THE FUND FLOW IMPACT ON STOCK RETURNS

A STUDY ON THE IMPACT OF FUND FLOWS ON STOCK RETURNS

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The Fund Flow Impact on Stock Returns: A Study on the Impact of Fund Flows on Stock Returns

Abstract:

This study examines the relationship between mutual fund flows and stock returns in the Swedish equity market. We measure each stock's exposure to fire-sale risk by examining its ownership structure and the share of free float held by mutual funds. Our results yield a positive relationship between fund flows and stocks' return, with a stronger relationship for outflows than inflows. We also find evidence of temporary mispricing caused by fund flows: stocks subject to flow-driven price pressure tend to reverse as market liquidity normalizes. However, our back tested trading strategy designed to exploit this pattern underperformed the market, indicating that generating practical, risk-adjusted excess returns is difficult.

Keywords: Mutual fund flows, Fire-sale risk, Liquidity shocks, Ownership Structure, Price Pressure

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1. Introduction

A central challenge in asset management is the constant risk of investor redemptions, which can force rapid and inefficient liquidation of portfolio holdings. The withdrawal can be made usually within days leaving the fund manager with a limited time of liquidating the investment in the portfolio. As a result, the fund manager may be forced to sell below the fundamental value due to the shortage of time (Coval and Stafford, 2007). This poses a fire-sale risk and explains how the occurrence becomes enhanced when it occurs at scale. As a result, the occurrence at scale could drive prices down, with reversals occurring as liquidity returns to the market. This mechanism illustrates how flows can induce a non-fundamental price (Aragon and Kim, 2023).

Sweden stands out among other countries when considering fire-sale risk. Firstly, Swedish households hold around 10% of their total financial assets in investment funds and 7% in listed equities, placing them among the leading countries in Europe (OECD, 2025). Moreover, approximately 70% of all Swedes hold private mutual funds, illustrating how widespread retail investing is in Sweden (Fondbolagens förening, 2024). Secondly, over the past decade, Swedish households have shifted their investment strategies — moving away from direct equity ownership towards indirect equity investments through funds, which has led to a substantial increase in fund ownership (OECD 2025). Thirdly, despite Sweden's strong savings culture, the financial knowledge is limited, where for instance 4 out 10 people believes funds are riskier than stocks (Finansinspektionen, 2023). Lastly, evidence shows that retail investors tend to liquidate their fund holdings due to financial constraints, suggesting that many investments are not based on fundamental market valuation (Fondbolagens förening, 2024). The combination of a broad retail investor base, large capital flows into mutual funds, and limited understanding of underlying securities raises an important question: in a relatively small equity market like Sweden's, could these dynamics amplify the risk of fire sales and contribute to non-fundamental stock price movements?

This paper makes three main contributions. Firstly, our research establishes the relationship between fund flows and stocks with a greater degree of fire-sale exposure. Earlier research has found a significant relationship in, for instance, the U.S. equity market, but we provide evidence that the same phenomenon exists within smaller equity markets such as Sweden (Aragon and Kim 2023). Secondly, we demonstrate that the commonly used Capital Asset Pricing Model developed by William Sharpe (1964) does not fully capture the drivers of stock returns. By including a constructed beta that reflects fund-flow sensitivity, we obtain a more comprehensive picture of the relationship between traditional factors and the return of a stock. Thirdly, our main finding shows how the inefficiencies associated with fire-sale risk potentially could be exploited by retail investors. By constructing a practical trading strategy, we illustrate how retail investors in theory could be able to act on these inefficiencies in the Swedish equity market.

While most prior research on fire-sale risk has focused on large and liquid markets such as the United States, considerably less is known about how these dynamics unfold in smaller, more concentrated markets. By extending the analysis to Sweden, our study contributes to the literature by examining how market size and investor composition shape the transmission of liquidity shocks. This perspective allows for an assessment of whether fire-sale mechanisms are universal features or if they are particularly pronounced in markets where retail participation and ownership concentration are high. Moreover, by focusing on Sweden, a country characterized by a strong savings culture and a large fund-based investment system, we highlight how even well-developed but relatively small markets can be vulnerable to systematic flow-induced price distortions.

In summary, our research illustrates how an extensive passive retail investor base often without detailed knowledge of the underlying holdings can induce non-fundamental price movements. This finding challenges the efficient market hypothesis by showing that stock prices are not determined solely by fundamentals, but also by investor flows and the liquidity dynamics they generate.

All this in consideration, the aim of the thesis is to answer the following question:

Do Swedish large- and mid-cap stocks with high mutual fund ownership react more strongly, in terms of short-term returns, to mutual fund inflows and outflows than low-ownership stocks, and does this create potential arbitrage opportunities possible to use for retail investors?

Earlier research by Greenwood and Thesmar (2011) into the subject has found that a stock's fragility, defined as the concentration of ownership among funds exposed to correlated liquidity shocks, can serve as a strong predictor of future volatility and price instability. Building on this idea, they examine how stock prices become more fragile when ownership is concentrated among investors who follow similar trading strategies or face correlated liquidity needs. The authors show that when many shareholders are likely to sell simultaneously due to funding shocks or similar risk exposure, a stock's price becomes more fragile—that is, more sensitive to small shocks. Thus, the paper highlights that a stock's vulnerability depends not only on the company's own risk profile, but also on the composition and behavior of its investors.

Furthermore, Aragon and Kim 2023 extend Greenwod and Thesmar's research by quantifying the relationship between fund flows and stock returns. Based on this information they constructed a portfolio based on investigating mutual fund flows and stocks' risk towards fire sales, which earns a positive alpha. However, their paper is rather complex for a retail investor to realize. Therefore, our research has a more practical view of trying to replicate their evidence on the Swedish equity market, but also make it possible for retail investors to utilize this inefficiency. This contribution will not only highlight the inefficiency, but also provide practical information of how investors can act on the information.

In our empirical analysis, we classify large- and mid-cap stocks listed on the swedish stock exchange into decile groups based on mutual fund ownership, where a high mutual fund owenership equals a greater fire-sale risk, by taking inspiration from Aragon and Kim (2023). The purpose of this classification is to investigate how exposure to fire-sale risk affects stock prices across different levels of mutual fund ownership.

Next an ordinary least square regression is conducted, where individual monthly excess stock returns are regressed on this paper's two key predictors, the overall market excess return and the aggregated individual fund flow for each stock. The result indicates a positive significant relationship on an aggregated level in line with Aragon and Kim (2023), where fund flows do impact stock returns, which explains how a large inflow (outflow) of capital to funds can induce a buying (selling) pressure. As a result, the price pressure causes anomalies in the market which could be utilized.

Complementary evidence from prior studies provides a strong rationale for our trading strategy. Ben-Rephael, Kandel, and Wohl (2011) show that roughly half of the price impact from aggregate fund flows reverses within ten trading days, indicating that such price shocks are temporary rather than reflecting fundamental value changes. Similarly, Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) highlight the behavioral dimension, showing that retail-driven fund flow imbalances can temporarily amplify anomalies before market liquidity restores equilibrium. Cella, Ellul, and Giannetti (2013) further document that during periods of market stress, large stock sales generate temporary price distortions, particularly

for stocks heavily held by short-term investors. Taken together, this evidence suggests that temporary price inefficiencies driven by fund flows exist across markets and time periods. Building on this research, we also found evidence in our results of a temporary price shock in the Swedish equity market, with prices reversing as liquidity returns. Building on this literature and supported by our own findings of a positive relationship between fund flows and stock returns, we propose a trading strategy designed to exploit these short-term inefficiencies.

Finally, we construct a trading strategy based on our earlier findings. The strategy focuses exclusively on outflows, as we found the strongest relationship between outflows and expected returns. Our results show that the reversal effect is strongest after two months. This timing is consistent with practical constraints, since fund flow data are published with a delay and therefore cannot be traded on immediately. Buy decisions are triggered by an outflow rule, described in more detail in Section 3.4. In brief, the rule says that a long position is taken when the theoretical fund flow is negative, and the stock belongs to a decile with higher exposure to fire-sale risk. Positions are held for one month and then liquidated. The portfolio uses the market portfolio as its base allocation. When qualifying outflow signals are detected, 50% of the portfolio is allocated to the strategy and 50% to the market portfolio. If no qualifying signals are present, the portfolio is fully invested (100%) in the market portfolio. The trading strategy underperformed the market in the sample period 2021 and 2022. In contrast to earlier research by, for instance, Aragon and Kim (2023), who found an alpha in their trading strategy. Additionally, the trading strategy contradicts our earlier positive findings.

2. Data and Methodology

2.1. Data

The empirical analysis focuses on firms listed on the Nasdaq Stockholm Stock Exchange's large- and mid-cap list. The delimitation to only incorporate these securities has been made as a trade-off between incorporating a large enough sample to ensure reliable testing and only incorporate stocks that are liquid and media-covered enough to believe that the average investor would be able to obtain information about fundamentals. Too small and illiquid stocks risk jeopardizing the reliability, as the average retail investor might struggle to find enough information at reasonable cost and large owners trading might disturb short-term returns on non-fundamental basis.

The dataset has been developed by the authors through combing information from four main data sources manually. Stocks listed on the large- and mid-cap lists and their respective free floats have been obtained from the *Holdings* database. The number of stocks on each list has been changing throughout the time-period due to new IPO:s, mergers and delistings. November, and December 2022 were the months with the largest sample of stocks, including 219 securities.

Monthly stock returns are obtained from the Swedish House of Finance *Finbas* database, covering monthly adjusted prices, including dividends, of all listed stocks in the Nordic. The dataset includes only common equity and excludes preferred shares to ensure consistency in return behavior. To control for aggregate market movements in our regressions, monthly return data of the OMXS30 index are included as a benchmark measure of the Swedish equity market. Since FinBas does not provide returns for OMXS30, the data have been collected from LSEG Workspace for the sample period. The OMXS30 is a suitable reference given its well-established role as the primary performance indicator of the Swedish equity

market. All returns are expressed as total returns, incorporating dividends, to reflect the actual investor realized return.

The dataset covers all Swedish open-ended mutual equity funds sometimes invested in a large- or midcap security between January 2013 and December 2022. Historical data on net flow and assets under management (AUM) for all Swedish-domiciled equity mutual funds holding the sample firms are retrieved from the Swedish House of Finance Morningstar database. Fund flows have been aggregated to a monthly level in line with the sample frequency. Meanwhile Swedish legislation demands funds to report net flows monthly, the holding of each fund is only required to be reported quarterly. Hence, changes in fund-exposure are on quarterly basis.

2.2. The Flow Factor

To test for individual fund flows' impact on stock returns, we have calculated a theoretical fund flow TFF per stock and month. This numerical flow is calculated for stock i by taking the net flow of each fund holding the stock and multiplying this flow with the fund's exposure to stock i. The sum of theses flows is the TFF. Although net flows are reported on a monthly basis, fund holdings are only reported on a quarterly basis. Hence, to calculate this theoretical flow of each security, we have assumed that each fund has a constant exposure for the entire duration of the following quarter until a new report is handed in. Mathematically, the calculation looks like:

$$TFF_{i,t} = \sum(NFF_{j,t} \times SFH_{j,i,t}) \quad (1)$$

Where $TFF_{t,i}$ is the Theoretical Fund Flow in or out of fund j at time t, $NFF_{j,i}$ is the net fund flow of fund j in time t and $SFH_{j,i,t}$ is the share of the fund holdings of fund j invested in security i at time t.

To standardize flow factors and make them comparable over time as the market capitalization and the value of the free float changes, and comparable against the flows of other securities, we have constructed a percentual theoretical flow factor *PTFF* defined as theoretical fund flow *TFF* divided by the market value of the free float. Mathematically, this equation is specified as follows:

$$PTFF_{i,t} = \frac{TFF_{i,t}}{MVFF_{i,t}} \quad (2)$$

$PTFF_{i,t}$ is the percentual theoretical fund flow for security i at time t, $TFF_{i,t}$ is the theoretical fund flow of security i at time t and $MVFF_{i,t}$ is the market value of the free float of security *i* at time *t*.

2.3. Conceptual Framework

To test our hypotheses, we have developed a conceptual framework of security pricing based on fund flow as one of the factors. Our framework is a further development of the *Capital Asset Pricing Model* developed by William Sharpe (1964) where the short-term return of a security is based on market return, the security's exposure to market risk and stock specific percentual theoretical fund flow (PTFF), defined as in equation (2), of the current period. The decision to use the CAPM rather than alternative asset pricing models is motivated by our focus on the perspective of retail investors. For instance, estimating Fama–French factor loadings is considerably more difficult for retail investors in the Swedish equity market.

Moreover, when constructing the trading strategy later in the paper, we consistently balance the benefits of increased model sophistication against the need for the strategy to be replicable by retail investors. Developing an overly complex strategy would likely result in a model that works in theory but is impractical to implement in reality. Therefore, we will employ the most intuitive and fundamental asset pricing model—CAPM.

We use a rolling regression with time varying betas to estimate the beta for market excess return and percentual theoretical fund flow. The beta for each variable is estimated based on the past two-year data. Furthermore, the model assumes that fund flows consist of a two-part risk that can be divided into one systematic component and one idiosyncratic component, or a fund-specific component, were we test for the systematic component. This is motivated by the fact that all stocks in our dataset are held by at least 15 funds, and up to 102 funds, and that the fund-specific idiosyncratic risk, for example a fund changing manager or adjusting its management fee, over time on average will be zero across all funds, and hence also across all stocks.

The model is specified as follows:

$$r_{i,t+1} = r_{f,t} + \beta_{i,t}^{M} \times \left(E\left[r_{m,t}\right] - r_{f,t}\right) + \beta_{i,t}^{F} \times \text{PTFF}_{i,t+1} + \epsilon_{i,t} \quad (3)$$

where $r_{i,t+1}$ is the return of stock *i* at time *t+1*, $r_{f,t}$ is the risk-free rate at time t, $\beta_{i,t}^{M}$ is the market beta defined as security *i*'s sensitivity to the market excess return at time *t* net of the fund flow, $r_{m,t}$ is the market return at time *t*, $\beta_{i,t}^{F}$ is the security *i*'s sensitivity to fund flows and $\text{PTFF}_{i,t+1}$ is the theoretical fund flow as a percentage of the market value of the free-float.

Furthermore, to avoid forward-looking bias, we divide the dataset into two periods. The years 2013–2020 are used to develop and test our models. We then use data from 2021–2022 to validate our findings and assess whether the results generalize to completely new data.

3. Results

In this section, we report the main findings of the relationship between stock returns and fund flows. The analysis follows a step-by-step empirical structure where each section builds on prior results, integrating statistical outputs and contextual reasoning throughout.

3.1. Hygiene tests

To establish a baseline and investigate whether the Capital Asset Pricing Model (CAPM) holds for our sample of stocks and returns, we run a CAPM regression over an equally weighted portfolio of our sample universe. The full testing will be conducted through forming various equally weighted portfolios. The rationale behind this is that we want to investigate whether there is a possibility to observe a relationship disregarding the size differences between firms. Would a value weighted portfolio be used, the largest portion of stocks in our sample would be the deciding factor of our results, and not whether the trend is observable on average in the Swedish equity market. Nonetheless, the equally weighted portfolio of our sample should still follow the market excess return quite closely, as all stocks have a market capitalization above the Swedish mid-cap threshold of 150 million SEK. Table 1 reports the regression result using stock's excess return as the dependent variable. The results are presented for the full sample (2013–2020) in table 1.

Table 1

	Portfolio
Intercept	0,000
	(0,001)
Market Beta	1,030***
	(0,045)
R^2	0,84
Adj R^2	0,84
N	117

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 1: The market excess return (MKT_ER) regressed on stocks' excess return between 2013 and 2020.

Table 1 confirms the CAPM model holds robustly across the sample, with a statistically significant beta slightly above 1. This suggests that our constructed portfolio, though equally weighted, co-move with the overall market in a way consistent with risk-return theory (Sharpe, 1964).

Next, we enhance our model by including the percentual theoretical fund flows (PTFF)**,** defined as the ratio of estimated net flows into mutual funds relative to the value of a stock's free float, elaborated on in section 2. This flow-based variable attempts to capture demand pressure from the investor base, a mechanism explored in theoretical and empirical work by Aragon and Kim (2023).

Table 2

	2013 - 2022	**2013 - 2014**	**2015 -2016**	**2017 - 2018**	**2019 - 2020**
Intercept	0,000	0,001	0,004**	0,001	-0,003
	(0,001)	(0,002)	(0,001)	(0,001)	(0,006)
Market Beta	0,992***	0,965***	1,013***	0,970***	1,012***
	(0,045)	(0,072)	(0,027)	(0,043)	(0,140)
PTFF	0,396**	-0,669	0,618*	-0,618	0,424
	(0,134)	(0,502)	(0,296)	(0,053)	(40,274)
R^2	0,86	0,89	0,98	0,96	0,77
Adj R^2	0,85	0,89	0,98	0,95	0,75
N	92	23	24	24	24

*Note: *p<0.1; **p<0.05;***p<0.01*

Table 2: The market excess return + theoretical fund flow regressed on stocks' excess return divided into different years between 2013 and 2020.

Several key takeaways emerge from these results. PTFF is positively associated with returns when significant. This supports the idea that price pressure from flows is real, at least at times. However, our proxy for the net flow is only significant for one of the four time periods. Thus, it appears as if our calculated theoretical flows only drive stock returns on the aggregated market at times. The heterogeneity in PTFF impact across sub-periods likely reflects variation in market regimes and investor behavior. For instance, the beta is

statistically significant in 2015 – 2016, but insignificant in 2017 – 2018. One interpretation is that during low-volatility or low-turnover regimes, flows exert less pressure on prices. But in periods of turbulence, e.g., pandemic-era liquidity shocks, even moderate net flows may move prices due to reduced market depth.

These findings confirm that investor behavior and portfolio composition are significant for asset pricing, at least at times, particularly in concentrated institutional ownership markets. Our results, which align with previous work showing that institutional flows can move prices independently of fundamentals (Aragon and Kim, 2023), suggest that open-ended mutual funds introduce a systematic demand shock in the Swedish context. This supports the view that fund flows are not idiosyncratic noise, but rather constitute a systematic return driver for certain stocks and periods, a factor not captured by traditional risk models.

3.2. Test of Hypotheses

Previous research by Greenwood and Thesmar (2011) has found that the composition and behavior of its investors affects the stock's vulnerability. They show how the volatility increases when ownership is concentrated among investors who follow similar trading strategies or face correlated liquidity needs. Interestingly, Aragon and Kim (2023) shows that US securities proportionally owned to a larger extent by mutual funds already has priced in what can be called the risk of a *fund-run*, in practice being the risk of retail investors withdrawing large sums of money in a coordinated way, often due to macro-economic factors, but not due to a fundamental shift in the outlook for a specific fund or security.

Furthermore, the research by Akbas, Armstrong, Sorescu, and Subrahmanyam (2015) looked into the data trying to establish a pattern between flow driven price pressure, in either way, and a trend that can be described as a reversal back to the fundamental price. The study found that a pattern on the overall population of listed securities was hard to find, but if one focuses on solely the securities with a significant flow factor, most of the flow driven price changes are reversed within 90 days of trading.

Having established a baseline above, showcasing that there is evidence supporting the fact that fund flows are impacting stock returns on the whole population, albeit to various degrees over time, we will try to see if we can find a difference between stocks held by open-ended mutual fund to different degrees, resulting in our first hypotheses:

Hypothesis 1

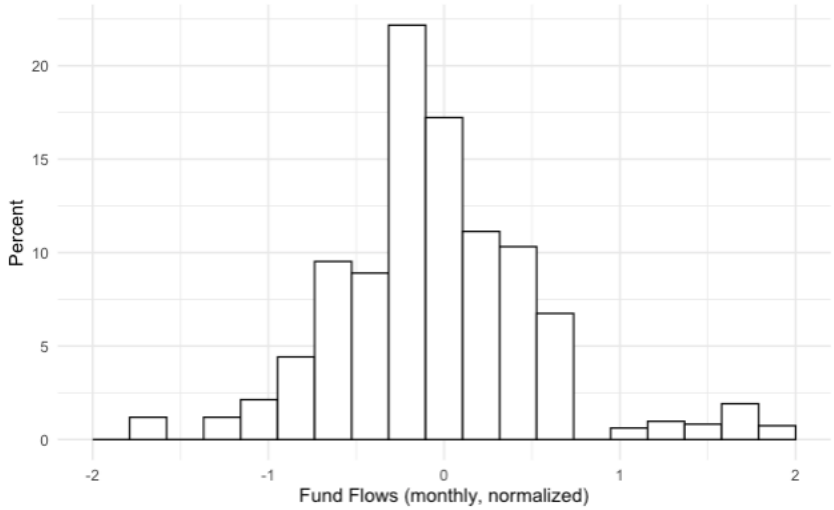
> *Stocks held to a larger extent by open-ended mutual funds will experience a stronger reaction to fund-flows, showcased by a larger beta, and stocks held to a lesser extent will neither have a particular large beta, nor will they have a significant relationship.*

However, this hypothesis does not answer the question regarding whether it is possible to find a pattern of reversal. To do that, we need to see whether stocks held by open-ended mutual funds experiencing large inflows (outflows) becomes overpriced (underpriced) in the following period(s) and how long, if ever, it takes for the price to adjust. If the price takes a long enough time to adjust, giving retail investor time to obtain and analyze the data on fund flows, stocks should in theory experience abnormal returns in future period before the price adjusts back to the fundamental value, giving rise to our second hypothesis.

Hypothesis 2:

> *The price reversals for funds with a significant relationship between fund flow and stock returns take more than one month to reverse back to the fundamental value, giving retail investors enough time to obtain and analyze data. In practice, the fund flow beta on lagged fund flows has a negative beta in the coming period(s).*

An interesting starting point is to analyze the distribution of fund flows



Graph 1: The distribution of the fund flows.

Fund flows appear to be somewhat normally distributed as by the result in graph 1, with many observations close to the median. However, this picture also yields an important implication – some flows are extreme. Fund managers, and retail investors to some degree, are likely aware of the importance of market liquidity and has developed their own strategy to coupe with this risk. Retail investors do likely keep part of their assets as liquid as possible, in practice as cash or on a bank account. Fund managers do likely also keep part of the fund's assets completely liquid, enabling them to meet smaller fund redemption by purely using cash and paying out. However, in times of abnormally large in- or outflows, this strategy will likely not work, meaning that they will have to liquidate positions to meet their obligation.

We start our hypotheses testing by dividing our dataset into ten portfolios, or deciles, based on the free-float share owned by mutual funds. The portfolios are dynamic in the sense that they are updated yearly based on changes in mutual fund holdings and free-float and is equally exposed to each stock in the portfolio every month.

If we regress market returns and theoretical fund flows on the return of our portfolios using the conceptual framework developed in 2.3, we yield the following returns:

Table 3

	Intercept	Market Beta	PTFF Beta	R^2	Adj. R^2	N
Decile 1	0,008 (0,006)	1,084*** (0,152)	-0,010 (0,156)	0,70	0,69	116
Decile 2	-0,008 (0,006)	1,101*** (0,151)	-0,044 (0,138)	0,66	0,66	116
Decile 3	-0,008 (0,006)	1,010*** (0,154)	0,022 (0,110)	0,69	0,68	116
Decile 4	-0,006 (0,006)	1,017*** (0,144)	0,253* (0,113)	0,79	0,79	116
Decile 5	-0,008 (0,006)	1,066*** (0,148)	0,111 (0,107)	0,75	0,75	116
Decile 6	-0,010 (0,006)	1.008*** (0,158)	0,026 (0,126)	0,68	0,67	116
Decile 7	0,002 (0,004)	1,119*** (0,099)	0,163* (0,093)	0,60	0,59	116
Decile 8	-0,000 (0,006)	0,759*** (0,117)	1,063*** (0,120)	0,80	0,79	116
Decile 9	-0,007 (0,005)	0,933*** (0,129)	0,857*** (0,134)	0,50	0,49	116
Decile 10	-0,007 (0,006)	0,982*** (0,134)	0,738*** (0,171)	0,68	0,67	116

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 3: The market excess return + the theoretical fund flows regressed on stocks' excess return divided into 10 deciles based on the free-float share owned by mutual funds.

Table 3 shows how the sensitivity of stock returns to fund flows varies across portfolios formed by mutual fund ownership. The CAPM betas are generally close to one for the lower ownership deciles but decline for the highest deciles, indicating that stocks with large mutual fund ownership behave less like the broad market and more like flow-driven assets. Furthermore, the PTFF beta, or the impact, of fund flows on stock returns increases as mutual fund exposure increases together with the significance level increasing. Hence, we can see that only for stocks with a relatively large mutual fund exposure, fund flows have a significant impact on stock returns. This contrast between low and high ownership deciles provides support for Hypothesis 1. It confirms that fire-sale risk is not a systematic market-wide phenomenon, but rather relates to what degree of the ownership is concentrated, which aligns with previous research of Greenwood and Thesmar's (2011). Thus, the stock's fragility becomes enhanced due to the concentrated ownership structure, which means that the stock price becomes more volatile to fund flows. Further on, we will thus only work with the deciles 7-10 as it is this group that appears to be of relevance when using fund flows to predict short-term returns.

That fund flows have an impact on short-term returns, at least for stocks with relatively high exposure to mutual funds, seems evident. However, what is interesting in regard to fund-flow pressure is if we can see any reversal back to a "fundamental" value as liquidity returns to the market, and how long this lag is. To test this, we will have to regress flows with a lag on return, and see if we can find an inverted relationship, that is a relationship with a negative sign. As supported by our previous regression in table 3, the relationship is only significant for stocks in the "high" group. Thus, we will only try the lagged flows on this portfolio. Regressing lagged flows of different magnitude on our portfolio yields the following results:

Table 4

	Intercept	**Market Beta**	**PTFF**	**R^2**	**Adj R^2**	**N**
1 month lag	0,003 (0,003)	1.095*** (0,078)	0,159 (0,174)	0,68	0,67	91
2 month lag	0,003 (0,003)	1,025*** (0,078)	-0,561** (0,195)	0,71	0,70	90
3 month lag	0,002 (0,002)	1,077*** (0,057)	0,150 (0,145)	0,80	0,89	89
4 month lag	0,002 (0,002)	1,085*** (0,057)	0,094 (0,146)	0,80	0,79	88
5 month lag	0,001 (0,002)	1,098*** (0,057)	-0,255 . (0,144)	0,81	0,80	87
6 month lag	0,001 (0,002)	1,097*** (0,059)	-0,113 (0,150)	0,80	0,80	86

*Note:*p<0.1;**p<0.05;***p<0.01*

Table 4: The market excess return + the theoretical fund flows regressed on stocks' excess return with a lag effect.

It is visible in table 4 that the strongest reversal effect seems to happen after 2 months have passed. Thus, it appears as if it takes approximately 2 months after a large flow-driven price change for prices to adjust back to the fundamental value of the security. The result should, however, be interpreted carefully. The lag effect is not calculated based on days and rather accumulated into months, which means that the reversal effect that is seen in table 4 should not be interpreted as an exact figure, rather an indication that there seems to be a reversal effect of the stock price around 2 months after a large flow-driven price change. In comparison, Rephael, Kandel, and Wohl (2011) have found that the reversal effect was shown already after 10 trading days. This research somewhat contradicts our results, since the result we have obtained is a significantly longer time period. But the main takeaway from our result and Rephael, Kandel, and Wohl (2011) is the fact that there is a reversal effect over several days. The time period could, though, vary.

The explanation of why there is a lagged effect as we interpret it is due to the fire sale effect. Thus, the market need time to adjust for the new stock price. Cella, Ellul, and Giannetti (2013) bring in the other perspective of how the short-term investors act during market stress where large stock sales generate temporary price distortions. Their findings show that short-term investors in fact amplify the effects of the market movement, since they

follow the same path as the fundholders who tend to have a longer investment horizon in this case. As a result, the market does not adjust instantly to the price change but rather needs time to readjust to the liquidity shock of the stock and wait until it has been stabilized.

To summarize, the results from table 4 support our second hypothesis that there is a significant relationship between fund flow and stock returns, and it takes more than one month to reverse back to the fundamental value, giving retail investors enough time to obtain and analyze data. However, the exact figure of 2 months according to our data shall be carefully used and should instead be interpreted as within a timeframe of around 2 months after a large flow-driven price change there will be some sort of reversal effect.

However, an interesting perspective to consider, which we have left out up until this point, is the effect of different flows. Although not stated, we have until this point assumed flows to be symmetrical in pressure on stock prices. In essence, that large inflows pressures prices in the same way as large outflows. This is necessarily not a clear-cut assumption to make. If a fund manager faces a redemption, their actions are limited. Either they can meet the obligation by using assets held as pure cash within the fund or they liquidate assets. If a fund manager faces a large inflow, the possible way of using this cash are many more. As with a redemption, the fund manager can increase the pool of liquid cash within the fund or increase the position of one or several assets held within the fund. However, the manager can also choose to invest in new assets, spreading the large inflow over a larger share of securities and thus reducing, or almost eliminating, the pressure put on any individual security. Hence, a reasonable thought is that large outflows are going to have a more profound impact on short term returns. To test this, we will run the same regressions as earlier, and as introduced into our conceptual framework, but have one separate regression for inflows and one separate regression for outflows.

Table 5

	Intercept	**Market Beta**	**PTFF**	**R**	**R^2**	**N**
Inflows	0,002 (0,008)	1,104*** (0,146)	-0,182. (0,0985)	0,91	0,89	116
Outflows	0,010 (0,008)	1,053*** (0,142)	0,323*** (0,093)	0,81	0,79	116

*Note: *p<0.1;**p<0.05***p<0.01*

Table 5: The market excess return + the theoretical fund flows regressed on stocks' excess return separated into fund inflows and outflows.

Table 5 shows that only the PTFF beta for outflows are significant. Thus, the results suggest that stocks subject to outflows are less driven by general market movements and are instead highly sensitive to the specific selling pressure. These results, supports hypotheses 1 for outflows, while the result for inflows do not supports it.

If we extend the analysis, trying to see the different effects depending on how exposed a stock is to mutual fund owners, the results look the following:

Table 6	Inflows				Outflows	
	Intercept	**Market Beta**	**PTFF**	**Intercept**	**Market Beta**	**PTFF**
1	0,002	1.063***	-0,161*	0,002	1,045***	0,170*
	(0,008)	(0,148)	(0,077)	(0,008)	(0,149)	(0,079)
2	0,003	1,080***	-0,170*	0,003	1,067***	0,183*
	(0,008)	(0,147)	(0,075)	(0,008)	(0,148)	(0,083)
3	0,002	0,966***	-0,168*	0,001	1,002***	0,154*
	(0,008)	(0,150)	(0,079)	(0,008)	(0,149)	(0,073)
4	-0,001	1,071***	-0,113	0,006	1,010***	0,225**
	(0,007)	(0,144)	(0,084)	(0,007)	(0,142)	(0,078)
5	-0,004	1,067***	-0,079	-0,001	1,015***	-0,034
	(0,008)	(0,148)	(0,077)	(0,002)	(0,060)	(0,038)
6	-0,003	1,081***	0,084*	-0,002	1,075***	0,122
	(0,008)	(0,157)	(0,041)	(0,008)	(0,157)	(0.085)
7	-0,001	1,215***	-0,145	0,001	1,118***	0,302***
	(0,009)	(0,162)	(0,078)	(0,008)	(0,156)	(0,078)
8	-0,007	1,117***	-0,007	0,020	0,899***	0,805***
	(0,007)	(0,142)	(0,958)	(0,006)	(0,122)	(0,112)
9	-0,004	1,112***	-0,126	0,020	0,976***	0,874***
	(0,007)	(0,147)	(0,142)	(0,006)	(0,123)	(0,120)
10	-0,003	1,131***	-0,141	0,001	1,023***	0,634***
	(0,008)	(0,148)	(0,148)	(0,007)	(0,139)	(0,138)

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 6: The market excess return + the theoretical fund flows regressed on stocks' excess return divided into deciles based on the free-float share owned by mutual funds. The data is separated into fund inflows and outflows.

Table 6 shows how outflows are always more significant than inflows, and have a larger beta, implying that a 1 percent outflow impact the stock returns much more than a 1-percent outflow. However, the PTFF beta do not linearly increase for outflows between the different deciles. In decile 8, there is a significant increase in the PTFF beta for outflows which corresponds to a value of 0,805. The data could thus be at a risk of having a too small sample, or perhaps have included a specific outlier, which impacts the results. However, more importantly considering the full picture, it becomes evident that the effect is the strongest for the 7th to 10th deciles, which supports our earlier reasoning from table 3 that there is a positive relationship between fund flows and stocks' return. Furthermore, by separating the flows into inflows and outflows the data shows that outflows have a greater impact on stocks' expected returns than inflows, since it is shown in our result that they constantly have a greater beta and are more significant.

Thus, it could be aligned with the reasoning of fund managers facing less options for outflows than for inflows. As a result, the fund manager is constrained to some degree to sell of the securities in the fund if the fund manager does not have enough liquid resources such

as cash. However, as previously mentioned, the fund manager will most likely only have a limited amount in cash, since having a too large cash balance would run the risk of missing the opportunity of investing the capital and earn a return, which is the purpose of the fund manager.

If we extend this reasoning to lagged flows, for significant portfolios or deciles 7 through 10, we get the following.

Table 7

	Inflows			Outflows		
	Intercept	**Market Beta**	**PTFF**	**Intercept**	**Market Beta**	**PTFF**
1 month lag	0,013 (0,006)	1.098*** (0,179)	-0,214 (0,401)	-0,001 (0,003)	1,094*** (0,073)	0,142 (0,191)
2 month lag	0,008 (0,007)	0,959*** (0,177)	-1,373 (0,683)	0,004 (0,003)	1,037*** (0,059)	-0,381** (0,131)
3 month lag	-0,005 (0,004)	1,058*** (0,089)	0,897* (0,388)	-0,004 (0,002)	1,078*** (0,068)	0,048 (0,150)
4 month lag	0,004 (0,003)	1,028*** (0,086)	0,252 (0,274)	0,000 (0,003)	1,127*** (0,074)	0,0598 (0,201)
5 month lag	-0,002 (0,003)	1,021*** (0,073)	-0,270 (0,256)	0,001 (0,003)	1,169*** (0,060)	-0,213 (0,194)
6 month lag	0,001 (0,003)	1,146*** (0,075)	0,173 (0,316)	0,001 (0,003)	1,096*** (0,085)	-0,312 (0,185)

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 7: The market excess return + the theoretical fund flows regressed on stocks' excess return with a lag effect. The data is separated into fund inflows and outflows.

Table 7 shows mixed results in comparison to table 4, where the flows were aggregated, and the reversal effect was shown after 2 months. The outflows beta is significant and negative, which aligns with the result in table 4. This should be evidence that there is a lag effect around 2 months for outflows, which also supports hypotheses 2. However, the result for the inflows is more difficult to interpret, since they differ from the result in table 4. It shows a significant value after 3 months, that is positive, which means that the effect continues to grow, which contradicts hypotheses 2. On the other hand, it shows a negative value on the second month, which aligns with hypotheses 2, but since it is not significant it is difficult to determine a definitive effect for inflows. Connecting to the results of table 5 and 6, it could be argued that the outflows have a greater effect on the stocks' expected return than the inflows.

3.3. Sector Effects

An interesting nuance is whether there are any visible sector different effects between the effect of price pressure due to fund flows. To test this, we have divided our dataset into different industries and target groups, trying to identify any such effects. These are presented below in table 8.

Table 8

	Intercept	Market Beta	PTFF	R	R^2	Fund Ownership
B2B	-0,001 (0,005)	1,023*** (0,047)	0,320* (0,136)	0,85	0,85	0,17
B2C	-0,000 (0,002)	0.967*** (0,057)	0,204 . (0,119)	0,77	0,76	0,19
Manufacturing	-0,010 (0,006)	1,107*** (0,149)	0,537* (0,239)	0,76	0,75	0,17
Real Estate	-0,006 (0,006)	0,998*** (0,153)	0,530** (0,170)	0,34	0,33	0,22
Retail	-0,012 (0,006)	1,043*** (0,160)	0,049 (0,107)	0,61	0,60	0,22
Financial Sector	-0,007 (0,006)	1,084*** (0,148)	0,218 (0,150)	0,73	0,72	0,16
Technology	-0,009 (0,006)	0,934*** (0,152)	0,587** (0,186)	0,71	0,69	0,16
Service	-0,004 (0,005)	1,070*** (0,639)	-0,639*** (0,132)	0,43	0,42	0,17
Medical Technology	-0,009 (0,006)	1,083*** (0,148)	0,306* (0,120)	0,34	0,33	0,14

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 8: The market excess return + the theoretical fund flows regressed on stocks' excess return divided into the following sectors: business to business, business to consumer, manufacturing, real estate, retail, financial sector, technology, service and medical technology.

As shown in Table 8, the results are mixed. Most sectors exhibit a positive and statistically significant relationship between fund flows and expected returns, reinforcing our earlier findings of a positive association. Investigating why some sectors do not display the same pattern falls outside the main scope of this paper. One possible explanation is the limited sample size, as dividing the data into sector-level subsamples results in relatively small observations. This may have influenced the estimates more than anticipated. Overall, the relationship between fund flows and stock returns remains positive at the sector level, supporting our previous conclusions.

3.4. Trading Strategy

The first step of developing a trading strategy is to decide what flows to act on. Based on our knowledge of which fund ownership deciles that are significant overall, deciles seven through ten, we now also want to establish which flows that actually are driving this level of significance. The winsorizing test below in figure 1 yields an unexpected result, the top and bottom flows are not significant. Rather, these decrease the overall significance of our model. Although surprising, our flows are purely theoretical and a possible explanation could be that

the largest positive flows and smallest negative flows actually are not hitting the stocks prices, but rather are handled in an alternative way, in practice implying that out theoretical flows are not equaling real flows in the stocks.

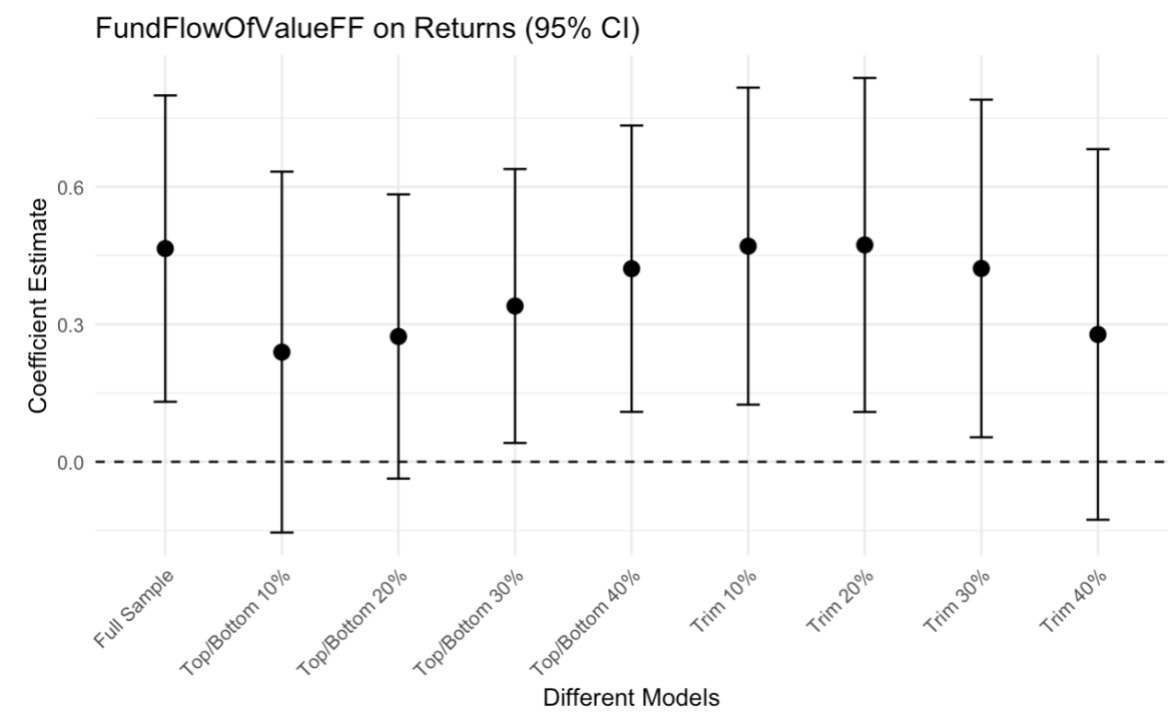


Figure 1: Windsorzing test of fund flow regression.

From figure 1, it is possible to see that a regression with 10% and 20% trimmed flows have the highest beta and are most significant and as more data is trimmed away, the beta estimate becomes insignificant once again. If we divide our monthly fund flows in to deciles, fund flow deciles, not to mix with the deciles used to classify fund ownership, fund ownership deciles, we see that the most significant flows are the flows that are in flow deciles 2, 3, 8 and 9, which are the flows we will act on in our trading strategy. As we previously have established that we only can find a significant lag-effect for outflows, the trading strategy will solely focus on outflows, which likely only will be present in the lower deciles during normal months.

Furthermore, when developing a trading strategy, we will make use of our previous findings in table 7 showcasing that the largest reversal effect for the significant decile groups is obtained after two months for outflows, and that no significant reversal effect for inflows can be found. In practice, information about fund flows is not possible to obtain in real time, but rather with a lag of between ten and fifteen days depending on the type of funds and if special grants have been given. Hence, it is not possible to trade on information about fund flows directly, but rather with a delay of at least ten days, which in our dataset with monthly observations is a delay of one month. As our regressions above suggest that most of the reversal effects have been obtained after two months, our trading strategy will thus incorporate a holding time of one month before trades made on outflows signals are liquidated. Our trading strategy is the following.

Each month, stocks are assigned to ownership deciles based on what share of the free float are held by mutual funds. Only firms in deciles seven through ten are included in the strategy universe as these are the deciles, we have deemed significant. Monthly theoretical fund flows are measured using the variable percentual theoretical fund flow, PTFF, and sorted into flow

deciles based on all previous flows analyzed in the data. An outflow signal, that is an outflow to act on, is generated when:

$$PTFF_{i,t} < 0, and\ FlowDecile_{i,t} \in \{2,3,8,9\}$$

Where $PTFF_{i,t}$ is the percentual theoretical fund flow of stock i in time t, $FlowDecile_{i,t}$ is the decile that the flow is placed in in relation to all other known flows. In reality, based on the distribution of fund flows, outflows will likely only be found in deciles 2 and 3. Due to the information delay, the strategy enters a long position at t = 1 if the abovementioned criteria is fulfilled, holds the stock for one month, which equals two months past the detected flow, and liquidates the position.

The portfolio has the market portfolio as a base, and allocates 50% to the market portfolio and 50% to the strategy if any outflow positions are detected. If no outflow signals fulfilling the criteria are detected, the strategy invests 100% in the market portfolio. The return of our strategy portfolio can be described as:

$$R_t^{Strategy} = \begin{cases} R_t^{Market}\ if\ no\ active\ positions\ exist, otherwise \\ 0{,}5R_t^{Market} + 0{,}5(average\ return\ of\ active\ long\ stocks)_t \end{cases}$$

The strategy returns are evaluated using our extended CAPM regression, including fund flows. Would we apply this strategy to the part of our dataset that we have used to analyze trends, and therefore being exposed to forward-looking bias, the cumulative return of our strategy would be:



Graph 2: Strategy returns vs market returns under forward looking bias.

Graph 2 displays how the trading strategy outperforms the cumulative market return during the same period. The result supports our previous findings of how mutual fund flows affect the stocks' prices and in fact the result supports the fire sale risk in the Swedish equity market. In comparison with Aragon and Kim (2023), who found an annual 3-7% alpha by constructing a somewhat similar trading strategy but with a focus on the U.S. equity market. However, the intercept of the regression, or our alpha, is still not significant. Although we clearly, during the time interval 2013 through 2020 would have a cumulative return larger

than the market return, we are not earning alpha during most months. Furthermore, this method is rather problematic as it is exposed to a look ahead bias – we are testing our method in the data we have used to construct it. It is not a surprise that it is, at least during some months, working.

For this reason, to test the strategy, we have saved two years of data during 2021 through 2022. The same trading strategy as the one above will be used on this data to see if we can achieve alpha, or a significant intercept. Our result from the regression shows the following.

Table 9

	Intercept	**Market Beta**	**R**	**R^2**	**N**
Full Sample	-0,015 (0,011)	1,267*** (0,225)	0,61	0,59	20

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 9: Results from the trading strategy and its comparison portfolios.



Graph 3: The cumulative returns of our strategy in comparison to the cumulative return to the market portfolio corresponding to our benchmark OMXS30.

Graph 3 displays how the trading strategy underperforms in relation to the cumulative market return during the same period. The result goes against our previous findings of how mutual fund flows affect the stocks' prices and is in fact in contrast. In comparison with Aragon and Kim (2023), who found an annual 3-7% alpha by constructing a somewhat similar trading strategy but with a focus on the U.S. equity market, we seem to not be able to profitably trade on theoretical fund flows.

While our earlier findings did not yield fully definitive evidence, but rather indications that suggest a relationship between mutual funds flows and stocks' returns, the trading strategy is an ultimate test. However, it appears as if, which is indicated by table 2, although the effect can be found long-term, it varies significantly between years. Furthermore, the

theoretical fund flows used by us are theoretical. In the end, there is little empirical evidence pointing towards that flows into or out from mutual funds would hit the fund in a proportional way. Lastly, it is important to remember that during the period of testing, the world experienced rough times. During 2022, Ukraine was invaded by Russia at the same time interest rates rose substantially. As seen by graph 3, our strategy yields returns close to those of the market until the end of 2022, when both the market and strategy returns becomes negative. A reasonable explanation of this is that our strategy detected outflows, which it acted on, which turned out to not reverse during the following two months. Hence, our large position in a few stocks that appear to have experienced smaller than market returns during this period, reduced the cumulative return of our strategy significantly. However, as evident by table 9, our strategy does not have a negative alpha, meaning that returns are not systematically below risk adjusted market returns.

The validity of the trading strategy may be subject to scrutiny. It is assumed that there are no transaction costs within our portfolio, which in reality is unlikely to be the case. As a result, the potential transaction costs would contribute to a decreased realizable alpha, or an even lower return in our case. Additionally, the accumulation of data and computing the theoretical fund flows requires a substantial sacrifice in time. Thus, with a limited investment, the transaction costs and the time spent collecting and integrating fund-flow data with the underlying securities may not be justified by the resulting return even if it would be a risk adjusted excess return.

3.5. A General Proxy

Calculating the theoretical fund flows are a time consuming, and highly manual, task. The information can thus be said to be too costly to produce for the average retail investor to earn enough alpha to justify the time invested. However, there is an additional opportunity, making the information much easier to obtain, namely the aggregated market fund flows on the Swedish fund market. These are collected and reported by *Fondbolagens Förening*, and published on their website with a three-week delay. If possible, a retail investor could in that case download all the necessary data in just a couple of minutes.

To use the market fund flows, we'll use equation 3, presented earlier, with some small adjustments. Instead of using a stock specific percentual theoretical fund flow, we will make use of the aggregated fund flow and adjust that to the aggregated value of the free float for all our stocks. Mathematically, this looks like:

$$PMFF_t = \frac{MFF_t}{\sum(FF_{i,t} * MC_{i,t})} \tag{4}$$

Where $PMFF_t$ is the percentual market fund flow in time t, MFF_t is the numerical market fund flow at time t, $FF_{i,t}$ is the free float of stock i at time t and $MC_{i,t}$ is the market capitalization of stock *i* at time *t*.

This term, $PMFF_t$, will then substitute PTFF, in our regression. Making the alternated version of equation 3 look like the following:

$$E(r_{i,t+1}) = r_{f,t} + \beta_{i,t}^{M} \times \left(E[r_{m,t}] - r_{f,t}\right) + \beta_{i,t}^{F} \times PMFF_t + \epsilon_{i,t} \tag{5}$$

Noticeably, the term *PMFF* does only vary depending on time, and not the stock or portfolio, during the regression. This is due to the exact reason making this more general

proxy easier to obtain – namely it being the flow for the whole market and not for individual stocks.

Performing the regression on the whole market yields the following results:

Table 10

	Intercept	Market Beta	PTFF	R	R^2	N
Full Sample	0,000 (0,000)	1,021*** (0,004)	0,000 (0,000)	0,84	0,84	92

*Note: *p<0.1; **p<0.05; ***p<0.01*

Table 10: The market excess return + theoretical fund flow based on the easier accessibly data from *Fondbolagens Förening* regressed on stocks' excess return on an aggregate level on the years between 2013 and 2021.

As could be suspected, the PTFF beta is insignificant. After all, the market fund flow includes all equity funds on the Swedish market, many of which are investing money in other stock exchanges besides the Swedish. The market fund flow thus seems to be too general of a proxy. However, considering the distribution of fund flows in table 1, we see that some theoretical flows appear to be of particular large size, perhaps that is the case for market fund flows as well. If we would try to regress returns only on those months were the flows are either in the top quartile or the bottom quartile, and only on the portfolios were we have seen the most significant effect in our previous regressions, we might be able to find a significant relationship.

Running such a regression yields:

Table 11

	Intercept	Market Beta	PMFF	R	R^2
Decile 7	0,001 (0,010)	0,985*** (0,235)	0,826 (0,422)	0,22	0,20
Decile 8	-0,000 (0,002)	1,088*** (0,062)	0,321** (0,112)	0,79	0,78
Decile 9	0,000 (0,002)	1,069*** (0,066)	0,137 (0,119)	0,75	0,74
Decile 10	0,000 (0,003)	1,056*** (0,077)	0,219 (0,139)	0,69	0,68

Note: *p<0.1; **p<0.05; ***p<0.01

Table 11: The market excess return + theoretical fund flow based on the easier accessibly data from *Fondbolagens Förening* regressed on stocks' excess return. The result displays the highest deciles from the 7th to 10th, where a higher decile means a higher value of the free-float share owned by mutual funds i.e. a greater degree to a potential fire-sale risk.

As could be suspected, an even more narrow version of the general proxy is not enough to generate significant results. Although decile 8 is significant, the overall portfolio and rest of the deciles are not. Even though this relationship has been observed on the US equity market, it is not visible for the period analysed here on the Swedish equity market. A likely

explanation is the size of the US equity market. The funds on the US equity market are to a vast majority invested in US securities, implying that a 1% fund flow in or out of a US fund often results in a 1% fund flow in or out of the US equity market. On the Swedish equity market, however, many funds are international ones, investing a substantial share in foreign markets, and especially the US equity market. As the aggregated flow in or out of funds listed on the Swedish stock exchange thus flows to a substantial part to foreign equity markets, only a small share actually impacts the Swedish exchange. Hence, it appears as if the aggregated flows on the Swedish market thus is too general of a proxy to be used when trying to seek alpha in trading.

4. Conclusion

We extend the traditional Capital Asset Pricing Model with a fund flow factor to explain the impact of deposits and withdrawals on mutual funds. By extending the traditional CAPM with a fund-flow factor, we provide evidence that non-fundamental drivers play a meaningful role in explaining stocks' returns in the Swedish equity market.

Our results show that fund flows have a positive impact on stock returns. Stocks that experience higher inflows exhibit higher short-term returns, while outflows correspond to lower returns, even after controlling overall market movements. However, the relationship is found to be stronger for outflows than inflows. Furthermore, this relationship becomes substantially stronger for stocks with high mutual fund ownership, supporting the idea that these securities are more exposed to fire-sale risk and thus more sensitive to liquidity shocks.

Beyond demonstrating this relationship, our results reveal a reversal pattern. According to our findings, the strongest reversal occurs approximately two months after the initial flow shock, suggesting that flow-induced price distortions are temporary and gradually reverse as liquidity returns to the market. This provides direct evidence of non-fundamental pricing dynamics in the Swedish equity market and challenges the notion of fully efficient price formation.

Finally, the result of the trading strategy is mixed. The strategy underperforms in relation to the cumulative market return during the same period, which goes against our previous findings of how mutual fund flows affect the stocks' prices. Thus, we encourage future research to test the effect on a greater time period and adjusting the strategy, since our strategy underperforms, while our earlier findings show a relationship between fund flows and stocks' expected returns.

Overall, our findings highlight that investor flows—rather than fundamentals alone—play a role in explaining short-term stock price movements. In a market where retail investors increasingly allocate savings through mutual funds, these flow-induced pressures can become systematic and meaningful.

Appendix

AI Disclosure

We have utilized ChatGPT in the writing process to check grammatical errors as well as in the coding process to spot errors.

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