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Short-term reversals, returns to liquidity provision and the costs of immediacy*

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A B S T R A C T

Some mutual funds act as contrarian traders, earning returns in the stock market by providing liquidity, while others demand liquidity and suffer costs of immediacy. The funds' liquidity demand has increased over time. On average, the mutual funds' costs of immediacy exceed their returns from providing liquidity by 1.9% pa. High market beta funds, large cap funds, and funds exposed to momentum suffer over 2.5% pa. in costs of immediacy. Other results are that mutual funds' average alpha becomes insignificant when the costs of immediacy are accounted for and in the cross-section, the funds' costs of immediacy predict their alphas.

1. Introduction

The returns that investors and market makers obtain from short-term contrarian trading in the equity market can be seen as a compensation from providing liquidity to other investors, whose order imbalances cause temporary price pressure in stocks, see e.g. Campbell et al. (1993) and Jegadeesh and Titman (1995). Along with Nagel (2012) and Jylhä et al. (2014), we refer to such returns from contrarian trading as "returns from providing liquidity." In turn, the investors whose trading causes the short-term price pressures in stocks, are said to demand liquidity, or, in other words, suffer costs of immediacy using the terminology of Demsetz (1968) and Grossman and Miller (1988). In this paper, we examine the relative importance of the returns from providing liquidity and the costs of immediacy for mutual funds on average, and for funds following different strategies. That is, we study how the mutual funds on average and in the cross-section position themselves relative to short-term return reversals in stocks. Second, we examine how mutual funds' liquidity provision and demand varies over time and how it affects their alphas.[1]

To determine whether mutual funds more commonly supply or demand liquidity, we follow a methodology that was introduced in Jylhä et al. (2014), who examined hedge funds' liquidity provision. Namely, we regress mutual funds' returns on a proxy for the returns from providing liquidity, measured by the returns to a short-term (one-week) contrarian long-short trading strategy, and standard risk factors. If the regression coefficient for the returns from providing liquidity is significantly positive for a given mutual fund, we conclude that it supplies more liquidity than it demands in the stock market. Such a fund acts as a contrarian trader and makes money from short-term reversals: it sells stocks with negative and buys stocks with positive weekly expected returns. If the regression coefficient is significantly negative, we conclude that the fund demands more liquidity than it supplies. In this case, the fund loses money from short-term reversals. Empirically, we find that mutual funds' average regression coefficient for the returns from providing liquidity is significantly negative, implying that the average mutual fund suffers more in costs of immediacy than it earns as returns from providing liquidity. According to our estimates, the average mutual fund loses up to 1.9% of its assets under management annually in costs of immediacy. This figure is net of the returns that it makes from providing liquidity.

Although we find that on average the mutual funds suffer more in costs of immediacy than what they make in returns from providing liquidity, there are significant cross-sectional differences.

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[1] In this paper, as in Nagel (2012) and Jylhä et al. (2014), the terms "liquidity provision" and "supply of liquidity" correspond with the notion of "supply of immediacy" in Demsetz (1968) and Grossman and Miller (1988). As we do, both Nagel (2012) and Jylhä et al. (2014) assume one-week price pressures in their studies. Short-term return reversals in stocks at one-month and one-week horizons were first documented in Jegadeesh (1990) and Lehman (1990).

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We find that the mutual funds' costs of immediacy are larger for those funds that experience large flows, and for funds, whose flows correlate highly with the aggregate mutual fund flows. The costs of immediacy depend also on the fund's strategy, and are larger for the funds that follow common dynamic trading strategies. For instance, the decile of funds that are the most exposed to the momentum factor suffers up to 4.6% p.a. in costs of immediacy, explaining why the momentum mutual funds cannot outperform despite large abnormal returns to momentum stocks; see e.g. Choi and Zhao (2021). Similarly, high market beta funds suffer 5.7% p.a. more in costs of immediacy than low beta funds. Finally, balanced funds suffer more costs of immediacy compared to other funds investing in equity.

How much the mutual funds suffer in costs of immediacy and how much they make in returns from providing liquidity is highly time-dependent. In our early sample prior to 1999, more funds supply than demand immediacy. In contrast, after the turn of the millennium, more funds demand as opposed to supply liquidity.[2]

According to our estimates the mutual funds' costs of immediacy affect markedly their alphas, and can thus explain part of the observed mutual funds' average underperformance. Consistent with the earlier literature, in a standard panel regression of fund returns on known risk factors, the average mutual fund alpha is negative as in e.g. Jensen (1968) and Malkiel (1995). Instead, when controlling for the mutual funds' costs of immediacy in the regression, the average alpha becomes insignificant. It therefore appears that part of the observed mutual funds' underperformance relative to a value-weighted stock market index can simply be an artifact of comparing two return series that treat the costs of immediacy differently: one series that is measured after the investors' costs of immediacy from entering to and exiting from their investments (mutual fund returns) and another series that is measured before any costs of immediacy or in fact any other trading costs (the value-weighted stock market index returns). Our conclusion that mutual funds' costs of immediacy markedly affect the funds' alphas holds also if we analyze the mutual funds' alphas using the calendar-time portfolio approach, or run fund-by-fund regressions and take a value-weighted average of the individual funds' alphas. In all these cases, controlling for the mutual funds' costs of immediacy from one-week equity market return reversals makes the funds' otherwise negative alphas become insignificant.[3]

One of our key findings is that in the cross-section the mutual funds' past costs of immediacy significantly predict the funds' future 4-factor alphas. Put differently, the funds that historically suffered the least costs of immediacy have significantly larger future alphas than other mutual funds. This finding has practical implications for the investors: it appears that investors suffer when investing in mutual funds with high past (and future) costs of immediacy. This finding holds across all quintiles of funds' past alphas. The differences in alphas are both statistically and economically significant. For instance, the difference in 4-factor alphas between funds in the lowest quintile of both past alphas and returns from providing liquidity and those in the highest is 3.4% p.a. for all equity funds. In our sample, both the past alphas, as e.g., in Huij and Verbeek (2007), and the costs of immediacy predict future returns.

Based on our results it is clear that funds' exposure to short-term reversal returns helps explain their alphas. One may be concerned, however, whether the funds' exposure to reversal returns truly reflects the funds' demand and supply of liquidity (in stocks with positive or negative short-term expected returns). We take several steps to confirm the validity of the methodology in Jylhä et al. (2014) and verify that we are indeed able to detect funds' that demand or supply liquidity at a weekly horizon. First, we examine the ANcerno data where we can track institutions' trades. We find that in the ANcerno data there exist institutions that consistently demand liquidity on those days when the Jylhä et al. (2014) methodology indicates that institutions demand liquidity (that is, buy stocks with low expected abnormal returns and sell stocks with high expected abnormal returns). Similarly, there exist other institutions that systematically supply liquidity on those days. The time-horizon of the liquidity demanding institutions' collective trading in the ANcerno dataset fits well with the assumed 5-day time-horizon in the Jylhä et al. (2014) approach. We find furthermore, that the liquidity supplying institutions profit from their short-term liquidity supplying trades, while the liquidity demanding institutions lose. This is in line with the premise of the Jylhä et al. (2014) approach.

2. Relation to the literature and the structure of the paper

Our research builds upon the extensive literature documenting short-term cross-sectional stock return reversals, and the research that relates these return reversals to investors' demand for immediacy in the stock market, see e.g. Grossman and Miller (1988), Jegadeesh (1990), Lehmann (1990), Chordia and Subrahmanyam (2004), and Avramov et al. (2006). Second, it is related to the research that estimates the returns to liquidity providing trading strategies that utilize cross-sectional return reversals, such as Khandani and Lo (2007, 2011), Nagel (2012), and Jylhä et al (2014).

Our analysis is particularly closely related to Da et al. (2011). Using data on quarterly changes in mutual funds' holdings, and on stock-specific order imbalances in the corresponding stocks, they provide evidence on which funds typically supply or demand liquidity in the stock market. Their focus is on mutual funds' medium-term liquidity demanding and liquidity providing strategies with one quarter lookback and investment horizon. This is in contrast to our paper, which concerns solely the costs and returns from short-horizon liquidity demanding and providing trading with a one-week investment horizon. Cella et al. (2013) is another paper that looks at mutual funds' liquidity demand and its effect on stock performance using the quarterly mutual funds' holdings data. They show that investors demand liquidity particularly during periods of market turmoil leading to return reversals in the underlying stocks.

Examining the one-week horizon liquidity demand and supply on mutual funds' performance (in addition to quarterly as examined in the aforementioned papers) is warranted given that funds' within quarter trades can have a large effect on funds' returns, as also noted in Da et al. (2011) as well as in Kacperczyk et al. (2006).[4] When examining the relationship between funds' liquidity demand at weekly and quarterly horizons

[2] One factor behind this can be the lower cost to demanding liquidity in the latter sample. Trading costs have declined over time, see Anand et al. (2013), partly due to changes in market structure at the NYSE in 2003 that improved market liquidity, see Hendershott et al. (2009). Another factor affecting this trend can be the rise of the hedge fund industry. Hedge funds have superior ability to provide liquidity as they can take short positions.

[3] It makes sense that mutual funds demand liquidity in the financial markets more than hedge funds, which according to Jylhä et al. (2014) supply liquidity. After all, the mutual funds in contrast to hedge funds offer liquidity to their investors by making the investments redeemable at a daily notice.

[4] In support of this, Jame (2018) finds that the hedge funds, who are exposed to the Jylhä et al. (2014) one-week returns from providing liquidity measure, make large returns from their liquidity provision at this frequency. He finds also that hedge funds are more likely to provide liquidity when trading with constrained mutual funds. Third result in Jame (2018) is that hedge funds make money particularly during periods with poor funding liquidity. We, in turn, find, as shown in Section 5 that mutual funds' demand for immediacy is at its highest at times of poor funding liquidity, as measured by the TED spread and broker-dealer leverage.

(in the Internet Appendix) we find that the two measures of liquidity demand are mainly two distinct phenomena. This implies that our results on the costs and benefits of the funds' within quarter liquidity demand and supply, associated with one week price pressures, are new to the literature.

There are many other papers that also provide evidence on the mutual funds' costs of immediacy or of their liquidity provision at different frequencies: For instance, Coval and Stafford (2007), Lou (2012), and Hau and Lai (2017) show that large mutual fund outflows and inflows lead to price pressure in the stocks that the mutual funds hold. In their samples stock prices take months to recover from liquidity demand by mutual funds with large outflows. Our findings complement theirs, as we find that fund flows lead to economically significant costs of immediacy for mutual funds also due to one-week horizon price pressures. More concretely, we find that the costs of immediacy related to one-week horizon price pressures for the funds in the largest absolute flow decile are 0.84% p.a. higher than those for funds in the smallest absolute flow decile.[5]

Much of the related work on the effects of mutual fund trading on mutual fund performance has a strict focus on the effect of transaction costs from trading. Transaction costs include direct trading expenses such as broker fees and commissions as well as indirect trading costs that come from the price impact from the institutions' own trading. The latter are measured either as the price change from trade initiation to average price at order execution or indirectly based on estimates of the stocks' average 15-minute price response to volume, using a methodology introduced in Hasbrouck (2009). These price pressure indicators aim to measure the cost of immediacy that is associated with one particular trade. In contrast, we look at the costs to funds from positioning wrongly in relation to one-week cross-sectional return reversal trades, where the week-long price pressures in stocks reflect the price impact not only from one institution's trades, but rather the collective price impact of all traders that today and in recent days have demanded immediacy. Da et al. (2011) and Coval and Stafford (2007) are at the other extreme of the spectrum, analyzing the costs of liquidity demand and returns from liquidity supply at the quarterly or even longer horizons.

Even though cost of immediacy from trading – say selling stocks with high one-week expected returns – is different conceptually from the direct trading costs that funds incur when trading, it turns out that for the mutual funds the two measures are related. Namely, we find that on average funds with high turnover experience also high costs of immediacy at the weekly horizon. A priori, the two measures – trading costs and the costs of immediacy - can be quite different, however. For instance, according to Jylhä et al. (2014) the hedge funds supply liquidity and thus have negative costs of immediacy (they make money on reversal trades), on average, but positive direct transaction costs. Also, according to Jame (2018), hedge funds' liquidity providing trades are profitable despite direct transaction costs.

One of the pioneering articles in the mutual fund transaction cost literature is Edelen (1999), which relates the mutual funds' underperformance to trading costs, in particular to those arising from liquidity-motivated trading associated with fund flows. He estimates first the mutual funds' flow induced trading and then its effect on the funds' performance. Our results are similar to the findings in Edelen (1999), Wermers (2000), and Edelen et al. (2013), in that the costs from trading – in our case the costs of immediacy - are found to be an important determinant of mutual funds' underperformance. To supplement the conclusions in Edelen (1999), we show that in the case of the costs of immediacy, several other factors besides mutual fund flows, such as the funds' use of common dynamic trading strategies, generate significant costs of immediacy due to price pressures and affect the mutual funds' average performance. Furthermore, in the case of the costs of immediacy that arise from a fund's flows, it matters how correlated the flows are with the current and past mutual fund industry flows.

Other papers that examine institutions' trading costs include Anand et al. (2012), who examine using trade level data within the ANcerno sample the institutions' execution costs from the execution shortfall, which is defined as the price impact after trade initiation. They show that such trading costs are persistent and vary across institutions. Frazzini et al. (2015) is yet another look at institutions' trading costs. They use the execution shortfall measure to examine the trading costs of one large institutional investor.[6]

One of the influential papers in the area of trading costs and within-day costs of immediacy is Anand et al. (2013). They use the ANcerno transaction data to classify institutional investors into institutions that demand liquidity and institutions that supply liquidity. Their definition of liquidity demand differs from ours, however, and thus the findings are not directly comparable. In their setting, an institution demands liquidity if it on average trades in the direction of stock returns. Given this, the focus is not as much on the price pressures related to the cross-sectional relative return reversals, whose effects Jylhä et al. (2014), Nagel (2012), and we examine, but on market level liquidity demand and supply that affects not only the direct daily price impact of trading, but also investors' degree of market participation and the entire market risk premium. The goal in their paper is to examine the impact of institutional trading on stock resiliency during the financial crisis of 2007-2009. Despite the differences in the approach and focus, there are many similarities in the findings. In line with what we find to be the case for mutual funds, they show that most institutions in their sample demand liquidity (based on their definition), the institutions' trading styles are persistent, and the trading style affects the trading performance of the institutions.[7]

Our work is also related to the literature on mutual funds' alphas, recently surveyed in Jones and Wermers (2011). Dong et al. (2019) document that mutual funds' exposure to liquidity risk markedly affects their alphas in the cross-section. This occurs, they argue, as shocks that make markets illiquid affect the informed traders' ability to trade through higher costs of immediacy. Finally, our results link tightly with Kacperczyk et al. (2006), who document that funds' past unobserved trading performance within quarter predicts their alphas.[8]

Our contribution to the literature is to estimate the mutual funds' average costs of immediacy from their positioning relative to short-term return reversals in the market, and present evidence

[5] Other related papers on mutual funds' cost of trading that are due to price pressures include e.g. Alexander et al. (2007), who show that trades motivated by funds' liquidity needs, or funds' excess liquidity, underperform the market. Bhattacharya et al. (2013) shows that mutual funds provide immediacy to other funds in the same mutual fund family, if those suffer from fire sales, while Ben-Rephael et al. (2011) finds that the aggregate mutual fund flows create price pressure on the entire stock market index. Koch et al. (2016), in turn, show that mutual fund trading causes commonality to liquidity.

[6] Busse et al. (2020) also examines funds' trading costs. Their key finding is that the direct trading costs are smaller for large funds, who choose to trade more liquid stocks. In contrast, we find that the costs of immediacy are higher for large compared to small funds. Finally, Novy-Marx and Velikov (2016) use the Hasbrouck (2009) model to analyze the costs of trading equity market anomalies. Cremers and Petajisto (2009) provide additional evidence on the effect of mutual funds' trading on funds' performance.

[7] They find also that across institutions, the cost of trading is more significant for small stocks, volatile stocks, and stocks with higher beta.

[8] Amihud and Goyenko (2013) show that funds' R^2 helps predict their returns. This finding can be related to our finding that common trading strategies exhibit large costs of immediacy, which affect alphas.

on which types of mutual funds suffer most from such costs of immediacy in the equity market. In contrast to Da et al. (2011) and Cella et al. (2013), our focus is on one-week horizon liquidity demand. Our finding that the costs of immediacy from trading are exceptionally large for funds, whose flows are correlated with the industry flows, large-cap funds, high market beta funds, and for funds exposed to the momentum strategy are new and relevant for both the academia and practice. Our second contribution is to show that mutual funds' observed underperformance is to a large extent driven by the mutual funds' bad positioning towards short-term reversal trades, which we use to measure costs of immediacy. Our third contribution is to show that the mutual funds' historical costs of immediacy significantly predict the funds' 4-factor alphas.[9] Fourth, our contribution is to show evidence on liquidity supply and demand for balanced funds. Fifth, we are the first to provide evidence of any type of within quarter liquidity demand and supply in such subsamples that cannot be studied with ANcerno data. Interestingly, the funds tendency to demand liquidity has changed markedly over time. Our final contribution is to present evidence that mutual funds' costs of immediacy are several times larger during periods of poor funding liquidity, as compared to other periods of time.

Our paper is organized as follows: In Section 3, we briefly document the time-varying, short-term reversal in stock returns and introduce the returns from providing liquidity concept. In this section we also validate the concept by looking at institutions' actual trades utilizing the ANcerno data. In Section 4, we present our main results related to mutual funds' costs of immediacy and their returns from providing liquidity. In Section 5, we study the determinants of mutual funds' propensity to demand or supply liquidity. In Section 6, we study the effect of costs of immediacy on mutual funds' performance. Section 7 concludes the paper. In the Internet Appendix, we further study the robustness of our main results that mutual funds on average demand liquidity and that there are significant amounts of both liquidity demanding and supplying institutions. We also provide additional evidence on that our approach is able to detect funds' demand and supply of liquidity.

3. Measuring the returns from providing liquidity and the costs of immediacy

3.1. The concept

In this paper, along with e.g. Khandani and Lo (2007, 2011), Nagel (2012), and Jylhä et al. (2014) we proxy for the returns from providing liquidity by the returns to a short-term contrarian long-short trading strategy. Because of short-term return reversal, see e.g. Jegadeesh (1990) and Lehmann (1990), short-term contrarian trading strategies have historically generated positive returns, which are seen as rewards from providing liquidity (see e.g. Jegadeesh and Titman, 1995). We proxy for the returns from providing liquidity by the returns to a similar contrarian trading strategy that was used in Jylhä et al. (2014), but show in the Internet Appendix that our main results are robust to alternative proxies of the returns from providing liquidity. The liquidity providers' returns from supplying liquidity correspond with the costs of demanding liquidity, referred to as costs of immediacy, to the counterparties of the trades.

Jylhä et al. (2014) measure is a proxy for the available returns from providing liquidity more generally, and its negative is a proxy for the investors' costs of immediacy. To the extent that the returns of this proxy correlate with the overall returns to providing liquidity it will help us estimate the funds' costs of immediacy in a regression analysis. Below, we describe the Jylhä et al. (2014) approach in greater detail.

3.2. The returns from providing liquidity (R_{LP})

In Jylhä et al. (2014), the proxy for the returns from providing liquidity is the returns to a contrarian long-short trading strategy in which trading is based on the stocks' expected 5-day excess returns. The strategy goes long in the stocks with positive 5-day expected excess returns and short in the stocks with negative expected excess returns. To calculate the expected 5-day excess returns, we first estimate the stocks' return reversal patterns by performing for each day the following cross-sectional regression: We regress the stocks' (indexed by i) next 5-days' (one week) excess returns following the close on day t, $R5_{i,t}$, on each of the stocks' past 20 days' (one month) excess returns, $R_{i,t-\tau}$, where $\tau \in \{0,..19\}$.[10]

The data set used in this estimation includes all stocks listed in the daily CRSP file from January 1, 1983 to the December 31, 2017, which fulfill the following requirements: 1) the security is an ordinary common stock, 2) the company is incorporated in the USA, 3) the stock is listed in the NYSE or the Amex, and 4) the company's SIC code is available and it is included in the Fama-French 49 industries. We make the data restrictions to reduce noise in our estimates. More specifically, we remove from our sample all stocks that 1) belong to the 5th percentile of all U.S. incorporated common stocks listed on the NYSE or the Amex, 2) have a share price below one dollar, i.e. penny stocks, and 3) have zero trading volume during a day when a position in the stock is presumably opened.[11,12]

The estimated average coefficients for the first 19 daily excess returns are all negative and 17 of them are statistically significant at 5% level, showing that there is a large amount of mean reversion in the data. This is in line with Jylhä et al. (2014), who study a shorter sample of data.

Next, we use these results on the return reversal patterns to estimate the available returns from providing liquidity. The Jylhä et al. (2014) measure of the returns from providing immediacy, R_{LP}, is the return to a zero-investment contrarian long-short trading strategy that utilizes short-term return reversals. More precisely, R_{LP} is the monthly return to a zero-investment long-short trading strategy where every day a long position is opened in all stocks with a positive expected 5-day return and a short position is opened in all stocks with a negative expected 5-day return. After 5 days, the positions are closed.

On any given day t, we use the stocks' expected 5-day excess returns evaluated at that time, denoted by $E_t(R5_{i,t})$, as portfolio

[9] The difference in the funds' Sharpe-ratios is also dramatic. The low-cost-of-immediacy funds have a 30% higher Sharpe-ratios than the high-cost-of-immediacy funds in the next two years. This difference is more pronounced for the low alpha funds. These results are available upon request.

[10] The excess returns are calculated by deducting from stocks' returns the returns to a corresponding equal-weighted Fama-French 49 industry index. In this case, the excess returns for stocks are more likely due only to price pressure from trading and not information, see Hameed and Mian (2015) for related evidence. Our results are qualitatively similar if we calculate the excess returns using equal-weighted or value-weighted CRSP indexes instead of the industry indexes, as shown in the Internet Appendix.

[11] As some of our specifications control for trading volume, we have excluded the stocks traded in the Nasdaq. The volume in Nasdaq is not comparable to the volume in the NYSE and the Amex due to differences in the trading systems, see e.g. Amihud (2002).

[12] We also performed our analysis with a sample that uses the 20th NYSE percentile cutoff for market capitalization and requires the stock prices to be greater than $5. In addition, we performed our analysis with a sample that only includes those stocks (based on the mutual funds' holdings data) that actually were held by mutual funds in the previous quarter. All of our results are qualitatively similar across the sample specifications.

Table 1
Summary statistics related to the liquidity providing trading strategy (R_{LP}).

Mean (%)	4.35
25th percentile (%)	1.21
Median (%)	4.23
75th percentile (%)	7.17
Volatility (%)	4.29
Months with positive return (%)	85.53
Sharpe ratio	1.01
4-factor alpha (%)	4.38
t-statistic for alpha	17.10

Notes: This table shows the statistics of the monthly returns from providing liquidity (R_{LP}). The returns from providing liquidity are the pre-transaction cost returns on a zero-investment long-short trading strategy in which the stocks' 5-day expected excess returns are used as portfolio weights when forming the long and the short portfolios for 5-day investments. These 5-day expected excess returns are calculated using the stocks' own past 20 trading days' excess returns and six-month moving averages of the coefficients for return reversal, from each of the past 20 trading days' excess returns, until six days prior to taking positions. Return statistics are based on averages of the returns of all open positions. Excess returns are calculated relative to the Fama-French industry indexes. Carhart (1997) 4-factor alpha is calculated using data from Kenneth French's website. Sample period is from January 1984 through December 2017.

weights when forming the long and the short portfolios.[13] When setting the portfolio weights, we assume that the time *t* estimates of the stocks' expected 5-day excess returns are based on the average regression coefficients from the 120 past days' (i.e., the past 6 months') cross-sectional regressions up to time *t-6*, the last day for which there is five-day forward return data at time *t*. The expected five-day returns at time *t*, $E_t(R5_{i,t})$, are then calculated using the stocks' past twenty days' returns up to time *t*.

Given that investments in the long-short portfolios are held for five days and opened daily there are 5 portfolios open at any point in time. The proxy for the returns from providing liquidity, R_{LP}, is calculated as the average return on all the five open zero-investment long-short trading portfolios. This aggregation procedure is similar to that in Jegadeesh and Titman (1993). Table 1 documents the pre-transaction cost returns on this liquidity providing trading strategy. Table 1 shows that the returns from providing liquidity are high even after controlling for standard risk factors.[14]

Fig. 1 shows the time series evolution of the monthly returns from providing liquidity. As Fig. 1 shows, the returns from providing liquidity have decreased over time, and have become lower especially after the turn of the millennium. This corresponds well with the notion that liquidity has improved over time. Jylhä et al. (2014) tie the decline in the returns from providing liquidity to increased speculative capital in the hedge funds that provide liquidity. Hendershott et al. (2009), in turn, present evidence that liquidity in the NYSE improved after the adoption of autoquote (that fostered algorithmic trading) in 2003.[15,16,17]

3.3. Controlling for liquidity risk

Our measure for the returns from providing liquidity makes use of the short-term return reversals, and thus might be correlated with the Pastor-Stambaugh (2003) liquidity risk factor, that also is related to short-term return reversals. Although the two concepts are quite different, to alleviate the concerns that our empirical results on funds' exposure to the returns from providing liquidity are in fact due to funds' exposures to liquidity risk, we control for the Pastor-Stambaugh liquidity factor in all our regressions.[18]

3.4. Validating the measure using the ANcerno data

To validate the selling pressure hypothesis as an explanation for the observed return reversal patterns, we turn to the ANcerno dataset that contains trade-level observations for hundreds of different institutions including hedge funds, mutual funds, pension funds, and other money managers. Our data cover the period 1999-2013. According to Puckett and Yan (2011) this dataset includes the trades of many of the largest institutional investors such as CalPERS, the YMCA retirement fund, Putman Investments, and Lazard Asset Management that in total account for 8% of the daily volume in CRSP.[19]

ANcerno data allow us to examine institutions' trading patterns and to see if some institutions systematically demand or supply liquidity. We classify the institutions in the ANcerno dataset as ANcerno liquidity demanders, ANcerno liquidity providers, or other institutions, based on their past year's trades' dollar-weighted average 5-day expected returns. The ANcerno liquidity demanders are institutions, who on average sell stocks that have a positive expected return and buy stocks that have a negative expected return. To be defined as an ANcerno liquidity demander, we require

[13] Lehmann (1990), Khandani and Lo (2011), and Nagel (2012) analyze the returns to contrarian trading strategies where portfolios are formed by using the negative of the stocks' past returns as portfolio weights. Given the evidence on return reversal, their portfolio weights also effectively correspond with the stocks' expected excess returns.

[14] The estimated mean monthly return to liquidity provision (4.35% in Table 2) is almost four times as large as the mean monthly return reported by Jylhä et al. (2014). This difference is explained by the different sample restrictions in the two studies and the fact that our sample period starts earlier. The returns from providing liquidity have declined over time, see Fig. 1. Khandani and Lo (2011) find also that return reversals have declined over time.

[15] Our measure of the returns from providing liquidity, R_{LP}, is a proxy for the true returns from liquidity provision. In our approach, we use the time variation in R_{LP} to identify the funds who supply and demand immediacy. For this purpose, it is sufficient that R_{LP} correlates with the true returns from providing liquidity. When estimating the funds costs of immediacy, one may be concerned by the fact that R_{LP} may over- or underestimate the true returns from providing liquidity. On the one hand, R_{LP} corresponds to the money left on the table at the end of the day, after many liquidity providing trades may have already been made during the day at higher or lower prices. On the other hand, R_{LP} may overestimate the returns as many liquidity supplying trades may have been made at worse prices on previous days. Our view is that the inaccuracy related to the level of this monthly proxy (be it systematically under- or overestimating the true returns from providing liquidity) should not affect the mean estimate of the costs of immediacy (beta R_{LP} x R_{LP}). If the proxy is inflated (deflated) relative to the true returns from providing liquidity, using the inaccurate proxy should mainly be reflected in a lower (higher) R_{LP} beta (in absolute value).

[16] To examine further the validity of our approach we test also how the funds are exposed to the run-up returns to time *t*, when R_{LP} portfolio is formed. Unreported results are as expected – the funds demanding liquidity are positively exposed to run-up returns while funds providing liquidity are negatively exposed to run-up returns.

[17] Chordia et al. (2014) argue that reversal returns as well as many other anomaly returns have decreased over time due to larger arbitrage capital, measured through hedge funds' AUM. Another possible explanation for this decline, presented in McLean and Pontiff (2016), is that academic publications increase investors awareness and attract speculative capital to markets that eliminates predictability.

[18] The correlation between the Pastor-Stambaugh liquidity factor and our proxy for the returns from providing liquidity is -0.046 during our sample period. Dong et al. (2019) study mutual funds' exposure to liquidity risk using a different liquidity risk measure, the Sadka (2006) liquidity factor. In a robustness test, reported in the Internet Appendix, we replace the Pastor-Stambaugh liquidity factor with the Sadka liquidity factor in our mutual funds' performance regressions. Results are qualitatively similar.

[19] Unfortunately, Abel Noser Solutions no longer provides a file that allows the matching of ANcerno client codes to corresponding investor names. As a result, we are unable to disentangle different institutional investor types.

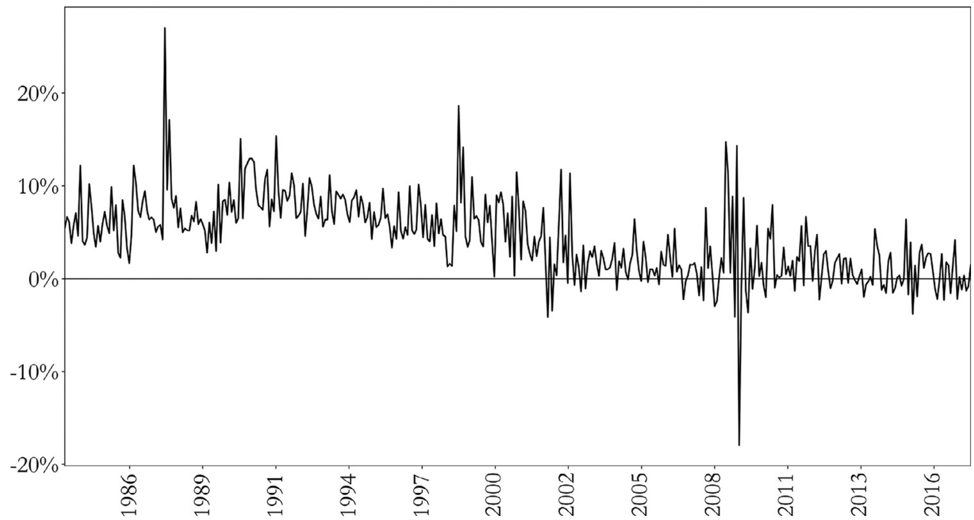


Fig. 1. Monthly returns from providing liquidity (R_{LP}). *Notes:* The returns from providing liquidity (R_{LP}) are estimated as the returns on a zero-investment long-short trading strategy in which the 5-day expected excess returns are used as portfolio weights when forming the long and the short portfolios for 5-day investments. These 5-day expected returns are calculated using the stocks' own past 20 trading days' excess returns and six-month moving averages of coefficients for return reversal, from each of the past 20 days' excess returns, until six days prior to taking positions. Portfolio returns are based on averages of the returns of all open positions. Excess returns are calculated relative to the Fama-French industry indexes. There is no consideration for transaction costs. Sample period is from January 1984 to December 2017.

that the institution's signed trades' volume-weighted expected return is significantly negative at a 5% level (one-tailed test). Accordingly, ANcerno liquidity providers are defined as institutions, whose signed volume-weighted expected return is significantly positive. The stocks' expected returns are calculated as in the calculation of the R_{LP}, see section 3.2. of the paper.

Fig. 2 shows how the ANcerno liquidity demanders' (Panel A) and providers' (Panel B) buy-sell ratios vary during a 11-day window surrounding days t in which we classify the stocks into deciles based on their 5-day expected returns. These findings help validate our approach in two important ways. First, Fig. 2 shows clearly that there are some institutions who systematically demand liquidity and others who systematically supply liquidity on the days with exceptionally high or low expected returns. Second, it validates the 5-day return horizon used in the R_{LP} measure, especially in relation to liquidity demand. It appears that after five days for stocks with exceptionally high or low expected returns the liquidity demanders' aggregate buy-sell ratios in high and low expected return stocks approach zero and thus their demand pressure alleviates.

We examine also the 5-day trading profits of the ANcerno liquidity providers and demanders. We find that the liquidity supplying funds in the ANcerno data make returns at the expense of the liquidity demanders, especially when the liquidity demanders sell stocks. The ANcerno liquidity suppliers' average abnormal 5-day return on their liquidity supplying trades are 0.24% on purchases and -0.01% on sales (abnormal return on sales is calculated as minus one times the stock's abnormal 5-day return). ANcerno liquidity demanders' abnormal return on their liquidity demanding trades are 0.03% on purchases and -0.22% on sales. So, the liquidity demanders lose money on sales and correspondingly the liquidity suppliers make roughly an equal amount of money on their liquidity supplying purchases. These figures are based on all stocks in the two extreme deciles of expected return.

4. Mutual funds' exposure to the returns from providing liquidity

It is not clear in advance whether mutual funds on average act as market makers and supply liquidity, or demand liquidity in the stock market. While there appears to exist returns from providing liquidity, as documented above, there are reasons to believe that the mutual funds might demand instead of supply liquidity. One reason, at least, is that the mutual funds, in contrast to hedge funds, do not typically have any redemption restrictions. That is, because in contrast to hedge funds the mutual funds offer their investors immediacy (ability to exit at will), the mutual funds, and their investors might be expected to incur costs of immediacy.

In this section, we first explore whether the mutual funds supply or demand liquidity in the stock market by regressing the mutual funds' returns on the R_{LP} measure of the returns from providing liquidity. If the regression coefficient for any given fund is statistically significantly positive, we conclude that the fund supplies liquidity. In turn, if the regression coefficient is significantly negative, we conclude that the mutual fund demands liquidity in the stock market.

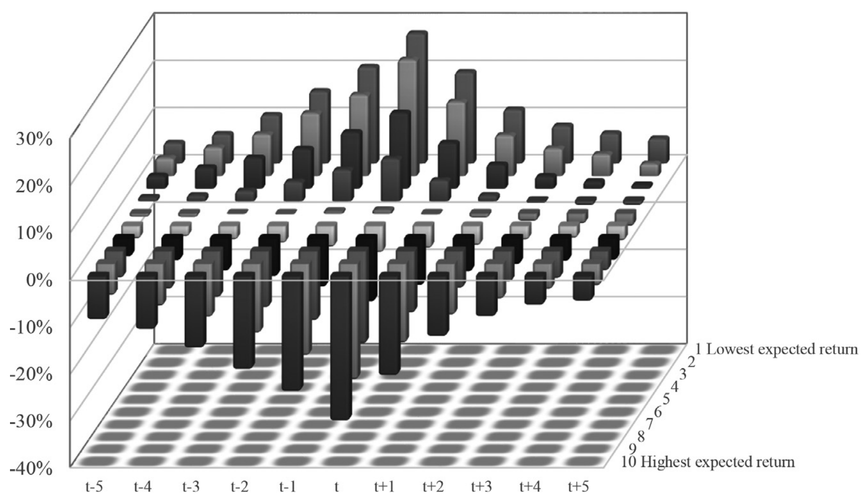
4.1. Data on mutual funds

Our monthly mutual fund net returns are based on the CRSP Survivor-Bias Free Mutual Fund Database, which lists all US mutual funds. Our sample includes only active equity and balanced funds. Sample period is from January 1, 1984 to the December 31, 2017. We combine different share classes of the same fund into a single fund using the Thomson Mutual Fund holdings database and the MFLINKS, available through the WRDS, similarly as Fama and French (2010). In addition, to be included in our sample, we require, as Linnainmaa (2013), that the mutual fund's combined net asset value has at some point in time exceeded $5 million in December 2017 dollars. This requirement is made in order to limit the effect of incubation bias (Evans, 2010). Table 2 provides the basic summary statistics of the variables used in this study.

4.2. Calendar-time regression

We start our analysis with the calendar-time portfolio approach by regressing all mutual funds' equal-weighted average returns on the returns from providing liquidity measure, R_{LP}, that is defined in Section 3, to see whether mutual fund returns on average are dependent on the returns from providing liquidity. As control variables, we use the CRSP value-weighted stock index return in excess of the risk-free rate, $(R_m - R_f)$, the Fama-French size (*SMB*)

A: ANcerno liquidity demanders' buy-sell ratios around the day *t*



B: ANcerno liquidity providers' buy-sell ratios around the day *t*

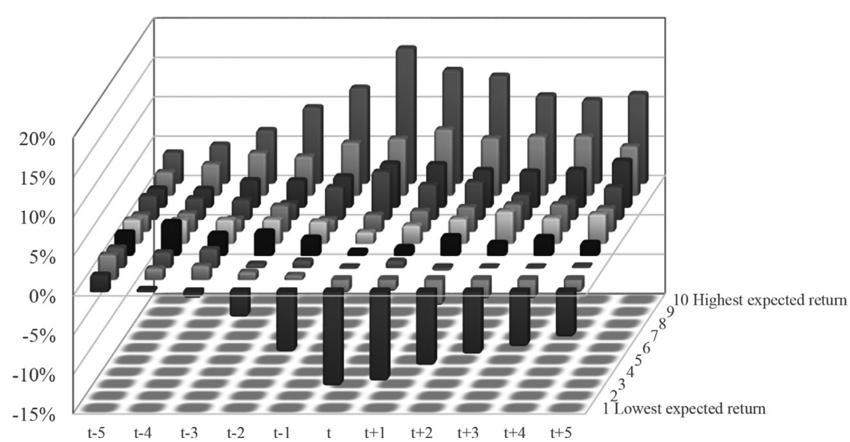


Fig. 2. Trading patterns of ANcerno liquidity demanders and providers. *Notes:* This figure shows how ANcerno liquidity demanders' (Panel A) and providers' (Panel B) buy-sell ratios vary during a 11-day window surrounding the day *t* in which we classify the stocks into deciles based on their 5-day expected returns. The results are shown separately for all the expected return deciles. We classify the institutions in the ANcerno dataset as ANcerno liquidity demanders and ANcerno liquidity providers, based on their past year's trades' dollar-weighted average 5-day expected returns. ANcerno liquidity demanders are institutions, who on average sell stocks that have a positive expected return and buy stocks that have a negative expected return. To be defined as an ANcerno liquidity demander, we require that their signed trades' volume-weighted expected return is significantly negative at 5% level (one-tailed test). Accordingly, ANcerno liquidity providers are defined as institutions, whose signed volume-weighted expected return is significantly positive. The stocks' expected returns are calculated as in the calculation of the R_{LP}. We calculate the ANcerno liquidity demanders' (providers') buy-sell ratios for every stock as the daily sum of their signed volumes, divided by their daily volume. For each day and for each expected return decile, we take the volume-weighted average of the stock specific buy-sell ratios. We report the time-series averages for each day in the 11-day window surrounding the day *t* for each expected return decile. Sample period is from January 2000 through December 2010 due to the availability of the ANcerno dataset.

Table 2
Descriptive statistics.

Mutual fund data	Mean	St.Dev.	1st quartile	Median	3rd quartile
Net monthly return (%)	0.64	4.74	-1.20	0.72	2.87
Monthly Flow / AUM (%)	0.74	9.98	-1.59	-0.35	1.37
Absolute Flow (%)	4.11	12.88	0.67	1.53	3.40
Annual turnover (%)	95.12	116.4	31.09	64.0	117.0
Flow correlation	0.18	0.27	-0.01	0.18	0.36

Notes: This table shows the descriptive statistics of the key variables used in the paper. *Flow / AUM* figures are calculated as in Frazzini and Lamont (2008). *Flow correlation* is the correlation of the fund's flow with the aggregate mutual fund flow calculated using the last two years' data. Data is on a monthly frequency except *Turnover* which is at an annual frequency. Our mutual fund sample includes active mutual funds that invest in equity. Active funds are as defined in Petajisto (2013) excluding funds that are flagged as index funds in CRSP. The sample period is from January 1984 through December 2017. Data is from the CRSP Mutual Fund database.

Table 3
Mutual funds' exposure to the returns from providing liquidity in calendar-time portfolios.

R_{LP}	-0.015	
	(-1.84)	
R_m-R_f	**0.732**	**0.733**
	(69.58)	(68.41)
SMB	**0.136**	**0.139**
	(9.43)	(9.69)
HML	0.014	0.016
	(0.76)	(0.88)
MOM	-0.020	-0.021
	(-1.33)	(-1.29)
R_{bond}	**0.169**	**0.161**
	(4.89)	(4.87)
Pastor-Stambaugh	**0.027**	**0.028**
	(2.11)	(2.10)
α (%)	-0.08	**-0.15**
	(-1.42)	(-2.89)
# observations	408	408

Notes: This table shows the results from calendar-time regressions in which mutual funds' equal-weighted monthly return in excess of the risk-free rate (R_i-R_f) is regressed on the returns from providing liquidity (R_{LP}) described in the text, the value-weighted US stock market index return in excess of the risk free rate (R_m-R_f), the Fama-French size (*SMB*) and value factors (*HML*), the momentum factor (*MOM*), a bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh (2003) liquidity factor. Risk free rate (R_f) is the one-month treasury bill rate. The bond return factor is downloaded from the Datastream, the Pastor-Stambaugh liquidity factor data is from Lubos Pastor's webpage and the other factor data is from Kenneth French's website. The *t*-statistics based on Newey West standard errors with 4 lags are shown below the coefficients, in parentheses. Sample period is from January 1984 through December 2017. All coefficients that are statistically significant at the 5% level are bolded.

and value (*HML*) factors, the Momentum factor (*MOM*), a bond return factor (R_b) calculated using Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh liquidity factor.

Whether mutual funds supply or demand liquidity can now be analyzed by running the following regression, where the mutual funds' average returns in excess of the risk-free rate, $R_t - R_f$, are regressed on the returns from providing immediacy, R_{LP}, and the above-mentioned K controls:

$$R_t - R_{f,t} = \alpha + \beta_1 R_{LP,t} + \sum_{k=1}^{K} \beta_k control_{k,t} + \varepsilon_t \quad (1)$$

Here ε_t denotes the error term.

As the results in Table 3 show, returns from providing liquidity coefficient is negative implying that mutual funds on average demand liquidity. Note also that when returns from providing liquidity variable is omitted, alpha is significantly negative. When it is included, alpha becomes insignificant.

4.3. Panel regression

Next, we consider the panel regression method. Panel regression provides an alternative estimate to calendar-time portfolio approach of the funds' overall exposure to the returns from providing liquidity. According to Petersen (2009) a panel regression with clustered standard errors gives unbiased estimates.

The results from a panel regression of Equation (2) are shown in Table 4. The controls are the same as in Equation (1).

$$R_{i,t} - R_{f,t} = \alpha + \beta_1 R_{LP,t} + \sum_{k=1}^{K} \beta_k control_{k,t} + \varepsilon_{i,t} \quad (2)$$

The results in Table 4 confirm our earlier finding that mutual funds on average demand immediacy. The fact that R_{LP} has a statistically significant negative coefficient even though we cluster the standard errors by fund and month is strong evidence that the negative dependence of fund returns on R_{LP} is a highly robust phenomenon. Furthermore, as in the calendar-time regressions, the average mutual fund alpha is insignificant when R_{LP} is included in the regression.

Table 4
Mutual funds' exposure to the returns from providing liquidity in a panel regression.

R_{LP}	**-0.028**	
	(-2.96)	
R_m-R_f	**0.746**	**0.745**
	(66.93)	(63.14)
SMB	**0.129**	**0.135**
	(8.94)	(9.17)
HML	0.023	0.026
	(1.38)	(1.57)
MOM	-0.019	-0.022
	(-1.64)	(-1.68)
R_{bond}	**0.246**	**0.236**
	(5.47)	(5.06)
Pastor-Stambaugh	**0.044**	**0.046**
	(3.71)	(3.67)
α (%)	-0.08	**-0.18**
	(-1.79)	(-3.69)
# observations	1,350,119	1,350,119

Notes: This table shows the results of panel regressions in which mutual funds' monthly return in excess of the risk-free rate (R_i-R_f) is regressed on common risk factors, and in the first specification also on the returns from providing liquidity (R_{LP}) described in the text. The risk factors used in the regressions are the value-weighted US stock market return in excess of the risk free rate (R_m-R_f), the Fama-French size (*SMB*) and value factors (*HML*), the momentum factor (*MOM*), the bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh liquidity factor. Risk free rate (R_f) is the one-month treasury bill rate. The bond return factor is downloaded from the Datastream, the Pastor-Stambaugh liquidity factor data are from Lubos Pastor's webpage, and the other factor data from Kenneth French's website. The *t*-statistics based on standard errors clustered by fund and month are shown in parentheses below the coefficients. Sample period is from January 1984 through December 2017. All coefficients that are statistically significant at the 5% level are bolded.

4.4. Fund by fund regressions

The panel and calendar-time approaches assume that all funds are exposed to R_{LP} equally and therefore can only give us an estimate of the average fund's behavior. To examine whether some funds demand and some supply liquidity, we next perform the regressions fund by fund :[20]

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{1,i} R_{LP,t} + \sum_{k=1}^{K} \beta_{k,i} control_{k,t} + \varepsilon_{i,t} \quad (3)$$

Here $\varepsilon_{i,t}$ denotes the fund-specific error term.

The results presented in Table 5 also support the conclusion that mutual funds on average demand liquidity in the stock market. The average coefficient of the returns from providing liquidity in the mutual fund return regression is negative (-0.03) and statistically very significant.

The benefit of the fund-by-fund regression methodology is that it allows us to examine differences in funds liquidity demand. In line with the previous results, we find that funds demand liquidity more commonly than supply it. The amount of individual funds that have a statistically significant negative exposure to R_{LP} at a five-percent confidence level to the returns from providing liquidity is 20.6%. This figure is statistically significantly higher than the threshold value 2.5%, which is the percentage of funds that we would expect to find to be statistically significantly negative (posi-

[20] To be included in the analysis, we require that the mutual funds have at least a 36-month return history.

tive) under the assumption that all funds in reality had zero exposure to the returns from providing liquidity.

We find also however that some funds supply liquidity. The fraction of funds with a positive coefficient to R_{LP}, i.e., funds that supply liquidity, equals 4.2%, which also significantly exceeds 2.5%. This implies that some funds supply, while others demand liquidity in the stock market. Proportion of funds having a negative coefficient (without requiring statistical significance) is 63.7%, consistent with the result that on average mutual funds demand liquidity. Additional evidence regarding mutual funds' demand for immediacy is presented in the Internet Appendix in Table A.4 and Table A.5.[21],[22]

The finding that mutual funds on average demand liquidity in these fund-by-fund regressions is highly robust. In the Internet Appendix, we study the robustness of this result using the bootstrapping methodology presented in Fama and French (2010). This robustness test allows us to analyze how cross-sectional correlations between funds affect the regression results. We find that when using the Fama and French (2010) methodology the bootstrapped t-statistics for R_{LP} is -8.1 as compared to the t-statistics of -19.3 from fund-specific regressions. Nonetheless, the estimate for the R_{LP} remains highly statistically significant. If we adjust the Fama and French (2010) methodology to allow for fund-specific sample periods, the bootstrapped *t*-statistics for the R_{LP} is -15.7. These results confirm that the result for fund-specific regressions in the Table 5, that the mean coefficient for R_{LP} is highly significantly negative, is robust.[23]

We show that the results shown in the panel B of the Table 5 are also robust. Using the critical values from the bootstrapped distributions instead of *t*-distribution we find that the proportions of funds with either significantly positive or negative coefficient to R_{LP} exceed significantly 2.5%. Recall again that 2.5% is the percentage of funds that we would expect to find to be statistically significantly negative (positive) under an assumption that all funds in reality had zero exposure to the returns from providing liquidity.

In the fund-by-fund regressions reported in Table 5, the average mutual fund alpha is negative. Its absolute value however is 14% smaller in the regressions where we include R_{LP}, thus controlling for the mutual funds' costs of immediacy, as compared to the average alpha from otherwise similar regressions that do not include R_{LP}. It is perhaps more relevant yet to look at the value-weighted average of the individual funds' alphas. In this case, the average alpha is very close to zero and insignificant when R_{LP} is included in the regressions and significantly negative when R_{LP} is not included. Hence also this analysis supports the idea that large part of the mutual funds' underperformance is related to their costs of immediacy.

Our results, thus consistently suggest that the observed mutual fund underperformance (significantly negative alpha), that has earlier been documented in the literature, is to a large extent due to a failure to account for the costs of immediacy from mutual funds' trading. Depending on the regression specification, our estimates of the costs of immediacy that mutual funds accrue lie between 1.0% to 1.9% p.a. These estimates are obtained by simply multiplying our estimate of the R_{LP} beta, shown in Tables 3 to 5, with the historical mean for the returns from providing liquidity, R_{LP}, during the sample period.

5. Factors that affect the active funds' demand for immediacy

5.1. Cross-sectional factors

Our approach makes it easy to explore factors that affect the mutual funds' demand for immediacy. Our basic premise is that a fund demands immediacy, and thus has costs of immediacy, if its R_{LP} beta is significantly negative, and that it demands more and has higher costs of immediacy the more negative its R_{LP} beta is. We conjecture also that funds with significantly positive R_{LP} betas earn more in returns from providing liquidity than what they suffer in costs of immediacy.

Our expectation is that mutual funds that have negative flows, flows that are highly correlated with other funds' flows, and high turnover funds should all have higher costs of immediacy than other funds. Second, we expect that funds, which heavily employ common dynamic trading strategies, such as momentum strategy, have higher costs of immediacy compared to other funds. Third, we expect large funds to experience larger costs of immediacy, as turning large portfolios is more costly. Finally, we expect high market beta funds (high beta reflecting lower cash positions we find) to suffer from costs of immediacy.

To investigate these issues, we repeat the fund-specific regressions defined in Equation (3), reported in Table 5, in non-overlapping 2-year time intervals. We test how the mutual funds' costs of immediacy depend on their portfolio and trading strategies. More specifically, we sort the funds in each 2-year sample period using their past 12-months' turnover, and their past betas for size, value, momentum, and market returns calculated using the previous 2-years of data, and fund size and monthly flows at the end of the sorting period. The results are presented in Fig. 3 and the related test statistics are shown in Table 6.

Table 6 and Fig. 3 show that:

1) High turnover mutual funds have high costs of immediacy. On the other hand, there is no evidence that low turnover funds suffer any costs of immediacy. The difference in the R_{LP} betas between the highest and lowest decile turnover funds is statistically significant at a 1% significance level.
2) Mutual funds which load heavily on the momentum factor have large costs of immediacy, and their R_{LP} betas are significantly lower than those of the funds that load least on the momentum. This finding, which clearly shows that mutual fund strategy matters for the costs of immediacy, is consistent with the previous finding in the literature that the transaction costs from following the momentum strategy are high; see e.g. Korajczyk and Sadka (2004) and Lesmond et al. (2004).
3) We find that the growth funds (funds with negative exposure to HML factor) have much higher costs of immediacy than value funds (positive exposure to the HML factor) and other funds. The differences are statistically highly significant.

[21] We examine the direction of funds' liquidity demanding trades by looking at the funds' exposure to the long and the short legs of R_{LP} separately. We find that 15.43% of funds appear to demand liquidity when purchasing, i.e., buy at high prices, and are afterwards significantly negatively exposed to the reversal profits proxied by the short leg return. Correspondingly, 9.36% of the funds demand liquidity when selling, selling at low prices, and thus underperform the market during the short-term reversals associated with the long-leg. 5.33% of funds buy at low prices, providing liquidity for other mutual funds, and are thus afterwards positively exposed to the long leg returns. 3.52% supply liquidity, selling at high prices, and overperform the market during the short-term reversals associated with the short-leg. The results are reported in full in the Internet Appendix.

[22] We also perform a Fama-MacBeth (1973) two-step regression to calculate the risk premium for R_{LP}. We find that it is negative and is equal to a third of the market risk premium in magnitude. In the second half of our sample R_{LP} risk premium is the only significant factor explaining fund returns and it also more than triples in magnitude when compared to the entire sample. This suggests that mutual funds' costs of immediacy have grown over time as the size of the industry has grown relative to the market. These results are reported in greater detail in the Internet Appendix. Fama-Macbeth regression results are shown in Table A5 in the Internet Appendix.

[23] This result is also robust to assuming an alternative factor model (the Fung and Hsieh (1997) mutual fund factor model, instead of the Carhart 4-factor model). In addition, as shown in the Internet Appendix, it is robust to assuming alternative proxies for the returns from providing liquidity presented in the literature.

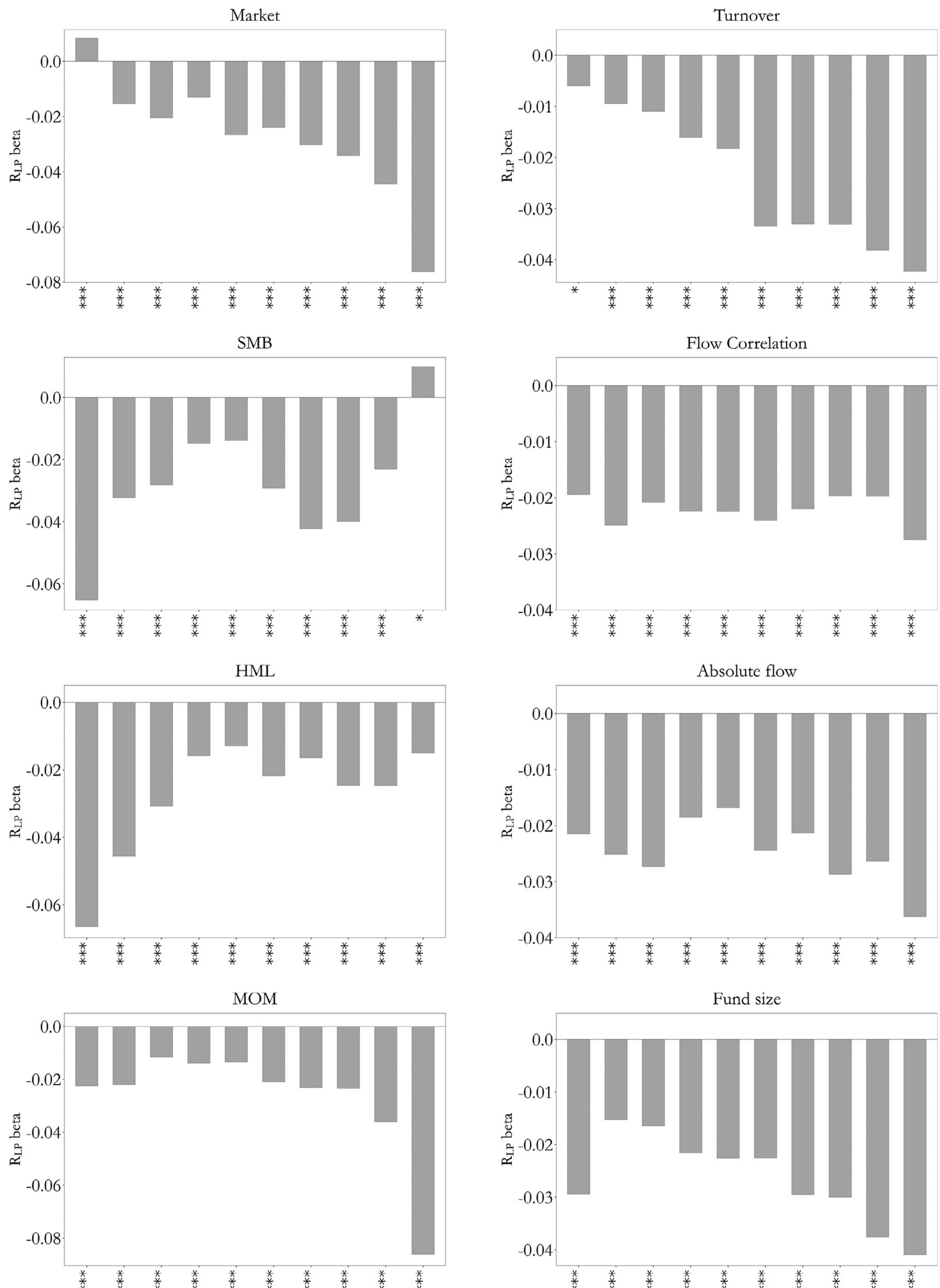


Fig. 3. Funds' costs of immediacy and fund characteristics. *Notes:* First fund-specific regressions similar to those in Table 5 without R_{LP} are performed over non-overlapping two-year intervals to obtain funds' factor betas (Market, SMB, HML, MOM). During the following two-year intervals, the regressions are repeated with R_{LP} included, to evaluate different types of funds' costs of immediacy. This figure shows the mean coefficients of R_{LP} across funds' past characteristics deciles, with the decile at the left having the smallest characteristic values. The considered characteristics are the fund's factor betas, fund's last sorting year's turnover, correlation of the fund's flow with the aggregate mutual fund flow, and the fund's absolute flow and size (measured at end of the sorting period). Here ***, ** or * are used to denote figures that are statistically significantly different from zero at 1%, 5% or 10% level.

Table 5
Mutual funds' exposure to the returns from providing liquidity in fund-specific regressions.

PANEL A	Equal-weighted coefficient	Equal-weighted coefficient	AUM-weighted coefficient	AUM-weighted coefficient
R_{LP}	**-0.021**		**-0.026**	
	(-19.29)		(-5.83)	
R_m-R_f	**0.792**	**0.792**	**0.745**	**0.745**
	(167.82)	(167.85)	(38.06)	(38.06)
SMB	**0.131**	**0.133**	**0.061**	**0.064**
	(39.06)	(40.2)	(4.38)	(4.69)
HML	**0.015**	**0.020**	**0.032**	**0.036**
	(4.31)	(5.98)	(2.29)	(2.55)
MOM	**-0.010**	**-0.014**	**-0.017**	**-0.210**
	(-7.71)	(-11.03)	(-3.19)	(-3.83)
R_{bond}	**0.231**	**0.228**	**0.288**	**0.282**
	(38.77)	(38.59)	(11.65)	(11.44)
Pastor-Stambaugh	**0.036**	**0.040**	**0.042**	**0.045**
	(25.59)	(27.23)	(7.30)	(7.28)
α (%)	**-0.16**	**-0.18**	-0.04	**-0.10**
	(-28.27)	(-42.96)	(-1.56)	(-5.50)
# of regressions	7,464	7,464	7,464	7,464

PANEL B	Funds with significantly negative coefficient	Funds with significantly positive coefficient	Aggregate AUM-weight of funds with a significantly negative coefficient	Aggregate AUM-weight of funds with a significantly positive coefficient
R_{LP}	**20.62%**	**4.16%**	28.26%	4.12%
	(100.26)	(9.22)		

Notes: Panel A shows the results from fund-specific regressions in which mutual funds' monthly return in excess of the risk-free rate (R_i-R_f), is regressed on the returns from providing liquidity (R_{LP}) described in the text, the value-weighted US stock market index return in excess of the risk free rate (R_m-R_f), the Fama-French size (*SMB*) and value factors (*HML*), the momentum factor (*MOM*), the bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh liquidity factor. Risk free rate (R_f) is the one-month treasury bill rate. The bond return factor is downloaded from the Datastream, the Pastor-Stambaugh liquidity factor data are from Lubos Pastor's webpage and the other factor data from Kenneth French's website. The equal- and AUM-weighted coefficient columns show the equal- and AUM-weighted average of the factor coefficients from the fund-specific regressions. The *t*-statistics for the equal-weighted mean coefficients are based on standard errors calculated from sample standard deviation $\hat{\sigma}$ as $\hat{\sigma}/\sqrt{n}$. The *t*-statistics for the value-weighted mean coefficients are based on standard errors calculated as $\hat{\sigma}/\sqrt{e}$, where $e = (\sum_{i=1}^{n} w_i)^2 / \sum_{i=1}^{n} w_i^2$ with $w_i, = 1 \ldots n$ being the weights. *t*-statistics are shown in parenthesis below the coefficients. Panel B shows the equal- and AUM-weighted proportions of individual funds for which the coefficient of R_{LP} is statistically significantly negative (positive) at a 5% level (two-tail test using Newey-West standard errors). The figures in parentheses below are *z*-statistics testing whether the proportion of funds is significantly different from 2.5% (which would be the proportion observed in case the R_{LP} and R_i-R_f are uncorrelated). Sample period is from January 1984 through December 2017. All coefficients that are statistically significant at the 5% level are bolded.

Da et al. (2011) come to similar conclusion looking at the costs of immediacy at a quarterly horizon.

4) Large-cap funds suffer from costs of immediacy. The R_{LP} betas of the lowest decile of funds sorted by the funds' *SMB* betas are significantly negative at 1% significance level. On the other hand, Small-cap funds earn returns from providing liquidity, although the positive R_{LP} beta is not statistically significant. This latter result is consistent with Keim (1999), which looks at the trading practices of one Small Cap fund, Dimensional Fund Advisors' 9-10 Fund.
5) We find that the low market beta funds earn returns from providing liquidity, while the high market beta funds have significant costs of immediacy. That is, the R_{LP} betas of the lowest decile of funds sorted by the funds' market betas are significantly positive, while the R_{LP} betas of the highest decile of funds are negative and significantly different from zero at 1% significance level. This finding is new and it is consistent with the idea that low market beta funds have larger cash holdings and thus less of a need to demand immediacy.
6) Large funds have higher costs of immediacy as we expected.
7) Magnitude of fund flows can also be expected to affect the costs of immediacy. In line with this, we find that funds with high absolute flows have higher costs of immediacy than funds with low absolute flows. The effect is statistically significant at 5% level.
8) It is plausible to think that the price impact from flow-induced trading, and thus the funds' costs of immediacy, are largest for those mutual funds whose flows are highly correlated with the other mutual funds' flows. To test this idea, we rank mutual funds into deciles based on the correlation of the fund's flow with the aggregate mutual fund flow calculated using the last two years' data. We find that funds whose flows correlate most with the aggregate flows suffer more from costs of immediacy. The effect is statistically significant at 5% level.

The differences in the realized costs of immediacy across fund types are large and often economically and statistically highly significant. For instance, the decile of funds that load the most heavily on momentum have an R_{LP} beta of -0.086, corresponding with annual costs of immediacy of 4.6%. Instead, the high market beta funds suffer 5.7% more in costs of immediacy compared to low beta funds. Funds exposed to large firms have 5% larger costs of immediacy than funds exposed to small firms.

From this research, it emerges that there are several factors that affect whether a mutual fund more commonly demands or supplies liquidity in the stock market. It appears that the important

Table 6
The effect of fund characteristics on R_{LP} betas and the funds' costs of immediacy.

Funds sorted by	Meandecile 1	Mean deciles 5&6	Mean decile 10	Difference deciles 10-1	Difference deciles 10-(5&6)	Difference deciles (5&6)-1	Costs of immediacy differences between deciles (positive number = cost)		
							10-1	10-(5&6)	(5&6)-1
Market	**0.008**	**-0.025**	**-0.076**	**-0.085**	**-0.051**	**-0.034**	5.67%	3.40%	2.27%
	(4.99)	(-9.87)	(-13.76)	(-15.09)	(-9.55)	(-9.04)			
SMB	**-0.065**	**-0.021**	0.009	**0.075**	**0.031**	**0.044**	-5.00%	-2.07%	-2.93%
	(-15.89)	(-11.27)	(1.70)	(10.51)	(6.37)	(11.04)			
HML	**-0.066**	**-0.017**	**-0.015**	**0.051**	0.002	**0.049**	-3.40%	-0.13%	-3.27%
	(-13.64)	(-11.64)	(-2.74)	(7.00)	(0.52)	(12.28)			
MOM	**-0.023**	**-0.017**	**-0.086**	**-0.064**	**-0.069**	0.005	4.27%	4.60%	-0.33%
	(-4.21)	(-11.90)	(-14.63)	(-7.99)	(-15.00)	(1.25)			
Turnover	-0.006	**-0.026**	**-0.042**	**-0.036**	**-0.016**	**-0.020**	2.40%	1.07%	1.33%
	(-1.74)	(-10.73)	(-11.34)	(-7.16)	(-3.79)	(-4.76)			
Fund Size	**-0.029**	**-0.023**	**-0.041**	**-0.012**	**-0.018**	0.007	0.80%	1.20%	-0.47%
	(-6.56)	(-15.34)	(-9.11)	(-2.28)	(-4.68)	(1.44)			
Absolute Flow	**-0.021**	**-0.021**	**-0.036**	**-0.015**	**-0.016**	0.001	1.00%	1.07%	-0.07%
	(-6.47)	(-8.54)	(-7.88)	(-2.63)	(-3.30)	(0.20)			
Flow	**-0.019**	**-0.023**	**-0.027**	**-0.008**	-0.004	-0.004	0.53%	0.27%	0.27%
Correlation	(-8.10)	(-13.21)	(-11.61)	(-2.39)	(-1.42)	(-1.27)			

Notes: First fund-specific regressions similar to those in Table 5 without R_{LP} are performed over non-overlapping two-year intervals to obtain funds' factor betas (market, SMB, HML, MOM). During the following two-year intervals, the regressions are repeated with R_{LP} included, to evaluate different types of funds' costs of immediacy. This table shows the mean coefficients of R_{LP} and the differences in the mean coefficients of R_{LP} between extreme and middle deciles of funds, sorted by the funds' past characteristics. The considered characteristics are the fund's factor betas, fund's last sorting year's turnover, correlation of the fund's flow with the aggregate mutual fund flow, and the fund's absolute flow and size (measured at end of the sorting period). The last 3 columns show the differences in the funds' estimated annual costs of immediacy across various characteristics deciles. The costs of immediacy are calculated as the negative of R_{LP} beta times the average annualized R_{LP} return. Positive figures imply costs of immediacy. Sample period is from February 1991 through December 2017. As there is an uneven number of years in our sample, we pooled the years 2015-2017 together. Figures that are statistically significant at 5% level are bolded.

determinants of this are a) the mutual fund's strategy and b) its size, c) fund flows and d) how correlated the fund's flows are with the industry flows.

5.2. Time variation in funds' costs of immediacy

5.2.1. Factors affecting funds' demand for liquidity

To examine how the funds' average costs of immediacy vary over time, we extend the panel regression (Equation 2) to include five conditioning variables. Namely, we now include dummies for NBER recessions and periods when the Pastor & Stambaugh liquidity measure is at least one standard deviation above its mean, and their interactions with R_{LP}. Third conditioning variable that we examine in a similar manner is the spread between 3-Month LIBOR based on US dollars and 3-Month Treasury Bill (TED spread). Fourth conditioning variable is broker-dealer leverage, as obtained from the FRED. Fifth conditioning variable is mutual fund flows to our sample funds.

Jylhä et al. (2014) find that the Pastor and Stambaugh liquidity measure affects reversals and hedge funds' propensity to supply liquidity. The role of financing conditions on costs of trading, as proxied by either TED spread or broker-dealer leverage, is highlighted e.g. in Anand et al. (2013), Jylhä et al. (2014), Jame (2016). Çötelioğlu et al. (2021), in turn, document evidence that hedge funds' tendency to supply liquidity is affected by the financing conditions. It is therefore natural to expect that financing conditions could also affect mutual funds' propensities to demand and supply liquidity. The financing conditions are often poorest in recessions.

Table 7 shows the results from such regressions and how the funds' exposure to R_{LP} varies over time.

As shown in Table 7, the coefficient for R_{LP} is most negative in illiquid markets (high Pastor and Stambaugh measure), during high TED spread or high broker-dealer leverage, and during the NBER recessions. This means that those are periods during which mutual funds demand liquidity the most. In a regression where we control for all the conditioning variables, only the interaction variables for the broker-dealer leverage and the TED spread are statistically significant at 1% level and large in magnitude. It thus seems that the mutual funds' demand for liquidity is most affected by the financial market conditions. As the alpha in the regressions where the TED spread is included is positive, these results also suggest that mutual funds' underperformance is driven to a large extent by their high costs of immediacy during periods when the liquidity is tight. At times of low funding liquidity, the funds' or their investors' demand immediacy from the equity market the most.

5.2.2. Rolling regressions

Several papers have examined mutual funds' demand for liquidity, mutual funds' trading costs, or persistence in funds' trading styles using transaction level data, see e.g., Edelen (1999); Anand et al. (2012) and (2013).[24] One of the closely related papers to ours is Anand et al. (2013). They use the ANcerno trading data to classify institutional investors into institutions that demand liquidity and institutions that supply liquidity. What they mean by liquidity demand and supply differs considerably from our definitions, however, and hence the results are not directly comparable. Their paper examines how institutions' trading style, characterized by the institutions' average positioning towards daily stock returns (that is being contrarian to contemporaneous daily equity returns or not), predicts funds' performance and stock market resiliency (how much trading impacts the contemporaneous prices).

Anand et al. (2013), as many others who examine institutions' demand for liquidity, or more generally their trading styles, is based on the ANcerno data that becomes available only from year 1999 onwards. Our methodology allows us to examine institutions' liquidity demand also in years before 1999, when quant trading was rare and hedge fund sector was undeveloped. It is interesting to see, if in our setting, the trading styles of mutual funds are persistent over time, when we also include the time prior to 1999. Perhaps this gives some indication of the robustness of the findings made also in other research papers that analyze institutions' trading styles with data that is available only post-1999.

[24] Papers looking at effects of institutions' lower frequency liquidity demand include Manconi et al. (2012), Greenwood and Nagel (2009), and Giannetti and Kahraman (2018).

Table 7
Time variation in mutual funds' exposure to the returns from providing liquidity

	(1)	(2)	(3)	(4)	(5)	(6)
R_{LP}	**-0.032**	-0.023	-0.017	0.002	-0.022	0.005
	(-3.05)	(-1.73)	(-1.67)	(0.16)	(-1.54)	(0.34)
R_{LP} * I(High P&S Level$_{t-1}$)	-0.039					-0.107
	(-0.38)					(-0.88)
R_{LP} * Absolute flow		-2.203				-0.517
		(-1.14)				(-0.28)
R_{LP} * NBER Recessions			**-0.047**			-0.028
			(-2.45)			(-1.31)
R_{LP} * TED spread				**-0.040**		**-0.046**
				(-2.77)		(-2.26)
R_{LP} * Leverage of broker-dealers					**-0.095**	**-0.163**
					(-2.11)	(-2.77)
I (High P&S Level$_{t-1}$)	0.002					0.002
	(0.01)					(0.21)
Absolute flow		0.159				0.058
		(1.42)				(0.49)
NBER Recessions			0.000			-0.000
			(0.00)			(-0.01)
TED spread				-0.000		0.000
				(-0.01)		(0.02)
Leverage of broker-dealers					-0.002	0.000
					(-0.46)	(0.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table shows the results of a panel regression in which mutual funds' monthly return in excess of the risk-free rate (*Ri-Rf*) is regressed on the returns from providing liquidity (R_{LP}), conditioning variables, their interactions with R_{LP}, and controls. The conditioning variables are dummies for lagged high level of the Pastor and Stambaugh (2003) liquidity measure *I* (*High P&S Level$_{t-1}$*) and the NBER recessions, the absolute of mutual fund flows to funds in our sample, the spread between 3-Month LIBOR based on US dollars and the 3-Month Treasury Bill (TED spread), and the leverage of broker-dealers. TED spread and the Leverage of the broker-dealers are obtained from the FRED. As controls we use the same variables as in Table 4. High Pastor and Stambaugh (*P&S*) periods are defined as being at least one standard deviation above the mean. The t-statistics based on standard errors clustered by fund and month are shown in parentheses below the coefficients. Sample period is from January 1991 through December 2017. All coefficients that are statistically significant at the 5% level are bolded.

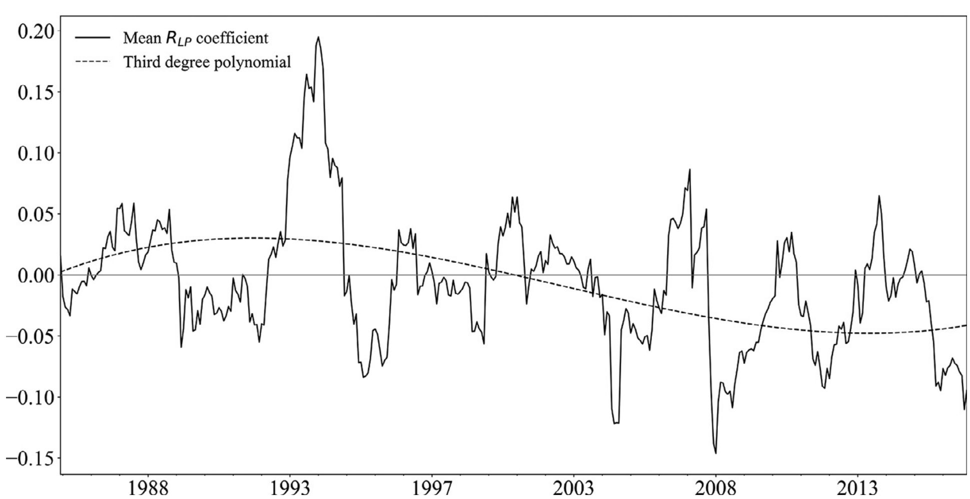


Fig 4. Rolling window regressions for funds' average exposure to R_{LP}. *Notes:* The figure shows the averages of the 24-months rolling window R_{LP} betas from fund-specific regressions, in which mutual funds' monthly return in excess of the risk-free rate (R_i-R_f), is regressed on common risk factors and the returns from providing liquidity (R_{LP}) described in the text. The risk factors used in the regressions are the value-weighted US stock market return in excess of the risk free rate (R_m-R_f), the Fama-French size (SMB) and value factors (HML), the momentum factor (MOM), the bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh liquidity factor. Risk free rate (R_f) is the one-month treasury bill rate. The bond return factor is downloaded from the Datastream, the Pastor-Stambaugh liquidity factor data are from Lubos Pastor's webpage, and the other factor data are from Kenneth French's website. Sample period is from January 1984 through December 2017. Dotted line shows a third-degree polynomial fit for the series.

What we find is that using our definition of liquidity demand and supply, pre-1999 mutual funds on average supplied liquidity. So, it appears that the mutual funds' average behavior in terms of their tendency to demand vs. supply liquidity has changed over time. It is only after 1999 that mutual funds started to more systematically demand liquidity. Factors that may contribute to this are first the emergence of the hedge fund industry after the mid 1990s, with superior ability to supply liquidity, and second, a decrease in the cost of demanding liquidity after the 2003 autoquote. Third potential factor can be an expansion in mutual funds' customer base over time to include less sophisticated investors that demand liquidity during market stress.

Using rolling regressions, Fig. 4 shows the average R_{LP} beta over time, while Fig. 5 shows the fraction of liquidity demanders and

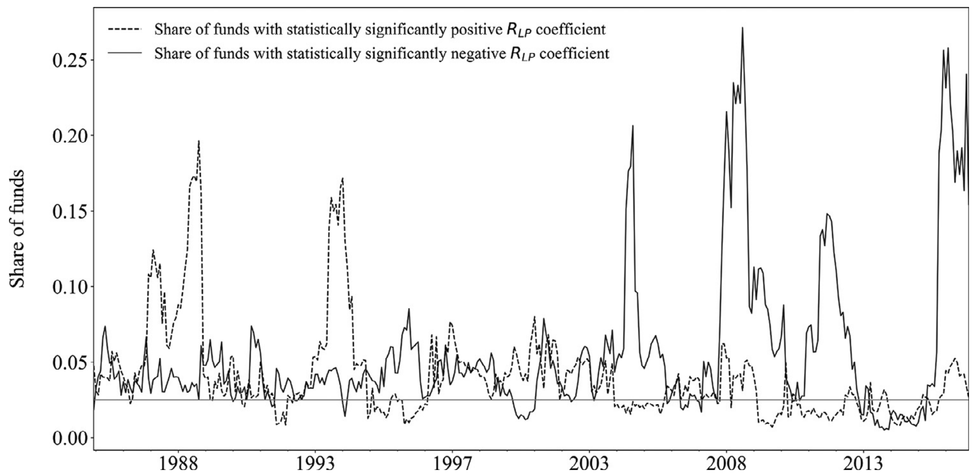


Fig. 5. Time-variation in the amount of liquidity demanders and liquidity suppliers in rolling regressions. *Notes:* The figure shows the shares of funds with significantly positive and significantly negative exposure to R_{LP} from 24-month rolling fund-specific regressions, in which mutual funds' monthly return in excess of the risk-free rate (R_i-R_f), is regressed on common risk factors and the returns from providing liquidity (R_{LP}) described in the text. The risk factors used in the regressions are the value-weighted US stock market return in excess of the risk-free rate (R_m-R_f), the Fama-French size (SMB) and value factors (HML), the momentum factor (MOM), the bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh liquidity factor. Risk free rate (R_f) is the one-month treasury bill rate. The horizontal line depicts the threshold value of 2.5%, which is the percentage of funds expected to be found to be statistically significantly negative (positive) under the assumption that all funds in reality had zero exposure to R_{LP}. The bond return factor is downloaded from the Datastream, the Pastor-Stambaugh liquidity factor data are from Lubos Pastor's webpage, and the other factor data from Kenneth French's website. Sample period is from January 1984 through December 2017.

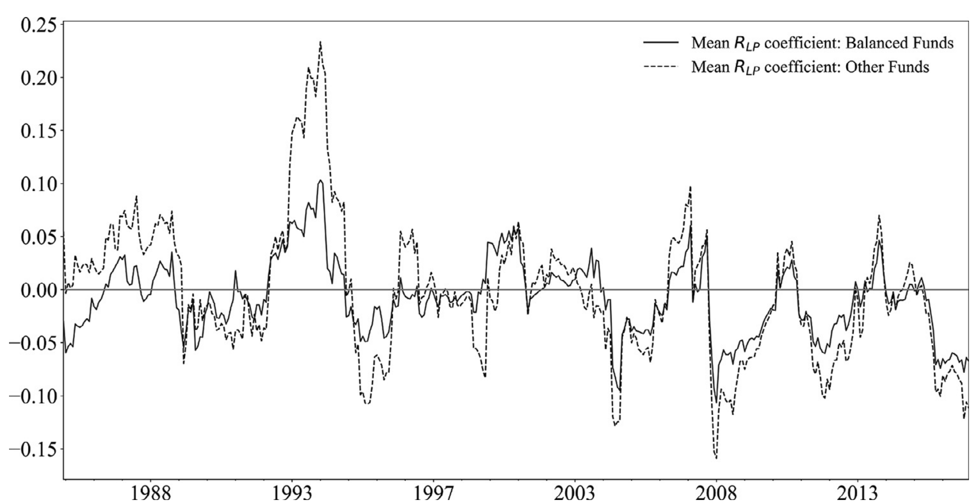


Fig. 6. Rolling window regressions for funds' average exposure to R_{LP} separately for balanced and other funds. *Notes:* The figure shows the averages of the 24-months rolling window R_{LP} betas from fund-specific regressions, in which mutual funds' monthly return in excess of the risk-free rate (R_i-R_f), is regressed on common risk factors and the returns from providing liquidity (R_{LP}) described in the text. Figures are shown separately for balanced and other funds. The risk factors used in the regressions are the value-weighted US stock market return in excess of the risk-free rate (R_m-R_f), the Fama-French size (SMB) and value factors (HML), the momentum factor (MOM), the bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh liquidity factor. Risk free rate (R_f) is the one-month treasury bill rate. The bond return factor is downloaded from the Datastream, the Pastor-Stambaugh liquidity factor data are from Lubos Pastor's webpage, and the other factor data from Kenneth French's website. Sample period is from January 1984 through December 2017.

suppliers. There seems to be waves of high aggregate liquidity demand and supply. First, there seems to be high demand for liquidity in the years 2003-2005. This may be linked to the Mutual Fund Scandal that occurred in late 2003 and took years to settle. Second, in line with Cella et al. (2013), we find that mutual funds appear to demand liquidity in the connection of the financial crisis in 2007-2009. Evidence of large liquidity demand following the Lehman Brothers collapse in 2008 is presented also in e.g., Hau and Lai (2017). Third, in years 2010-2012, the Euro crisis may be a factor behind the large liquidity demand at that time. Finally, the last spike in liquidity demand that we see right at the end of our sample is likely to be linked to large outflows from the mutual funds in our active fund sample in 2016-2018.[25]

Interestingly there is a large spike in liquidity supply around 1994. The spike in itself may be driven by the dropping of the 1991

[25] We examined the time variation in all funds' propensity to supply and demand liquidity also using regression analysis. The result that mutual funds supplied liquidity prior to 1999 is statistically significant. Results are available upon request.

Table 8
Balanced funds' exposure to the returns from providing liquidity in fund-specific regressions.

PANEL A	Equal-weighted coefficient	Equal-weighted coefficient	AUM-weighted coefficient	AUM-weighted coefficient
R_{LP}	**-0.025**		**-0.024**	
	(-12.52)		(-3.21)	
R_m-R_f	**0.596**	**0.595**	**0.616**	**0.616**
	(70.69)	(71.05)	(19.21)	(19.33)
SMB	**0.033**	**0.037**	-0.021	-0.018
	(7.47)	(8.21)	(-1.23)	(-1.05)
HML	**0.049**	**0.055**	**0.102**	**0.104**
	(9.92)	(11.29)	(5.38)	(5.58)
MOM	**-0.018**	**-0.021**	**-0.029**	**-0.031**
	(-8.61)	(-10.04)	(-3.52)	(-3.81)
R_{bond}	**0.333**	**0.331**	**0.344**	**0.337**
	(30.70)	(30.60)	(8.34)	(8.19)
Pastor-Stambaugh	**0.028**	**0.032**	**0.033**	**0.034**
	(13.33)	(14.36)	(4.14)	(4.02)
α (%)	**-0.17**	**-0.22**	**-0.08**	**-0.14**
	(-16.78)	(-28.24)	(-2.04)	(-4.83)

PANEL B	Funds with significantly negative coefficient	Funds with significantly positive coefficient	Aggregate AUM-weight of funds with a significantly negative coefficient	Aggregate AUM-weight of funds with a significantly positive coefficient
R_{LP}	**27.40%**	3.07%	33.35%	2.03 %
	(63.02)	(1.41)		

Notes: Panel A shows the results from fund-specific regressions in which balanced mutual funds' monthly return in excess of the risk-free rate (R_i-R_f) is regressed on common risk factors and the returns from providing liquidity (R_{LP}) described in the text. The risk factors used in the regressions are the value-weighted US stock market return in excess of the risk free rate (R_m-R_f), the Fama-French size (SMB) and value factors (HML), the momentum factor (MOM), the bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, and the Pastor-Stambaugh liquidity factor. Risk free rate (R_f) is the one-month treasury bill rate. The bond return factor is downloaded from the Datastream, the Pastor-Stambaugh liquidity factor data is from Lubos Pastor's webpage, and the other factor data from Kenneth French's website. The equal- and AUM-weighted coefficient rows show the equal- and AUM-weighted average of the factor coefficients from the fund-specific regressions. The t-statistics for the equal-weighted mean coefficients are based on standard errors calculated from sample standard deviation $\hat{\sigma}$ as $\hat{\sigma}/\sqrt{n}$. The t-statistics for the value-weighted mean coefficients are based on standard errors calculated as $\hat{\sigma}/\sqrt{e}$, where $e = (\sum_{i=1}^{n} w_i)^2 / \sum_{i=1}^{n} w_i^2$ with $w_i, = 1 \ldots n$ being the weights. t-statistics are shown in parenthesis below the coefficients. The table also shows the equal- and AUM-weighted proportions of individual funds for which the coefficient of R_{LP} is statistically significantly negative (positive) at a 5% level (two-tail test using Newey-West standard errors). The figures in parentheses below are z-statistics testing whether the proportion of funds is significantly different from 2.5% (which would be the proportion observed in case the R_{LP} and R_i-R_f are uncorrelated). Sample period is from January 1984 through December 2017. All coefficients that are statistically significant at the 5% level are bolded.

recession years from the rolling regressions. More interesting yet is the overall tendency of funds to supply more liquidity at that time, which is likely to be linked to the high returns from providing liquidity in the early part of our sample.

5.3. Balanced versus other funds

We find that balanced funds demand more immediacy than other funds. Their coefficient for R_{LP} is more negative on average than the coefficient for other funds, as shown in Table 8 (comparing it to Table 5), and the percentage of funds with significantly negative coefficient is larger. As of now, we know little about demand for liquidity and costs of liquidity for bond funds, with a notable exception of Anand et al. (2020), and we know nothing about the liquidity demand and supply for balanced funds. Interestingly, the patterns in liquidity demand are highly similar over time for the two types of funds, and consistently more pronounced for the balanced funds; see Figure 6. One potential explanation for this is that the customer base in balanced funds is more risk averse, which could lead them to demand more immediacy at times when investors collectively seek liquidity to lower their risks.

6. The effect of the costs of immediacy on cross-sectional alphas

The funds' costs of immediacy seem to affect the mutual funds' performance also in the cross-section as shown in Table 9.

Table 9 shows that both funds' past alphas and R_{LP} betas affect their alphas. The effect of R_{LP} beta is significant across all past alpha quintiles. The differences in alphas are also economically significant: For instance, the difference in 4-factor alphas between funds in the lowest quintile of both past alphas and R_{LP} betas and those in the highest is 3.4% p.a. In our sample, both past alphas, as in Huij and Verbeek (2007), and costs of immediacy predict future returns.[26]

We find also that the difference in alphas between highest and lowest R_{LP} beta decile funds increases at times of illiquidity. For instance, in years of illiquid time periods, i.e. in times of recessions, the difference in alphas between the extreme R_{LP} quintiles

[26] We estimate the lagged R_{LP} betas using the previous two years' data, similarly as we estimate (lagged) style betas in Section 5.1.

Table 9
Monthly alphas of double-sorted portfolios based on past alpha and past R_{LP} exposure.

Panel A. Alphas. All funds							
		R_{LP}					
		Low	2	3	4	High	High-Low
		-0.23	**-0.16**	**-0.17**	**-0.13**	**-0.12**	**0.11**
		(-24.84)	(-27.49)	(-37.65)	(-26.24)	(-13.33)	(8.72)
Past Alpha	Low	**-0.29**	**-0.26**	**-0.26**	**-0.21**	**-0.23**	0.06
		(-10.71)	(-14.80)	(-19.78)	(-13.54)	(-7.69)	(1.46)
	2	**-0.26**	**-0.19**	**-0.21**	**-0.17**	**-0.14**	**0.12**
		(-14.62)	(-18.48)	(-27.37)	(-18.17)	(-9.25)	(5.22)
	3	**-0.26**	**-0.15**	**-0.16**	**-0.14**	**-0.09**	**0.17**
		(-14.14)	(-16.33)	(-24.51)	(-15.87)	(-7.34)	(7.71)
	4	**-0.19**	**-0.11**	-0.13	**-0.10**	**-0.07**	**0.12**
		(-11.97)	(-11.23)	(-16.45)	(-9.69)	(-4.73)	(5.54)
	High	**-0.15**	**-0.08**	**-0.07**	**-0.06**	**-0.07**	**0.08**
		(-6.70)	(-5.54)	(-6.27)	(-4.28)	(-3.18)	(2.59)
Panel B. Alphas. Equity funds.							
		R_{LP}					
		Low	2	3	4	High	High-Low
		-0.12	**-0.08**	**-0.08**	**-0.06**	**-0.07**	**0.05**
		(-11.26)	(-13.06)	(-11.49)	(-8.60)	(-5.42)	(2.78)
Past alpha	Low	**-0.25**	**-0.15**	**-0.14**	**-0.12**	**-0.15**	0.10
		(-8.00)	(-7.79)	(-6.37)	(-5.21)	(-4.15)	(1.90)
	2	**-0.15**	**-0.12**	**-0.10**	**-0.11**	**-0.12**	0.03
		(-8.72)	(-10.26)	(-7.40)	(-8.55)	(-7.00)	(1.30)
	3	**-0.12**	**-0.07**	**-0.09**	**-0.06**	**-0.07**	**0.05**
		(-7.18)	(-5.97)	(-9.14)	(-5.03)	(3.98)	(1.97)
	4	**-0.09**	**-0.08**	**-0.05**	**-0.06**	**-0.06**	0.03
		(-4.72)	(-5.96)	(-4.02)	(-5.18)	(-3.62)	(1.00)
	High	0.01	-0.02	-0.02	**0.04**	0.03	0.02
		(0.36)	(-1.03)	(-0.96)	(2.05)	(1.00)	(0.45)

Notes: The table presents monthly average alphas (%) for the 25 double-sorted portfolios based on funds' past alphas and R_{LP} betas. In addition, in the last column we show the differences between the alphas for the extreme R_{LP} quintiles. Panel A presents the alphas for the entire sample, where the alphas and the past alphas are calculated using the Carhart (1997) model, that is extended with the bond return factor (R_{bond}), based on Barclays Capital Aggregate Bond index, in order to account for the presence of balanced funds in our sample. R_{LP} betas are calculated using the same model extended with the returns to providing liquidity (R_{LP}). Panel B presents the alphas for the subsample of funds investing only in equity (equity funds), where alphas and past alphas are calculated using the standard Carhart (1997) model. R_{LP} betas are calculated using the same model extended with the returns from providing liquidity R_{LP}. We perform these regressions separately for all non-overlapping two-year periods. As there is an uneven number of years in our sample, we pooled the years 2015-2017. All coefficients that are statistically significant at the 5% level are bolded. Sample period is from January 1991 to December 2017. The *t*-statistics are shown below the mean coefficients in parentheses.

is higher: 2.8% pa. vs. 0.94%. Our findings thus suggest that some funds have very high costs of immediacy in recessions.

7. Conclusions

We present evidence that some mutual funds systematically act as contrarian traders and earn returns in the stock market by providing liquidity to investors, while others systematically demand liquidity and suffer costs of immediacy. On average, the mutual funds' costs of immediacy exceed their returns from providing liquidity annually by up to 1.9% of the mutual funds' assets under management. This amount is sufficient to explain at large extent the mutual funds' historically observed underperformance.

We find that the funds with high turnover, high flows, flows that correlate with industry flows, high market beta funds, large funds, funds highly exposed to the momentum strategy and balanced funds suffer the most in costs of immediacy. Funds average cost of immediacy is time-varying and has increased over time. Finally, the funds' historical costs of immediacy significantly predict their Carhart 4-factor alphas.

Credit author statement

Anna Ignashkina, Kalle Rinne and Matti Suominen all participated in concept development, empirical research and writing.

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Declaration of Competing Interest

None.

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Supplementary materials

Supplementary data associated with this article can be found, in the online version, at doi:10.1016/j.jbankfin.2022.106430.

References

Alexander, G., Cici, G., Gibson, S., 2007. Does motivation matter when assessing trade performance? An analysis of mutual funds. Rev. Financ. Stud. 20, 125–150.
Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Market. 5, 31–56.
Amihud, Y., Goyenko, R., 2013. Mutual fund's R2 as predictor of performance. Rev. Financ. Stud. 26, 667–694.
Anand, A., Irvine, P., Puckett, A., Venkataraman, K., 2012. Performance of institutional trading desks: an analysis of persistence in trading costs. Rev. Financ. Stud. 25, 557–598.
Anand, A., Irvine, P., Puckett, A., Venkataraman, K., 2013. Institutional trading and stock resiliency: evidence from the 2007-2009 financial crisis. J. Financ. Econ. 108, 773–797.
Anand, A., Jotikasthira, C., Venkataraman, K., 2020. Mutual fund trading style and bond market fragility. Rev. Financ. Stud. 6, 2993–3044.
Avramov, D., Chordia, T., Goyal, A., 2006. Liquidity and autocorrelations in individual stock returns. J. Finance 61, 2365–2394.
Bhattacharya, U., Lee, J., Pool, V., 2013. Conflicting family values in mutual fund families. J. Finance 68, 173–200.
Ben-Rephael, A., Kandel, S., Wohl, A., 2011. The price pressure of aggregate mutual fund flows. J. Financ. Quant. Anal. 46, 585–603.
Busse, J., Chordia, T., Jiang, L., Tang, Y., 2020. Transaction costs, portfolio characteristics, and mutual fund performance. Manag. Sci. (forthcoming).
Campbell, J., Grossman, S., Wang, J., 1993. Trading volume and serial correlation in stock returns. Q. J. Econ. 108, 905–939.
Cella, C., Ellul, A., Giannetti, M., 2013. Investors' horizons and the amplification of market shocks. Rev. Financ. Stud. 26, 1607–1648.
Choi, J., Zhao, K., 2021. Carhart (1997) Mutual fund performance persistence disappears out of sample. Crit. Finance Rev. (forthcoming).
Chordia, T., Subrahmanyam, A., 2004. Order imbalance and individual stock returns: theory and evidence. J. Financ. Econ. 72, 485–518.
Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. J. Financ. Econ. 86, 479–512.
Cremers, M., Pejajisto, A., 2009. How active is your fund manager? A new measure that predicts performance. Rev. Financ. Stud. 22 (9), 3329–3365 September 2009.
Çötelioğlu, E., Franzoni, F., Plazzi, A., 2021. What constraints liquidity provision? Evidence from institutional trades. Rev. Finance 25, 485–717.
Da, Z., Gao, P., Jagannathan, R., 2011. Impatient trading, liquidity provision, and stock selection by mutual funds. Rev. Financ. Stud. 24, 675–720.
Demsetz, H., 1968. The cost of transacting. Q. J. Econ. 82, 33–53.
Dong, X., Feng, S., Sadka, R., 2019. Liquidity risk and mutual fund performance. Manag. Sci. 65 (3), 1020–1041.
Edelen, R., 1999. Investor flows and the assessed performance of open-end mutual funds. J. Financ. Econ. 53, 439–466.
Edelen, R., Evans, R., Kadlec, G., 2013. Shedding light on 'invisible costs': trading costs and mutual fund performance. Financ. Anal. J. 69, 33–44.
Evans, R., 2010. Mutual fund incubation. J. Finance 65, 1581–1611.
Fama, E., French, K., 2010. Luck versus skill in the cross-section of mutual fund returns. J. Finance 65, 1915–1947.
Fama, E., MacBeth, J., 1973. Risk, return, and equilibrium: Empirical tests. J. Polit. Econ. 81 (3), 607–636.
Frazzini, A., Lamont, O., 2008. Dumb money: mutual fund flows and the cross-section of stock returns. J. Financ. Econ. 88, 299–322.
Frazzini, A., Israel, R., Moskowitz, T., 2015. Trading costs of asset pricing anomalies. AQR working paper doi:10.2139/ssrn.2294498.
Fung, W., Hsieh, D., 1997. Empirical characteristics of dynamic trading strategies: the case of hedge funds. Rev. Financ. Stud. 10, 275–302.
Giannetti, M., Kahraman, B., 2018. Open-end organizational structures and limits to arbitrage. Rev. Financ. Stud. 31, 773–810.
Greenwood, R., Nagel, S., 2009. Inexperienced investors and bubbles. J. Financ. Econ. 93, 239–258.
Grossman, S., Miller, M., 1988. Liquidity and market structure. J. Finance 43, 617–633.
Hameed, A., Mian, G., 2015. Industries and stock return reversals. J. Financ. Quant. Anal. 50, 89–117.
Hasbrouck, J., 2009. Trading costs and returns for U.S. equities: estimating effective costs from daily data. J. Finance 64 (3), 1445–1477.
Hau, H., Lai, S., 2017. The role of equity funds in the financial crisis propagation. Rev. Finance 21, 77–108.
Hendershott, T., Jones, C., Menkveld, A., 2009. Does algorithmic trading improve liquidity? J. Finance 66, 1–33.
Huij, J., Verbeek, M., 2007. Cross-sectional learning and short-run persistence in mutual fund performance. J. Bank. Finance 31, 973–997.
Jame, R., 2016. Liquidity provision and the cross section of hedge fund returns. Manag. Sci. 64 (7), 2973–3468.
Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. J. Finance 45, 881–898.
Jegadeesh, N., Titman, S., 1995. Short-horizon return reversals and the bid-ask spread. J. Financ. Intermed. 4, 116–132.
Jensen, M.C., 1968. The performance of mutual funds in the period 1945-1965. J. Finance 23, 389–416.
Jones, R.C., Wermers, R., 2011. Active management in mostly efficient markets. Financ. Anal. J. 67, 29–45.
Jylhä, P., Rinne, K., Suominen, M., 2014. Do hedge funds supply or demand liquidity? Rev. Finance 18, 1259–1298.
Kacperczyk, M., Sialm, C., Zheng, L., 2006. Unobserved actions of mutual funds. Rev. Financ. Stud. 21, 2379–2416.
Keim, D., 1999. An analysis of mutual fund design: the case of investing in small-cap stocks. J. Financ. Econ. 51, 173–194.
Khandani, A., Lo, A., 2007. What happened to the quants in August 2007? J. Invest. Manag. 5, 5–54.
Khandani, A., Lo, A., 2011. What happened to the quants in August 2007? Evidence from factors and transactions data. J. Financ. Market. 14, 1–46.
Koch, A., Ruenzi, S., Starks, L., 2016. Commonality in liquidity: a demand-side explanation. Rev. Financ. Stud. 29, 1943–1974.
Korajczyk, R., Sadka, R., 2004. Are momentum profits robust to trading costs? J. Finance 59, 1039–1082.
Lehmann, B., 1990. Fads, martingales, and market efficiency. Q. J. Econ. 105, 1–28.
Lesmond, D., Schill, M., Zhou, C., 2004. The illusory nature of momentum profits. J. Financ. Econ. 71, 349–380.
Linnainmaa, J., 2013. Reverse survivorship bias. J. Finance 68, 789–813.
Lou, D., 2012. A flow-based explanation for return predictability. Rev. Financ. Stud. 25, 3457–3489.
Manconi, A., Massa, M., Yasuda, A., 2012. The role of institutional investors in propagating the crisis of 2007-2008. J. Financ. Econ. 104, 491–518.
McLean, R.D., Pontiff, J., 2016. Does academic research destroy stock return predictability? J. Finance 71, 5–32.
Malkiel, B., 1995. Returns from investing in equity mutual funds 1971 to 1991. J. Finance 50, 549–572.
Nagel, S., 2012. Evaporating liquidity. Rev. Financ. Stud. 25, 2005–2039.
Novy-Marx, R., R, Velikov, M., 2016. A taxonomy of anomalies and their trading costs. Rev. Financ. Stud. 29 (1), 104–147.
Pastor, L., Stambaugh, R., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 111, 642–685.
Petersen, M., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Rev. Financ. Stud. 22 (1), 435–480.
Puckett, A., Yan, X., 2011. The interim trading skills of institutional investors. J. Finance 66, 601–633.
Sadka, R., 2006. Momentum and post-earnings announcement drift anomalies: the role of liquidity risk. J. Financ. Econ. 80, 309–349.
Wermers, R., 2000. Mutual fund performance: an empirical decomposition into stock-picking talent, style, transaction costs, and expenses. J. Finance 55, 1655–1695.