Joakim Kvamvold

Three essays on the impact of "rule-based" trading activity

Thesis for the degree of Philosophiae Doctor

Trondheim, May 2015

Norwegian University of Science and Technology
Faculty of Social Sciences and Technology Management
Department of Economics

NTNU – Trondheim
Norwegian University of
Science and Technology

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Trondheim, April 2015

Joakim Kvamvold

Contents

Introduction

This thesis consists of three papers analyzing the impacts of "rule-based" trading on market prices of stocks. Many large investors (i.e., institutions and mutual funds) often encounter the need to trade stocks as a consequence of predetermined rules set in the managers' mandate. That many investors pursue the same strategy is referred to as *herding behavior* in the literature. Such behavior may have implications for market prices of the assets the investors crave. However, according to the *efficient market hypothesis* (EMH), changes in demand should not manifest in changing stock prices.

The theoretical basis for the EMH was developed in the 1960s by Eugene Fama.[1] In a nutshell, the EMH postulates that changes in the prices of stocks (and other financial instruments) must reflect new information, implying that demand curves for stocks are horizontal. Scholes (1972) claims that demand curves for stocks are downward sloping when analyzing block trades. Many other studies concerning block trades conclude in the same manner (see e.g., Kraus and Stoll (1972) or Mikkelson and Partch (1985)).

Shleifer (1986) points to an obvious flaw in analyzing large block trades: "... an offer to buy a large block may signal good news about the stock, thus entailing a price increase.". In an event study, Shleifer (1986) finds that stocks included in the broad S&P 500 index experience abnormal returns at and preceding the announcement date of the inclusion. The increase of a stock's price when the stock is added to an index is commonly known as an index price premium, and is documented in other markets and asset classes as well. However, this effect does not violate the EMH. The inclusion of a stock into an index might certify the quality of the stock, and send a signal to investors regarding the expected future performance of the stock.

The comovement literature emerged from the index premium literature inspired by Shleifer (1986). In addition to receiving a price premium, a large body of empirical studies shows that prices of included stocks also increase comovement with prices of existing constituents of the same index. This evidence is found for both the Nikkei 225 index (Greenwood and Sosner, 2007) and the S&P 500 index (Barberis et al., 2005; Wurgler, 2011; Goetzmann and Massa, 2003).

The most plausible reason for these effects is that many investors only invest in a subset of all available stocks. This "habitat view" of investing is presented in a

[1]See Fama (1970) for an excellent review of the EMH.

joint work by Barberis and Schleifer (2003). For instance, index-linked mutual funds track an index as their investment strategy. The increasing popularity of index funds coincides with an increase in pairwise correlations between returns on constituents of the S&P 500 (Sullivan and Xiong, 2012). Also, Morck and Yang (2001) argue that these effects are larger for stocks that are covered by many indices.

There has been speculation in some past research whether the effects discussed above can explain the momentum effect documented by Jagadeesh and Titman (1993). Evidently, stocks that have performed well in the past continue to do so in the future. If stocks are included in an index because they have performed well, inclusion might increase the good performance and give rise to the momentum effect. However, the literature lacks convincing evidence that can support this hypothesis.

In a recent working paper, Chen et al. (2014) flip this argument upside-down when they claim that the increase in comovement is due to changes in fundamentals. By matching stocks with relatively good past performance, evidence of excess comovement disappears. If excess comovement can be explained by past performance, so could also the index premium. My thesis helps shed light on this ongoing discussion in the literature.

Implications from the findings of research in this discipline of finance are of interest for practitioners. If prices react to changes in demand, following the herd can be very costly for investors. Altering the benchmark portfolio or timing purchases in a different manner can avoid costs associated with the aforementioned stock price anomalies. However, at the present time, we cannot with absolute certainty claim that the anomalies exist.

Chapter I: The impact of dividend payments on stock returns

In this chapter, I analyze the impact of dividend payments on stock returns. An empirical problem when analyzing price impacts in stocks is to find events that are unrelated to changes in information. The announcement of a dividend payment is made public several weeks before the actual distribution of dividends to investors. There is no reason to believe that other firm specific or market moving events coincide with the distribution of dividends. Thus, dividend distributions can be considered to be an "exogenous" inflow of funds to investors. If investors choose to reinvest the dividends, the dividend distribution should cause a temporary positive shift in the demand curve for stocks. Because of the three day settlement period for stocks, I expect to see an increase in the price of stocks three days prior to the dividend distribution date.

Indeed, using an event study-approach similar to Ogden (1994), I find that average standardized abnormal returns are statistically positive three days prior to the distribution date, as well as on the actual distribution date. Changes in trading volume on these trading days are also significantly positive, and stocks with the largest turnover ratio experience the largest abnormal returns. This is evidence that increases in demand do cause movements in prices.

I also document a positive correlation between ownership share by professional investors (i.e., institutions and mutual funds) and returns three days prior to the distribution of dividends. On the actual distribution date, however, stocks with low professional ownership perform relatively better.

Since dividend payments are unrelated to changes in information, the dividend payment process for stocks is ideal when analyzing price impacts. The results in this chapter provide new evidence towards a demand driven explanation for changes in stock prices on certain trading days.

Chapter II: Mutual funds' trading causes price impacts in their benchmark portfolios

In Chapter II, I examine trading caused by net flows to mutual funds invested at the Oslo Stock exchange. A problem with past research in this field is that stocks included in one index are often also part of other indices. Thus, it is difficult to isolate the effect from mutual funds' trading activity on stock returns. The Norwegian stock market is very uncluttered, thus, acting as a nice laboratory to test for possible effects from investor flows on returns. Also, because of the simplicity of the Norwegian stock market, it is easy to discriminate between actively managed funds and index-linked mutual funds.

Using a regression approach, I find that net flows to the two different types of funds affect returns on stocks for different parts of the stock exchange. These results are consistent with the initial empirical findings by Lou (2012). He analyzes the effect from aggregate fund flows on aggregate market returns. The primary difference with Chapter II is that I can identify which indices the mutual funds use as their benchmark. Thus, the identification of the effect is cleaner. I am also able to observe net flows directly, while Lou (2012) estimates net flows as the net difference in holdings. For all purposes our results are similar, and I provide additional evidence towards a demand driven price impact in stock returns using data from a different period and a different market.

Further, I create quintile portfolios sorted on the stocks' market capitalization. I find the price impact to be larger for smaller stocks. According to Lee et al. (1991), investor sentiment affects small stocks to a larger degree than large stocks. However, I do not find evidence that investor sentiment drives the results in the size-sorted portfolios.

Lastly, I conduct an approach similar to that of Warther (1995) as a robustness check. I use an AR-model to estimate the expected and unexpected components of net flows. I find that unexpected net flows to mutual funds are correlated with returns on the appropriate benchmark for the mutual funds. Again, reported results favor a demand driven explanation for changes in prices of the portfolio of stocks the mutual funds use as their benchmark.

Chapter III: Index trading and portfolio risk

Chapter III in this thesis is a joint work with Snorre Lindset. Recent studies have concluded that trading in exchange traded funds (ETFs) causes increased volatility in the underlying stocks (Da and Shive, 2013; Ben-David et al., 2014). Again, the Norwegian stock market acts as a laboratory, because of its simplicity. We use this laboratory to test for possible effects between trading in ETFs and volatility.

In a time-series framework, we look for correlation between trading volume in ETFs and return variances on three different subsets of the market. We use the same data set as in Chapter II, and find that the trading volume in ETFs is correlated with return variances on a portfolio of underlying stocks, and also with the return variance on portfolios of stocks to which the ETFs have no exposure. We do not find similar effects for flows to mutual funds.

When testing for causality we find weak, if any, evidence that trading in ETFs causes return variances to increase. Thus, our results indicate that other market factors drive both trading volume in ETFs and volatility.

Main contributions and future research

Current literature struggles to dodge the bullet when confronted with the *efficient market hypothesis*. Neither block trades nor common flows to investors are necessarily unrelated to changes in information. In this thesis, I use the dividend payment process and the simple Norwegian stock market in an attempt to isolate the effect from changes in demand on stock prices.

The increasing popularity of index-linked assets makes this research important for practitioners and investors. The market share of investors using passive allocation strategies is likely to continue to increase, thus, further research is important so that we can understand the implications from this "new" trend in investing.

Investing is a globalized activity. Further research using several markets and several asset classes in the same study could provide more general conclusions. In addition, looking into the movement of funds between asset classes would be an interesting step further.

Lastly, past research has mostly discussed returns. More research on the trade-offs between risk and return could reveal important information to investors.

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Chapter I

The impact of dividend payments on stock returns

The impact of dividend payments on stock returns*

Joakim Kvamvold†

Abstract

This paper examines price impacts in NYSE and AMEX stocks caused by reinvestments of dividends. Results provide evidence that stocks experience abnormal returns three days prior to the distribution of dividends, as well as on the actual distribution date. Event study estimates, using data from 2000 to 2013, show that increases in turnover coincide with the abnormal returns. Cross-sectional regression results indicate that the effect from professional ownership on returns is positive. Overall, the results provide strong evidence that price impacts associated with dividend payments are demand driven.

Keywords: Price impact, dividends, institutional investors, mutual funds.

JEL classifications: G11, G12, G14, G23

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†Norwegian University of Science and Technology, Department of Economics, Dragvoll, N-7491 Trondheim, Norway. E-mail: joakim.kvamvold@svt.ntnu.no

1 Introduction

A large body of literature finds that flows to investors are positively correlated with stock prices. In this paper, I analyze how the distribution of dividends impacts stock prices. I create a portfolio of stocks and perform analysis on two categories of the portfolio holdings. For each trading date, I categorize the portfolio's stocks as either *dividend-payers* or *non-dividend-payers*.

In an event study, I find that the *average standardized abnormal return*[1] for *dividend-paying* stocks is 0.13% three business days prior to the dividend payment date and 0.11% on the actual distribution date. I attribute the aforementioned positive return to the fact that investors are able to reinvest dividends three business days prior to the actual distribution date. Investors are able to do so because of the three day settlement period for stocks. I do not find similar effects on the standardized abnormal returns for *non-dividend-paying* stocks.

In a cross-sectional analysis on raw returns, I find that the positive effect on returns three business days prior to the distribution date is positively correlated with ownership share by institutional investors for the *dividend-payers*. For non-dividend-paying stocks, I find returns three business days prior to the payment date to be positively correlated with ownership share by mutual funds. Stock returns on the distribution date are negatively correlated with ownership by both institutional investors and mutual funds. These results indicate that professional investors (i.e., institutions and mutual funds) reinvest dividends three days prior to the distribution date, while private investors wait until the actual distribution of the dividend.

In a frictionless market, with equally well-informed investors, unexpected changes in asset prices are a result of new information. Edelen and Warner (2001) use daily data and conclude that flows to investors and stock returns are positively correlated simply as a result of new information. The distribution of dividends is not likely to be associated with new information since the announcement of dividends is made several weeks in advance. Two hypotheses regarding non-information-related supply and demand shocks for stocks dominate the literature (see e.g., Scholes (1972)). The *price pressure hypothesis* postulates that a non-information-related demand shock temporarily drives prices away from their fundamental value, with a reversal of prices over the subsequent days. In contrast, the *imperfect substitutes hypothesis* postulates that a demand shock leads to a permanent effect on prices. Kraus and

[1] The term average standardized abnormal return is explained in more detail later.

Stoll (1972) find that positive block trading (purchasing) by institutions leads to a permanent price increase in stocks, while negative block trading (selling) leads to a temporary price decrease in stocks. However, it has been debated in the literature whether block trading is unrelated to changes in information.

The price impact literature is primarily focused on analyzing changes in net holdings (i.e., flows) to investors to address price impact effects in stocks. Several papers find that flows to investors are correlated with stock returns (Warther, 1995; Lou, 2012; Coval and Stafford, 2007). These results are related to the literature that documents that as stocks are included in an index, they receive an index price premium. This effect is present for both the S&P 500 index (Wurgler, 2011; Goetzmann and Massa, 2003) and the Nikkei 225 index (Greenwood and Sosner, 2007). Basak and Pavlova (2013) construct a theoretical model that explains how institutional investors tilt their portfolio towards index stocks, and Gompers and Metrick (2001) find that institutions' demand accounts for price increases in stocks.

The comovement literature is related to the price impact literature and states that correlated demand by investors creates comovement in prices for index constituents (Barberis et al., 2005). However, Chen et al. (2014) claim that the comovement effect is a manifestation of the momentum effect documented by Jagadeesh and Titman (1993).

A common problem in past research is that both common flows to investors and block trading may contain information. Surprisingly little attention has been devoted to dividend flows, which certainly adds to flows to investors. The advantage of analyzing dividends to investors is that all information concerning the dividend payment is made public long before the actual distribution to investors takes place. As a consequence, abnormal returns on or around the distribution date are not likely to be explained by information induced trading. Thus, two opposing hypotheses remain. Both the price pressure hypothesis and the imperfect substitution hypothesis postulate a price increase as a result of increasing demand, but a reversal of prices is only consistent with the price pressure hypothesis. Ogden (1994) finds that investors' participation in reinvestment plans leads to an increase in stock returns during the distribution date and the following trading days. I take that analysis a few steps further and analyze whether increases in stock returns are related to ownership by institutions and/or mutual funds. I also check whether there is a spill-over effect from dividend distributions on stocks that are not paying dividends, but are likely to be part of the same benchmark portfolio as the dividend-paying stocks. First, I find evidence that the effect of dividend distributions on stock returns has moved to an earlier period than what Ogden (1994) finds during his sample period. Second, I find that increasing stock returns are concentrated on two particular trading dates related to the dividend payment date. Third, I find evidence that stocks with high ownership by professional investors tend to have higher returns three days prior to the distribution date, while stocks with low ownership by professional investors tend to have relatively higher returns on the distribution date.

The paper is organized as follows. In the next section, I explain details concerning the dividend payment process and details concerning institutional and mutual fund ownership. In Section 3, I present the data and some of the methodology used in the event study. Section 4 contains the main empirical analysis, while the final section summarizes the paper.

2 Need to know

2.1 Dividend payment process

Four dates are important to understand in the dividend payment process (see Figure 1). At the *declaration date,* the dividend paying company announces the *ex-dividend-*, *record-*, and *payment dates.* The size of the dividend is also made public on the declaration date. Thus, no new information regarding the dividend payment is made available to the market after the declaration date. All holders of the company's stock prior to the ex-dividend date are entitled to the dividend payment. After the ex-dividend date, buyers of the stock do not have the right to receive the dividend. The record date is usually two trading days after the ex-dividend date. All holders of the stock on record will receive the dividend. The record date is set so that the company can get on record all investors that held the stock one day prior to the ex-dividend date. Finally, the dividend is transferred to investors on the payment date. The payment date is usually two to five weeks after the ex-dividend date.

Some companies offer investors the ability to participate in dividend reinvestment plans. If an investor participates in such a plan, dividends are automatically reinvested in the stock of the dividend-paying company.

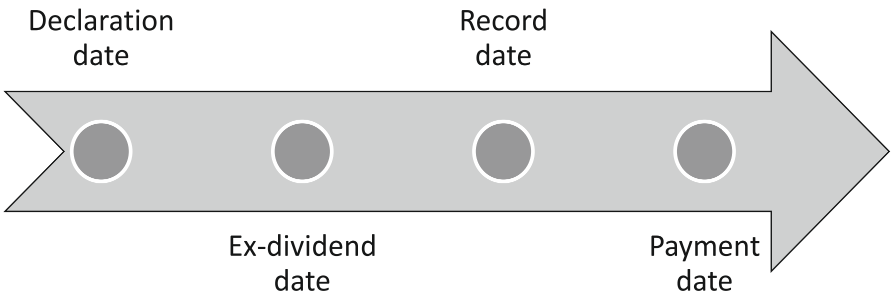


Figure 1: This figure illustrates the different dates associated with the dividend payment process of stocks. The distance between the dots is not proportional to the expected time between the different dates.

2.2 Stock portfolios and benchmarks

Mutual funds usually measure the performance of their stock portfolio relative to a predetermined benchmark of stocks, e.g., the S&P 500 index. Portfolio managers' mandate usually includes a maximum tracking error, where the tracking error is measured as the portfolio's performance relative to the benchmark's performance. For index-linked mutual funds, this tracking error is very tight, whereas for active investors this tracking error is a bit looser. Regardless of whether the fund is invested passively or actively, changes in the benchmark portfolio must also lead to changes in the stock portfolio for the fund. For instance, changes in the benchmark portfolio can happen as a result of changes to the weighting of the benchmark, revisions of the benchmark, or as a result of dividend payments.

In this paper, I am only concerned with the changes in the portfolios and benchmarks induced by dividend payments. When a constituent of the index goes ex-dividend, the index reinvests the dividend in all stocks that are part of the same index. This happens on the ex-dividend date. If portfolio managers have cash in their portfolio, they can replicate the benchmark perfectly by doing the same exercise, or by using cash as collateral for investments in futures. However, portfolio managers with a relatively tight tracking error do not have room for much cash in their portfolios, since cash will reduce the beta of the portfolio relative to the beta of the benchmark.

The settlement time for stock purchases is three trading days.[2] As a result of the settlement time, investors are able to reinvest dividends three days before the actual distribution of the dividend. Thus, I expect to see an increase in demand

[2]The settlement period was reduced from 5 trading days to 3 trading days on June 7, 1995.

for benchmark constituents during the payment date and three days preceding this date. This effect should be present not only for the dividend paying stocks, but also for non-paying constituents of the benchmark portfolio. According to Ogden (1994), who conducts a similar study using data from 1962 to 1989, some investors receive their dividends as checks by mail. I analyze a more recent period, and I see it as a less likely way of distribution during my sample period. In addition, if investors do receive dividends by mail, I cannot be certain that they reinvest the dividend immediately. Based on the arguments above, I refer to the *dividend payment period* as $t = -3$ to $t = 0$ trading days, when the payment date is set to $t = 0$. One can argue that some investors want to divide large trading blocks over a longer period to avoid bidding up the price of the stock. Indeed, some dividend reinvestment plans state that they do take into account price pressure effects when reinvesting investors' dividends. However, investors who smooth their purchases over time do this exactly to avoid impacts in the stock prices. As a consequence, these trades will not contribute to price impacts if executed carefully.

3 Data and portfolio construction

I seek to study the effect of dividend payments on stocks held by professional investors (i.e., mutual funds and institutional investors). To this end, I search the Thomson Reuters database on mutual funds holdings at year end from 1999 through 2012. Funds not based in the US are excluded. I omit international funds, growth funds and funds that do not invest in stocks, resulting in a total of 352 mutual funds. I omit growth funds to avoid that potential high ownership in venture stocks will bias the results. Among the holdings of the remaining funds, I only include common stocks traded on the NYSE or AMEX. I also exclude holdings where either the CUSIP, ticker, industry code, price, or shares outstanding are missing. I calculate the mutual funds' ownership share of all remaining stocks, and form a portfolio of stocks with high mutual fund ownership at every year end. On average this portfolio consists of 351 stocks each year. This is an agnostic way of defining stocks that are part of a benchmark used by mutual funds. I also find the share of institutional ownership for the same stocks from Thomson Reuters. Mutual funds' ownership is not part of the institutional ownership data.

Institutional ownership exceeds 100 percent for some stocks. Obviously, institutions cannot own more than 100 percent of any stock. Two likely reasons can explain this excess ownership. First, different reporting dates by institutions might cause some ownership shares to exceed 100 percent. Secondly, shorting of stocks can cause problems regarding reported ownership. If one investor lends stocks to another investor, and both claim ownership of the stock when they report their holdings, ownership may exceed 100 percent. However, in cases where reported ownership by institutions exceeds 100 percent, institutional ownership must be very high. Therefore, I do not consider this to be of much concern.

Finally, I download daily security data for the portfolio from the Center for Research in Security Prices (CRSP) database from January 2000 through September 2013. I exclude stocks where either the stock's price, payment date or dividend amount is missing for any day during the sample period.

3.1 Event study

I estimate abnormal returns using the mean adjusted returns method discussed by Brown and Warner (1980). The abnormal performance of any security is the raw return minus an estimate of the mean return, standardized by the estimated standard deviation of that security's return. When estimating the mean returns, I avoid using returns before the payment date since both the declaration date and the ex-dividend date precedes the payment date. Thus, I use ex post returns on the stocks to estimate the mean performance. In addition, I avoid using the days immediately following the dividend payment period to stay clear of potential problems regarding misspecification of the dividend payment period. Therefore, I chose to estimate the first and second moments of returns from $t = 6$ to $t = 55$.[3] For standardized abnormal return on stock i, I estimate

$$a_{i,t} = \frac{r_{i,t} - \bar{r}_i}{\hat{\sigma}(r_i)},$$

where a is standardized abnormal returns, r is raw logarithmic returns, $\bar{r}$ is estimated mean returns in the estimation period, and $\hat{\sigma}(r)$ is the estimated standard deviation of returns in the estimation period.

Some could argue that a market-based model is a better benchmark when performing

[3]The estimation period is set somewhat arbitrary. Robustness checks using different estimation periods provide similar results.

event study analysis. However, I am analyzing the effect from dividend payments on aggregated market returns. Hence, I cannot use a market based model as a benchmark. Also, Brown and Warner (1980) show that this simple model can perform just as well as a market-based model in event studies.

To evaluate the estimated results in the event study, I use a parametric CDA t-test and a non-parametric sign test. Both tests are explained in detail in Brown and Warner (1980).

4 Analysis

4.1 An event study of dividend payments

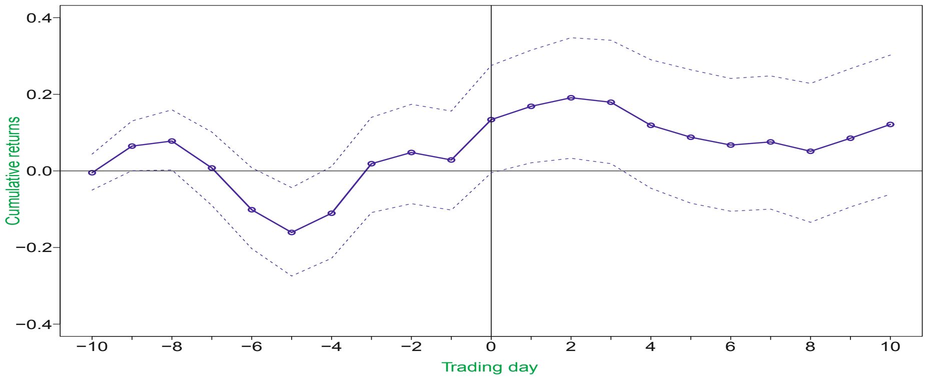
I define the dividend yield on the portfolio as the total dividend distributions of portfolio stocks divided by the portfolio's market capitalization. I organize all trading days in descending order based on the portfolio's dividend yield. In total, 2,550 distribution days over a period of 3,436 trading days make up the sample. Since a majority of the trading days have some type of distribution, I isolate the top decile of the ordered trading days, resulting in a sample consisting of days where the portfolio experiences large dividend payments. Large dividend payments of this magnitude occur on average on more than 17 days each year. Thus, these distributions are not rare events.

Further, I divide portfolio holdings into two categories, *dividend-payers* and *non-dividend-payers*. For each day in the sample, all stocks that distribute dividends of at least 0.25 percent[4] of the firm value to their owners *on that particular date* are considered to be a dividend payer. Stocks that do not distribute any cash at that date are considered to be a non-dividend-payer. Stocks that distribute dividends of between 0 and 0.25 percent of the firm value are not considered as part of any of the categories. On dates where a stock pays a dividend, it is regarded as a dividend-payer, while on all other days it is regarded as a non-dividend payer.

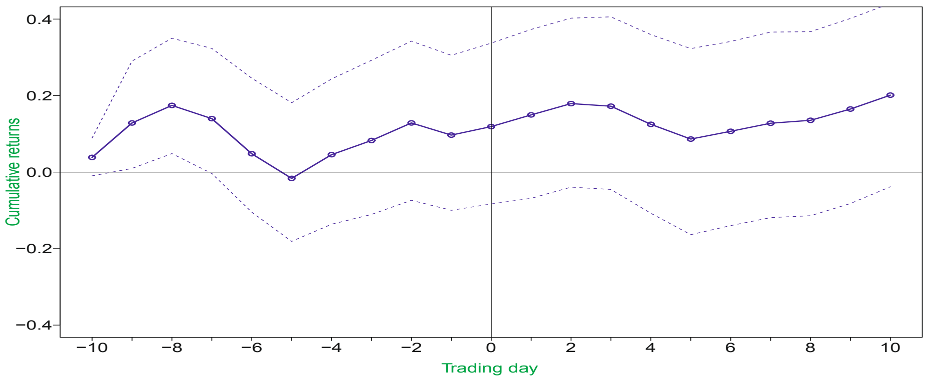
A total of 2,434 *dividend-payers*/payment dates exist in the sample, while *non-dividend-payers*/payment dates amounts to a total of 68,891 observations. I create a random sample of 2,434 non-dividend-payers/payment dates to save computing

[4] A cut-off similar to that used by Ogden (1994).

time when I perform an event time analysis on the two categories of stocks.[5] I present an illustration of cumulative returns for the two categories in Figure 2. When we look at the cumulative returns series, we want to pay attention to the slope between returns. Notice the steep positive slope on trading day $t = -3$ and trading day $t = 0$ in the upper panel in Figure 2. Table 1 presents empirical results for the same event study, and shows that standardized abnormal returns on trading days $t = -3$ and $t = 0$ are significantly positive for the dividend-payers.



(a) Dividend-payers



(b) Non-dividend-payers

Figure 2: Panel a) shows the cumulative return series of standardized abnormal returns for dividend-paying stocks. Panel b) shows the cumulative return series of standardized abnormal returns for non-dividend paying stocks. Standardized abnormal return is calculated by subtracting the average return for trading days 6 through 55 from the raw portfolio returns. These differences are standardized by the estimated standard deviation of returns for trading days 6 through 55. Ninety-five percent confidence intervals, estimated using a bootstrapping method, enclose the expected value.

[5]Estimated results with other random samples provide results that for all purposes are the same.

Table 1: Average standardized abnormal return on equally weighted portfolios formed over a subsample of stocks on the NYSE and AMEX for 21 trading days. The payment date is trading day 0. The payment period is defined as trading days -3 through 0. Standardized abnormal return is calculated by substracting the average return for trading days 6 through 55 from the raw portfolio returns. These differences are standardized by the estimated standard deviation of returns for trading days 6 through 55. *pos/neg* is the ratio of observed positive returns to observed negative returns. t-values for the parametric CDA t-test and a non-parametric sign test are estimated using a method described by Brown and Warner (1980). Values in bold indicate significance at the 5%-level.

	Dividend-payers				Non-dividend-payers			
Trading day(s)	$\bar{a}_t$	$CDA(t)$	pos/neg	$sign(t)$	$\bar{a}_t$	$CDA(t)$	pos/neg	$sign(t)$
-10	0.00	-0.11	1.07	1.66	0.04	0.99	**1.10**	**2.24**
-9	0.07	1.65	1.07	1.66	**0.09**	**2.33**	1.04	0.79
-8	0.01	0.31	0.97	-0.73	0.05	1.19	1.04	0.88
-7	-0.07	-1.67	**0.87**	**-3.20**	-0.03	-0.90	**0.88**	**-2.90**
-6	**-0.11**	**-2.58**	**0.81**	**-4.82**	**-0.09**	**-2.38**	**0.83**	**-4.35**
-5	-0.06	-1.41	**0.84**	**-4.14**	-0.06	-1.67	**0.85**	**-3.56**
-4	0.05	1.19	1.05	1.15	0.06	1.61	1.03	0.57
-3	**0.13**	**3.07**	**1.24**	**5.04**	0.04	0.96	1.03	0.75
-2	0.03	0.69	1.02	0.47	0.05	1.19	**1.12**	**2.55**
-1	-0.02	-0.46	0.96	-1.07	-0.03	-0.82	1.01	0.26
0	**0.11**	**2.50**	**1.18**	**3.84**	0.02	0.58	**1.11**	**2.28**
1	0.03	0.82	1.03	0.60	0.03	0.79	0.93	-1.58
2	0.02	0.53	1.02	0.55	0.03	0.76	0.98	-0.35
3	-0.01	-0.28	0.94	-1.54	-0.01	-0.18	0.94	-1.36
4	-0.06	-1.43	0.93	-1.79	-0.05	-1.23	**0.91**	**-2.15**
5	-0.03	-0.74	0.94	-1.41	-0.04	-1.00	**0.86**	**-3.34**
6	-0.02	-0.48	0.98	-0.38	0.02	0.53	0.98	-0.48
7	0.01	0.19	0.99	-0.26	0.02	0.55	1.00	0.09
8	-0.02	-0.58	0.92	-1.96	0.01	0.20	1.04	0.83
9	0.03	0.81	1.01	0.26	0.03	0.76	0.99	-0.13
10	0.04	0.85	1.07	1.54	0.04	0.94	1.02	0.53
-3 - 0	**0.24**	**2.39**			0.07	0.81		
0 - +3	0.15	1.48			0.07	0.83		
-3 - +5	0.20	1.30			0.04	0.30		
n	2,434				2,434			

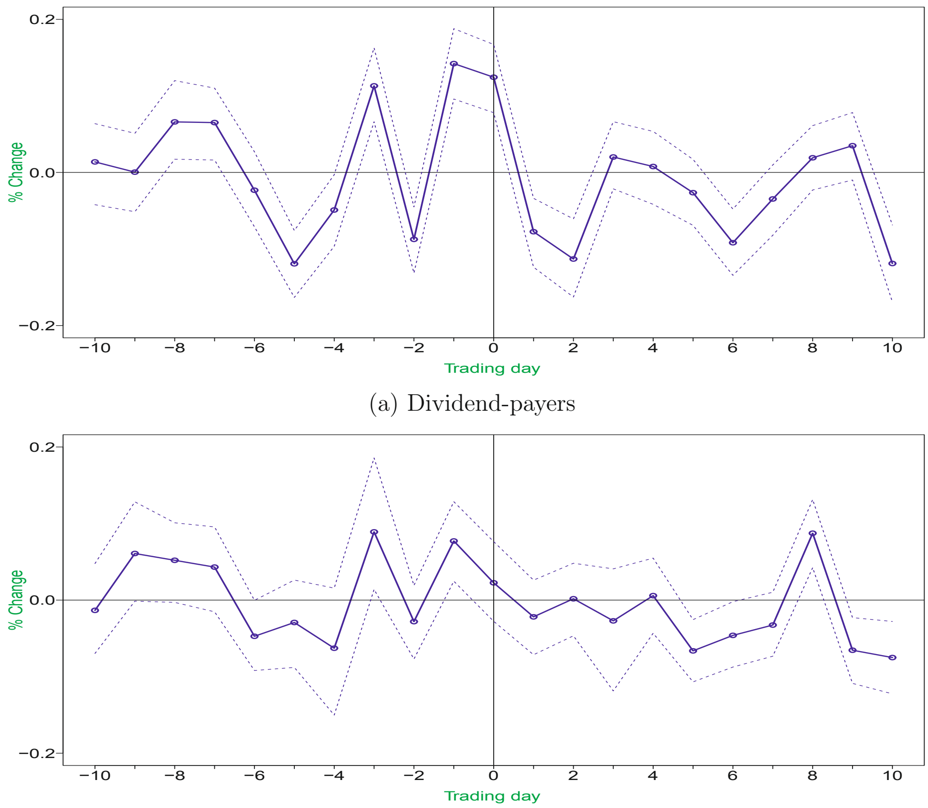
Based on the results of the event study, it appears that there is an effect on returns on dividend-paying stocks, but not on the stocks in the category *non-dividend-payers*. As seen in Table 1, only two daily return observations are positive and statistically significant for the dividend-payers, measured by the CDA t-value. Although dividends are distributed to investors at $t = 0$, most investors are allowed to reinvest their dividends three days prior to the distribution. This evidently leads to a price impact at $t = -3$. The estimated results in Table 1 indicate that there is no spill-over effect to benchmark constituents that do not pay dividends.

The negative returns immediately prior to the dividend payment period is difficult to explain, and might be coincidental. However, the pattern in returns is strikingly similar to the pattern presented by Ogden (1994). He also estimates statistically significant negative returns immediately prior to the dividend payment period, even though his dividend payment period is defined differently.

The estimated standardized cumulative abnormal return for the *dividend payment period* ($t = -3$ to $t = 0$) is significant at the 5%-level for the dividend-payers. The estimated standardized cumulative return during the dividend payment period used by Ogden (1994) ($t = 0$ to $t = +3$) is not significant. If an investor purchases the dividend paying stocks at $t = -4$, he can expect a positive abnormal standardized return of 0.24 percent over the next four days. If done 17 times every year, the expected accumulated abnormal standardized return using this strategy will be over 4 percent annually. The estimated standardized cumulative return between trading days $t = -3$ to $t = +5$ is not statistically significant. The lack of significance does not necessarily mean that returns reverses, as the standard error increases when estimating cumulative returns over a longer period. However, an indication of a reversal of returns can be seen in the illustration in the upper panel of Figure 2.

I expected stocks in the category *non-dividend-payers* to behave more like the *dividend-payers,* since investors with index-linked portfolios have to reinvest dividends in the entire benchmark. Three likely reasons may explain the lack of initial results for the non-dividend paying stocks. First, a price pressure effect may exist for stocks with high ownership by institutional investors and/or mutual funds. This effect might become marginalized when I estimate returns for an equally weighted portfolio of stocks with large variability in ownership in the event study. Second, reinvestments of dividends may be too small to create a significant effect in highly liquid stocks. Thirdly, (index-linked) mutual funds have gained popularity in recent years. Therefore, the effect may be larger in a more recent sample.

To ensure that the reported effect is due to changes in demand, I also estimate the effect on changes in trading volume for the two categories of stocks. As expected, Figure 3 illustrates spikes in changes in trading volume for the dividend-paying stocks on trading days $t = -3$ and $t = 0$. The results are not equally clear for non-dividend-paying stocks, but a positive change in trading volume can be seen for trading day $t = -3$. Also, there appears to be an increase in trading activity at trading day $t = -1$, which can indicate that some investors anticipate an increase in returns and try to front run investors who reinvest dividends at $t = 0$.



(a) Dividend-payers

(b) Non-dividend-payers

Figure 3: Panel a) shows the daily change in standardized abnormal trading volume for dividend-paying stocks. Panel b) shows the daily change in standardized abnormal trading volume for non-dividend paying stocks. Standardized abnormal trading volume is calculated by subtracting the average trading volume for trading days 6 through 55 from the daily trading volume. These differences are standardized by the estimated standard deviation of daily trading volume for trading days 6 through 55. Ninety-five percent confidence intervals, estimated using a bootstrapping method, enclose the expected value.

4.2 25 portfolios

As a robustness check I construct 25 portfolios as follows. I order all dividend-paying stocks based on their market capitalization and sort them into quintiles. Further, I sort these quintiles into new quintiles based on their daily turnover ratio. In Panel A of Table 2, I order stocks based on their turnover ratio at trading day $t = -3$, while in Panel B I order stocks based on their turnover ratio at trading day $t = 0$.

Results reported in Table 2 show that the positive returns occur for the portfolios

Table 2: This table shows descriptive statistics for 25 stock portfolios formed on turnover (LIQ) and market capitalization (mc). The table also reports average mutual fund ownership ($\bar{os}_{mf}$), average institutional ownership ($\bar{os}_{ii}$), average dividend yield ($\bar{dy}_i$) and average abnormal returns ($\bar{a}$). $t(a)$ is t-value for the cumulative abnormal returns. Average market capitalization is in million USD. Values in bold indicate significance at the 5%-level. In Panel A, portfolios are constructed based on turnover at trading day $t = -3$, while in Panel B portfolios are constructed based on turnover at trading day $t = 0$.

Panel A	LIQ-quintile					LIQ-quintile				
mc -quintile	high	2	3	4	low	high	2	3	4	low
	$\bar{os}_{ii}$					$\bar{os}_{mf}$				
high	65%	61%	57%	57%	67%	1.74%	1.38%	0.85%	0.89%	1.11%
2	73%	71%	70%	68%	71%	2.13%	1.64%	2.23%	1.44%	1.05%
3	74%	71%	68%	69%	71%	2.29%	1.98%	1.92%	1.36%	1.60%
4	82%	76%	66%	73%	72%	1.91%	2.45%	2.35%	1.23%	1.65%
low	78%	68%	55%	68%	62%	2.67%	4.73%	2.53%	1.63%	1.81%
	$\bar{dy}_i$					$\bar{mc}$				
high	0.93%	0.78%	0.74%	0.86%	0.77%	110 309	149 601	150 996	180 858	68 580
2	0.73%	0.75%	0.64%	0.69%	0.64%	27 925	28 778	29 546	33 192	21 855
3	0.71%	0.78%	0.79%	0.81%	0.75%	12 250	12 418	12 650	14 624	11 086
4	0.73%	0.75%	0.84%	0.80%	0.86%	5 377	5 741	5 580	6 595	4 575
low	0.83%	0.89%	0.87%	0.87%	1.00%	1 795	2 039	2 061	2 604	1 331
	$\bar{a}$ at $t = -3$					$t(\bar{a})$				
high	0.22%	0.28%	0.15%	-0.02%	-0.12%	1.73	1.57	1.01	-0.11	-0.93
2	0.26%	0.18%	0.16%	0.04%	0.07%	1.86	1.27	1.13	0.29	0.52
3	**0.26%**	0.23%	0.17%	-0.03%	**-0.27%**	**2.18**	1.66	1.60	-0.31	**-2.37**
4	**0.68%**	0.23%	0.20%	**-0.42%**	-0.15%	**5.58**	1.77	1.60	**-3.83**	-1.32
low	**0.55%**	0.18%	-0.19%	0.14%	-0.01%	**4.06**	1.35	-1.61	1.47	-0.09

Panel B	LIQ-quintile					LIQ-quintile				
mc -quintile	high	2	3	4	low	high	2	3	4	low
	$\bar{os}_{ii}$					$\bar{os}_{mf}$				
high	69%	61%	61%	61%	56%	1.76%	1.18%	1.34%	0.94%	0.76%
2	74%	72%	71%	71%	65%	1.93%	1.93%	2.12%	1.91%	0.92%
3	77%	73%	71%	68%	63%	1.75%	1.47%	3.19%	1.49%	1.26%
4	84%	79%	73%	71%	63%	1.34%	1.81%	2.03%	2.35%	2.03%
low	79%	74%	66%	61%	51%	2.40%	4.03%	2.86%	1.77%	2.27%
	$\bar{dy}_i$					$\bar{mc}$				
high	0.88%	0.84%	0.86%	0.74%	0.76%	103 430	134 622	132 946	133 397	150 865
2	0.66%	0.72%	0.73%	0.72%	0.62%	27 857	27 311	28 399	28 816	28 744
3	0.69%	0.78%	0.80%	0.77%	0.79%	12 382	12 671	12 679	12 889	12 384
4	0.81%	0.75%	0.81%	0.75%	0.85%	5 381	5 484	5 815	5 702	5 439
low	0.96%	0.81%	0.87%	0.85%	0.97%	1 822	2 048	2 175	2 056	1 746
	$\bar{a}$ at $t = 0$					$t(\bar{a})$				
high	**0.59%**	0.17%	0.03%	-0.17%	**-0.35%**	**4.47**	1.79	0.23	-1.31	**-2.72**
2	**0.41%**	0.25%	0.13%	0.04%	-0.24%	**3.58**	1.82	1.29	0.28	-1.72
3	**0.28%**	0.19%	0.07%	0.08%	**-0.24%**	**2.82**	1.92	0.59	0.81	**-2.45**
4	**0.32%**	**0.27%**	0.09%	0.11%	**-0.23%**	**2.87**	**2.40**	0.92	0.94	**-2.02**
low	**1.00%**	**0.43%**	0.07%	0.05%	-0.15%	**9.02**	**3.92**	0.64	0.45	-1.36

holding stocks with a high turnover ratio. This observation is consistent with a demand driven explanation of the abnormal returns. We also see from Panel A that returns on the portfolios holding the largest stocks are less significant. The dividend yield and ownership shares are fairly similar for the portfolios, and do not seem to be correlated with the abnormal returns on the portfolios. Another interesting observation is that portfolios holding stocks that experience a *low* turnover appear to perform relatively poorly at the event date. It is difficult to argue why they experience this poor performance.

4.3 Regression study

I perform a regression analysis to identify whether returns on trading days $t = 0$ and $t = -3$ can be explained by ownership shares by institutional investors and/or mutual funds. I also include variables to control for known market anomalies. I estimate regressions for both *dividend-payers* and *non-dividend-payers*. In this section, *all* dividend-paying stocks are put in the former category, as opposed to the event study where I added the condition that the dividend yield had to be at least 0.25 percent. I relax this condition to allow for greater variability in the dividend yield of dividend paying companies.

I use a cross-sectional approach in the regression study. The left-hand side variable is raw returns on stocks on trading days $t = -3$ and $t = 0$. I include the dummy variable JAN, and the interaction term $JAN * mc$ to account for the January effect discussed by Keim (1983). The variable JAN takes the value one for the month of January, and zero for all other months. The variable mc is a time-series of the market capitalization of the companies. The variable dy_i is each individual dividend paying stock's dividend yield, and is used when analyzing stocks that are *dividend-payers*. Stocks in the *non-dividend-payers* category do not pay dividends by construction. Thus, I use the dividend yield on the entire portfolio (dy_p) as an explanatory variable for the returns on these stocks. Further, I add the variables os_{mf} and os_{ii}, to account for ownership by mutual funds and institutional investors, respectively. Both ownership variables are ratios of total ownership. I add the variable LIQ to account for potential effects from liquidity on returns. I measure LIQ by dividing trading volume on shares outstanding for the stock (i.e., turnover). The American Association of Individual investors published a guide listing 877 companies that offer dividend reinvestment plans in 1998 (Scott, 1998). I assume a stock to have a dividend reinvestment plan if it is listed in this guide. The dummy variable DRP

takes the value one for all companies with a dividend reinvestment plan, and zero for all other stocks.

High ownership by itself should not lead to higher return on a stock. High ownership by mutual funds or institutions should only be relevant to explain returns if the dividend yield is also high. I add the product of os_{mf} and dy_i, and os_{ii} and dy_i to regressions on the group of dividend-paying stocks, while I add the product of os_{mf} and dy_p, and os_{ii} and dy_p to regressions for the group of non-dividend-paying stocks. For the dividend-payers I estimate

$$\begin{aligned} r =& \beta_0 + JAN + mc + JAN * mc + dy_i + dy_p + LIQ + DRP + os_{mf} + os_{ii} \\ &+ dy_i * os_{mf} + dy_i * os_{ii} + \epsilon, \end{aligned} \tag{1}$$

while for the non-dividend-payers, I estimate

$$\begin{aligned} r =& \beta_0 + JAN + mc + JAN * mc + dy_i + dy_p + LIQ + DRP + os_{mf} + os_{ii} \\ &+ dy_p * os_{mf} + dy_p * os_{ii} + \epsilon, \end{aligned} \tag{2}$$

where the explanatory variables of interest are the interaction terms between the two ownership variables and the two variables for dividend yield.

The first column in Table 3 shows a positive effect from dividend yield on returns for when the ownership variables are unaccounted. As seen in the second column in Table 3, it is a significant positive effect, at $t = -3$, from institutional ownership on the dividend-paying stocks when the dividend yield is also high. In addition, in the second column, the coefficient for dividend yield shows that stocks with zero professional ownership performs relatively poorly on trading day $t = 0$. I do not find that high ownership by mutual funds has a significant effect on returns on dividend-payers.

For non-dividend-paying stocks, the effect from high ownership by mutual funds is positive and significant, while the ownership share by institutions is not. Institutional investors may for different reasons have large ownership shares in particular companies. For instance, a government may want to hold shares in companies that provide vital infrastructure. Mutual funds, on the other hand, are often invested against broad indices to hold well diversified portfolios. These potential differences in investing style could explain why institutional ownership matters for dividend-payers, while mutual fund ownership matters for stocks that do not pay dividends.

As the results in Table 4 show, the effect from the two interaction terms on returns

Table 3: This table reports results from a cross-sectional regression analysis for stock return's response to ownership shares by institutional investors and mutual funds on trading day $t = -3$. The January effect is controlled for by the variable JAN and the interaction term $JAN * mc$, where mc is the market capitalization of the stock. Other control variables include liquidity (LIQ) and dividend repurchasing programs (DRP). dy_i is the dividend yield for the individual stocks, while dy_p is the dividend yield for the portfolio. os_{mf} and os_{ii} are ownership shares in the stocks by mutual funds and institutional investors, respectively. The primary variables of interest are the four interaction terms at the bottom. The coefficients are estimated using an OLS approach. Standard errors are shown in parentheses. * indicates significance at the 10%-level, ** indicates significance at the 5%-level, and *** indicates significance at the 1%-level using a two-tailed test.

	Dividend-payers		Non-dividend-payers	
	(1)	(2)	(3)	(4)
JAN	-0.008^{***}	-0.008^{***}	-0.001^{***}	-0.001^{**}
	(0.003)	(0.003)	(0.001)	(0.001)
mc	-0.016^{*}	-0.019^{**}	0.005	0.005
	(0.009)	(0.009)	(0.004)	(0.004)
$JAN * mc$	0.120^{**}	0.121^{**}	0.0004	-0.0003
	(0.052)	(0.052)	(0.015)	(0.015)
dy_i	0.206^{*}	-1.449^{***}		
	(0.110)	(0.537)		
dy_p			-5.692^{***}	-5.529^{*}
			(0.611)	(2.843)
LIQ	0.0001^{***}	0.0002^{***}	0.0002^{***}	0.0002^{***}
	(0.00005)	(0.00005)	(0.00001)	(0.00001)
DRP	0.001	0.001	-0.0002	-0.0002
	(0.001)	(0.001)	(0.0003)	(0.0003)
os_{mf}		0.010		-0.012
		(0.015)		(0.008)
os_{ii}		-0.018^{***}		-0.00003
		(0.007)		(0.002)
$dy_i * os_{mf}$		-1.210		
		(2.246)		
$dy_i * os_{ii}$		2.355^{***}		
		(0.743)		
$dy_p * os_{mf}$				53.196^{**}
				(21.179)
$dy_p * os_{ii}$				-0.887
				(3.678)
$Constant$	0.001	0.014^{***}	0.003^{***}	0.002^{*}
	(0.001)	(0.005)	(0.0004)	(0.001)
Observations	2,012	2,012	52,820	52,820
R^2	0.013	0.018	0.008	0.008
Adjusted R^2	0.010	0.013	0.008	0.008

Table 4: This table reports results from a cross-sectional regression analysis for stock return's response to ownership shares by institutional investors and mutual funds on trading day $t = 0$. The January effect is controlled for by the variable JAN and the interaction term $JAN * mc$, where mc is the market capitalization of the stock. Other control variables include liquidity (LIQ) and dividend repurchasing programs (DRP). dy_i is the dividend yield for the individual stocks, while dy_p is the dividend yield for the portfolio. os_{mf} and os_{ii} are ownership shares in the stocks by mutual funds and institutional investors, respectively. The primary variables of interest are the four interaction terms at the bottom. The coefficients are estimated using an OLS approach. Standard errors are shown in parentheses. * indicates significance at the 10%-level, ** indicates significance at the 5%-level, and *** indicates significance at the 1%-level using a two-tailed test.

	Dividend-payers		Non-dividend-payers	
	(1)	(2)	(3)	(4)
JAN	0.013**	0.013**	0.016***	0.016***
	(0.005)	(0.005)	(0.001)	(0.001)
mc	0.006	0.0004	−0.005	−0.006
	(0.008)	(0.009)	(0.003)	(0.004)
$JAN * mc$	−0.037	−0.041	−0.077***	−0.080***
	(0.095)	(0.094)	(0.026)	(0.026)
dy_i	−0.496***	2.314***		
	(0.110)	(0.505)		
dy_p			11.594***	−1.135
			(0.497)	(2.290)
LIQ	0.00000	0.00005	−0.0001***	−0.0001***
	(0.00004)	(0.00004)	(0.00001)	(0.00001)
DRP	0.001	0.001	0.0001	0.00004
	(0.001)	(0.001)	(0.0002)	(0.0002)
os_{mf}		−0.032*		0.063***
		(0.018)		(0.010)
os_{ii}		0.014**		−0.010***
		(0.007)		(0.002)
$dy_i * os_{mf}$		4.853*		
		(2.741)		
$dy_i * os_{ii}$		−4.364***		
		(0.698)		
$dy_p * os_{mf}$				−163.224***
				(24.698)
$dy_p * os_{ii}$				19.227***
				(2.947)
$Constant$	0.004***	−0.005	−0.005***	0.002*
	(0.001)	(0.005)	(0.0003)	(0.001)
Observations	2,818	2,818	72,626	72,626
R^2	0.010	0.034	0.013	0.015
Adjusted R^2	0.008	0.031	0.013	0.014

is reversed at trading day $t = 0$. Negative short term return autocorrelation could explain the reversed effect. However, Sias and Starks (1997) find that return autocorrelation for individual securities is *positively* related to institutional ownership. The most probable explanation for the reversed effect from the interaction terms on returns is simply that professional investors, like institutions and mutual funds, are able to reinvest dividends at $t = -3$, while private investors reinvest their dividends at $t = 0$. The coefficient for dividend yield, in the second column in Table 4, shows that stocks with zero professional ownership perform relatively better than do other stocks on trading day $t = 0$.

4.4 Timeseries of interaction terms

I estimate Equations (1) and (2) for trading days $t = -7$ to $t = +7$ to study how the effects from professional ownership on returns vary on days surrounding the distribution date. I visualize the time-series properties of the interaction terms $dy_i * os_{ii}$ and $dy_p * os_{mf}$ in Figure 4, and report estimated coefficient sizes in Table 5. For both dividend-payers and non-dividend-payers, the positive coefficients are always prior to the payment date. This observation indicates that positive price impacts occur prior to the actual distribution of dividends for stocks with large ownership by professional investors. In addition, coefficients for both categories of stocks are significantly negative on trading day $t = 0$. This observation suggests that stocks with a *low* degree of professional ownership perform relatively better than do stocks with a *high* degree of professional ownership on trading day $t = 0$.

4.5 Clustering

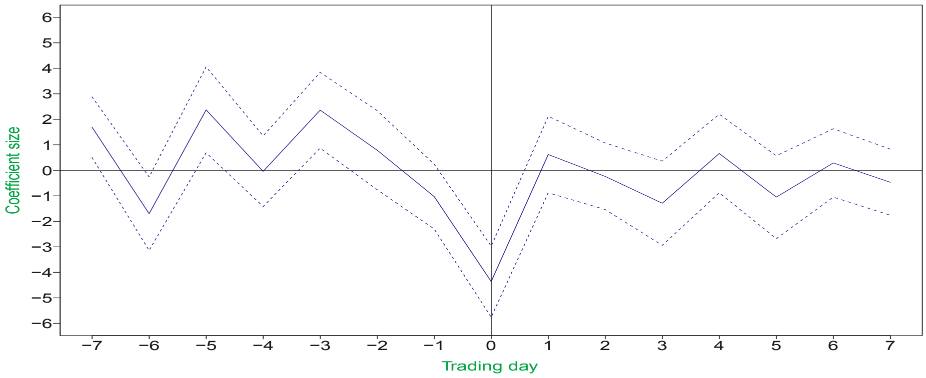
Many securities may, for different reasons, experience coinciding events during a specific month or year. The effect from the event might also be different for different months or years. Such effects are called clustering effects. To account for possible clustering effects, I run the event time analysis for individual months and years. As the significant event time results are found for the dividend payers, I only perform this robustness check for this category of stocks. Table 6 reports estimated results for the event study on individual years, while Table 7 reports estimated results for the event study on individual months.

When splitting the sample in these manners, the number of observations decreases

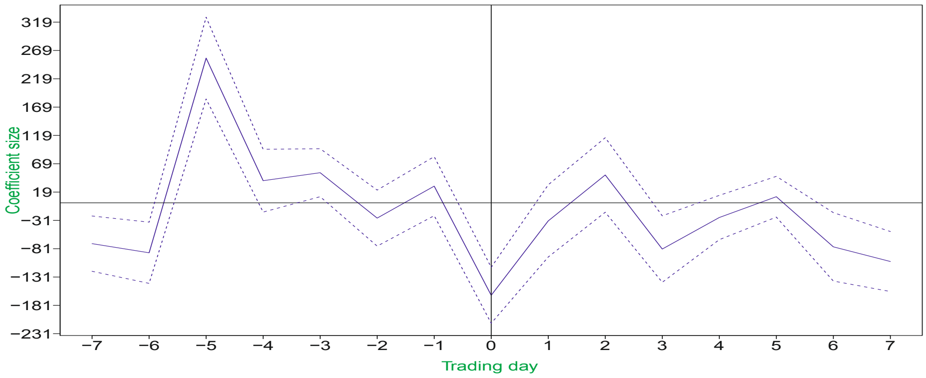
Table 5: This table reports coefficient sizes for the interaction terms $dy_i * os_{ii}$ and $dy_p * os_{mf}$ using a cross-sectional analysis on different trading days. dy_i and dy_p are dividend yields on the individual stocks and the portfolio, respectively. os_{mf} and os_{ii} are ownership shares in the stocks by mutual funds and institutional investors, respectively. * indicates significance at the 10%-level, ** indicates significance at the 5%-level, and *** indicates significance at the 1%-level using a two-tailed test.

	Dividend-payers		Non-dividend-payers	
Trading day	$dy_i * os_{ii}$	$se(dy_i * os_{ii})$	$dy_p * os_{mf}$	$se(dy_p * os_{mf})$
-7	1.69^{***}	0.60	-72.04^{***}	24.40
-6	-1.70^{**}	0.72	-88.17^{***}	27.02
-5	2.37^{***}	0.84	255.50^{***}	36.09
-4	-0.04	0.69	39.10	27.72
-3	2.36^{***}	0.74	53.20^{**}	21.18
-2	0.79	0.77	-26.96	24.73
-1	-1.03	0.64	29.46	26.06
0	-4.36^{***}	0.70	-163.22^{***}	24.70
1	0.62	0.75	-31.91	31.87
2	-0.24	0.65	49.18	32.89
3	-1.29	0.82	-81.61^{***}	29.34
4	0.66	0.77	-25.94	19.55
5	-1.05	0.81	10.81	17.98
6	0.29	0.67	-77.68^{**}	30.20
7	-0.47	0.65	-103.60^{***}	26.48

drastically for each individual estimation. As seen in Table 6 and Table 7, few of the returns for the individual years and months are statistically significant. For trading day $t = -3$ in Table 6, none of the returns are significant at the 5%-level, and only four returns are significant at the 10%-level. At trading day $t = 0$, one return is statistically positive at the 5%-level, and three additional returns are positive at the 10%-level. Still, the estimated return is statistically significant on trading day $t = 0$ over the period 2000 to 2006, and statistically significant on trading day $t = -3$ over the period 2007 to 2013. It is interesting that the significant return "moves" from $t = 0$ to $t = -3$ for the more recent sample. The increased popularity of index-linked funds might explain this phenomenon, but the evidence provided here is weak with regards to this hypothesis. Earlier, I hypothesized that increased popularity of index funds could lead to a stronger effect in a more recent sample. If anything, results reported in Table 6 show the opposite. The estimated cumulative return for the dividend payment period ($t = -3$ to $t = 0$) is stronger for data between 2000 and 2006 than for the more recent period. Nevertheless, the results in Table 6 and Table



(a) Dividend-payers



(b) Non-dividend-payers

Figure 4: Panel a) shows a time-series for the interaction term $dy_i * os_{ii}$. Panel b) shows shows a time-series for the interaction term $dy_p * os_{mf}$. A two standard error confidence interval enclose the expected value of the interaction terms.

7 show that the results in the initial analysis are not driven by a clustering effect, and that the high volatility of stock returns requires a large number of observations in order to identify abnormal returns.

4.6 Implications

Overall, the effects on returns shown in this paper should cause an incentive for other investors to provide liquidity on trading days surrounding the distribution date for dividends. However, transaction costs could eliminate a potential profit for liquidity providers. Regardless of the potential to exploit these forced reinvestments, the results show that forced reinvestments of dividends are costly, as investors must

Table 6: Average standardized abnormal return on equally weighted portfolios formed over a subsample of stocks on the NYSE and AMEX for 21 trading days. The payment date is trading day 0. The payment period is defined as trading days -3 through 0. Standardized abnormal return is calculated by substracting the average return for trading days 6 through 55 from the raw portfolio returns. These differences are standardized by the estimated standard deviation of returns for trading days 6 through 55. T-values for the parametric CDA t-test are estimated using a method described by Brown and Warner (1980). Values in bold indicate significance at the 5%-level.

	2000		2001		2002		2003		2004		2005		2006		2000-2006	
Trading day(s)	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$
-3	0.31	1.79	0.10	0.50	0.16	0.84	-0.09	-0.52	0.31	1.96	0.20	1.28	-0.16	-1.21	0.12	1.64
-2	0.00	-0.02	0.15	0.76	0.22	1.12	0.13	0.71	-0.24	-1.53	0.13	0.79	0.12	0.97	0.06	0.83
-1	0.03	0.18	0.32	1.62	0.12	0.62	-0.14	-0.78	-0.07	-0.43	0.01	0.04	-0.02	-0.13	0.02	0.22
0	0.28	1.65	0.38	1.92	0.23	1.21	-0.07	-0.39	0.10	0.67	0.24	1.53	-0.01	-0.10	**0.15**	**2.05**
1	0.32	1.84	**-0.43**	**-2.17**	**-0.42**	**-2.17**	**0.39**	**2.21**	-0.21	-1.34	0.15	0.97	-0.01	-0.06	-0.04	-0.54
2	-0.01	-0.06	0.37	1.88	**-0.41**	**-2.13**	-0.20	-1.11	0.08	0.52	0.13	0.84	-0.11	-0.85	-0.04	-0.50
3	0.13	0.73	0.01	0.07	-0.07	-0.37	-0.12	-0.69	0.03	0.17	0.00	0.00	0.09	0.70	0.01	0.18
−3-0	0.62	1.52	0.94	1.90	0.73	1.78	-0.17	-0.43	0.10	0.28	0.58	1.81	-0.06	-0.23	**0.34**	**2.40**
0-+3	0.72	1.76	0.33	0.67	-0.67	-1.62	0.00	0.01	0.00	0.01	0.53	1.66	-0.04	-0.15	0.09	0.60
n	119	119	71	71	140	140	102	102	176	176	191	191	189	189	988	988

	2007		2008		2009		2010		2011		2012		2013		2007-2013	
Trading day(s)	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$
-3	0.05	0.28	0.31	1.84	-0.15	-1.03	0.10	0.41	0.20	1.40	0.24	1.83	0.34	1.30	**0.14**	**2.52**
-2	-0.10	-0.60	-0.01	-0.06	-0.13	-0.88	0.16	0.65	0.12	0.84	-0.01	-0.05	0.49	1.87	0.01	0.18
-1	-0.11	-0.65	0.03	0.15	-0.25	-1.73	-0.12	-0.50	0.03	0.20	0.06	0.47	0.30	1.14	-0.04	-0.78
0	0.05	0.30	-0.15	-0.90	0.26	1.78	**0.87**	**3.52**	**-0.31**	**-2.20**	0.19	1.43	-0.20	-0.77	0.08	1.43
1	0.05	0.28	0.17	1.01	0.18	1.23	**0.55**	**2.23**	-0.24	-1.71	0.09	0.64	-0.35	-1.32	0.08	1.52
2	-0.12	-0.70	0.00	0.00	0.06	0.38	0.08	0.34	0.15	1.08	0.14	1.06	0.04	0.16	0.06	1.10
3	**0.35**	**2.09**	-0.21	-1.23	0.00	-0.03	-0.31	-1.24	-0.08	-0.58	0.03	0.26	0.17	0.65	-0.03	-0.51
−3-0	-0.11	-0.35	0.17	0.45	-0.27	-0.78	**1.46**	**2.45**	0.03	0.09	0.21	0.74	0.93	1.59	0.18	1.29
0-+3	0.33	1.04	-0.19	-0.50	0.49	1.41	**1.20**	**2.01**	-0.41	-1.07	0.45	1.61	-0.37	-0.58	0.19	1.36
n	178	178	280	280	270	270	130	130	275	275	269	269	44	44	1,446	1,446

Table 7: Average standardized abnormal return on equally weighted portfolios formed over a subsample of stocks on the NYSE and AMEX for 21 trading days. The payment date is trading day 0. The payment period is defined as trading days -3 through 0. Standardized abnormal return is calculated by substracting the average return for trading days 6 through 55 from the raw portfolio returns. These differences are standardized by the estimated standard deviation of returns for trading days 6 through 55. T-values for the parametric CDA t-test are estimated using a method described by Brown and Warner (1980). Values in bold indicate significance at the 5%-level.

	JAN		FEB		MAR		APR		MAY		JUN		JAN-JUN	
Trading day(s)	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$
-3	-0.07	-0.23	0.10	0.60	-0.11	-0.80	0.00	0.01	0.18	0.97	**0.25**	**2.14**	0.10	1.45
-2	0.08	0.26	-0.05	-0.27	-0.12	-0.83	-0.04	-0.15	-0.05	-0.27	0.00	0.04	-0.04	-0.64
-1	-0.04	-0.14	0.16	0.96	**-0.30**	**-2.08**	0.09	0.33	0.00	0.02	0.11	0.96	-0.02	-0.28
0	0.42	1.39	**0.48**	**2.86**	0.03	0.20	0.03	0.10	0.35	1.92	0.09	0.78	**0.15**	**2.21**
1	0.14	0.48	-0.02	-0.13	-0.04	-0.27	0.13	0.47	**0.43**	**2.38**	0.05	0.46	0.08	1.15
2	**-0.62**	**-2.07**	-0.15	-0.88	0.21	1.47	-0.13	-0.48	-0.17	-0.95	0.05	0.42	0.02	0.24
3	0.27	0.89	-0.17	-1.01	-0.14	-1.00	-0.02	-0.06	-0.07	-0.38	0.01	0.11	-0.05	-0.81
−3-0	0.39	0.48	**0.69**	**2.11**	-0.50	-1.94	0.08	0.15	0.48	1.12	0.46	1.91	0.19	1.34
0-+3	0.21	0.25	0.14	0.43	0.06	0.22	0.01	0.01	0.54	1.26	0.21	0.86	0.19	1.36
n	31	31	141	141	382	382	72	72	144	144	419	419	1,189	1,189

	JUL		AUG		SEP		OCT		NOV		DEC		JUL-DEC	
Trading day(s)	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$	$\bar{a}_t$	$CDA(t)$
-3	-0.53	-1.76	0.17	0.92	0.11	0.84	0.43	1.90	0.23	1.34	0.23	1.78	**0.16**	**2.71**
-2	0.27	0.91	0.29	1.58	0.04	0.29	-0.10	-0.43	0.19	1.10	0.06	0.49	0.10	1.67
-1	-0.04	-0.13	-0.07	-0.40	-0.03	-0.20	0.19	0.86	-0.31	-1.79	0.06	0.46	-0.02	-0.35
0	-0.05	-0.18	-0.03	-0.14	0.11	0.84	-0.01	-0.06	-0.05	-0.27	0.16	1.19	0.06	1.08
1	**-0.73**	**-2.43**	-0.09	-0.48	0.04	0.32	-0.24	-1.07	-0.03	-0.19	0.25	1.89	-0.01	-0.11
2	-0.05	-0.16	0.02	0.12	0.07	0.52	-0.05	-0.24	0.16	0.92	-0.02	-0.17	0.03	0.48
3	-0.02	-0.05	-0.20	-1.06	0.07	0.54	-0.01	-0.04	0.25	1.42	0.03	0.20	0.03	0.49
−3-0	-0.35	-0.54	0.36	1.04	0.23	0.94	0.51	1.06	0.07	0.18	0.51	1.45	**0.30**	**1.97**
0-+3	-0.85	-1.32	-0.29	-0.83	0.29	1.18	-0.32	-0.66	0.33	0.87	0.41	1.15	0.11	0.75
n	69	69	154	154	366	366	131	131	155	155	370	370	1,245	1,245

purchase stocks when the price is high. Investors can potentially avoid this extra cost by reinvesting dividends over a longer period. In most cases, performance evaluations (for instance, tracking error) act as a barrier to be “smart” about such issues. A relaxation of risk measurements around the distribution of dividends could improve the performance for professional investors who seek to reinvest their dividends.

5 Summary

This paper shows that standardized abnormal returns on stocks are higher three trading days prior to the dividend distribution date, as well as on the distribution date itself. This effect occurs as investors reinvest dividends in the dividend-paying stock, thus, raising the dividend-paying stock’s price. Since both trading volume and abnormal returns are high coincidentally, an increase in demand seems to be the explanation for this phenomenon. The effect is not a result of known anomalies, such as the January effect, and there is no spill-over effect to other stocks that are part of the same benchmark. However, ownership by mutual funds appears to be relevant for explaining abnormal returns on non-dividend paying stocks. Cumulative returns that stretches further than the defined dividend payment period are insignificant. Thus, the results are consistent with the price pressure hypothesis, which states that prices deviate temporarily from their fundamental value.

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Appendix

A Variable definitions

Variables used in the paper are described in Table A.1.

Table A.1: Variable definitions and sources.

Variable	Description	Source
a	Standardized abnormal return.	
r	Raw logarithmic return.	
pos/neg	Ratio of observed positive returns to observed negative returns.	
JAN	Variable that takes the value one for months of January, and zero otherwise.	
mc	Market capitalization.	CRSP
dy_i	Dividend yield on individual stocks.	CRSP
dy_p	Dividend yield on portfolio.	CRSP
LIQ	Stock turnover (liquidity measure).	CRSP
DRP	Dividend reinvestment plan.	Scott (1998)
os_{mf}	Ownership share by mutual funds.	Thompson Reuters
os_{ii}	Ownership share by institutional investors.	Thompson Reuters

B 25 alternative portfolios

As an alternative robustness check, I construct 25 portfolios as follows. I order all dividend-paying stocks based on their daily dividend yield and sort them into quintiles. Further, I sort these quintiles into new quintiles based on their institutional ownership. I order on these criterias because I seek to explain the variation in standardized abnormal returns by the variation in dividend yield and institutional ownership. Table B.1 shows that the degree of ownership by institutional investors and the degree of ownership by mutual funds are positively correlated. We can also see that the average market capitalization for the 25 portfolios varies greatly for the portfolios in the low and high quintiles. Only four portfolios experience a significant positive cumulative return during the dividend payment period. Thus, a trading strategy that is constructed to take advantage of the abnormal returns during the dividend payment period appears to be difficult to implement.

Table B.1: This table shows descriptive statistics for 25 stock portfolios formed on dividend yield (dy_i) and ownership share by institutional investors (os_{ii}). The table also reports average mutual fund ownership ($\bar{os}_{mf}$), average market capitalization ($\bar{mc}$) and cumulative abnormal returns during the *dividend payment period* (a). $t(a)$ is t-value for the cumulative abnormal returns. Average market capitalization is in million USD. Values in bold indicate significance at the 5%-level.

os_{ii}	dy_i-quintile					dy_i-quintile				
-quintile	high	2	3	4	low	high	2	3	4	low
			$\bar{os}_{ii}$					$\bar{os}_{mf}$		
high	82%	84%	86%	89%	93%	2.06%	3.43%	3.78%	3.08%	3.42%
2	70%	70%	76%	79%	81%	1.48%	1.67%	1.59%	3.02%	2.41%
3	62%	65%	70%	74%	76%	1.88%	1.49%	1.37%	1.77%	2.11%
4	54%	59%	64%	66%	69%	1.22%	1.21%	0.95%	1.94%	1.31%
low	41%	47%	53%	52%	55%	1.30%	1.12%	1.01%	0.84%	1.11%
			$\bar{dy}_i$					$\bar{mc}$		
high	1.61%	0.94%	0.70%	0.53%	0.36%	10 107	11 557	13 183	9 954	12 827
2	1.34%	0.94%	0.71%	0.53%	0.36%	26 814	24 942	21 982	20 002	17 282
3	1.39%	0.92%	0.71%	0.53%	0.36%	44 205	51 583	22 771	28 982	22 374
4	1.34%	0.96%	0.70%	0.54%	0.35%	53 044	81 017	49 509	25 745	15 500
low	1.40%	0.96%	0.71%	0.54%	0.36%	9 269	28 807	85 904	138 563	72 663
			a					$t(a)$		
high	-0.17%	0.49%	-0.15%	-0.47%	-0.08%	-0.54	1.68	-0.53	-1.72	-0.24
2	0.49%	0.38%	0.24%	-0.23%	**0.51%**	1.68	1.66	0.98	-0.95	**2.24**
3	0.25%	0.41%	0.24%	0.14%	0.21%	1.06	1.59	1.03	0.56	0.86
4	0.31%	0.26%	**0.69%**	0.03%	0.26%	0.95	1.17	**2.84**	0.15	1.15
low	**0.89%**	**0.67%**	0.25%	0.33%	0.07%	**2.96**	**2.15**	1.25	1.4	0.27

Table B.2 shows the maximum standardized abnormal return observed for the 25 portfolios during the dividend payment period. Out of the 25 returns, 15 are significantly positive. Among these 15 returns, 11 are observed at trading day $t = -3$.

This observation is an indication that positive price pressure is concentrated at trading day $t = -3$. Seen together with the absence of positive cumulative returns reported in Table B.1, it is likely that return reversal is present.

Table B.2: The top panel of this table shows the maximum daily standardized abnormal return during the dividend payment period for 25 different portfolios. The middle panel shows corresponding t-values. The bottom panel shows at which trading day the maximum daily standardized returns are observed. Values in bold indicate significance at the 5%-level.

	dy_i-quintile				
os_{ii} -quintile	high	2	3	4	low
			$max(a)$		
high	0.19	**0.32**	0.12	0.08	0.04
2	**0.32**	**0.28**	**0.20**	0.10	**0.25**
3	0.15	**0.25**	**0.18**	**0.25**	**0.21**
4	**0.34**	**0.18**	**0.33**	0.12	0.15
low	**0.33**	**0.36**	0.17	**0.27**	0.09
			$t(a)$		
high	1.42	**2.59**	0.99	0.60	0.45
2	**2.59**	**2.60**	**2.01**	0.91	**2.24**
3	1.49	**2.40**	**2.02**	**2.22**	**1.97**
4	**2.33**	**1.97**	**3.18**	0.98	1.34
low	**2.42**	**2.62**	1.86	**2.54**	0.81
			Trading day		
high	-3	**-3**	0	-1	0
2	**-3**	**0**	**-3**	-2	**-3**
3	-1	**-3**	**-3**	**-3**	**-3**
4	**-3**	**-2**	**-3**	0	-2
low	**-3**	**0**	-2	**0**	-3

Chapter II

Mutual funds' trading causes price impacts in their benchmark portfolios

Mutual funds' trading causes price impacts in their benchmark portfolios*

Joakim Kvamvold†

Abstract

Current literature concerning price impacts finds it difficult to distinguish between demand driven price impacts and information induced price changes. Using monthly data, I examine trading caused by net flows to mutual funds invested at the Oslo Stock Exchange. My results indicate that trading by index-linked mutual funds and actively managed funds causes price impacts on different parts of the stock exchange. I do not find the effect on returns to be explained by new information, and do not find evidence for price reversals. Hence, I provide evidence towards a demand driven explanation for price movements in stocks.

Keywords: Price impact, mutual funds, investment flows, portfolio returns.

JEL classifications: G11, G12, G14

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†Norwegian University of Science and Technology, Department of Economics, Dragvoll, N-7491 Trondheim, Norway. E-mail: joakim.kvamvold@svt.ntnu.no

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 (see e.g., 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.[1] These findings are in line with the findings of Warther (1995), who reports that aggregated security returns are unrelated to *expected* fund flows, but highly correlated with *unexpected* fund flows. However, Warther (1995) fails to establish whether the positive correlation is caused by new information or changes in demand. Using a similar approach, I find that expected fund flows can predict future returns for a subset of the stocks listed on the stock exchange. This finding suggests that the stock market is inefficient.

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

[1] If a mutual fund performs well, investors tend to invest more money in that mutual fund. As a consequence, the fund adds to its current holdings, which in turn increases demand (and prices) for the holdings, thus, attracting even more capital to the fund. This positive spiral is referred to as positive feedback trading in the literature.

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 comove 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. This behaviour may introduce a common factor in the returns on constituents of the benchmark against which fund's performance is measured. 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. My results neither indicate trading in response to information, nor do I find evidence for return reversals. Hence, I provide evidence towards the imperfect substitution hypothesis.

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. Lou (2012) also claims that flows to mutual funds partly accounts for the momentum effect reported by Jagadeesh and Titman (1993). However, in a recent paper, Chen et al. (2014) claim that excess comovement in stocks is a manifestation of momentum. If this is the case, momentum can also account for the effects reported by Lou (2012). I add to this discussion by analyzing flows to mutual funds and the effect from flows on returns on their designated benchmark portfolios.

I use data on net flows for all Norwegian mutual funds with Norway as primary in-

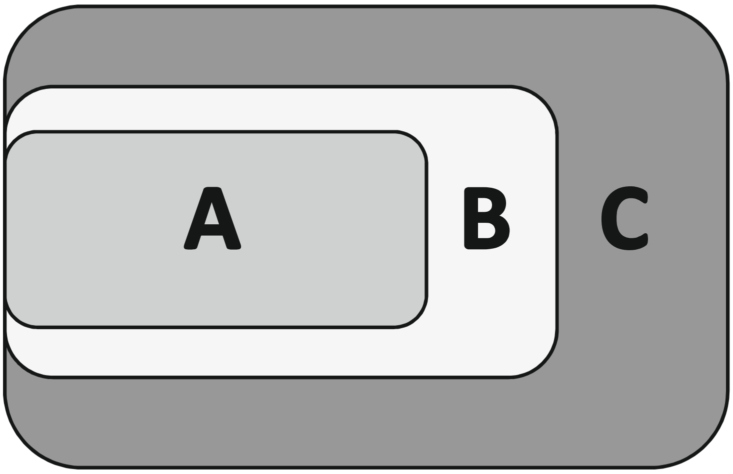

Figure 1: Illustration of Oslo Stock Exchange. The stock exchange consists of all stocks in sets A, B and C. The stocks in set A are the constituents of the OBX index. $A \cup B$ is the set containing the constituents of the broader index OSEBX and C is the set of stocks excluded from both indices.

vestment 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 0.8 percentage points when net flows to the funds increase by one standard deviation. For actively managed funds, the effect is even larger. When net flows to actively managed funds increase by one standard deviation, monthly returns on the benchmark portfolios for actively managed funds increases between 1.7 and 2.0 percentage points depending on the sample period. I also find this effect to be almost twice as large for small stocks than as for large stocks.

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.

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 2, 2006 through May 1, 2013. In the final sample, I only include stocks with a minimum of 10 trades on average per day, or shares with a liquidity provider scheme.[2] I also collect information about which stocks the OBX index and the OSEBX index include during the same time 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 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 six months turnover ratio. On average, 1.7 stocks are excluded from the index every six months, and 2.0 new stocks are included. The difference is due to more mergers and acquisitions than demergers. In total, during the sample period, 43 unique companies have been constituents of the OBX index. The sample number of constituents in the OSEBX index varies between 53 and 69, with an average of 62. The 25 stocks included in the OBX are always

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

Table 1: This table presents descriptive statistics for the observations of returns on three portfolios: A, B, and C. Monthly returns are calculated as the sum of daily logarithmic total returns for the last 22 trading days. Panel A includes observations from February 2009 through April 2013. Panel B includes observations from January 2006 through April 2013.

Panel A	r_A	r_B	r_C
Means:	$9.4 \cdot 10^{-3}$	$6.8 \cdot 10^{-3}$	$3.7 \cdot 10^{-3}$
Standard deviations:	$5.0 \cdot 10^{-2}$	$4.6 \cdot 10^{-2}$	$3.6 \cdot 10^{-2}$
Correlation matrix:			
r_A	1.00	0.69	0.70
r_B		1.00	0.83
r_C			1.00
Panel B			
Means:	$5.2 \cdot 10^{-4}$	$-5.7 \cdot 10^{-3}$	$6.4 \cdot 10^{-4}$
Standard deviations:	$7.3 \cdot 10^{-2}$	$6.6 \cdot 10^{-2}$	$4.2 \cdot 10^{-2}$
Correlation matrix:			
r_A	1.00	0.63	0.78
r_B		1.00	0.65
r_C			1.00

also included in the broader index OSEBX. The number of daily returns I calculate for stocks that are excluded from both indices ranges between 38 and 79, with an average of 60.

Table 1 presents descriptive statistics for the returns on portfolio A, B, and C. In Figure 2, I plot a time series for the same portfolio returns. Estimated correlation coefficients for returns on the three portfolios are between 0.63 and 0.83, indicating high correlation between the returns series. The estimated figures in the two panels of Table 1 are fairly consistent. Returns on portfolio C are less volatile than returns on portfolios A and B. Returns on all three portfolios are especially volatile between May 2008 and February 2009 (see Figure 2).

2.2 Mutual funds data

I use mutual funds data from the Norwegian Fund and Asset Management Association (Verdipapirfondenes forening). Monthly observations are from January 2006 through April 2013. I consider a total of nine mutual funds to be index-linked. 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

Figure 2: This diagram shows the monthly value-weighted portfolio return on three different portfolios at the Oslo Stock Exchange.

"index", "OBX", or "OSEBX" in their names. 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 10.00% in April 2013. 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 (as seen in Figure 3). 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, and I define it as

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

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_{mutual} 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_{mutual} 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 $-1{,}248$ million NOK and 3,577 million NOK. As seen in Figure 3, 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_{mutual} 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 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.

Figure 3: 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 equalled approximately six NOK.)

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.

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

Table 2: This table presents correlation coefficients between selected variables. The variables f_{index} and f_{mutual} 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.

	f_{index}	f_{mutual}	r_A	r_B	r_C
f_{index}	1.00	0.15	0.22	0.11	0.08
f_{mutual}		1.00	0.48	0.40	0.49
r_A			1.00	0.69	0.70
r_B				1.00	0.83
r_C					1.00

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 2 show that flows to index-linked mutual funds have a higher correlation with returns on portfolio A than with returns on portfolios B and C. Net flows to actively managed funds (f_{mutual}) 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.

3.2 A regression study

Motivated by the findings reported in Table 2, I test whether returns on portfolios A, B, and C move in the same direction as 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. To this end, I let monthly portfolio return $r_{i,t}$, $i = A, B, C$, be the endogenous variable. I use monthly net flows to index-linked mutual funds (f_{index}) and monthly net flows to actively managed mutual funds (f_{mutual}) as explanatory variables.

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 re-

Figure 4: This figure shows monthly trading volume in 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}). Trading volumes are in billion NOK.

cent 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, ETFs with both positive and negative exposure to the market exists, providing me an opportunity to discriminate between positive and negative investor sentiment. 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.

Therefore, I use public transactions in the ETFs as a proxy for investor sentiment. I name the variable for positive sentiment v_{BULL}, and the variable for negative sentiment v_{BEAR}. The positive sentiment variable includes ETFs with a positive exposure to the market, both leveraged and unleveraged ETFs. The negative sentiment variable includes ETFs with a negative exposure to the market. v_{BEAR} only includes leveraged ETFs. All ETFs are constructed to have exposure to the OBX index (portfolio A).

Three occurrences of interest take place in 2008. First, 2008 is the year when net flows to index-linked mutual funds become more volatile (see Figure 3). Second, leveraged ETFs are introduced to the Norwegian market in 2008; as a consequence, the trading volume in ETFs starts to pick up (see Figure 4). Thirdly, 2008 is the year when the financial crisis begins. To eliminate the possibility that results are driven by the crash in 2008, I begin the main analysis in February 2009. Also, I exclude observations during the most turbulent period of the financial crisis (May 2008 through January 2009) when doing robustness checks.[3] I now estimate

$$\begin{aligned} r_{i,t} = \beta_0 + \beta_1 f_{index,t} + \beta_2 f_{mutual,t} + \beta_3 v_{BULL,t} + \beta_4 v_{BEAR,t} + \beta_5 f_{index,t-1} \\ + \beta_6 f_{mutual,t-1} + \beta_7 v_{BULL,t-1} + \beta_8 v_{BEAR,t-1} + \epsilon_t, \quad i = A, B, C. \quad (2) \end{aligned}$$

Table 3 reports estimated results for Equation (2). As seen in Table 3, net flows to index-linked mutual funds are positively related to returns on portfolio A. The standard deviation of f_{index} is 0.208. Thus, an increase of one standard deviation in net flows implies an increase in monthly returns on portfolio A of approximately 0.8 percentage points.

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 between net flows to active mutual funds and returns exists even when controlling for investor sentiment. The standard deviation of f_{mutual} is 0.549, which implies an increase in monthly returns on all three portfolios of approximately 2 percentage points as a response to an increase of one standard deviation in net flows. 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.

Coefficients for all variables are statistically significant in the first column of Table 3. This observation can indicate that investors trade as a response to information.

[3] Including observations between May 2008 and February 2009 in the regressions provides similar results.

However, the negative (positive) coefficient for ETFs with a positive (negative) exposure to the market, suggests either that flows to mutual funds introduce a factor in the returns or that information is interpreted differently by traders in ETFs and investors in mutual funds. The negative coefficient for v_{BULL} and positive coefficient for v_{BEAR} might suggest that traders in ETFs are dominated by contrarians (i.e. selling when prices rise, and vice versa). However, it is difficult to argue why this asset class should be dominated by investors with different trading strategies than by investors who trade mutual funds. In addition, coefficients for trading volume in ETFs are insignificant when adding lagged variables. This result is an indication that trades by mutual funds cause price impacts for the appropriate benchmark portfolio, assuming that new information is available to all investors. Also, information concerning the aggregated market cannot be the driver of these results, as coefficients for f_{index} are insignificant 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.

I add lagged variables to check whether return reversals are present. 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. Due to a limited number of observations, I cannot include several lags of each variable. Thus, this is a weak test to exclude the possibility of price reversals.

I extend the sample period with approximately three years as a robustness check. Trades in ETFs before the leveraged contracts were introduced are virtually non-existing. Hence, I do not include v_{BULL} and v_{BEAR} in the robustness check. For the robustness check I estimate

$$r_{i,t} = \beta_0 + \beta_1 f_{index,t} + \beta_2 f_{mutual,t} + \beta_5 f_{index,t-1} + \beta_6 f_{mutual,t-1} + \epsilon_t, \quad i = A, B, C. \tag{3}$$

Table 4 presents estimated results for Equation (3). In contrast to the previous results, net flows to index funds do not have a positive effect on returns on portfolio A. On the other hand, net flows to actively managed funds still have a positive effect on returns on all three portfolios. Assets under management for index-linked mutual funds have increased dramatically in recent years, reaching 10% of the market capitalization of the domestic mutual funds market, with Norway as the primary investment region. Index funds gained popularity during/after the financial crisis (see Figure 3). If flows to mutual funds reflect new information, the coefficient for

Table 3: This table reports regression analyses of three different value-weighted portfolios' returns in response to net flows to index-linked and actively managed mutual funds. The independent variables f_{index} and f_{mutual} are net flows to index-linked mutual funds and actively managed mutual funds, respectively. These two variables are the independent variables of interest. Trading volume in "positive sentiment" ETFs (v_{BULL}) and trading volume in "negative sentiment" ETFs (v_{BEAR}) are added as control variables. The coefficients are estimated using an OLS approach using monthly data from February 2009 through April 2013. All variables for flows and trading volumes are in billion NOK. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level using a two-tailed test.

Dependent variable	r_A	r_A	r_B	r_B	r_C	r_C
β_0	$8.7 \cdot 10^{-3}$	$6.9 \cdot 10^{-3}$	$2.3 \cdot 10^{-2}$	$2.5 \cdot 10^{-2}$	$-8.6 \cdot 10^{-4}$	$7.1 \cdot 10^{-2}$
	(0.66)	(0.62)	(1.85)	(2.46)*	(-0.08)	(1.28)
f_{index}	$3.8 \cdot 10^{-2}$	$5.7 \cdot 10^{-2}$	$1.2 \cdot 10^{-2}$	$4.8 \cdot 10^{-3}$	$1.3 \cdot 10^{-3}$	$-5.9 \cdot 10^{-5}$
	(2.04)*	(2.19)*	(0.74)	(0.21)	(0.06)	(-0.00)
f_{mutual}	$4.5 \cdot 10^{-2}$	$4.9 \cdot 10^{-2}$	$3.7 \cdot 10^{-2}$	$3.7 \cdot 10^{-2}$	$3.3 \cdot 10^{-2}$	$3.4 \cdot 10^{-2}$
	(4.86)**	(3.88)**	(4.36)**	(3.95)**	(4.71)**	(3.45)**
v_{BULL}	$-1.2 \cdot 10^{-2}$	$-5.7 \cdot 10^{-3}$	$-9.2 \cdot 10^{-3}$	$-2.0 \cdot 10^{-3}$	$-1.6 \cdot 10^{-3}$	$-5.3 \cdot 10^{-4}$
	(-2.93)**	(-0.88)	(–2.59)*	(-0.32)	(-0.65)	(-0.61)
v_{BEAR}	$1.1 \cdot 10^{-2}$	$4.0 \cdot 10^{-3}$	$4.2 \cdot 10^{-2}$	$-1.6 \cdot 10^{-3}$	$1.5 \cdot 10^{-3}$	$-3.9 \cdot 10^{-3}$
	(2.47)*	(0.37)	(0.91)	(-0.14)	(0.41)	(-0.96)
$f_{index,t-1}$		$-5.3 \cdot 10^{-2}$		$2.0 \cdot 10^{-2}$		$2.9 \cdot 10^{-3}$
		(-1.67)		(0.63)		(0.60)
$f_{mutual,t-1}$		$-5.6 \cdot 10^{-3}$		$-1.1 \cdot 10^{-3}$		$-1.3 \cdot 10^{-3}$
		(-0.59)		(-0.10)		(-1.09)
$v_{BULL,t-1}$		$-7.2 \cdot 10^{-3}$		$-9.6 \cdot 10^{-3}$		$6.0 \cdot 10^{-4}$
		(-1.52)		(-1.53)		(1.31)
$v_{BEAR,t-1}$		$1.1 \cdot 10^{-2}$		$8.1 \cdot 10^{-3}$		$6.0 \cdot 10^{-4}$
		(1.14)		(0.77)		(1.31)
Adjusted R^2	22.04%	32.02%	18.63%	15.89%	17.85%	19.60%
No. observations	51	51	51	51	51	51

f_{index} should still be significant. Results in Table 4 rather indicate that flows to index funds are not large enough to introduce price impacts when observations prior to 2009 are included. I estimate standard deviations for f_{mutual} for the extended sample, and find the effect on returns to be approximately 1.7 percentage points for flows to actively managed funds. The effect from trades committed by actively managed funds is approximately the same size as before. We also see in Table 4 that the coefficients for f_{mutual} are approximately the same size regardless of which regression is estimated. These results add strength to the hypothesis that flows to mutual funds affect returns on stocks in the portfolios the mutual funds use as benchmarks. Lagged variables are still insignificant. Hence, the results provide evidence towards the imperfect substitution hypothesis.

Table 4: This table reports regression analyses of three different value-weighted portfolios' returns in response to net flows to index-linked and actively managed mutual funds. The independent variables f_{index} and f_{mutual} are net flows to index-linked funds and actively managed mutual funds, respectively. These two variables are the independent variables of interest. The coefficients are estimated using an OLS approach using monthly data from January 2006 through April 2013. Observations between May 2008 and February 2009, the most turbulent period of the financial crisis, are excluded. All variables for flows are in billion NOK. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level using a two-tailed test.

Dependent variable	r_A	r_A	r_B	r_B	r_C	r_C
β_0	$9.3 \cdot 10^{-3}$	$1.1 \cdot 10^{-2}$	$3.8 \cdot 10^{-3}$	$2.8 \cdot 10^{-3}$	$2.6 \cdot 10^{-3}$	$2.8 \cdot 10^{-3}$
	(1.58)	(1.84)	(0.67)	(0.45)	(0.73)	(0.74)
f_{index}	$1.6 \cdot 10^{-2}$	$3.2 \cdot 10^{-2}$	$8.5 \cdot 10^{-3}$	$-1.8 \cdot 10^{-3}$	$-7.0 \cdot 10^{-3}$	$-4.5 \cdot 10^{-3}$
	(0.71)	(1.15)	(0.57)	(-0.10)	(-0.37)	(-0.21)
f_{mutual}	$2.7 \cdot 10^{-2}$	$3.2 \cdot 10^{-2}$	$2.5 \cdot 10^{-2}$	$2.2 \cdot 10^{-2}$	$2.5 \cdot 10^{-2}$	$2.5 \cdot 10^{-2}$
	(3.23)**	(3.47)**	(3.34)**	(2.53)*	(4.92)**	(4.78)**
$f_{index,t-1}$		$-4.3 \cdot 10^{-2}$		$2.5 \cdot 10^{-2}$		$-1.1 \cdot 10^{-2}$
		(-1.77)		(0.98)		(-0.62)
$f_{mutual,t-1}$		$-5.1 \cdot 10^{-3}$		$6.6 \cdot 10^{-3}$		$3.0 \cdot 10^{-3}$
		(-0.60)		(0.61)		(0.67)
Adjusted R^2	11.29%	11.18%	11.21%	10.50%	22.43%	20.87%
No. observations	79	79	79	79	79	79

3.3 Size-sorted portfolios

In this subsection, I sort stocks in portfolio B and portfolio C descending in market capitalization. I do not include stocks in portfolio A when forming size-portfolios. I form equally-weighted quintile portfolios semi-annually from January 2006 through April 2013. I denote returns on the portfolio with the largest stocks r_{q1}, returns on the portfolio with the second largest stocks r_{q2}, and so on.

Table 5 presents descriptive statistics for the quintile portfolios. Average monthly returns appear to be lower for the smallest stocks. In addition, standard deviations for the portfolio returns are higher the smaller the stocks in the quintile portfolio become. Returns on small stocks tend to have a larger share of idiosyncratic risk than do large stocks, and we can see such pattern in the correlation matrix in Table 5. The estimated numbers in the two panels of Table 5 are fairly consistent regardless of the sample period.

When estimating the effect from mutual fund flows on returns on the quintile portfolios, I use Equation (2). Even though net flows to index-linked mutual funds do not cause trading in stocks in the quintile portfolios directly, I include this flow

Table 5: This table presents descriptive statistics for the observations of returns on size-sorted quintile portfolios formed semi-annually. Returns on the portfolio with the largest stocks are denoted r_{q1}, returns on the portfolio with the second largest stocks are denoted r_{q1}, and so on. Returns are calculated as monthly sums of daily logarithmic total returns. Panel A includes observations from February 2009 through April 2013. Panel B includes observations from January 2006 through April 2013.

Panel A	r_{q1}	r_{q2}	r_{q3}	r_{q4}	r_{q5}
Means:	$5.9 \cdot 10^{-3}$	$1.1 \cdot 10^{-2}$	$1.5 \cdot 10^{-2}$	$-1.0 \cdot 10^{-2}$	$-2.3 \cdot 10^{-2}$
Standard deviations:	$6.0 \cdot 10^{-2}$	$7.6 \cdot 10^{-2}$	$8.4 \cdot 10^{-2}$	$1.1 \cdot 10^{-1}$	$1.2 \cdot 10^{-1}$
Correlation matrix:					
r_{q1}	1.00	0.82	0.78	0.70	0.48
r_{q2}		1.00	0.78	0.73	0.56
r_{q3}			1.00	0.75	0.55
r_{q4}				1.00	0.52
r_{q5}					1.00
Panel B	r_{q1}	r_{q2}	r_{q3}	r_{q4}	r_{q5}
Means:	$-2.8 \cdot 10^{-3}$	$-6.0 \cdot 10^{-3}$	$-3.8 \cdot 10^{-3}$	$-1.9 \cdot 10^{-2}$	$-2.6 \cdot 10^{-2}$
Standard deviations:	$7.3 \cdot 10^{-2}$	$9.0 \cdot 10^{-2}$	$1.0 \cdot 10^{-1}$	$1.2 \cdot 10^{-1}$	$1.2 \cdot 10^{-1}$
Correlation matrix:					
r_{q1}	1.00	0.80	0.71	0.67	0.55
r_{q2}		1.00	0.74	0.69	0.57
r_{q3}			1.00	0.68	0.57
r_{q4}				1.00	0.51
r_{q5}					1.00

variable to control for possible fund flows *between* actively and passively managed funds. Table 6 reports estimated results for a regression analysis of the five different size-portfolios' returns in response to net flows to mutual funds and trading volume in ETFs.

The estimated results in Table 6 indicate that net flows to mutual funds have a stronger effect on returns on stocks of smaller companies. The coefficients for net flows regressed on r_{q4} and r_{q5} are the two largest coefficients, while the coefficients for net flows regressed on r_{q1} and r_{q2} are the two smallest coefficients. The effect on returns on the portfolio consisting of the second smallest stocks is more than twice as large as the effect on returns on the portfolio containing the largest stocks. Mutual

Table 6: This table reports regression analyses of five different portfolios' returns in response to net flows to index-linked and actively managed mutual funds. The five portfolios are size-sorted, equally-weighted portfolios. Returns on the portfolio with the largest stocks are denoted r_{q1}, returns on the portfolio with the second largest stocks are denoted r_{q2}, and so on. The independent variables f_{index} and f_{mutual} are net flows to index-linked funds and actively managed mutual funds, respectively. These two variables are the independent variables of interest. Trading volume in "positive sentiment" ETFs (v_{BULL}) and trading volume in "negative sentiment" ETFs (v_{BEAR}) are added as control variables. The coefficients are estimated using an OLS approach using monthly data from February 2009 through April 2013. All variables for flows and trading volumes are in billion NOK. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level using a two-tailed test.

Dependent variable	r_{q1}	r_{q2}	r_{q3}	r_{q4}	r_{q5}
β_0	$2.2{\cdot}10^{-2}$	$1.2{\cdot}10^{-3}$	$2.9{\cdot}10^{-2}$	$4.0{\cdot}10^{-2}$	$-1.9{\cdot}10^{-2}$
	(1.29)	(0.06)	(1.07)	(1.36)	(-0.49)
f_{index}	$2.8{\cdot}10^{-2}$	$2.2{\cdot}10^{-2}$	$1.6{\cdot}10^{-2}$	$2.4{\cdot}10^{-2}$	$-1.3{\cdot}10^{-2}$
	(1.27)	(0.72)	(0.36)	(0.40)	(-0.18)
f_{mutual}	$5.0{\cdot}10^{-2}$	$6.4{\cdot}10^{-2}$	$6.8{\cdot}10^{-2}$	$1.1{\cdot}10^{-1}$	$8.4{\cdot}10^{-2}$
	(5.09)**	(4.55)**	(3.53)**	(4.73)**	(2.90)**
v_{BULL}	$-1.2{\cdot}10^{-2}$	$-3.0{\cdot}10^{-3}$	$-3.2{\cdot}10^{-3}$	$-1.8{\cdot}10^{-2}$	$7.4{\cdot}10^{-3}$
	(-2.24)*	(-0.58)	(-0.39)	(-2.21)*	(0.62)
v_{BEAR}	$6.2{\cdot}10^{-3}$	$2.5{\cdot}10^{-3}$	$4.5{\cdot}10^{-3}$	$1.6{\cdot}10^{-4}$	$-1.5{\cdot}10^{-2}$
	(0.99)	(0.36)	(-0.52)	(0.02)	(-1.13)
Adjusted R^2	20.19%	15.73%	14.07%	28.26%	10.93%
No. observations	51	51	51	51	51

funds' trading is likely to account for a larger share of total trades for small stocks than for large stocks, thus creating a larger effect on returns on small stocks. Again, flows to index-linked mutual funds do not have any effect on returns on stocks in portfolios B and C.

Some could argue that these results are driven by investor sentiment. According to Lee et al. (1991), investor sentiment has a larger effect on small stocks than on large stocks. However, coefficients for trading volume in ETFs are significant only for two of the portfolios. If flows to mutual funds is a better proxy for investor sentiment, I would expect coefficients for flows to the index-linked mutual funds to be statistically significant as well. They are not for any of the portfolios. Again, the results suggest that information concerning the aggregated market is not the driver of the results. Coefficients for f_{mutual} are significant for all portfolios. It is very unlikely that positive firm specific information is present for all five portfolios

Table 7: This table reports regression analyses of five different portfolios' returns in response to net flows to index-linked and actively managed mutual funds. The five portfolios are size-sorted, equally-weighted portfolios. Returns on the portfolio with the largest stocks are denoted r_{q1}, returns on the portfolio with the second largest stocks are denoted r_{q2}, and so on. The independent variables f_{index} and f_{mutual} are net flows to index-linked funds and actively managed mutual funds, respectively. The coefficients are estimated using an OLS approach using monthly data from January 2006 through April 2013. Observations between May 2008 and February 2009, the most turbulent period of the financial crisis, are excluded. Both variables for flows are in billion NOK. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level using a two-tailed test.

Dependent variable	r_{q1}	r_{q2}	r_{q3}	r_{q4}	r_{q5}
β_0	$3.7{\cdot}10^{-3}$	$7.5{\cdot}10^{-5}$	$4.3{\cdot}10^{-3}$	$-1.7{\cdot}10^{-2}$	$-2.1{\cdot}10^{-2}$
	(0.55)	(0.01)	(0.44)	(-1.40)	(-1.32)
f_{index}	$1.1{\cdot}10^{-2}$	$1.9{\cdot}10^{-2}$	$3.1{\cdot}10^{-2}$	$-5.1{\cdot}10^{-3}$	$-2.5{\cdot}10^{-2}$
	(0.49)	(0.62)	(0.83)	(-0.09)	(-0.49)
f_{mutual}	$3.4{\cdot}10^{-2}$	$4.5{\cdot}10^{-2}$	$4.4{\cdot}10^{-2}$	$7.4{\cdot}10^{-2}$	$5.3{\cdot}10^{-2}$
	(3.58)**	(4.24)**	(3.54)**	(2.88)**	(3.77)**
Adjusted R^2	14.43%	15.13%	13.51%	18.19%	8.74%
No. observations	79	79	79	79	79

at the same time. Thus, the results indicate that the effect on returns is demand driven.

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.

I extend the sample period, excluding observations for the financial crises, to perform a robustness check. Again I exclude the variables for trading in ETFs. I report results for estimations on size-portfolios for the extended sample period in Table 7.

The two largest coefficients are found for regressions on r_{q4} and r_{q5}. Likewise, the coefficient for net flows in the regression on r_{q1} is the smallest I estimate. This robustness check adds strength to the hypothesis that mutual fund flows affect smaller stocks to a larger degree, and that this result is not a manifestation of information induced trading.

3.4 Model using expected and unexpected net flows

It is common to regard fund flows as being highly predictable. Warther (1995) uses an AR(3)-model to estimate the expected and unexpected components of net flows. Further, he finds that returns are highly correlated with unexpected flows to mutual funds, but unrelated to concurrent expected flows. Based on the habitat view presented in Barberis et al. (2005) and the results in Warther (1995), I also hypothesize that unexpected net flows to mutual funds are correlated with returns for the appropriate benchmark for the mutual funds.

In contrast to Warther (1995), an AR(1)-model has the best explanatory power of flows to both index-linked mutual funds and actively managed funds in my data set (see Appendix B for estimated results). For the AR-models I estimate adjusted R^2 of 12% and 27% for index-linked and actively managed funds, respectively. Warther (1995) estimates adjusted R^2 of 44% with his AR(3)-model.

By predicting one-step-ahead values for net flows I get the expected flows. The unexpected part of net flows is captured by the residual. I use the expected and unexpected flows to index-linked mutual funds and actively managed funds to explain returns on portfolios A, B, and C. To this end, I estimate

$$r_{i,t} = \beta_0 + \beta_1 \hat{f}_{index,t} + \beta_2 \tilde{f}_{index,t} + \beta_3 \hat{f}_{mutual,t} + \beta_4 \tilde{f}_{mutual,t} + \epsilon_t, \quad i = A, B, C, \quad (4)$$

where $\hat{f}$s indicate concurrent expected net flows to the two categories of funds and $\tilde{f}$s indicate unexpected net flows to the same categories of funds. Table 8 presents estimated results for Equation (4).

The estimated results in Table 8 show that unexpected flows to actively managed funds have a positive effect on returns for all three portfolios. Also, unexpected flows to index funds have a significant effect on returns on portfolio A. This result is in line with the research of Warther (1995). In addition, I estimate a positive significant coefficient for *expected* flows to actively managed funds on returns on portfolio C. The positive coefficient for expected flows on returns on portfolio C can be a result of the size-effect analyzed in the previous section.

If future returns on some stocks can be estimated using current information, market inefficiency is present. The inconsistency of the result when I run regressions on different endogenous variables indicates either that the result is caused by a size-effect or that the result is spurious. To reduce the possibility that the result is

Table 8: 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 an AR(1)-model. The final coefficients are estimated using an OLS approach using monthly data from February 2009 through April 2013. 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 5%-level, and ** indicates significance at the 1%-level using a two-tailed test.

Dependent variable	r_A	r_B	r_C
β_0	$1.2 \cdot 10^{-2}$	$-2.3 \cdot 10^{-3}$	$-2.3 \cdot 10^{-3}$
	(1.29)	(-0.21)	(-0.33)
$\hat{f}_{index}$	$-8.5 \cdot 10^{-2}$	$6.0 \cdot 10^{-2}$	$-2.3 \cdot 10^{-2}$
	(-1.56)	(1.03)	(-0.50)
$\tilde{f}_{index}$	$5.6 \cdot 10^{-2}$	$6.0 \cdot 10^{-3}$	$4.2 \cdot 10^{-3}$
	(2.24)*	(0.30)	(0.19)
$\hat{f}_{mutual}$	$2.5 \cdot 10^{-2}$	$2.1 \cdot 10^{-2}$	$4.1 \cdot 10^{-2}$
	(1.16)	(0.94)	(2.52)*
$\tilde{f}_{mutual}$	$5.3 \cdot 10^{-2}$	$3.5 \cdot 10^{-2}$	$3.0 \cdot 10^{-2}$
	(5.30)**	(3.75)**	(4.05)**
Adjusted R^2	25.15%	10.70%	18.50%
No. observations	51	51	51

spurious, I perform the same analysis using an extended sample as a robustness check. Again, an AR(1)-model best predicts net flows to both index-linked funds and actively managed mutual funds. I estimate Equation (4) again, where $\hat{f}$s and $\tilde{f}$s are estimated using the whole sample. Table 9 shows estimated results for the extended sample.

In contrast to the results presented in Table 8, I find no significant effect from expected net flows to actively managed funds on returns for any of the portfolios. However, the coefficient for $\hat{f}_{mutual}$ on returns on portfolio C is still close to being significant at the 5%-level. This result suggests that returns on stocks in portfolio C might be predictable by analyzing flows to mutual funds. The (weak) evidence of market inefficiency disfavours the efficient market hypothesis, thus, adding strength to a demand driven explanation of the effect from flows on returns.

Table 9: 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 an AR(1)-model. The final coefficients are estimated using an OLS approach using monthly data from January 2006 through April 2013. Observations between May 2008 and February 2009, the most turbulent period of the financial crisis, are excluded. Both 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 5%-level, and ** indicates significance at the 1%-level using a two-tailed test.

Dependent variable	r_A	r_B	r_C
β_0	$1.6 \cdot 10^{-2}$	$-1.2 \cdot 10^{-3}$	$3.1 \cdot 10^{-3}$
	(2.34)*	(-0.15)	(0.64)
$\hat{f}_{index}$	$-7.9 \cdot 10^{-2}$	$6.2 \cdot 10^{-2}$	$-3.3 \cdot 10^{-2}$
	(-1.50)	(1.09)	(-0.81)
$\tilde{f}_{index}$	$3.2 \cdot 10^{-2}$	$-1.8 \cdot 10^{-3}$	$-4.5 \cdot 10^{-3}$
	(1.15)	(-0.10)	(-0.21)
$\hat{f}_{mutual}$	$1.1 \cdot 10^{-2}$	$4.7 \cdot 10^{-2}$	$3.7 \cdot 10^{-2}$
	(0.38)	(1.26)	(1.93)
$\tilde{f}_{mutual}$	$3.2 \cdot 10^{-2}$	$2.2 \cdot 10^{-2}$	$2.5 \cdot 10^{-2}$
	(3.47)**	(2.53)*	(4.78)**
Adjusted R^2	11.18%	10.50%	20.87%
No. observations	79	79	79

4 Conclusion

In this paper, I develop 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. Nor does lagged variables indicate price reversal in stock returns. Hence, my results point in the direction of the imperfect substitution hypothesis discussed in the literature. I also find that the price impact is larger for small stocks, and that market inefficiency might be present. A question in need for further research is whether this effect occurs because of a fund manager's trading account for a larger share of the liquidity provided in small stocks.

Index-linked mutual funds in Norway have just reached a market capitalization large enough to provide information regarding price impact effects, 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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Appendix

A Variable definitions

Table A.1: Variable definitions and sources.

Variable	Description	Source
r_A	Monthly returns on portfolio A. Monthly returns are calculated as the sum of daily logarithmic total returns over the last 22 trading days.	Oslo Stock Exchange
r_B	Monthly returns on portfolio B. Monthly returns are calculated as the sum of daily logarithmic total returns over the last 22 trading days.	Oslo Stock Exchange
r_C	Monthly returns on portfolio C. Monthly returns are calculated as the sum of daily logarithmic total returns over the last 22 trading days.	Oslo Stock Exchange
f_{index}	Net flows to Norwegian index-linked mutual funds with Norway as the primary investment region. The variable is in billion NOK.	Norwegian Fund and Asset Management Association
f_{mutual}	Net flows to Norwegian actively managed funds with Norway as the primary investment region. The variable is in billion NOK.	Norwegian Fund and Asset Management Association
v_{BULL}	Trading volume in ETFs with a positive exposure to the OBX index. The variable is in billion NOK.	Oslo Stock Exchange
v_{BEAR}	Trading volume in ETFs with a negative exposure to the OBX index. The variable is in billion NOK.	Oslo Stock Exchange

B Autoregressive models

In an autoregressive model, the dependent variable depends on its own previous values. Previous studies have found that flows to mutual funds are highly predictable. Using two AR-models, I am able to estimate the expected and unexpected components of net flows. Estimated results for the AR-models are reported in Table B.1. I use the Akaike information criterion to determine how many lags to include in the chosen model.

Table B.1: This table reports regression results for autoregressive models where the dependent variables f_{index} and f_{mutual} are net flows to index-linked funds and actively managed mutual funds, respectively. AIC is the Akaike information criterion. Panel A includes observations from February 2009 through April 2013. Panel B includes observations from January 2006 through April 2013, where observations between May 2008 and February 2009 are excluded. Both variables for flows are in billion NOK. * indicates significance at the 5%-level, and ** indicates significance at the 1%-level using a two-tailed test.

Panel A	f_{index}				f_{mutual}			
Constant	0.05	0.05	0.05	0.05	0.09	0.07	0.07	0.06
	(1.77)	(1.77)	(1.62)	(1.64)	(1.22)	(0.97)	(0.94)	(0.83)
Lag 1	0.38	0.39	0.39	0.40	0.53	0.44	0.44	0.44
	(2.84)**	(2.72)**	(2.71)**	(2.69)**	(4.43)**	(3.18)**	(3.04)**	(3.01)**
Lag 2		-0.04	-0.06	-0.06		0.17	0.17	0.15
		(-0.30)	(-0.39)	(-0.40)		(1.23)	(1.13)	(0.97)
Lag 3			0.05	0.06			0.01	-0.02
			(0.34)	(0.42)			(0.06)	(-0.12)
Lag 4				-0.05				0.07
				(-0.32)				(0.52)
Adj. R^2	12.39 %	10.72 %	9.05 %	7.27 %	27.12 %	27.88 %	26.35 %	25.20 %
AIC	-3.24	-3.20	-3.16	-3.13	-1.48	-1.47	-1.43	-1.40
N	51	51	51	51	51	51	51	51

Panel B	f_{index}				f_{mutual}			
Constant	0.04	0.04	0.04	0.04	0.07	0.06	0.06	0.06
	(2.37)*	(2.51)*	(2.14)*	(2.20)*	(0.83)	(0.80)	(0.77)	(0.74)
Lag 1	0.39	0.40	0.40	0.40	0.26	0.23	0.22	0.22
	(3.11)**	(3.43)**	(3.46)**	(3.43)**	(2.30)*	(2.26)*	(2.31)*	(2.34)*
Lag 2		-0.04	-0.05	-0.05		0.11	0.09	0.09
		(-0.45)	(-0.49)	(-0.49)		(1.08)	(0.92)	(0.86)
Lag 3			0.04	0.06			0.06	0.04
			(0.38)	(0.47)			(0.53)	(0.36)
Lag 4				-0.05				0.09
				(-0.57)				(0.92)
Adj. R^2	13.90 %	12.88 %	11.88 %	10.89 %	5.41 %	5.32 %	4.50 %	4.12 %
AIC	-3.57	-3.54	-3.52	-3.50	-0.76	-0.75	-0.73	-0.71
N	79	79	79	79	79	79	79	79

Chapter III

Index trading and portfolio risk

Index trading and portfolio risk*

Joakim Kvamvold† Snorre Lindset‡

Abstract

We use data from the Oslo Stock Exchange. Our findings indicate that trading in ETFs are correlated with the return variance both on a portfolio of the underlying index constituents and portfolios with non-constituents. The correlation between ETF trading and the return variance on the portfolio of the underlying index constituents are higher than for the other portfolios, but we cannot claim causality. We do not find similar effects from flows to index-linked mutual funds.

Keywords: ETFs, index funds, portfolio return variance.

JEL classifications: G11, G12, G23

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†Norwegian University of Science and Technology, Department of Economics, Dragvoll, N-7491 Trondheim, Norway. E-mail: joakim.kvamvold@svt.ntnu.no

‡Norwegian University of Science and Technology, Department of Economics, Dragvoll, N-7491 Trondheim, Norway. E-mail: snorre.lindset@svt.ntnu.no

1 Introduction

In this paper, we study trading in index-linked assets and the variance of portfolio returns. Based on data from the Norwegian stock market, we find that return variances are correlated with trading volume in exchange traded funds (ETFs). We do not find that flows to index-linked mutual funds are correlated with return variances.

The Norwegian stock market is a small, yet mature market. The market has many of the same characteristics as larger and more important stock markets when it comes to return distributions and risk premiums (see e.g., Che et al. (2009) for a comparison of the Norwegian stock market and the US stock market). There are two main stock indices in Norway; the OBX index and the OSEBX index (both indices are described in detail in Appendix A). The OSEBX is a broader index than the OBX index. The market and its indices can be illustrated with the three sets in Figure 1. The OBX index contains the stocks in the set A. The OSEBX index contains the stocks in the set $D = A \cup B$. If E is the set of all stocks listed on the Oslo Stock Exchange, the set $C = E \backslash D$ is the set of all stocks that are excluded from the indices OBX and OSEBX. For our analysis, it will be important to isolate the returns on the stocks in the three sets A, B, and C.

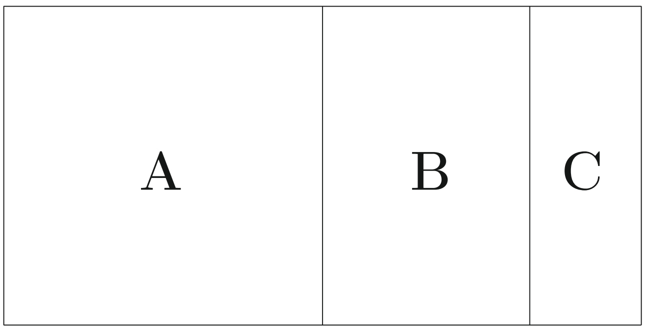

Figure 1: Illustration of Oslo Stock Exchange. The stock exchange consists of all stocks in sets A, B, and C. The stocks in set A are the constituents of the OBX index. $A \cup B$ is the set containing the constituents of the broader index OSEBX and C is the set of stocks excluded from both indices.

The main advantage of analyzing a small stock market is illustrated in Figure 1. The figure shows how uncluttered the Norwegian stock market is. Considering the US stock market, there is a wide range of different indices that are tracked by index funds and ETFs. Many of the indices overlap, and funds tracking one index will also partially track other indices that have many of the same constituents. Thus, for a large market with many indices and many index funds, it is far more difficult to isolate the effects of index trading than for a small and uncluttered market like the one we analyze in this paper. Although ETFs written on sectors do exist on the Oslo Stock Exchange, trading volumes are zero or close to zero for all trading days in our sample.

There is an extensive literature documenting that as stocks are included in an index, they receive an index price premium and that inclusion also affects return comovement with returns on other constituents of that index. These effects are 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). Barberis et al. (2005) attribute the return-comovement effect to the fact that stocks that are included in the index enter a new "habitat" used by many investors as a benchmark. Morck and Yang (2001) argue further that this effect grows with the growth of indexing (more indices covering the same stocks). Barberis and Schleifer (2003) argue that many investors allocate funds to *categories* such as growth stocks and investment grade bonds, not to individual securities. They show that such "style investing" can lead to increased price comovement between the assets within a category. ETFs and index funds work in the same way as categories. Bai et al. (2012) and Trainor Jr. (2010) analyze the effect from ETFs' rebalancing trades on returns and volatility. While Bai et al. (2012) find that these trades move prices and increase volatility, Trainor Jr. (2010) finds similar effects to be spurious. Sullivan and Xiong (2012) find that it is likely that the increased popularity of index-linked mutual funds and ETFs increases pairwise return correlations for constituents of the benchmark portfolio. They conclude that this increase will increase systematic risk on an investor's portfolio; hence, reducing diversification possibilities.

Da and Shive (2013) find evidence that ETF activity affects return comovement. The effect is stronger for small and illiquid stocks. The effect is also stronger during periods of market turbulence. Ben-David et al. (2014) analyze the effect from ETF ownership on the volatility of individual stocks. They document that stocks owned by ETFs exhibit significantly higher intraday and daily volatility.

One problem in the empirical part of this field of research is that it is difficult to identify flows into the markets made by index-linked portfolios. Here, is another advantage of analyzing a small stock market. We have exclusive data on all domestic mutual funds with Norway as the primary investment region and can identify those who are linked to indices. We also have data on all trades in ETFs that are linked to the OBX index. This information enables us to separate the effects from trades in index-linked mutual funds and from trades in ETFs. Our research question is related to the above literature. We study the correlation between index-linked trading (i.e., ETF trading and fund flows) and return variances. In addition, we include some tests to identify any causality between trading and variance.

2 Hypotheses

Index funds track the return on the index they follow. To this end, they trade in the constituents of the index and do not trade in stocks outside of the index. Similarly, ETF providers try to mimic (a function of) the returns on given indices and trade in stocks or derivatives of those indices. The habitat hypothesis of investing holds that many investors only trade in a subsample of all securities available in the market place. According to this hypothesis, when investors, for different reasons, change their exposure to the assets in the habitat, the change induces a common factor in the asset returns. This observation also applies to trading by index funds and ETFs. A reduction in assets under management for an index fund leads to a proportional sell-off of all securities in the index. Similarly, providers and market makers of ETFs rebalance their positions on a daily basis, either by trading in derivatives or in the index constituents.

For simplicity, we refer to the value weighted portfolio of stocks from set A as portfolio A and similarly for other stock portfolios. Based on the results in Da and Shive (2013) and Ben-David et al. (2014), we hypothesize that trading in ETFs leads to higher return variance for portfolio A. Based on the habitat hypothesis, we also hypothesize that trading (i.e., net inflows or outflows) by index-linked mutual funds leads to higher return variance for portfolio $D = A \cup B$. Index futures traded on the Oslo Stock Exchange are on the OBX index (set A). As many funds use futures contracts to adjust their exposure to the stock market, the effect of flows on return variances may be different for portfolios A and B. On the one hand, use of futures contracts can make the return variance for portfolio A more sensitive to flows than the return variance for portfolio B. On the other hand, the stocks in set A are included in the index because of their high liquidity.

3 Data

3.1 Stocks

We collect daily close prices and dividend payments from all stocks quoted on the Oslo Stock Exchange from January 2, 2006 through May 1, 2013. We only include stocks with a minimum average of 10 trades per day, or stocks with a liquidity provider. We also collect information about which stocks that are included in the OBX index and the OSEBX index during the same period. We calculate daily total log-returns and match these returns with data on which stocks that are included in the OBX index and the OSEBX index. If there are missing values in the time series of prices, returns are not estimated for that date and the consecutive date. We 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).

The number of constituents in the OBX index has always been 25. It consists of the 25 most liquid stocks based on six months turnover ratio. On average, 2.4 stocks are excluded from the index every six months, and 2.7 new stocks are included. The difference is due to more mergers and acquisitions than demergers. In total, during our sample period, a total of 44 unique companies have been constituents of the index. The number of constituents in portfolio B varies in our sample between 17 and 36, with an average of 29. The 25 stocks included in OBX are always also included in the broader index OSEBX. The number of daily returns that we calculate for stocks that are excluded from both indices ranges between 47 and 79, with an average of 60. Missing values for constituents of OBX usually occur on the first date following revisiting dates of the index. Returns for newly included stocks are not calculated for the inclusion date. Descriptive statistics for the returns on portfolios A, B, and C are presented in Table 1.

Table 1: This table presents descriptive statistics for daily returns on the value-weighted portfolios A, B, and C from February 2009 through April 2013. The first three rows show the maximum value, average value, and minimum value for the daily log-returns. The mid three rows show the corresponding values for return variances, where return variances are estimated using the past 22 trading days. The last three rows show the maximum, average, and minimum number of daily observations of stock returns.

	A	B	C
$\bar{r}_{max}$	7.03%	3.89%	3.37%
$\bar{r}_{mean}$	0.05%	0.03%	0.01%
$\bar{r}_{min}$	-7.06%	-5.12%	-9.94%
$\bar{\sigma}^2_{max}$	0.2571	0.0907	0.0430
$\bar{\sigma}^2_{mean}$	0.0555	0.0188	0.0079
$\bar{\sigma}^2_{min}$	0.0058	0.0027	0.0012
N_{max}	26	36	79
N_{mean}	24	29	60
N_{min}	21	17	47

3.2 Return variances

First, we calculate portfolio weights for portfolios of stocks in the sets A, B, and C and use the log-returns on the individual stocks to calculate value-weighted portfolio returns. We then use portfolio returns for the last 22 trading days to estimate the variance of the portfolio returns. We denote the return variances σ^2_A, σ^2_B, and σ^2_C, respectively. In Figure 2, we plot time series for these return variances and the differences $\sigma^2_{AB} \equiv \sigma^2_A - \sigma^2_B$, $\sigma^2_{AC} \equiv \sigma^2_A - \sigma^2_C$, and $\sigma^2_{BC} \equiv \sigma^2_B - \sigma^2_C$. Not surprisingly, return variances are particularly high during the financial crisis of 2008/2009.

3.3 Mutual funds

We use mutual funds data from the Norwegian Fund and Asset Management Association (Verdipapirfondenes forening). These data are monthly and range from January 2006 through April 2013. We classify a total of nine mutual funds as index funds. This number includes both current funds and closed funds. Index-linked funds are selected on the criteria of having the words "index", "OBX", or "OSEBX" in their names. Compared to the entire domestic mutual funds market, with Norway as the primary investment region, index-linked funds' share of assets under manage-

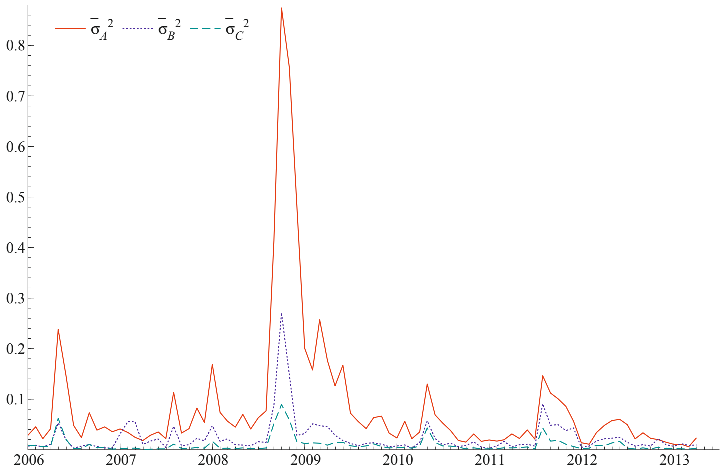

Figure 2: This figure shows time-series of return variances for portfolios A, B, and C.

ment increases from 2.48% in January 2006 to 10.00% in April 2013. The market share grows steadily from year to year. However, we note that even though the growth in assets under management is steady, the absolute values of net flows into these funds are more arbitrary, both in nominal terms and relative to the mutual funds market as a whole. Net flows to mutual funds are widely used to explain stock *returns*. Our focus is on return *variances*. We expect both positive and negative values of net flows to be correlated with return variances. Thus, we let the variable f_{index} represent the absolute value of net flows into the index-linked mutual funds, and define it as

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

where N is the number of index-linked mutual funds with Norway as the primary investment region during month t, and $inflows_{t,i}$ and $outflows_{t,i}$ are the in- and outflows for fund i in month t. On a monthly basis, the lowest monthly absolute value of net flows into index funds is 0.03 million NOK and the highest monthly value is 951 million NOK. This value is not steadily growing, although the absolute value of net flows appears to have a higher mean post 2009 (see Figure 4).

The variable f_{index} is close to zero in months where signings and redemptions are almost equal. However, as seen in Figure 3, this potential underestimation of flows does not seem to be a major problem in our data.

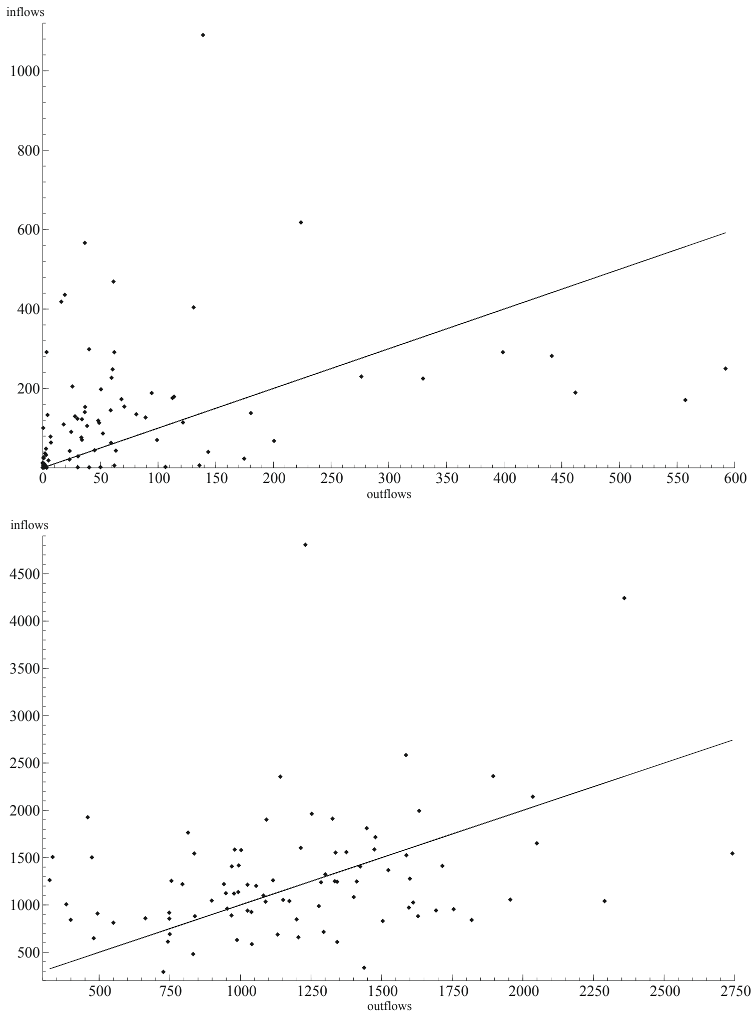

Figure 3: The top panel of this figure shows inflows plotted against outflows for the index funds. The bottom panel shows inflows plotted against outflows for other mutual funds with Norway as their primary investment region. Values in both panels are in million NOK. (In early June 2013, one USD equaled approximately six NOK.)

We could alternatively have defined the variable as the sum of signings and redemptions.[1] For many of the months in our sample, this variable construction is a better

[1]The sum of the signings and redemptions is calculated as

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

where both $inflows$ and $outflows$ take non-negative values. Estimations using this measure for measure of the funds' stock trading, but not so for all trading months. The sum of signings and redemptions at the end of many years in our data is much higher than it is in other months. The reason why the funds report high outflow and inflow of funds at year end is because life insurers and pension funds do "simultaneous" redemptions and signings in order to realize gains/losses on their investment portfolio. Policyholders are guaranteed a minimum yearly return on their funds. Whether gains/losses are realized or occur as paper gains/losses affects how yearly returns to policyholders are calculated. This activity does not lead to more stock trading by the mutual funds and is the main reason for our choice of how to construct the variable f_{index}.

Most index funds are benchmarked to the larger OSEBX index. However, this index is very similar to the OBX index. For instance, the market capitalization of OBX stocks included in OSEBX amounts to 91% of the market capitalization of OSEBX, 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 on November 16, 2012 is 97% of the trades in OSEBX. As OBX and OSEBX are so similar, we pool index funds with either index as a benchmark together. The mandate of some mutual funds provides them the opportunity to trade in derivatives. In practice, this means that when investors purchase or sell shares in these mutual funds, the portfolio manager often trades in index futures instead of the constituents of the index. Since futures are only available for the narrowest index, OBX, most of the trades will be made in this index' derivatives.

3.4 ETFs

While net flows into index-linked mutual funds can be observed directly and used as a reliable proxy for trades made by these funds, this is not the case for ETFs. ETFs are traded at the stock exchange and the market maker can trade in the index constituents, futures contracts, and other derivatives to hedge his positions. However, when a bank is the market maker, we do not know if the bank has traded as a market maker or as a broker. One market participant we have spoken with says that trades executed as market maker have a lower fee to the stock exchange than trades executed as a broker. Unfortunately, the stock exchange was not able to supply us with data discriminating between the different types of trades. Thus, we do not have quantitative data on the market makers' trades related to the ETFs.

trades made by mutual funds are reported in Appendix B, but do not change our conclusion.

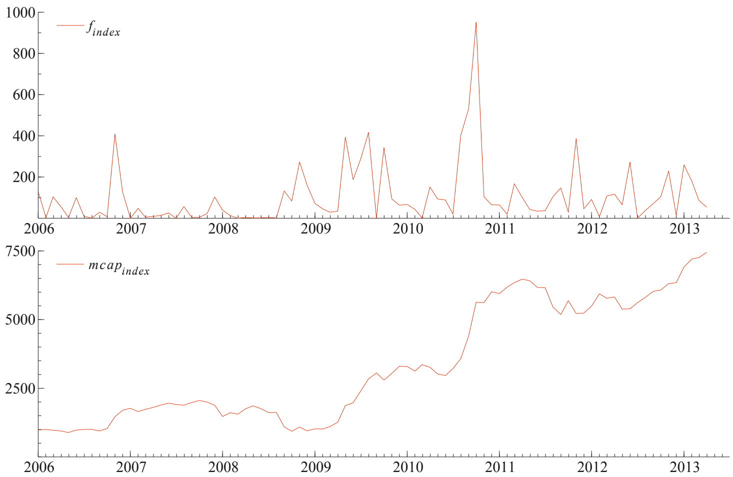

Figure 4: The top panel of this figure shows the absolute value of net flows to index-linked mutual funds (f_{index}). The bottom panel shows assets under management for the same funds ($mcap_{index}$). Values in both panels are in million NOK. (In early June 2013, one USD equaled approximately six NOK.)

Therefore, we use public trades made in the ETFs as a proxy for how much the market maker trades in the index constituents, or derivatives of these. The level of direct trading in ETFs is larger than what is needed by the market maker, but the variation in direct trading is likely to be a good proxy for the variation in trades committed by the market maker. Also, we analyze if there is a relationship between ETF trading and portfolio risk. We let the variable v_{ETF} measure the trading volume in ETFs.

Trading in the first index ETFs written on OBX takes place in early 2005. In January 2008, two popular leveraged ETFs are introduced in the Norwegian market and in June 2008, two similar leveraged ETFs are introduced by another financial institution. Market participants refer to the leveraged ETFs as "bull" and "bear". The exposure to the changes in the price of the OBX index is constructed to be 2 for the bull funds and -2 for the bear funds. The fund providers reach this exposure by trading in the futures market. The futures positions are rebalanced daily.

As Figure 5 shows, ETFs' share of total trading volume increases dramatically in 2008. The increase in the ratio of ETF trading volume to total trading volume coincides with the stock market crash in the fall of 2008. ETF trading volume consists of both trading in bull, bear, and unlevered ETFs. The spike in this ratio can hardly be explained by the fact that the market value of the stocks traded is lower after the crash. The sole explanation is the introduction of the popular bull and bear ETFs.

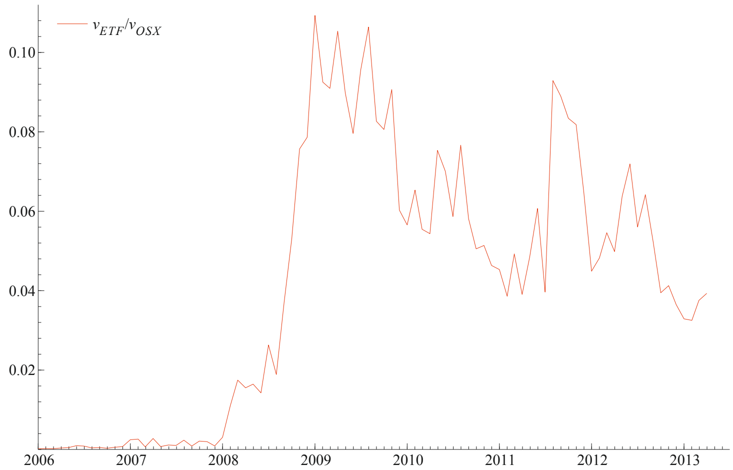

Figure 5: This figure shows the ratio of ETF trading volume to total trading volume on the Oslo Stock Exchange.

4 Empirical analysis

4.1 Empirical observations

We sort monthly trading volume v_{ETF} from February 2009 through April 2013, a total of 51 observations, from highest to lowest. We pool these volumes together into quartiles and calculate the average volume for each quartile. The return variances for portfolios A, B, and C are also pooled together in the same manner. The results are reported in Table 2.

The empirical observation in Table 2 indicates that portfolio variances on all three portfolios are high when trading in ETFs is high and low when trading is low. The same procedure is repeated for flows to index-linked mutual funds (f_{index}), but no clear pattern emerges. It thus seems like there is correlation between trading volume in ETFs and return variances for the three portfolios.

Two occurrences of interest for our analysis take place in 2008. Firstly, this year is when leveraged ETFs are introduced to the Norwegian market; as a consequence,

Table 2: The first column shows different quartiles, were $Q1$ has the highest trading volume/flow, Q2 the second highest trading volume/flow, and so on. Column *Volume* shows average monthly trading volume in billion NOK within the four different quartiles. Column *Flows* shows average monthly net flows (in billion NOK) to index funds within the four different quartiles. Columns A, B, and C show average return variance for portfolio A, portfolio B, and portfolio C, respectively. Return variances are annualized by assuming 252 trading days per year. Monthly data from February 2009 through April 2013 are used to calculate the figures in this table.

	ETFs				Index-linked mutual funds			
	Volume	σ_A^2	σ_B^2	σ_C^2	Flows	σ_A^2	σ_B^2	σ_C^2
Q1	11.654	0.0743	0.0193	0.0103	0.3721	0.0499	0.0143	0.0055
Q2	8.765	0.0768	0.0235	0.0091	0.1203	0.0505	0.0219	0.0104
Q3	6.030	0.0303	0.0118	0.0051	0.0617	0.0505	0.0119	0.0054
Q4	3.111	0.0295	0.0162	0.0062	0.0205	0.0582	0.0214	0.0088

the volume of trading in ETFs starts to pick up. Secondly, this year is when the financial crisis starts. Clearly, it is not ETF trading in Norway that causes the financial crisis. It may be that the financial crisis has amplified trading in ETFs, and at the same time increasing return variances for all three portfolios. Thus, the financial crisis can be the reason for the positive correlation between the trading volume in ETFs and the portfolio variances reported in Table 2.

4.2 ETF-trading, fund flows, and return variances

We want to analyze to what degree trading volume in ETFs and flows to mutual funds are correlated with the portfolio variances of the three different portfolios. To this end, we let our left-hand side variable be $\sigma_{i,t}^2$, $i = A, B, C$. Motivated by the findings reported in Table 2, we seek to analyze statistically whether trades executed by mutual funds and trading volume in ETFs are correlated with the portfolio variances of the three portfolios.

ETFs are only exposed to returns on the stocks in portfolio A. Thus, any correlation between trading volume in ETFs and the return variances of portfolios B and C is evidence against a causal relationship between ETF-trading and portfolio variance. Index-linked mutual funds are invested against stocks in both portfolios A and B. Any correlation between flows to these funds and return variance of portfolio C is evidence against a causal relationship between flows and volatility.

Portfolio variances can be correlated with other variables as well. Kvamvold (2014) finds that flows to actively managed mutual funds affect portfolio returns for portfolios A, B, and C. We include flows to these funds (the variable is f_{mutual} and is calculated the same way as the variable f_{index}) to test if it also correlates with the portfolio variances. Distribution of dividends add to mutual fund flows. We include an interaction term between the dividend yield and assets under management for both index-linked mutual funds ($d_y * mcap_{index}$) and active mutual funds ($d_y * mcap_{mutual}$). Trading volume is a necessary condition for portfolio variance. We therefore include the variables v_{OSX} and v_{OSX}^2 (total trading volume at the Oslo Stock Exchange and the squared trading volume). We estimate

$$\sigma_{i,t}^2 = \beta_0 + \beta_1 f_{index,t} + \beta_2 f_{mutual,t} + \beta_3 v_{ETF,t} + \boldsymbol{\beta}_4 \boldsymbol{X}_t + \epsilon_t, \quad i = A, B, C. \tag{1}$$

where

$$\mathbf{X} = \begin{bmatrix} d_y * mcap_{index} \\ d_y * mcap_{mutual} \\ v_{OSX} \\ v_{OSX}^2 \end{bmatrix},$$

and ϵ is the error term. The estimation results for Equation (1) are presented in Table 3.

The coefficient estimates are not significant for flows to index funds and mutual funds. The coefficient estimates for trading volume in ETFs are positive and significant for all three portfolios. This observation indicates that there can be some unobserved factor driving both trading volume in ETFs and portfolio variances. However, we note that the coefficient for portfolio A (0.0158) is approximately three times the value of the estimated coefficient for portfolio B (0.0055), and approximately six times the estimated coefficient for portfolio C (0.0024).

The information-diffusion theory postulates that information is incorporated at different rates for different sets of stocks (Barberis et al., 2005). However, we do not find estimated coefficients for lagged values of f_{index} and v_{ETF} to be significant. In addition, adding these lagged variables does not significantly change estimated coefficients. However, these results may be driven by investor sentiment. Investors that invest in mutual funds are often regarded as being less informed, smaller investors. This argument can be extended to trading in ETFs as well. Lee et al. (1991) argue that such investor sentiment affects small stocks more than it does large stocks. If the results are driven purely by investor sentiment, we should see the smallest estimated coefficient in the regression on portfolio variance of portfolio

A, with larger coefficients for the variance of portfolios B and C. Results in Table 3 show the opposite; smaller coefficients are estimated for portfolios containing the smallest stocks.

Table 3: This table reports regressions of return variances on flows to mutual funds (f_{index} and f_{mutual}) and trading volume in ETFs (v_{ETF}). The vector $\boldsymbol{X}$ includes interaction terms between the dividend yield on the stock exchange and market capitalization for the two categories of mutual funds, trading volume on the stock exchange, and squared trading volume on the stock exchange. Monthly data from February 2009 through April 2013 are used in the regressions. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level for a two-tailed test.

Left-hand side variable	σ_A^2	σ_B^2	σ_C^2	σ_A^2	σ_B^2	σ_C^2
intercept	0.0018	0.0425	0.0177	0.0284	0.0338	0.0144
	(0.39)	(2.14)*	(1.70)	(0.51)	(1.57)	(1.52)
f_{index}	-0.0567	-0.0171	-0.0064	-0.0538	-0.0227	-0.0095
	(-1.62)	(-1.42)	(-1.40)	(-1.61)	(-1.79)	(-1.62)
f_{mutual}	0.0168	-0.0041	-0.0005	0.0159	-0.0026	0.0004
	(0.86)	(-0.76)	(-0.20)	(0.79)	(-0.55)	(0.20)
v_{ETF}	0.0158	0.0055	0.0024	0.0154	0.0063	0.0029
	(4.24)**	(2.34)*	(2.70)**	(3.72)**	(2.49)*	(2.95)**
$f_{index,t-1}$				-0.0058	0.0015	-0.0011
				(-0.25)	(0.15)	(-0.30)
$f_{mutual,t-1}$				0.0008	-0.0075	-0.0051
				(0.08)	(-1.47)	(-2.53)*
$v_{ETF,t-1}$				0.0009	-0.0011	-0.0005
				(0.42)	(-0.84)	(-0.94)
$\boldsymbol{X}$	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.5647	0.3432	0.4288	0.5336	0.3501	0.4806
degrees of freedom	43	43	43	40	40	40

5 Causality tests

In Section 4, we find positive correlation between ETF trading volume and portfolio variance. In this section, we look for indications of causality using several different approaches.

5.1 Difference in portfolio variances

A priori, we do not expect ETF-trading to affect the return variances on portfolios B and C, c.f. the results in Table 3. Significant coefficients for the differences σ_{AB}^2 and

σ^2_{AC} indicate an effect from ETF-trading. As index funds are exposed to portfolios A and B, and not portfolio C, any significant causal relationship between flows and portfolio variances provides significant coefficients for the differences σ^2_{AC} and σ^2_{BC}. We test for the difference between the coefficient values by estimating the equation

$$\begin{aligned} \sigma^2_{i,t} =& \beta_0 + \beta_1 f_{index,t} + \beta_2 f_{mutual,t} + \beta_3 v_{ETF,t} \\ &+ \boldsymbol{\beta}_4 \boldsymbol{X}_t + \epsilon_t, \quad i = AB, AC, BC. \end{aligned} \tag{2}$$

Results from estimating Equation (2) are presented in Table 4. Reported coefficients are not significant for the variable f_{index}. We note that the coefficients for the variable v_{ETF} are significant for the left-hand side variables σ^2_{AB} and σ^2_{AC}, indicating a higher correlation between trading volume in ETFs and return variance on portfolio A than on portfolios B and C. These results support the hypothesis that trading in ETFs affects return variance for portfolio A.

Table 4: This table reports regressions of return variances on flows to mutual funds (f_{index} and f_{mutual}) and trading volume in ETFs (v_{ETF}). The dependant variables are differences between return variances on portfolios A, B, and C, where $\sigma^2_{AB} \equiv \sigma^2_A - \sigma^2_B$, $\sigma^2_{AC} \equiv \sigma^2_A - \sigma^2_C$, and $\sigma^2_{BC} \equiv \sigma^2_B - \sigma^2_C$. The vector $\boldsymbol{X}$ includes interaction terms between the dividend yield on the stock exchange and market capitalization for the two categories of mutual funds, trading volume on the stock exchange, and squared trading volume on the stock exchange. Monthly data from February 2009 through April 2013 are used in the regressions. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level for a two-tailed test.

Left-hand side variable	σ^2_{AB}	σ^2_{AC}	σ^2_{BC}
$intercept$	-0.0245	0.0002	0.0248
	(-0.62)	(0.01)	(2.10)
f_{index}	-0.0396	-0.0503	-0.0107
	(-1.57)	(-1.53)	(-1.21)
f_{mutual}	0.0209	0.0172	-0.0036
	(1.16)	(0.92)	(-1.00)
v_{ETF}	0.0103	0.0134	0.0031
	(3.84)**	(4.00)**	(2.00)
$\boldsymbol{X}$	Yes	Yes	Yes
Adjusted R^2	0.5062	0.5171	0.1978
degrees of freedom	43	43	43

Assets under management for index-linked mutual funds have increased dramatically in recent years, reaching 10% of the market capitalization of the domestic mutual funds market with Norway as the primary investment region. Index-linked mutual funds are primarily held by institutional investors. At the time of this writing 85.19% of assets under management in index-linked mutual funds is held by institutional investors. These investors do not trade frequently, but rather follow a buy-hold strategy. In a sense, we can say that the passively managed funds are held by passive investors. Trades by index-linked mutual funds are executed when clients move money in or out of the funds, when the index is rebalanced, or when dividends are paid. These trades are either rare or small in nominal value. Other mutual funds have a higher share of private investors and, thus, are more exposed to investor sentiment. The majority of assets under management are managed by non-index funds, and these funds invest most of their funds in the OBX stocks. Lately, some actively managed funds have been criticized for letting most of their funds become index linked. Thus, a significant part of the flows measured by f_{mutual} may in reality be linked to the OBX index. Even purely active managed funds will invest a large part of their funds in stocks in set A, as there are not all that many other stocks in which to invest. The lack of significant t-values in Table 4 together with the argumentation above indicate that net flows to mutual funds do not affect portfolio risk.

ETFs have high trading volumes, even at intraday frequencies. When there are price movements in the ETFs, the market maker of the ETF may have to trade in underlying instruments or derivatives of these instruments to reach his desired exposure to the market. Whether trades are made in the underlying instruments or derivatives should not matter since arbitrageurs will bid up the value of stocks if the market maker buys derivatives. It does not even matter if the market maker has to trade at all, because if the value of the ETFs differs from the value of the underlying instruments, arbitrageurs will want to trade in the underlying to gain on this difference.

We could imagine that mutual funds, index-linked or others, trade in ETFs, thus, affecting the trading volume in ETFs. However, most of the volume in ETF trading comes from trading in leveraged ETFs. These funds are known to have poor performance long term in a buy-hold strategy (see e.g., Haga and Lindset (2012)), and are as such not suited for mutual funds.

5.2 Difference in differences

To further analyze the possible effect of index-trading on returns covariances, we use a difference-in-differences technique (DID). An important assumption for using DID is that the variables have common trends. The time series in Figure 2 suggest that the assumption of common trends is a reasonable one. We consider two time periods, January 2006 through August 2008 and February 2009 through April 2013. We have intentionally left out the most turbulent period of the financial crisis. We make this omission to avoid the jump in our explanatory variable that occurs after the introduction of leveraged ETFs. Trading volume in both ETFs and in index-linked mutual funds looks stationary pre and post the excluded period. The "treatment group" is considered to be the stocks in set A, while we use the stocks in set B and set C as "control groups". The last period is the "treatment" period where trades in both ETFs and index-linked mutual funds are considerably higher than in the first period. We estimate the regressions

$$\bar{\sigma}_{it}^2 = \beta_0 + \beta_1 I + \beta_2 T + \beta_3 IT + \epsilon_t, \quad i = A, B \quad \text{or} \quad i = A, C, \tag{3}$$

where I is an indicator function taking the value 1 for the treatment group and 0 otherwise. A significant coefficient for this indicator function shows that the average return variance for the treatment group is higher throughout the sample period. The indicator function T takes the value 1 in our last time period (treatment period) and 0 otherwise. A significant coefficient for this indicator function shows that the return variances differ in the two periods. ϵ is the error term. The estimation results are given in Table 5. The coefficients for IT is not significant. These results indicate that there has been no effect on portfolio variance for the treatment group after the introduction of ETFs and the increased popularity of index funds. The significant coefficient for the treatment group (I) simply shows that portfolio A has a greater portfolio variance throughout the sample period.

5.3 Granger causality

As hypothesized, trading in ETFs may lead to increased portfolio variance. Conversely, it may be the case that increased volatility attracts investors in ETFs. A Granger causality test sets out to determine the direction of causality. We use the Akaike Information Criteria (AIC) to analyze the most efficient number of lagged variables to include in the Granger causality test. Results for the test are reported in

Table 5: Estimation results for difference in differences regressions. Return variance on portfolio A is the treatment group. In column AB, return variance on portfolio B is the control group. In column AC, return variance on portfolio C is the control group. I is a dummy variable taking the value one for the treatment group, while T is a dummy variable taking the value one for the treatment period. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level for a two-tailed test.

	AB	AC
$intercept$	0.0181	0.0065
	(6.42)**	(2.84)**
I	0.0415	0.0531
	(4.36)**	(5.66)**
T	0.0007	0.0014
	(0.15)	(0.51)
IT	-0.0048	-0.0055
	(-0.29)	(-0.35)

Table 6. Lagged variables for portfolio variances on any of the three portfolios show no effect on future trading volume in ETFs. A one-month lag in trading volume has a significant effect on the return variance on portfolio A. Together, these results indicate that v_{ETF} Granger-cause σ_A^2. However, this is a weak test for causality as the test requires the cause to happen prior to the effect. It is reasonable to believe that trading and changes in variances are determined simultaneously.

5.4 Discontinuity design

Stocks are included in the OBX index based on their turnover ratio. We do not have exact rankings of the turnover of the constituents in the OBX index. Fortunately, we do know which stocks are included and excluded at a semi-annual basis. The stocks that enters and exit the OBX index are likely to be more comparable than portfolios A and B. We construct an equally weighted portfolio consisting of the stocks that enter the OBX index. These stocks stay in the portfolio until they have "matured" in the OBX index for six months. Semi-annually, new stocks enter the portfolio as they are included in the index. Similarly, we construct a portfolio for the stocks that exit the OBX index. Both portfolios consist of between one and three stocks. We estimate Equation (1), where the left-hand side variables are portfolio variances on the portfolio of stocks that enter (σ_{IN}^2) and exit (σ_{OUT}^2) the OBX index. In 2009,

Table 6: This table presents results where Granger causality is tested between portfolio variances and trading volume in ETFs. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level for a two-tailed test.

Endogenous variable	σ^2_A	σ^2_B	σ^2_C	v_{ETF}	v_{ETF}	v_{ETF}
constant	0.0266	0.0131	0.0037	0.6119	0.7107	0.6049
	(1.81)	(1.75)	(1.22)	(0.67)	(0.63)	(0.80)
$\sigma^2_{i,t-1}$	0.1744	0.4065	0.2529	-6.0102	17.0865	22.8297
	(1.15)	(3.64)**	(2.60)*	(-0.44)	(0.66)	(0.65)
$\sigma^2_{i,t-2}$	-0.1181	0.0584	0.0454	9.6724	-21.5788	-56.1810
	(-0.99)	(0.39)	(0.47)	(0.75)	(-0.97)	(-1.29)
$\sigma^2_{i,t-3}$	0.2490	-0.1046	-0.0158	-0.2766	3.3333	-3.6609
	(1.64)	(-1.17)	(-0.17)	(-0.03)	(0.18)	(-0.15)
$\sigma^2_{i,t-4}$	-0.1236	0.1518		-8.6203	-6.6145	
	(-1.02)	(4.16)**		(-1.35)	(-0.73)	
$\sigma^2_{i,t-5}$	0.1771			7.9993		
	(2.45)*			(1.92)		
$v_{ETF,t-1}$	0.0053	0.0000	0.0001	0.4879	0.3828	0.3680
	(2.19)*	(0.03)	(0.21)	(2.04)*	(1.86)	(2.10)*
$v_{ETF,t-2}$	0.0020	0.0002	0.0000	0.0157	0.2115	0.2531
	(1.06)	(0.20)	(0.00)	(0.15)	(1.43)	(1.94)
$v_{ETF,t-3}$	-0.0016	0.0009	0.0001	0.2729	0.3113	0.3049
	(-0.81)	(1.21)	(0.27)	(2.39)*	(2.38)*	(2.58)*
$v_{ETF,t-4}$	-0.0041	-0.0018		-0.0496	-0.0088	
	(-2.29)*	(-1.95)		(-0.27)	(-0.04)	
$v_{ETF,t-5}$	-0.0014			0.1164		
	(1.81)			(0.63)		

there are no stocks exiting set A for set B, as the exclusions from set A are due to mergers. We therefore estimate these regressions from January 2010. Estimated results are reported in Table 7.

The estimated results in Table 7 show that trading volume in ETFs is correlated with both the return variance on the portfolios with stocks entering and exiting the OBX index. ETFs have no exposure to stocks exiting the OBX index. Thus, the results in Table 7 suggests that an omitted variable drives both trading volume in ETFs and return variances. Although this is a test for "local effects", i.e., only the stocks entering and leaving the index, it points in the direction that there is not a causal relationship between ETF-trading and return variances.

Table 7: This table reports regressions of return variances on flows to mutual funds (f_{index} and f_{mutual}) and trading volume in ETFs (v_{ETF}). The dependant variables are return variances on equally weighted portfolios consisting of stocks recently included in the OBX index (σ^2_{IN}) or recently excluded from the OBX index (σ^2_{OUT}). The vector $\boldsymbol{X}$ includes interaction terms between the dividend yield on the stock exchange and market capitalization for the two categories of mutual funds, trading volume on the stock exchange, and squared trading volume on the stock exchange. Monthly data from January 2010 through April 2013 are used in the regressions. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level for a two-tailed test.

Left-hand side variable	σ^2_{IN}	σ^2_{OUT}
$intercept$	0.6140	0.2458
	(2.67)*	(1.28)
f_{index}	0.1833	-0.0508
	(1.92)	(-0.30)
f_{mutual}	0.1026	0.1012
	(1.77)	(0.75)
v_{ETF}	0.0646	0.0880
	(4.68)**	(5.84)**
$\boldsymbol{X}$	Yes	Yes
Adjusted R^2	0.3845	0.4390
degrees of freedom	32	32

6 Conclusion

We have used data from the Norwegian stock market to analyze if there is a relationship between index trading and return variances. The advantage of using this small stock market as our laboratory is that it is small and uncluttered. The data show a strong and significant correlation between trading volume in ETFs and the return variance on a portfolio of the underlying index constituents. A correlation that is significant, but at the same time significantly smaller, is also found between trading volume and the return variance on two portfolios only consisting of non-constituents. We find no effects on return variances from flows to index funds or actively managed mutual funds. Although we find strong evidence of correlation between ETF trading volume and return variances, we do not find support for the hypothesis that there is a causal relationship between trading and return variances. Da and Shive (2013) and Ben-David et al. (2014) use a cross sectional analysis and find support for this hypothesis. A disadvantage by analyzing a small market is that the amount of data precludes us from doing a similar cross sectional analysis.

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Appendix

A Indices

In this Appendix, we provide information about the three main stock indices on the Oslo Stock Exchange.

A.1 OBX

The OBX Total return index consists of 25 constituents. These constituents are the most liquid stocks available on the Oslo Stock Exchange. The liquidity measure is based on the last six months' trading volume. The OBX index is adjusted for dividends and it is revised every six months. Several capping rules apply to the index. The largest component is not allowed to exceed 30% of the total value. Remaining stocks are capped at a maximum 15%, while non-EEA-stocks are set to a maximum 10%. Between revising dates, the number of stocks of each index member are held constant. The OBX is a publicly traded index with both futures and options written with the OBX as an underlying instrument.

The index always has 25 index members. However, because of mergers, splits, reversed splits, revising dates, etc. we lack return observations for all 25 stocks for a few days in our sample. For the vast majority of dates, we have returns for all 25 stocks that are included in the index.

A.2 OSEBX

The Oslo Stock Exchange benchmark index is an investible index that consists of the most traded stocks on the Oslo Stock Exchange. It is revised twice per year and it is adjusted for dividend payments and other corporate actions. Between revising dates, the number of stocks of each security is fixed. Although not a rule, all OBX stocks are also part of the OSEBX. In other words, all the 25 most liquid stocks are always among the constituents of OSEBX.

The number of underlying instruments varies. Our estimation results use data from February 2009 through April 2013. In this period, the index has had between 53 and 61 underlying instruments. Our observed returns in the same period have been between 38 and 61. Missing returns occur on revising dates or as a result of mergers, reversed splits or other corporate actions.

A.3 OSEAX

The Oslo Stock Exchange All-Share index consists of all listed shares on the stock exchange. The index is adjusted for dividend payments and other corporate actions. The OSEAX includes all stocks on Oslo Stock Exchange and is comparable to the union of sets A, B, and C.

B Alternative variable for mutual fund trading

In this Appendix, we use an alternative variable for trading made by mutual funds. If signings and redemptions are equally large during a month, our preferred variable in the paper will show no flow-induced trading by mutual funds. In this Appendix, we alternatively define the variable as the sum of signings and redemptions. The sum of the signings and redemptions is calculated as

$$\hat{f}_j = \sum_{i=1}^{N} (inflows_{t,i} + outflows_{t,i}), \quad j = index, mutual,$$

where both $inflows$ and $outflows$ take non-negative values. With this alternative variable specification, we estimate

$$\sigma^2_{i,t} = \beta_0 + \beta_1 \hat{f}_{index,t} + \beta_2 \hat{f}_{mutual,t} + \beta_3 v_{ETF,t} + \boldsymbol{\beta_4 X_t} + \epsilon_t, \quad i = A, B, C, \tag{4}$$

where $\boldsymbol{X}$ is a vector of control variables and ϵ is the error term. Table B.1 shows estimated results for Equation (4).

Table B.1: This table reports estimation results of return variances in response to flows to mutual funds ($\hat{f}_{index}$ and $\hat{f}_{mutual}$) and trading volume in ETFs (v_{ETF}). The vector $\boldsymbol{X}$ includes interaction terms between the dividend yield on the stock exchange and market capitalization for the two categories of mutual funds, trading volume on the stock exchange, and squared trading volume on the stock exchange. Monthly data from February 2009 through April 2013 are used in the regressions. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level for a two-tailed test.

Left-hand-side variable	σ^2_A	σ^2_B	σ^2_C
intercept	0.0417	0.0383	0.0137
	(1.31)	(2.16)*	(1.40)
$\hat{f}_{index}$	-0.0411	-0.0034	-0.0018
	(-1.47)	(-0.43)	(-0.52)
$\hat{f}_{mutual}$	0.0008	0.0013	0.0017
	(0.18)	(0.59)	(1.27)
v_{ETF}	0.0169	0.0053	0.0025
	(3.95)**	(2.24)*	(2.87)**
controls	Yes	Yes	Yes
Adjusted R^2	0.5509	0.3102	0.4284
degrees of freedom	43	43	43

Furthermore, we investigate the relationship between index-linked trading and return variances on portfolio A relative to portfolios B and C by estimating

$$\sigma^2_{i,t} = \beta_0 + \beta_1 \hat{f}_{index,t} + \beta_2 \hat{f}_{mutual,t} + \beta_3 v_{ETF,t} + \boldsymbol{\beta_4 X_t} + \epsilon_t, \quad i = AB, AC, BC. \quad (5)$$

Table B.2 shows estimated results for Equation (5). Again, we find a positive, significant effect from ETF-trading on return variances for all portfolios.

Table B.2: This table reports estimation results of return variances in response to flows to mutual funds ($\hat{f}_{index}$ and $\hat{f}_{mutual}$) and trading volume in ETFs (v_{ETF}). The dependant variables are differences between return variances on portfolios A, B, and C, where $\sigma^2_{AB} \equiv \sigma^2_A - \sigma^2_B$, $\sigma^2_{AC} \equiv \sigma^2_A - \sigma^2_C$, and $\sigma^2_{BC} \equiv \sigma^2_B - \sigma^2_C$. The vector $\boldsymbol{X}$ includes interaction terms between the dividend yield on the stock exchange and market capitalization for the two categories of mutual funds, trading volume on the stock exchange, and squared trading volume on the stock exchange. Monthly data from February 2009 through April 2013 are used in the regressions. The t-values (reported in parentheses) are robust (adjusted using the method of Andrews (1991)). * indicates significance at the 5%-level, and ** indicates significance at the 1%-level for a two-tailed test.

Left-hand-side variable	σ^2_{AB}	σ^2_{AC}	σ^2_{BC}
intercept	0.0033	0.0279	0.0246
	(0.16)	(1.05)	(2.35)*
$\hat{f}_{index}$	-0.0377	-0.0393	-0.0016
	(-1.68)	(-1.46)	(-0.25)
$\hat{f}_{mutual}$	-0.0005	-0.0009	-0.0005
	(-0.17)	(-0.27)	(-0.38)
v_{ETF}	0.0116	0.0144	0.0028
	(3.83)**	(3.71)**	(1.78)
controls	Yes	Yes	Yes
Adjusted R^2	0.4945	0.5083	0.1584
degrees of freedom	43	43	43