Do Mutual Funds Supply or Demand Immediacy?*

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February 12 2013

We estimate a proxy for the returns to market makers from providing immediacy by looking at the returns to a zero-investment contrarian long-short trading strategy that utilizes short-term return reversals. These market makers' returns from providing immediacy correspond with costs of immediacy to other investors. We then estimate the net returns mutual funds make from providing immediacy (or lose in costs of immediacy) by running regressions, fund by fund, where we explain the mutual funds' monthly returns with our estimate of the monthly returns from providing immediacy. We find that, on average, equity mutual funds lose annually 0.3%-0.6% of their assets under management in costs of immediacy. Mutual funds' costs of immediacy vary significantly by fund strategy and depend on the fund flows. The mutual funds with large outflows, funds whose flows correlate with industry flows, and the mutual funds that are highly exposed to momentum strategy suffer most from the costs of immediacy. Mutual funds' historical costs of immediacy affect their future alphas.

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* These results were in part earlier presented in our working paper "Short-term reversals, returns from providing immediacy and the costs of immediacy." We thank Robin Greenwood, Antti Ilmanen, Zhiguo He, Petri Jylhä, Ron Kaniel, Matti Keloharju, Juhani Linnainmaa, Patrik Sandås, Jos van Bommel and the seminar participants at the Aalto University School of Economics, Bank of Finland, Luxembourg School of Finance, French Finance Association meetings in St. Malo and the Econometric Society World congress in Shanghai for their comments. Contact details of the authors: Kalle Rinne: Address: Luxembourg School of Finance / University of Luxembourg, 4 Rue Albert Borschette, L-1246 Luxembourg, Luxembourg, E-mail: kalle.rinne@uni.lu. Matti Suominen: Address: Aalto University School of Economics, P.O. Box 21210, FI-00076 Aalto, Finland. E-mail: matti.suominen@aalto.fi, tel.: +358-50-5245678.

1. INTRODUCTION

Academic research has documented significant stock return reversals at one-week and one-month horizons (See, e.g., Jegadeesh, 1990, and Lehmann, 1990). The Finance literature links the short-term return reversals with imperfect liquidity in financial markets (See, e.g., Grossman and Miller, 1988). In illiquid markets, short-term return reversals emerge from transitory investors' portfolio imbalances, due to imperfect risk-bearing ability of market makers. For instance, when an investor with an urgent need to sell a given stock arrives at the stock market, the stock price must temporarily decline below its fundamental value to induce market makers to provide immediacy, i.e., to become counterparties to the investor's trades and clear the market. Later, when new investors arrive at the market, prices revert to fundamentals.

A statistical arbitrageur can also act as a market maker. Having estimated short-term return reversal patterns using past data, observing recent past returns, he can also provide immediacy to the stock market by shorting the stocks with the lowest expected future returns (stocks that have gone up) and by taking a long position in the stocks with the highest expected future returns (stocks that have gone down). Following this logic, along with the recent literature, see e.g., Nagel (2012), we proxy for the returns from providing immediacy by the returns to a zero-investment contrarian long-short trading strategy. More precisely, we look at a long-short trading strategy that sells short all stocks with a negative expected return, where the expected returns are estimated using past returns and past estimates of return reversal, and goes long in all the stocks with positive expected returns. Consistent with the findings in the literature, see e.g. Khandani and Lo (2011), the monthly returns to our immediacy providing contrarian

trading strategy are significantly positive. These returns from providing immediacy correspond with costs of immediacy to the counterparties of the trades.

The question that we ask in this paper is whether mutual funds make more returns from acting time to time as market makers, and thus providing immediacy in the stock market, than they suffer in the costs of immediacy. This is an empirical question: On the one hand, the mutual fund managers are well-trained professionals who closely monitor the market. As such they are well equipped to supply immediacy in the stock market when other investors require immediacy. On the other hand, unlike hedge funds, which typically require early notification for withdrawals, mutual funds often face sudden redemptions and thus may well have to execute their orders in a hurry, thus suffering from the costs of immediacy. In addition, the execution of many of their dynamic trading strategies lead to costs of immediacy.

Our approach to estimating whether mutual funds more commonly make returns from providing immediacy, or suffer costs of immediacy, is to run regressions, fund by fund, where we explain the mutual funds' monthly returns with our estimate of the monthly returns from providing immediacy. If the regression coefficient is significantly positive, we conclude that the fund more commonly supplies immediacy, if the coefficient is significantly negative we argue the fund typically demands immediacy. The size of the regression coefficient and the average returns from providing immediacy can then be used to estimate the dollar amount of the net returns from providing immediacy (costs of immediacy) for any given mutual fund.

Our results from such regressions indicate that for most equity mutual funds the costs of immediacy exceed their returns from providing immediacy - and that the equity mutual funds have lost, on average, 0.3%-0.6% of their assets under management annually in the costs of immediacy (net of the returns that they make from providing immediacy). We find, as expected, that the funds' costs of immediacy are larger for those funds that experience outflows, and for funds, whose flows correlate highly with the industry flows. In addition, we find that the mutual funds' costs of immediacy depend significantly on the fund's strategy. One further finding is that our measure of the mutual funds' costs of immediacy predicts the funds' alphas: The funds that historically suffered the least costs of immediacy have significantly larger future alphas than the funds that historically suffered the most costs of immediacy.

Our paper is related to several strands of literature. First, it builds upon the extensive literature documenting short-term stock return reversals, and the research that relates the reversals to investors' demand for immediacy in the stock market, see Grossman and Miller (1988), Campbell, Grossman and Wang (1993), Jegadeesh and Titman (1995), Chordia and Subrahmanyam (2004) and Avramov, Chordia and Goyal (2006). Second, it is related to the research that estimates the available returns to immediacy-providing trading strategies, such as Khandani and Lo (2007, 2011) and Nagel (2012). Most closely it is related to Jylhä, Rinne and Suominen (2012). By using the same methodology as we do, they find that hedge funds on average make positive returns from supplying immediacy in the stock market.

Our paper is also closely related to the prior literature that evaluates mutual funds' trading costs. In their pioneering work, Edelen (1999) and Wermers (2000) find that mutual funds lose significantly on trading costs. They argue, as we do, that the mutual funds trading losses can be attributed to the funds' need for immediacy that is caused by the in- and outflow of funds to the mutual funds. Our results complement and extend their results. Importantly, our methodology allows us to study the extent of the costs of immediacy using a much more comprehensive sample of funds compared to, say, Edelen (1999): more than four thousand equity funds versus the 166 in his sample. The second advantage of our approach is the small data requirement. Our methodology requires information only on fund returns, whereas Wermers (2000) had to rely on data on mutual funds' holdings as well as outside estimates of mutual funds' trading costs. One must note, however, that compared to the two aforementioned papers, we aim to look at a different question: we try to estimate the mutual funds' net trading revenues (costs) from providing (demanding) immediacy, whereas the focus in Edelen (1999) and Wermers (2000) is only on the costs of trading.

One shortcoming of our approach is that it only reveals information of the average costs of immediacy (or the average returns from providing immediacy) for a mutual fund in any given period of time. In reality, sometimes a given fund supplies and at other times it demands immediacy in the stock market: thus sometimes it makes returns from immediacy and at other times suffers costs of immediacy. This makes it difficult to detect the funds' full exposure to our proxy for the returns from providing immediacy. We deal with this problem in two ways: by estimating the coefficients over shorter non-overlapping time periods and by conditioning our estimates on fund flows. For a large

fraction of the funds we are thus able to statistically significantly detect the funds' average exposure to the returns from providing immediacy.

Our approach allows us to look at how the mutual funds' costs of immediacy depend on their trading strategies as well as on other conditioning variables. Da, Gao and Jagannathan (2010), using data on mutual funds' quarterly holdings, find that some funds, notably the Dimensional Fund Advisors, make returns by providing immediacy, while others, such as index funds, suffer from the costs of immediacy. Their results complement the earlier findings of Keim (1999) related to the Dimensional Fund Advisors. Using our approach we can find additional evidence on which types of funds supply and which demand immediacy in the stock market. We also find that index funds' demand immediacy, as we find that their tracking error is negatively related to our proxy for the returns from providing immediacy at times of index revisions. In addition, we find, for instance, that funds that are heavily exposed to the momentum factor suffer significant costs of immediacy (during our entire sample period such funds' costs of immediacy are on average minus 2.2% p.a.).

There are yet other papers that provide evidence of the time varying costs of immediacy for mutual funds: For instance, Coval and Stafford (2007) and Hau and Lai (2012) show that large mutual fund outflows and inflows cause price pressure in the stocks that the mutual funds' hold, leading to costs of immediacy. Their findings are consistent with our finding that the main source of the costs of immediacy for mutual funds is fund outflows. Zhang (2009), in turn, shows that some mutual funds gain by providing immediacy to distressed funds, i.e. funds having larger outflows. Other papers related

to mutual funds' cost of trading include Alexander, Cici and Gibson (2007), who show that trades motivated by funds' liquidity needs or funds' excess liquidity underperform the market. Ben-Rephael, Kandel and Wohl (2011), in turn, find that aggregate mutual fund flows create price pressure. Closely related is also Koch, Ruenzi and Starks (2010), which shows that mutual fund trading causes commonality to liquidity.

Our main contribution to the literature is to apply a new methodology to estimate the mutual funds' costs of immediacy (net of their returns from providing immediacy), and present new evidence on the important question of which types of mutual funds demand and which supply immediacy in the financial markets. Another contribution is to show that mutual funds' historical costs of immediacy predict the funds' alphas. Our results also indicate that the costs of immediacy suffered by the mutual fund industry are economically significant. According to our estimates, forty-five percent of the mutual funds' historical underperformance to the US value weighted stock market index is due to costs of immediacy.

Our paper is organized as follows: In section 2, we document the time-varying, short-term mean reversion in stock returns and study the returns from providing immediacy. In Section 3 we present our main results related to the costs of immediacy to mutual funds. Section 4 concludes the paper.

2. Measuring the returns from providing immediacy

2.1. Data

For the estimation of the stock return reversal patterns, our dataset includes all stocks listed in the daily CRSP file from the 1st of January 1983 to 31st December 2008, which fulfill the following requirements: 1) the security is an ordinary common stock, 2) the company is incorporated in the US, 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 and French 48 industries, excluding the industry Other. Further, when estimating the returns from providing immediacy, we make additional data restrictions to reduce noise in our estimates. First, we remove from our sample all stocks that belong to the smallest decile of all US-incorporated common stocks listed on the NYSE or the Amex. Second, we eliminate penny stocks by removing from our sample all stocks that have a share price below five dollars. Finally, we require that a stock must have a positive trading volume during each day when a position in the stock is presumably opened.

2.2. Short-term return reversal

To estimate the return reversal patterns in excess returns we perform for each day a cross-sectional regression, in which we regress the stocks' (indexed by *i*) next 5-days' (one week) excess returns following the close on day *t*, $R_{i,t+5}$, on each of the stocks' past 20 days' (one month) excess returns, $R_{i,t-\tau}\, R_{i,t-\tau}$, where $\tau \in \{0,..19\}$, and vector of controls $C_{i,t}$:

$$R_{i,t+5} = \alpha_t + \sum_{\tau=0}^{19} \beta_{t-\tau} R_{i,t-\tau} + \beta_{t,C} C_{i,t} + \varepsilon_{i,t}. \quad (1)$$

Here α_t is the intercept in the regression, while $\varepsilon_{i,t}$ is a stock specific error term. As controls in the baseline regression we use two variables that are constructed by multiplying the past months' (20-days') excess returns with either the stocks' monthly (log of) trading volume or the firms' (log of) market capitalization at time *t*.[1]

An estimate of the short-term expected excess returns due to return reversals, following day *t,* is then obtained by combining the estimated coefficients $\hat{\beta}_{t-\tau}$ and $\hat{\beta}_C$ from equation (1), estimated with data up to period *t*, with the last 20-days' returns and the values of the controls at time *t*.

When estimating equation (1) we calculate the excess returns by deducting from stocks' returns the returns to a corresponding equal-weighted Fama and French 48 industry index. We define our excess returns relative to industry indices as in this case the excess returns for stocks are more likely due only to price pressure from trading and not information. Our approach is in this respect similar to that of Hameed and Mian (2012) who also define excess returns relative to industry indices.[2]

Rinne and Suominen (2012) show that a model's explanatory power to forecast short-horizon returns improves significantly when we include each of the past twenty days' returns in a forecasting regression instead of just the past month's (roughly twenty days) return as is commonly done. In addition, they show evidence that the mean

[1] These two controls are motivated by the findings presented Campbell, Grossman, and Wang (1993), Pástor and Stambaugh (2003) and Khandani and Lo (2011). Inclusion of the controls does not materially
[2] In the cross-sectional regressions of equation (1) at any given date *t*, we include only stocks that belong to the same Fama and French industry index during the entire 25-day estimation interval.

reversion in excess returns is gradual, suggesting that optimal contrarian trading strategies that provide immediacy might have longer trading horizon than one day (as is assumed in Khandani and Lo, 2011). This turns out to be the case, motivating our choice to forecast 5-days' as opposed to one day's returns in regression (1). Additional motivation for the five day trading horizon in estimating the returns from providing immediacy is presented in the next section of the paper.

The estimated average coefficients $\hat{\beta}_{t-\tau}$ from regression (1) are all negative and statistically highly significant, showing that there is a large amount of mean reversion in the data. In addition, the coefficient for the second control is significant and has the expected sign given the results presented in Khandani and Lo (2011): the coefficient of market capitalization interacted with past month's return is positive. Although the coefficient for the first control is not on average statistically significantly different from zero, we include this control in our regression as it is statistically significant (at 10% level) in as many as forty percent of the daily cross-sectional regressions. It is not significant in the entire sample as in the early sample period the sign for this coefficient is positive but it turns negative in the 1990s. It makes no difference to our results if we leave out this control variable from our regressions. The regression results are presented in Table 1 below.

[Insert Table 1]

Next, we use these results on the return reversal patterns to estimate the available returns from providing immediacy.

2.3. Estimating the returns from providing immediacy

Similarly as e.g. Khandani and Lo (2011) and Nagel (2012), we proxy for the available returns from providing immediacy, R_{IMM}, by the return to a zero-investment contrarian long-short trading strategy that utilizes short-term return reversals. More precisely, our proxy for R_{IMM} is the monthly return to a zero-investment long-short trading strategy where every day a long position is opened in stocks with a positive expected 5-day return and a short position is opened in stocks with a negative expected 5-day return. After 5 days, such positions are closed. We focus on an immediacy providing trading strategy where all positions are closed after 5-days (one week) as this, using our portfolio rule (discussed below), results in a higher Sharpe-ratio after accounting for estimated transaction costs than otherwise similar trading strategies where positions are closed after one day (as in Khandani and Lo, 2011) or one month, as shown in Table A1 in the Appendix. Given this, this is the strategy that would be applied by funds that supply immediacy. We do not experiment with other holding periods. Our approach here is identical to that in Jylhä, Rinne and Suominen (2012).

Lehman (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, these portfolio weights effectively correspond with stocks' expected excess returns. In line with their approach, and Jylhä, Rinne and Suominen (2012), we also use the stocks'

expected 5-day excess returns evaluated at time *t,* denoted by $E_t(R_{i,t+5})$, as portfolio weights when forming the long and the short portfolios.[3]

Now, given *N* stocks in the universe of potential stocks where positions can be taken on day *t*, the assumed portfolio weights $\omega_{i,t}^{L}$ in the long and $\omega_{i,t}^{S}$ in the short portfolios on day *t* are

$$\omega_{i,t}^{L} = \frac{I_{E_t(R_{i,t+5})>0} E_t(R_{i,t+5})}{\sum_{j=1}^{N} \left| I_{E_t(R_{j,t+5})>0} E_t(R_{j,t+5}) \right|}$$
$$\omega_{i,t}^{S} = \frac{I_{E_t(R_{i,t+5})<0} E_t(R_{i,t+5})}{\sum_{j=1}^{N} \left| I_{E_t(R_{j,t+5})<0} E_t(R_{j,t+5}) \right|}. \quad (2)$$

Here I_Z denotes an indicator function that equals one if *Z* is true and zero otherwise.

When setting the portfolio weights in (2) we assume that the mutual funds' time *t* estimates of stocks' expected 5-day excess returns are based on 120 past days' (i.e., the past 6 months') cross sectional regressions of (1) up to time *t-6*, the last day for which there is five-day return data at time *t*. The expected five-day returns at time *t*, $E_t(R_{i,t+5})$, can then be calculated using the stocks' past twenty days' returns up to time *t*, past month's trading volume and firms' market capitalizations at time *t*.

[3] Besides corresponding with the common portfolio rule in similar contexts in the literature, this approach can be motivated theoretically. Under the assumptions that the short-horizon returns are solely due to price pressure and independent across securities, and the assumption that investors have CARA utility functions, the investors' optimal portfolio allocations are linear in the expected returns of the assets.

Our proxy for the returns from providing immediacy, R_{IMM}, is the weighted average return on all open positions to the zero-investment long-short trading strategy described above.[4] Table 2 documents the pre-transaction cost returns on our immediacy providing trading strategy. As is evident from Table 2, the returns from providing immediacy are high, even after controlling for standard risk factors.

[Insert Table 2]

Figure 1, in turn, shows the time series evolution of the monthly returns from providing immediacy.

[Insert Figure 1]

2.4 Controlling for liquidity risk

Our measure for the returns from providing immediacy makes use of the short-term return reversals, and thus might be correlated with the Pástor-Stambaugh liquidity risk factor, that also is related to short-term return reversals (Pástor and Stambaugh, 2003). Although the two concepts are quite different, to alleviate the concerns that our empirical results on funds' exposure to the returns from providing immediacy are in fact due to funds' exposures to liquidity risk we control for the Pástor-Stambaugh liquidity factor in all of the mutual fund performance regressions.[5] The correlation between the Pástor-Stambaugh liquidity factor and our proxy for the returns from

[4] Overlapping portfolios are aggregated using the Jegadeesh and Titman (1993) method. Daily return of R_{IMM} is the average of five portfolios' returns without daily rebalancing.
[5] Data for the Pástor-Stambaugh liquidity factor is obtained from Ľuboš Pástor's webpage.

providing immediacy is -0.06 during our sample period. Finally, as Dong et al (2012) study mutual funds' exposure to liquidity risk using a different liquidity risk measure, the Sadka (2006) liquidity factor, in unreported tests we replace the Pástor-Stambaugh liquidity factor with the Sadka liquidity factor in our mutual fund performance regressions.[6] The results show that our findings are not driven by funds' exposure to liquidity risk, irrespective whether it the latter is estimated using the Pástor-Stambaugh or the Sadka liquidity factor.

3. Do mutual funds supply or demand immediacy?

It is not clear in advance whether mutual funds on average act as market makers and supply immediacy, or demand immediacy in the stock market. While there appears to exist returns from providing immediacy, as documented above, and while according to Jylhä, Rinne and Suominen (2012) hedge funds seem to supply immediacy, there are reasons to believe that the mutual fund might demand instead of supplying immediacy.

In this section, we explore the mutual funds' supply or demand of immediacy by regressing the mutual funds' returns on our measure of the returns from providing immediacy. If the mean of the regression coefficients for all funds is statistically significantly positive we conclude that mutual funds typically supply immediacy, if the mean regression coefficient is negative, we conclude that the mutual funds typically demand immediacy.

[6] Data for the Sadka liquidity factor is obtained from Ronnie Sadka's webpage.

3.1. Data on mutual funds

Our monthly mutual fund returns are based on the CRSP Survivor-Bias Free Mutual Fund Database, which lists all US mutual funds. Our sample, which includes both pure equity funds and balanced funds, is from 1st of January, 1984 to the 31st of December, 2008.[7] We combine different share classes of the same fund into a single fund using Thomson Mutual Fund holdings database and MFLINKS available through WRDS, similarly as in Fama and French (2010) and Linnainmaa (2012). In addition, to be included in our sample, we require as Linnainmaa (2012) that the mutual fund's combined net asset value has exceeded $5 million in December 2008 dollars. This requirement is made in order to limit the effect of incubation bias (Evans, 2010). We also divide our sample into active and index funds so that we can study whether these fund types differ with regards to their exposure to the returns from providing immediacy. Active funds are studied in sections 3.2-3.5 and index funds in the section 3.6.[8]

Table 3 provides the basic summary statistics of the variables used in this study.

[Insert Table 3]

3.2. Mutual funds' exposure to the returns from providing immediacy

We start our empirical analysis by examining whether mutual fund returns are dependent on the returns from providing immediacy. Let us first define the explanatory

[7] Our sample starts in 1984 as the pre-1984 mutual fund returns are deemed unreliable according to e.g. Elton, Gruber and Blake (2001) and Fama and French (2010).
[8] Funds are classified as index funds using data from Antti Petajisto`s webpage. We exclude enhanced index funds.

variables used in the regression: Returns from providing immediacy, R_{IMM}, equal the returns from providing immediacy as defined in section 2.3. 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 and French size (*SMB*) and value (*HML*) factors, the Carhart Momentum factor (*MOM*), a bond return factor (R_b) calculated using Barclays Capital Aggregate Bond index and the Pástor-Stambaugh liquidity factor.

Whether mutual funds supply or demand liquidity can now be analyzed by running the following regression, where the mutual funds' returns in excess of the risk free rate, $R_{i,t} - R_f$, are regressed on the returns from providing immediacy, R_{IMM}, and the above-mentioned *K* controls:[9]

$$\mathrm{R}_{i,t} - \mathrm{R}_{f,t} = \alpha_i + \beta_{1,i}\mathrm{R}_{IMM,t} + \sum_{k=1}^{K} \beta_{k,i} control_{k,t} + \varepsilon_{i,t} \qquad (3)$$

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

[Insert Table 4]

The results presented in Table 4 support the conclusion that mutual funds, on average demand immediacy in the stock market. First, the average coefficient of the returns from providing immediacy in the mutual fund return regression is negative (-0.019) and statistically very significant (associated *t*-statistic is 7.9). Second, the amount of individual funds that have a statistically significant negative exposure at a five-percent confidence level to the returns from providing immediacy is 8.0%. 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 (positive) under the assumption that all funds in reality have a zero loading on the returns from

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

providing immediacy. However, also the fraction of funds with a positive coefficient to R_{IMM}, i.e. funds that supply immediacy, exceeds 2.5%. This implies that some funds supply, while others demand immediacy in the stock market.

3.3. Robustness of the main result to different selection of controls

To test whether our main result that mutual funds on average demand immediacy is robust to different factor specifications and not biased by missing variables, we replace our former control variables in regression (3) with the eight factors used to explain mutual fund returns in Fung and Hsieh (1997). In this test, our sample is from the beginning of 1987 to the end of 2008.[10] The controls are the returns on the MSCI USA equity market index, the MSCI World excluding USA equity market index, the MSCI Emerging Market equity index, the JP Morgan US Government Bond index, the JP Morgan Global Government bond excluding USA index, the middle-rate of the Eurodollar one month deposit rates, the returns on gold (Gold Bullion LBM), a foreign exchange investment in the Federal Reserve Trade-weighted Exchange index and additionally the Pástor-Stambaugh liquidity factor. In line with Fung and Hsieh (1997) we use mutual fund return, not the fund's return in excess of the risk free rate, as the dependent variable.[11]

[10] Our sample starts in 1987 as the non-US government bond return data and the JP Morgan Global excluding US government bond index become available at that time.

[11] In these regressions, one month Eurodollar deposit rate (a proxy for risk-free rate) is used as an independent variable. The results remain qualitatively similar if the mutual funds' returns in excess of the risk-free rate are used as the dependent variables instead.

We again find that the returns from providing immediacy, R_{IMM}, is highly statistically significant in explaining mutual funds' returns. This shows that our former result is robust to different factor specifications. As before, mutual funds on average demand immediacy. One difference to the previous result, however, is that now the proportion of funds that seem to supply immediacy is only marginally larger than the proportion that would be expected in a similar test if no fund had any exposure to the returns from providing immediacy.

[Insert Table 5]

3.4. Discussion

The results presented in the two previous sections are consistent with the findings in Edelen (1999), who, using the semiannual flow and trading reports of 166 mutual funds, finds that the underperformance of open-end mutual funds can be attributed to the costs of liquidity-motivated trading. Wermers (2000) is another paper that looks at the effect of transaction costs on mutual fund performance. One difference between our findings and the findings in these two papers, however, is that our estimate of the costs of immediacy to mutual funds is smaller (0.3%-0.6% p.a. *vs*. 1.4% p.a. and 1.6% p.a.).[12] One factor that partly explains the difference in results is that our sample includes also balanced funds, some of which have little equity market exposure. Secondly, our sample is from a later period of time when liquidity most likely was better and the costs of immediacy thus smaller. Third, our estimate of the costs of

[12] These figures are obtained by simply multiplying our estimates of R_{IMM} beta shown in Tables 4 and 5 with the historical mean for the returns from providing immediacy during the sample period.

immediacy is net of any returns that the fund makes by providing immediacy to other investors.

3.5. Factors that affect mutual funds' costs of immediacy

We next explore what factors affect mutual funds' costs of immediacy. Our expectation is that funds that have negative flows should have higher costs of immediacy. Second, we expect that funds, which heavily employ dynamic trading strategies, such as momentum trading, have higher costs of immediacy. Based on previous research, we expect also that value funds demand less immediacy (see Da et al., 2011), and that at least some of the small cap funds (funds investing in small market capitalization stocks) supply immediacy, instead of demanding it (see Keim, 1999).

To investigate these issues, we repeat the regression (3), as reported in Table 4, in non-overlapping two year time intervals.[13] For each two year sample, we first sort the funds using the previous 12 months' flow into signed flow quintiles, and show that the funds with outflows in the past, on average, suffer costs of immediacy, while funds with past inflows have approximately zero costs of immediacy. The difference in the costs of immediacy between the negative past flow and positive past flow funds is statistically significant at the 1% level. As fund flows are highly autocorrelated, this finding suggests that most of the mutual funds' costs of immediacy are caused by outflow of funds from the mutual funds.

[13] To be included in the analysis, we require that the mutual funds have at least a 18-month return history during the 2-year period

In additional tests we sort the funds in each two year sample using their past 12-months' turnover, their past size, value, momentum and market betas, always conditioning on the sign of previous 12 months' flow. The results are presented in Figure 2. This analysis shows that also the fund strategy, not only the fund flows, affect the mutual fund's costs of immediacy.

[Insert Figure 2]

Figure 2 shows that:

1) Mutual funds that have high turnover and negative flows have high costs of immediacy (1.0% p.a.), but the costs of immediacy to funds with high turnover and positive flows are close to zero. Irrespective of the fund flows, high turnover funds suffer significantly more in the costs of immediacy than low turnover funds.
2) Mutual funds which load heavily on the momentum factor have large costs of immediacy irrespective of fund flows, and their costs of immediacy are significantly larger than those of the low momentum beta funds. This finding, which clearly show that mutual fund strategy matters for the costs of immediacy, is consistent with the previous finding that transaction costs from following the momentum strategy are high; see e.g. Korajczyk and Sadka (2004) and Lesmond, Schill and Zhou (2004).
3) Both the funds with high and low HML-betas (value and growth funds) suffer from costs of immediacy when they have negative flows.
4) Small Cap funds, i.e., funds with high exposure to SML factor, make returns from providing immediacy (consistent with Keim, 1999) when they have inflows, but

suffer from costs of immediacy when they have outflows. There are no similar differences in the costs of immediacy of large cap funds.

5) Finally, consistent with the idea that low market beta funds have larger cash holdings and thus less of a need to demand immediacy, we find that the low market beta funds make returns from providing immediacy, while the high market beta funds have significant costs of immediacy.

The differences in the realized costs of immediacy across fund types are large and often economically and statistically highly significant. For instance, funds which load heavily on momentum have a R_{IMM} beta of minus 0.13, corresponding with annual costs of immediacy of -2.2% (this is obtained by simply multiplying these funds' R_{IMM} beta with the historical mean for the returns from providing immediacy). In turn, funds that load least on the momentum factor have a R_{IMM} beta of 0.03, corresponding with positive returns from providing immediacy of (0.6% p.a.).

From this research, it emerges that there are several factors that affect whether a mutual fund more commonly demands or supplies immediacy in the stock market. It appears that the important determinants of this are a) the mutual funds' strategy and b) fund flows.

To investigate the effect of fund flows further, we repeat the regression (3), and include both the lagged mutual fund flow and an interaction term where we interact the lagged mutual fund flow with R_{IMM} in the regression. The results are provided in Table 6.

[Insert Table 6]

These results support the earlier findings of a large effect of fund flows on the mutual funds' need to demand immediacy: it appears that mutual funds demand immediacy especially during crises when investors pull their money from the mutual funds, consistent with Hau and Lai (2012). The relationship between mutual fund flows and mutual funds' propensity to supply immediacy is also depicted in Figure 3.

[Insert Figure 3]

It is plausible to think that the price impact from flow induced trading, and thus the fund's costs of immediacy, are largest for those mutual funds whose flows are highly correlated with other mutual funds. 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, as Figure 4 shows, that only funds whose flows correlate sufficiently with the aggregate flows suffer from costs of immediacy. Instead, funds whose flows have low correlation with the aggregate flows earn returns from providing immediacy.

3.6. Costs of Immediacy and Index funds

In order to study whether index funds' tracking error is affected by the costs of immediacy we run the following regression, where the index funds' returns in excess of a benchmark index return, $R_{i,t} - R_{BM}$, are regressed on the returns from providing immediacy, R_{IMM}, and K controls:

$$R_{i,t} - R_{BM,t} = \alpha_i + \beta_{1,i} R_{IMM,t} + \sum_{k=1}^{K} \beta_{k,i} control_{k,t} + \varepsilon_{i,t}. \quad (4)$$

Here, $\varepsilon_{i,t}$ denotes the fund specific error term. We use as controls the Fama and French size (*SMB*) and value (*HML*) factors, the Carhart Momentum factor (*MOM*) and the Pástor-Stambaugh liquidity factor.

In some specifications we also control for the absolute value of an adjusted measure of fund flow, *abs(FlowAdj)*. As the costs of immediacy for an index fund can be expected to be affected not only by its own flow, but also on the industry flow (i.e., flows to funds tracking the same index), we make an adjustment to fund flows to take into account this idea. In particular, we calculate the adjusted fund flow $FlowAdj_{t-1}$ as:

$$FlowAdj = Flow * I_{Sign\ Flow=Sign\ Industry\ Flow} \quad (5)$$

The underlying idea here is that the fund is expected to suffer costs of immediacy only if its flow has the same sign as the industry flow. Also, as the index funds' purchases and sales are limited to stocks that are included in the index, in contrast to non-index funds, we expect both in- and outflows of funds to the mutual fund to cause significant costs of immediacy. Because of this, we use the absolute value of the adjusted fund flow instead of the adjusted fund flow in these regressions. As other variables in these regressions we include a dummy for periods when the fund flow is zero or it has the opposite sign from the industry flow, as well as a dummy for periods with index

rebalancing. In addition, we interact all these variables with our measure of the costs of immediacy, R_{IMM}.

Table 7 shows the regression results. In the last regression we limit the sample to S&P 500 index funds only, in order to study the effects of index rebalancing. For other indexes we do not have this data. The results in Table 7 show that especially during months with many constituent changes in the index, the index funds suffer from the costs of immediacy. There is also evidence that when the sign of a fund's flow differs from the sign of the industry flow, the funds make returns from providing immediacy.

[Insert Table 7]

3.7. Costs of Immediacy and Mutual Fund Underperformance

It is interesting to see if to what extent our estimates of the costs of immediacy can explain mutual funds' observed underperformance to the value weighted equity index; see for example Gruber (1996) and Carhart (1997).

Using our estimate of the average costs of immediacy for mutual funds (presented in Table 4), Figure 5 shows the effect of the costs of immediacy on mutual fund underperformance by depicting the three separate time series. First, it shows the mutual funds' realized cumulative returns and, second, the cumulative returns to the CRSP value weighted stock index. Finally it shows the hypothetical cumulative returns to mutual funds, had the mutual funds not suffered any costs of immediacy. In this series

we have added to the mutual fund's cumulative realized return in every month our estimate of the mutual funds' realized costs of immediacy (obtained by multiplying the negative of the estimated coefficient for R_{IMM} from Table 4 by the realized return from providing immediacy in that month, R_{IMM}).

[Insert Figure 5]

Our estimate of the realized costs of immediacy amounts to 45% of the magnitude of the mutual funds historical underperformance to the CRSP value weighted stock market index.

Finally, costs of immediacy seem to affect mutual funds' performance also in the cross-section: Figure 6 shows that the funds' alphas increase when their lagged regression coefficient to the returns from providing immediacy increases. For funds who provided immediacy in the past, the alpha is not significantly different from zero, while for funds that demanded immediacy in the past, the alpha is significantly negative. The difference in alphas between funds in the lowest lagged R_{IMM} beta decile and the highest lagged R_{IMM} beta decile is 14 basis points monthly (1.7% pa.). This difference is statistically significant at the 1% level.

[Insert Figure 6]

4. Conclusions

We have provided new evidence on the costs of immediacy to mutual funds. Our results suggest that mutual funds on average demand immediacy in the stock market, and given this, suffer from costs of immediacy. Their costs of immediacy are economically significant and account for 45% of the mutual funds underperformance to the CRSP value weighted stock market index. We find that the costs of immediacy to mutual funds are largest when the mutual funds experience outflows, and when their flows correlate with the industry flows. Other results are that the costs of immediacy depend on the fund's strategy. It appears that especially the funds that have high exposure to the momentum factor suffer large costs of immediacy. Finally we show that the mutual funds' costs of immediacy predict their future alphas.

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Table 1: Pattern of return reversal

This table shows the average coefficients, $\widehat{\boldsymbol{\beta}}_{t-\tau}$, from daily cross-sectional regressions (Equation 1 in the text) where stocks' 5-day future excess returns R_{t+5} are regressed on each of the stocks' past twenty days' excess returns, $R_{t-\tau}$, where $\tau \in \{0,1,2,3,\ldots,19\}$ and controls $Ln(Volume)xR_{t,t-19}$ and $Ln(Market\ Capitalization)x\ R_{t,t-19}$. Here $R_{t,t-19}$ refers to past 20 days' excess return. The excess returns are calculated relative to the corresponding equal-weighted Fama-French 48 industry index returns. Sample period is from 1/1983 through 12/2008. T-statistics based on Fama-Macbeth standard errors adjusted for first order autocorrelation are shown next to coefficients in parenthesis. All coefficients that are statistically significant at the 5% level are bolded.

R_{t+5}					
R_t	**-0.195**	(-49.27)	R_{t-10}	**-0.051**	(-13.79)
R_{t-1}	**-0.121**	(-30.61)	R_{t-11}	**-0.050**	(-13.40)
R_{t-2}	**-0.100**	(-26.20)	R_{t-12}	**-0.049**	(-13.53)
R_{t-3}	**-0.086**	(-22.70)	R_{t-13}	**-0.049**	(-13.94)
R_{t-4}	**-0.076**	(-20.39)	R_{t-14}	**-0.048**	(-13.51)
R_{t-5}	**-0.070**	(-18.20)	R_{t-15}	**-0.047**	(-12.64)
R_{t-6}	**-0.063**	(-17.41)	R_{t-16}	**-0.045**	(-12.08)
R_{t-7}	**-0.060**	(-16.47)	R_{t-17}	**-0.042**	(-11.99)
R_{t-8}	**-0.055**	(-15.35)	R_{t-18}	**-0.042**	(-11.87)
R_{t-9}	**-0.052**	(-14.36)	R_{t-19}	**-0.040**	(-12.17)
Intercept				**-0.001**	(-13.92)
Controls:					
$Ln(Volume)xR_{t,t-19}$				-0.001	(-1.31)
$Ln(Market\ Capitalization)xR_{t,t-19}$				**0.005**	(4.51)
Number of daily regressions				6555	
Average number of observations				2014	
Average Adjusted R^2				0.062	

Table 2: Return statistics for the immediacy providing trading strategy

This table shows the statistics of daily and monthly returns from providing immediacy with 5-day holding period. Sample period is from 1/1984 through 12/2008. The returns from providing immediacy are the pre-transaction cost returns on a zero-investment long-short trading strategy in which five- day expected excess returns are used as portfolio weights when forming the long and short portfolios (Equation 2) and positions are held the corresponding period of time. The expected returns are calculated using six month moving averages of coefficients for return reversal (Equation 1), until six days prior to taking positions. Return statistics are based on averages of the returns of all open positions. Fama and French / Carhart 4-factor alpha is calculated using data from Kenneth French's website.

	Daily	Monthly
Mean	0.10	2.16
25th percentile	-0.10	0.67
Median	0.09	1.97
75th percentile	0.29	3.43
Volatility	0.45	2.51
Positive return %	63.4 %	83.7 %
Sharpe-ratio	0.23	0.86
4-factor alpha	0.08	1.90
t-statistics for alpha	(13.65)	(8.59)

Table 3: Descriptive statistics

This table shows the descriptive statistics of the mutual fund variables used in the paper. The sample period is from January 1984 through December 2008. Return and Flow / AUM are at a monthly frequency while Turnover is at an annual frequency.

	Mean	St.Dev.	1st quartile	Median	3rd quartile
Active funds					
Return	0.60	5.55	-1.93	0.93	3.54
Flow / AUM	1.12%	11.33%	-1.43%	-0.11%	1.74%
Annual turnover	96.3%	127.8%	34.0%	66.0%	116.0%
Index funds					
Return	0.54	5.13	-1.98	1.10	3.69
Tracking error	-0.10	0.85	-0.20	-0.05	0.04
Flow / AUM	1.69%	15.68%	-0.63%	0.45%	2.09%
Annual turnover	53.0%	180.3%	6.0%	12.0%	27.0%

Table 4: Mutual funds' exposure to the returns from providing immediacy

This table shows the summary statistics from fund-specific regressions in which mutual funds' monthly returns in excess of the risk-free rate, R_i-R_f, are regressed on the returns from providing immediacy, R_{IMM}, described in the text, the value weighted US stock market index return in excess of the risk free rate, R_m-R_f, Fama-French size (*SMB*) and value factors (*HML*), Carhart momentum factor (*MOM*), a bond return factor (R_b), based on Barclays Capital Aggregate Bond index and Pástor-Stambaugh liquidity factor. Risk free rate, R_f, is the one-month treasury bill rate. The bond return factor is downloaded from Datastream, Pástor-Stambaugh liquidity factor data is from Ľuboš Pástor's webpage and the other factor data are from Kenneth French's website. The mean coefficient column shows the average of the factor coefficients from the fund-specific regressions. The t-statistics are shown below the mean coefficients, in parentheses. The other two columns show the proportion of individual funds for which the coefficient of R_{IMM} is statistically significantly negative (positive) at the 5% level (two-tail test using Newey-West standard errors). The figures in parentheses below are z-statistics testing whether the proportion is equal to 2.5% (which would be the proportion observed in case the R_{IMM} and R_i-R_f are uncorrelated). All coefficients that are statistically significant at the 5% level are bolded.

Mutual fund return R_i-R_f	Mean Coefficient	Proportion of funds in which coefficient of R_{IMM} is statistically significantly **negative**	Proportion of funds in which coefficient of R_{IMM} is statistically significantly **positive**
R_{IMM}	**-0.019**	8.02%	5.44%
	(-7.88)	(22.67)	(12.09)
Controls	Mean Coefficient		
R_m-r_f	**0.935**		
	(178.59)		
SMB	**0.133**		
	(32.30)		
HML	**0.066**		
	(12.38)		
MOM	**0.045**		
	(16.02)		
R_b	**0.032**		
	(4.95)		
Pastor&Stambaugh	-0.001		
	(-1.15)		
α	**-0.001**		
	(-13.59)		
# of Fund-level regressions	4116		

Table 5: Mutual funds' cost of immediacy with Fung and Hsieh (1997) controls

This table shows the summary statistics from fund-specific regressions in which mutual funds' monthly returns, R_i, are regressed on the returns from providing immediacy, R_{IMM}, described in the text, and the following controls: returns to MSCI USA equity market index return ($R_{m,US}$), MSCI World excluding USA equity market index ($R_{m,NON-US}$), MSCI Emerging Market equity index ($R_{m,EMERGING}$), JP Morgan US Government Bond index ($R_{b,US\ GOV}$), Non-US Government bond index ($R_{b,NON-US\ GOV}$), return on one-month Eurodollar deposit evaluated using middle rates ($R_{EURO\$}$), and the returns on Gold Bullion LBM index (R_{GOLD}), a Foreign exchange-investment in the Federal Reserve trade-weighted Exchange index using major currencies (R_{FX}) and Pástor-Stambaugh liquidity factor. The foreign exchange index return is obtained from the Federal Reserve, Pástor-Stambaugh liquidity factor data is from Ľuboš Pástor's webpage and the other factor data are downloaded from Datastream. The Mean coefficient column shows the average of the factor coefficients from the fund-specific regressions. The t-statistics are shown below the mean coefficients, in parentheses. The other two columns show the proportion of individual funds for which the coefficient of R_{IMM} is statistically significantly negative (positive) at the 5% level (two-tail test using Newey-West standard errors). The figures in parentheses below are z-statistics testing whether the proportion is equal to 2.5% (which would be the proportion observed in the case where the R_{IMM} and R_i are uncorrelated). All coefficients that are statistically significant at the 5% level are bolded.

Mutual fund return, *Ri*	Mean	Proportion of funds in which coefficient of R_{IMM} is statistically significantly **negative**	Proportion of funds in which coefficient of R_{IMM} is statistically significantly **positive**
R_{IMM}	**-0.036**	8.32%	3.38%
	(-11.87)	(23.84)	(3.60)
Controls	Mean		
$R_{m,US}$	**0.602**		
	(87.81)		
$R_{m,NON-US}$	**0.199**		
	(36.69)		
$R_{m,EMERGING}$	**0.105**		
	(35.49)		
$R_{b,US\ GOV}$	**0.048**		
	(8.11)		
$R_{b,NON-US\ GOV}$	**-0.142**		
	(-16.70)		
$R_{EURO\$}$	**0.599**		
	(9.88)		
R_{GOLD}	**0.021**		
	(8.53)		
R_{FX}	**-0.347**		
	(-30.12)		
Pastor&Stambaugh	**-0.003**		
	(-3.23)		
α	**-0.002**		
	(-6.78)		
# of Fund-level regressions	4085		

Table 6: Mutual funds' exposure to the returns from providing immediacy and fund flow

This table shows the summary statistics from fund-specific regressions in which mutual funds' monthly returns in excess of the risk-free rate, R_i-R_f, are regressed on the returns from providing immediacy, R_{IMM}, described in the text, the fund's past months' flow (divided by the fund's total assets under management measured at the beginning of month *t-1), $Flow_{t-1}$,* and the interaction of R_{IMM} and $Flow_{t-1}$, and controls. As controls we use 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 Carhart momentum factor (*MOM*), a bond return factor (R_b), based on Barclays Capital Aggregate Bond index and the Pástor-Stambaugh liquidity factor. The risk free rate R_f is the one-month treasury bill rate. The bond return factor is downloaded from Datastream, the Pástor-Stambaugh liquidity factor data is from Ľuboš Pástor's webpage and the data for other control factors are from Kenneth French's website. Flow data is from the CRSP Mutual Fund Database. The t-statistics are shown below the mean coefficients, in parentheses. All coefficients that are statistically significant at the 5% level are bolded.

	Mutual fund return R_i-R_f
R_{IMM}	**-0.027**
	(-9.16)
R_{IMM} * $Flow_{t-1}$	**0.435**
	(3.69)
Controls	
R_m-R_f	**0.936**
	(174.01)
SMB	**0.133**
	(31.38)
HML	**0.071**
	(13.30)
MOM	**0.045**
	(15.47)
R_b	**0.043**
	(6.50)
Pástor-Stambaugh	0.000
	(0.30)
$Flow_{t-1}$	**0.006**
	(2.30)
A	**-0.001**
	(-14.17)
# of Fund-level regressions	3986

Table 7: Index funds' exposure to the returns from providing immediacy

This table shows the summary statistics from fund-specific regressions in which index funds' monthly tracking error, i.e. its return in excess of the benchmark index, R_i-R_{BM}, are regressed on the returns from providing immediacy, R_{IMM}, described in the text, the absolute value of a flow measure $abs(FlowAdj_{t-1})$, described in the text, a dummy for time periods when sign of fund's flow differs from the sign of the flow of the total flow to index funds tracking the same index, *Rebalancing* dummy, which takes a value equal to one when there are more than the median number of index constituent changes during that month, the interaction of R_{IMM} with the flow measure, and the two dummy variables, and controls. As controls we use the Fama-French size (*SMB*) and value factors (*HML*), the Carhart momentum factor (*MOM*) and the Pástor-Stambaugh liquidity factor. The Pástor-Stambaugh liquidity factor data is from Ľuboš Pástor's webpage and the data for the other control factors are from Kenneth French's website. Flow data is from the CRSP Mutual Fund Database. The t-statistics are shown below the mean coefficients, in parentheses. All coefficients that are statistically significant at the 5% level are bolded.

	Mutual fund return R_i-R_B	Mutual fund return R_i-R_B	Mutual fund return R_i-R_B	Mutual fund return R_i-R_B
R_{IMM}	-0.007	-0.019	0.001	**0.023**
	(-1.07)	(-1.37)	(0.16)	(3.08)
R_{IMM} * $Abs(FlowAdj_{t-1})$		-0.313	-0.123	-0.167
		(-0.98)	(-0.43)	(-0.63)
R_{IMM} * $Sign_{Flow} \neq Sign_{IndexFlow}$		0.016	**0.010**	0.013
		(0.95)	(2.16)	(1.96)
R_{IMM} * *Rebalancing*				**-0.031**
				(-5.01)
Controls				
SMB	**0.021**	**0.024**	**0.017**	**0.016**
	(3.36)	(3.52)	(3.92)	(3.95)
HML	0.013	0.014	**0.033**	**0.031**
	(0.91)	(0.95)	(4.16)	(3.94)
MOM	**-0.016**	**-0.014**	**-0.015**	**-0.016**
	(-3.98)	(-3.43)	(-9.42)	(-9.40)
Pástor-Stambaugh	-0.001	0.000	-0.002	-0.002
	(-0.70)	(-0.27)	(-1.37)	(-1.88)
$Abs(FlowAdj_{t-1})$		-0.024	-0.015	**-0.014**
		(-1.23)	(-1.95)	(-2.03)
$Sign_{Flow} \neq Sign_{IndexFlow}$		-0.001	0.000	**0.000**
		(-0.98)	(-1.80)	(-2.01)
Rebalancing				0.000
				(-0.85)
α	-0.001	0.000	**-0.001**	**-0.001**
	(-5.46)	(-0.64)	(-9.73)	(-8.04)
Sample	All index funds	All index funds	S&P500 funds	S&P500 funds
# of Fund-level regressions	113	112	62	62

Figure 1: Monthly returns from the immediacy providing trading strategy.

This figure presents the annual averages of the monthly returns during our sample period 1/1984-12/2008 from the immediacy providing trading strategy with a 5-day holding period. The returns from providing immediacy are estimated as the returns on a zero-investment long-short trading strategy in which the five day expected excess returns are used as portfolio weights when forming the long and the short portfolios. These expected returns are calculated using six month moving averages of coefficients for return reversal from regression (1) until six days prior to taking positions. Portfolio returns are based on averages of the returns of all open positions. There is no consideration for transaction costs.

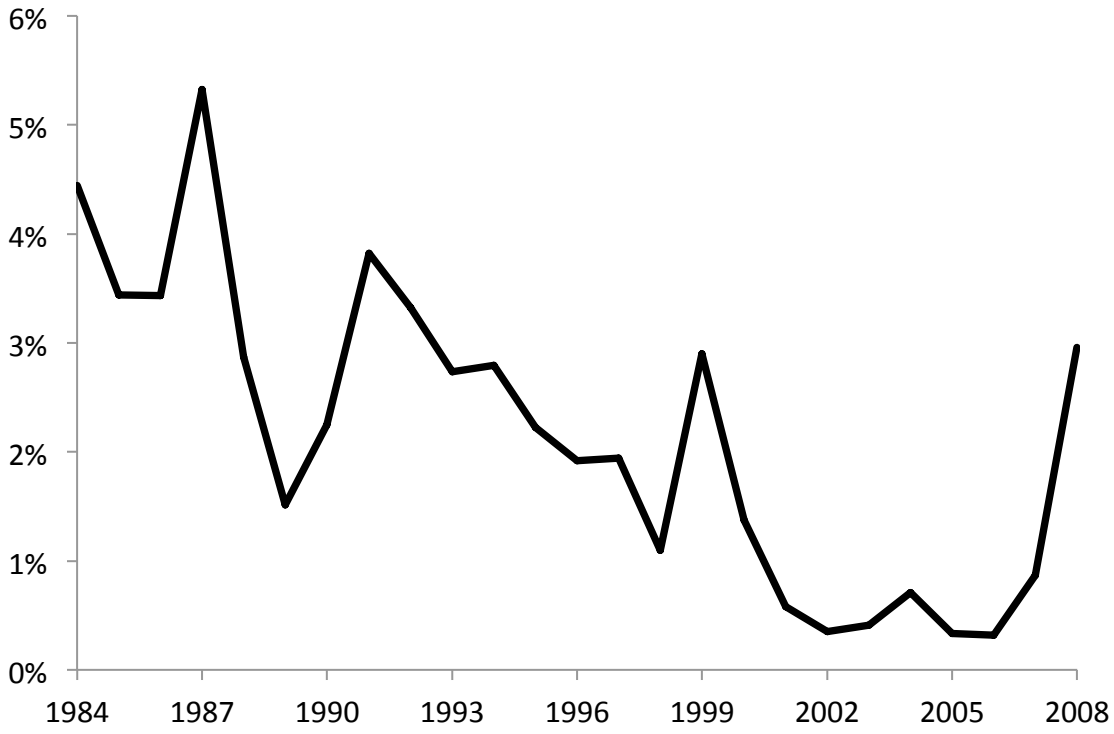


Figure 2: Costs of immediacy and fund characteristics

These figures show the average coefficient of R_{IMM} from regressions similar to (3) in signed flow quintiles as well as different characteristics deciles, conditioning on the sign of the flow. The reported coefficients are based on fund-specific regressions (similar to those in Table 4) in which mutual funds' monthly returns in excess of risk-free rate, R_i-R_f, are regressed on the returns from providing immediacy, R_{IMM}, 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 Carhart momentum factor (*MOM*), a bond return factor (R_b), based on Barclays Capital Aggregate Bond index, and the Pástor-Stambaugh liquidity factor. In order to account for time variation in fund characteristics and to estimate the effect of fund flow on the funds' supply of immediacy we performed these regressions separately for all non-overlapping two-year periods of data and report the average coefficients from those regressions in these figures. Below, the funds are divided into signed flow quintiles based on their flow measured on the year *t-1,* or into characteristics deciles based on their turnover measured in year *t-1* or their past two years' factor betas. Light green (dark grey) bars show the average coefficients when lagged flow is positive (negative). Fund turnover data is from CRSP. The fund flow is the annual average of the monthly fund flows (divided by the fund's beginning of the month total assets under management).

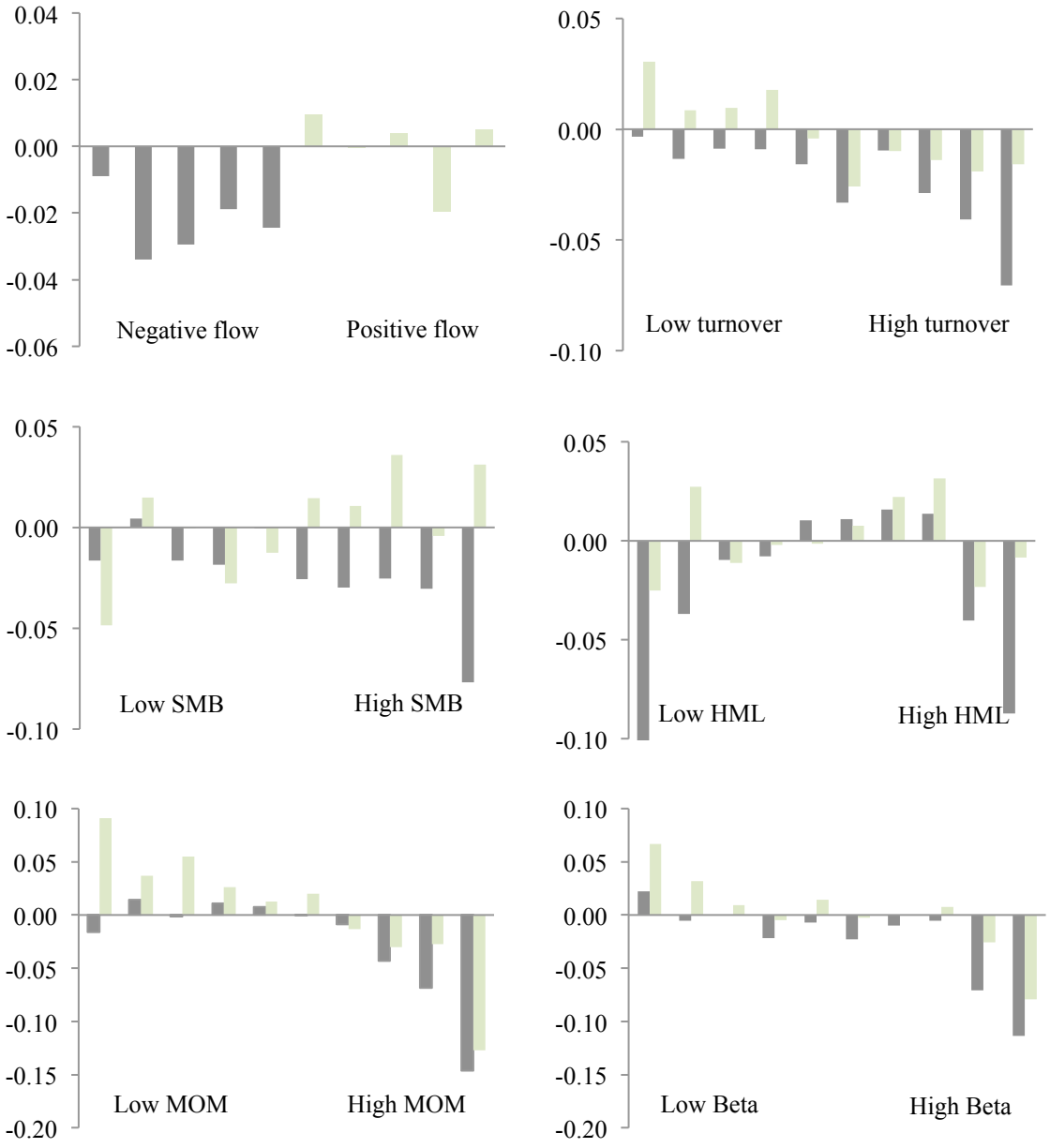


Figure 3: Provision of immediacy and fund flow

This figure shows the average coefficient for R_{IMM} conditional on past month's fund flow. Coefficients are based on fund-specific regressions (in Table 6) in which mutual funds' monthly returns in excess of the risk-free rate, R_i-R_f, are regressed on the returns from providing immediacy variable, R_{IMM}, described in the text, fund i's past flow divided by its total assets under management (measured at the beginning of the month t-1), referred to as $Flow_{t-1}$, and the interaction of R_{IMM} and $Flow_{t-1}$, and controls. As controls we use 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 Carhart momentum factor (*MOM*), a bond return factor (R_b), based on Barclays Capital Aggregate Bond index and the Pástor-Stambaugh liquidity factor. The dotted lines present the 95% confidence interval of the average coefficient. Flow data is from the CRSP Mutual Fund Database.

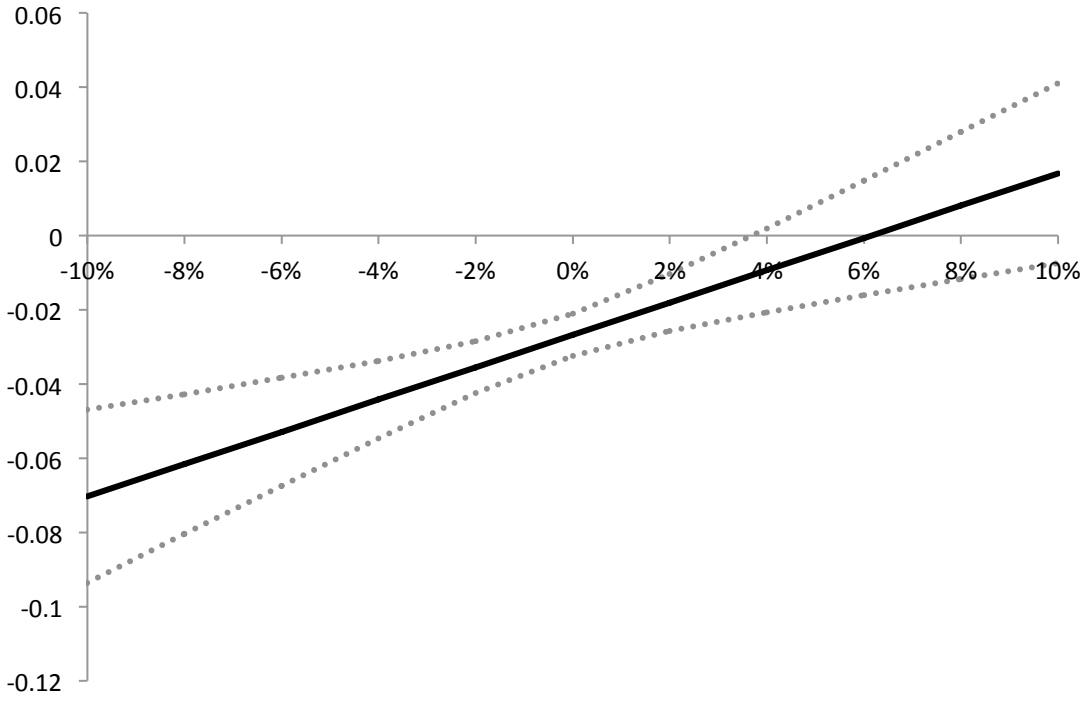


Figure 4: Fund flow correlation and costs of immediacy

This figure shows the average coefficient of R_{IMM} from regressions similar to (3) in fund flow correlation deciles, where funds are divided into deciles based on the fund's flow's correlation with the aggregate industry flows, still conditioning on the sign of the fund's flow. The coefficients are based on fund-specific regressions (similar to those in Table 4) in which mutual funds' monthly returns in excess of risk-free rate, R_i-R_f, are regressed on the returns from providing immediacy, R_{IMM}, 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 Carhart momentum factor (*MOM*), a bond return factor (R_b), based on Barclays Capital Aggregate Bond index, and the Pástor-Stambaugh liquidity factor. In order to account for time variation in fund characteristics and to estimate the effect of fund flows on the supply of immediacy we performed these regressions separately for all non-overlapping two-year periods of data and report the average coefficients from those regressions in these figures. Light green (dark grey) bars show the coefficients when the lagged flows are positive (negative). The fund flow is the fund's dollar flow divided by its beginning of the month total assets under management, and the aggregate fund flow is the assets under management weighted average of the fund flows.

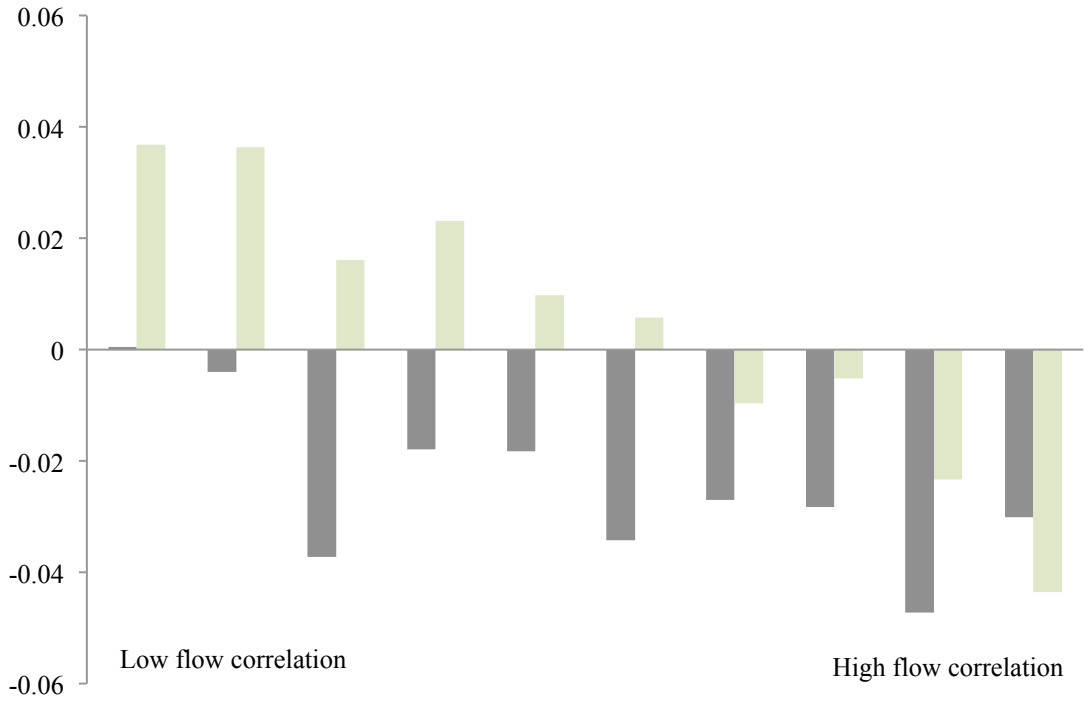


Figure 5: The effect of the costs of immediacy on mutual funds' returns

This figure shows the effect of the costs of immediacy on mutual fund returns. The value-weighted CRSP index is compared to an equal-weighted index for mutual fund investments with monthly rebalancing, and to a equal-weighted index for mutual fund investments (with monthly rebalancing) to which our estimates of the mutual funds' monthly costs of immediacy are added. The monthly estimates of the costs of immediacy equal the negative of the average coefficient for R_{IMM} presented in Table 4 multiplied by the monthly return from providing immediacy, R_{IMM} (defined in the text). Mutual fund returns are based on the CRSP Survivor-Bias Free Mutual Fund Database.

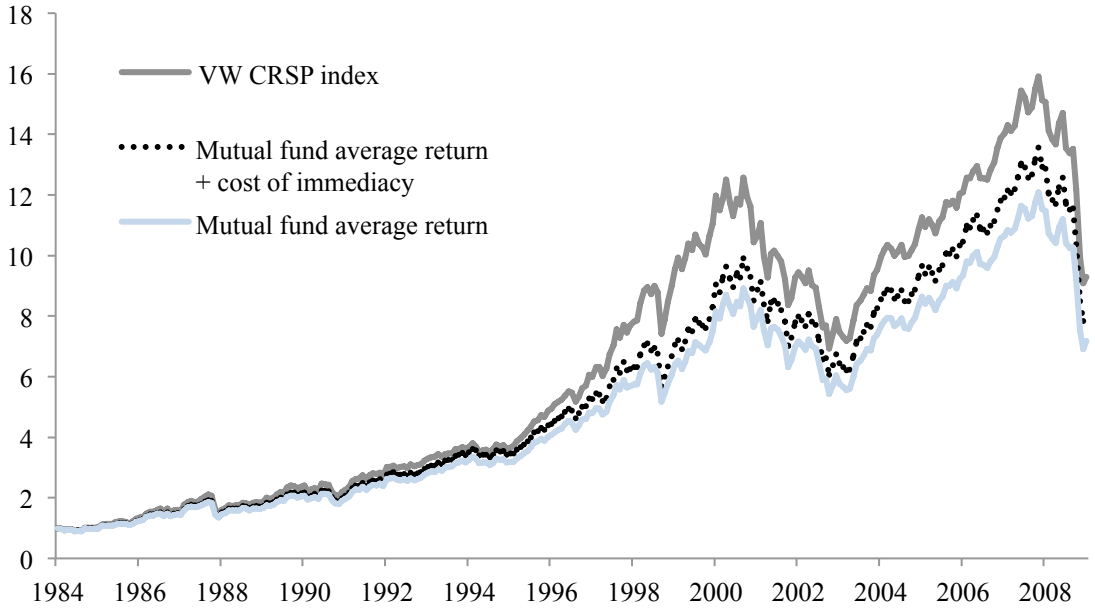
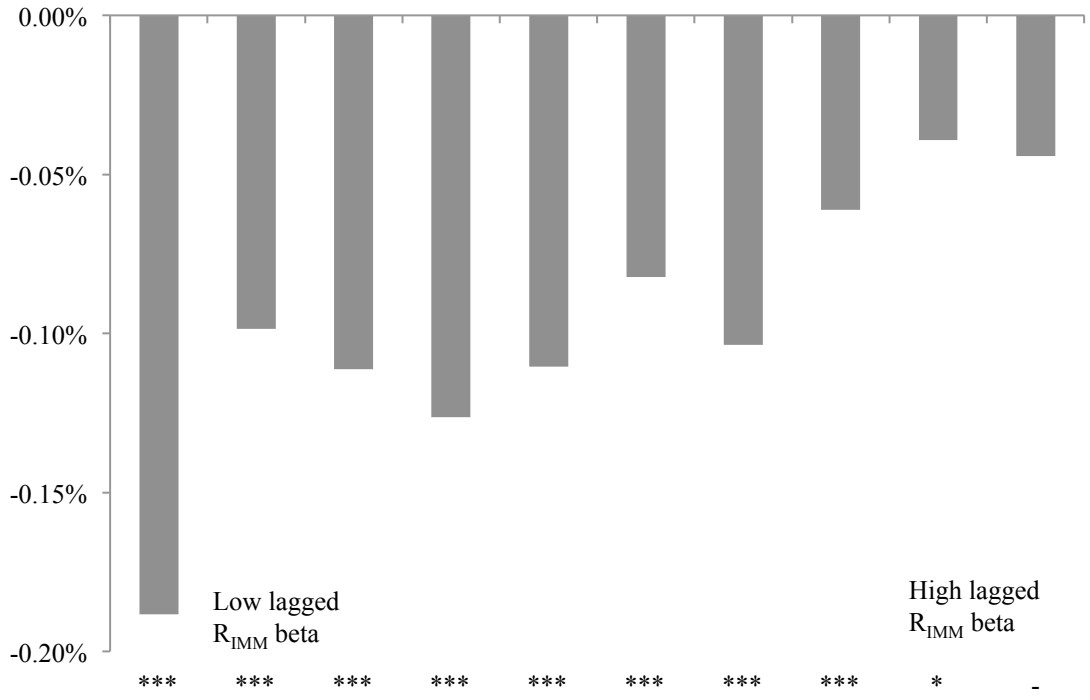


Figure 6: Fund alpha and costs of immediacy

This figure shows the effect of the costs of immediacy on mutual fund alphas. More specifically it shows the average alpha from regressions similar to (3) in lagged R_{IMM} beta deciles. Alphas are based on fund-specific regressions (similar to those in Table 4) in which mutual funds' monthly returns in excess of risk-free rate, R_i-R_f, are regressed on the returns from providing immediacy, R_{IMM}, 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 Carhart momentum factor (*MOM*), a bond return factor (R_b), based on Barclays Capital Aggregate Bond index, and the Pástor-Stambaugh liquidity factor. These regressions are performed separately for all non-overlapping two-year periods. The reported figures are averages from those regressions. Below, funds are divided into R_{IMM} beta deciles based on their R_{IMM} betas calculated using the past two years' data. Here three, two or one star is used to denote a coefficient that is statistically significantly different from zero at 1% , 5% or 10% level.



Appendix:

The effect of holding period on the returns from providing immediacy

Table A1: Return statistics for the immediacy providing trading strategy with broker commissions

Monthly return statistics for an immediacy providing trading strategy with different holding periods (1, 5 and 20 days) are calculated for the period 1/1984- 12/2008 using following estimates for broker commissions: 17 basis points per trade during 1980s, 5 basis points per trade during the 1990s and 3 basis points per trade after 2000. Estimates are based on Chan and Lakonishok (1993) and de Groot, Huij and Zhou (2011). The returns from providing immediacy are the returns to a zero-investment long-short trading strategy similar to that described in Section 2, in which expected holding period excess returns are used as portfolio weights when forming the long and the short portfolios (as in Equation (2)). These expected returns are calculated using six month moving averages of coefficients for return reversal, from regressions similar to Equation (1), but with stocks' one day, 5-day or 20-day future excess return as dependent variables, until two, six or 21 days prior to taking positions. Return statistics are based on averages of the returns of all open positions.

	R1	R5	R20
Mean	-4.58	0.93	0.28
25th percentile	-7.77	-0.51	-0.33
Median	-3.38	0.76	0.32
75th percentile	-1.30	2.15	0.95
Volatility	5.16	2.34	1.59
Positive return %	14.7 %	64.7 %	63.7 %
Sharpe ratio	-0.89	0.40	0.17

As Table A1 shows, the Sharpe ratio is the highest assuming a 5-day holding period.