Front-running of mutual fund fire-sales*

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Abstract

We show that a real-time trading strategy which front-runs the anticipated forced sales by mutual funds experiencing extreme capital outflows can generate substantial returns. The profit stems from selling pressure among stocks that are below the NYSE mean size and cannot be explained with the arrival of public information. We show that the largest stocks also exhibit downward price pressure, but prices revert before the front-running strategy can detect it. The duration of the anticipated selling pressure has decreased from about a month in the 1990s to about two weeks in the most recent decade. Our results suggest that publicly available information on fund flows and holdings can aggravate the situation of mutual funds that are already in distress.

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1 Introduction

Coval and Stafford (2007) show that selling pressure among the common stocks of mutual funds in distress can create a transitory price pressure, moving prices away from fundamentals. Since fund flows are to a certain extent predictable and there is publicly available information on fund holdings, there might be an incentive among sophisticated investors to exploit the price pressure effects and short-sell stocks before the anticipated trades of mutual funds in distress. Consequently, we investigate the performance of a hypothetical trading strategy based on public information which shorts the anticipated forced sales by mutual funds expected to experience extreme capital outflows. Our results indicate that such a trading strategy can be very profitable, generating an alpha of 50 basis points per month.

The profitability of the trading strategy stems from stocks that are below the NYSE mean size. Outflow-driven price pressure starts about three months before the construction of our short portfolio and continues during the portfolio holding period. We report that prices revert in the months following the holding period, indicating that the source of success of the trading strategy is transitory price pressure caused by the extreme capital outflows of mutual funds. The arrival of unexpected stock-specific information or the realization of analyst's forecasting error cannot explain the success of the front-running strategy, ruling out alternative information-based explanations. Even though the stocks generating the success of the strategy are below the NYSE mean size, they are evenly distributed across the top three size quintiles. This implies that trading costs should not be very large and the strategy could be implemented in real time.

Our analysis of the above NYSE mean size stocks reveals that they are also subject to outflow-driven selling by mutual funds, but the price pressure among those stocks is more transitory and is harder to exploit. By the time they are included in the short portfolio, their prices have already started to revert. There are at least two reasons why price pressure could be weaker among the largest stocks. First, institutional ownership is generally higher among larger, more liquid stocks (e.g. Gompers and Metrick (2001)). This means that fresh liquidity would arrive faster for larger stocks. Second, information on fundamentals is easier to obtain. Barth et al. (2001), among others, point that the number of analysts covering a stock is strongly positively related to firm size, even after controlling for other stock characteristics.

We further examine time differences in the returns of the front-running strategy and report a decreasing pattern in risk-adjusted performance. The strategy is particularly successful before 2000, when downward price pressures last for about a month. After 2000, reversals start earlier and the front-running strategy profits from price pressures lasting for a couple of weeks. Thus, despite the decreasing trend in returns, the front-running strategy still offers attractive returns.

The results in this paper offer an important channel through which the situation of funds already in distress could be aggravated. Funds experiencing substantial capital outflows face an easy to implement free-riding trading strategy that could have very negative effects on their performance. Front-running has the potential to create negative-feedback spirals through which the distress of funds experiencing outflows could be exacerbated via the front-running trades of other investors. Furthermore, there are broad market-wide implications of front-running such as price overshooting, reduced liquidity when it is most needed, movement of prices away from fundamentals, and increased volatility (see Brunnermeier and Pedersen (2005) and De Long et al. (1990)).

In general, extreme fund inflows might also result in an upward price pressure providing other market participants with opportunities for front-running. However, there are two reasons why we focus on flow induced sales rather than the potential flow induced buys. First, funds with high inflows have some discretion in what to do with the inflow of money – they can scale upwards, initiate new positions, or retain cash for a few days/weeks until undervalued stocks are identified. In contrast, funds with high inflows can only scale down their positions. Thus, while funds with high inflows have the opportunity to trade based on information in new positions, funds with high outflows have no choice but to trade due to necessity. This makes the link between flows and price pressure stronger on the short side.

Second, front-running could be potentially very dangerous for funds in distress. However, this may not necessarily be the case for funds with high inflows. A front-runner who anticipates a fund's flows would go long in that fund's stocks, but the fund manager might decide not to scale her positions and hence buy other stocks.

This will benefit the fund manager who can cash the price effects associated with the front-runner's buys. This makes investigating front-running of outflow-driven sales more important as it has direct implications for funds that are already in distress.

To formerly investigate the profitability of the real-time front-running strategy, we construct an expected price-pressure measure which quantifies the anticipated selling pressure among the common holdings of funds with expected high outflows. To forecast fund flows, we rely on the well-documented flow-performance relationship by, among others, Sirri and Tufano (1998), Ippolito (1992), and Chevalier and Ellison (1997). Investors tend to put their money in funds with a recent successful track record and tend to pull money out of funds with a poor track record, which implies forecastability of fund flows. We use this predictability to estimate where most of the selling pressure would be on a fund level. To select the stocks most likely to experience downward selling pressure, we select the stocks most widely held by funds expected to experience extreme outflows, netting out possible buying pressure from funds expected to experience extreme inflows.

The data provides strong support for the forecastability of downward selling pressure among funds in distress. We show that over the 1990 – 2010 period the trading strategy produces a five-factor alpha of 50 basis points per month. The results are highly statistically significant and economically important. Generally, it is difficult to disentangle information from price pressures and hence determine the source of profitability of such a strategy. We apply an indirect approach and examine price reversals around the portfolio holding month. More specifically, we estimate five-factor alphas of our short portfolio around the holding month. We find strong evidence for reversals following outflow-induced price pressure and report strong negative alphas before and during the holding period and high positive alphas immediately after the holding period. Furthermore, we look at the effect of two variables known in the literature to explain sudden price changes in stocks: unexpected stock earnings and realization of analysts' forecast errors. Consistent with the literature, these variables have an explanatory power in the whole cross-section of stock returns, but they cannot capture the return of the expected fire-sales. This rules out alternative information-based explanations for the success of our strategy.

We also show that the front-running strategy does a poor job in capturing price pressure effects among the largest stocks in the sample. We report a strong selling pressure among those stocks prior to the holding period measured by a five factor alpha. However, the alpha is highly positive during the holding period which indicates that reversals among those stocks start before the trading strategy can anticipate them. This implies that a successful front-running strategy should not focus on stocks where liquidity and analyst coverage can very quickly dissipate the price pressures caused by funds in distress.

To examine time-differences in the success of the strategy, we construct a 10-year rolling five-factor alpha and examine its development over time. We report a trend of decreasing alpha over time. Before 2000, the front-running strategy has higher returns because it can detect price pressures a month before they start reverting. After 2000, the success of the strategy has decreased because the duration of the identifiable price pressures has decreased to two weeks. Thus, despite the decreasing trend, the strategy can still generate economically important results. This implies that front-running of funds in distress continues to be a viable, easy to implement trading strategy that may have profound negative effects on funds in distress.

Our paper is related to a recently developed body on price pressures within equity markets. The common ground among this literature is that it recognizes that short-term demand curves can be less than perfectly elastic due to non-informational demand shifts. For example, Mitchell et al. (2004) show that around mergers, uninformed shifts in demand among professional investors creates transitory price pressure. Related to mutual funds, Ben-Rephael et al. (2011) point to short-lived price distortions caused by aggregated daily flows to mutual funds in Israel and Lou (2011) explains mutual fund persistence and stock momentum with the price pressure caused by the flow-induced trading of mutual funds. The price pressure caused by mutual fund flows seems to be realized by the firms' managers – Khan et al. (2011) show that when a stock is overvalued due to high mutual fund inflows, the probability of an SEO and insider sales tends to increase. The paper closest to ours is by Coval and Stafford (2007). They identify ex-post the price-pressure effects caused by funds in distress and focus on their price impact. They further show that there is price pressure predictability among stocks with expected high outflows. However, for this predictability to be exploited by investors, only public information has to be used. This is where we step in and contribute to the literature. We show that this negative price pressure predictability can be exploited by investors who use public information only. Moreover, we show that this predictability cannot be exploited among the largest stocks, because their prices revert before the real-time front-running strategy can identify the price pressures. Last but not least, we show that the front-running strategy's returns are decreasing over time but they can still be substantial.

Our paper demonstrates that front-running of mutual fund flow-induced sales is a viable option, but it does not show whether it is actually implemented by sophisticated investors. This is hard to test due to unavailability of trading data – we do not really observe who trades what. Chen et al. (2009) investigate whether hedge funds engage in such front-running activities but due to this unavailability of data they can only provide an indirect evidence. They show that the average return on long/short strategies by hedge funds increases with a larger fraction of the mutual fund industry being in distress. To our knowledge, the only paper that provides more direct evidence of actual front-running activities in general is by Cai (2009). He shows that during the LTCM crash, market makers front-ran customer orders coming from a particular clearing firm. Although Cai does not observe the identity of the firm, its orders closely matched various features of LTCM's trades through Bear Stearns[1].

Our paper is also related to a body of literature showing the investment benefits of institutions' portfolio disclosure. Verbeek and Wang (2010) investigate the performance of mutual fund copycat funds – funds that duplicate the disclosed holdings of active mutual funds, and find that such funds can generate higher returns than their target funds. Brown and Schwartz (2010) look at hedge funds and find no evidence that investors can benefit from disclosed hedge fund holdings, attributing the difference from the Verbeek and Wang (2010) study to the much more frequent portfolio rebalancing of hedge funds in comparison to mutual funds. They do, however, provide some indirect evidence that hedge funds front-run their own positions, prior to disclosure, in expectation of copy-cat investors. Wermers et al. (2010) show that the relative stock overweighting/underweighting in the

[1]For a textbook discussion on different forms of front-running, please see Chapter 11 from Harris (2002)

cross-section of fund managers contains information on future returns that could be exploited. More related to our study, Zhang (2009) shows that some mutual fund managers can consistently identify the flow-induced sales of mutual funds in distress and benefit from providing liquidity.

2 Data Construction and Sample Statistics

This study combines a number of commonly used databases - CRSP Mutual Fund Database, Thomson Financial CDA S12 equity holdings database, the CRSP monthly and daily stock files, Compustat, and I/B/E/S. The CRSP Mutual Fund Database provides monthly fund net investor returns, total assets and annual data on expenses, fees, and other fund characteristics. The Thomson Financial/CDA database covers quarterly/semi-annual holdings of mutual funds, as reported to the SEC or voluntarily reported by the funds, which we link to the monthly and daily CRSP stock files in order to obtain information on holdings' prices and returns (adjusting for stock splits and other share adjustments). Both mutual fund databases are free of survivorship bias and linked via the MFLINKS tool provided by WRDS. Our study focuses on US domestic actively-manged equity mutual funds, for which the data is most complete and reliable. Thus, we exclude index, balanced, bond, money market, sector, and international funds, as well as funds who do not invest primarily in stock equities. Since most actively managed US equity funds offer different share classes to investors, we sum the net assets over different share classes and take asset-weighted share class average of different attributes such as returns and expense ratios. More details on the merging process and sample selection is available in Appendix A. We also use accounting data from Compustat and analyst forecast data from I/B/E/S for constructing our public information variables discussed later.

The summary statistics of our sample are presented in Table 1. In total, we span 2639 US actively managed mutual funds during the 1990 - 2010 period, which is in line with previous studies. The number has grown from 457 in 1990 to 1321 in 2010 and peaks around the dot com bubble. We present medians rather than means because there are a few exceptionally large funds which drive the sample means upwards. The median number of stocks in the portfolios of those funds is

73 which implies a reasonable degree of diversification. The median assets under management is \$211 million and has steadily grown over time. The returns of mutual funds vary over time and follow the business cycle, with a median of 1.11 % per month. Turnover and expense ratios are stable over time with median yearly values of 63% and 1.17%, respectively.

The yearly flow patterns indicate that there are no specific years where few extreme fund flows were observed. Although the mean and median value of monthly flows varies over time, the monthly flow percentile numbers in the last two columns indicate that a substantial number of funds had a very negative or positive extreme flows in any year. The lowest decile of fund flows in our sample is -3.27% per month, but it never gets above -2.5%. This is particularly important for our study since high negative monthly fund flows are the source of the stock price pressure patterns that our front-running strategy tries to exploit.

3 Constructing the fire-sale front-running strategy

Following standard procedures in the literature, we define flows for fund j during month t as the return-adjusted difference in total net assets (TNA) between the start and end date of month t:

$$flow_{j,t} = (TNA_{j,t} - TNA_{j,t-1} * (1 + Return_{j,t}))/TNA_{j,t-1} \tag{1}$$

3.1 Forecasting fund flows

The front-running strategy that we investigate in this paper profits from the likely price pressures of funds that are about to experience extreme outflows. Hence, for this strategy to work, we need to forecast fund-specific flows and identify the funds that are most likely to cause price pressure in prices. The summary statistics, reported in Table 1, indicate that extreme inflows are realized as frequently as extreme outflows. Coval and Stafford (2007) and Lou (2011) show that these extreme inflows can also cause buying price pressure. This implies that our front-running strategy has to net out any buying pressure from the selling pressure. Therefore, in order to identify both buying and selling pressure, we forecast extreme fund outflows *and* inflows.

To accomplish this, we rely on the well-documented persistence of fund flows and the predictability of investors chasing past returns. Sirri and Tufano (1998), Ippolito (1992), and Chevalier and Ellison (1997), among others, show that mutual fund investors have the tendency to invest in successful funds and withdraw money from losing funds. This indicates that fund flows are strongly related to past fund flows and returns. However, the relationship between flows and performance is non-linear – fund flows respond stronger to past successful performance rather than past poor performance.

This indicates that modeling separately extreme inflows and extreme outflows might produce better results than modeling all fund flows together. We use separate logistic regressions for estimating the probability of a fund to experience extreme outflows *or* extreme inflows. In the first logistic regression we estimate the probability of a fund to experience extreme outflows and assign the binary dependent variable a value of 1 if the fund was in the lowest decile of the fund flow distribution and 0 otherwise. We use a separate logistic regression to model the probability of a fund to experience extreme inflows where the binary dependent variable is 1 if the fund was in the top decile of the fund flow distribution and zero otherwise. We use the same set of fund-specific characteristics as explanatory variables in both models. More specifically,

$$P\{Extreme\_Flow_{j,t} = 1\} = \frac{1}{1 + e^{-z}} \tag{2}$$

$$z = \alpha_t + \sum_{\kappa=1}^{n} \beta_{\kappa,t} flow_{j,t-\kappa} + \sum_{\kappa=1}^{n} \gamma_{\kappa,t} R_{j,t-\kappa} + \delta_{1,t} ln(TNA)_{j,t-1} + \delta_{2,t} ln(TNA)^2_{j,t-1} \tag{3}$$

where $R_{j,t}$ is the net return for fund j in month t and $ln(TNA)_{j,t}$ refers to the log of total net assets of fund j in month t. Consistent with Coval and Stafford (2007), we exclude funds whose information is too different between CRSP and CDA ($1/1.3 < TNA^{CRSP}_{j,t}/TNA^{CDA}_{j,t,}$) and funds with too extreme changes in TNA

$(-0.5 < \Delta TNA_{j,t}/TNA_{j,t-1} < 2.0)$.

The number of lagged flows and returns to be included in (3) can be determined empirically. In general, the higher order the lag, the smaller the effect size would be, because investors' decisions are mainly based on most recent data. Our results indicate that including flows and returns at lag 4 and beyond might produce results opposite to what economic theory predicts – a negative relationship between fund flows and past flows and returns. Therefore, we use only flows and returns during months $t-1$, $t-2$, and $t-3$. We further include log and log squared of net assets in order to capture possible non-linear differences in flows relating to fund size.

Each month we run the two logistic regressions and report the average of each estimated coefficient in Table 2. Standard errors are estimated using the time series of estimated coefficients (in a similar fashion to a Fama-Macbeth regression). The results are in line with those documented previously in the literature – lagged flows, returns, and net assets have a very strong explanatory power of current extreme flows, both in terms of statistical significance and economic magnitude. Similarly to the vast body of literature, we find that more recent information is more important for investors' asset allocation decisions, which is manifested in the decreasing magnitude of estimated betas and gammas from lag 1 to 3.

We want to construct an implementable front-running strategy, so using the averaged coefficients in Table 2 would result in a look-ahead bias. To make sure there's no look-ahead bias, we use the most recent estimates in month t, in order to forecast fund flows in month $t+1$. This means that we only use the most recent publicly available information for forecasting next month's flows[2]. We expect a fund to experience extreme inflows if it is in the top decile of the forecasted probability of experiencing extreme inflows. Similarly, we expect a fund to experience extreme outflows if it is in the top decile of the forecasted probability of experiencing extreme outflows.

Table 3 reports descriptive statistics of the funds with expected high inflows and outflows. On average, we expect 123 funds to receive an extreme inflow/outflow in

[2]We also tried to minimize the impact of estimation error by averaging the estimated coefficients over the last 5 months and then using those averages for forecasting the probability of funds to experience extreme flows. Results remain largely unchanged and we therefore proceed with the more simple specification where we use the most recent beta, gamma, and delta estimates.

the next period. This is an artifact of the way we construct our strategy – the expected funds with high outflows (inflows) are the ones in the top decile of estimated probability of experiencing outflows (inflows). Generally, funds with extreme flows are not big in size. The small median number of assets under management – $228 and 196 million is line with this. The higher mean numbers indicate that sometimes the size of the funds with high probability of experiencing extreme flows can be substantial. In contrast to the average fund in our sample, funds with expected high inflows/outflows hold more stocks in their portfolios – the median is 100 for the funds with high expected inflows and 91 for the funds with high expected flows. Table 1 shows that the medians for the whole sample is 73 stocks. The true flow values in the last two columns are particularly important - they indicate that our forecasting model really captures funds with extreme flows. The median number is higher for the funds with high expected inflows - this reflects the fact that the flow-performance relationship is stronger for funds with high inflows than outflows. Hence, it is easier to forecast extreme inflows than extreme outflows.

We further evaluate the out-of-sample fit of our morel using the realized flow distributions in the forecasted month. If a fund within the top decile of *estimated probability of experiencing* outflows in month t is in the bottom decile of *realized* flows in month t, then we consider that fund to be a correctly identified outflow fund. Similarly, if a fund within the top decile of *estimated probability of experiencing* inflows in month t is in the top decile of *realized* flows in month t, then we consider that fund to be a correctly identified inflow fund. We are able to correctly forecast 48% (30%) of the funds with extreme inflows (outflows), with a standard deviation of 10% (8%). In contrast, using the OLS approach of Coval and Stafford (2007) for forecasting the *actual* fund flows results in 42% (27%) of correctly forecasted funds with extreme inflows (outflows), with a standard deviation of 10% (8%). This indicates that our logistic regression approach that models separately funds with expected inflows and funds with expected outflows produces better tail flow forecasts than a model where the actual flows of all funds are modeled jointly.

3.2 Expected fire-sales

Forecasting fund flows can tell us which funds are potentially going to be involved in flow-driven transactions. To identify where exactly to expect price pressures, we need to look at the funds' portfolio holdings. Following Coval and Stafford (2007), we expect to observe more price pressure among commonly held stocks. The more-widely a stock is held by funds with expected high outflows, the more likely it is that this stock will experience a strong downward selling pressure. Therefore, the anticipated flow-induced sales should be concentrated among the most-widely held holdings of funds with high expected outflows.

Lou (2011) points that around 60 cents of each dollar invested in a mutual fund is used for scaling current positions up. Thus, despite the opportunity to invest in other stocks or to hold cash, a substantial number of money flow in successful funds is used for scaling positions, potentially causing buying pressure in prices. Therefore, in order to estimate the selling pressure on the stock level, we follow Coval and Stafford (2007) and subtract the selling pressure in a stock from the buying pressure in a stock. The differences should net out any buying pressure effects from the selling pressure of funds in distress and hence provide us with a better estimate of where to expect downward selling pressure.

For each stock i that is held by the funds with expected high inflows and outflows, we sum the holdings of all funds with expected high inflows and subtract the holdings of all funds with expected high outflows. We scale this expected pressure variable using the average stock trading volume between months $t-12$ and $t-6$. More specifically,

$$E_t(Pressure\_1_{i,t+1}) = \frac{\sum_j (N_{j,i,t}|E_t(high\_inflows) - \sum_j (N_{j,i,t}|E_t(high\_outflows)}{AvgVolume_{i,t-12:t-6}} \tag{4}$$

$N_{j,i,t}$ refers to the number of stocks i held by fund j, as of the latest publicly disclosed holdings of fund j prior to portfolio construction. Following standard practices in the literature, we assume a two month delay between the true portfolio holdings date reported in CDA Thomson Reuters and the date the holdings became known to the public. For example, consider a fund that reports on a quarterly basis. If the fund reported in the end of January, we start using its reported holdings in the end of March and include them for calculating the expected stock level pressure in (4) for months April, May, and June (adjusted for stock splits and other stock adjustments). For July we start using the newly publicly disclosed holdings in the end of June, which refer to fund level holdings for the end of April. Since a substantial number of funds report on a semi annual basis during our sample, we include those funds' holdings in (4) if they were disclosed to the public at most 6 months ago.

This stock level expected price pressure variable looks very similar to the one constructed by Coval and Stafford (2007). In fact, the main difference between our measure and theirs is that we use publicly available information only. The flow forecast of Coval and Stafford (2007) is based on Fama-Macbeth estimates spanning their whole data sample while we use real-time data. More importantly, they don't use a delay of fund level stock holding information becoming available to the public. While their analysis shows that there is predictability of flow-driven trades, it can not show whether this can be exploited by investors. Similarly, Lou (2011) shows that there is price pressure predictability in stock prices following the aggregate flows in the mutual fund industry, but this does not imply that his predictability can be exploited by investors.

The stocks with the highest expected downward price pressure are the ones with the highest probability of being commonly sold by funds in distress. Therefore, we select the stocks in the lowest decile of (4), which are the stocks ex-ante most likely to be in an outflow-driven sell in the next month. We take an equal-weighted average of all stocks in that portfolio. We call the stocks in that portfolio $Expected\ Fire - sales$ and refer to the one-month holding period of that portfolio as the $Holding\ Period$. Thus, estimating Expected Pressure happens at the beginning of the event month when we select the $Expected\ Fire - sales$. Rebalancing happens at the end of the $Holding\ Period$. We link the rebalanced portfolio returns and form a time-series of returns of the front-running strategy.

Table 4 reports the characteristics of the stocks expected to be fire-sales during the holding period. On average, we select 252 stocks in the expected fire-sale portfolio.

The total number of months for testing the fire-sale front-running strategy is 246. In only two of them we have less than 25 stocks in the portfolio. We further subdivide the sample along the NYSE mean size, which is month-specific. The majority of the stocks are below the mean - on average there are 194 below mean stocks per month and 58 above mean stocks. There are 244 months with more than 25 stocks below the mean and only 156 months with more than 25 stocks above the mean. Yet, stocks below the NYSE mean size are not illiquid stocks. Since the size distribution is highly skewed to the left, the mean size is located in quintile 5. There are less than 15% of the stocks that fall below the third quintile, which implies that shorting the expected fire sale stocks should not be hindered by short sale constraints or illiquidity. In terms of book-to-market ratio, we observe a tilt towards low book-to-market stocks among the below-mean stocks. This is consistent with fire-sales being stocks that are already in distress. In terms of previous 12-month returns, we don't observe more even distributions, without any tilt towards past losers or winners.

4 Performance of the expected fire-sales

We evaluate the performance of the anticipated fire-sales using a five-factor asset pricing model, including the excess return of the market, SMB, HML, Momentum and the traded liquidity factor of Pastor and Stambaugh (2003). Throughout this paper, we require at least 25 stocks per month, otherwise we drop that month's portfolio observation. Results are reported in Table 5. Overall, the expected fire-sale stocks generate a negative alpha which is not statistically different from zero. The SMB loading indicates that the front-running strategy is slightly tilted towards small stocks. Since the front-running strategy covers expected fire-sales, we observe a negative loading on Momentum. Systematic liquidity, proxied by Pastor and Stambaugh's traded liquidity factor, has a very low loading indicating little connection between the returns of the strategy and systematic liquidity.

The results in Panel A of Table 5 indicate that going short in all stocks with high expected flow-induced outflows cannot be profitable. We show that this happens because the performance of the strategy is blurred by the most liquid stocks who revert before the front-running strategy can detect the flow-induced selling pressure. The results in Panels B and C hint in this direction. The alpha of the below mean stocks is -50 basis points, which is statistically highly significant and economically very large. However, the alpha of the long stocks is highly positive – 86 basis points per month.

To investigate this sharp difference in returns between the two type of stocks in grater detail, we look at the five-factor alphas of the expected fire-sale stocks before and after the holding period month. Results over the 1990 – 2000 period are presented in Panel A of Table 6. We can see that the positive alpha of large stocks, shown in Panel C of Table 5, is because reversals in those stocks start before the front-running algorithm can detect the price pressures. We observe a sharp negative alpha in the month preceding the holding period and a very quick reversal during the event month. Thus, liquidity has already arrived on the market before we can exploit the flow-induced trading. The smaller stocks have a more gradual price pressure pattern – pressure starts a few months before they are included in the front-running strategy and reverts in the 3 months following the holding period.

Our results indicate that liquidity arrives faster for larger stocks which prevents the front-running algorithm from exploiting the price pressure effects caused by funds in distress. Large stocks are subject to a greater analyst coverage which diminishes information asymmetries – liqudity providers can more easily attribute the price decline to a non-informed shock and step in the market to restore prices to fundamentals. In contrast, smaller stocks are subject to less analyst coverage. Hence, liquidity providers would be less certain to assign the price decrease to a transitory downward price pressure than to something that they don't know.

Another reason why price pressure effects might be stronger for smaller stocks is that institutional investors prefer to hold larger, more liquid stocks (for example, see Gompers and Metrick (2001)). Greater institutional coverage implies that fresh liquidity arrives faster for larger stocks and consequently their prices restore faster to fundamentals.

5 Time-variation in returns

In this section, we examine time-variation in the returns of the expected fire-sales. In Figure 1, we plot the 120 month moving five-factor alpha of the expected fire-sales and of the subset of small stocks. We observe a very clear decreasing trend in alpha. This graph suggests that by the end of 2010, the monthly profitability of the trading strategy has already evaporated. One reason why this might happen is that markets have become more efficient and the magnitude of the price pressures has decreased. Another possibility is that following the first paper on price pressures by Coval and Stafford (2007), sophisticated investors have engaged in such front-running activities and driven the profits to zero.

Panels B and C of Table 6 concur the above evidence. The average pattern among large and small stocks in columns 2 and 3 show that the identifiable pressure effects were stronger before 2000. This is especially the case for small stocks. Columns 4 and 5 show that in the first half of the sample, there were economically very large price drops in the 3 months preceding portfolio construction and the whole holding period. After 2000, the size of the price pressure effects before the holding period has decreased, but during the holding period returns are zero, followed by reversals in the following month. Columns 6 and 7 report that the magnitude of the reversals among large stocks during the holding period has increased.

However, both Table 6 and Figure 1 are based on a monthly holding period. A closer investigation in daily patterns throughout the holding month reveals that ex-ante identifiable price pressures, lasting for about a month in the 1990s, have decreased their duration and last for only two weeks after 2000. Figure 2 plots the cumulative abnormal daily returns of one dollar invested in the expected fire-sales at the beginning of the holding period. Abnormal returns are measured as stock returns in excess of a value-weighted daily average of all CRSP stocks. Panel A examines the excess returns of the small and large expected fire-sales over the whole sample and confirms out previous findings – small stocks experience substantial negative returns and large stocks show high positive returns. However, the time when reversals start is different between the 1990s in Panel B and the 2000s in Panel C. During the 90s, small stocks experience small price decreases until the end of the holding month while large stocks experience some positive returns. In contrast, after 2000, reversals among the small stocks start much earlier - around 10 trading days after the estimation of the expected pressure variable. This explains why the monthly alpha estimate of the small stocks in the second half of our sample is roughly zero. Nevertheless, Figure 1 indicates that outflow induced price pressures could still be anticipated after 2000, but the duration of the holding period has to be reduced to two weeks.

There are number of potential explanations why the identifiable price pressure duration has decreased over time. In general, any financial market development that has lead to more capital provision, better information processing, and efficiency improvements is a potential candidate. Such developments may include greater institutional presence, information technology advances, financial engineering, growth in the supply of arbitrage capital, etc.

6 Alternative information explanations

Despite the transitory price pressure patterns reported in the previous sections, one might still conjecture that the success of the anticipated fire-sale strategy is driven by the incorporation of information. For example, an analyst forecast error, predicting higher than the actual earnings of a company might result in a very negative stock price reaction, once the earnings are announced and the error has been comprehended by market participants. This would result in a negative price reaction that could potentially drive the high abnormal returns documented earlier.

To test such information based explanations, we perform a Fama-MacBeth regression, regressing the returns of all stocks in the universe on common stocks characteristics known in the literature to forecast stock returns, and two information variables. The dependent variable is stock returns in month t. Following Jiang et al. (2009), we use the following explanatory variables - Log(size), defined as log of the market cap of the stock in month $t-1$; Log(B/M), defined as the book to market ratio at the most recent fiscal year-end, assuming a four month reporting lag (i.e. the most recent data used is from month $t-4$); PrRet, defined as the average 12 month stock return as of the end of month $t-1$; Lev, defined as the ratio of book value of assets to debt value of assets as of the most recent fiscal year end, assuming a four month reporting lag (i.e. the most recent data used is from month $t-4$); Short_big, defined as a dummy variable equal to 1 if the stock is above the mean NYSE stock size and the stock is included in our short portfolio and 0 otherwise; and Short_small, defined as a dummy variable equal to 1 if the stock is below the mean NYSE stock size and the stock is included in our short portfolio and 0 otherwise. The two information variables are standardized unexpected earnings (SUE) and analyst forecast error (FER). SUE is defined as reported quarterly earnings per share (EPS) in excess of EPS four quarters ago, scaled by the standard deviation of EPS over the past eight quarters or a minimum of four quarters (data is from Compustat). I include SUE in the regression if the EPS were announced in months $t-2$, $t-1$, or t. FER is defined as the realized quarterly EPS in excess of the mean of analysts EPS forecasts for that quarter, scaled by the previous year's book value of equity per share (data comes from IBES). I include FER in the regression of the EPS were announced in months $t-2$, $t-1$, or t. We correct for possible autocorrelation and heteroscedasticity using Newey-West standard errors with 3 lags.

The results, reported in Table 7, cannot provide support for the alternative information based explanations. In the first specification, we do not include the two variables related to unexpected earnings. Consistent with our previous findings, the small stock dummy is negative and significant, while the large stock dummy is positive and significant. Including SUE and FER in the second specification, we still observe a positive value for the short_big dummy and a negative value for the short_small dummy. Thus, unexpected earnings and realization of analysts' forecast error cannot explain the patter we observe in the previous section. Combined with the strong reversals documented in Table 6, we can rule out alternative information based explanation and conclude that our front-running strategy captures the transitory price pressure associated with the outflows of mutual funds in distress.

7 Robustness checks

To test the robustness of our results, we investigate the sensitivity of the expected pressure variable (4) to different expected flow breakpoints and data-cleaning procedures. Furthermore, we experiment with selecting the bottom 15 and 5% (instead of 10%) stocks of the expected pressure distribution as our expected fire-sales. Last, instead of taking an equal-weighted return of the expected fire-sales, we weigh the stocks according to the expected pressure, giving more weight to stocks with high expected downward price pressure (lower expected pressure, as defined in (4)). Results from these test (unreported) show that the profitability of the trading strategy remains despite altering the front-running algorithm.

<This section is to be completed.>

8 Conclusion

This paper investigates the returns of a real-time trading strategy which front-runs the anticipated fire-sales by mutual funds experiencing extreme capital outflows. Our results indicate that publicly available information on flows and holding of funds in distress offers viable investment opportunities. We show that the profitability of the strategy comes from the price pressure caused by funds in distress and identify important cross-sectional difference in the duration of those reversals. Despite a decreasing trend in the duration of price pressures that could be exploited, the trading strategy still offers substantial returns.

The trading strategy has two-building blocks. First, fund flows can be reasonably well-predicted due to the alpha chasing behavior of investors. Generally, investors' investments are directed towards funds with recent successful record, and money is redeemed out of funds with a recent poor record. This allows the anticipation of selling pressure on the fund level. Second, stocks most-widely held by funds in distress are the one with an ex-ante highest probability of experiencing outflow-induced selling pressure.

We should keep in mind that the profits of the front-running strategy do not necessarily have to be at the expense of mutual funds in distress. We borrow a numerical example from Chen et al. (2009) to illustrate this point. Consider that the front-running algorithm anticipates a substantial selling pressure in 100 shares of stock A 2 periods from now. Current price of stock A is $100 per share. Without front-running, risk-averse investors would absorb the selling demand at time 2 for $98 per share. Alternatively, the front-runner might short-sell 50 units of stock A at time 1 at price $99 per share and risk-averse liquidity providers would absorb the 100 selling pressure at time 2 at price $98 per share. In essence, this implies that the distressed fund(s) still sell stock A at $98 per share at time 2, but the rest of the market buys 50 shares at time 1 for $99 per share and another 50 shares at time 2 for $98. This simple example illustrates that the front-running profits might come from the general public and not the distressed funds.

Yet, one might easily provide numerous counter-examples where front-running can actually harm funds in distress. For instance, in the above example, if the fund's need to sell 100 shares at time 2 is exacerbated by the price effect of the front-runner's short-sale at time 1, then the distressed mutual funds suffer from front-runners. This implies that our study might have important implications for funds in distress that experience substantial outflows. We do not directly show the potential negative consequences on funds in distress that could be caused by front-runners, but our results indicate that funds with substantial outflows might suffer from the short-selling activities of front-runners. In times of distress, the last thing that fund managers need is predatory short selling that might drive down the value of their assets even further. Regulators are then left with the task to think how to protect funds in distress from the potentially destructive front-running of other market participants.

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Appendices

Appendix A Database Construction and Sample Selection

We start by selecting all US open-ended mutual funds from the CRSP mutual fund database and Thomson Financial CDA database from January 1990 till June 2010. To ensure that we cover the universe of domestic diversified equity funds, for which the holdings data is most reliable, we select in our sample only funds with one of the following objective codes, provided by Lipper, Wiesenberger, and Strategic Insight and available in the CRSP Mutual Fund Database:

- Lipper: 'EI', 'EIEI', 'EMN', 'FLX', 'G', 'GI', 'I', 'LCCE', 'LCGE', 'LCVE', 'LSE', 'MC', 'MCCE', 'MCGE', 'MCVE', 'MLCE', 'MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE', 'SESE', 'SG'
- Wiesenberger:'SCG', 'AGG', 'G', 'G-S', 'S-G', 'GRO', 'LTG', 'I', 'I-S', 'IEQ', 'ING', 'GCI', 'G-I', 'G-I-S', 'G-S-I', 'I-G', 'I-G-S', 'I-S-G', 'S-G-I', 'S-I-G', 'GRI', 'MCG'
- Strategic Insight: 'SCG','GRO','AGG','ING','GRI','GMC'

Furthermore, we include funds only if they have one of the following investment objective codes in the Thomson Financial database: aggressive growth, growth, growth and income, or unclassified, thus excluding any international, bond, asset allocation, precious metal and sector funds. Then, we drop funds that hold less than 80% or more than 105% in common stocks, as reported by CRSP. We also drop index funds by removing funds that contain in their CRSP-reported fund name the strings 'INDEX', 'INDE', 'INDX', 'S&P", or 'MSCI'. From Thomson Financial database, we remove overlapping report dates and file dates caused by fund mergers and name changes. We also delete funds that hold less than 10 stocks or manage less than $5 million.

If a fund offers multiple share classes to investors, we aggregate across different share classes. For total net assets (TNA) under management, we sum the TNAs of individual shares. For funds's age, we select the age of the oldest share class. For the other fund attributes (expenses, turnovers, etc.), we take the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes.

We link the two mutual fund databases, using the MFLINKS database provided by WRDS. More information on how MFLINKS assigns a unique fund identifier to each fund in the two databases can be found in Wermers (2000). We manually check the MFLINKS databases for assigning reports from different Thomson Financial funds to the same fund in MFLINKS, and resolve such problems manually.

Table 1: **Descriptive Statistics.**
This table provides summary statistics for our mutual fund sample. Net Assets are measured in millions of US dollars, turnover and expense ratios are expressed as percentages per year, and flows are expressed in percentages per month. Note that CRSP does not provide turnover ratios for 1991.

Year	# of funds	# of stocks	Net Assets	Net Return	Turnover	Expenses	Monthly Flows			
		Median	Median	Median	Median	Median	Median	Mean	Perc10	Perc90
1990	457	55	120	-0.24	58	1.20	-0.10	0.38	-6.58	6.91
1991	545	54	120	2.70	.	1.18	0.12	1.39	-2.99	6.72
1992	611	57	135	0.95	55	1.20	0.50	2.33	-2.55	7.45
1993	785	61	164	1.26	61	1.19	0.53	1.93	-2.66	7.70
1994	923	65	142	0.24	56	1.17	0.32	1.40	-2.74	6.10
1995	1012	66	155	2.44	63	1.20	0.35	1.86	-2.74	6.57
1996	1100	70	205	1.85	64	1.21	0.45	1.92	-2.86	6.65
1997	1269	72	195	2.29	68	1.20	0.42	1.91	-3.10	7.06
1998	1345	71	214	2.79	70	1.23	0.05	1.16	-3.74	5.71
1999	1446	68	222	1.47	71	1.23	-0.32	0.57	-4.55	5.49
2000	1556	72	257	-0.78	74	1.23	-0.01	1.24	-3.96	6.36
2001	1639	74	231	-0.14	77	1.25	-0.05	1.02	-2.56	5.37
2002	1719	76	184	-2.05	70	1.29	-0.31	0.72	-3.17	5.18
2003	1791	77	176	2.04	66	1.31	0.02	0.95	-2.52	4.70
2004	1815	81	208	1.36	62	1.28	-0.17	0.82	-2.74	4.62
2005	1809	77	231	0.39	62	1.25	-0.39	1.53	-3.07	4.74
2006	1755	77	267	1.25	63	1.23	-0.45	0.63	-3.12	4.13
2007	1774	77	307	0.94	63	1.18	-0.53	0.03	-3.33	3.25
2008	1678	75	249	-2.41	70	1.18	-0.73	-0.37	-3.97	2.94
2009	1555	76	223	3.73	69	1.18	-0.53	0.20	-3.25	3.06
2010	1321	80	315	2.95	63	1.17	-0.58	-0.09	-2.98	2.59
2000 - 2010	2639	73	211	1.11	66	1.23	-0.17	0.90	-3.27	5.09

Table 2: **Logistic Regression Results.**
This table provides the results from the fund flow logistic regressions described in Section 3.1. Each month, we perform logistic regressions where the dependent variable equals to 1 if the fund flow is the top decile of fund flows and 0 otherwise (Panel A) or the dependent variable equals to 1 if the fund flow is the bottom decile of fund flows and 0 otherwise (Panel B). Explanatory variables are fund flows at lag 1, 2, 3, fund net returns at lag 1, 2, 3 and the log of net assets and log squared of net assets at lag 1. The estimated coefficients are averaged across time and standard errors are calculated using the standard error of the mean.

	Panel A: Extreme Flows								
	Intercept		Flow			Fund Net Returns		Ln(TNA)	Ln^2(TNA)
		Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag1
Est	-2.381	12.095	8.913	5.925	14.051	7.223	4.866	-0.104	-0.01
StE	0.135	1.28	1.23	0.65	1.362	1.332	0.936	0.043	0.004
	Panel B: Extreme Outflows								
	Intercept		Flow			Fund Net Returns		Ln(TNA)	Ln^2(TNA)
		Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag1
Est	-2.217	-10.144	-6.292	-4.484	-10.959	-3.027	-3.652	0.041	-0.018
StE	0.101	1.653	2.272	0.751	1.832	2.104	0.861	0.038	0.004

Table 3: **Characteristics of Funds with Expected Extreme Flows.**
This table provides characteristics of funds that were forecasted to experience extreme flows, according to Section 3.1. Each month, we use the estimated coefficients from the logistic regression models to estimate next month's probability of a fund to experience extreme flows. If a flow is in the top decile of the estimated probability distribution to experience extreme inflows, then we select that funds as an Expected Inflow Fund. If a flow is in the top decile of estimated probability distribution to experience extreme outflows, then we select that funds as an Expected Outflow Fund. Net Assets are reported in millions of US dollars. True flow refers to fund flows during the holding period, expressed as percentage of net assets.

	# of Funds		Net Assets		# of stocks		True Flow	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Expected Inflow Funds	123	134	537	228	100	93	7.81	7.15
Expected Outflow Funds	123	134	588	196	91	89	-1.63	-2.16

Table 4: **Characteristics of the Expected Fire-sale Stocks.**
This table provides summary statistics for the expected fire-sale stocks. "All" refers to all expected fire sale stocks, "Small" refers to the expected fire sales that are below the mean NYSE stock size that month, and "Large" refers to the expected fire sales that are above the mean NYSE stock size that month. In Panel A, we report the average number of observations, the number of months for which we have observations, and the number of months for which we have more than 25 observations. In Panels B, C, and D we report the distribution of stocks along five book-to-market, size, and last 12 month return month specific NYSE quintiles.

			Panel A: Frequencies		
	Observations Average	Months	Months|obs>25		
All	252	246	244		
Small	194	246	244		
Large	58	238	156		
			Panel B: B/M		
	Q1 (low) (%)	Q2 (%)	Q3 (%)	Q4 (%)	Q5 (high) (%)
All	22.63	24.27	21.82	18.70	12.58
Small	19.01	22.72	22.52	21.05	14.70
Large	36.21	30.05	19.22	9.91	4.61
			Panel C: Size		
	Q1	Q2	Q3	Q4	Q5
All	2.84	11.50	23.18	30.22	32.26
Small	3.59	14.57	29.37	38.30	14.16
Large					100.00
			Panel D: PrRet		
	Q1	Q2	Q3	Q4	Q5
All	17.44	21.02	20.36	22.14	19.04
Small	19.85	20.80	18.66	20.83	19.86
Large	8.41	21.86	26.74	27.01	15.98

Table 5: **Five Factor Alphas of Expected Fire-Sales During the Holding Period.** This table reports the risk-adjusted performance of the fire-sale front-running strategy. At the end of each month, we rebalance the short portfolio according to the description in Section 3.2. The equal-weighted portfolio returns are linked to form a time series of returns. In Panel A, we select all expected fire sales. In Panel B, we select expected fire sales that are below the mean NYSE stock size that month, and in Panel C we select the expected fire sales that are above the mean NYSE stock size that month. The risk factors included in the model are excess market returns (Mkt), SMB, HML, MOM, and the traded liquidity factor of Pastor and Stambaugh (2003).

	Alpha	Mkt	Smb	Hml	Mom	Liq
			A: All Stocks			
Est	-0.18	1.18				
StdE	0.21	0.05				
Est	-0.38	1.18	0.42	0.36		
StdE	0.18	0.04	0.06	0.06		
Est	-0.19	1.09	0.44	0.28	-0.22	
StdE	0.17	0.04	0.05	0.06	0.03	
Est	-0.22	1.09	0.45	0.29	-0.22	0.05
StdE	0.17	0.04	0.05	0.06	0.03	0.04
			B: Small Stocks			
Est	-0.49	1.22				
StdE	0.24	0.05				
Est	-0.74	1.20	0.52	0.40		
StdE	0.21	0.05	0.06	0.07		
Est	-0.48	1.08	0.55	0.30	-0.31	
StdE	0.18	0.04	0.05	0.06	0.03	
Est	-0.50	1.08	0.56	0.31	-0.31	0.04
StdE	0.18	0.04	0.05	0.06	0.03	0.04
			C: Large Stocks			
Est	0.83	1.06				
StdE	0.27	0.06				
Est	0.77	1.08	-0.04	0.08		
StdE	0.28	0.06	0.08	0.09		
Est	0.83	1.06	-0.04	0.07	-0.05	
StdE	0.28	0.07	0.08	0.09	0.05	
Est	0.86	1.06	-0.04	0.07	-0.05	-0.09
StdE	0.28	0.07	0.08	0.09	0.05	0.08

Table 6: **Five Factor Alphas of Expected Fire-Sales Around the Holding Period.** This table reports the risk-adjusted performance of the fire-sale front-running strategy around the holding period. At the end of each month, we rebalance the short portfolio according to the description in Section 3.2. We track the returns of the expected fire sales during the holding period month and during the 6 months before and after the event month. The equal-weighted portfolio returns are linked to form a time series of returns. "All" refers to all expected fire sales, "Small" refers to expected fire sales that are below the mean NYSE stock size that month, and "Large" refers to expected fire sales that are above the mean NYSE stock size that month. The risk factors included in the model are excess market returns (Mkt), SMB, HML, MOM, and the traded liquidity factor of Pastor and Stambaugh (2003).

Month	All		Small		Large	
	Est	StdE	Est	StdE	Est	StdE
	Panel A: 1990 – 2010					
-6	0.64	0.17	0.50	0.18	1.38	0.29
-5	0.68	0.19	0.44	0.19	1.14	0.25
-4	0.34	0.18	-0.02	0.19	1.22	0.26
-3	-0.49	0.19	-0.75	0.20	0.17	0.26
-2	-0.95	0.18	-1.18	0.19	-0.06	0.27
-1	-1.46	0.19	-1.43	0.20	-1.02	0.29
Holding Month	-0.22	0.17	-0.50	0.18	0.86	0.28
1	0.38	0.17	0.48	0.18	0.04	0.24
2	0.36	0.16	0.35	0.17	0.27	0.23
3	0.26	0.17	0.22	0.17	0.49	0.29
4	-0.01	0.17	0.01	0.17	-0.30	0.24
5	0.06	0.15	0.09	0.17	-0.26	0.23
6	0.15	0.16	0.20	0.17	0.31	0.29
	Panel B: 1990 – 2000					
-6	0.64	0.24	0.41	0.26	1.23	0.31
-5	0.78	0.24	0.33	0.23	1.19	0.27
-4	0.64	0.25	0.23	0.26	1.23	0.29
-3	-0.68	0.28	-1.14	0.29	0.26	0.32
-2	-0.98	0.25	-1.30	0.25	-0.04	0.33
-1	-1.43	0.27	-1.43	0.27	-1.00	0.35
Holding Month	-0.41	0.21	-0.70	0.24	0.52	0.33
1	-0.06	0.26	0.25	0.27	-0.11	0.32
2	0.50	0.23	0.66	0.25	0.11	0.31
3	0.06	0.23	0.13	0.24	-0.02	0.29
4	-0.13	0.23	-0.02	0.23	-0.56	0.28
5	-0.25	0.18	-0.22	0.19	-0.56	0.27
6	-0.23	0.22	-0.16	0.24	-0.70	0.33
	Panel C: 2000 – 2010					
-6	0.77	0.25	0.68	0.26	1.97	0.53
-5	0.61	0.30	0.52	0.31	0.98	0.46
-4	0.19	0.27	-0.07	0.28	1.31	0.46
-3	-0.51	0.28	-0.61	0.30	-0.10	0.46
-2	-0.82	0.29	-0.97	0.30	0.22	0.48
-1	-1.51	0.29	-1.36	0.30	-1.02	0.50
Holding Month	0.69	0.29	0.07	0.28	1.67	0.54
1	0.68	0.25	0.66	0.26	0.31	0.40
2	0.32	0.24	0.20	0.25	0.53	0.41
3	0.39	0.26	0.29	0.26	1.06	0.53
4	0.10	0.25	0.04	0.26	0.05	0.42
5	0.17	0.25	0.16	0.27	0.01	0.39
6	0.40	0.25	0.37	0.24	1.21	0.50

Table 7: **Alternative Information Explanations.**
This table reports the results of Fama-Macbeth regressions, where each the returns of all stocks in the universe are regressed on a number of variables, known in the literature to predict stock returns. Each variable is described in Section 6. The table reports the the time-series averages of the monthly cross-sectional regressions. We use Newey-West standard errors with 3 lags.

	Model 1		Model 2	
	Est	StdE	Est	StdE
Intercept	2.79	1.21	2.83	1.20
Log(size)	-0.13	0.07	-0.13	0.06
Log(b/m)	0.15	0.11	0.14	0.11
PrRet	1.71	3.44	0.56	3.43
Lev	-0.03	0.44	-0.06	0.44
Short_small	-0.32	0.15	-0.33	0.15
Short_large	1.35	0.33	1.35	0.33
Sue			0.06	0.01
Fer			1.17	0.36

Figure 1: **Rolling 120 Month Alphas of the Front-Run Fire Sales**.
This Figure reports the rolling 120 month alphas of the stocks included in the front-running strategy. "All" refers to all expected fire sales and "Small" refers to expected fire sales that are below the mean NYSE stock size that month. The risk factors included in the model are excess market returns (Mkt), SMB, HML, MOM, and the traded liquidity factor of Pastor and Stambaugh (2003). The horizontal axis indicates the final month of the 120-month investment window.

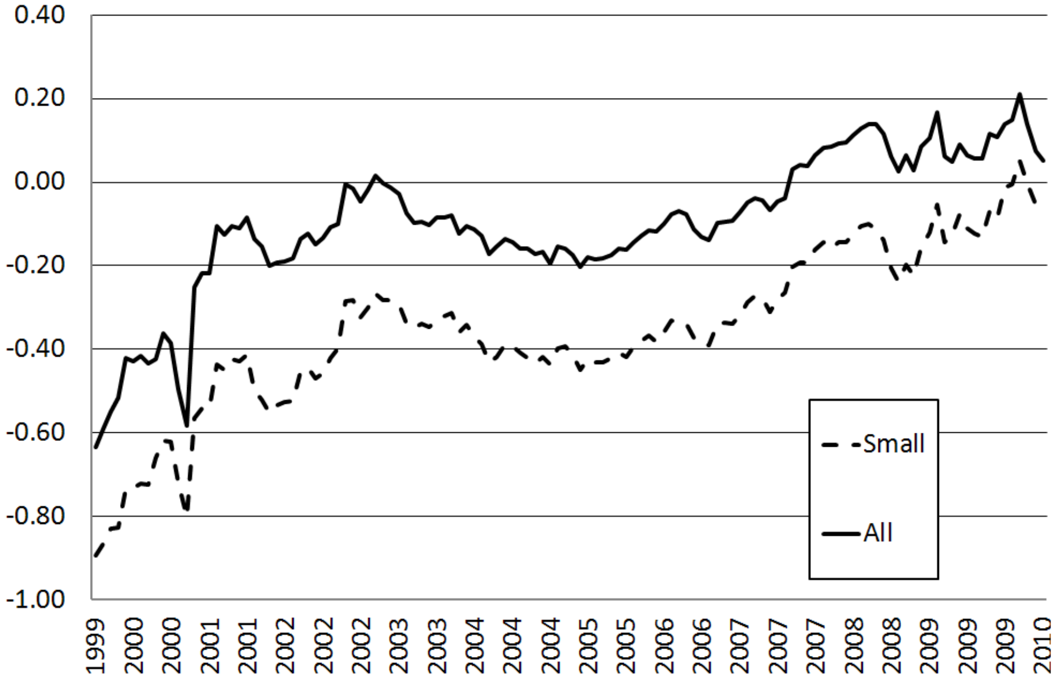

Figure 2: **Average Daily Cumulative Excess Returns During the Holding Period**.
This Figure reports the average daily cumulative excess returns of one dollar invested in the beginning of the holding period. Excess returns are defined as stock returns minus a value-weighted return of all stocks in CRSP on the day. “All” refers to all expected fire sales and “Small” refers to expected fire sales that are below the mean NYSE stock size that month.