



Mutual Fund Flows and Benchmark Portfolio Returns[#]

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ABSTRACT

I examine trading caused by net flows to mutual funds invested at the Oslo stock exchange. My results show that trading by index-linked mutual funds and actively managed funds are correlated with returns on different segments of the stock exchange. Neither investor sentiment, nor feedback trading explain this correlation. I argue that information cannot explain the results. Hence, I provide evidence that changes in demand matters for stock prices.

Keywords: Mutual Funds, Investment Flows, Portfolio Returns

JEL Classifications: G11, G12, G14

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1. INTRODUCTION

In this paper, I investigate whether net flows to mutual funds cause demand driven price impacts in stocks. Specifically, price impacts in stocks that are constituents of the indices the mutual funds use as benchmarks. I use data from the Norwegian stock market and regress portfolio returns on flows to mutual funds. I find that mutual fund flows are positively correlated with returns on constituents of the appropriate benchmark portfolios, and argue that this effect is a result of changes in the demand for stocks.

Three opposing hypotheses are heavily discussed in the literature: The efficient market hypothesis, the price pressure hypothesis, and the imperfect substitution hypothesis (Scholes, 1972 or Harris and Gurel, 1986). The efficient market hypothesis postulates that prices only reflect underlying values of the stocks. In an efficient market,

unanticipated changes in prices reflect changes in investors' information sets. When new information is made available to the market participants, prices change and remain unchanged until new information is made available. If all investors in mutual funds possess the same information, flows to mutual funds are expected to move in the same direction as the prices of stocks. This positive correlation is a response to new information, not to demand driven price impacts. As a consequence, prices reach a new fundamental value. Edelen and Warner (2001) use daily data and find common response in returns and mutual fund flows to be a manifestation of new information or positive feedback trading.

If large investors (i.e., institutions and mutual funds) place large orders in the market, stock prices may temporarily deviate from their fundamental value according to the price pressure hypothesis. Assuming, at the current prices, that all holders of stocks are satisfied with their holdings, a temporary price increase is needed in order for current holders to be willing to sell their stocks. The prices are expected to return to their fundamental value because the increase in demand is temporary. However, it is difficult to distinguish between the price pressure effect and information induced trading as we do not know how long we should expect price reversals to take. Lou (2012) finds that expected flow-induced trading positively predicts future returns in the short run, and negatively in the long run. My test for price pressure is weak, due to a limited number of observations, but does not indicate return reversals.

A third view is presented by Barberis et al. (2005). They present a habitat view of investing that is based on the observation that many investors trade in a subsample of all securities available in the market. The continuation of this literature documents that as stocks are included in an index, they receive an index price premium. Stocks included in the index also tend to co-move with other constituents after inclusion. This effect is present for both the S&P 500 index (Barberis et al. 2005, Wurgler, 2011, Goetzmann and Massa 2003, Morck and Yang, 2001) and the Nikkei 225 index (Greenwood and Sosner, 2007). When investors, for different reasons, change their exposure to the assets in the habitat, this change induces a common factor in the asset returns. Benchmark indices are examples of such habitats. Thus, this behavior may introduce a common factor in the returns on constituents of benchmark indices. The habitat view is similar to the imperfect substitution hypothesis, which assumes that stocks are not close substitutes. Under this hypothesis, prices move in response to changes in demand, but a price reversal is not expected.

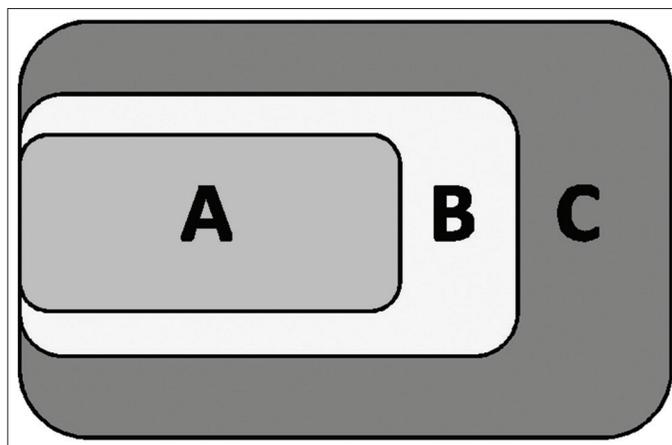
When analyzing individual securities, Coval and Stafford (2007) find that mutual funds tend to invest inflows in existing holdings and liquidate holdings to pay for redemptions. Lou (2012) finds similar results when analyzing the effect from aggregated flows on aggregated market returns. I add to this discussion by analyzing flows to mutual funds and the effect from flows on returns on their designated benchmark portfolios.

This paper builds on the findings of Warther (1995), who reports that aggregated security returns are unrelated to expected fund flows, but highly correlated with unexpected fund flows. The results could potentially be caused by investor sentiment. Warther (1995) estimates correlations between flows to equity funds and returns on other types of securities as a robustness check, but investor sentiment could differ between asset classes. Using a more granular approach, I find that mutual fund flows are positively correlated with returns on their designated benchmark portfolios.

I use data on net flows for all Norwegian mutual funds with Norway as primary investment region and I can identify mutual funds linked to indices. This information enables me to separate the effects from flows to index-linked mutual funds and flows to actively managed mutual funds. Figure 1 illustrates how uncluttered the Oslo stock exchange is. For instance, in the US stock market, many indices overlap. In addition, large index providers have many investible sub-indices, thus, making it difficult to isolate the effect from flows to index-linked portfolios on returns. Analyzing a small, uncluttered market makes it easy to identify what index a mutual fund uses as a benchmark, and to isolate the effect from trades made by mutual funds on returns.

I find that monthly returns on benchmark portfolios for index-linked mutual funds increase by approximately 0.74% points when unexpected net flows to the funds increase by one standard deviation. For actively managed funds, the effect is even larger. When unexpected net flows to actively managed funds increase by one standard deviation, monthly returns on the benchmark portfolios for actively managed funds increases between 0.67% and 1.49% points.

Figure 1: Illustration of Oslo stock exchange



The stock exchange consists of all stocks in sets A , B and C . The stocks in set A are the constituents of the OBX index. $A \cup B$ is the set containing the constituents of the broader index OSEBX and C is the set of stocks excluded from both indices.

My research question is related to the literature that discusses a positive correlation between investors' flows and returns. I add to this discussion, as I am able to separate the effects on returns from actively and passively invested mutual funds. Because I am able to identify the benchmark portfolio for each individual mutual fund, the causal link between flows and returns is better identified than for studies analyzing aggregate flows and aggregate market returns on different asset classes.

2. DATA

2.1. Stock Data

I collect daily close prices and dividend payments for all stocks listed on the Oslo stock exchange from January, 2006 through July, 2015. I only include stocks with a minimum of 10 trades on average per day, or shares with a liquidity provider scheme¹. I also collect information about which stocks the OBX index and the OSEBX index include during the same period. I calculate daily logarithmic total returns for all individual stocks and assign them to the correct index. If there are missing values in the time series of prices, returns are not estimated for that date and the consecutive date. I have three sets of returns series:

1. Returns on stocks included in the OBX index (set A in Figure 1).
2. Returns on stocks included in the OSEBX index, but excluded from the OBX index (set B in Figure 1).
3. Returns on stocks that are excluded from both indices (set C in Figure 1).

I construct value-weighted portfolios of the stocks in the three sets, A , B , and C . I assume 22 trading days each month, and sum weighted log-returns on portfolios A , B , and C for the last

¹ Some companies have agreements with market makers to reduce spreads between bid and ask prices and to ensure that liquidity is provided in their stocks.

22 trading days to create monthly observations. I denote these portfolio returns as $r_{A,t}$, $r_{B,t}$ and $r_{C,t}$ respectively.

The number of constituents in the OBX index has always been 25. The index consists of the 25 most liquid stocks based on 6 months turnover ratio. On average, 1.70 stocks are excluded from the index every 6 months, and 1.95 new stocks are included. The difference is due to more mergers and acquisitions than demergers. In total, during the sample period, 57 unique companies have been constituents of the OBX index. The sample number of constituents in the OSEBX index varies between 53 and 81, with an average of 62.5. The 25 stocks included in the OBX are always also included in the broader index OSEBX. The number of daily returns I calculate for stocks that are excluded from both indices ranges between 49 and 83, with an average of 61.

2.2. Mutual Funds Data

I use data for mutual funds with Norway as primary investment region from the Norwegian Fund and Asset Management Association (Verdipapirfondenes forening). Monthly observations are from January 2006 through July 2015. I consider a total of nine mutual funds to be index-linked, while I consider 59 mutual funds to be actively managed. The total number of funds includes both current funds and funds that have been closed. I select index-linked mutual funds based on the criteria that they have the word “index,” “OBX,” or “OSEBX” in their names. All other funds are considered to be actively managed.

Some mutual funds that claim to be actively managed are invested closely to one of the indices. Unfortunately, I am not able to quantify to what extent mutual funds are actively managed. Some index-linked mutual funds use the OBX as their benchmark, while most use the OSEBX. The OSEBX index is very similar to the OBX index. For instance, the market capitalization of OBX stocks amounts to 91% of the market capitalization of OSEBX stocks as of November 16, 2012. Constituents of the OBX index are chosen because of their high liquidity, and the market value of trades in OBX stocks on November 16, 2012 is 97% of the market value of trades in OSEBX stocks. Since trades in constituents of OBX account for such a high percentage of trades in OSEBX stocks, I pool index-linked mutual funds (with either index as a benchmark) together. In addition, the mandate of some mutual funds provides fund managers the opportunity to trade in derivatives. A mutual fund manager I have spoken with claims that they often trade in index futures, instead of the constituents of the index, as a response to short term flows. Since futures are only available for the narrowest index, the OBX, most of the trades will be made in this index' derivatives, regardless of what index is used as a benchmark. Both futures and underlying stocks are liquid instruments. Thus, whether trades are made in the underlying stocks or derivatives should not matter since arbitrageurs will buy the underlying stocks if the portfolio managers buy derivatives.

Compared to the domestic mutual funds market, with Norway as the primary investment region, index-linked funds' share of assets under management increases from 2.48% in January 2006 to 11.53% in July 2015. The market share grows steadily from year to year. Even though the growth in assets under management for

index-linked mutual funds is steady, net flows to these funds are more arbitrary (Figure 2). Net flows to mutual funds are commonly used as an explanatory variable in the literature concerning investor flows and stock returns. I let the variable f_{index} represent net flows to index-linked mutual funds,

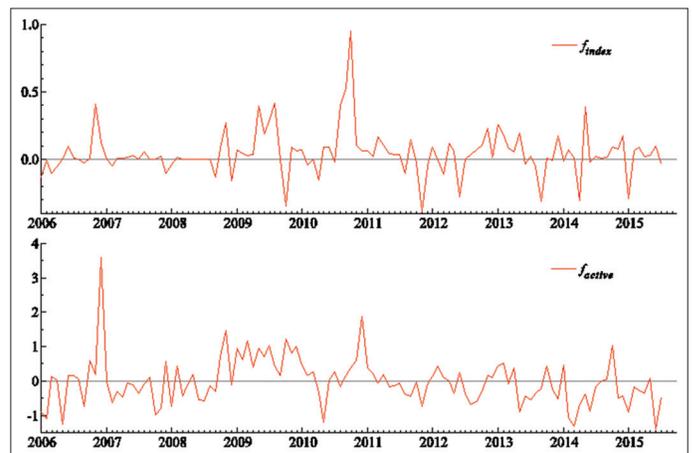
$$f_{index,t} = \sum_{i=1}^N (inflows_{t,i} - outflows_{t,i}),$$

Where, N is the number of domestic index-linked mutual funds, with Norway as the primary investment region, during month t . $inflows_{t,i}$ and $outflows_{t,i}$ are the signings and redemptions in fund i during month t . I let the variable f_{active} represent net flows to all other domestic mutual funds with Norway as the primary investment region. I assume that these funds are actively managed. I calculate the variable f_{active} in the same way as I calculate f_{index} .

On a monthly basis, the lowest monthly value of f_{index} is -386 million NOK and the highest monthly value is 951 million NOK. For the actively managed funds, the corresponding figures are -1,387 million NOK and 3,577 million NOK. As seen in Figure 2, both flow variables seem to be stationary, although the variation in net flows to index-linked mutual funds is considerably higher post 2009 than pre 2009.

A possible shortcoming of the variables f_{index} and f_{active} is that net flows become (close to) zero in months where signings and redemptions are (almost) equally large. I could alternatively have split the variable in signings and redemptions, representing a mutual fund's buying and a mutual fund's selling of stocks. For many of the months in my sample, this construction of the flow variables is likely to be a better measure for the funds' trading. However, signings and redemptions in the months close to year-end are often much higher than in other months. A market participant claims that life insurers and pension funds often redeem mutual fund shares, and sign new shares for the same amount, in order

Figure 2: Net flows to mutual funds



Top panel shows the value of net flows to index-linked mutual funds. Bottom panel shows the value of net flows to actively managed mutual funds. Values in both panels are in billion NOK. In early June 2013, one USD equaled approximately six NOK. Net flows are calculated using data provided by the Norwegian Fund and Asset Management Association.

to realize gains/losses on their holdings. This activity is reported as regular signings and redemptions by the mutual funds but do not cause trading by the mutual funds' managers. When I use net flows, I avoid this noise in the explanatory variables.

3. A NET FLOW EFFECT IN PORTFOLIO RETURNS

3.1. Hypotheses and Initial Empirical Observations

Index-linked mutual funds track the index they use as a benchmark. To this end, mutual fund managers trade in constituents of the index (i.e., stocks in portfolio *A* and *B*) and do not trade in stocks outside the index (i.e., stocks in portfolio *C*). Index futures traded on the Oslo stock exchange are for the OBX index (portfolio *A*). As many index funds use futures contracts to adjust their exposure to the stock market, the correlation between concurrent flows to index funds and returns is likely to be higher for portfolio *A* than for portfolio *B*. On the other hand, actively managed mutual funds' trading is relatively more concentrated in the stocks in portfolio *B* and portfolio *C*.

Lou (2012) reports that fund managers in general liquidate holdings dollar-for-dollar in response to outflows, while the response to signings leads to a slightly lower purchase of stocks. Thus, flows to index-linked mutual funds and/or other mutual funds should be correlated with returns on stocks in the appropriate portfolios if flows matter for stock prices.

Based on the arguments above, I hypothesize that net flows to index-linked mutual funds are positively related to returns on stocks in portfolios *A* and *B*, but not *C*. Similarly, I hypothesize that net flows to actively managed mutual funds are positively related to returns on a value-weighted portfolio of stocks in portfolios *A*, *B*, and *C*. My hypotheses are consistent with both demand driven returns and information driven returns. I distinguish between the two different drivers of returns in the analysis and when I discuss the results.

The initial empirical observations presented in Table 1 show that flows to index-linked mutual funds have a higher correlation with returns on portfolios *A* and *B* than with returns on portfolio *C*. Net flows to actively managed funds (f_{active}) are more correlated with returns on all three portfolios. The low correlation between the two flow variables does not necessarily suggest that investors possess different information, but rather indicates that flows in response to common information account for a small amount of total flows. Hence, investor sentiment does not seem to be the primary driver of common flows.

Estimated correlation coefficients for returns on the three portfolios are between 0.63 and 0.76, indicating high correlation between the returns series. We can also see in Table 1 that returns on portfolio *C* are less volatile than returns on portfolios *A* and *B*.

3.2. Model using Expected and Unexpected Net Flows

Motivated by the findings reported in Table 1, I test whether returns on portfolios *A*, *B*, and *C* move in the same direction as

Table 1: Descriptive statistics

	f_{index}	f_{active}	r_A	r_B	r_C
Means	4.5×10^{-2}	-1.5×10^{-2}	5.9×10^{-3}	-1.7×10^{-3}	3.5×10^{-4}
Standard deviations	1.7×10^{-1}	6.9×10^{-1}	6.6×10^{-2}	6.0×10^{-2}	4.0×10^{-2}
Correlation matrix					
f_{index}	1.00	0.22	0.10	0.09	0.06
f_{active}		1.00	0.21	0.13	0.25
r_A			1.00	0.63	0.76
r_B				1.00	0.63
r_C					1.00

This table presents descriptive statistics for selected variables. The variables f_{index} and f_{active} are net flows to index-linked mutual funds and actively managed mutual funds, respectively. Returns on portfolio *A* are denoted r_A , returns on portfolio *B* are denoted r_B , and returns on portfolio *C* are denoted r_C . Monthly returns from January 2006 through July 2015 are calculated as the sum of daily logarithmic total returns for the last 22 trading days

flows to mutual funds. In particular, I want to isolate the effect from flows to index-linked mutual funds and flows to actively managed funds. It is common to regard fund flows as being highly predictable. Warther (1995) uses an autoregressive model (AR-model) to estimate the expected and unexpected components of net flows². Further, he finds that aggregate market returns are highly correlated with unexpected flows to mutual funds, but unrelated to concurrent expected flows. Based on the habitat view presented by Barberis et al. (2005) and the results shown by Warther (1995), I also hypothesize that unexpected net flows to mutual funds are correlated with returns for the appropriate benchmark for the mutual funds.

Assets under management for index-linked mutual funds have increased dramatically in recent years, reaching 11.53% of the market capitalization of the domestic mutual funds market, with Norway as the primary investment region in July 2015. Index funds gained popularity during/after the financial crisis (Figure 2). To eliminate the possibility that results are driven by the crash in 2008, and to better utilize the variation in flows to index funds, I begin the analysis in February 2009.

According to the Akaike information criterion, an AR(1)-model has the best explanatory power of flows to index-linked mutual funds, and an AR(2)-model best predicts flows to actively managed funds (Table 2 for estimated results). For the AR-models I estimate adjusted R^2 of 5.45% and 25.88% for index-linked and actively managed funds, respectively.

The estimated net flows from the AR-models gives us the expected net flows. The unexpected part of net flows is captured by the residual. I use the expected and unexpected net flows to index-linked and actively managed funds to explain returns on portfolios *A*, *B*, and *C*. To this end, I estimate:

$$r_{i,t} = \beta_0 + \beta_1 \hat{f}_{index,t} + \beta_2 \tilde{f}_{index,t} + \beta_3 \hat{f}_{active,t} + \beta_4 \tilde{f}_{active,t} + \epsilon_t, \quad i = A, B, C. \quad (1)$$

Where, \hat{f}_s indicate concurrent expected net flows to the two

2 In an autoregressive model, the dependent variable depends on its own previous values.

Table 2: Autoregressive models

Dependent variable	f_{index}			f_{active}		
Constant	0.04 (2.63)**	0.04 (2.74)***	0.04 (2.34)**	-0.01 (-0.18)	-0.02 (-0.28)	-0.02 (-0.31)
Lag 1	0.26 (1.74)*	0.25 (1.73)*	0.25 (1.69)*	0.49 (6.31)***	0.38 (5.57)***	0.37 (5.19)***
Lag 2		0.04 (0.50)	0.03 (0.34)		0.22 (2.57)**	0.20 (2.14)**
Lag 3			0.04 (0.48)			0.06 (0.62)
Adj. R ²	5.45%	4.35%	3.23%	23.21%	25.88%	25.12%
AIC	-3.35	-3.33	-3.30	-1.25	-1.27	-1.25
N	78	78	78	78	78	78

This table reports regression results for autoregressive models where the dependent variables f_{index} and f_{active} are net flows to index-linked funds and actively managed mutual funds, respectively. AIC is the Akaike information criterion. The coefficients are estimated using monthly data from February 2009 through July 2015. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews, 1991). Both variables for flows are in billion NOK. *Indicates significance at the 10%-level, **indicates significance at the 5%-level, and ***indicates significance at the 1%-level using a two-tailed test

Table 3: Regression results

Dependent variable	r_A	r_B	r_C
β_0	1.4×10^{-2} (1.92)*	4.8×10^{-3} (0.63)	3.5×10^{-3} (0.57)
\hat{f}_{index}	-8.8×10^{-2} (-1.16)*	5.7×10^{-2} (0.93)	2.0×10^{-2} (-0.41)
\tilde{f}_{index}	4.0×10^{-2} (1.86)*	1.0×10^{-2} (0.67)	4.6×10^{-3} (0.23)
\hat{f}_{active}	9.4×10^{-4} (0.06)	6.7×10^{-4} (0.05)	1.8×10^{-2} (1.38)
\tilde{f}_{active}	2.9×10^{-2} (2.87)***	1.8×10^{-2} (1.96)*	1.3×10^{-2} (1.70)*
Adjusted R ²	10.45%	1.24%	0.74%
No. obs.	78	78	78

This table reports regression results where the endogenous variables are returns on three different portfolios at the Oslo stock exchange. The independent variables, \hat{f} and \tilde{f} , are expected net flows and unexpected net flows, respectively. Expected and unexpected net flows are estimated using AR-models. The final coefficients are estimated using an OLS approach using monthly data from February 2009 through July 2015. Flow variables are in billion NOK. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews, 1991). *Indicates significance at the 10%-level, and ***indicates significance at the 1%-level using a two-tailed test

categories of funds and \hat{f}_s indicate unexpected net flows to the same categories of funds.

The estimated results in Table 3 show that unexpected flows to actively managed funds have a positive effect on returns for all three portfolios. Also, unexpected flows to index funds are positively related to returns on portfolio A. The standard deviation off_{index} is 0.184. Thus, an increase of one standard deviation in unexpected net flows implies an increase in monthly returns on portfolio A of approximately 0.74% points. The effect from flows to index-linked mutual funds is not significant on returns on stocks outside the benchmark portfolio (portfolio C). Index-linked mutual funds are primarily invested in securities that are part of portfolio A. In addition, mutual fund managers of index-linked funds primarily trade in futures on the OBX index (portfolio A) as a response to short term flows. This behavior might explain the lack of significant results from flows to index funds on returns on portfolio B.

Actively managed mutual funds include sector funds, growth funds, momentum funds, etc. In aggregate, these funds have all stocks listed on the Oslo stock exchange as part of their investment universe (stocks in portfolios A, B, and C). According to estimated results in Table 3, a significant positive relationship exists between net flows to active mutual funds and returns on all three portfolios.

The standard deviation of $\tilde{f}_{active,t}$ is 0.513, which implies an increase in monthly returns on portfolio A of 1.49% points, an increase in monthly returns on portfolio B of 0.92% points, and an increase in monthly returns on portfolio C of 0.67% points as a response to an increase of one standard deviation in net flows.

Some could argue that these results are driven by investor sentiment. However, according to Lee et al. (1991), investor sentiment has a larger effect on small stocks than on large stocks. In my analysis, portfolio A consists of the largest stocks, while portfolio C consists of the smallest stocks. The reported effect on returns in Table 3 is over twice as large for portfolio A as for portfolio C. Also, information concerning the aggregated market cannot be the driver of these results, as coefficients for \tilde{f}_{index} are not statistically significant for returns on portfolio B and portfolio C. Therefore, estimated results support the hypothesis that flows to mutual funds affect returns on the portfolios the mutual funds use as benchmarks.

I lag the explanatory variables in Equation (1) with one period to investigate whether return reversals are present. If net flows for the previous period affect returns for the next period negatively we cannot reject the price pressure hypothesis.

As we can see from the estimated results in Table 4, none of the lagged variables are significant, indicating that price reversals are not present. However, it is difficult to know how fast reversals are supposed to happen. At one extreme we could expect reversals to happen intraday, while some studies look for price reversals over periods of up to several years. Due to the lack of intraday data and a limited number of observations, I am not able to perform a more extensive analysis to differentiate between the price pressure hypothesis and the imperfect substitution hypothesis.

3.3. Investor Sentiment and Feedback Trading

If investors are optimistic, returns on stocks and flows to mutual funds can be jointly determined by the psychology of the market participants. In earlier research, flows to mutual funds have been used as a proxy for investor sentiment. However, in recent years, investors have started trading heavily in exchange traded funds (hereby called ETFs). I argue that trades in ETFs are a more reliable proxy for investor sentiment than are flows to mutual funds, especially in the short run. While signings in mutual funds can take a couple of days, ETFs are traded “instantaneously” at

the stock exchange. Also, ETFs are cheaper and more tax efficient (Poterba and Shoven, 2002). In addition, Gutierrez et al. (2009) find that returns and volatility on Asian ETFs traded in the U.S. are more correlated with U.S. markets than Asian markets. These results are indicative that investor sentiment matter for trading in ETFs.

All ETFs in my sample are constructed to have exposure to the OBX index (portfolio *A*), and ETFs with both positive and negative exposure to the market exists. ETFs with positive exposure to the market are referred to as *BULL*, and exist as both leveraged and unleveraged securities. ETFs with negative exposure to the market are referred to as *BEAR*, but only include leveraged securities.

A secondary market transaction in an ETF represents both a buy order and a sell order. A buyer of an ETF with positive exposure to the market must be optimistic, while a seller can be either neutral or negative. If many sellers are neutral, high trading volume in ETFs will indicate positive aggregated market sentiment. The same argument applies for transactions in ETFs with negative exposure to the market.

Table 4: Regression results with lagged variables

Dependent variable	r_A	r_B	r_C
β_0	3.4×10^{-3} (0.42)	3.9×10^{-2} (0.45)	-5.6×10^{-4} (-0.07)
$\hat{f}_{index,t-1}$	1.1×10^{-1} (1.16)	1.0×10^{-1} (1.16)	6.0×10^{-2} (0.70)
$\tilde{f}_{index,t-1}$	-2.7×10^{-2} (-1.13)	1.2×10^{-2} (0.67)	-7.4×10^{-3} (-0.55)
$\hat{f}_{active,t-1}$	2.9×10^{-3} (0.16)	1.2×10^{-3} (0.08)	1.3×10^{-2} (0.80)
$\tilde{f}_{active,t-1}$	3.1×10^{-2} (0.32)	3.6×10^{-3} (0.35)	1.1×10^{-2} (1.42)
Adjusted R ²	-2.48%	-2.91%	0.19%
No. obs.	77	77	77

This table reports regression results where the endogenous variables are returns on three different portfolios at the Oslo stock exchange. The independent variables, \hat{f} and \tilde{f} , are expected net flows and unexpected net flows, respectively. Expected and unexpected net flows are estimated using AR-models. The final coefficients are estimated using an OLS approach using monthly data from March 2009 through July 2015. Flow variables are in billion NOK. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews, 1991). *Indicates significance at the 10%-level

Table 5: Regression results with sentiment variable

Dependent variable	r_A	r_B	r_C
β_0	2.1×10^{-2} (2.26)**	1.0×10^{-2} (1.17)	4.1×10^{-3} (0.54)
\hat{f}_{index}	-1.1×10^{-1} (-1.36)	4.2×10^{-2} (0.71)	-2.1×10^{-2} (-0.42)
\tilde{f}_{index}	4.0×10^{-2} (1.91)*	1.0×10^{-2} (0.69)	4.6×10^{-3} (0.23)
\hat{f}_{active}	1.6×10^{-2} (0.83)	1.3×10^{-2} (0.80)	2.0×10^{-2} (1.09)
\tilde{f}_{active}	2.9×10^{-2} (2.99)***	1.8×10^{-2} (2.05)**	1.3×10^{-2} (1.70)*
Sentiment	-8.8×10^{-3} (-2.03)**	-7.3×10^{-3} (-1.63)	-8.8×10^{-4} (-0.22)
Adjusted R ²	13.90%	3.76%	-0.09%
No. obs.	78	78	78

This table reports regression results where the endogenous variables are returns on three different portfolios at the Oslo stock exchange. The independent variables, \hat{f} and \tilde{f} are expected net flows and unexpected net flows, respectively. Expected and unexpected net flows are estimated using AR-models. The final coefficients are estimated using an OLS approach using monthly data from February 2009 through July 2015. Flow variables are in billion NOK. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews, 1991). *Indicates significance at the 10%-level, **indicates significance at the 5%-level, and ***indicates significance at the 1%-level using a two-tailed test

As seen in Figure 3, trading volumes in both categories of ETFs are highly correlated. To avoid potential problems concerning multicollinearity I chose to use the difference between the two trading volumes as a proxy for investor sentiment. I use public transactions in the ETFs as a proxy for investor sentiment when I estimate

$$r_{i,t} = \beta_0 + \beta_1 \hat{f}_{index,t} + \beta_2 \tilde{f}_{index,t} + \beta_3 \hat{f}_{active,t} + \beta_4 \tilde{f}_{active,t} + \beta_5 sentiment_t + \epsilon_t, \quad i = A, B, C. \quad (2)$$

Estimated results for Equation 2 are presented in Table 5, and show that a significant positive relationship between net flows to active mutual funds and returns exists even when controlling for investor sentiment. The effect from unexpected flows to both categories of funds is approximately the same size as earlier. The negative coefficient for the sentiment variable suggests that traders in ETFs are dominated by contrarians (i.e., selling when prices rise, and vice versa), or that information is interpreted differently by traders in ETFs and investors in mutual funds. However, information concerning the aggregated market cannot be the explanation for the significant coefficients for net flows, as coefficients for \tilde{f}_{index} are not significant for returns on portfolio *B* and portfolio *C*. If the relationship between flows and returns is driven by information, it needs to be firm-specific information concerning the individual stocks in the different portfolios. It is very unlikely that positive firm specific information is present for all three portfolios at the same time. Thus, the results indicate that the effect on returns is demand driven, and that trades by mutual funds cause price impacts for the appropriate benchmark portfolio.

Another possibility is that the results are driven by feedback trading. Feedback trading means that flows to funds increase as a response to an increase in returns. However, as we can see from the results in Table 6, lagged returns do not explain unexpected net flows to either actively or passively managed funds.

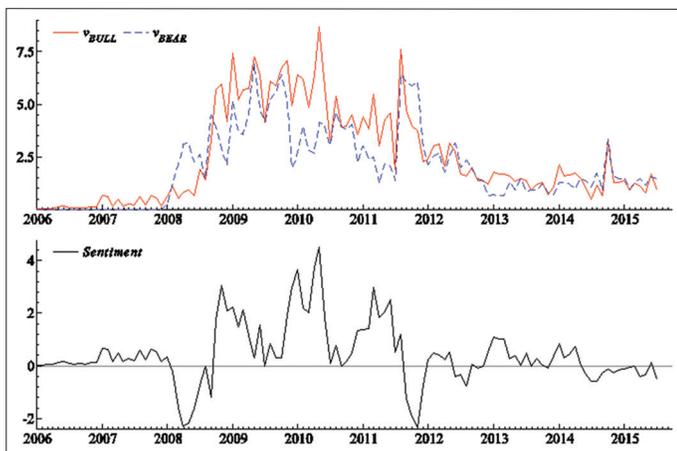
A final possibility is that mutual fund investors are informed traders, and that flows to mutual funds contain information about future returns. However, the literature treats mutual fund investors as the least informed investors in the market, making this view inconsistent with existing literature.

Table 6: Regression results for feedback trading

Dependent variable	\tilde{f}_{index}			\tilde{f}_{active}		
Constant	-0.00 (-0.05)	-0.00 (-0.06)	0.00 (0.05)	0.01 (0.22)	0.00 (0.05)	-0.00 (-0.01)
$r_{A,t-1}$	0.10 (0.22)			-1.39 (-1.12)		
$r_{B,t-1}$		0.16 (0.35)			-0.36 (-0.28)	
$r_{C,t-1}$			-0.38 (-0.50)			0.23 (0.14)
Adj. R ²	-1.26%	-1.18%	-0.75%	0.19%	-1.23%	-1.29%
N	78	78	78	78	78	78

This Table 6 reports regression results where the dependent variables \tilde{f}_{index} and \tilde{f}_{active} are unexpected net flows to index-linked funds and actively managed mutual funds, respectively. The coefficients are estimated using monthly data from February 2009 through July 2015. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews, 1991). Both variables for flows are in billion NOK.

Figure 3: Trading volume in exchange traded funds. The upper panel shows monthly trading volume in exchange traded funds (ETFs) with positive exposure to the OBX index (v_{BULL}), and monthly trading volume in ETFs with negative exposure to the OBX index (v_{BEAR}). The lower panel shows the difference in trading volume between the two types of ETFs. Trading volumes are in billion NOK



4. CONCLUSION

In this paper, I use a model to examine the effect from net flows to mutual funds on stock returns. I discriminate between actively and passively invested funds, and find that flows to either category of funds affect different stock prices. Specifically, flows affect returns on stocks that are constituents of the benchmark against which a mutual fund measure returns. While previous research often attributes correlated flows and returns to information trading, I argue that information is not the driver of my results. Investor sentiment or feedback trading do not explain the statistical coherence found in the data.

Estimating regressions with lagged variables do not indicate price reversals in stock returns. However, I am not able to clearly distinguish between the price pressure hypothesis and the imperfect substitution hypothesis due to a limited number of observations.

Index-linked mutual funds in Norway have only recently become popular, which supplies me with a limited time series of data.

A revisiting of this analysis when more data are available will be useful. Also, completing a similar analysis using data from other stock exchanges will provide useful information about the relationship between investor flows and returns.

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