How Well Do Traders Condition on the Uniqueness of Their Signals?

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Abstract

This paper shows hedge funds and mutual funds neglect to properly invert prices to infer other traders' signals when trading on earnings announcements. This leads to predictable excess trading when many funds have similar signals, because they underestimate how much of their information is already incorporated in prices. Consistent with this excess trading causing temporary price impact, a portfolio long stocks that had excess selling and short stocks that had excess buying has an annualized Sharpe ratio near 1.0 after hedging exposure to common risk factors. Our findings are useful for understanding how asset prices are affected when a trader underestimates how many other investors follow similar investment strategies.

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Earnings announcements are a large information shock that generate substantial trading—volume in the two days after an announcement is 50% higher than normal (Frazzini and Lamont 2007). The investors trading on these announcements face a complicated inference problem. They need to condition on both the signal they extract from the the announcement and on what the market price implies about other investors' signals. However, due to cognitive or computational constraints, investors may neglect to properly invert prices to infer other traders' signals (Vayanos, Eyster, and Rabin 2018). One implication is investors may trade too much when they all have similar signals, because they underestimate how much of their information is already incorporated in prices. This over trading can lead to excess temporary price impact, reducing performance. This is a particularly important concern for quantitative hedge funds, many of whom follow similar investment strategies.

This paper examines these issues by studying changes in hedge fund and mutual fund holdings around earnings announcements. We use hedge fund and mutual fund holdings data from the Factset Lionshares database to form fund-specific estimates of how the funds owning a stock will typically trade following an extreme positive or extreme negative earnings surprise.[1] Our empirical model allows estimated parameters to vary over time, across funds, and to be different for positive and negative surprises. We then examine whether the stock's price is affected if the institutions owning the stock are predicted to either mostly want to increase or decrease their positions. We hypothesize that when a stock's owners all have similar preferred holdings, if the institutions do not fully condition on this similarity, then the predicted trading demand will be negatively correlated with future returns.

The resulting fund-level estimates show wide and persistent variation in the preferred holdings of hedge funds and mutual funds. In aggregate, funds sell both positions with positive surprises and positions with negative surprises, similar to the v-shape retail investors in Ben-David and Hirshleifer (2012). However, when examined at the fund level we find roughly the same percent of funds are contrarian, trend-chasing, and v-shape investors. These differences are also persistent. Preferred holdings estimates of a fund as of a given year are still strongly correlated with estimates

[1]When data is available, we analyze each fund of an asset management company individually. Otherwise, we treat the entire holdings of the asset management company as one fund.

five years later.

We next perform out-of-sample tests to determine whether our estimates of a fund's preferred holdings is useful for predicting the fund's trading. Each month, for every stock with an earnings surprise in the top or bottom decile, we aggregate predicted trading over the next quarter by funds that owned the stock as of the end of the prior month. We then regress these funds' actual change in ownership over the following quarter on our expected trading measure. Following a large earnings surprise, a one-standard deviation change in our predicted trading measure predicts around a 0.15 standard deviation change in the next quarter stock-level ownership by funds that owned the stock at the time of the announcement. The predictability is also stronger for stocks with negative earnings surprises, consistent with negative surprises being more important for triggering re-balancing decisions.

We also find that this predictable trading demand has important pricing consequences. We take two stocks with the same initial earnings surprise but opposite direction of predicted trading. If many of a stock's owners are predicted to sell following a negative surprise, this could temporarily depress the stock's price, resulting in higher returns going forward. To test this prediction, we form value-weighted portfolios that buy stocks we predict funds sold and short stocks we predict funds bought. Consistent with our prediction, a three-month overlapping holding period portfolio constructed following Jegadeesh and Titman (1993) has a monthly alpha of 0.47%, with a t-statistic of 3.67, after hedging out exposure to market, value, size, momentum, investment, profitability, and post-earnings announcement drift factors. The alpha corresponds to an annualized Sharpe ratio of nearly 1.0.

Our focus on *ex-ante* estimates of trading demand is a distinguishing feature of our empirical framework. We study how well investors condition on the ex-ante preferred holdings of other stock owners and evaluate the magnitude of errors in this conditioning. Evidence of competition neglect has been shown in real capital investments in competitive industries (e.g., Hoberg and Phillips (2010), Greenwood and Hanson (2015)). Our study explores such effects in the stock market setting, which requires estimating ex-ante trading demand. Ex-post ownership and realized trading after earnings announcements do not allow identifying these effects, because they combine both expected and unexpected trading into one quantity.

Our results contrast with the evidence on forced transactions induced by investor flows into and out of mutual funds (e.g., Coval and Stafford (2007), Lou (2012)).[2] In that setting, forced trading creates price pressure that pushes prices away from fundamentals, which subsequently creates sharp return reversals. In our setting, the trading is discretionary and caused by a fund's stock holdings preference rather than investor redemptions or inflows (e.g., Basak and Pavlova (2013), Hombert and Thesmar (2014)). Systematic mutual fund trading patterns can also arise from capital gains overhang (Frazzini 2006) or portfolio salience (Hartzmark 2014), but our measure is distinct from both effects. None of the variation in our predicted trading measure comes from the timing of when the existing owners bought the stock (overhang) or how the stock's performance compares to the rest of the owner's portfolios (salience). Overall, in these scenarios, those investors who provide liquidity are compensated by earning positive abnormal returns.[3]

Our findings are also relevant to research on crowded trading strategies and correlated trading.[4] Investors have concerns about the amount of capital chasing a strategy, because when a strategy is crowded, it may be less profitable, more risky, and potentially destablizes prices. For example, Lou and Polk (2013) and S. Huang, Lou, and Polk (2016) show comovement within a trading strategy is negatively correlated with the strategy returns. Hanson and Sunderam (2014) show evidence that value and momentum strategy returns are lower when arbitrage capital is high. These papers focus on time-series variation in anomaly strategy returns and risk. Our paper focuses on the cross-section, showing return effects for the specific stocks with earnings surprises that funds are buying or selling intensely.

Our study is also related to but distinct from prior research on style investing (e.g., Barberis and Shleifer (2003), Peng and Xiong (2006))[5] or the preference for momentum stocks. Specifically, we focus on earnings news because these news events create sudden shocks that induce large trading

[2]Cella, Ellul, and Giannetti (2013) find that short-horizon institutional investors created significant prices pressure around the Lehman Brother bankruptcy.

[3]Such investors may include retail investors or sophisticated liquidity providers (e.g., Kaniel, Saar, and Titman (2008), Kaniel et al. (2012), Brogaard et al. (2017)).

[4]Correlated trading may also arise from commonality in ownership (e.g., Greenwood and Thesmar (2011); Anton and Polk (2014)), correlated trading signals, or herding behavior (e.g., Nofsinger and Sias (1999), Wermers (1999), Sias (2004), Dasgupta, Prat, and Verardo (2011), Koch (2017)).

[5]Style investing has implications for asset prices(e.g., Chan, Chen, and Lakonishok (2002), Teo and Woo (2004), Froot and Teo (2008), Wahal and Yavuz (2013), Grinblatt et al. (2017)).

demand.[6] Recent evidence suggests that this variation in the demand for and supply of specific asset characteristics affects asset prices (e.g., Choi and Sias (2012), Edelen, Ince, and Kadlec (2016), Koijen and Yogo (2017)). We focus on recent earnings news, in the form of earnings announcement surprises, because it is a salient characteristic that changes quickly, and thus has the potential to generate large innovations in demand for securities.[7]

1 Data

1.1 Mutual Fund/13F Fund and Stock Data

We use holdings data for mutual funds and 13F institutions. Mutual fund holdings data of U.S. securities is collected from Factset Lionshares fund holdings for the period January 2000 to December 2016. Coverage is low until Fall 2002, so we start our main analysis using estimates formed beginning January 2003. The 13F holdings are from the Factset Lionshares 13F database. In our main results, we combine mutual fund holdings data with 13F institution holdings, excluding 13F mutual fund companies. We treat 13F institutions as individual funds, because we are unable to observe individual fund-level holdings for these entities. Factset gathers data from voluntary disclosures and mandatory SEC filings for all registered mutual funds. We use unadjusted holdings and accordingly split-adjust holdings based on the report date.

We choose Factset Lionshares as our main source of holdings instead of Thomson for the following reasons. Factset collects additional voluntary disclosures and reports monthly holdings for a large number of funds. More funds and higher frequency of reporting potentially provides more statistical power in predicting fund trading. Moreover, the WRDS bulletin dated April 11, 2017 reports data quality issues in the Thomson holdings data. As of the writing of this draft, these issues have not been resolved.[8]

Stock return data is obtained from the CRSP monthly stock file. Portfolio return analysis begins

[6]Grinblatt, Titman, and Wermers (1995) show mutual funds vary in their preference for stocks with high versus low past returns. Studies also show investors have different preferences over a wide variety of additional characteristics and that these preferences change over time (e.g., Bennett, Sias, and Starks (2003), Griffin, Harris, and Topaloglu (2003)).

[7]Studies use the revelation of public news events to uncovered fund/manager skill (e.g., Kacperczyk and Seru (2007), Da, Gao, and Jagannathan (2011), A. G. Huang, Tan, and Wermers (2016))

[8]Our main results hold using Thomson s12 holdings data with the caveat that data quality issues may induce noise in these estimates.

January 2003 and ends in December 2016. We limit our sample of stocks to US equities defined as CRSP share code 10 and 11. When forming return portfolios, we also exclude all stocks below five dollars and with market capitalizations in the two smallest NYSE size deciles in the month before portfolio formation. For later return analysis, we require that a stock at least one year return data from CRSP and reports positive book equity in the most recent annual report.

Table 1 reports summary statistics of stock characteristics in return portfolio formation months. We report total assets, market equity, book-to-market ratio, gross profitability, asset growth, past return ($t-12$ to $t-2$), and past month return. We also report our measure of expected trading for both + and - earnings surprises. The mean estimates for both are negative, suggesting on average selling after large earnings surprises. This evidence is also consistent with the pattern of "V-shape" trading documented in (Ben-David and Hirshleifer 2012). We discuss in measure construction in greater detail in the next section.

1.2 Earnings Surprises

Our estimates of portfolio holdings require a measure of the earnings surprise for a stock. We use the cumulative market-adjusted abnormal return (CAR) from one day before an earnings announcement to one day afterward. The window straddles the reported announcement date to account for information leakage beforehand and delayed reaction afterward.

CARs are a good market-based measure of the magnitude of information released by an earnings announcement. Surprises based on deviations of announcements from analyst forecasts suffer from limited availability in small-cap stocks, retroactive back-filling, and analyst forecast bias. One concern with CAR in our context is that it might be endogenous to ownership. Therefore, in robustness tests we show that our results are similar using analyst earnings surprise measures.

We classify stocks with CARs in the top decile as having positive earnings surprises and stocks with CARs in the bottom decile as having negative earnings surprises. Decile breakpoints are formed utilizing all earnings announcements from the beginning of the sample until the month before the earnings announcement.

2 Predicting Trading Around Earnings Announcements

2.1 Modelling Fund Portfolio Weights

We estimate how a fund will trade a stock after an earnings announcement using their past trading behavior. We identify this behavior by modelling the weight a fund puts on a stock as a function of the stock's most recent earnings announcement. We prefer to model weights rather than shares, because weights avoids the differences in shares outstanding across stocks. Since our goal is to identify funds with different trading tendencies, we estimate these position weight models separately for each fund. For example, the model produces one set of model estimates for the Fidelity Magellan Fund and a completely different set of model estimates for the Fidelity Contrafund. This allows us to capture trading differences among funds.

We only model the weights of stocks already in the fund's portfolio. Conceptually, to know how a fund manager adjusts weights in response to an earnings announcement, we should know which stocks the manager is watching or, equivalently, the manager's investment universe. We cannot know exactly the set of stocks a manager is watching. However, it is likely that the manager is monitoring the stocks already in the portfolio. For example, Chen et al. (n.d.) find that mutual fund managers are much more likely to search for Edgar filings on stocks they already own. Thus, we have more power to identify the effect of an earnings announcement on rebalancing decisions by looking at the existing portfolio.

Our model is

$$\begin{aligned} ln(w_{i,s,t}+1) = {} & \beta_{1,i} Surprise^{1}_{s,t} + \beta_{10,i} Surprise^{10}_{s,t} \\ & + \gamma_{1,i} ln(w_{notrade,i,s,t}+1) + \gamma_{2,i} newpos_{i,s,t-1} \\ & + \gamma_{3,i} reportgap_{i,t} + \epsilon_{i,s,t} \end{aligned} \tag{1}$$

where i is a fund, s is a stock, t is time, w is a portfolio weight times 100, $Surprise^{1}_{s,t}$ is a dummy variables indicating the stock's announced earnings fell in the bottom earnings announcement surprise decile that quarter, $Surprise^{10}_{s,t}$ is a dummy indicating the stock's earnings surprise was in the top decile that quarter. The coefficients on $Surprise^{1}_{s,t}$ and $Surprise^{10}_{s,t}$ are the main focus.

There are also the following control variables: $w_{notrade,i,s,t}$ is the weight the fund would have on the stock if it did not trade between $t-1$ and t, $newpos_{i,s,t-1}$ is a dummy variable indicating the stock was a new position the last quarter, and $reportgap_{i,t}$ is the number of months since the last report date. The time t refers to a holdings report date, and $t-1$ is the latest report date from half a month to six and a half months ago. Portfolio weights are calculated as 100 times the position value divided by the portfolio value. The weight in a stock if the fund did not trade, $w_{notrade,i,s,t}$, is

$$\frac{portvalue_{i,t-1} \times w_{i,s,t-1} \times (1 + ret_{s,[t-1,t]})}{portvalue_{i,t}},$$

where $portvalue_{i,t}$ is the portfolio value at t and $ret_{s,[t-1,t]}$ is the stock's return since the last report date. We use log weights because we believe changes are likely to be proportional. It is possible to include additional stock characteristics (e.g., size, value) but we keep the model simple to focus on the effects of earnings surprise. To insure that stock characteristics are not behind our findings, we include controls for stock characteristics when analyzing future return.

To account for changing behavior and potentially changing fund managers, we estmate the model over rolling 27 month (approxmiately two-year) window[9] and pool all observations in the estimation window. We only include report dates for which the fund reported at least 10 positions, and we require at least four such report dates in the prior two years. With semi-annual reporting, four report dates in the past two years captures funds that have reported at every opportunity in the past two years. To estimate a model, we require the estimation window holdings to include at least one holding in each of the top and bottom earnings surprise deciles.

In parts of our analysis, we are interested in predicted fund weights. Bayesian regression tends to work better for prediction because the approach shrinks imprecise estimates towards prior values. For this reason, our portfolio weight model is a Bayesian OLS regression with the standard conjugate prior that the β's are normally distributed given σ: $\beta \sim N(\beta_0, \sigma^2 A^{-1})$, giving us

$$\widehat{\beta} = (X^T X + A)^{-1}(X^T X \times \beta_{ols} + A\beta_0)$$

[9]We use the past 27 months to account for slight lags between the current report day of year and the two-year ago report day of year.

where $\widehat{\beta}$ is the estimate we use, β_{OLS} is the standard OLS beta estimate, X is the matrix of explanatory variables, β_0 is our prior for betas, and A is our prior precision matrix. We shrink coefficients towards a "no-trade prior", by which we mean our coefficient prior is one for the no-trade weight and zero for all other coefficients. The prior precision matrix A is a diagonal matrix with the entry for each coefficient $\beta_{0,i}$ equal to the standard deviation of the corresponding explanatory variable times 200 (like a prior sample size for the portfolio of 200 positions). This results in a weighted average of our prior and β_{OLS} that shifts more towards β_{OLS} when the OLS estimate is more precise (i.e., has a lower standard error).

2.2 Discussion of Model Estimates

Table 2 presents summary statistics of these model coefficients for all Lionshares Funds and Lionshares 13F entities. The top panel reports estimates from the full sample. The median estimates on both the $\beta_{1,i}$ and $\beta_{10,i}$ are negative. This implies that funds typically sell on both positive and negative extreme news events. This evidence is consistent with the "V-shape" trading pattern documented in Ben-David and Hirshleifer (2012). The positive coefficient estimate on $NewPosition$ suggests that funds tend to build a position over consecutive holding periods in a newly initiated position. We also report medians of the model coefficients for funds sorted into quintiles by their coefficient on either negative surprise or positive surprises. Strong symmetric trend-chasing or contrarian behavior is consistent with opposite signs on the positive/negative earnings surprise coefficients for these funds. For the most part, there does appear to be a negative correlation between the coefficients on positive and negative surprises, but it is not particularly strong. The next panel report median coefficient estimates for only the mutual funds in our sample. The estimates are similar to the full sample.

We compare model coefficient estimates between hedge funds and mutual funds. While the median model coefficients remain negative, there is more variation in the estimates among hedge funds. This suggests that hedge funds adjust holdings more rapidly in response to earnings surprises than mutual funds.

To better understand the trading types across funds, we report the fraction of funds in our sample that exhibit distinct trading styles. The first type of trading style is a contrarian strategy that tends to buy on extreme bad news and sell on extreme good news. In contrast, a trend trading style tends to buy on extreme good news and sell on extreme bad news. Motivated by the findings in Ben-David and Hirshleifer (2012), we also classify a V-shape trading style as one that sells on both extreme good and bad news. The cutoff breakpoint to define whether a fund buy or sells on extreme news is set at either the 25th or 75th percentile of pooled absolute value of all positive and negative surprise coefficients in the sample.

Table 3 reports the distribution of fund style types in our sample of funds. We report the median coefficient estimates for $\beta_{1,i}$ and $\beta_{10,i}$, the number of funds in each type, and the fraction (%) among the sample of funds. The top panel reports the distribution for the full sample. Based on the 25% cutoff value, contrarian, trend, and V-shape funds make up 15.2%, 17.6%, and 20.7% of the sample, respectively. The relative distribution of funds is similar using the 75% cutoff. Using the 75% cutoff, approximately 53.5% of funds can be classified into one of these three strategies, while the other 46.5% do not strongly follow such trading styles. While in aggregate institutions sell on both good and bad news (i.e., V-shape investors), at the fund level it is not more common than contrarian or trend-chasing behavior. There is also not a disproportionate amount of trend-chasing behavior among funds.

In the next two panels, we separately report fund style type distributions for the mutual fund sample (Lionshares funds) and 13f hedge fund sample. We find relatively more contrarian fund style types among 13f hedge funds. Moreover, the coefficient estimates among 13f hedge funds are larger in magnitude than the mutual funds. This suggests that hedge funds of each group are likely to trade more aggressively around earnings announcements.

Figure 2 shows two Fidelity funds with different types of trading behavior that the model captures. The Fidelity Trend fund says in its marketing that it buys stocks with strong recent performance. The estimated model coefficient are consistent with this type of strategy. The coefficient estimate on good earnings news (blue line) is generally positive suggesting that the Trend fund buys stocks with good news. The Trend fund tends to sell on bad earnings news (red line) as the coefficient estimate is generally negative throughout the sample. In contrast, the Fidelity Value fund has an opposite pattern in coefficient estimates. This fund tends to have a negative coefficient on good news (blue line), but a positive coefficient on bad news (red line).

Figure 3 shows the holdings-weighted average model coefficients for funds owning the stock of Apple and Dell. For the Apple stock, the bad news model coefficient (red line) was initially positive around 2003, but became negative shortly afterwards. The good news model coefficient estimate (blue line) turned positive during this period. In the 2005 to 2012 time span, the funds owning Apple are predicted to sell if Apple reported negative earnings and buy or hold their position if it reported positive earnings. This likely reflects changes in investor composition as Apple experienced significant growth in their iPod, iPhone, and iPad products. Towards 2013, as sales growth slowed, the model coefficients of both good and bad news converged towards zero. This is consistent with the ownership base shifting away from funds chasing earnings momentum as the company's growth slowed.

Dell's stock also experienced changes in stock coefficients which are anecdotally related to changes in their business fundamentals. Before 2006, the bad news model coefficient (red line) was negative, but turned positive afterwards, while the good news model coefficient (blue line) was initially positive, but turned negative. This change in investor composition correlates with the maturation of the PC manufacturing market and slower growth in Dell's sales.

Figure 4 shows that the coefficient estimates for funds are persistent for both negative (top panel) and positive (bottom panel) earnings surprises over the next five years. Specifically, we sort funds into five groups at time $t = 0$ based on $\beta_{1,i}$ and $\beta_{10,i}$. Then, we track those funds over the next five years. There is some overlap in the estimation data the first two years, but by year three the parameters are estimated in completely different data than year 0. The plots show that funds in the extreme groups continue to exhibit greater surprise coefficients in the next few years. This suggests that our model is estimating a persistent characteristic trait of a fund's trading behavior.

2.3 Predicting Future Trading

Given the model of holdings as a function of earnings surprises, we estimate how a fund will trade if a stock holding has an earnings surprise next quarter. Each month, for every fund in the sample, we have model parameters estimated as of the fund's last report date. For example, if the Fidelity Contrafund reports holdings on December 31st, 2005, we have model parameters estimated based on holdings reported between January 1st, 2003, and December 31st, 2005. These parameters are utilized for estimating how Contrafund trades holdings following earnings announcements from January 1st, 2006, until the Contrafund's next report date.

For example, assume the Contrafund holds Intel, and Intel announces Q4 earnings in February 2006. We estimate predicted trading in Intel for the Contrafund as

$$\widehat{trade_{i,s,t}} = shares_{i,s,t-1} \times (e^{\widehat{\beta_{1,i,t}} Surprise^1_{s,t} + \widehat{\beta_{10,i,t}} Surprise^{10}_{s,t}} - 1), \tag{2}$$

where $\widehat{\beta_{1,i}}$ and $\widehat{\beta_{10,i}}$ are the estimated model parameters, $Surprise^1_{s,t}$ and $Surprise^{10}_{s,t}$ are dummies indicating if Intel's realized earnings surprise was in the top or bottom decile, and $shares_{t-1}$ is the Contrafund's reported holdings in Intel as of their last report date before the start of the earnings announcement month. This means the last report date before February 1st, 2006, which for the Contrafund was December 31st, 2005. We generate a predicted trading value for all other funds holding Intel as of their last report date before February 1st, 2006, in a similar manner.

In some tests we compare our predicted trading measure to actual trading. We define actual trading as the fund's reported stock holdings as of the last report date no more than four months after the earnings announcement minus the fund's reported holdings as of the last report date before the earnings announcement month. In the Intel and Contrafund example, June 2006 is four months after the earnings announcement month. If the Contrafund's last report date before June 30th, 2006, is March 31st, 2006, we define actual trading as the change in its holdings between the December 31st, 2005, and March 31st, 2006, report dates. If the Contrafund does not report holdings again until after June 30th, 2006, we define actual trading as zero. If Contrafund never reports after December 31st, 2005, we remove the fund from the sample as of January 1st, 2006, and do not try to predict or evaluate trading in response to Intel's February 2006 earnings announcement.

We generate a total predict trading $\widehat{trade_{s,t}}$ for a stock s by summing all the predicted shares traded values among all funds (I) owning Intel going into the earnings announcement month.

$$\widehat{trade_{s,t}} = \sum_{i=1}^{I} \widehat{trade_{i,s,t}} \tag{3}$$

We do the same for actual trading as well. At this stage, we remove any stock for which there appears to be a holdings data error: we remove any fund that reports holding more than 25% of the stock's shares outstanding going into the announcement month, any stock where our calculated actual trading is more than 50% of shares outstanding, any stock where our predicted trading is more than 50% of shares outstanding, and any stock for which total fund ownership going into the earnings announcement month is more than 100% of shares outstanding.

2.4 Evaluating Trading Predictions

To evaluate how well we predict trading, we compare our measure of total predicted trading by funds owning a stock to their actual trading from their last reported holdings before the announcement to three months after the earnings announcement month. Section 2.3 describes in detail how we calculate total predicted shares traded and total actual shares traded. These comparisons are done at the stock level and, importantly, are out of sample tests. The trading predictions are formed from parameters estimated in the roughly two-years *before* the earnings announcement, and we evaluate predictions based on actual trading from the last report date before the earnings announcement to the next report date afterwards.[10]

Table 4 reports regressions that test how well the model predicts future trading. The sample is restricted to stocks reporting either a negative or positive earnings surprise because we only predict trading for these only stocks. The dependent variable is actual total shares traded divided by shares outstanding. The main independent variable of interest is summed predicted trading by existing fund owners ((3)), divided by shared outstanding. We also include a dummy variable indicating negative surprises and an interaction term to capture whether our predicted trading measure performs differently for stocks with positive versus negative earnings surprises. Variables are winsorized at 1% and 99%, and standardized to ease interpretation. Standard errors are clustered by quarter and stock.

The first column reports results for the full sample of funds (i.e., both mutual funds and all 13F funds). The results indicate that predicted trading measure, $\widehat{trade_{s,t}}$, has a strong positive

[10]It is always out of sample, but the exact timing of the earnings announcement relative to report dates depends on when a fund reports. See Section 2.3 for details.

correlation with actual trading. The coefficient estimate indicates a one-standard deviation increase in predicted trading forecasts around a 0.15 standard deviation increase in actual trading. The intercept captures the average change for stocks with positive earnings surprises, and the negative surprise coefficient is the average effect for negative surprises. Since neither is significantly different from zero, this suggests that for the full sample of funds, there is no difference in predicted trading for positive or negative earnings surprises.

The second column includes an interaction of predicted trading with a negative earnings surprise. The results indicated that the prediction is better for stocks with negative earnings surprises. The coefficient estimate on predicted trading in this specification indicates performance among stocks with positive earnings surprises. The implied effect for stocks with negative earnings surprises is the sum of the coefficients on predicted trading and predicted trading interacted with the negative surprise dummy. Therefore, the implied effect for stocks with negative (positive) earnings surprise is that a one standard deviation change in predicted trading leads to 0.169 (0.125) standard deviation change in realized trading. While the coefficients imply relatively large effects, the R^2, though, is modest. This is likely a result of the trade-off in choosing to implement the Bayesian adjustment. The adjustment limits the standard deviation of the predicted trading measure so that it only predicts trading when the data provides a precise estimate of a sizeable coefficient; this provides a strong correlation between predicted and actual trading when trades are predicted, but the R^2 is small because we often do not predict much trading.

We also evaluate trading predictions separately for the mutual fund sample and 13F hedge funds. Consistent with the full sample results, the coefficient estimate on predicted trading is statistically positive in the sub-samples of mutual funds and 13F hedge funds. The model also shows better performance for mutual funds relative to hedge funds. Comparing mutual funds (columns 3) to hedge funds (column 5), the model produces higher $r - square$ for mutual funds and the coefficient estimates on predicted trading is also larger. Column 4 shows that for mutual funds, the model is better able to predict trading for negative earnings surprise. However, for hedge funds, there is no difference in predicted trading for negative earnings surprise.

3 Portfolios Formed on Predicted Trading

We next test whether a stock's price is affected by its fund owners' preferences for stocks with a particular type of earnings news. The basic idea is to find two stocks with the same magnitude of earnings surprise but different ownership bases: one stock owned by investors who want to sell conditional on the earnings surprise, another stock owned by investors who want to buy conditional on the earnings surprise. For illustration purposes, imagine Microsoft and Intel both have large positive earnings surprises, but the fund owners of Microsoft like stocks with positive earnings surprises and want to buy more, whereas Intel owners do not like stocks that have positive earnings surprises and so want to sell. All else equal, we expect the implied buying in Microsoft to push the price above fundamental value, and the implied selling of Intel to push the price below fundamental value. Importantly, this liquidity shock is predictable ex-ante based on previously observed trading preferences. Going forward, we expect Intel, the stock funds are selling, to have higher returns than Microsoft, the stock funds are buying.

3.1 Portfolio Formation

To test this prediction, we form portfolio using the following approach. At the end of each month, we gather stocks that experienced positive or negative earnings surprises during the past calendar quarter. Frazzini and Lamont (2007) find that elevated trading volume following earnings announcements falls back to pre-announcement levels after approximately 7 days. Therefore, we exclude those earnings announcements that occurred in the last ten calendar days of the portfolio formation month to avoid potential confounding effects of elevated trading volume. To ensure the stocks are actively traded, we also exclude stocks with prices below 5 dollars and market capitalizations below the 20th percentile of NYSE stocks at the start of the formation month. Then, we sort stocks with positive earning surprises into quintile portfolios based on predicted shares traded by existing fund owners divided by the natural log of average trading volume in the quarter before the earnings announcement. We scale by trading volume to capture the magnitude of the predicted trading shock compared to typical trading in the security. We repeat this sort for stocks with negative earnings surprises.

We form zero-cost portfolios that are long the quintile of stocks with the lowest predicted trading (stocks funds are selling) and short stocks with the highest predicted trading (stocks funds are buying). To avoid a single stock dominating the portfolio, we limit individual stock positions in both the long and short legs to a maximum of 5%. By forming long-short portfolios within the extreme earnings surprise deciles, we hedge out any return effects from post-earnings announcement drift. We then evaluate whether the stocks we expect funds to sell have higher returns than the stocks we expect funds to buy.

One consequence of our portfolio formation method is large variation in the number of stocks in the portfolio. This is partly because we use earnings surprise breakpoints formed from an expanding sample of all earnings announcements before the present month. For example, the number of stocks in the negative surprise portfolio of stocks we expect funds to sell ranges from 9 to 63, with a standard deviation of 10 stocks. This creates time-varying volatility in the test portfolios. To account for this varying volatility, we lever or de-lever the portfolios to an expected 15% annualized volatility with a maximum of 2x leverage. We use an ex ante estimate of the volatility of the portfolio formed at time t. Specifically, we estimate expected volatility as the realized volatility over months $t-12$ to $t-1$ of the exact portfolio (same stocks) formed in month $t=0$.

Before we report portfolio returns, we first examine the characteristics from the entire pooled cross-section of stocks that experienced negative and positive earnings surprise. We report the following characteristics: the book-to-market ratio (BM), gross profitability (GP), past month return, fund ownership, market value, price, and past return from month $t-12$ to $t-2$. We separately examine the predicted sell and buy portfolios.

Table 5 reports the summary statistics for stocks in the negative earnings surprise portfolios. The predicted selling portfolio contain larger growth stocks that had good recent stock performance relative to the stocks in the predicted buying portfolio. These stocks characteristics are perhaps typical of stocks owned by investors who prefer to chase earnings momentum.

We report the summary statistics for stocks in the positive earnings surprise portfolios in Table 6. The predicted buying portfolio shares many similarities with the predicted selling portfolio of negative earnings surprise news in Table 5. The portfolio contains larger, more profitable growth stocks that had good recent stock performance relative to the stocks in the predicted selling portfolio.

3.2 Test Portfolio Returns

Table 7 reports the average value-weighted future returns for the portfolios sorted on earnings surprise and predicted trading. We report results for both portfolios formed using returns and portfolios formed using a stock's abnormal return. Abnormal returns are calculated by matching a stock to a benchmark portfolio with matching size, book-to-market, and price momentum following Daniel, Grinblatt, Titman, and Wermers (1997), henceforth DGTW. We begin by separately analyzing the portfolio returns after negative and positive earnings surprises before combining the analysis together. To examine the persistence of the future returns, we report returns for each of the six months after portfolio formation. Combining the positive and negative surprise portfolio diversifies the portfolios, providing more power to detect the hypothesized effects.

To analyze the combined effects of predictable trading around both good and bad news, we estimate the average of the portfolio returns. Our main focus is the zero-cost portfolios in the right most column of each column group. They report the difference between the returns of stocks mutual funds are expected to sell and those they are expected to buy. Looking at the long-short portfolio formed using unadjusted returns, we see positive returns in all the first three months: 0.19%, 0.46%, and 0.58%. The second and third month returns are significantly different from zero. The results for the long-short DGTW-adjusted are similar. This finding is consistent with price reversal following the predicted trading on the earnings announcement. The difference in returns is not significant in the next three months, consistent with price pressure subsiding.

To test whether returns are jointly positive over the three post-sort months, we form a three-month overlapping holding period portfolio following Jegadeesh and Titman (1993). The first column in Table 8 shows the three-month overlapping holding period return for the portfolio formed on unadjusted returns. The mean return is 0.42% per month, with a t-statistic of 3.26. Controlling for market, size, value, momentum, investment, profitability, and post-earnings announcement drift factors, we see the monthly alpha rises to 0.47%, with a t-statistic of 3.67. We include the post-earnings announcement drift factor for robustness, but this should be mostly hedged via portfolio construction that goes long-short within earnings surprise deciles. The annualized Sharpe ratio can be calculated by multiplying the t-statistic by $\sqrt{\frac{12}{NMonths}}$. This works out to nearly 1.0, which is fairly large.

We also report the results for the DGTW-adjusted portfolio. The alpha of the overlapping portfolio in the third column is 0.73, with a t-statistic of 3.14. This *t*-statistic is lower than for the alpha in the in the factor model in column two. A natural question is whether this is because the DGTW adjustment is doing a better job hedging the portfolio, perhaps due to a loading on some interaction between value, size, or momentum. To check this hypothesis, we see if the DGTW-adjusted portfolio loads on our factors in the next two columns. The regression shows there is some residual factor exposure in the DGTW-adjusted portfolio. But after controlling this residual factor exposure, the DGTW-adjusted alpha has a *t*-statistic similar to that of the regular return portfolio after controlling for factor exposure. This result suggests the factors provide a useful additional hedge.

Figure 5 plots the cumulative abnormal returns of the long-short portfolio in column 1 of Table 8. We leverage the portfolio to have the same standard deviation as the excess return on the market in the sample, and plot the cumulative returns of both zero-cost portfolios over the full sample. Despite the short time-series, the figure illustrates strong average performance with no large crashes.

Overall, the portfolio return analysis supports the prediction that predictable trading pressure is related to future returns.

4 Conclusion

This paper studies the predictability of fund trading around earnings announcements. We identify fund specific preferences for holding stocks with recent positive or negative earnings surprises. This allows us to estimate how every fund will trade each of its existing positions if the stock has an earnings surprise the next quarter. Aggregating this fund-level trading up across all funds owning a stock, we have a stock-level prediction of how all the funds owning a stock will trade. In out of sample tests, we find this predicted trading explains around 2.5% of the variation these existing owners' trading in the quarter following the earnings announcement.

When the ownership base is diverse, trades by owners that want to sell will balance out with trades by owners that want to buy. But if most owners want to sell, the selling pressure can create temporary price effects that cause future returns to be high. Indeed, we find that a portfolio long the stocks mutual funds are expected to sell and short those they are expected to buy has a Sharpe ratio of nearly 1.0 after hedging out exposure to the market, size, value, momentum, and post-earnings announcement drift factors.

These findings relate to a broad literature on the heterogeneity of investors' portfolio choices. These portfolio choices tend to vary according to observable asset characteristics. This variation can come from differences in beliefs about how those characteristics relate to future returns, differences in non-tradeable wealth that creates different hedging motives, or actual differences in innate portfolio preferences. In our case, we focus on a easily observable and fast changing asset characteristic: earings news.

The finding that we can predict trading and returns out of sample is important for several reasons. It is somewhat surprising that around 2.5% of the cross-sectional variation in funds' trading following an earnings announcement is explained by those mutual funds' past trading of stocks with the same magnitude of earnings surprise. There is a lot of varied information that comes out in an earnings release. However, this finding indicates that meaningful proportion of what determines how a fund changes it's portfolio is quantifiable by the magnitude of the surprise. Additionally, from funds' perspective, it means that they pay a cost in terms of reduced liquidity when they hold stocks owned by other funds with similar preferences for earnings news. It also speaks to concerns of investors in more exotic strategies that are concerned their portfolios can be affected if investors with similar preferences are holding the same stocks. These findings suggest that if a stock is held by hedge funds all following similar quant strategies, then the stock price can be affected if they all voluntarily decide to exit because the stock no longer passes their quantitative filters.

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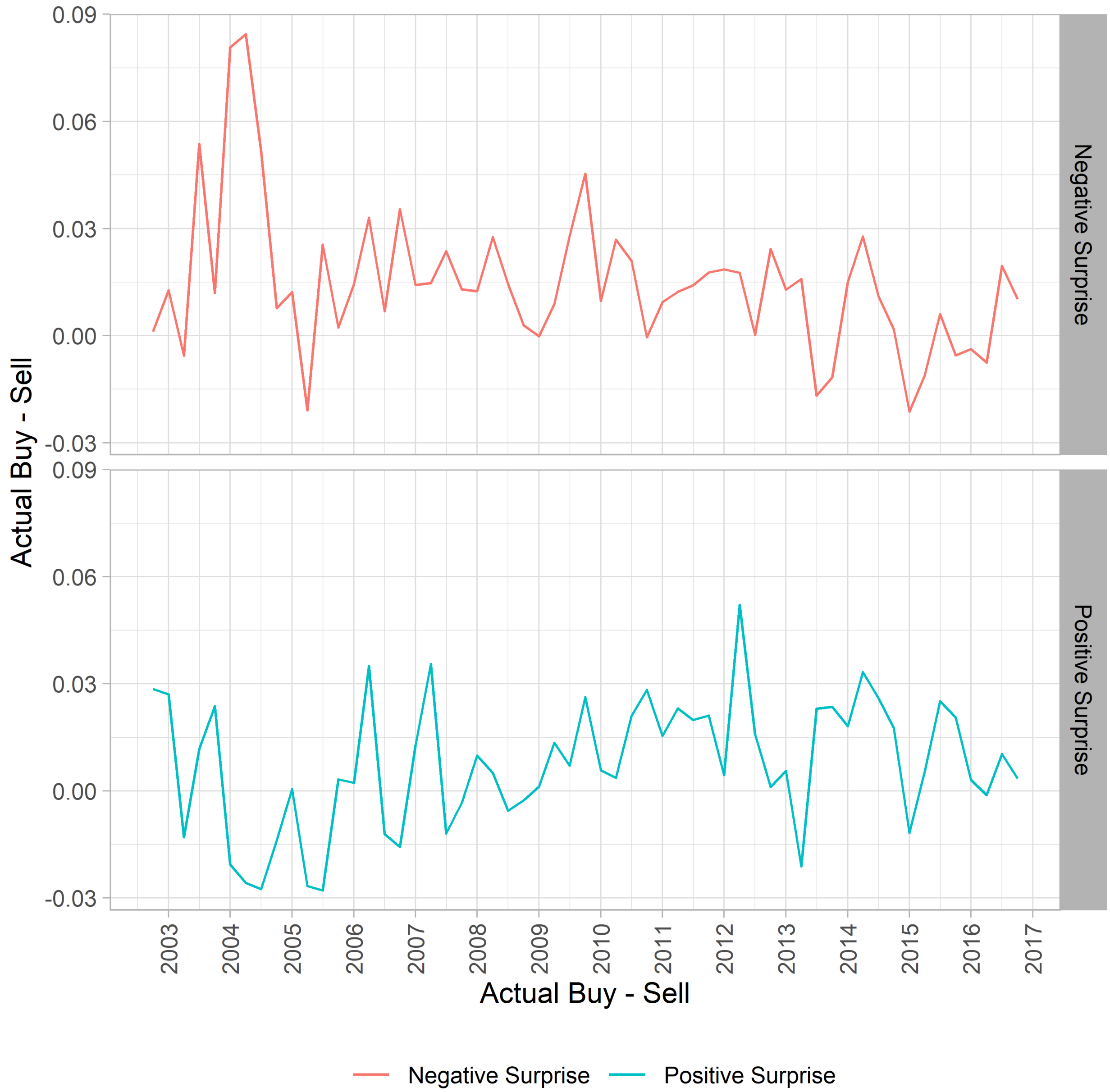
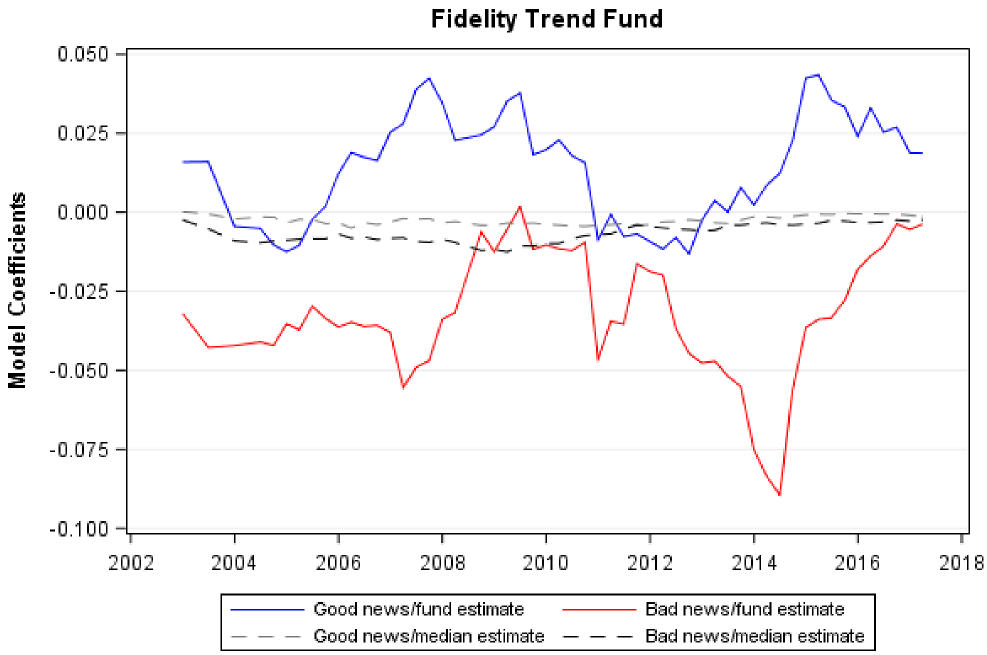


Figure 1: Changes in Mutual Funds' holdings for predicted trading portfolios.
The plot shows the average change in holdings as a percent of shares outstanding for the buying portfolio minus the change for the selling portfolio. The changes are plotted separately for stocks with positive vs. negative earnings surprises.



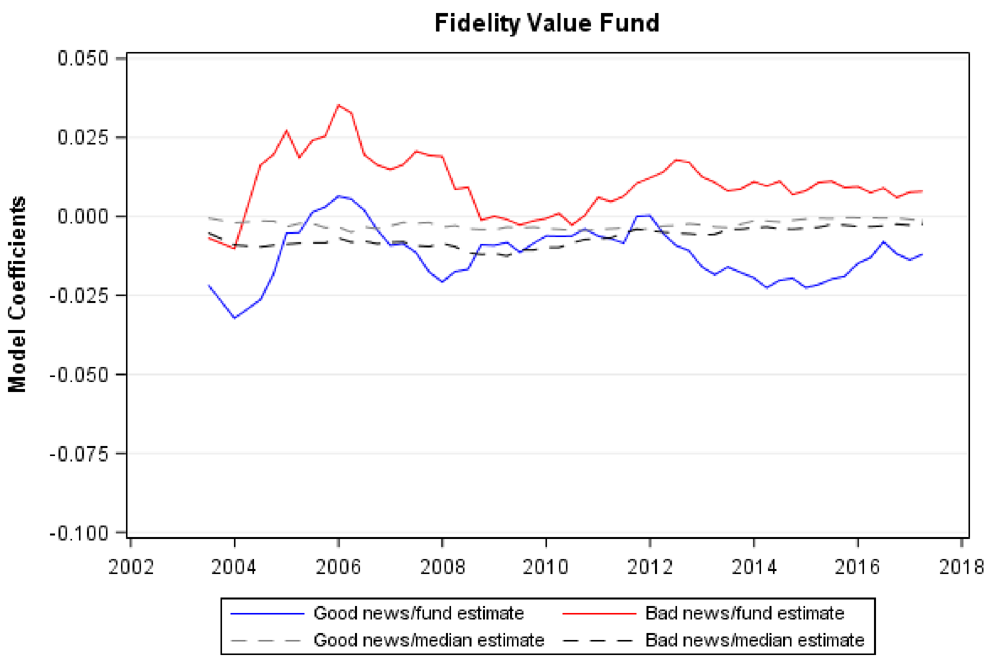


Figure 2: Examples of estimated model coefficients for two Fidelity funds.
This figure shows the estimated model coefficients for the Fidelity Trend fund and the Fidelity Value fund during the sample period. The blue/red line is the estimated coefficient for good/bad news. The dashed grey/black lines are the median estimated coefficients across all funds for good/bad news.

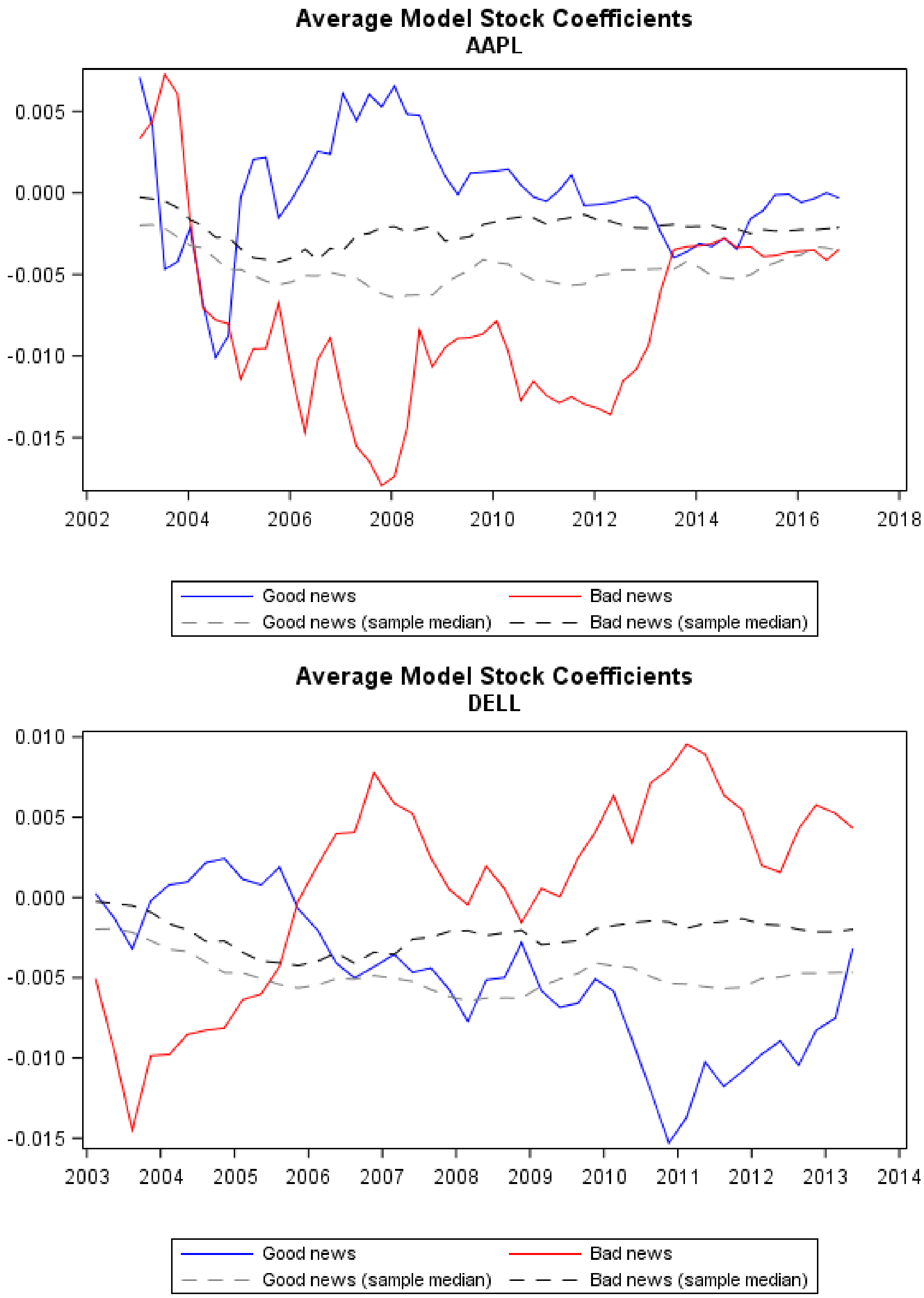


Figure 3: Examples of estimated model coefficients for Apple and Dell.
This figure shows the estimated model coefficients for Apple and Dell stock during the sample period. The blue/red line is the estimated coefficient for good/bad news.

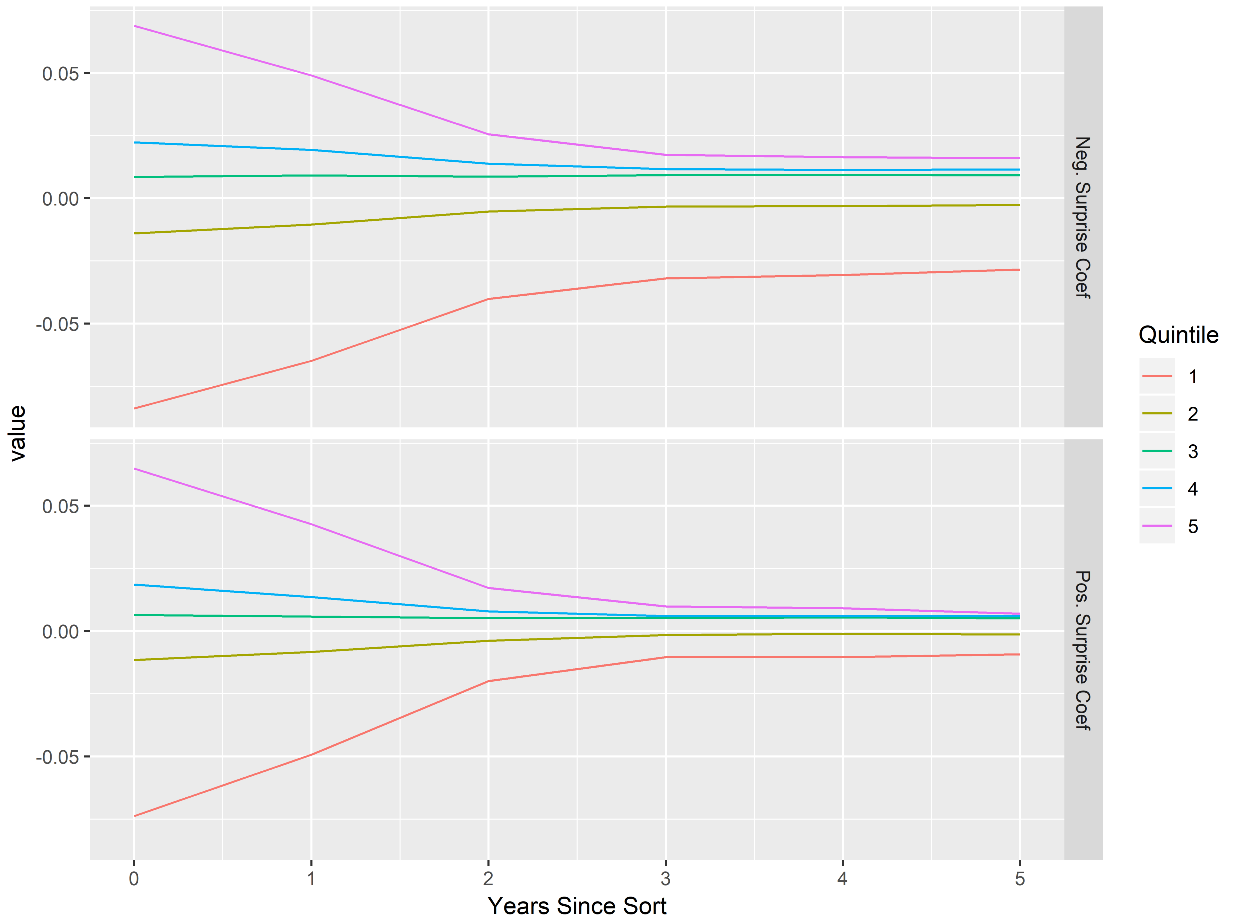


Figure 4: Persistence of Surprise Coefficients.
This table plots the persistence of model coefficients for the funds. For each fund, we calculate average negative and positive coefficient estimates each year. Then we sort all funds in a year into quintiles based on the magnitude of their estimated coefficient. The figure plots average coefficients for those quintiles over the next 5 years. A fund must have estimates available for each of the next 5 years to be included in the figure.

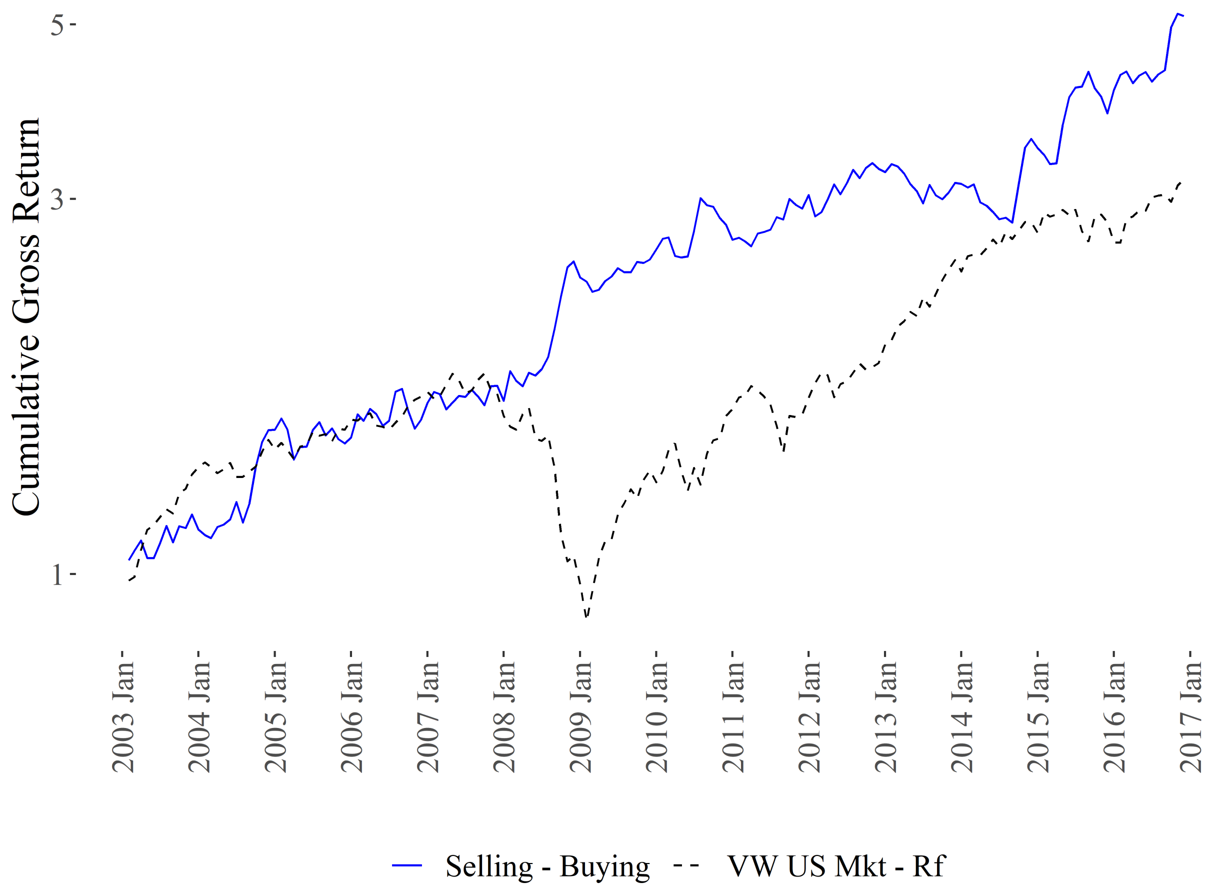


Figure 5: Cumulative Returns of Selling Minus Buying Portfolio.
The portfolio is value-weighted, held for 3 months after formation, and scaled to have the same volatility as the excess return on the value-weighted US stock market.

Table 1
Summary Statistics

This table reports summary statistics for the sample of stocks used in the paper. Total assets (\$M) are total assets in millions at the latest fiscal year end. Market equity (\$m) is the market capitalization in millions in month $t-1$. B/M is the book-to-market ratio in month $t-1$. Asset growth (%) is the annual growth in total assets in the latest fiscal year. Gross profitability (%) is the ratio of gross profits to assets in the latest fiscal year. Return $t-12$ to $t-2$ (%) is the cumulative stock return between months $t-12$ to $t-2$. Return $t-1$ (%) is the stock return in month $t-1$. The data below comes from the CRSP database.

	Mean	Std Dev	P1	P25	P50	P75	P99
$\widehat{trade} \mid +$	-30.51	100.79	-410.95	-30.40	-7.95	0	82.08
$\widehat{trade} \mid -$	-24.92	102.47	-430.09	-28.70	-5.99	1.73	148.81
Total Assets (\$M)	15807	90845	40	643	1877	6321	269425
Market equity (\$M)	8605	26514	284	910	1906	5344	138017
B/M	0.57	0.52	0.04	0.28	0.46	0.73	2.23
Asset Growth (%)	36.03	1004.47	-29.80	0.90	8.24	20.67	314.48
Gross Profitability (%)	29.88	25.44	-19.53	11.04	26.23	42.89	105.59
Return $t-12$ to $t-2$ (%)	19.48	60.54	-65.908	-7.67	12.03	34.55	214.20
Return $t-1$ (%)	1.54	11.82	-28.82	-4.22	1.26	6.79	36.51

Table 2
Model Coefficient Estimates

This table reports pooled model coefficient estimates from all Lionshares Fund and Lionshares 13f entities. There is one model estimate per entity per report date passing required filters. The main sample includes mutual funds in the Lionshares Fund database plus all 13f institutions except mutual fund companies. The mutual fund sample includes all funds in the Lionshares fund database, and the hedge fund sample includes all hedge funds in the Lionshares 13f. We report the 25th, median and 75th percentile of coefficient estimates for each of the covariates in the model. We also sort the sample into the top and bottom quintile of funds based each negative earnings coefficient estimate or the positive earnings coefficient estimate. We report the median coefficient estimate of each respective covariate. $w_{notrade}$ is the portfolio weight the fund would put on the position if it did not trade. NewPosition is a dummy for new positions. ReportGap is the number of months since the last report date Negative Earnings is a negative earnings surprise dummy. Positive Earnings is a positive earnings surprise dummy.

				Sorted on Coefficient			
	All Funds			Negative Earnings		Positive Earnings	
Coefficient	P25	P50	P75	Sellers	Buyers	Sellers	Buyers
Mutual Fund + 13f All - 13f Mutual Fund (Main Sample)							
SurpriseP10	-0.029	-0.003	0.014	0.003	-0.012	-0.074	0.045
SurpriseP01	-0.039	-0.005	0.013	-0.095	0.044	-0.005	-0.024
ReportGap	-0.033	-0.009	0.001	-0.027	-0.019	-0.018	-0.027
NewPosition	-0.003	0.023	0.066	0.034	0.037	0.031	0.034
$w_{notrade}$	0.915	0.972	0.998	0.954	0.966	0.955	0.958
Mutual Fund							
SurpriseP10	-0.029	-0.002	0.016	0.005	-0.012	-0.075	0.048
SurpriseP01	-0.042	-0.006	0.013	-0.100	0.045	-0.005	-0.026
ReportGap	-0.036	-0.012	0.001	-0.031	-0.020	-0.021	-0.030
NewPosition	0.000	0.032	0.075	0.040	0.045	0.039	0.039
$w_{notrade}$	0.921	0.973	0.999	0.959	0.969	0.961	0.961
13f Hedge Fund							
SurpriseP10	-0.058	-0.012	0.026	0.002	-0.025	-0.110	0.074
SurpriseP01	-0.053	-0.006	0.035	-0.116	0.085	0.001	-0.026
ReportGap	-0.069	-0.031	-0.005	-0.051	-0.046	-0.039	-0.056
NewPosition	-0.057	-0.014	0.031	-0.021	-0.018	-0.015	-0.024
$w_{notrade}$	0.726	0.869	0.948	0.867	0.877	0.875	0.864

Table 3
Fund Type Classification

This table reports classifications of fund types based on coefficient estimates on good/bad news from our model. Funds are classified each report date into categories based on the magnitude of estimated coefficients on positive and negative surprise dummies. A fund is classified as $contr-both$ if it tends to buy negative surprise stocks and sell positive surprise stocks. A fund is classified as $trend-chase$ if it tends to sell negative surprise stocks and buy positive surprise ones. A fund is classified as v-shape if it tends to sell both positive and negative surprise stocks. Funds that do not fit one of these categories because their coefficient is too small are left out of the table. A coefficient is considered non-zero if the absolute value is greater than a cutoff value. The cutoff is either 25% or 75% percentile of pooled absolute value of all positive and negative surprise coefficients in the sample. The main sample includes mutual funds in the Lionshares Fund database plus all 13f institutions except mutual fund companies. The mutual fund sample includes all funds in the Lionshares fund database, and the hedge fund sample includes all hedge funds in the Lionshares 13f.

Cutoff	Type	Negative Earnings	Positive Earnings	N	%
Mutual Fund + 13f All - 13f Mutual Fund (Main Sample)					
	contr-both	0.045	-0.065	60,731	15.175
25%	trend-chase-both	-0.078	0.045	70,396	17.590
	v-shape	-0.061	-0.056	82,789	20.686
	contr-both	0.096	-0.131	10,332	2.582
75%	trend-chase-both	-0.140	0.100	13,082	3.269
	v-shape	-0.123	-0.123	15,417	3.852
Mutual Fund					
	contr-both	0.046	-0.067	45,799	14.838
25%	trend-chase-both	-0.080	0.046	56,744	18.384
	v-shape	-0.065	-0.059	61,411	19.896
	contr-both	0.097	-0.135	7,623	2.470
75%	trend-chase-both	-0.143	0.101	10,199	3.304
	v-shape	-0.128	-0.128	11,618	3.764
13f Hedge Fund					
	contr-both	0.072	-0.084	3,293	17.764
25%	trend-chase-both	-0.096	0.073	2,735	14.753
	v-shape	-0.084	-0.083	3,294	17.769
	contr-both	0.135	-0.152	459	2.476
75%	trend-chase-both	-0.164	0.133	467	2.519
	v-shape	-0.153	-0.155	537	2.897

Table 4
Out of Sample Model Performance

This table reports regressions of stock level changes in holdings of a stock's existing fund owners on their predicted change in holdings. The changes for each fund are measured from the last report date before the stock's earnings announcement month to three months later after the announcement month. Predicted changes are based on fund-level parameters estimated before the announcement month and actual holdings as of the last report date before the announcement month. Predicted and actual trading for each fund is aggregated up to the stock level to get the stock-level variables in the regression. Changes in holdings are measured as a percent of shares outstanding, winsorized at the 1% and 99% level, and standardized. Standard errors are clustered by report quarter and stock. The main sample includes mutual funds in the Lionshares Fund database plus all 13f institutions except mutual fund companies. The mutual fund sample includes all funds in the Lionshares fund database, and the hedge fund sample includes all hedge funds in the Lionshares 13f.

	All.1	All.2	MF.1	MF.2	HF.1	HF.2
Intercept	0.005	0.006	0.010	0.015	−0.017	−0.017
	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Predicted Trading	0.147***	0.125***	0.148***	0.085***	0.102***	0.113***
	(0.011)	(0.016)	(0.011)	(0.016)	(0.016)	(0.022)
Negative Surprise	−0.012	−0.012	−0.022	−0.022	0.038*	0.038*
	(0.020)	(0.020)	(0.020)	(0.020)	(0.021)	(0.021)
× Predicted Trading		0.044**		0.116***		−0.025
		(0.022)		(0.022)		(0.032)
Adj. R^2	0.022	0.022	0.022	0.025	0.010	0.011
Num. obs.	9971	9971	9970	9970	8681	8681

$^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 5
Predicted Trading Portfolio Summary: Negative Surprises

This table summarises the pooled cross-section of all stock observations for portfolios sorted on predicted trading following an earnings surprise. For each variable, we report percentiles from the 10th to the 90th. The variables are the book-to-market ratio (BM), gross profitability (GP), past month return (lagRET), mutual fund ownership (MFown), market value (MV), price (PRC), and cumulative past return from month $t-12$ to $t-2$ (Prior212).

Variable	Port	pctl10	pctl25	pctl50	pctl75	pctl90
BM	Fund Buying	0.20	0.32	0.53	0.85	1.25
	Fund Selling	0.11	0.18	0.31	0.51	0.83
GP	Fund Buying	0.05	0.16	0.28	0.47	0.70
	Fund Selling	0.09	0.20	0.33	0.50	0.69
lagRET	Fund Buying	-0.13	-0.06	0.01	0.08	0.16
	Fund Selling	-0.16	-0.07	0.00	0.06	0.13
% Own	Fund Buying	0.24	0.43	0.59	0.70	0.80
	Fund Selling	0.37	0.50	0.61	0.69	0.76
MV	Fund Buying	0.62	0.85	1.46	3.10	7.29
	Fund Selling	1.12	1.87	3.99	9.97	25.74
PRC	Fund Buying	7.90	11.68	18.01	27.80	40.31
	Fund Selling	11.62	18.38	30.51	47.02	70.05
PRIOR212	Fund Buying	-0.47	-0.28	-0.08	0.20	0.57
	Fund Selling	-0.28	-0.05	0.21	0.56	1.00

Table 6
Predicted Trading Portfolio Summary: Positive Surprises

This table summarises the pooled cross-section of all stock observations for portfolios sorted on predicted trading following an earnings surprise. For each variable, we report percentiles from the 10th to the 90th. The variables are the book-to-market ratio (BM), gross profitability (GP), past month return (lagRET), mutual fund ownership (MFown), market value (MV), price (PRC), and cumulative past return from month $t-12$ to $t-2$ (Prior212).

Variable	Port	pctl10	pctl25	pctl50	pctl75	pctl90
BM	Fund Buying	0.11	0.17	0.29	0.49	0.84
	Fund Selling	0.21	0.32	0.50	0.78	1.10
GP	Fund Buying	0.11	0.21	0.36	0.53	0.75
	Fund Selling	0.06	0.17	0.30	0.44	0.62
lagRET	Fund Buying	-0.15	-0.07	0.00	0.08	0.17
	Fund Selling	-0.14	-0.06	0.00	0.07	0.16
% Own	Fund Buying	0.26	0.41	0.57	0.68	0.76
	Fund Selling	0.35	0.50	0.60	0.68	0.77
MV	Fund Buying	0.72	1.11	2.19	5.05	12.96
	Fund Selling	0.78	1.32	2.77	6.41	18.42
PRC	Fund Buying	13.21	22.01	35.23	55.70	93.50
	Fund Selling	8.78	14.22	23.17	37.13	56.73
PRIOR212	Fund Buying	-0.36	-0.08	0.24	0.64	1.23
	Fund Selling	-0.49	-0.27	-0.04	0.20	0.51

Table 7

Event-time Returns for Predicted Trading Portfolios

Stocks with earnings surprises are sorted each month into quintiles based on predicted trading by existing mutual fund owners of the stock. The table shows value-weighted returns for the bottom (selling) and top (buying) quintiles in the first six months after formation. The left columns are for portfolios formed using returns. The right columns are for portfolios formed using abnormal returns based on a characteristics-matched benchmark following Daniel, Grinblatt, Titman, and Wermers (1997) prior to portfolio formation. CR and CAR are the average cumulative sell minus buy returns. To account for time-varying volatility resulting from varying numbers of stocks in the portfolios, the portfolios are individually leveraged to an expected annualized volatility of 15 percent, with a maximum of 2x leverage. We estimate expected volatility as the realized volatility over months $t-12$ to $t-1$ of the exact portfolio (same stocks) formed in month $t=0$. Earnings surprises are stocks with returns in the top or bottom cumulative abnormal return decile on the day of and day after the announcement. Trading for each mutual fund is estimated based on how the mutual fund changes its holdings in a stock following an earnings suprise. Predicted trading is added up across all funds owning a stock to create a stock-level measure. Each fund has separate parameter estimates for positive and negative surprises.

	Returns								DGTW-adjusted Returns							
	Selling		Buying		Sell - Buy				Selling		Buying		Sell - Buy			
Month	avg	t-stat	avg	t-stat	avg	t-stat	CR	t-stat	avg	t-stat	avg	t-stat	avg	t-stat	CAR	t-stat
Average Neg. & Pos.																
1	0.53	1.68	0.34	1.02	0.19	1.33	0.19	1.33	0.03	0.19	-0.48	-2.31	0.51	1.99	0.51	1.99
2	0.79	2.44	0.33	0.98	0.46	2.98	0.65	2.98	0.37	1.94	-0.37	-1.92	0.74	2.71	1.25	3.27
3	0.80	2.41	0.22	0.61	0.58	3.62	1.22	4.45	0.29	1.50	-0.62	-2.65	0.90	3.05	2.13	4.46
4	0.78	2.37	0.42	1.16	0.36	2.19	1.55	4.98	0.24	1.17	-0.12	-0.56	0.37	1.33	2.45	4.48
5	0.66	1.97	0.33	0.92	0.34	2.16	1.86	5.26	0.15	0.73	-0.23	-1.03	0.38	1.40	2.74	4.65
6	0.83	2.46	0.51	1.46	0.32	2.04	2.18	6.08	0.45	2.22	-0.04	-0.21	0.49	1.86	3.21	5.14
Positive Surprise																
1	0.79	2.36	0.70	1.98	0.09	0.42	0.09	0.42	0.42	1.69	-0.07	-0.24	0.49	1.37	0.49	1.37
2	0.83	2.34	0.33	0.86	0.51	2.20	0.60	1.87	0.38	1.35	-0.42	-1.39	0.80	2.03	1.29	2.41
3	0.90	2.44	0.16	0.40	0.74	3.08	1.32	3.51	0.44	1.53	-0.78	-2.34	1.22	3.00	2.47	4.05
4	0.95	2.61	0.60	1.76	0.35	1.48	1.66	3.79	0.54	1.81	-0.04	-0.12	0.57	1.41	3.01	4.24
5	0.83	2.22	0.51	1.55	0.32	1.35	1.97	3.94	0.45	1.55	-0.02	-0.05	0.47	1.19	3.45	4.39
6	0.94	2.48	0.55	1.57	0.39	1.48	2.36	4.32	0.68	2.52	0.06	0.18	0.62	1.47	4.06	4.43
Negative Surprise																
1	0.28	0.84	-0.01	-0.03	0.29	1.12	0.29	1.12	-0.35	-1.36	-0.88	-2.88	0.53	1.34	0.53	1.34
2	0.75	2.24	0.34	0.95	0.42	1.60	0.71	1.92	0.35	1.25	-0.32	-1.18	0.68	1.62	1.21	2.08
3	0.70	2.03	0.28	0.71	0.42	1.44	1.11	2.41	0.13	0.47	-0.46	-1.43	0.59	1.29	1.79	2.37
4	0.61	1.81	0.24	0.54	0.37	1.35	1.43	2.69	-0.05	-0.18	-0.21	-0.73	0.16	0.43	1.89	2.22
5	0.50	1.46	0.14	0.33	0.35	1.24	1.74	2.68	-0.14	-0.52	-0.44	-1.59	0.29	0.78	2.03	2.17
6	0.72	2.05	0.46	1.15	0.26	0.88	1.99	3.05	0.23	0.74	-0.14	-0.53	0.37	0.98	2.35	2.37

Table 8

Time-series Alphas of Selling minus Buying portfolio

Stocks with earnings surprises are sorted each month into quintiles based on predicted trading by existing fund owners of the stock. The first set of columns are for portfolios formed using returns. The second set of columns are for portfolios formed using abnormal returns based on a characteristics-matched benchmark following Daniel, Grinblatt, Titman, and Wermers (1997) prior to portfolio formation. The table shows value-weighted portfolios long the bottom (selling) and short the top (buying) quintiles. To account for time-varying volatility resulting from varying numbers of stocks in the portfolio, the long and short legs of the portfolio are individually leveraged to an expected annualized volatility of 15 percent, with a maximum of 2x leverage. We estimate expected volatility as the realized volatility over months $t-12$ to $t-1$ of the exact portfolio (same stocks) formed in month $t=0$. The holding period is three months. Earnings surprises are stocks with returns in the top or bottom cumulative abnormal return decile on the day of and day after the announcement. Trading for each fund is estimated based on how the fund changes its holdings in a stock following an earnings suprise. Predicted trading is added up across all funds owning a stock to create a stock-level measure. Each fund has separate parameter estimates for positive and negative surprises. T-statitistics are in parentheses. Standard errors are calculated following Newey and West (1987) with three lags.

	Ret:1	Ret:2	Ret:3	DGTW:1	DGTW:2	DGTW:3
α	0.42	0.48	0.47	0.73	0.86	0.84
	(3.26)	(3.77)	(3.67)	(3.14)	(3.78)	(3.72)
RmRf		−0.06	−0.06		−0.15	−0.14
		(−1.41)	(−1.40)		(−1.64)	(−1.63)
SMB		0.05	0.05		−0.04	−0.03
		(0.81)	(0.85)		(−0.39)	(−0.29)
HML		0.02	0.02		0.17	0.16
		(0.37)	(0.27)		(1.20)	(1.17)
MOM		0.05	0.05		0.06	0.05
		(1.56)	(1.42)		(1.00)	(0.90)
PEAD		−0.10	−0.10		−0.09	−0.08
		(−2.12)	(−1.88)		(−0.81)	(−0.71)
RMW			0.02			0.06
			(0.29)			(0.42)
CMA			0.02			0.02
			(0.17)			(0.12)
Num. obs.	167	167	167	167	167	167