all 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 2 through 4, this seems primarily driven by negative flow quarters. In Panel B of Table 7 we test specifically for a U-shaped conditional relationship. First, we run 114 quarterly cross sectional regressions based on model (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.

C. Changes in mutual fund ownership

Last, we use changes in mutual fund ownership. Specifically we compute the absolute value of the change in $mfown_i$ from $t\text{-}1$ to t, and denote this variable $|\Delta mfown_{i,t}|$. The change in ownership reflects an amount of trading that we can be certain took place, and that these trades were in the same direction. We are limited by data availability to compute changes on a quarterly basis. Therefore while changes in ownership reflects with certainty some amount of correlated trading, an important drawback is that this captures only the lower bound.

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 8. We use the absolute value of the change in *mfown* in the first column, and a dummy variable equal to one if the absolute change is in the top quartile that quarter, and zero otherwise, in the second column. 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 6, 7, and 8 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.

IV. Robustness Tests

Thus far, we have shown that the relationship between β_{HI} and *mfown* is robust to different specifications regarding functional form and structure of the error term. We find additional support for our hypothesis through several refinements of our main variable of interest; turnover-weighted *mfown*, *mfown* conditional on flows, and changes in *mfown.* In this section we address 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 Table 9 we show that our results are not driven by common returns or common volatility, and in Table 10 we show that our results are not specific to the structure or 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 (2). We call this variable mutual fund return beta. Adding that 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 9. Regarding the new control variable, we find a significantly positive impact of the mutual fund return beta on β_{HI}. This shows that common return effects (as a proxy for information affecting the returns of high mutual fund ownership stocks) also has an impact on commonality in liquidity among these stocks. More importantly, 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 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 model (2) using the β_{HI} from this modified first stage model as dependent variable are presented in column 6 in Panel A of Table 9.[21] We still find a highly significant positive impact of *mfown* on $\beta_{HI.}$

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

One may also be concerned that our results are driven by comovements in volatility among stocks with high mutual fund ownership which might be caused by joint changes in the riskiness of the funds owned by mutual funds. To address this 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 9 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; columns 7 through 11). 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 also not change the results obtained from the standard second stage regression (column 12).

Finally, we repeat our whole analysis using turnover instead of the Amihud illiquidity ratio as an alternative liquidity measure.[22] Results are presented in the first column of Table 10. There continues to be a strong positive relationship between ownership and commonality using turnover.

Overall, these findings show that our previous results are not driven by return or volatility comovements among stocks with high mutual fund ownership or any other mechanical effect which might arise due to the definition of the Amihud liquidity measure.

In the remainder of this section we now show that our results are also 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 [model (2)] using the variety of first-stage β_{HI} estimates.

[22] 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.

These results are reported in columns 2 through 9 of Table 10. In the first approach, instead of using value-weighted portfolio 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 10, column 2, compared to 0.836 in column 2 of Table 4). In the second approach, we employ our standard time series estimation procedure (model 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 10, 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 reported in the fourth and fifth column of Table 10 use a 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. Thus, as suggested by Cometon-Forde, Hendershott, Jones, Moulton, and Seasholes (2009), 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.

Lastly, 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 (and its returns). We then use liquidity betas on this portfolio as 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 at all related to mutual fund ownership.

IV. 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 funds are an important factor in explaining commonality in liquidity. We use a two-step process similar to the one suggested in Coughenour and Saad (2004) by first regressing 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 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 driven by time trends in commonality and mutual fund ownership or by stock characteristics such as firm size, liquidity 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 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 chose mutual funds as a group of investors whose trades are expected to be correlated and eventually give rise to commonality because in this case we can easily observe the portfolios of all funds as well as the liquidity shocks this group of investors faces. This does of course not preclude that the correlated trading of other investors like hedge funds or other institutional investors might also give rise to commonality.

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Table 1: Summary Statistics

Panel A reports summary statistics for select variables for the full sample. *mfown* is the number of shares owned by mutual funds scaled by shares outstanding. *size* is market value of the firm in millions. *illiq(avg)* is average over the quarter of the absolute value return scaled by dollar volume (in millions). β_{mkt} and β_{HI} are estimates from the time series regression in Equation 1. *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 and standard deviations for subsamples of firms by *mfown* quartile ranked quarterly.

Panel A: Full Sample	N	Mean	Std Dev	Min	Max	Median
mkt equity (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			
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: Summary – Time Series Estimates of Liquidity Betas

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 market portfolio and a portfolio of high mutual fund ownership stocks and controls.

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

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 estimate on the high *mfown* liquidity portfolio, and the right columns summarize the beta on 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. The top panel summarizes these estimates for a selection of quarters and the bottom summarizes all five year sub-periods and the full sample. The five-year and full samples report the averages of the quarterly summary items. For example, for the period 1980-1985, the average of the 20 β_{mkt} quarterly estimates is 0.29 and the average t-statistic is 4.82.

				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
Averages of quarterly summary items																	
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: Average Betas – Sorts

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 uses dependent sorts. First we sort on firm size each quarter, then within size bins we sort on *mfown* (similarly for illiq(avg)). All t-statistics are on the difference in sample averages paired by quarter.

Panel A: One way sorts

		Average β_{HI}								Average β_{mkt}				
				mfown							mfown			
	Lo	2	3	Hi	Hi - Lo	H-L tstat		Lo	2	3	Hi	Hi - Lo	H-L tstat
	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							firm size		
	Lo	2	3	Hi	Hi - Lo	H-L tstat		Lo	2	3	Hi	Hi - Lo	H-L tstat
	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)							illiq(avg)		
	Lo	2	3	Hi	Hi - Lo	H-L tstat		Lo	2	3	Hi	Hi - Lo	H-L tstat
	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

					mfown							mfown		
		Lo	2	3	Hi	Hi - Lo	H-L tstat		Lo	2	3	Hi	Hi - Lo	H-L tstat
	Small	0.18	0.28	0.26	0.27	0.09	(2.33)	Small	0.09	0.06	0.10	0.12	0.03	(1.02)
firm size	2	0.22	0.27	0.36	0.42	0.20	(6.63)	2	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)	3	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)	Big	0.61	0.61	0.50	0.40	-0.21	(-6.79)
					mfown							mfown		
		Lo	2	3	Hi	Hi - Lo	H-L tstat		Lo	2	3	Hi	Hi - Lo	H-L tstat
	Lo	0.14	0.24	0.33	0.43	0.29	(12.07)	Lo	0.68	0.61	0.48	0.37	-0.31	(-9.78)
avgillq	2	0.27	0.31	0.40	0.44	0.17	(5.92)	2	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)	3	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)	Hi	0.11	0.06	0.12	0.13	0.02	(0.85)

Table 4: Pooled OLS: β_{HI} on *mfown* and controls

This table reports results from the following regression using a variety of alternate specifications:

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

where β_{HI} is estimated as in equation (1). *mfown* and ln(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. Panel A uses the standard measure of *mfown* and Panel B uses a dummy equal to 1 if *mfown* is in the top quartile in a given quarter, 0 otherwise.

Panel A	(1)	(2)	(3)	(4)	(5)
mfown	0.896***	0.838***	0.457***	0.557***	1.009***
	(14.73)	(13.12)	(4.580)	(5.333)	(9.226)
lnme		-0.00213	0.0187**	-0.00528	1.75e-05
		(-0.559)	(1.966)	(-1.097)	(0.00389)
illiq(avg)		-0.0890***	-0.0529**	-0.103***	-0.0954***
		(-4.750)	(-2.230)	(-5.497)	(-2.780)
Observations	120413	120413	120413	120413	120413
R^2	0.012	0.012	0.055	0.002	0.002
Panel B					
mfown (dummy)	0.127***	0.120***	0.0431***	0.120***	0.118***
	(11.37)	(10.69)	(3.092)	(9.063)	(9.451)
lnme		0.00369	0.0231**	0.00355	0.00300
		(0.968)	(2.438)	(0.727)	(0.686)
illiq(avg)		-0.106***	-0.0541**	-0.102***	-0.117***
		(-5.590)	(-2.272)	(-5.383)	(-3.366)
Observations	120413	120413	120413	120413	120413
R^2	0.011	0.011	0.055	0.002	0.002
Time effects	Y	Y	Y		
Firm effects			Y		
Time clusters				Y	
Firm clusters	Y	Y	Y	Y	
Fama MacBeth					Y

Table 5: Pooled OLS: β_{HI} on *mfown*, Subsamples

This table reports results from the following regression using various sub-samples:

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

where β_{HI} is estimated as in equation (1). *mfown* and ln(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. Panel A uses the standard measure of *mfown* and Panel B uses a dummy equal to 1 if *mfown* is in the top quartile in a given quarter, 0 otherwise. Quarter dummies are included in all regressions. Standard errors are clustered by stock.

Panel A	size				illiq(avg)			
	Lo	2	3	Hi	Lo	2	3	Hi
mfown	0.155	0.738***	0.761***	1.008***	1.016***	0.668***	0.659***	0.151
	(1.109)	(6.805)	(6.412)	(6.900)	(7.118)	(5.307)	(5.963)	(1.038)
ln(size)	0.0513***	0.0301	-0.0336	-0.0733***	-0.0800***	-0.0344*	0.0108	0.0192
	(3.183)	(0.989)	(-1.200)	(-5.397)	(-6.443)	(-1.904)	(0.696)	(1.538)
illiq(avg)	-0.0334	-0.304	0.347	-1.032	-20.46***	-4.011*	1.038	-0.0402*
	(-1.571)	(-1.425)	(1.214)	(-0.877)	(-2.885)	(-1.756)	(1.405)	(-1.932)
Observations	30057	30120	30150	30086	30057	30120	30150	30086
R^2	0.010	0.023	0.018	0.018	0.018	0.021	0.021	0.010

	1980-85	86-90	91-95	96-00	2001+	Down mkt	Up mkt
mfown	1.095***	1.487***	1.187***	0.349***	1.006***	0.950***	0.785***
	(3.485)	(5.003)	(7.613)	(2.851)	(12.64)	(9.632)	(10.43)
ln(size)	0.0161*	-0.000719	0.00379	0.000437	-0.00489	0.00948*	-0.00734*
	(1.648)	(-0.0733)	(0.619)	(0.0647)	(-0.843)	(1.686)	(-1.695)
illiq(avg)	-0.0763	-0.0662	-0.0991***	-0.0465	-0.0889***	-0.0674***	-0.101***
	(-1.579)	(-1.006)	(-2.731)	(-0.805)	(-3.863)	(-2.661)	(-3.772)
Observations	21915	15885	51717	26587	38348	37325	83088
R^2	0.007	0.010	0.009	0.011	0.018	0.016	0.011

Panel B	size				illiq(avg)			
	Lo	2	3	Hi	Lo	2	3	Hi
mfown (dummy)	0.0108	0.109***	0.0971***	0.138***	0.131***	0.0889***	0.0822***	0.0154
	(0.372)	(5.403)	(5.052)	(6.202)	(6.324)	(4.640)	(3.922)	(0.480)
ln(size)	0.0551***	0.0348	-0.0311	-0.0781***	-0.0881***	-0.0408**	0.00392	0.0199
	(3.494)	(1.142)	(-1.099)	(-5.716)	(-7.057)	(-2.280)	(0.250)	(1.593)
illiq(avg)	-0.0345	-0.372*	0.184	-1.462	-22.71***	-4.495**	0.835	-0.0425**
	(-1.628)	(-1.751)	(0.647)	(-1.210)	(-3.209)	(-1.969)	(1.132)	(-2.060)
Observations	30057	30120	30150	30086	30057	30120	30150	30086
R^2	0.010	0.023	0.017	0.018	0.017	0.020	0.020	0.009

	1980-85	86-90	91-95	96-00	2001+	Down mkt	Up mkt
mfown (dummy)	0.0728***	0.116***	0.116***	0.0770***	0.166***	0.140***	0.111***
	(2.790)	(4.092)	(6.723)	(3.247)	(9.394)	(7.561)	(8.379)
ln(size)	0.0159	-0.00198	0.00477	0.00195	0.00671	0.0163***	-0.00195
	(1.620)	(-0.200)	(0.767)	(0.296)	(1.170)	(2.895)	(-0.451)
illiq(avg)	-0.0844*	-0.0808	-0.110***	-0.0551	-0.113***	-0.0852***	-0.116***
	(-1.749)	(-1.225)	(-3.021)	(-0.954)	(-4.799)	(-3.369)	(-4.315)
Observations	21915	15885	51717	26587	38348	37325	83088
R^2	0.007	0.009	0.008	0.011	0.015	0.015	0.010

Table 6: Pooled OLS: Turnover-weighted *mfown*

The following 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+):

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

Column 1 uses twmfown and for comparison column 2 uses the standard (unweighted) mfown over the same sample for which turnover is available (1999+), and both in column 3. To facilitate comparison of coefficients, the last three columns 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)		(8.313)	(15.45)		(8.313)
mfown		0.925***	0.185		0.0935***	0.0188
		(12.65)	(1.601)		(12.65)	(1.601)
ln(size)	-0.00259	-0.00305	-0.00352	-0.00259	-0.00305	-0.00352
	(-0.536)	(-0.603)	(-0.718)	(-0.536)	(-0.603)	(-0.718)
illiq(avg)	-0.0750***	-0.0787***	-0.0733***	-0.0750***	-0.0787***	-0.0733***
	(-3.387)	(-3.551)	(-3.312)	(-3.387)	(-3.551)	(-3.312)
Observations	48907	48907	48907	48907	48907	48907
R^2	0.021	0.020	0.021	0.021	0.020	0.021

Table 7: *mfown* and Mutual Fund Flows

The following table reports results on the impact of *mfown* conditional on fund flows. We define dummy variables based on one of three measures of flows; aggregate net flows, aggregate inflows, and 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. Columns 6-9 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%	$> 1\%$
mfown	0.765***	0.762***	0.717***	0.726***	1.174***	0.852***	0.710***	0.935***
	(11.13)	(11.33)	(9.521)	(9.105)	(7.973)	(7.043)	(8.006)	(7.140)
hiabsflow * mfown	0.395***							
	(3.115)							
negnetflow * mfown		0.575***						
		(3.913)						
hiinflow * mfown			0.369***					
			(3.407)					
hioutflow * mfown				0.309***				
				(2.838)				
ln(size)	-0.00192	-0.00179	-0.00195	-0.00216	-0.000504	-0.00830	-0.00230	0.00366
	(-0.503)	(-0.470)	(-0.510)	(-0.567)	(-0.0621)	(-1.225)	(-0.473)	(0.520)
illiq(avg)	-0.0880***	-0.0880***	-0.0872***	-0.0875***	-0.106**	-0.135***	-0.0960***	-0.0157
	(-4.699)	(-4.697)	(-4.644)	(-4.677)	(-2.138)	(-3.620)	(-3.526)	(-0.536)
Observations	120413	120413	120413	120413	16873	23900	53604	26036
R^2	0.012	0.012	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 8: Changes in *mfown*

We regress β_{HI} at t on the absolute value of changes in *mfown* from $t-1$ to t and lagged size and lagged average illiquidity:

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

In the second column 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.

$\lvert\Delta_{t-1,t} mfown\rvert$	1.029***	
	(4.620)	
$\lvert\Delta_{t-1,t} mfown\rvert$ (dummy)		0.0399***
		(9.265)
ln(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 9: Robustness: Controlling for Return and Volatility Covariation

The top panel controls for commonality in returns and the bottom panel common volatility. We show the main result is robust common returns and volatility in a variety of ways. The first column repeats the standard regression of β_{HI} on mutual fund ownership (as in the first two columns of Table 4) 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. Columns 2-5 run the standard regression on cross-sectional subsamples sorted by the return beta. The last column runs the standard regression, but controls for return covariation in the first stage. Specifically, Column 6 uses as the dependent variable 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, substituting returns-squared for returns, as a proxy for volatility. These results are reported in the bottom panel.

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)	(5.343)	(5.889)	(4.453)	(5.437)	(12.08)
ln(size)	0.000901	-0.0260***	-0.0126*	0.0174**	0.0468***	0.00125
	(0.246)	(-4.671)	(-1.911)	(2.541)	(6.729)	(0.315)
illiq(avg)	-0.0807***	-0.0641***	-0.121***	-0.0950	-0.0709**	-0.0707***
	(-4.325)	(-2.637)	(-3.057)	(-1.632)	(-2.093)	(-3.332)
mutual fund	0.0510***					
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
	(7)	(8)	(9)	(10)	(11)	(12)
mfown	0.830***	0.673***	0.839***	0.638***	0.671***	0.800***
	(13.01)	(6.161)	(7.072)	(5.324)	(5.640)	(11.93)
ln(size)	-0.00196	-0.0145**	-0.0230***	0.0117*	0.0352***	0.00174
	(-0.515)	(-2.317)	(-3.476)	(1.869)	(5.220)	(0.441)
illiq(avg)	-0.0876***	-0.0663***	-0.139**	-0.157***	-0.0627*	-0.0948***
	(-4.691)	(-2.719)	(-2.267)	(-3.949)	(-1.879)	(-4.564)
mutual fund	0.00224***					
phantomasreturn^2 beta	(4.836)					
Observations	120413	30057	30120	30150	30086	120413
R^2	0.012	0.014	0.015	0.015	0.022	0.012

Table 10: Robustness: Alternate Measures of Liquidity Betas

We repeat the standard regression of β_{HI} on mutual fund ownership (as in the first two columns of Table 4) using alternate measures of the liquidity betas. Column 1 uses as the dependent variable the liquidity beta estimate on an equal-weighted portfolio of high *mfown* stocks instead of value-weighting. Column 2 reports results using a sum beta which equals β_{HI} plus the betas on lead and lag values of the high *mfown* portfolio (measured in the standard way). In column 3 we use β_{HI} on the typical high *mfown* portfolio, but we also control for liquidity covariation with stocks in the same industry (lead, lag, and contemporaneous changes in the industry portfolio as identified by two-digit SIC code). Column 4 uses β_{HI} from a similar time series regression as in column 3, but we also include contemporaneous, lead and lag returns on the high *mfown* portfolio as well as those on the industry portfolio. Columns 5 and 6 use only one portfolio in the time series beta estimation, the market portfolio and the high *mfown* portfolio respectively. Column 7 reports results using changes in liquidity from a five day moving average (as opposed to a first difference). Specifically we compute the change in illiquidity as the log of the ratio of Amihud's illiquidity measure at day t to the average of this measure of the previous five trading days. Column 8 uses turnover instead of Amihud's illiquidity measure. The last column uses the beta on a portfolio of randomly selected stocks. Specifically we choose 25% of the stocks in each quarter and compute a value-weighted change in daily liquidity for this random portfolio. Quarter dummies are included in all regressions and standard errors are clustered by stock.

	(1) turnover	(2) equal weight	(3) sum betas	(4) industry controls	(5) ind and ret controls	(6) β_{mkt} only	(7) β_{HI} only	(8) quasi-differencing	(9) random MO port
mfown	1.830***	2.063***	0.810***	0.761***	0.760***	0.314***	0.504***	0.721***	0.0611
	(18.96)	(15.19)	(6.866)	(11.67)	(9.489)	(7.787)	(12.41)	(12.58)	(1.459)
ln(size)	-0.0712***	0.0491***	-0.0176***	-0.00566	-0.000336	0.114***	0.101***	-0.00462	0.00269
	(-12.10)	(6.505)	(-2.734)	(-1.515)	(-0.0657)	(43.78)	(40.11)	(-1.453)	(1.199)
illiq(avg)	-0.128***	-0.0903**	-0.0694*	-0.0790***	0.00898	-0.00385	-0.0277***	-0.0778***	0.00794
	(-2.708)	(-2.352)	(-1.947)	(-3.918)	(0.119)	(-0.386)	(-2.582)	(-3.932)	(0.517)
Observations	120413	120413	120413	120114	120114	120413	120413	120413	120413
R^2	0.017	0.007	0.006	0.008	0.005	0.075	0.066	0.014	0.012