Commonality in Liquidity: A Demand-Side Explanation

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We hypothesize that a source of commonality in a stock's liquidity arises from the correlated liquidity demand of the stock's investors. Focusing on correlated trading of mutual funds, we find that stocks with high mutual fund ownership have comovements in liquidity about twice as large as those for stocks with low mutual fund ownership. Further analysis shows that the channels for these comovements derive from both common ownership across funds and funds' correlated liquidity shocks. We obtain inferences supporting causality from an exogenous flow shock for mutual funds in the aftermath of the 2003 mutual fund scandal. (*JEL* G10, G14)

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A stock's liquidity and the associated risks from potential illiquidity are important factors in investors' decisions. Liquidity has been shown to covary strongly across stocks, i.e., there is commonality in liquidity.[1] Understanding commonality in liquidity is important because it can influence expected

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[1] See, for example, Amihud and Mendelson (1986) and Amihud and Mendelson (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; as well as Chordia, Roll, and Subrahmanyam (2000); Hasbrouck and Seppi (2001); Huberman and Halka (2001); Brockman, Chung, and Pérignon (2009); Hameed, Kang, and Viswanathan (2010); and Karolyi, Lee, and van Dijk (2012) regarding commonality in liquidity.

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returns (e.g., Pastor and Stambaugh 2003) and Acharya and Pedersen 2005). Conceptually, commonality in liquidity can arise from supply-side or demand-side sources. Previous studies have found support for supply-side sources of commonality in liquidity (e.g., Coughenour and Saad 2004; Comerton-Forde et al. 2010; Karolyi, Lee, and van Dijk 2012). However, other studies indicate that these supply-side explanations cannot drive all of the observed commonality (e.g., Brockman and Chung 2002; Bauer 2004).[2] In this study we hypothesize that commonality arises from a particular demand-side source, mutual fund trading. We provide evidence in support of this hypothesis, finding that mutual funds, through their trading, are large contributors to commonality in liquidity.

The intuition for our hypothesis is as follows. If a group of investors in a set of stocks trades in the same direction with similar timing, then these stocks will likely experience large trade imbalances at the same points in time. Such an effect can arise when stocks are held by the same investors and are traded at the same time (*common ownership*), but it can also arise when stocks are held by different investors who face *correlated liquidity shocks*. 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. Mutual funds generally hold large, well-diversified portfolios and 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. Further, previous research provides evidence of herding and correlated trading by mutual funds, as well as other institutional investors.[3] Consequently, we hypothesize that stocks with high mutual fund ownership 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 the Amihud (2002) measure of daily stock liquidity and measures of mutual fund ownership, we estimate the relationship between a stock's own liquidity and the liquidity of a portfolio of stocks with high mutual fund ownership (excluding the respective stock itself, if applicable). For the sake of brevity we label the regression coefficient of an individual stock's liquidity on the high mutual fund ownership portfolio liquidity, β_{HI}, the mutual fund liquidity beta.

[2] These studies 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] 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 (2014); and Greenwood and Thesmar (2011).

Consistent with our hypothesis of a positive relation between β_{HI} and mutual fund ownership, we find that stocks with high mutual fund ownership have β_{HI} coefficients that are on average about twice as large as are those for stocks with low mutual fund ownership, controlling for other factors. After establishing this basic result, we extend our investigation in two directions: We first conduct additional analysis to ascertain causality in the relationship between mutual fund ownership and β_{HI}. After finding supportive evidence in favor of a causal relationship, we then examine the channels through which such a causal relation could exist. In these latter tests we also explicitly distinguish the role of funds' liquidity demand from liquidity supply.

In terms of ascertaining a causal relation, we first examine whether our results could be driven by individual stock characteristics that jointly determine systematic liquidity and mutual fund ownership.[4] Using double sorts, as well as multivariate regression tests, we determine that our main findings are not driven by preferences of mutual funds for stocks with certain time-invariant characteristics or by time-varying preferences for certain industries or investments styles. To address further endogeneity concerns, we consider a natural experiment and conduct differences-in-differences tests. Specifically, the mutual fund late trading scandal of 2003 caused significant outflows for the 20 fund families that were directly affected by the scandal, but not for other funds.[5] These outflows resulted in plausibly exogenous shocks to the mutual fund ownerships of the firms held by the affected funds. In our differences-in-differences analysis, we compare the changes in the commonality of liquidity for stocks whose mutual fund ownership was affected by the scandal with those not affected. The results of this analysis are consistent with our earlier results, supporting our hypothesis that mutual fund ownership causes commonality in liquidity.

Because we cannot directly observe individual fund trades, our primary analyses use mutual fund ownership at the stock level as a proxy for mutual fund trading, that is, we assume that stocks *held* by mutual funds to a large degree are also *traded* by mutual funds to a large degree. Consequently, we develop proxies for mutual fund trading and classify this trading as either voluntary (for example, trading based on similar investment strategies, herding behavior, or correlated rebalancing needs) or involuntary (caused by liquidity shocks from fund flows).

The level of *voluntary trading* will be reflected in the fund's turnover ratio, after controlling for the fund's flow-induced trading. Voluntary trading should be correlated across funds because fund managers react to the same kinds of public information, rely on many of the same information sources, and often

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

[5] These fund families are identified in Zitzewitz (2009). Kisin (2011) and Anton and Polk (2014) have employed this scandal as an exogenous shock in different settings.

follow similar investment styles with similar catalysts. If voluntary trading is correlated across funds as these rationales suggest, we expect that firms with higher *turnover-weighted* mutual fund ownership should have particularly high commonality in liquidity. We provide evidence consistent with this hypothesis.

A mutual fund's *involuntary or forced trading* will be observed when the fund experiences liquidity shocks in its inflows or outflows, creating buying or selling pressure (Coval and Stafford 2007; Khan, Kogan, and Serafeim 2012; Ben-Rephael, Kandel, and Wohl 2011). If this buying or selling pressure is correlated across stocks, it will result in commonality in liquidity. Further, the effects of inflows and outflows should differ because funds have the ability to accumulate cash when they face inflows. In contrast, outflows can force the fund to trade to meet redemptions (e.g., Edelen and Warner 2001). In the latter case, mutual funds clearly demand liquidity, which allows us to identify directly whether liquidity demand drives commonality under these conditions.

We find strong evidence suggesting that flow-driven liquidity shocks are an important driver of the relationship between mutual fund ownership and commonality in liquidity. The effect of mutual fund ownership on a firm's mutual fund liquidity beta, β_{HI}, appears about 50% greater in quarters with negative aggregate mutual fund flows. This evidence is consistent with our hypothesis that the 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 the liquidity demand of mutual funds contributes to commonality in liquidity because of their correlated trading.

Two primary, but not mutually exclusive, channels exist through which mutual fund ownership and trading can drive commonality in liquidity. In the first channel, the relationship is driven by the fact that some stocks are held by multiple funds at the same time. For example, if multiple funds holding both IBM and Ford shares trade these shares with similar timing, such as in response to their investors' outflows, these stocks will experience correlated liquidity demand and the associated commonality in liquidity. We label this the "common ownership" channel, similar to the Anton and Polk (2014) findings that the extent to which mutual fund ownership is connected across a pair of stocks leads to correlation in the stocks' returns. Second, Greenwood and Thesmar (2011) provide the insight that comovements in returns across stocks can arise even without common ownership across stocks because of correlated liquidity shocks across investors. For example, some funds might hold Ford but not IBM, whereas other funds might hold IBM but not Ford. If both groups of funds face a contemporaneous liquidity shock, then the correlated flow-induced trading in the Ford and IBM stocks translates into correlated liquidity shocks across the two stocks even though they are not jointly held. We label this channel the "correlated liquidity shocks" channel.

To differentiate between these two channels, we use stock-pair level tests to determine whether commonality in liquidity differs depending on whether stocks are held by the same set of funds or distinct funds. Adopting an approach similar to Anton and Polk (2014) but applied to commonality in liquidity rather than returns, we find that the pairwise correlation in the liquidity of two stocks increases in the degree of common mutual fund ownership, i.e., the level of ownership of all funds that at the same time hold both stocks. These results support the hypothesis that the "common ownership" channel plays an important role in explaining commonality in liquidity. However, consistent with the ideas put forth by Greenwood and Thesmar (2011), we also find a significant additional influence on pairwise correlations emanating from the *non*overlapping holdings, which suggests that comovements in liquidity increase with mutual fund ownership even if there is *no* common ownership. This finding supports the hypothesis that both the "common ownership" and the "correlated flows" channels play a role in commonality in liquidity.

Our study contributes to several lines of research. It contributes to the broad empirical literature on stocks' liquidity and commonality in liquidity.[6] The literature on commonality in liquidity has primarily focused on the supply-side provision of liquidity (Coughenour and Saad 2004; Comerton-Forde et al. 2010). We contribute 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); however, their focus is on liquidity levels, whereas our contribution is to show that liquidity demand has an effect on liquidity covariances. Hameed, Kang, and Viswanathan (2010) focus on liquidity supply, but also analyze the effect of correlated liquidity demand. Consistent with our results that mutual fund ownership leads to comovements in liquidity, they find that comovements in stock-level order imbalance measures help to explain commonality.[7] We identify a primary source of these comovements.

In particular, our findings complement and go beyond the literature connecting institutional ownership with commonality in liquidity. This connection was first suggested by Chordia, Roll, and Subrahmanyam (2000), with consistent evidence provided by Kamara, Lou, and Sadka (2008). However, their results could be driven by common time trends in institutional ownership levels and commonality of certain stocks, whereas our setting controls for common time trends. We conduct direct tests of the connection between commonality in liquidity and the common trading of investors. Further, we show that the resulting common liquidity exists precisely within the set of

6 See, for example, Amihud and Mendelson (1986); Brennan, Chordia, and Subrahmanyam (1998); Chordia, Roll, and Subrahmanyam (2000); Jacoby, Fowler, and Gottesman (2000); Hasbrouck and Seppi (2001); Amihud (2002); Pastor and Stambaugh (2003); Acharya and Pedersen (2005); Sadka (2006); Korajczyk and Sadka (2008); Hasbrouck (2009); Brockman, Chung, and Pérignon (2009); Hameed, Kang, and Viswanathan (2010); Lee (2011); and Karolyi, Lee, and van Dijk (2012).

7 Further, Massa (2004) and Massa and Phalippou (2005) examine the relation between institutional investor ownership and the level of stock liquidity. The effect of liquidity demanding trades on movements in market prices is also examined in Hendershott and Seasholes (2009).

stocks subject to common trading. Finally, we are able to identify a causal effect of mutual fund ownership on commonality based on the mutual fund scandal.

The importance of the correlated trading explanation of commonality that we test in this study is also highlighted by Karolyi, Lee, and van Dijk (2012), who 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 investors' liquidity demand explaining commonality. We conduct a different analysis from theirs, with our results on the role of flow-induced forced trading providing evidence in support of their hypothesis regarding correlated trading.

Our findings also contribute to the literature on the influence of institutional investors on stock returns.[8] For example, Greenwood (2009) shows that common trading patterns of index investors can give rise to substantial excess comovement of stock returns.[9] More closely related to our study are Greenwood and Thesmar (2011) and Anton and Polk (2014) as described previously. We contribute to their findings by showing potential channels through which institutional investors can give rise to commonality in liquidity and we implement the Anton and Polk (2014) approach in a liquidity rather than return framework. Consequently, our study is distinct in establishing the link between correlated trading and comovement in liquidity.

1. Commonality in Liquidity and Mutual Fund Ownership

1.1 Data and variable construction

Our initial sample is based on mutual fund holdings from the CDA/Spectrum database over the 1980 to 2010 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.

1.1.1 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.[10] The fraction of ownership $mfown_{i,t}$, in

8 See, for example, Sias and Starks (1997); Gompers and Metrick (2001); and Sias, Starks, and Titman (2006).

9 Pirinsky and Wang (2004) and Kumar and Lee (2006) find that correlated trading among institutional and retail investors, respectively, gives rise to return comovements. 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).

10 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 2 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

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 also use a turnover-weighted measure of mutual fund ownership. In that case, when summing ownership across funds within a stock, we weight ownership by turnover,

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

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 stock i's return on day d divided by the dollar volume of stock i's trading 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., Korajczyk and Sadka 2008; Hasbrouck 2009). In addition, Goyenko et al. (2009) show that the Amihud measure is a good proxy for price effect.

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 effect 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,

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

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.[11] We calculate the daily change in stock illiquidity for

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.

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 the effects of nonstationarity. However, in light of concerns of over-differencing, we also

Table 1
Summary statistics

Panel A: Full sample

	N	Mean	Std dev	Min	Max	Median
mfown	121,592	0.11	0.08	0.00	1.00	0.09
twmfown	60,764	0.11	0.07	0.00	1.00	0.10
firm size (millions)	121,592	5,149	17,936	4	571,197	1,066
illiq(avg)	121,592	0.06	0.41	<0.001	108.97	0.005
aggregate flows (% of mkt cap)	122	0.20%	0.28%	−0.75%	0.96%	0.07%

Panel B: By *mfown* quartile

	mfown (ranked quarterly)			
	LO	2	3	HI
	Mean, (Std dev), Median			
mfown	0.04	0.09	0.13	0.20
	(0.03)	(0.04)	(0.06)	(0.09)
	0.03	0.08	0.13	0.20
twmfown	0.04	0.08	0.12	0.18
	(0.03)	(0.03)	(0.04)	(0.07)
	0.04	0.08	0.11	0.17
firm size (millions)	4,916	7,947	4,799	2,934
	(23,501)	(23,724)	(11,053)	(6,086)
	571	1,302	1,373	1,151
illiq(avg)	0.13	0.05	0.04	0.04
	(0.75)	(0.26)	(0.14)	(0.14)
	0.02	0.004	0.003	0.003

Table 1 reports summary statistics for select variables. Panel A reports statistics for the full sample of stock quarters over the 1980Q2–2010Q3 period. Panel B reports means, medians, and standard deviations for subsamples of firms. *mfown* is the number of shares owned by mutual funds scaled by shares outstanding. *firm size* is the market value of the firm's equity at the end of the quarter. *illiq(avg)* is the average over the quarter of the absolute daily return scaled by daily 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.

all common stocks on the NYSE and AMEX that trade above $5 per share, that trade on day *d* and *d-1*, and that have at least 40 return observations in a quarter.[12] To prevent outliers from affecting our analysis, we eliminate the top and bottom 1% of observations of our measure.

1.1.2 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 121,592 stock quarters with both mutual fund ownership data and stock price

replicate the main results using the difference in Amihud's illiquidity measure from its 5-day moving average. Further, to ensure that our later analysis is not driven by return comovements, we explicitly control for return (and volatility) comovements in our robustness tests in Section B.1 in the Internet Appendix.

12 Results are similar if we use $2 as a cutoff and if we require a minimum of 30 or 50 observations. We have also replicated our main results after excluding all stocks with a market capitalization below the NYSE bottom decile breakpoint.

data sufficient to calculate liquidity betas. Using the turnover-weighted mutual fund ownership reduces the sample to 60,764 stock quarters because quarterly turnover data are only available beginning in 1999. The median firm has about \$1 billion in market equity, and 9% of its shares are owned by mutual funds. The turnover-weighted mutual fund ownership is roughly equivalent to the unweighted mutual fund ownership in the full sample.[13] In the last row, we report summary statistics on aggregate quarterly net flows for the equity mutual fund industry, based on our sample. Specifically, from the second quarter in 1980 to the third quarter of 2010, mutual funds generally experience inflows; however, aggregate flows are negative in 26 of the quarters, with the largest aggregate quarterly outflow equaling 0.75% of the market capitalization of the CRSP universe, compared with the largest aggregate quarterly inflow of 0.96%.

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 the means, standard deviations, and medians of the selected variables. There is a quite substantial cross-sectional difference in *mfown*: the mean varies from 4% in the lowest quartile up to 20% in the top quartile. Similar numbers have been obtained for *twmfown*. Average firm equity is about \$3 billion in the highest quartile of *mfown* compared with \$5, \$8, and \$5 billion for the first, second, and third quartiles, respectively. Further, there exists a monotonic relationship between mutual fund ownership and average illiquidity, where average illiquidity, *illiq(avg)*, is defined as the average daily Amihud illiquidity measure over the quarter. Moving from the lowest to highest quartile of *mfown*, *illiq(avg)* drops from 0.13 to 0.04.

1.2 Two-step process

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 2.1). 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 2.2).

1.2.1 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 stock illiquidity with value-weighted market illiquidity (Chordia, Roll, and Subrahmanyam

[13] Comparing the two only over the sub-period in which turnover data are available (1999+), we find that the average unweighted ownership is roughly 0.15. This difference is consistent with a typical turnover ratio that is slightly less than one (in our sample, the asset-weighted average turnover over this period is 0.8).

2000).[14] 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.

For each firm we run time-series regressions of the firm's daily change in illiquidity, $\Delta illiq_{i,t}$, on changes in the high mutual fund ownership portfolio's illiquidity, $\Delta illiq_{mfown,t}$, and changes in the market illiquidity, $\Delta illiq_{mkt,t}$, as well as control variables. Specifically, we estimate the following regression for each stock across trading days in a given quarter separately:[15]

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

We focus on changes, or to be precise, changes in logs, because we want to investigate the similarity in movements in liquidity. Further, this approach helps to avoid econometric problems because of 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, whereas the market returns are included to control for possible correlations between returns and our illiquidity measure. The squared stock return is included to capture any effect of volatility that could be related to liquidity.[16]

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 (2010) of our sample. The left-hand side of each panel reports the average of the mutual fund liquidity beta coefficients, β_{HI}, across all firms in that quarter and the percentage of beta coefficients that are positive. The average β_{HI} is positive in each quarter. The table also reports the number of stocks in the portfolio and the average firm size and illiquidity. The right-hand side of the table summarizes the same variables for the market liquidity beta coefficients, which are also always positive on average.

Panel B summarizes the time-series regression output by 5-year periods, as well as for the overall sample period. We again find positive mean β_{HI} estimates,

[14] Results using equal-weighted portfolios are very similar (see Section 6).

[15] To proxy for market liquidity we use the value weighted average of all stocks in our sample. We present results from stability tests using alternative definitions and weighting schemes for market liquidity in Section B.3 of the Internet Appendix.

[16] We show in robustness tests (Section B.3 in the Internet Appendix) that this particular specification of the first stage time-series regressions is not crucial to our main results.

Table 2
Summary of the time series estimates of liquidity betas

Panel A: Representative quarters

	HI *mfown* portfolio							Market portfolio					
	R^2	β_{HI}	*% pos*	*size*	*mfown*	*illiq(avg)*	*# stocks*	β_{mkt}	*% pos*	*size*	*mfown*	*illiq(avg)*	*# stocks*
1980Q2	0.30	0.26	0.54	578	0.07	0.09	160	0.15	0.54	908	0.03	0.12	639
1980Q3	0.29	0.18	0.56	440	0.09	0.24	196	0.35	0.61	833	0.04	0.33	785
1980Q4	0.30	0.50	0.66	537	0.09	0.11	193	0.18	0.56	935	0.04	0.13	772
...													
1995Q1	0.29	0.29	0.62	2,052	0.20	0.02	198	0.25	0.55	3,683	0.11	0.04	791
1995Q2	0.29	0.16	0.54	2,159	0.20	0.01	210	0.32	0.58	3,840	0.11	0.05	839
1995Q3	0.29	0.31	0.58	2,306	0.22	0.02	217	0.41	0.61	3,973	0.12	0.04	868
1995Q4	0.31	0.54	0.63	2,732	0.20	0.01	225	0.25	0.57	4,204	0.11	0.03	901
...													
2010Q1	0.31	0.35	0.63	3,460	0.24	0.01	294	0.37	0.64	7,592	0.14	0.03	1,177
2010Q2	0.40	0.32	0.62	3,345	0.27	0.01	300	0.50	0.65	7,928	0.17	0.02	1,200
2010Q3	0.38	0.50	0.67	2,976	0.23	0.01	295	0.20	0.57	7,066	0.13	0.03	1,181
Panel B: 5-year quarterly averages and full sample													
1980–1985	0.29	0.30	0.58	626	0.08	0.11	176	0.24	0.57	1,195	0.04	0.15	704
1986–1990	0.31	0.33	0.58	1,313	0.10	0.06	172	0.23	0.57	2,411	0.05	0.07	689
1991–1995	0.30	0.27	0.57	1,879	0.16	0.03	200	0.33	0.59	3,462	0.09	0.06	799
1996–2000	0.28	0.27	0.57	4,040	0.22	0.02	331	0.23	0.57	5,621	0.12	0.05	1,323
2000–2005	0.28	0.29	0.59	4,248	0.24	0.02	330	0.32	0.61	6,921	0.14	0.05	1,321
2006+	0.33	0.34	0.62	3,682	0.29	0.01	317	0.41	0.64	8,010	0.17	0.04	1,270
Full sample	0.30	0.30	0.59	2,525	0.18	0.04	252	0.30	0.59	4,493	0.10	0.07	1,007

Table 2 reports summary statistics on liquidity betas with respect to a high mutual fund ownership portfolio, β_{HI}, and a market portfolio of NYSE and AMEX stocks, β_{mkt}. The high mutual fund ownership portfolio contains the top 25% of all firms with respect to their mutual fund ownership, *mfown*. 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 measures for a portfolio of high mutual fund ownership stocks and for the market portfolio, as well as control variables:

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

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 liquidity (when applicable). The left columns summarize the coefficient estimates for the high *mfown* liquidity portfolio, and the right columns summarize the coefficient estimates for the market liquidity portfolio. In each quarter we record the average beta and the percent that are positive. Panel A reports averages for representative quarters, and Panel B reports averages over 5-year periods and the full sample.

which are equal to 0.3 for the overall sample period and vary between 0.27 and 0.34 in the 5-year subsamples.

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, *mfown*.

1.2.2 Mutual fund ownership and commonality in liquidity. 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 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, whereas 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 0.21, compared with 0.38 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 covaries 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 high mutual fund ownership portfolio liquidity than small and illiquid stocks. However, the difference in β_{HI} across these quartiles is much smaller than across the *mfown*-sorted quartiles.

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

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 β_{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.

Table 3
Average betas sorted

Panel A: One-way sorts

	Average β_{HI}						Average β_{mkt}					
mfown	Lo	2	3	Hi	Hi-lo	H-L tstat	Lo	2	3	Hi	Hi-lo	H-L tstat
	0.21	0.28	0.34	0.38	0.17***	(10.22)	0.28	0.36	0.32	0.28	-0.00	(−0.13)
firm size	Lo	2	3	Hi	Hi-lo	H-L tstat	Lo	2	3	Hi	Hi-lo	H-L tstat
	0.24	0.34	0.37	0.27	0.03*	(1.92)	0.12	0.24	0.31	0.58	0.45***	(23.47)
illiq(avg)	Lo	2	3	Hi	Hi-lo	H-L tstat	Lo	2	3	Hi	Hi-lo	H-L tstat
	0.29	0.36	0.33	0.23	−0.06***	(−3.44)	0.55	0.32	0.24	0.13	−0.42***	(−21.57)

Panel B: Dependent sorts: First on *firm 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
firm size	Small	0.17	0.25	0.27	0.26	0.10***	(3.38)	Small	0.10	0.09	0.13	0.17	0.07***	(2.65)
	2	0.26	0.33	0.36	0.40	0.14***	(5.40)	2	0.26	0.24	0.23	0.22	−0.04	(−1.48)
	3	0.28	0.35	0.41	0.44	0.16***	(5.59)	3	0.33	0.32	0.28	0.28	−0.05*	(−1.84)
	Big	0.15	0.25	0.31	0.38	0.23***	(8.95)	Big	0.68	0.62	0.52	0.44	−0.24***	(−7.81)
		mfown							*mfown*					
		Lo	2	3	Hi	Hi-lo	H-L tstat		Lo	2	3	Hi	Hi-lo	H-L tstat
illiq(avg)	Lo	0.16	0.26	0.33	0.42	0.26***	(9.65)	Lo	0.69	0.60	0.50	0.40	−0.30***	(−8.98)
	2	0.28	0.36	0.41	0.41	0.14***	(5.07)	2	0.41	0.32	0.29	0.28	−0.13***	(−4.94)
	3	0.27	0.33	0.35	0.39	0.12***	(4.66)	3	0.25	0.24	0.23	0.22	−0.04	(−1.52)
	Hi	0.16	0.25	0.25	0.25	0.09***	(3.23)	Hi	0.13	0.08	0.12	0.17	0.03	(1.13)

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*. The last two columns in each block show the difference between average β_{HI} and β_{mkt}, respectively, in the highest and the lowest quartile with respect to the respective characteristics, as well as the t-statistics indicating statistical significance of the difference. All t-statistics are on the difference in sample averages paired by quarter and clustered by firm and time. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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. The effect is weaker but still highly significant even among the most illiquid stocks. The latter are the stocks that are least held by mutual funds and that we thus 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} on the previous quarter's mutual fund ownership, controlling for firm size and average illiquidity. In our main specification, we include time-fixed effects and cluster the standard errors at the firm and time-dimension level to account for time-series and cross-sectional dependence. The specification is

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

The results of this regression are presented in Panel A of Table 4. The first model in the table shows the results for the full sample for the regression of β_{HI} on mutual fund ownership and time dummies only. Consistent with our earlier results, we find that stocks with high mutual fund ownership exhibit strong comovement, evidenced by the significant coefficient estimate of 0.94 for the effect of *mfown*. Because this regression includes time-fixed effects, the higher β_{HI} cannot be caused by the common time trend in mutual fund ownership levels and liquidity comovements documented in Kamara, Lou, and Sadka (2008).

In Model 2 we include controls for the stock's size and average liquidity.[18] 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. The result is also economically significant—a one-standard deviation increase (0.08) in mutual fund ownership is associated with a 0.074 increase in β_{HI}, which equates to a 25% increase from its mean of 0.30.

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. These fixed effects subsume the effect of any time-invariant firm-level characteristic that fund managers may have stable preferences for and that might have an effect on commonality. We also continue to include time-fixed effects and cluster standard errors at the firm level. Although the coefficient estimate on β_{HI} is somewhat reduced (to 0.47), it is still positive and highly significant at the 1%-level. This result shows that time-invariant unobservable heterogeneity is not driving our main findings. The possibility remains that funds have time-varying preferences for certain

[18] In Section B.2 of the Internet Appendix, we also show results where we estimate this model in subsamples constructed based on market capitalization and illiquidity.

Table 4
β_{HI} on *mfown* and controls

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
mfown	0.94***	0.93***	0.47***	0.72***	0.70***	1.08***	1.15***
	(10.49)	(9.85)	(4.75)	(9.85)	(9.46)	(10.59)	(3.92)
		[<0.01]					
ln(firm size)		−0.00	0.02**	−0.02**	0.01*	−0.00	−0.01
		(−0.68)	(2.05)	(−2.19)	(1.73)	(−1.19)	(−0.56)
		[0.45]					
illiq(avg)		−0.04*	−0.02*	−0.03**	−0.04*	−0.10***	−0.82*
		(−1.93)	(−1.82)	(−1.97)	(−1.94)	(−3.60)	(−1.74)
		[<0.01]					
Observations	121,485	121,485	121,485	110,401	110,401	121,485	2,420
R-squared	0.013	0.013	0.055	0.048	0.027		

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
mfown(dummy)	0.10***	0.10***	0.02	0.07***	0.06***	0.09***	0.09***
	(7.95)	(7.78)	(1.54)	(6.16)	(5.69)	(9.73)	(2.93)
ln(firm size)		0.00	0.02**	−0.02*	0.01***	−0.00	−0.02
		(0.41)	(2.41)	(−1.87)	(2.89)	(−1.01)	(−0.99)
illiq(avg)		−0.04**	−0.02*	−0.03**	−0.04*	−0.13***	−0.89**
		(−1.97)	(−1.82)	(−1.98)	(−1.96)	(−3.82)	(−2.16)
Observations	121,485	121,485	121,485	110,401	110,401	121,485	2,420
R-squared	0.012	0.012	0.055	0.047	0.026		
Time effects	*Y*	*Y*	*Y*				
Firm effects			*Y*				
DGTW-time effects				*Y*			
Industry-time effects					*Y*		
Time clusters	*Y*	*Y*					
Firm clusters	*Y*	*Y*	*Y*	*Y*	*Y*		
Fama MacBeth						*Y*	
Fama MacBeth (20 portfolios)							*Y*

Table 4 reports results from pooled OLS (models 1-5) or Fama MacBeth (models 6 and 7) specifications of the following regression:

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

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. Panel A (B) reports *mfown* (a dummy equal to one if *mfown* is in the top quartile in that quarter, zero otherwise) as the main independent variable. In Model 4 we include combined DGTW-time effects, where in each year we assign each stock to one of 125 size, book-to-market, and momentum bins following Daniel, Grinblatt, Titman, and Wermers (1997). Then, we include an indicator variable for each bin-year. In Model 5 we include an indicator variable for each industry-year combination. The last two models use a Fama-MacBeth specification with Newey-West standard errors computed using maximum lags. Model 6 reports the time-series averages of cross sectional coefficients using each firm as a unit of observation. Model 7 uses 20 portfolios as the units of observation. We first sort stocks into 1 of 20 portfolios based on $\beta_{HI,i,t-1}$, and then compute the beta of each portfolio, $\beta_{HI,port,t}$ at time t as the equal weighted average of the individual stocks' $\beta_{HI,i,t}$. The independent variables in Model 7 are also equal weighted averages of the stocks in the portfolio. For Panel A, Model 2, we also report p-values in brackets, which reflect the significance of the coefficients relative to their respective distributions from 1,000 placebo regressions in which $\beta_{HI,i,t}$'s are randomly assigned to stocks. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

stocks (e.g., Blume and Keim 2014). For example, it could be the case that fund managers herd into a value strategy in some years, but prefer growth stocks at other times. Alternatively, fund managers could have preferred tech stocks before the dot-com bubble, but not after its burst. Thus, in Models 4 and 5, we include a set of dummy variables for 125 characteristic-based benchmark portfolios per year to control for time-varying investment style preferences and for each of the 48 Fama-French industries per year to control for time-varying industry preferences.[19] We obtain coefficient estimates for the effect of *mfown* of 0.72 and 0.70, respectively, i.e., a slight reduction as compared with the coefficient estimate of 0.93 in the baseline case from Model 2, suggesting that time-varying preferences for certain stock characteristics indeed explain a part of our effect, but the remaining effect is still large and highly significant.

Model 6 uses a Fama and MacBeth (1973) specification in which we use Newey-West standard errors with maximum lags. We again find a positive relationship between the mutual fund liquidity beta and mutual fund ownership that is both economically and statistically significant and of similar magnitude as in Models 1 and 2.

Further, our results might be affected by measurement error and an errors-in-variables problem. As long as these errors are uncorrelated with second-stage determinants of β_{HI}, this should lead to an attenuation bias that would eventually work against findings in favor of our hypothesis. Nevertheless, to address the potential effect of measurement error, we conduct a robustness test in which we follow a procedure similar to Fama and MacBeth (1973) and run an analysis based on portfolios rather than individual stocks. Specifically, we sort stocks into 20 portfolios based on their β_{HI} estimated using data from the previous quarter. Then, we reestimate the β_{HI} for the stocks in each of the 20 portfolios using data from the current quarter, and calculate the portfolio $\beta_{HI,port}$ by computing the equal-weighted average of these reestimated β_{HI}'s. Finally, we run cross-sectional regressions in which we relate the average *mfown* of all stocks in the portfolio at the beginning of the quarter to the portfolio's $\beta_{HI,port}$. Results summarizing the time series of the cross-sectional estimates are presented in Model 8. We find that the effect of *mfown* in this specification is still highly significant and the coefficient estimate is now even slightly higher than in the standard specification, amounting to 1.15. These stronger results are consistent with attenuation bias because of measurement error in the original specification. Overall, this analysis suggests that measurement errors in liquidity betas are not problematic for our analysis.

Because we have no direct prediction on the functional form of the relationship between ownership and commonality, in Panel B of Table 4, we

19 Daniel, Grinblatt, Titman, and Wermers (1997) assign all stocks in the CRSP universe to 1 of 125 style portfolios that are defined along the size-, value-, and momentum-dimension. Stock assignments to portfolio are updated yearly. The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm.

repeat our tests using an indicator variable for high mutual fund ownership rather than a continuous variable. Specifically, 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. This specification allows a natural economic interpretation: Models 1 and 2 in the table indicate that stocks in the highest mutual fund ownership quartile have a β_{HI} in the next quarter that is 0.10 higher than that of stocks outside the top quartile. This is a large economic effect given the unconditional mean β_{HI} of 0.30.[20]

As our main independent variable, β_{HI}, are estimates from time-series regressions for each fund and quarter, these estimates may be cross correlated. To examine the nature of the dependence in our β_{HI} estimates, we examine the correlation in the error terms from our estimate of Equation (1). Following Chordia, Roll, and Subrahmanyam (2000), we estimate the regression $\varepsilon_{j',t=}\gamma_{j,0}+\gamma_{j,1}\varepsilon_{j,t}+\xi_{j,t}$ for each quarter and each unique pair of funds j' and j, where $\varepsilon_{j,t}$ is the error from Equation (1) on day t for fund j.

We find that there is slightly more cross correlation than what one would expect because of chance.[21] To mitigate the concern that our second-stage results are influenced by this cross correlation, we first check several different first-stage specifications, including a variety of alternative controls. We report the results in Table B-3 in the Internet Appendix and find that our results are similar across specifications. Next, we conduct placebo regressions by randomly assigning β_{HI}'s to stocks and then repeating the second-stage regression. This preserves any cross correlation in the liquidity beta estimates. We report average coefficients and t-statistics in Model 15 of Table B-3 in the Online Appendix. On average, all coefficients are zero and insignificant. When comparing our actual estimates to the entire placebo distributions, we find that our estimated coefficient on *mfown* and the t-statistic both lie to the right of the entire respective distributions. In Model 2 of Table 4, we report p-values comparing our estimated coefficients to these placebo distributions. The coefficient on *mfown* is highly statistically significant. Therefore, we conclude that though there is slightly more dependence in β_{HI}'s than one would expect because of chance, this dependence is not materially affecting our inference.

Overall, our findings from this section provide evidence of strong commonality in liquidity for stocks with high mutual fund ownership. The effect stands robust to various assumptions regarding unobserved heterogeneity and independence of observations, as well as functional form.

[20] In the specification that includes firm fixed effects, we find no significant effect of the dummy variable. This is not surprising, given that the fixed effect removes most of the variation in *mfown(dummy)*. In contrast, we find significant results in Panel A with firm fixed effects and the continuous *mfown* variable.

[21] The mean (median) t-statistic on $\gamma_{j,1}$ is 0.057(0.051). Further, 17.2% of these t-statistics have absolute value greater than 1.645; 10.6% have absolute value greater than 1.96.

2. Evidence from a Natural Experiment

Given the possibility that mutual fund managers prefer stocks with certain time-varying characteristics that are correlated with comovements in liquidity and for which we have no controls, our previous tests may not completely control for endogeneity.[22] To address such remaining endogeneity concerns, we employ an identification strategy in which we use a shock to fund flows that affects some but not all funds, thus, resulting in cross-sectional variation in ownership that exists for reasons plausibly unrelated to future commonality in liquidity. Specifically, we identify 20 fund companies that negotiated a settlement with the Securities and Exchange Commission regarding allegations of illegal trading behavior (Zitzewitz 2009). The funds belonging to these companies experienced significant outflows beginning in the last quarter of 2003, when news of the problem became public, and lasting through 2006. In contrast, fund families unaffected by the trading scandal experienced inflows over this period. Consequently, stocks initially owned to a high degree by funds implicated in the scandal experienced significant drops in mutual fund ownership relative to those not owned by these funds (see Kisin [2011] for details). We use this shock to mutual fund ownership for identification of our main treatment effect. Specifically, we estimate the following differences-in-differences regression using observations from 3 years before the scandal (July 2000 to June 2003) and 3 years after the end of the scandal in December 2006 (January 2007 to December 2010):

$$\beta_{HI,i,t} = a + b_1 treatment_i \times post + b_2 treatment_i + b_3 mfown_{i,2003} + b_4 ln(size_{i,t-1}) + b_5 illiq(avg)_{i,t-1} + time\ dummies + \varepsilon_{i,t}, \quad (3)$$

where $treatment_i$ is an indicator set to one if the fraction of firm i owned by mutual funds belonging to the 20 scandal families in September 2003 is high (either top quartile or decile). *Post* is a dummy that takes on the value of one for all quarters after December 2006, and $mfown_{i,2003}$ is the overall level of mutual fund ownership in stock i in September 2003. The *post* variable is not included separately because Equation (3) is estimated including time-fixed effects, which capture the baseline effect of possibly different levels of the dependent variable in the period after December 2006. We expect a negative coefficient on the interaction term *treatment* $\times$ *post* because firms owned by funds affected by the scandal-driven outflows face an exogenous reduction in their mutual fund ownership levels. The regression is estimated with standard errors clustered along the firm and the time dimension. The results are shown in Table 5.

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22 Given the risks associated with commonality in liquidity and the shareholder purchase and redemption mechanism for open-end funds, equity mutual fund managers would be expected to avoid stocks with high commonality in liquidity. Thus, everything else equal, to be able to diversify liquidity risk, we would expect fund managers to focus more on those stocks whose liquidity does not display as much comovement in liquidity (i.e., the low commonality stocks) rather than actively choosing such stocks.

Table 5
Difference in difference: Mutual fund scandal

Panel A: Dependent variable	(1) *treatment* is top quartile β_{HI}	(2) *treatment* is top decile β_{HI}	(3) *treatment* is top quartile mfown	(4) *treatment* is top decile mfown
treatment×post	−0.158***	−0.186***		
	(−3.77)	(−3.00)		
treatment	0.075***	0.100**	−0.0062***	−0.0063*
	(2.87)	(2.56)	(−2.68)	(−1.95)
$mfown_{2003}$	1.095***	1.080***	0.61***	0.61***
	(10.19)	(10.70)	(17.72)	(17.64)
ln(firm size)	−0.012	−0.012	−0.00***	−0.00***
	(−1.29)	(−1.25)	(−4.09)	(−4.25)
illiq(avg)	−0.023*	−0.023*	−0.00**	−0.00**
	(−1.71)	(−1.78)	(−2.00)	(−1.99)

Panel B: Randomized treatment assignment: 5,000 repetitions		
Coefficient on *treatment ×post*		
Mean	−0.052	−0.028
5th percentile	−0.11	−0.12
95th percentile	0.01	0.06
Percentile of actual estimate from Panel A	<1%	<1%
t-statistic on *treatment×post*		
Mean	−1.29	−0.51
5th percentile	−3.01	−2.24
95th percentile	0.26	1.11
Percentile of actual *t*-statistic from Panel A	1%	<1%

Table 5 reports results from pooled OLS regressions of β_{HI} on treatment and control firms before and after the mutual fund "scandal" in 2003. We identify "treatment firms" as those with high ownership in September 2003 by funds implicated in the scandal. The treatment identifier is set to one if the shares owned by scandal funds in September 2003 scaled by shares outstanding is in the top quartile (Models 1 and 3) or decile (Models 2 and 4). The sample includes the 3 years before and after the mutual fund scandal period, which lasted from September 2003 through December 2006. Thus *post* is an indicator variable equal to one for all quarters after December 2006. We also include as a control total mutual fund ownership in September 2003, mfown_{2003}. We do not include *post* as a stand-alone independent variable because all regressions include time effects. In Columns 3 and 4, we report results from a regression of the level of mutual fund ownership in the post period on the treatment indicator as well as $mfown_{2003}$ and controls. Standard errors are always clustered in two dimensions, firm and time. In Panel B we summarize results from placebo regressions. We randomly assign funds as "scandal" or "not scandal" based on the true proportion of funds implicated in the scandal. We then identify treatment firms the same way as in Panel A and repeat this procedure 5,000 times. Panel B summarizes the distributions of the coefficient and *t*-statistic on the variable of interest, *treatment×post*. We report the average, 5th and 95th percentiles among the 5,000 replications. In the last row, we report the percentiles of where our actual coefficient estimates and *t*-statistics (those in Panel A) fall within these distributions. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The treatment indicator is set to one if this measure is in the top quartile (Model 1) or top decile (Model 2). In both specifications, we find a negative and significant coefficient on *treatment* × *post*, indicating that firms with high exposure to scandal funds in 2003, and the resulting lower fund ownership levels several years later, have significantly lower subsequent common liquidity after the end of the scandal period in 2006 compared with firms owned more by funds not belonging to the scandal families. For example, in Model 1 we find a differences-in-differences estimate of -0.158. This is a large economic effect, considering that the unconditional average mutual fund liquidity beta in this sample period is 0.254.

With our differences-in-differences approach, we assume that the exogenous shock on ownership after September 2003 is strong enough to have a significant effect on mutual fund ownership levels in the examination period after December 2006. To check whether this is a reasonable assumption, in Table 5, we also report results from regressions of the level of mutual fund ownership during the post period as a function of the treatment variable. These results are presented in Columns 3 and 4. The negative and significant coefficient on *treatment* confirms that firms owned by funds implicated in the scandal did experience lower levels of mutual fund ownership following the scandal.

Two concerns may arise about our differences-in-differences results. The first potential concern is that our estimated negative treatment effect is due to some alternative mechanical explanation rather than the low ownership of mutual funds resulting from the scandal. The second potential concern is that our standard errors are biased. Bertrand, Duflo, and Mullainathan (2004) point out that the standard errors in a typical differences-in-differences regression may be biased if firm characteristics are persistent. Even though clustering standard errors as we do helps alleviate the second concern, an alternative approach that helps address both concerns is to conduct placebo tests, and examine the distributions of coefficients and t-statistics.

In our placebo regressions we randomly assign each fund to either being a "scandal" fund or not and we compute *treatment* in the same ways as defined previously. We then run the regressions specified in Models 1 and 2 in Panel A. We do this 5,000 times and summarize the distributions of the coefficients and t-statistics on the variable of interest in Panel B of Table 5. Importantly, in all specifications, both our coefficient estimates and t-statistics are significantly different from the averages from the placebo regressions. For example, results from Model 1 in Panel B show that the 5$^{\text{th}}$ and 95$^{\text{th}}$ percentiles of the coefficient on $treatment \times post$ are -0.099 and 0.046, respectively. Our estimate of -0.158 in Panel A lies clearly to the left of the 5$^{\text{th}}$ percentile (at the 1$^{\text{st}}$ percentile), i.e., we find a significant difference from the placebo mean. We obtain similar results comparing the t-statistics in Panel A to the distribution of t-statistics from the placebo regressions in the lower part of Panel B.

These results show that firms that are heavily held by scandal funds experience lower levels of commonality after the scandal as compared with firms not held by scandal funds to the same extent. Overall, the evidence based on the scandal-driven exogenous shock to mutual fund ownership of affected stocks presented in this section supports the hypothesis that causation runs from mutual fund ownership to commonality (and not vice versa) and further alleviates potential remaining endogeneity concerns.

3. Reasons for Mutual Fund Trading and Liquidity Demand

In the previous sections we have provided evidence consistent with the hypothesis that the level of mutual fund ownership in a stock drives commonality in the stock's liquidity. However, our analysis hitherto does not provide definitive insights into the specific channels via which mutual fund ownership can give rise to commonality. We claim that this relationship exists because mutual fund ownership is an important proxy for the likelihood that trading in these stocks will be correlated. To understand better the mechanisms through which high mutual fund ownership gives rise to commonality, we now refine our basic analysis to examine the relationship between other proxies for mutual fund trading and commonality in liquidity.[23]

We employ two proxies for mutual fund trading that are designed to capture different trading motivations: voluntary correlated trading (based on turnover-weighted mutual fund ownership) and forced correlated trading (i.e., flow-induced trading). Whereas the first could be due to either the liquidity supply or liquidity demand of mutual funds, the latter clearly reflects liquidity demand.

3.1 Voluntary correlated trading

As pointed out earlier, the level of trading in mutual funds should be related to the commonality in liquidity of the stocks held. Thus, to allow for differences in trading activity among mutual funds, we incorporate the fund's turnover ratio into our ownership measure. When summing ownership across funds within a stock, we weight the mutual fund ownership by the holding fund's turnover ratio to compute $twmfown_{i,t}$ as defined in Section 1.1. Moreover, because the turnover ratio as reported in CRSP is corrected for flow-induced trading, this measure reflects voluntary trading. Because CRSP does not report quarterly fund turnover before 1999, the sample period for this analysis begins in 1999.

Our hypothesis implies that the turnover-weighted measure, to the extent that it is a good proxy for correlated trading, is strongly associated with high commonality in liquidity. The results are reported in Table 6. The first model includes *twmfown* and time effects only.[24] We find a highly significant positive effect of *twmfown* on commonality. Results in the remaining models show that the relation with *twmfown* is robust to our standard controls and various regression specifications.

Our hypothesis further implies that, to the extent that weighting by turnover better proxies for correlated trading, ownership by high turnover funds should be more strongly related to common liquidity compared with ownership by funds with low turnover. To check whether the association of *twmfown* with commonality in liquidity is stronger than that of *mfown*, in Panel B of Table 6, we present results where we use standardized dependent and independent variables, and only use observations beginning in 1999 for both regressions. We indeed

[23] Although we do not observe individual mutual fund trades, consistent with our results, Aymo and Gil-Bazo (2014) provide evidence that correlated trading can lead to commonality in liquidity based on transaction data for a sample of institutional investors.

[24] To be consistent, we also define the high mutual fund ownership portfolio based on *twmfown* and calculate the first-stage β_{HItw} based on it. Results using our standard definition for β_{HItw} in the first stage are very similar.

Table 6
Turnover-weighted *mfown*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A				β_{HItw}			
twmfown	1.409***	1.391***	0.488***	1.016***	1.012***	1.344***	4.197***
	(11.23)	(10.81)	(3.84)	(10.07)	(10.03)	(11.48)	(3.94)
ln(firm size)		0.003	0.135***	0.022*	0.013***	−0.006	−0.075**
		(0.45)	(9.46)	(1.79)	(2.81)	(−0.76)	(−2.09)
illiq(avg)		−0.025	0.004	−0.010	−0.020	−0.227***	−1.047**
		(−0.97)	(0.41)	(−0.72)	(−0.86)	(−7.68)	(−2.29)
Observations	60,784	60,784	60,784	53,413	53,413	60,784	920
R-squared	0.020	0.020	0.087	0.057	0.045		
Time effects	*Y*	*Y*	*Y*				
Firm effects			*Y*				
DGTW-time effects				*Y*			
Industry-time effects					*Y*		
Time clusters	*Y*	*Y*					
Firm clusters	*Y*	*Y*	*Y*	*Y*	*Y*		
Fama MacBeth						*Y*	
Fama MacBeth (20 portfolios)							*Y*

Panel B: Standardized variables	(1) β_{HItw}	(2) β_{HI}
twmfown	0.073***	
	(10.72)	
mfown		0.060***
		(9.90)
ln(firm size)	0.005	−0.004
	(0.62)	(−0.58)
illiq(avg)	−0.008	−0.010*
	(−0.96)	(−1.65)
Observations	60,784	60,784
R-squared	0.018	0.007
Time effects	*Y*	*Y*
Time clusters	*Y*	*Y*
Firm clusters	*Y*	*Y*

Table 6 reports results from pooled OLS (Models 1 through 5) or Fama-MacBeth (Models 6 and 7) specifications of the regression:

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

where $\beta_{HItw,i,t}$ is estimated in a regression similar to Equation (1), in which we replace the liquidity of a high mutual fund ownership portfolio with that of a high turnover-weighted mutual fund ownership portfolio. Panel A repeats the same specifications as in Table 4. In Panel B, we use standardized variables to facilitate comparison of the coefficients. Model 1 in Panel B is the same as Model 2 of Panel A. Model 2 in Panel B is the same as Model 2 of Panel A in Table 4. The sample period starts when quarterly turnover data are available, i.e. in 1999. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

find a stronger effect using turnover-weighting relative to unweighted mutual fund ownership. The coefficient estimate for *twmfown* is about 22% larger than that for *mfown*.

The strong effect of voluntary mutual fund trading on commonality suggests that trades of individual mutual funds do not cancel out, which is consistent with the view that mutual funds tend to trade on the same information or follow similar investment style strategies, which eventually leads to correlated liquidity demand and thus commonality in liquidity.

3.2 Involuntary correlated trading

Thus far, we argue that mutual fund trades consume liquidity. However, mutual funds can also act as liquidity suppliers (Da, Gao, and Jagannathan 2011). Therefore, in this section, we focus on the effects of liquidity shocks mutual funds themselves face by estimating the relation between β_{HI} and *involuntary* correlated trading. This approach helps to isolate cases in which commonality effects arise via a demand-side channel.

We infer differences in involuntary or forced trading intensities by conditioning mutual fund ownership on aggregate fund flows.[25] Flows can lead to buying or selling pressure of mutual funds, i.e., liquidity demand. Our hypothesis, therefore, is that the relation between mutual fund ownership and common liquidity should be stronger during periods in which the mutual fund industry experiences large flows. We expect mutual fund ownership to be a better proxy for correlated trading during periods of large flows, and particularly when there are large outflows over inflows, because after using up cash reserves, outflows must be met by selling stocks currently held, but the funds have more degrees of freedom in handling inflows: they can first be used to accumulate cash, purchase futures, and eventually be spread across more stocks to mitigate price effect.[26]

To examine the effect 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 (CRSP universe) at the beginning of the quarter. From the flow data we calculate three dummy variables; *negflows* equals one if aggregate flows in a quarter are negative, whereas *strongposflow* (*strongnegflow*) equals one if aggregate flows in a quarter are in the top (bottom) 10% of all quarters, and zero otherwise, representing the largest net inflow (outflow) quarters. Each of these dummy variables is interacted with *mfown* in Equation (2). We continue to use time-fixed effects to pick up general increases or decreases in systematic liquidity during periods of extreme flows. Thus, we do not additionally include *strongposflow* or *strongnegflow* in the regressions because the baseline effects are already captured by these time-fixed effects.

The results of these regressions are reported in Table 7. In Model 1 the coefficients indicate that as hypothesized, the effect of mutual fund ownership on commonality is much stronger during periods of mutual fund outflows. Specifically, the coefficient on *mfown* is 0.87 in quarters with aggregate inflows, compared with 0.87 + 0.38 = 1.25 during quarters with aggregate outflows. Moreover, this additional effect of *mfown* during outflow quarters is significant,

[25] Chordia, Roll, and Subrahmanyam (2011) find that fund flows are partially responsible for the increased turnover in equity markets over recent years. Further, 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.

[26] 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.

Table 7
Common liquidity, fund ownership and mutual fund flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full sample				Subsamples: Agg flows as % of US mkt cap			
					< 0%	0 to 0.25%	0.25 to 0.5%	> 0.5%
mfown	0.87***	0.88***	0.93***	0.87***	1.27***	0.96***	0.90***	0.64***
	(8.28)	(8.44)	(9.30)	(7.79)	(7.38)	(7.26)	(5.31)	(2.69)
mfown×negflow	0.38**							
	(2.02)							
mfown×strongnegflow		0.38*		0.38*				
		(1.92)		(1.92)				
mfown×strongposflow			−0.01	0.06				
			(−0.02)	(0.25)				
ln(firm size)	−0.00	−0.00	−0.00	−0.00	−0.02	0.01	−0.00	−0.01
	(−0.67)	(−0.68)	(−0.70)	(−0.68)	(−1.55)	(0.83)	(−0.09)	(−1.06)
illiq(avg)	−0.00*	−0.00*	−0.00*	−0.00*	−0.00	−0.00	−0.00	−0.00
	(−1.93)	(−1.93)	(−1.92)	(−1.93)	(−1.32)	(−1.59)	(−0.69)	(−0.99)
Observations	121,412	121,412	121,412	121,412	23,332	47,609	26,293	24,178
R-squared	0.013	0.013	0.013	0.013	0.013	0.015	0.012	0.011

Table 7 reports results from a pooled OLS regression of β_{HI} on *mfown* conditional on fund flows. Flows are measured contemporaneously with β_{HI}. The dummy variable *negflow* equals one if aggregate net flows are negative in that quarter, and zero otherwise. *strongnegflow* (*strongposflow*) equals one if the aggregate net flows (scaled by total market capitalization) are in the bottom (top) 10% of quarters, and zero otherwise. These flow variables are not included as stand-alone independent variables because the regressions include time fixed effects. Models 5 through 8 use subsamples of data based on quarterly aggregate flows. Standard errors are clustered in two dimensions, firm and time. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

both economically and statistically. Further in Models 2 and 3, we find a strong additional effect of *mfown* on β_{HI} during the quarters with the largest negative flows (bottom 10%), but no additional effect in the quarters with the largest positive flows. Very similar results are obtained when we include both of these indicator variables in Model 4. Our results are consistent with the hypothesis that fund outflows lead to correlated liquidity demand by mutual funds. They are also consistent with the Coval and Stafford (2007) results regarding mutual fund fire sales.

We also split our sample into subsamples according to the level of aggregate fund flows, where we again scale aggregate flows by total market capitalization. Models 5 through 8 show the results using the base regression from Equation (2) for each of these subsamples. The strong relation between commonality in liquidity and mutual fund ownership holds in each of the subsamples. Further, comparing the magnitudes of the coefficients on *mfown* across the subsamples suggests a negative relationship between the magnitude of liquidity commonality and aggregate net flows, as would be expected if mutual fund ownership has a greater effect during periods when many funds face outflows.

The implicit assumption underlying our analysis is that mutual fund trading affects stocks' liquidity levels (as shown in, e.g., Chen et al. 2004). Generally, the effect of trading on liquidity can arise because of inventory costs or asymmetric information (Ho and Stoll 1981). If inventory costs are primarily responsible for the liquidity effects, it suggests that the driving force should be price pressure emanating from noninformative trades, which is consistent with our flow-based results. On the contrary, if funds trade on private information, to not only influence the level of liquidity but also give rise to commonality in liquidity, such private information would have to be correlated across stocks and funds. We conduct several tests and find little evidence for the asymmetric information explanation.[27]

Overall the findings from this section using alternative proxies for mutual fund ownership are consistent with our previous results. The findings show that both voluntary trading and involuntary trading, i.e., flow-induced liquidity demanding trades, give rise to commonality in liquidity.

4. Overlapping Ownership and Common Liquidity Shocks

To understand in more detail which mutual fund ownership structures give rise to our main result—and specifically whether it is driven by common ownership or correlated flows—we now conduct an analysis on the stock-pair level. Greenwood and Thesmar (2011) find that comovement in returns is expected even if fund ownership across stocks does not overlap across funds, as long as the funds receive correlated liquidity shocks. Additionally, Anton and Polk (2014) find that the extent to which mutual fund ownership is "connected" across a pair of stocks is an important determinant of the correlation in their returns. They argue that the returns of stocks that are held by the same investors should co-move strongly. These channels for the correlation in stock *returns* (i.e., correlated liquidity shocks and common ownership) would also be expected to explain the commonality in liquidity that we have documented. Thus, in this section we test for the sources of the commonality.

To determine whether our previous results are driven by either or both of these channels, we adapt the Anton and Polk (2014) methodology and examine the relation between mutual fund ownership and comovements in liquidity on the stock-pair level. To do so, for each stock pair and quarter in the sample we calculate the pairwise correlation in the two stocks' changes in the log Amihud illiquidity ratio. Using this proxy for comovements in liquidity as the dependent variable, we examine the relation with mutual fund ownership using two approaches: (1) For each stock pair, we compute a measure of common ownership (*sum common mfown*) as the sum of the percentage ownership among all funds that own *both* stocks in the pair in the respective quarter. (2) For each stock pair, we compute the sum of the percentage ownership of all funds that

[27] To analyze whether asymmetric information plays an important role in our context, in unreported tests we follow a methodology similar to that in Chordia, Roll, and Subrahmanyam (2000) and estimate sensitivities of liquidity to order size. We find that stocks with high mutual fund ownership have liquidity more sensitive to average dollar order size, consistent with an inventory risk driver of liquidity. In addition, motivated by Da, Gao, and Jagannathan (2011), we examine whether the effect of mutual fund ownership differs among stocks with differing levels of the Easley et al. (1996) PIN measure. We find that the relation between mutual fund ownership and commonality in liquidity is significantly weaker among high PIN stocks, a result again inconsistent with an asymmetric information explanation.

Table 8
Pairwise correlations in liquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
sum common mfown	0.0047***		0.0043***				
	(8.92)		(10.84)				
sum mfown		0.0025***	0.0010**				
		(4.35)	(2.22)				
interaction of common mfown				0.0032***		0.0026***	
				(8.65)		(11.24)	
interaction of mfown					0.0026***	0.0018***	
					(4.57)	(3.47)	
interaction of |*netflows*|							0.0008***
							(3.01)
Controls	Y	Y	Y	Y	Y	Y	Y

Table 8 reports results from Fama-MacBeth (1973) regressions of the pairwise correlation in liquidity on mutual fund ownership measures. For each unique pair of stocks in a given quarter, we compute the correlation in the two stocks' changes in log Amihud illiquidity over quarter t. All dependent variables are measured over quarter $t-1$. *sum common mfown* is the sum across both stocks of the percent of shares owned by funds that own both stocks. *sum mfown* is computed similarly, but it includes all funds' ownership, not just funds that own both stocks. Both are normalized in each cross section to have zero mean and unit standard deviation. *interaction of mfown* and *interaction of common mfown* are computed in the same way, but instead of using the sum of the two stocks' ownership, we use the product. |*netflows*| for any stock i equals $|\sum_j fundflow_j \cdot w_{i,j}|$, where $fundflow_j$ is the dollar flows to or from fund j and $w_{i,j}$ is the weight of stock i in fund j's portfolio. *interaction of* |*netflows*| is the product of the two stocks' |*netflows*|. Controls included in all regressions but not reported are size, book to market, and average illiquidity for each of the individual stocks in the pair. We report Newey-West (1987) standard errors using four lags. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

invest in either stock in the respective quarter, *sum mfown*. We normalize both measures to have zero mean and unit standard deviation. The difference between the measures is that the second measure also takes into account ownership by mutual funds that own one of the stocks in the pair, but not the other. In the regression we also include the book to market, log size, and average illiquidity of both stocks as control variables.

In Table 8, we report results from a Fama-MacBeth regression specification with Newey-West standard errors. In Model 1, we only include *sum common mfown* and the control variables. We find a highly significant positive effect of common ownership on pairwise correlations in liquidity, confirming our previous aggregate level results. In Model 2, we replace *sum common mfown* by *sum mfown* and again find a highly significant coefficient estimate. In Model 3, we include both measures in the same regression—they are both significantly positively related to the liquidity correlations at the 1% and 5% level, respectively. Moreover, common ownership appears to have the stronger influence on commonality, suggesting that common ownership plays an important role in determining stocks' comovements in liquidity. However, the still statistically and economically significant marginal effect of *sum mfown* in Model 3 (where we also control for the effect of *sum common mfown*) shows that nonoverlapping holdings also play a role as suggested by Greenwood and Thesmar (2011). Thus, while the common ownership channel appears to play the more important role in explaining comovements in liquidity, nonoverlapping ownership also has an important additional effect, which as hypothesized by Greenwood and Thesmar, is likely to be driven by flow-induced trading. This finding suggests that both the correlated liquidity shocks channel and the common ownership channel are important in explaining commonality in liquidity.

One concern is that the measures for mutual fund ownership can have a high magnitude in cases in which only one of the stocks in the pair is owned by the mutual funds to a very large degree. Thus, to capture the situation in which *both* stocks in the pair are owned by mutual funds, we also calculate the interaction of (common) mutual fund ownership between the two stocks of each pair. These measures are useful because they are only high when both stocks exhibit high levels of (common) mutual fund ownership at the same time. Results using these alternative measures are presented in Models 4 to 6. They confirm our earlier findings from Models 1 to 3. Again, the interaction of common ownership has the strongest effect, but also the interaction of total ownership has a positive effect, which is now even significant at the 1% level. As both variables are normalized, we can also directly compare the magnitude of the coefficient estimates. For example, in Model 6 the estimate for the effect of the interaction of common ownership amounts to 0.26%, whereas the coefficient estimate for the effect of the interaction of total ownership amounts to 0.18%, i.e., the effect of overlapping ownership is roughly 50% stronger than the marginal effect of total ownership (which then has to be driven by nonoverlapping ownership).

We further examine flow-driven trading in each stock-pair unit. Because the unit of analysis is stock pairs, we can estimate a relation between common liquidity and flow-induced trading within the cross section, which complements our earlier findings on aggregate fund flows. For each fund and quarter, we allocate the flows over the quarter to each of the fund's holdings according to its portfolio weights, thus, making the implicit assumption that funds scale up or down existing holdings proportionally in response to flows (Pollet and Wilson 2008). Then, within each stock we aggregate these allocated flows across funds. Specifically, we measure the net flows to or from stock i in a quarter as $|\mathrm{netflows}|_{\mathrm{i}} = |\sum_j \mathit{fund\ flow}_j \cdot w_{i,j}|$, where $\mathit{fund\ flow}_j$ is the dollar flows to or from fund j and $w_{i,j}$ is the weight of stock i in fund j's portfolio. In this way, we allocate aggregate flows in the quarter to each stock in the sample, and include these stock-level flows in the stock-pair unit of analysis. In Model 7 we interact the two stock's |netflows| and include this as an independent variable. The positive and significant coefficient indicates that the correlation between the two stocks' liquidity tends to be higher for stocks owned by funds that experienced flows over the respective quarter.

5. Robustness Tests

We conduct a number of additional tests to examine the stability of our results, the details of which are provided in the Internet Appendix. First, we show that our main results were also obtained if we analyzed comovements in order imbalances (rather than liquidity). Then, we provide evidence that our results are robust to controlling for commonality in returns or volatility. We also show that our results are robust across a variety of subsamples based on firm characteristics, time periods, and macroeconomic conditions. Moreover, we show that our results are not dependent on specific assumptions regarding the construction of the liquidity and returns of the market and mutual fund portfolios, or even on the measure of liquidity itself. For instance, we replicate our main results using the bid-ask spread measure derived by Corwin and Schultz (2012). Finally, we provide some evidence that absolute changes in mutual fund ownership (instead of ownership levels), which serve as a lower bound for overall mutual fund trading in a stock, also have a significantly positive effect on commonality.

6. Conclusion

We hypothesize that mutual fund liquidity demand reflected in the correlated trading among investors in a stock largely held by mutual funds is an important explanation for commonality in liquidity across stocks. Using data on mutual fund ownership and stock liquidity from NYSE and AMEX stocks, we find evidence suggesting that mutual fund trading is an important factor in explaining commonality in liquidity. We use a two-step process and first regress a stock's individual liquidity on the liquidity of two portfolios: a portfolio consisting of stocks with high mutual fund ownership and a market portfolio. This regression results in two liquidity betas per stock and quarter: 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 solely 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 levels, or other unobservable time-invariant stock characteristics that might jointly determine systematic liquidity and mutual fund ownership.

To alleviate further endogeneity concerns, we take advantage of a natural experiment and examine the commonality among stocks for which mutual fund ownership exogenously dropped because of the mutual fund late trading scandal in 2003. We find commonality is significantly lower among affected stocks even several years after the event.

Our hypothesis also suggests that the relation between commonality in liquidity and mutual fund ownership should be stronger in situations with greater mutual fund trading. The results of several additional tests support our hypothesis. First, we find that the commonality in liquidity is stronger in stocks owned by mutual funds with high turnover ratios. Second, we find that the commonality is greater during periods of negative aggregate mutual fund flows. Finally, we further examine commonality in liquidity across stock pairs and find results consistent with those of Greenwood and Thesmar (2011) and Anton and Polk (2014) for comovements in stock returns. Consistent with Greenwood and Thesmar's results, we find that commonality in liquidity exists for stocks owned by different funds that have common flow shocks. Consistent with Anton and Polk, we find that commonality in liquidity exists for stock pairs with common ownership.

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 et al. 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 from large investors in the stock. These results suggest that mutual fund trading may add to a stock's risk, 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 on their funds of liquidity shocks from 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 study we have selected mutual funds as a group of investors to be examined for correlated trading and resulting commonality. Of course, this does not preclude the possibility that the correlated trading of additional important groups of investors, such as hedge funds or other institutional investors, might also give rise to commonality.

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