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Essays on the Investment Decisions of Individual and Institutional Investors

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Doctor of Philosophy

Business

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A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
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Abstract

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This dissertation investigates the investment decisions of individual and institutional investors. In the first essay, ("Organizational Structure and Fund Performance: Pension Funds vs. Mutual Funds"), I examine how differences in organizational structure influence the investment choices and performance of pension funds and mutual funds. I present evidence which suggests that the additional layers of delegation found in the pension fund industry generate agency costs that hinder pension fund performance. In the second essay, ("Understanding the S&P 500 Composition Effect: Evidence from Transaction Data", joint work with Clifton Green) we shed new light on the S&P 500 composition effect by examining the investment decisions of index funds and individual investors around S&P 500 composition changes. Our central finding is that that many index funds are willing to accept tracking error in exchange for better execution prices. In the third essay, ("Retail Investor Industry Herding", joint work with Qing Tong), we examine the industry wide investment decisions of individuals (retail investors). We find that retail investors herd into industries, and that industry herding can forecasts industry returns. The industries most heavily bought by retail investors significantly underperform the industries most heavily sold by retail investors over the subsequent 3 to 12 months. Taken together, our results suggest that retail investors categorize stocks by industry, and that industry-wide sentiment contributes significantly to the poor performance of retail investors.

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Introduction

This dissertation investigates the investment decisions of individual and institutional investors in order to provide new evidence on three distinct questions. In the first essay, ("Organizational Structure and Fund Performance: Pension Funds vs. Mutual Funds"), I examine how differences in organizational structure influence the investment choices and performance of pension funds and mutual funds. I hypothesize that the additional layers of delegation found in the pension fund industry generates agency costs that hinder pension fund performance. Corporate treasurers, who have an incentive to reduce their own job risk, tend to hire pension fund managers with low tracking error. This may result in pension fund managers underweighting profitable investment opportunities in stocks outside of their benchmark. Consistent with this hypothesis, I find that pension funds tilt their trading towards S&P 500 stocks, both in absolute terms and relative to mutual funds. Moreover, I show that the trades made by pension funds in non-S&P 500 stocks significantly outperform their trades in S&P 500 stocks. After adjusting for risk and transaction costs, I estimate that that the tracking error constraint imposed on pension funds weakens the performance of pension funds' trades by roughly 30 basis points per year.

In the second essay, ("Understanding the S&P 500 Composition Effect: Evidence from Transaction Data", joint work with Clifton Green) we shed new light on the S&P 500 composition effect by examining the investment decisions of index funds and individual investors around S&P 500 composition changes. We find index funds begin rebalancing their portfolios with the announcement of S&P 500 composition changes and do not fully establish their positions until weeks after the effective date. This result indicates that index funds are willing to accept tracking error in order to mitigate the effects of price pressure. Consistent with their efforts to minimize price pressure, the effective date price response has fallen by roughly half in recent years. We find that retail investor are net buyers of newly added stocks, however much of this effect is driven by retail investors' preference for certain firm characteristics. Moreover, we find inclusion returns are related to changes in liquidity, but are unrelated to contemporaneous changes in breadth of ownership. The results cast doubt on the role that the investor recognition hypothesis plays in explaining the index composition effect; and suggest that improvements in fundamentals cause both the increase in breadth of ownership and the permanent abnormal returns associated with inclusion.

In the third essay, (“Retail Investor Industry Herding”, joint work with Qing Tong), we examine the industry-wide investment decisions of individuals (retail investors). We find strong evidence that retail investors herd into and out of the same industries. Retail investor industry herding is distinct from firm-level herding and persists even after controlling for herding into stocks with similar size and book-to-market ratios. Moreover, retail investor industry herding forecasts industry returns. Over weekly horizons, industries heavily bought by retail investors significantly outperform industries heavily sold by retail investors, while over quarterly horizons industries heavily bought by retail investors significantly underperform industries heavily sold by retail investors. We decompose the poor performance of retail trades documented by Barber, Odean, and Zhu (2008) and Hvidkjaer (2008) and estimate that roughly 60% is due to poor industry selection. Taken together, our results suggest that retail investors categorize stocks by industry and that industry-wide sentiment contributes significantly to the poor performance of retail investors.

First Essay: Organizational Structure and Fund Performance: Pension Funds vs. Mutual Funds

1. Introduction

Defined benefit pension funds currently manage over $6 trillion dollars in total assets, roughly 50% of which is invested in equities (Standard and Poor's (2007)). The majority of these equities are managed by active fund managers who attempt to generate higher returns through superior stock selection. The investment decisions of these fund managers have profound implications for pension plan sponsors (i.e. the corporation), beneficiaries (i.e. the employee), and shareholders. Poor stock selection results in increased pension deficits (or reduced surpluses). These deficits often leave corporations with diminished profits, weaker credit ratings, higher borrowing costs, and reduced capital expenditures (Rauh, (2006)). Pension deficits can also harm current employees through lower wages and benefits, as well as increased job cuts. Thus a better understanding of the determinants of the investment decisions and performance of pension fund managers is critically important.

In this paper, I examine whether organizational structure is a factor that affects pension fund performance. The organizational structure of the pension fund industry is distinct from the mutual fund industry. In the mutual fund industry, retail investors directly allocate their own personal wealth to the mutual fund of their choice. In the pension fund industry, the employees of a corporation typically delegate investment choices to a corporate treasurer who then selects a pension fund. This additional layer of delegation offers several benefits. Pooling the assets of many small investors allows treasurers greater negotiating power and monitoring capacity (Bauer and Frehen, (2009)). In addition, Del Guercio and Tkac (2002) provide evidence that corporate treasurers are more financially sophisticated than the average retail investor. Their greater financial sophistication may allow them to better identify skilled fund managers.

However, delegation may also result in agency costs. Rational investors desire high risk adjusted returns, but treasurers may have a different objective. For example, Lakonishok, Shleifer, and Vishny (1992) argue that since the treasurer must answer to senior management in the event of poor fund performance, treasurers will allocate funds to managers who are likely to reduce their own job risk. Consistent with this hypothesis, Del Guercio and Tkac (2002) find that flow in the pension fund industry is strongly related to characteristics that can be justified ex-post to superiors such as low tracking error, the recommendations of external consultants, and personality attributes such as credibility and reputation. Del Guercio and Tkac (2002) find the negative relationship between tracking error and flow is most pronounced for pension funds with strong performance, suggesting that funds are punished for deviating from a benchmark even if it results in outperformance. In contrast, Del Guercio and Tkac (2002) find that flow in the mutual fund industry is unrelated to tracking error and is more strongly related to prior performance.[1]

The purpose of this paper is to empirically examine whether this additional layer of delegation found in the pension fund industry generates agency costs that impair pension fund performance. Specifically, I investigate whether the treasurer's emphasis on tracking error weakens pension fund performance by discouraging pension funds from deviating from their given benchmark. There are good theoretical reasons to expect this to be the case. Since fund manager compensation is typically tied to the size of the fund, rational fund managers will choose investment strategies that maximize the expected net asset value of the fund. Given this objective, pension fund managers have a natural incentive to perform well; both because high returns mechanically increase the size of the fund, and because net flows into the fund are positively related to prior performance. However, the findings of Del Guercio and Tkac (2002) also indicate that net flows into the fund are negatively related to tracking error. In fact, for pension fund managers outperforming the S&P 500, a 1% reduction in tracking error augments net flows by

[1] Several other papers document a strong relationship between mutual fund flow and prior performance. See, for example, Patel, Zeckhauser, and Hendricks (1991), Ippolito (1992), or Sirri and Tufano (1998).

roughly the same magnitude as a 1% increase in Jensen's alpha.[2] Thus, when making an investment decision, pension funds must weigh the benefits of higher expected returns with the costs of greater expected tracking error. My hypothesis predicts that, in certain cases, the costs of greater expected tracking error will exceed the benefit of higher expected returns, resulting in pension funds underweighting profitable investment opportunities.

This hypothesis yields several testable implications. First, pension funds will engage in less active management than mutual funds. Second, pension funds will tilt their trading towards stocks in their given benchmark, both in absolute terms and relative to mutual funds who are less constrained by tracking error. Pension funds' aversion to stocks outside of their benchmark will be particularly strong amongst the most volatile stocks. Pension funds will also be less aggressive in trading on short-term momentum, since this investment strategy generates significant deviations from benchmark weights. Most importantly, if pension fund managers have some stock selection skill, then these constraints likely impair pension fund performance.[3] For example, tracking error constraints may result in pension funds underweighting (relative to mutual funds) profitable investment opportunities in stocks outside of their benchmark. This suggests that the trades of pension funds will underperform the trades of mutual funds.

Using a proprietary dataset containing roughly 7 million executed trades by pension funds and 11 million executed trades by mutual funds; I find support for all the above hypotheses. To test whether pension funds tilt their trading towards stocks in their benchmark, I examine the trading of pension funds and mutual funds whose benchmark is likely to be the S&P 500. I choose the S&P 500 because it is the most prevalent benchmark for institutional investors.[4] Each

[2] Specifically, a 1% reduction in tracking leads to a $790.52 increase in net flows, while a 1% increase in Jensen's alpha results in a $781.37 increase.
[3] Tracking error constraints likely impair risk adjusted performance even if fund managers have no skill. Roll (1992) proves that optimal tracking error volatility portfolios (i.e. portfolios that maximize expected returns for given level of tracking error volatility) will not be mean variance efficient unless the benchmark is also mean variance efficient.
[4]http://www.russell.com/JP/PDF/Index/2006_Russell_US_Benchmark_Survey(E).pdf

month I compute the average fraction of a stock's market capitalization that is traded by pension funds and mutual funds (hereafter percentage traded). For every 1% traded in a non-S&P 500 stock, pension funds trade 1.68% in S&P 500 stocks, while mutual funds trade only 1.05% in S&P 500 stocks. Pension fund tilting towards S&P 500 stocks, both in absolute terms and relative to mutual funds, persists even after controlling for differences in size, liquidity, book-to-market, and measures of prudence such as a firm's age and credit rating (Del Guercio, (1996)). I also find that pension funds tend to avoid trading volatile stocks, while mutual funds prefer stocks with high volatility. Moreover, pension fund tilting towards S&P 500 stocks increases in stock price volatility, suggesting that pension funds are particularly averse to trading highly volatile non-S&P 500 stocks. Lastly, I find no significant relationship between pension fund net trading and prior returns, suggesting that pension funds do not implement short-term momentum strategies. In contrast, I find strong evidence that mutual funds engage in momentum trading.[5] Taken together, these findings suggest that tracking error concerns significantly impact the investment decisions of pension funds.

I next investigate how the differing investment strategies of pension funds and mutual funds influence their performance. Specifically, I examine the performance of stocks bought and sold by pension funds and mutual funds over holding periods ranging from 5 trading days to 240 trading days. Across all horizons, I find that the trades of pension funds underperform the trades of mutual funds. For example, the stocks bought by pension funds outperform (insignificantly) the stocks sold by pension funds by roughly 7 basis points over a 180 day holding period. In contrast, the stocks bought by mutual funds significantly outperform the stocks sold by mutual funds by 81 basis points over a 180 day holding period. In sum, the trades of mutual funds significantly outperform the trades of pension funds by roughly 74 basis points. However, some of this effect is driven by differences in momentum trading. The DGTW (Daniel, Grinblatt,

[5] Several other studies include Grinblatt, Titman, and Wermers (1995) and Badrinath and Wahal (2001) also document momentum trading by mutual funds.

Titman, and Wermers (1997)) adjusted performance differential drops to a statistically insignificant 45 basis points.

Next, I separately examine the performance of pension fund and mutual fund trades in S&P 500 and non-S&P 500 stocks. Consistent with non-S&P 500 stocks being less efficiently priced, I find that the trades made by both pension funds and mutual funds in non-S&P 500 stocks significantly outperform their trades in S&P 500 stocks. For example, the trades of pension funds in non-S&P 500 stocks earn DGTW-adjusted returns of roughly 98 basis points over 180 day horizons, while their trades in S&P 50 stocks lose 33 basis points. The difference of 131 basis points is highly significant. Moreover, pension funds' strong performance in non-S&P 500 stocks is not confined to the smallest stocks. If I limit my analysis to the largest 1000 stocks, I find that the trades of pension funds in non-S&P 500 stocks earn DGTW-adjusted returns of 175 basis points over 180 day horizons. These results suggest that tracking error constraints weaken pension fund performance by incentivizing pension funds to underweight profitable investment opportunities in stocks outside of their benchmark.

To assess the economic importance of this effect, I compute the hypothetical performance of pension funds under the assumption that pension funds traded non-S&P 500 stocks to the same extent as mutual funds. After accounting for transaction costs, I estimate that over a 180 day investment horizon, the hypothetical performance of the trades made by pension funds would earn a DGTW-adjusted return of 22 basis points, a statistically significant 27 basis points increase over their realized performance. Moreover, the standard error of the hypothetical portfolio would increase by only 4 basis points. Similarly, if mutual funds traded non-S&P 500 stocks to the same extent as pension funds, the performance of their trades would deteriorate by roughly 20 basis points.

The remainder of this paper is organized as follow. Section 2 discusses related literature. Section 3 describes the data and presents descriptive statistics. Section 4 investigates the investment decisions of pension funds and mutual funds. Section 5 examines the performance of pension funds and mutual funds. Section 6 concludes.

2. Related Literature

This paper contributes to the growing literature linking fund manager trading to their implicit incentives to increase assets under management. For example, prior research has found that the performance-flow relationship in the mutual fund industry is convex; investors reward winners much more strongly than they punish losers (see Ippolitio (1992) or Sirri and Tufano (1998)). Several papers have documented that mutual fund managers adapt their investment decisions in order to benefit from this convex performance-flow relationship. For example, Chevalier and Ellison (1997) find that mutual funds managers respond to their incentive to increase variance. Similarly, Carhart, Kaniel, Musto, and Reed (2002) find evidence that managers with the best performance inflate quarter-end portfolio prices with last minute purchases of stocks already held to improve their year-end ranking. This paper extends this literature by focusing on the potentially adverse incentives that follow from the performance flow relationship in the pension fund industry.

This paper also contributes to the debate over organizational structure and fund performance. Bauer and Frehen (2008), estimate that pension funds outperform mutual funds, after expenses, by roughly 200 basis points per year. They argue that pension funds have greater negotiating power and monitoring capacity which limits their exposure to hidden agency costs. However, Lakonishok, Shleifer, and Vishny (1992) analyze the returns of 769 pension plans over the period of 1983-1989 and find that these funds underperform the S&P 500 by roughly 260 basis points per year before fees and expenses. Lakonishok et al. (1992) note that the pension fund underperformance of 260 basis points is larger than the gross underperformance documented in the mutual fund literature and “cautiously conclude” that mutual funds have outperformed pension funds. They conjecture that the extra layer of agency costs in the pension fund industry may be driving pension fund under performance. However, performance differences can be driven by a variety of factors unrelated to organizational structure, such as fund manager skill. By documenting that tracking error constraints lead to pension funds underweighting profitable investment opportunities, I provide more direct evidence that organizational structure influences fund performance.

3. Data and Descriptive Statistics

3.1 Data

I obtain stock returns, share prices, dividend payments, number of shares outstanding, and turnover from CRSP. I obtain book value of equity, S&P credit ratings, and S&P 500 membership data from Compustat. I obtain data on institutional trading from Abel Noser Corp. Abel Noser is a consulting firm that helps institutional investors track and evaluate their transaction costs.[6] The data cover equity transactions by a large sample of institutional investors from January 1, 1999 to December 31, 2005. Private discussions with Abel Noser indicate that the database does not suffer from survivorship bias. Due to privacy concerns, the data does not include the actual names of the clients or fund-specific information such as total net assets value, fund holdings, fund age, expense ratio, etc. However there is an institution type variable that allows me to distinguish between money managers (e.g. Vanguard or Fidelity) and pension plan sponsors (e.g. CALPERS or United Airlines). Moreover, the data contain a client identifier that is unique to each fund family/plan sponsor and a manager code that corresponds to the different portfolio managers within the fund. Each executed trade also includes the date of execution, the stock traded, the number of shares trades, the execution price, and whether the execution was a buy or a sell.

An additional source for institutional trading is the Thomson (CDA/Spectrum S34) data. The data include the quarterly holdings of all fund families with greater than $100 million in equities. Portfolio holdings data begin in the first quarter of 1980 and end in the fourth quarter of

[6] Abel Noser data is similar to Plexus data, a competing transaction cost consulting firm. Plexus data has been used in several academic studies such as Keim and Madhavan (1995, 1996, and 1997). Studies that have analyzed Abel Noser data include Chemmanur,He, and Hu (2009) and Puckett and Yan (2008).

2007. Thus, relative to Abel Noser, the Thomson data include more fund families, span a longer horizon, and allow me to analyze the performance of fund holdings. However, the Thomson data have several limitations. First, pension fund data are only available at the fund family level. The quarterly holdings of a fund family (e.g. Calpers) represent a combination of the quarterly holdings of several fund managers with different benchmarks (e.g. The Calpers Large Cap Blend Fund, The Calpers Small Cap Value Fund, etc.). As a result, I cannot use Thomson data to examine whether fund managers tilt their trading toward stocks in their benchmark. In addition, trading can only be inferred from changes in quarterly holding. This is problematic for at least two reasons. First, changes in quarterly holdings do not reflect intra-quarter roundtrip trades (i.e. the purchase and sale of the same stock within the same quarter). Second, quarterly holdings data are not able to accurately identify the exact timing and execution price of a given trade. Given these limitations, most of my analysis relies on the Abel Noser data. However, when appropriate, I will also provide results using the Thomson data.

3.2 Expenses

Neither Abel Noser nor Thomson provides data on expense ratios. In contrast to mutual funds, pension funds do not have one expense ratio; instead expenses are determined through negotiations between the plan sponsor and the fund family, and depend heavily on the size of the mandate. As a result, analysis of pension fund performance is typically reported gross of expenses (e.g., Lakonishok, Shleifer, and Vishny (1992) and Busse, Goyal, and Wahil (2009)). Following this literature, I will compare the gross performance of pension funds and mutual funds. In doing so, a critical assumption is that the investment strategies chosen by pension funds generate similar expenses as the investment strategies chosen by mutual funds.

This assumption may seem unreasonable, particularly in light of previous studies that find pension funds tend to charge lower expenses than mutual funds. For example, French (2008) reports that the total expenses of pension funds in 2005 was roughly 30 basis points, while the total expenses of mutual funds was roughly 100 basis points.[7] However, this comparison is misleading because pension funds and mutual funds provide different services to their clients. Both pension funds and mutual funds provide portfolio management services such as research and security selection. However, mutual funds are also responsible for business and administrative expenses such as the preparation and filing of tax reports, the preparation of prospectuses and shareholder reports, a call center, and a staff to support such operations. Although pension fund beneficiaries also receive these services, they are typically provided internally by the pension plan's board of trustees, offices, and staff; not by the external money managers.

It is more appropriate to compare the expenses of pension funds to mutual fund subadvisors. Like external managers for pension plans, mutual fund subadvisors provide research and security selection, but are typically not responsible for other administrative expenses. The Investment Company Institute reports that the average expenses charged by pension funds was 28 basis points while the average expenses charged by subadvisors was 31 basis points.[8] This finding suggests that the cost of research and security selection is comparable for both pension funds and mutual funds.

3.3. Identifying the Benchmark

This study examines actively managed funds whose benchmark is likely to be the S&P 500. I focus on the S&P 500 because it is the dominant benchmark amongst institutional investors. For example, in 2002 (the midpoint of my sample), 1009 institutional investors with over $1.7 trillion in total assets reported the S&P 500 as their benchmark. The next most common benchmark was the Russell 2000 with 289 institutional investors and $198 billion in total assets.[9] I take the following steps to remove funds that are unlikely to be actively managed funds

[7] French (2008) defines total expenses as the expense ratio plus an annualized load, which measures the weighted average load paid by investors in mutual funds.
[8] See: http://www.ici.org/pdf/fm-v12n5.pdf
[9] http://www.russell.com/JP/PDF/Index/2006_Russell_US_Benchmark_Survey(E).pdf

benchmarked to the S&P 500. First, to remove passively managed funds, I exclude a fund if over 95% of the total dollar volume traded by the fund was in S&P 500 stocks. I also exclude a fund if less than 60% of its total dollar volume was traded in S&P 500 stocks. Since the S&P 500 typically represents over 70% of the value weighted market, funds unable to meet this restriction are unlikely to be benchmarked to the S&P 500. Lastly, I exclude funds that traded over 3000 different stocks in a given year, as these funds are likely to be broad market funds (e.g. Wilshire 5000 funds).

Table 1 presents descriptive statistics for the sub-sample of funds that are likely to be actively managed and benchmarked to the S&P 500. Panel A reports aggregate Abel Noser trading data. The data includes 2161 portfolio managers responsible for over 18 million executed trades and over $4.5 trillion in total volume. Table 1 also separately examines the trading of pension funds and mutual funds. The sample includes 1984 pension fund managers and 177 mutual fund managers.[10] Despite the fact that mutual funds represent only 8.2% of the total sample, they account for over 60% of all executed trades and over 65% of the total dollar volume traded in the sample.

Panel B further investigates the trading of pension funds and mutual funds by examining the cross-sectional distribution of fund manager trading each month. The reported coefficients are the time-series average of 84 monthly observations. The average (median) pension fund trades 40 (24) stocks a month while the average (median) mutual fund trades 183 (123) stocks in a given month. Similarly, the average pension fund executes 111 trades a month while the average mutual fund executes over 4,000 trades a month. Comparing the ratio of executed trades to stocks traded suggests that mutual funds break up their orders into smaller trades much more frequently than do pension funds. Nevertheless, mutual funds still tend to execute larger trades than do pension

[10] The likely explanation for the predominance of pension funds in the sample is that transaction cost analysis has traditionally been targeted at pension funds due to government mandates that required pension trustees to monitor the brokerage relationships of their external money managers. The use of transaction cost analysis, however, is growing in popularity amongst mutual funds. For more information see Anderson (2006).

funds ($445,000 vs. $330,000). The average mutual fund trades over $1 billion in a given month while the average pension fund trades $22 million.

Much of mutual fund trading seems to be driven by their very short holding periods. Monthly round trip trades (i.e. the purchase and sale or the sale and repurchase of the same stock in the same month) are a sizable fraction of all mutual fund trading. Roughly 25% (20%) of all trades made by the average (median) mutual fund are monthly round-trip trades. In contrast, roughly 4.0% (0%) of all trades made by the average (median) pension fund are monthly round trip trades. Some of this difference may be driven by liquidity motivated trading due to fund inflows and outflows. However, fund managers typically hold some of their assets in cash, so flow shocks that reverse themselves over short horizons (e.g. within the month) are unlikely to lead to significant trading. Thus differences in the monthly round trip trading of mutual funds and pension funds are not likely to be driven entirely by differences in liquidity based trading. One explanation for this difference is that mutual funds, who are less constrained by tracking error, are more aggressive in searching for transient mispricing. They actively trade on this mispricing and quickly reverse their position once the stock price has reverted back to its fundamental value. Consistent with this interpretation, I find that the intra-monthly roundtrip trades of mutual funds do earn significant abnormal returns.[11]

4. The Investment Decisions of Pension Funds and Mutual Funds

4.1 Measuring Active Management

In this section, I investigate the degree of active management amongst pension funds and mutual funds. If tracking error constraints influence the investment decisions of pension funds, then pension funds will be more reluctant than mutual funds to deviate from benchmark weights. To test this, I compute the “active share” for pension funds and mutual funds. Proposed by Cremers and Petajisto (2009), active share decomposes a portfolio into a 100% position in the

[11] Puckett and Yan (2009), who analyze the same dataset, also find that the intra-quarter roundtrip trades of mutual funds are highly profitable.

benchmark index plus a zero-net investment in a long-short portfolio. For example, a fund might have 100% invested in the S&P 500, plus 20% in active long positions and 20% in active short positions; resulting in an active share of 20%.

One complication is that my data does not include fund holdings, thus I cannot compute how a fund's holding deviate from benchmark weights. Instead, each month I compute a trading based active share. My active share measure is defined as follows:

$$Active\ Share = \frac{1}{2}\sum_{i}\left|\frac{DolBought_{i,t}}{\sum_i DolBought_{i,t}} - \frac{DolSold_{i,t}}{\sum_i DolSold_{i,t}}\right|$$

Where $DolBought_{\,i,t}$ $(DolSold_{i,t})$ is equal to the total dollar volume bought (sold) by pension funds or mutual funds in stock *i* during month *t* and $\sum_i DolBought_t$ $(\sum_i DolSold_t)$ equals the total dollar volume bought (sold) by pension funds or mutual funds across all stocks in month *t.*

To gain intuition for this measure, consider an index fund. If there were no index changes in month *t,* the trading of an index fund would be driven entirely by fund flows. When funds get inflows they will buy stocks in proportion to their index weight (e.g. 3% of inflows will be used to buy Microsoft) and when funds get outflows they will sell stocks in proportion to their index weight (e.g. 3% of redemptions will be covered by selling Microsoft). Thus the active share for this index fund would be zero. However, amongst actively managed funds, funds will buy and sell stocks in different proportions. For example, Microsoft may account for 4% of pension funds total buys and only 2% of pension funds total sells, resulting in an active long position of 2% in Microsoft. To measure the active management of pension funds and mutual funds over the course of one month, I simply take the sum of the absolute value of all positions. I divide by two to ensure that the active share does not exceed 100% (i.e. I do not count the long and the short side of the positions separately). Thus, active share measures the percentage of fund trading in a given month that generates active long-short positions.

Table 2 reports the time-series mean and standard deviation of the monthly estimates of active share based on the aggregate trading of pension funds and mutual funds. To account for serial correlation, I calculate the standard deviation of the mean using the Newey-West correction with 12 lags. Panel A reports the results for the full sample of stocks. The average active share amongst pension fund managers is 39.54%, while mutual funds managers have an active share of 48.19%. The difference of 8.65% is highly significant and suggests that mutual funds are more actively managed than pension funds. I also decompose the total active share into the active share due to trading S&P 500 and non-S&P 500 stocks. Mutual funds engage in significantly greater active management in both S&P 500 and non-S&P 500 stocks, although this effect is significantly greater in non-S&P 500 stocks.

One concern is that differences in mutual funds' active management amongst non-S&P 500 stocks is concentrated in very small stocks, perhaps because fiduciary responsibilities prohibit pension funds from trading smaller non-S&P 500 stocks (Del Guercio, (1996)). To address this concern, each month, I sort stocks into 4 groups based on the market capitalization at the beginning of the month. The first group (large stocks) consists of the 500 largest stocks; the second group (medium stocks) includes the next 500 largest stocks, the third group (small stocks) contains the next 2000 largest stocks, and the last group (microcaps) includes all remaining stocks (roughly 3500 stocks). Panels B through E reveal that mutual funds engage in significantly more active management amongst non-S&P 500 stocks across all four size groups.

4.2 Pension Fund and Mutual Fund Trading and Firm Characteristics

In this section, I use a regression approach to examine differences in the characteristics of the stocks traded by pension funds and mutual funds. The regressions use 3 dependent variables:

$$PF\_TILT_{i,t} = \frac{PF\_DOL\_VOL_{i,t}}{Marketcap_{i,t}} \Big/ \sum_i PF\_DOL\_VOL_{i,t} * 10^{10}$$

$$MF\_TILT_{i,t} = \frac{MF\_DOL\_VOL_{i,t}}{Marketcap_{i,t}} \Big/ \sum_i MF\_DOL\_VOL_{i,t} * 10^{10}$$

$$DIF_{i,t} = PF\_TILT_{i,t} - MF\_TILT_{i,t}$$

In words, $\frac{PF\_DOL\_VOL_{i,t}}{Marketcap_{i,t}}$ is the percentage of a stock's market capitalization traded (percent traded) by pension funds in a given month. Since the percent traded by pension funds in any given stock is highly correlated with the total trading activity of pension funds, I scale percent traded by the total dollar volume traded by pension funds in that given month. Multiplying by 10 billion is an arbitrary scaling factor that makes the coefficients and standard errors more readable. Thus, $PF\_TILT_{i,t}$ captures the percentage of a stock's market capitalization that would be traded by pension funds in a given month, if they traded \$10 billion dollars in that month. $MF\_TILT_{i,t}$ is defined analogously.

I examine the extent to which pension fund and mutual fund tilting is related to several firm characteristics. The variable of primary interest is SP, a dummy variable which equals one if the stock is a member of the S&P 500 index. Other variables include: VOL – total volatility measured as the standard deviation of monthly gross returns over the previous two years. MARKETCAP – market capitalization calculated as share price at the beginning of the month times total shares outstanding. BM – book-to-market ratio defined as book value for the fiscal year end before the most recent June 30 (taken from Compustat) divided by market capitalization on December 31st during that fiscal year. TURN – the average monthly turnover over the prior three months. PRC – defined as the share price at the beginning of the month. Age – firm age calculated as the number of month since first returns appear in CRSP. CR – a numerical proxy for a firm's credit rating, where a higher numerical score corresponds to a better credit rating. Each improvement in a credit score corresponds to a 1 point improvement, with scores ranging from 0 (not ranked) to 22 (AAA).[12] D/P – dividend yield calculated as the sum of all dividends over the prior year scaled by the average stock price over the prior year. DIV – a dummy variable which equals one if the stock pays a dividend. I use natural logs for all of the above variables

[12] NR signifies not ranked because of insufficient data. Thus NR is not intended to indicate a stock's quality. However, my use of credit scores is motivated by the findings of Del Guercio (1996) that banks and other institutions with fiduciary responsibilities tend to prefer stocks with high rating and avoid stocks that are unrated.

except for SP, CR, and DIV. I limit my analysis to largest 1000 firms in a given month. I exclude smaller stocks because they represent less than 20% of total trading but would account for over 85% of total observations; and would thus have an undue influence on regression estimates.[13]

Table 3 reports the regression coefficient and standard errors from monthly Fama-MacBeth (1973) regressions. The standard errors are adjusted for serial correlation by using Newey-West standard errors with 12 lags.[14] The results from the univariate regression (columns 1, 4, and 7) indicate that pension funds exhibit a strong preference for S&P 500 stocks while mutual funds have no significant preference for S&P 500 stocks. The coefficients suggest that for every $10 billion dollars traded, pension funds trade 6.88% of the average non-S&P 500 stock and 11.45% of the average S&P 500 stock. In contrast, mutual funds trade 9.80% of the average non-S&P 500 stock and 10.31% of the average S&P 500 stock. In other words, for every 1% traded in non-S&P 500 stocks, pension funds trade 1.68% in S&P 500 stocks, compared with only 1.05% for mutual funds.

These results are consistent with pension funds responding to their incentive to reduce tracking error by tilting their trading towards stocks in their benchmark. However, there are other plausible interpretations. Perhaps pension funds avoid trading non-S&P 500 stocks because these stocks tend to be more illiquid, and thus more costly to trade. Alternatively, differences in fiduciary responsibilities may explain pension funds' stronger preference for S&P 500 stocks. Moreover, if pension fund tilting towards S&P 500 stocks is motivated, at least in part, by tracking error concerns, then pension funds should be particularly reluctant to trade volatile non-S&P 500 stocks.

To explore these questions, I run the following Fama-MacBeth regression:

[13] Including all stocks significantly strengthens the central conclusion, that pension funds tilt their trading towards S&P 500 stocks to a greater extent than mutual funds.

[14] In unreported results, I've repeated the analysis using a panel regression with month dummy variables and standard errors clustered by firm. Results are very similar.

$$Tilt_{i,t} = B_0 + B_1SP_{i,t} + B_2VOL_{i,t} + B_3MARKETCAP_{i,t} + B_4BM_{i,t} + B_5TURN_{i,t} + B_6PRC_{i,t} + B_7AGE_{i,t} + B_8CR_{i,t} + B_9D/P_{i,t} + B_{10}DIV_{i,t} + \varepsilon_{i,t}$$

where "$Tilt_{i,t} =$ is either $PF\_TILT_{\boldsymbol{i,t}}$, $MF\_TILT_{\boldsymbol{i,t}}$, or $DIF\_TILT_{\boldsymbol{i,t}}$. The results of this regression are presented in columns 2,5, and 8. Columns 3,6, and 9 augment this reaction by including an interaction term between SP and VOL.

Several interesting findings emerge. First, pension funds do have a preference for liquidity (as measured by turnover); however even after controlling for liquidity pension funds still exhibit a strong preference for S&P 500 stocks. Moreover mutual funds appear to have a similar preference for liquidity, thus controlling for liquidity has no significant effect on pension funds' preference towards S&P 500 stocks relative to mutual funds. Second, both pension funds and mutual funds tend to tilt their trading away from large stocks. After controlling for mutual funds tendency to tilt their trading towards relatively smaller stocks, mutual funds do prefer S&P 500 stocks. However, pension funds still tilt their trading towards S&P 500 stocks to a significantly greater extent than mutual funds.

There is some evidence that differences in fiduciary responsibilities contribute to differences in the trading behavior of pension funds and mutual funds. Relative to mutual funds, pension funds show a strong preference for dividend paying stocks. However, both pension funds and mutual funds exhibit a similar aversion to stocks with high dividend yields. This result suggests that pension funds preference for dividend paying stocks is not driven by tax differences or risk preferences, but instead because non-dividend paying stocks are more likely to be viewed as imprudent investments.[15] However, pension funds do not exhibit a strong preference for older stocks or stocks with higher credit rating, two other measures that often proxy for prudence (Del Guercio, (1996)). Moreover, pension funds preference for S&P 500 stocks persists even after controlling for these measures of prudence.

[15] The Second Restatement of Trusts by the American Law Institute (1959) specifically cites dividend paying stocks as an example of a prudent investment.

Pension funds and mutual funds also have very different attitudes towards stock price volatility. Pension funds tend to tilt their trading away from volatile stocks while mutual funds have a strong preference for volatility. Since volatility stocks are often viewed as imprudent, pension funds' relative aversion to stock price volatility may also be driven by their greater fiduciary responsibilities. Alternatively, mutual funds' preference for volatility may stem from the performance-flow relationship in the mutual fund industry. Since investors tend to rewards big winners but fail to punish big losers, mutual funds have a natural incentive to take on volatility (Chevalier and Ellison, (1997)). In contrast, because the performance-flow relationship in the pension fund industry is essentially linear and because pension funds managers are punished for tracking error volatility, pension funds have an incentive to avoid volatile stocks (Del Guercio and Tkac (2004)). The results from columns 3,6, and 9 indicate that pension funds tilting towards S&P 500 stocks, both in absolute terms and relative to mutual funds, is positively related to a firm's volatility. In other words, pension funds are particularly averse to trading highly volatile non-S&P 500 stocks. Taken together, the findings of Table 3 suggest that tracking error constraints lead to pension funds underweighting their trading in non-S&P 500 stocks.

4.3 Momentum Trading

Tracking error constraints may also hinder pension funds' ability to exploit the well known momentum effect (Jegadeesh and Titman, (1993)). Since overweighting recent winners and underweighting recent losers can result in significant deviations from benchmark weights, pension funds likely underweight momentum strategies relative to mutual funds. To examine momentum trading by pension funds and mutual funds, each day I compute the value-weighted (by total dollar volume traded) gross return of all stocks bought and sold by pension funds and mutual funds over the prior 60, 120, and 240 trading days.

Table 4 reports the time-series average across all days. Standard errors are computed using the Newey-West correction with 60 lags. The prior returns of the stocks bought by pension funds are not significantly different from the prior returns on the stocks sold by pension funds.

This suggests that the investment decisions of pension funds are unrelated to prior performance. This is in sharp contrast to mutual funds who engage in significant momentum trading. For example, the stocks bought by mutual funds have outperformed the stocks sold by mutual funds by roughly 300 basis points over the prior 60 trading days. Moreover, the net trades of mutual funds (i.e. buys – sells) have earned significantly greater returns than the net trades of pension funds over the prior 60 and 120 trading days. This finding is consistent with the idea that tracking constraints result in pension funds underweighting profitable momentum strategies relative to mutual funds.

5. The Performance of Pension Funds and Mutual Funds

The results of the previous section suggests that the negative relationship between tracking error and fund flows in the pension fund industry does impact the investment decisions of pension funds managers. Specifically, relative to mutual funds, pension funds engage in less active management, tilt their trading towards stocks in their benchmark, and are less aggressive in trading on short-term momentum. In this section, I examine whether these differences in investment decisions lead to differences in performance

5.1 Total Performance

To assess pension fund and mutual fund performance, each day I compute the value-weighted (by total dollar volume traded) return of all stocks bought and sold by pension funds and mutual funds over the subsequent 5, 20, 60, 120, 180, and 240 trading days. The returns are computed using the actual execution price but do not include trading commissions. I eliminate all trades where the execution price reported by Abel Noser is outside of the daily high and low price reported by CRSP.[16]

Panel A of Table 5 reports the time-series average of the daily estimates of gross returns (i.e. non-risk adjusted returns). I use Newey-West standard errors in computing the t-statistics due

[16] The execution price reported by Abel Noser lies within the CRSP daily high and low price for roughly 99.9% of all trades. I've repeated the analysis including these .1% of trades under the assumption that the execution price was equal to the CRSP closing price, results are virtually identical.

to the serial correlation induced by overlapping periods.[17] The performance of pension fund trades (i.e. buys – sells) is insignificantly different from zero across all holding periods. In contrast, the stocks bought by mutual funds significantly outperform the stocks sold by mutual funds for all horizons except for the 240 day holding period. Mutual funds' performance over short horizons is particularly strong. For example, the stocks bought by mutual funds outperform the stocks sold by mutual funds by 55 basis points over holding periods of 20 trading days. The standard error of this portfolio is only 13 basis points indicating that mutual fund performance is greater than 4 standard errors away from zero. This estimate is not only statistically significant, but also economically important; this outperformance translates into an annualized outperformance of nearly 7%.

I next investigate whether pension fund underperformance is driven by differences in the characteristics of stocks traded by pension funds and mutual funds. For example, mutual funds may earn higher returns than pension funds simply because the engage in momentum trading to a significantly greater extent than pension fund. To examine this issue, I repeat the analysis above using DGTW-adjusted returns (Daniel, Grinblatt, Titman, and Wermers (1997). DGTW-benchmark portfolios are constructed by first sorting all stocks into quintiles based on market capitalization. Then within each size quintile, stocks are sorted into quintiles based on book-to-market ratio, resulting in 25 different portfolios. Within each portfolio, stocks are once again sorted into quintiles based on prior 12 month returns, resulting in 125 portfolios. Benchmark portfolio returns are then computed as the value-weighted holding period buy and hold return for each of these 125 portfolios.[18] The benchmark for each stock is the portfolio to which it belongs.

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[17] The number of lags used to compute the standard errors is equal to: max (60, 1 + holding period). I limit the number of lags to 60 trading days, because the returns on pension fund and mutual fund portfolios are serially uncorrelated for periods of greater than 60 trading days.

[18] For more details on the DGTW-benchmark construction procedure see DGTW (1997) or Wermers (2004) The DGTW benchmarks are available via http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm

The DGTW-adjusted return for each stock is the difference between the stock return and the benchmark portfolio return over a particular holding period.

Panel B of Table 5 reports the DGTW-adjusted performance of pension funds and mutual funds. The DGTW-adjusted performance of pension funds is similar to their gross performance. Pension fund performance is very close to zero, ranging from -8 basis points (240 days) to 4 basis points (20 days). In contrast, the DGTW-adjusted performance of mutual funds is always lower than their gross performance. For example, over a 20 day holding period, mutual fund performance falls from 55 basis points to 38 basis points. Over 180 day horizons, mutual funds performance declines from 81 basis points to 40 basis points.

To get a better sense for what accounts for the sizable difference between mutual funds' gross and DGTW-adjusted performance, I compute one-factor, three-factor, and four-factor alphas for the 20 day buy-sell portfolios of mutual funds and pension funds.[19] Specifically, I run a time-series regression where the dependent variable is the 20 day return on the portfolio of the stocks bought by pension funds (or mutual funds) less the return on the portfolio of stocks sold by pension funds (or mutual funds). The one-factor model uses the market factor (MKT-RF) as the only independent variable, the three-factor model includes the Fama and French (1993) factors (MKT-RF, SMB, and HML), and the four-factor model adds momentum (MKT-RF, SMB, HML, UMD).

The one-factor, three-factor, and four-factor alphas for the 20 day buy-sell mutual fund portfolios are 55, 51, and 43 basis points, all of which are statistically significant. Mutual funds do load positively on SMB and UMD, indicating that mutual funds are net buyers of small stocks and momentum stocks. The results suggest that the difference between mutual funds gross and DGTW-adjusted returns can be attributed in part to their tendency to be net buyers of small stocks, but is primarily driven by their aggressive momentum trading. The one-factor, three-factor, and four-factor alphas for the pension fund portfolios are 1, 3, and 2 basis points

[19] Factor loadings are similar for other holding periods.

respectively; none of which are statistically significant. Pension funds do have a significant negative loading on HML, but do not load significantly on UMD. Thus, pension funds' failure to implement momentum strategies contributes to their weaker gross performance relative to mutual funds.

Even after controlling for differences in characteristics, there is still some evidence that mutual funds outperform pension funds. Over holding periods of less than 20 days, mutual funds significantly outperform pension funds. Indeed, the trades of mutual funds outperform the trades of pension funds by more than 28 basis points over 5 day holding period, which is nearly 7 standard errors away from zero. To get a better sense for mutual funds short-term outperformance, I examine the performance of pension fund and mutual fund trades from execution price to close of trading (hereafter 1 day return). I find that the 1 day return of the stocks traded by pension funds earn 3 basis points while the 1 day return of stocks traded by mutual funds earn an impressive 20 basis points. These results suggest that difference in brokers and execution quality also contribute to mutual fund outperformance. However, even after controlling for differences in execution costs, mutual funds still exhibit short-term outperformance. If pension funds and mutual funds simply bought all stocks at the end of day closing price, mutual funds would still outperform pension funds by a statistically significant 9 basis points over the subsequent 5 trading days. Moreover, although mutual fund outperformance is no longer statistically significant over longer horizons, outperformance of more than 45 basis points over a 180 day holding period is not an economically trivial difference.

5.2 Performance in S&P and Non-S&P 500 Stocks

I next investigate the performance of pension funds and mutual funds in S&P 500 and non-S&P 500 stocks. Since non-S&P 500 stocks tend to be smaller stocks with less analyst coverage, it seems plausible that these stocks are less efficiently priced, and thus offer profitable investment opportunities to sophisticated investors such as pension funds and mutual funds. Moreover, if pension fund performance is significantly higher amongst non-S&P 500 stocks, then pension funds' tendency to underweight their trading in non-S&P 500 stocks is a factor that contributes to pension funds' underperformance relative to mutual funds.

Table 6 reports the net performance (i.e. buys – sells) of pension funds and mutual funds for the subset of non-S&P 500 and S&P 500 stocks for holding periods ranging from 5 to 240 trading days. Panel A reports the gross returns. The main finding is that over longer holding periods both pension funds and mutual funds have some skill in trading non-S&P 500 stocks. For example, over a 180 day holding period, the non-S&P 500 stocks bought by pension funds outperform the non-S&P 500 stocks sold by pension funds by over 130 basis points. Similarly, the non-S&P 500 stocks bought by mutual funds outperform the non-S&P 500 stocks sold by mutual funds by over 245 basis points. In sharp contrast, neither pension funds nor mutual funds exhibit any skill in trading S&P 500 stocks. Moreover, both pension fund and mutual funds' performance in non-S&P 500 stocks is significantly greater than their performance in S&P 500 stocks.

Panel B of Table 6 repeats the analysis using DGTW-adjusted returns. Over 180 day holding periods, pension fund and mutual fund performance fall slightly to 98 and 200 basis points, respectively. However, both estimates remain statistically and economically significant. In addition, pension fund and mutual fund performance in non-S&P 500 stocks remains significantly greater than their performance in S&P 500 stocks. The results suggest that non-S&P 500 stocks represent profitable investment opportunities for sophisticated investors. Thus, tracking error constraints that result in pension funds tilting their trading towards S&P 500 stocks have an adverse effect on pension fund performance.

One concern, however, is that the majority of pension fund and mutual fund outperformance in non-S&P 500 stocks occurs in very small and illiquid stocks. If so, it may be erroneous to conclude that pension funds could improve performance by taking larger positions, since there may be significant market impact associated with trading these very small stocks. To address this concern, Panel C of Table 6 reports the DGTW-adjusted performance amongst the subset of the largest 1000 stocks; thus this analysis excludes small stocks and microcap stocks. The results indicate that pension fund and mutual fund outperformance is actually stronger amongst the larger non-S&P 500 stocks. Over 180 day holding periods, pension fund and mutual fund performance increases to 175 and 271 basis points, respectively. Both estimates are greater than 2.5 standard errors away from zero.

5.3 Performance in Non-S&P 500 and S&P 500 stocks by Firm Characteristics

I next examine whether pension fund and mutual fund outperformance in non-S&P 500 stocks is related to other firm characteristics. Each month, I rank the largest 1000 firms (i.e. I continue to exclude small and microcap stocks) on the following firm characteristics (as previously defined in section 4.2): market cap, book-to-market, turnover, volatility, and age. I split stocks based on the median breakpoint. For example, the 500 stocks with the highest book to market are classified as value and the 500 stocks with the smallest book to market are classified as growth. Amongst each group (e.g. value and growth) stocks are further subdivided by S&P 500 membership.

Table 7 reports the DGTW-adjusted performance results for holding periods of 240 trading days for all firm characteristics. Across all firm characteristics, the trades of pension funds and mutual funds in non-S&P 500 stocks earn positive returns; although some estimates are not statistically significant. The strong performance of pension funds and mutual funds in non-S&P 500 stocks is concentrated in larger non-S&P 500 stocks. Pension fund and mutual fund outperformance in non-S&P 500 stocks is also statistically significant in growth stocks, high and low turnover stocks, volatile and non-volatile stocks, and younger stocks. The finding that pension fund strong performance in non-S&P 500 stocks is concentrated in larger stocks and is present in the most liquid stocks (as measured by turnover) suggests that pension funds could likely improve total performance if they took larger total positions in their non-S&P 500 trades.

5.4 Implied Performance

Just how much do pension funds lose by tilting their trading towards S&P 500 stocks? To answer this question, I compute the hypothetical performance of pension funds under the assumption that they traded non-S&P 500 stocks to the same extent as mutual funds. Thus the stocks traded and turnover remain identical for both pension funds and mutual funds, but the dollar volume traded in each stock is multiplied by a scaling factor. The scaling factor is determined from the coefficients of the following Fama-MacBeth regression: $Tilt_{i,t} = B_0 + B_1 SP_{i,t}$. As in Table 3, the regression is estimated for the subset of the largest 1000 stocks. I focus on the largest 1000 stocks because increasing the dollar volume traded in very small stocks is unlikely to be a feasible trading strategy given the significant price impact incurred when trading small stocks. The results of the panel regression indicate that for every 1% traded in non-S&P 500 stocks, pension funds (mutual funds) trade 1.68% (1.05%) in S&P 500 stocks. In other words, if pension funds and mutual funds had to allocate their trading to an S&P 500 and non-S&P 500 stock with equal market caps, pension funds would trade roughly 62.87% (1.68/2.68) in the S&P 500 stock while mutual funds would trade roughly 51.21% (1.05/2.05) in the S&P 500 stock. Thus, I scale PF dollar volume in S&P 500 stocks by 0.82 (51.21/62.87). Similarly, I scale PF dollar volume in large (i.e. stocks amongst the largest 1000) non-S&P 500 stocks by 1.31 ((100-51.21)/(100-62.87)). The dollar volume traded for small stocks remains unchanged. I also estimate how much mutual fund performance would deteriorate if they traded S&P 500 stocks to the same extent as pension funds. Using analogous reasoning, I scale MF dollar volume in S&P 500 (non-S&P 500) stocks by 1.22 (0.77).

Trading larger amounts in non-S&P 500 may result in additional price impact. Following Wermers (2000), I estimate execution costs using the Keim and Madhavan (1997) model. Specifically, my equation for estimating the total cost of executing a purchase of stock *i,* as a percentage of the total value of the trade, is

$C_i^B = 1.098 + 0.336D_i^{Nasdaq} + 0.092Trsize_i - 0.084Log(mcap_i) + 13.807(^1/_{P_i})$.

D_i^{Nasdaq} is a dummy variable that equals one if the stock is traded on the Nasdaq and zero otherwise. $Trsize_i$ is the total dollar volume of the trade scaled by the market capitalization of stock $i.Log(mcap_i)$ is the natural log of the market capitalization of the stock (expressed in $ thousands), and P_i is the stock price at the time of the trade. Similarly, my equation for estimating the total cost of executing a sale of stock *i,* as a percentage of the total value of the trade, is

$C_i^S = 0.979 + 0.058D_i^{Nasdaq} + 0.214Trsize_i - 0.059Log(mcap_i) + 6.537(^1/_{P_i})$.

I then compute the hypothetical execution cost of buys as:

$$EX\_Price^B = Price^{Abel} * \frac{1 + Ex\_Cost^{Hypothetical}}{1 + Ex\_Cost^{Actual}}$$

$Price^{Abel}$is the original execution price reported by Abel Noser, $Ex\_Cost^{Hypothetical}$ is the computed execution using the hypothetical dollar volume of the trade, and Ex_Cost^{Actual} is the computed execution cost using the actual dollar volume of the trade. Similarly, I compute the hypothetical execution costs of sells as

$$EX\_Price^S = Price^{Abel} * \frac{1 - Ex\_Cost^{Hypothetical}}{1 - Ex\_Cost^{Actual}}$$

Table 8 reports the DGTW-adjusted hypothetical returns of pension funds and mutual funds.[20] For reference, the actual returns (from Table 5) are also presented. If pension funds traded S&P 500 stocks to the same extent as mutual funds, the trades of pension funds would earn 22 basis points over a 180 day holding period. This is a statistically significant 27 basis point increase over their actual performance of -5 basis points. Not surprisingly, by loading more heavily on non-S&P 500 stocks, the standard error of the hypothetical portfolio does increase, but the magnitude of this increase is a relatively small 5 basis points. Similarly, if mutual funds traded S&P 500 stocks to the same degree as pension funds, the performance of mutual funds'

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[20] Using gross returns yields similar results.

trades would decline to roughly 20 basis points over a 180 day holding period. This represents a statistically significant 20 basis point reduction in performance. Moreover, the standard error of the portfolio would decline by only 7 basis points. These findings indicate that pension fund tilting towards S&P 500 stocks results in a significant reduction in the performance of their trades.

5.5. Thomson Data

In this section, I examine pension fund and mutual performance using quarterly holdings data provided by Thomson. The Thomson data include all fund families with greater than $100m in equity holdings and spans 28 years, from 1980 to 2007. Most importantly, the Thomson data allow me to compare the performance of the both the trades and the holdings of pension funds and mutual funds.

5.5.1 Thomson Trading Results

I first compare the performance of pension fund and mutual fund trades. I infer trading by computing changes in quarterly holdings. Each quarter, I compute the value-weighted (by total dollar volume trade) return of all stocks bought and sold by pension funds and mutual funds. I label the formation period (i.e. the period in which the trade occurred) as “Qtr 0”. I compute returns over the prior one and two quarters as well as the subsequent one and two quarters. For example, suppose during quarter 1 of 1980 (Q1 1980), pension funds bought 200 shares of IBM and sold 100 shares of Microsoft. “Qtr 0” would be the return of IBM in Q1 1980 less the return of Microsoft in Q1 1980. “Qtr 1” would be the return of IBM in Q2 1980 less the return of Microsoft in Q2 1980, and “Qtr 2” would be the return of IBM from the beginning of Q2 1980 to end of Q3 1980 less the return of Microsoft from the beginning of Q2 1980 to end of Q3 1980.

Panel A of Table 9 reports the gross returns of the net trading (i.e. buys – sells) of pension funds and mutual funds across the different holding periods. The Qtr -1 result indicates that pension funds do not engage in significant momentum trading. In contrast, the stocks bought by mutual funds outperformed the stocks sold by mutual funds by over 300 basis points over the prior quarter. These findings are consistent with the Abel Noser momentum trading results (see Table 4). The Qtr -2 results suggest that pension funds do tend to be momentum traders over the prior two quarters; however, mutual funds are still significantly greater momentum traders than pension funds.

The Qtr 0 results reveal an astounding difference between the trading of pension funds and mutual funds. During the formation period, the stocks bought by pension funds earn essentially the same return as the stocks sold by pension funds, while the stocks bought by mutual funds outperform the stocks sold by mutual funds by over 770 basis points. Interpreting this difference requires some speculation. If mutual fund trading occurred at the very end of the quarter, this would suggest that mutual funds are significant short-term momentum traders. On the other hand, if mutual funds trading occurred at the very beginning of the quarter, this would suggest that the stocks traded by mutual funds earn significantly positive returns over short horizons. Both of these results are consistent with the Abel Noser findings, and both likely contribute to the extreme differences in the Qtr 0 result.[21]

The stocks bought by pension funds do not significantly outperform the stocks sold by pension funds over the subsequent one or two quarters. However, the stocks bought by mutual funds outperform the stocks sold by mutual funds by about 92 basis points over the subsequent quarter and by 181 basis points over the subsequent two quarters. Moreover, the trades of mutual funds outperform the trades of pension funds by roughly 152 basis points over the subsequent two quarters. Panel B of Table 9 indicates that some of mutual fund outperformance is due to simply following momentum strategies. Over the subsequent two quarters the DGTW-adjusted performance of mutual fund trades drop to 103 basis points and their outperformance over pension funds drops to a statistically insignificant 115 basis points. The performance results using the Thomson trading data are highly consistent with the Abel Noser findings (see Table 5). The results provide confirmatory evidence that the trades of pension funds underperform the trades of

[21] Price pressure may also contribute to the significant formation period returns.

mutual funds and that pension funds' reluctance to implement profitable momentum strategies contributes to their underperformance.

5.5.2 Thomson Holding Results

While the above results indicate that the trades of pension funds significantly underperform the trades of mutual funds, it is not obvious how big of an impact trading differences have on the performance of total holdings. To assess the performance of pension fund and mutual fund holdings, I compute four measures of fund performance. The first is the total net asset weighted gross performance of pension fund and mutual fund holdings. I also compute three-factor alphas, four-factor alphas, and DGTW-adjusted returns.

Panel A of Table 10 reports the performance of holdings under the assumption that all trades were made at the very end of the quarter, while Panel B of Table 10 reports the performance of holdings under the assumption that all trades were made at the very beginning of the quarter. If you assume mutual fund trading occurs entirely at the end of the quarter (Panel A), then the holdings of mutual funds exhibit only modest outperformance. The three-factor alpha for mutual funds is about 18 basis points per quarter and mutual funds outperform pension funds by a statistically insignificant 12 basis points per quarter. Moreover, after controlling for momentum mutual funds exhibit no outperformance, both in absolute terms and relative to pension funds. On the other hand, if mutual fund trading occurs entirely at the beginning of the quarter (Panel B), then mutual funds exhibit substantial outperformance. Mutual funds earn a three-factor alpha of roughly 82 basis points per quarter. Controlling for momentum reduces mutual fund abnormal returns to between 32 and 53 basis points per quarter, both of which remain economically and statistically significant. Moreover, mutual funds outperform pension funds by about 75 basis points per quarter before controlling for momentum and by roughly 24 to 54 basis points after controlling for momentum.

Given that mutual funds tend to trade on short-term momentum, the assumption that mutual funds trade at the beginning of the quarter almost certainly overstates mutual fund performance. However, given the short-term performance results of mutual fund documented using the Abel Noser data, the assumption that mutual funds trade at the end of quarter almost certainly understates mutual fund performance. As a compromise, in unreported results, I also compute pension fund and mutual fund performance assuming that all trades were bought at the midpoint of the quarter. Under this assumption, I find that mutual funds outperform pension funds by roughly 40 basis points per quarter before controlling for momentum, and by about 13 to 25 basis points per quarter after controlling for momentum. All estimates are statistically significant and suggest that differences in the performance of trades do meaningfully impact the performance of total holdings.

6. Conclusion

In this paper, I argue that the treasurer's emphasis on tracking error distorts the investment decisions of pension funds and impairs pension fund performance. Consistent with this position, I find that relative to mutual funds, pension funds are less actively managed, tilt their trading towards stocks in their benchmark, and are less aggressive in implementing momentum strategies. Further, I show that the trades of pension funds significantly underperform the trades of mutual funds. Much of pension funds' relative underperformance can be explained by pension funds reluctance to implement momentum strategies and by their underweighting of profitable investment opportunities in non-S&P 500 stocks, despite a demonstrated ability to generate abnormal returns in these stocks. These results provide evidence that the additional layer of delegation found in the pension fund industry likely generates significant agency costs, and suggests that the current organizational structure of the pension fund industry may be suboptimal.

Second Essay: Understanding the S&P 500 Composition Effect: Evidence from Transaction Data

1. Introduction

Composition changes to the Standard and Poor's 500 Index have a substantial impact on stock prices. Stocks newly added to the S&P 500 rise 7.35% on average between announcement and the effective date, and stocks removed from the index fall by 7.56%. Several explanations have been offered for this phenomenon. Shleifer (1986) argues that index composition changes are information-free and suggests the price response reflects downward-sloping demand curves for stocks. Investors require beneficial prices to trade with passive index funds due to the lack of close investment substitutes. Harris and Gurel (1986) make a similar argument but suggest the effect is temporary. Short-run liquidity constraints lead to price pressure which they argue reverses in the weeks following the index change.

Other researchers suggest inclusion in the S&P 500 may influence a firm's fundamental value. Denis, McConnell, Ovtchinnikov, and Yu (2003) find evidence that stocks added to the index experience higher operating performance which they suggest may be explained by better monitoring due to increased visibility. In other work, Chen, Noronha, and Singal (2004) suggest index inclusion may add value by increasing investor recognition in the sense of Merton (1987). Specifically, index additions may improve breadth of ownership which would result in a lower required rate of return and higher prices for added firms. They conjecture the change in investor recognition should be stronger for index additions than deletions and find supporting evidence that index additions lead to more permanent price impacts than deletions.[22]

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[22] Work that supports either short- or long-term downward sloping demand curves includes Beneish and Whaley (1996), Lynch and Mendenhall (1997), Kaul, Mehrotra, and Morck (2000), Wurgler and Zhuravskaya (2002), and Greenwood (2005). Research that emphasizes changes to firm fundamentals following additions and deletions includes Goetzmann and Gary (1986), Dhillon and Johnson (1991), Elliot, Van Ness, Walker, and Warr (2006), and Cai (2007).

In this article, we shed new light on the S&P 500 index composition effect by studying the trades of index funds and retail investors around additions and deletions. The prevailing view holds that index funds adjust their portfolios on the effective date. Beneish and Whaley (1996) suggest indexers can enhance returns by trading during the announcement period, yet Blume and Edelen (2004) find the tracking errors associated with trading early are high relative to those observed in practice. On the other hand, Elton, Gruber, and Busse (2004) find no relation between tracking error and investor flows into index funds which suggests investors might support trading strategically around composition changes. Transaction level data allows us to investigate how index funds respond to the anticipated price pressure associated with index changes. We also examine how strategic trading by index funds influences the magnitude of the effective date price response.

Transaction data for retail investors also permits sharper inferences regarding investor recognition than in previous work. Chen, Noronha, and Singal (2004) examine the number of shareholders in the year around index changes and find a greater increase in shareholders for included stocks than for deleted stocks, which they attribute to increased investor recognition. Examining a similar variable in a multivariate setting, Elliott, Van Ness, Walker, and Warr (2006) conclude changes in investor recognition are the primary driver of the permanent inclusion effect.

However, studying the number of shareholders over longer horizons makes it difficult to assess the relation between breadth of ownership and returns. For example, Hvidkjaer (2006) finds that retail investors tend to be significant net buyers of stocks that have done well over the past 6 to 24 months. Thus, the strong past returns associated with index inclusion may be driving the increases in breadth of ownership rather than index membership per se.

Moreover, omitted factors such as improvements in liquidity or operating earnings may lead to both higher returns and the increase in breadth of ownership. For example, Denis, McConnell, Ovtchinnikov, and Yu (2003) find evidence that stocks added to the index experience improvements in forecasted earnings per share, and Hegde and McDermott (2003) find that added stocks experience a significant improvement in liquidity following inclusion. Analyzing the trades of retail investors in the days, weeks, and months following composition changes allows us to better understand the relation between inclusion returns and increased ownership. Specifically, the higher frequency data allows us examine whether changes in breadth of ownership are related to prior returns, or whether returns are related to past (or contemporaneous) changes in breadth of ownership.

Our analysis of 215 index additions and 87 deletions reveals a number of new and interesting results. We find index funds tend to trade newly added or deleted stocks beginning with the announcement of the composition change, and they do not fully establish their positions until weeks after the effective date. For example, of the $214 million traded on average by our sample of index funds in the period between the announcement and 5 days after the effective date, we find roughly 50% takes place before or after the effective date. Trading away from the effective date has a beneficial impact on performance. Using transaction prices, we calculate that trading strategically around the effective date saves index funds in our sample over $500 million relative to trading at the closing price on the effective date.

The decision to trade strategically around the effective date is largely driven by fund characteristics. Large index funds which demand the most liquidity are more likely to trade before and after the effective date. Moreover, once a fund instigates a plan to break up trades around the effective date it tends to continue the practice at future composition changes. At the stock level, we find that index funds are more likely to trade illiquid stocks before the effective date. After controlling for liquidity, index funds are more likely to trade larger stocks early. All the observed patterns are consistent with index funds responding to price pressure associated with index changes. Consistent with their efforts, we find the effective date price return has fallen by roughly half in recent years.

Our results also help clarify the effects of S&P 500 index inclusion on investor awareness. We find increases in the number of new households who buy both added and deleted stocks in the 4 weeks following composition changes which is consistent with attention-based trading (Barber and Odean, 2008), but inconsistent with the asymmetric predictions of the investor recognition hypothesis. Moreover, the fact that new households are buying both added and deleted stocks during which time the price impact differs suggests the permanent price effect for index additions may not be fully explained by the investor recognition hypothesis. Over longer horizons, 6 months to 12 months after the composition change, we find added stocks do experience greater increases in new household purchases than deleted stocks. However, after controlling for firm characteristics such as returns, earnings surprises, and changes in liquidity, we are able to explain more than half of the increase in new household buying which suggests much of the increase in breadth of ownership following inclusion is driven by changes to firm fundamentals.

We next regress the cumulative abnormal return from the announcement date to 60 days after the effective date on firm characteristics. In the cross-section, we find no relation between these inclusion returns and contemporaneous increases in breadth of ownership, but a relation does exist between inclusion returns and increases in breadth of ownership 6 to 12 months after the effective date. The results are consistent with new investors responding to the event period returns and the corresponding improvements in fundamentals rather than driving the price response. Taken together, our results cast doubt on the role of the investor recognition hypothesis in explaining the inclusion effect.

Our results add to the literature in two areas. First, we are among the first to examine the specific actions of index funds around index changes. Our findings indicate that index funds respond strategically to the price pressure associated with composition changes. They demonstrate a willingness to accept tracking error in exchange for better execution prices before and after index changes. Moreover, our results suggest that increased strategic trading by index funds has resulted in a smaller effective date price response. Second, our analysis of retail investor trading provides an opportunity to distinguish between improved investor recognition and other fundamental explanations for the inclusion effect. Our findings of a delayed investor response to inclusion suggests that anticipated and realized improvements in fundamentals are responsible for both the increase in breadth of ownership and the permanent abnormal returns associated with inclusion in the S&P 500.

The rest of the paper is organized as follows: Section 2 describes the sample. Section 3 presents evidence on stock returns following S&P composition changes and discusses potential explanations. Section 4 examines index trading around index changes and hypotheses related to price pressure. Section 5 examines retail investor trading and investigates hypotheses related to the investor awareness. Section 6 concludes.

2. Data and Descriptive Statistics

2.1 Transaction Data

The institutional transaction data is obtained from Abel Noser Corporation. Abel Noser is a consulting firm that helps institutional investors track and evaluate their transaction costs. Clients include pension plan sponsors such as CALPERS and retail money managers such as Fidelity. Pucket and Yan (2008) estimate that the Abel Noser trading accounts for roughly 8% of the total CRSP daily dollar volume. Hu (2008), Goldstein, Irvine, Kandel, and Wiener (2008), Chemmanur, He, and Hu (2009), and Lipson and Puckett (2007) also analyze data from Abel Noser.

The data contains a client identifier that is unique to each fund family and a manager code that corresponds to the different portfolio managers within the firm. The dataset captures all the trades for a portfolio manager in any given month, which allows us to infer which funds are S&P 500 index funds from the funds' trading behavior. We identify index funds by searching for portfolio managers that trade over 450 S&P 500 stocks in a month who also trade no more than 5% of stocks that were not members of the S&P 500. Portfolio managers that meet the criteria for a particular month are flagged as potential index funds. We then analyze the time-series behavior of the portfolio managers. If a manager's trades involve S&P 500 stocks over 95% of the time throughout the entire time series, then that portfolio manager is classified as an index fund.

One concern is that our criteria may include "enhanced" index funds that target the index but try to improve performance through active investing. In practice, it is very rare for active index funds to hold over 450 index stocks. For example, at the end of our sample period (December 2005) Morningstar lists 21 enhanced index funds with an S&P 500 benchmark. Of these 21 funds, only 3 specialty funds held enough S&P 500 stocks to meet our criteria (two of the funds were double-beta funds and the other followed an equal-weighted rather than value-weighted index). More importantly, the prospectuses of index funds are typically flexible enough to accommodate strategic trading around composition changes. Although they usually hold many more, most index funds constrain themselves to hold no more than 80% of the stocks in the index. Moreover, some index funds include language in their prospectus that specifically permits trading strategically around composition changes.[23] Thus, our results are unlikely to be driven by actively managed funds.

Table 11 provides summary statistics for the Abel Noser data. The sample begins January 1, 1999 and ends December 31, 2005. We were able to identify 56 S&P 500 index funds and 2562 other fund managers. On an average day, the non-index fund managers make over 50,000 trades and trade over 420 million shares representing approximately $127 billion worth of stock. Index funds accounts for nearly 2.7 million shares and over $100 million in volume per day.

The transaction data for individual investors is obtained from a large discount brokerage, and contains the holdings and trades for 78,000 households (158,034 accounts) from January 1991 to December 1996. Barber and Odean (2000, 2001), Graham and Kumar (2006), and Kumar

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[23] For example, the prospectus for the Allegiant S&P 500 Index contains the following language: "The Fund may purchase a security that is scheduled to be included in the S&P 500 Index prior to the effective inclusion date. The Fund may also temporarily continue to hold a security that has been deleted from the S&P 500 Index."

(2009) are among the studies that analyze the data. Our emphasis is on how changes to the S&P 500 index influences investor awareness, and we examine the number of households that purchase added and deleted stocks. Table 11 provides summary statistics for the sample of individual investors. Not surprisingly, individuals tend to make much smaller trades than institutions. The average dollar volume for individuals is $11,224, whereas the average dollar volume for non-index fund institutions $241,733.50.

2.2 S&P 500 Index Composition Changes

Composition changes to the S&P 500 Index are usually instigated by the need to remove a firm. Stocks may be deleted from the index because they represent an industry that is declining in importance, or if the stock itself is no longer representative of an important industry. Stocks may also be deleted for event-driven reasons such as mergers or bankruptcy. Additions are typically announced along with deletions to maintain 500 stocks in the index. In selecting which stock to add, Standard and Poor's considers the firm's industry along with firm-specific characteristics such as size, liquidity, and operating performance.

The data on S&P 500 Index composition changes is obtained from Jeff Wurgler's website and updated with information from Standard and Poor's website and Dow Jones Newswire for announcement dates. In recent years, Standard and Poor's has sought to announce composition changes several days before they become effective. In our sample, the mean (median) number of trading days between the announcement date and the effective date is 5 (4). There is variation, however, with some added stocks becoming effective on the announcement date and others with over 20 days between announcement and effective date.

The composition change sample matches the time period of the transaction data and begins with 306 index changes. We first eliminate 11 name changes that do not require trading. Next, since we are interested in index fund trading prior to the effective date, we eliminate 34 index changes where the difference between the announcement date and effective date is one day or less. As in Chen, Noronha, and Singal (2004), we also require return data in CRSP for at least 60 trading days before the event and 90 trading days after the event, which helps eliminate changes that do not require trading such as bankruptcies or mergers. Lastly, we remove stocks with price less than $5 at announcement date. After the filters, there are 215 additions and 87 deletions.

The sample is split into two periods: 1999-2005 corresponding to the transaction data for institutional investors, and 1991-1996 for the individual investor sample. The composition change sample includes 145 additions corresponding to the institutional trading data and 70 additions corresponding to the individual trading data. There are 46 and 41 deletions corresponding respectively to the institutional and individual trading data.

3. Stock Returns Following Index Composition Changes

We begin with an examination of abnormal stock returns around S&P 500 index composition changes. We compute abnormal returns by comparing each added or deleted stock to benchmark portfolios based on size and book-to-market.[24] Market capitalization is measured on the day prior to the announcement date and compared to the corresponding monthly NYSE breakpoints. Stocks above (below) the median breakpoint are classified as large (small). Book-to-market ratio is calculated using data from Compustat for the fiscal year prior to the composition change and compared to yearly NYSE breakpoints. Stocks in the lowest (highest) 3 deciles are considered growth (value), and stocks in the middle 4 deciles are considered neutral. The abnormal returns for added and deleted stocks are computed as the buy and hold raw return of the stock less the buy and hold value-weighted return of its corresponding size and book to market portfolio. Using equal-weighted benchmarks produces similar results.

[24] Data on decile breakpoints and the six benchmark portfolios is obtained from Ken French's website.

We calculate abnormal returns for a number of intervals around the event.[25] The results are reported in Table 12. The announcement date effect of 3.76% for additions and -4.02% for deletions is highly significant both economically and statistically. It is similar for both sample periods and roughly symmetric for additions and deletions. We also document significant abnormal returns between the announcement date and effective date (2.44% for additions and -1.72% for deletions). As suggested by Beneish and Whaley (1996), the gradual price response is consistent with risk arbitragers buying (selling) added (deleted) stocks between the announcement date and effective date in order to profitably reverse their position on the effective date when index funds demand liquidity. Price pressure from arbitragers moves prices, which suggests that part of the announcement to effective date return is due to either short-term or long-term downward sloping demand curves.

A new finding from Table 12 is the sizable decrease in the effective date return in the recent period. The effective date return for additions (deletions) is 2.13% (-3.01%) during the 1991-1996 sample period. However, this falls to 0.71% (-1.52%) during the 1999-2005 period. Multiplying returns for removed stocks by -1 and averaging across additions/deletions, we find a decrease of 1.56% across the sample periods with a t-statistic of 2.93. A reduced effective date return is consistent with index funds seeking out ways to mitigate the price pressure associated with index changes. Blume and Edelen (2004) suggest that indexers and counterparties such as hedge funds may pre-commit to trade at the closing price on the effective date, which would reduce the demand shock on the effective date. We investigate whether index funds transact at beneficial prices by trading before or after the effective date, and we examine whether the reduction in price impact corresponds to an increase in strategic trading on the part of index funds.

[25] Index composition changes are announced after the close of trading, and changes take place after the close of trading on the effective date.

Consistent with previous work, we find that additions and deletions experience price reversals after the effective date, and that the magnitude of the reversal is greater for deletions. In the full sample, the mean return for additions from the announcement date to 60 days after the effective date is 4.95% vs. -0.53% for deletions. Chen, Noronha, and Singal (2004) argue the asymmetric effect reflects changes in investor recognition for added stocks. On the other hand, added stocks may also experience improvements in fundamentals such as liquidity or the informational environment of the firm which could explain the permanent price response for added stocks.[26] In Section 4 we examine transaction data for individual investors to provide new insights regarding the investor recognition hypothesis, but first we analyze index fund trading behavior.

4. Index Fund Trading Around S&P 500 Index Composition Changes

The natural rebalancing strategy for index funds following composition changes is to buy added stocks and sell deleted stocks on the effective date near the closing price. This allows funds to closely track the index but likely produces high transactions costs due to price pressure. Wurgler and Zhuravskaya (2002) estimate that in 1996 index funds traded 8.4% of a stock's outstanding shares after an index change. Inducing investors to provide the liquidity necessary to rebalance their portfolios requires index funds to trade at inferior prices. Lynch and Mendenhall (1997) and Beneish and Whaley (1996) find evidence of increased trading volume between the announcement and effective dates, yet this could be driven by hedge funds and other arbitrageurs seeking to profit by the effective date response. We examine the specific trades of index funds to investigate whether they are willing to accept tracking error in an attempt to mitigate the effects

[26] If investors correctly anticipated that added stocks, but not deleted stocks, tend to experience either improved recognition or improved fundamentals, then this effect should be incorporated into the announcement date return, and the subsequent reversals, due to price pressure, should be of a comparable magnitude. The fact that the announcement date price effect is similar, and that additions have a smaller reversals, suggests that investors are responding to either improved recognition or improved fundamentals (or both) with some delay.

of price pressure. Specifically, we examine net trading for index funds and for other institutions around index changes.

Figure 1 plots the average percentage net buying of index funds for the 145 additions and 46 deletions in our sample. For each stock, percentage net buying is computed as the net share volume traded in a stock scaled by the stock's shares outstanding. Consistent with an emphasis on minimizing tracking error, index funds trade significant amounts of stock on the effective date. The index funds in our sample trade roughly 0.60% of a stock's market capitalization on the effective date. The average market capitalization of added (deleted) stock in our sample is roughly \$13.3 billion (\$6.7 billion). Thus index funds buy roughly \$80 million of added stocks and sell roughly \$40 million of deleted stocks on the effective date. Figure 1 also provides evidence that index funds trade around the effective data in an attempt to mitigate transaction costs. The plot reveals a gradual increase in net buying of added stocks from days -5 to -1, which suggests that index funds are buying added stocks before the effective date. Similarly, the gradual decline from day 1 through day 5 indicates that funds continue to buy added stock after the effective date. The net selling of deletions reveals a similar pattern. The results in Figure 1 provide evidence that index funds trade around the effective data in an attempt to mitigate transaction costs.

Table 13 provides more detailed results. The analysis splits trading into 3 periods: between the announcement date and effective date, the effective date, and 1 to 5 days after the effective date.[27] The table reports the percentage net trading (multiplied by 100) for both index funds and all other institutional investors in our sample. Panel A focuses on index additions. The table shows that index funds are substantial net buyers of added stocks before the effective date. Index funds in our sample buy 0.24% of an added stock before the effective date which corresponds to roughly one third of all trading between the announcement date and effective date.

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[27] The number of days between announcement and effective date varies. Thus, the periods in Table 3 do not correspond to specific days in Figure 1.

The last column reveals that index funds are significant net buyers of added stocks after the effective date as well (0.33%). Together, 50% of the purchases of added stocks made by index funds between the announcement and 5 days after the effective date take place either before or after the effective date.

Not surprisingly, the other institutions in our sample are significant net sellers of added stocks both between the announcement date and effective date and on the effective date. The net selling of institutions on the effective date is considerably smaller in magnitude than the net buying by index funds. This may be related to the fact that our sample is not the full universe of institutional traders, but individuals may also be providing liquidity to index funds around index changes (e.g. Kaniel, Saar, and Titman, 2008).

Panel B provides similar evidence for deletions. The results reveal that index funds are significant net sellers of deleted stocks both before and after the effective date. The net selling of deleted stocks by index funds is similar in magnitude to their net buying of added stocks during each period. For deletions, 25% of all index fund trading occurs before the effective date, 45% occurs on the effective date, and 30% occurs in the five days following the effective date. The percentages for additions are 21%, 50%, and 29%, respectively. Panel B shows other institutions do not provide sufficient liquidity to index funds for deleted stocks, which suggests the difference is coming from individual investors. We examine individual trading behavior in Table 18 and find supporting evidence.

One concern is that index funds purchasing added stocks after the effective date may reflect new investor flows into the fund rather than a delayed response to the event. We address this issue by comparing index fund purchases to a benchmark stock. We measure trading as a percentage of shares outstanding, thus any index stock could serve as a benchmark. We select the next largest stock in the index to help control for the stock's prominence in the index which may be relevant for tracking error. If a fund receives inflows, then to match the index they should trade the same percentage of the added stock as the benchmark stock.

Table 14 presents the net buying of added stocks, the net buying of the benchmark stock, and the difference in net buying. We extend the analysis to 120 trading days after the effective date to examine how long index funds take to fully establish their position. The table shows the delayed buying documented in Table 13 is not driven by fund flows. Controlling for fund flows over the five day period after the effective date actually increases average net buying (from 0.586% to 0.587%). Table 14 also reveals that abnormal buying extends well past 5 trading days after the effective date. Net buying is still highly significant 16 to 30 trading days and even 31 to 60 trading days after the effective date, which implies some index funds wait more than six weeks to fully rebalance their portfolios following index changes. The results from Figure 1 and Tables 13 and 14 provide convincing evidence that index funds trade around the effective date to reduce the effects of price pressure on transaction costs.

The return results in Table 12 show that effective date price responses have fallen in recent years. We examine whether this is consistent with an increase in strategic trading on the part of index funds by partitioning the index fund sample into the 1999-2000 and 2001-2005 periods which comprise 101 and 89 index recompositions, respectively. In untabluated results, we find in the early sample that 50.2% of trading that occurs between the announcement and 5 days after the effective date takes place on the effective date. In the later sample this number falls to 39.6%, and the difference is significant with a t-statistic of 2.32. Analogously, the effective date price response falls from 1.25% (t-stat 2.21) in the early period to 0.51% (t-stat 1.41) in the later period, however the difference is not reliably different from zero. Taken together, the evidence suggests that index funds are increasingly taking measures to reduce price pressure which is consistent with the statistically significant fall in the effective date price response between our earlier sample (1991-1996) and the latter sample (1999-2005).

We next examine how index funds' strategic trading impacts their investment performance. Specifically, for each trading day on or before the effective date, we compute abnormal returns as:

$$\left[\frac{(CP_{ED}-XP_t)}{XP_t}-\frac{(SP_{ED}-SP_t)}{SP_t}\right]I. \tag{1}$$

Similarly, for trading days after the effective date we compute abnormal returns as:

$$\left[\frac{(XP_t-CP_{ED})}{CP_{ED}}-\frac{(SP_t-SP_{ED})}{SP_{ED}}\right]I, \tag{2}$$

where CP_{ED} is the closing price for the added/deleted stock on the effective date, XP_t is the volume weighted average purchase/sale price on event day *t,* I is an indicator variable that is 1 (-1) for additions (deletions). and SP_{ED} and SP_t are the closing prices for the S&P 500 Index on the effective date and event date *t*.[28] We adjust for S&P 500 price movements based on the assumption that index funds raise the capital needed to buy added stocks by reducing their positions in their other holdings.[29] This measure gives us an abnormal return for each added or deleted stock on each event day it is traded. To create an aggregate abnormal return for early (or late) trading, we value weight the abnormal return on each event day by the total dollar volume traded on that day.

The results are presented in Table 15. In total, our sample of index funds trade \$5.0 billion between the announcement and effective date for additions, \$11.4 billion on the effective date, and an additional \$4.9 billion in the five days after the effective date. The numbers for deletions are an order of magnitude smaller due to the small sample of deletions and their lesser role in the value-weighted index (\$0.69, \$1.86 and \$0.50 billion).

For additions we find index funds save \$2.35 million per composition change with their pre-event trading and \$0.91 million from trading after the event, and both are highly statistically

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[28] Stocks prices are adjusted for various distributions (e.g. stock splits, dividends, etc.) so that comparisons can be made between event day and effective date prices.

[29] An alternative assumption would be to assume they raise the capital by selling the deleted stock. However, incorporating deletions is complicated by the fact that most deletions were the result of mergers, tender offers, bankruptcies, etc. Moreover, the typical deleted stock is significantly smaller than the typical added stock. This difference would be covered by index funds reducing their positions in other S&P 500 stocks.

significant. The corresponding numbers for deletions are \$0.35 million and 0.05 million, although neither is statistically different from zero. Larger firms weigh more heavily in the index, so they are likely to play a larger role in our dollar measures. We also calculate the percentage change in price relative to the effective date close, using the transaction-weighted price across funds but equal-weighting across additions/deletions. In percentage terms, index funds save 2.10% by trading added stocks early and 1.54% by trading added stocks late, and both are statistically different from zero at the 1% level. The results for deletions are 0.44% and 0.55%; neither estimate is statistically significant. The results in Table 15 indicate that strategic trading around composition changes can have a meaningful effect on fund performance.

Although we provide convincing evidence that index funds trade in strategic ways around index composition changes, we still observe that roughly 50% of index fund trading volume occurs on the effective date. One potential explanation is that index funds are reluctant to trade away from the effective date due to the increased tacking error associated with such strategies. We investigate this issue by examining the tradeoffs between beneficial transaction prices and tracking error volatility. Specifically, we consider the returns and tracking error volatility associated with several possible trading strategies, including buying added stocks the day after the announcement date, 1 day prior to the effective date, on the effective date, and 1, 5, 10, and 20 trading days following the effective date.

We compute abnormal returns associated with each trading strategy. For strategic trading before or on the effective date, abnormal returns are computed using equation 1; for trading after the effective date, abnormal returns are computed using equation 2. We scale the abnormal returns for each index addition by its weight in the S&P 500, which is measured as the market capitalization of the added stock on the announcement date divided by the market capitalization of the S&P 500. For example, if buying an added stock following the announcement date results in an abnormal return of 200 bps, and the stock represents 1% of the total market capitalization of the S&P 500, then the transaction would contribute two basis points to the funds' aggregate abnormal return. Summing across each index change in a given year provides an estimate of the impact of strategic trading on total fund performance.

Table 16 presents the results. On average, index funds are able to enhance their annual performance by 10.5 bps by trading the day after the announcement date. However, trading following the announcement does generate significant variation in returns. Across years, the variation in abnormal returns is 11.3 bps. Dividing the return improvement by the tracking error volatility indicates that this strategy produces an information ratio of 0.93. Alternative investment strategies, such as trading the day before or the day after the effective date result in significantly less outperformance (roughly 4 to 5 bps) but also generally less tracking error volatility. Trading entirely on the effective date generates an average savings of only 1.6 bps, however, the strategy also results in the smallest tracking error volatility, just 1.2 bps, and an information ratio of 1.30.[30]

The results suggest that the optimal trading strategy for index funds depends on how the funds weigh the benefits of higher expected returns with the costs of greater expected tracking error. The information ratio (abnormal return over tracking error volatility) is maximized by trading on the effective date, which may explain why roughly half of index fund trading takes place on the effective date. On the other hand, Elton, Gruber, and Busse (2005) find that index fund flows are significantly related to performance but are unrelated to tracking error volatility. Thus, if a fund manager is interested in maximizing assets under management; our evidence suggests the optimal strategy is to trade strategically around the effective date, and specifically on the date following the announcement.

4.1 Determinants of Strategic Trading by Index Funds

In this section we investigate cross-sectional variation in strategic trading around composition changes. Specifically, we estimate logit regressions for strategic trading on a number

[30] Information ratios in excess of one are rare. Goodwin (1998) analyzes 48 actively managed mutual funds benchmarked to the S&P 500 and finds that they have an average information ratio of 0.11 with a standard deviation of 0.37.

of stock and fund characteristics. The dependent variable is 1 if the fund engages in pre- or post-event trading and 0 otherwise. Pre-event trading is defined as trading between the announcement and effective date, and post-event trading is defined as having abnormal net buying as defined in Table 14.

We consider three fund-specific independent variables. Fund Volume is a proxy for the size of the fund and is measured as the total dollar volume for all stocks traded by the fund in the 21 trading days prior to the index change. After controlling for total volume, Trade Size, measured as the average dollar volume during the 21 days before the event, measures the fund's propensity to break up trades into smaller amounts to mitigate price pressure which may reflect a greater emphasis on reducing transaction costs. Finally, we hypothesize that funds may be persistent in strategic trading around composition changes and include a dummy variable, Lagged Strategic Trading, which is 1 if the index fund traded early or late for any previous composition changes and 0 otherwise.

In addition to fund characteristics, we analyze several stock characteristics. We conjecture that price pressure may be a greater concern for less liquid stocks and large stocks, which play a more prominent role in the value-weighted index. We include Amihud's (2002) measure of illiquidity computed over the 21 trading days prior to the announcement date and the natural log of stock market capitalization the day prior to the announcement date. We also include an NYSE dummy variable to control for the fact that specialist markets may be better than dealer markets at mitigating the price effects of a demand shock (Elliot and Warr, 2003).

Wurgler and Zhuravskaya (2002) find that stocks with fewer available substitutes have larger abnormal returns after being added to the index. We examine whether substitutability influences index fund trading behavior using Wurgler and Zhuravskaya's (2002) A1 arbitrage risk proxy, which is calculated as the root mean squared error from a market model regression using daily data over the 270 to 20 days prior to the announcement date (using their A2 measure produces similar results). Lastly, we include the announcement date abnormal return which may measure anticipated price pressure related to the event.

The logit regression results are presented in Table 17, where standard errors for the Z-scores are clustered by fund.[31] Unconditionally, of the 2279 fund/addition observations 44.67% involve strategic trading. The results in Table 17 indicate that fund characteristics help explain variation in strategic trading around index composition changes. Large funds are more likely to trade strategically. The coefficient on Fund Volume is positive and significant; interpreting the marginal effect at the average level of the independent variables suggests an additional $1 billion dollars of fund trading over the previous month increases its likelihood of trading strategically by 65%. After controlling for total fund volume, funds that trade in smaller average amounts are significantly more likely to trade strategically, which is consistent with a greater emphasis on reducing price pressure and a lower concern for tracking error. Also, funds that have previously traded strategically are significantly more likely (28%) to continue doing so. The results suggest certain funds emphasize minimizing tracking error while others consistently take actions to mitigate the price pressure associated with index changes.

At the stock level, funds are significantly more likely to trade illiquid stocks strategically. After controlling for liquidity, funds more often trade large stocks strategically, consistent with their more prominent role in the index. When we examine fund-level and stock-specific variables separately, the results show the majority of the explanatory power comes from fund-specific variables. The regression on fund variables alone has a pseudo R^2 of 20.69%, whereas for stock-specific variables the pseudo R^2 is 9.25% (both specifications include year dummies). Including both fund-specific variables and stock-specific variables raises the pseudo R^2 slightly to 21.95.

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[31] We include year dummies to capture any time trend. To conserve space the coefficients on the intercept and year dummies are not reported in the table. However, the year dummies confirm the pattern of increasing strategic trading discussed in the previous section. Using 2002 as the omitted year, the year coefficients for 1999 through 2005 are -0.27, -0.36, omitted, 0.39, 0.60, 1.62, and 1.66. The last two coefficients are statistically significant with t-statistics of 3.63 and 3.99.

In untabulated findings, we find similar results for the smaller sample of index deletions. Of the 492 fund/deletion observations, 62% involve strategic trading. The sign and magnitude of the coefficients are similar to those in Table 17, but the general level of statistical significance is lower. For example, at the fund level, lagged strategic trading and total fund volume remain positive and highly significant, while trade size remains negative but is no longer significantly different from zero. At the stock level, market cap and announcement date return remain positive and significant, however illiquidity is no longer significantly positive.

Taken together, the results in this section support the hypothesis that index fund trading around the effective date is driven by price pressure concerns. However, price pressure alone is not able to explain all of the return patterns documented in Table 12. For example, price pressure predicts a symmetric response for additions and deletions, yet Table 12 reveals that part of the inclusion effect for additions is permanent while the inclusion effect for deletions fully reverses. One possibility is that changes to the index have an asymmetric effect on investor recognition. We next explore this hypothesis.

5. The Effects of S&P 500 Index Composition Changes on Investor Recognition

In an analytical survey of the index composition effect, Elliott, et al. (2006) concludes changes in investor recognition are the primary driver of the permanent inclusion effect. Their analysis follows Chen, Noronha, and Singal (2004), which examines changes in breadth of ownership by comparing the number of shareholders before the announcement to the number of shareholders no less than nine months after the effective date. Both studies find a significant increase in breadth of ownership for added stocks but no increase for deleted stocks. They interpret this evidence as consistent with the Merton (1987) investor recognition hypothesis which predicts that an increase in the breadth of ownership will reduce the firm's required rate of return, causing a contemporaneous price increase consistent with the inclusion effect.

The investor recognition hypothesis stems from Merton (1987) which develops a model where investors are only aware of a subset of available securities and trade stocks within this subset. Chen, Noronha, and Singal (2004) hypothesize that being added to the S&P 500 index alerts more investors to its existence and consequently results in an increased breath of ownership. On the other hand, investors do not become similarly unaware of stocks deleted from the index, thus the investor recognition hypothesis predicts an asymmetric effect for household buying in added and deleted stocks.

However, the evidence presented in previous work regarding index inclusion and breadth of ownership is consistent with alternative interpretations. First, differences in the breadth of ownership measured over relatively long horizons as in Chen, Noronha, and Singal (2004) may be confounded by changes to firm fundamentals following index inclusion. For example, improvements in operating performance (Denis et al., 2003) or liquidity (Hegde and McDermott, 2003) could lead to both the increases in breadth of ownership and the abnormal returns associated with S&P 500 inclusion. More generally, the strong returns associated with index inclusion may themselves cause increased ownership rather than the other way around.

We focus on individual investors in our analysis, who are more likely than institutions to be influenced by the search costs associated with the investor recognition hypothesis. By analyzing the number of new individual shareholders in the days, weeks, and months following composition changes we are able to better determine the causal relationship between changes in breadth ownership and abnormal returns. If index inclusion itself improves investor awareness, we may expect increases in breadth of ownership to begin relatively quickly and gradually build after the index change. However, if retail investors are reacting to improvements in fundamentals and/or strong past returns, then the increase in breadth of ownership may occur primarily over longer horizons. For example, Hvidkjaer (2006) finds that retail investors are contrarian traders over short horizons (the past 3 months) and momentum traders over longer horizons (6 to 24 months), which suggests that much of the increase in breadth of ownership may occur more than 120 trading days after the announcement date.

We use the number of new unique households buying a stock as a proxy for investor awareness. We focus on new households; since investors are presumable aware of stocks they already hold. To be considered a new household, the household must have never traded or held the stock before the period being analyzed. Focusing on the number of new distinct households that purchase the stock provides a better proxy for awareness than trade-based metrics such as the total dollars bought or the number of buys which could be influenced by a small number of investors.

We define percentage abnormal buying as the number of new households who purchase stock after the announcement date less the number of new households who purchase the stock during the same interval before the announcement scaled by the number of households who owned the stock prior to interval before the announcement. We consider three separate intervals following the index recomposition. The short-term analysis examines trading 1 to 20 days before and after the announcement, and we analogously examine periods 21-120 and 121-240 days before and after the announcement. The data includes index changes where the firm being added or deleted has CRSP daily data for the pre- and post-event period. Individual transaction data also needs to be available for the period under consideration.[32]

5.1 Benchmarking Procedure

We consider changes in investor awareness relative to several benchmarks. Our first comparison is with all other stocks (i.e. non-index change stocks) that were held by at least three retail investors at the time of the announcement. We also compare new household purchases to matching stocks based on size and book-to-market. We identify all stocks that lie within 70% and 130% of the index change stock's market capitalization at the time of the announcement.

[32] The analysis is symmetric around the announcement date so we relax our earlier filter regarding the number of trading days between the announcement date and effective date.

Amongst these stocks, we select the firm whose book-to-market ratio is closest to that of the added (or deleted) stocks to be the matching firm.

In addition, we create benchmarks based on firm fundamentals. Specifically, we match based on improvements in operating performance, liquidity, and recent stock returns. We compute changes in operating performance using analysts' forecasts from I/B/E/S similar to Denis et al. (2003). Specifically, we examine the change in the median analyst forecast for one year ahead earnings per share around index composition changes. The pre-event (post-event) median forecast is calculated using analysts' estimates issued closest to the announcement date that were made no earlier (later) than 80 trading days prior to (after) the announcement.[33]

For each added or deleted stock, we compute a benchmark which includes all companies in the I/B/E/S database for which we can calculate a median EPS forecast for the pre- and post-announcement periods. For our sample of 45 added firms with earnings data, we find that the average added firm experiences a percentage increase in EPS forecast of 0.46% (t-stat = 0.31) after being added to the index. However, the benchmark portfolio experiences an average percentage decline in EPS forecasts of -3.81% (t-stat -5.63). The difference between added stocks and the benchmark, 4.27%, is highly significant. These findings are consistent with Denis et al. (2003) who show that relative to benchmark companies; newly included stocks experience significant increases in EPS forecasts. For our sample of 19 deleted firms, we find that the average deleted firm experiences a decline in EPS forecast of -3.31% which is insignificantly different from the benchmark portfolio.

We also examine changes in liquidity. We compute liquidity using the Amihud (2002) illiquidity measure. For each index change, we define the pre-announcement illiquidity measure as the average daily illiquidity over the 80 trading days prior the announcement date. Similarly, the post-announcement illiquidity is computed as the average daily illiquidity measure over the

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[33] The same subset of analysts are used both before and after the event. See Denis et al. (2003) for more details.

80 days subsequent to the announcement date. We compute the percentage change in illiquidity as the difference divided by the average level of illiquidity.

For our sample of 65 added stocks, we find that the average change in illiquidity is -21.1% (t-statistic -7.75) suggesting a significant improvement in liquidity (i.e. decline in illiquidity). The average control firm experiences a change in illiquidity of -1.6% (t-statistic -1.45). The difference between added stocks and the benchmark is -19.5% (t-statistic -7.50). In contrast, for our sample of 37 deleted firms we find that the average change in illiquidity is 8.1% (t-statistic 1.38), and the difference between deleted stocks and their benchmark is 7.1% (t-statistic = 1.21). The results above confirm that added stocks experience significant increases in expected operating performance and liquidity while deleted stocks do not.

We next investigate whether this asymmetry in fundamentals is driving the asymmetry in breadth of ownership. To do this, we place all added/deleted stocks into a portfolio based on percentage change in operating performance and percentage change in liquidity.[34] First, we split all companies in the I/B/E/S database with requisite data into three groups based on the percentage change in EPS forecast. We then split each percentage change EPS forecast group into 3 groups based on percentage change in illiquidity. This results in 9 total benchmark portfolios.

Our last control is based on the absolute returns of a stock between the announcement date and the effective date. Barber and Odean (2008) document attention-based trading among retail investors and show that extreme returns leads to abnormal buying among retail investors. Matching based on absolute event returns controls for the phenomenon that some investors may trade based on the event return without being aware of why prices moved. Specifically, we further split the 9 EPS/liquidity portfolios into groups based on the absolute event return; resulting in 27 total portfolios. The percentage change in abnormal buying for each benchmark

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[34] Sorting based on the change in EPS and change in liquidity (as opposed to percentage change) yields similar results.

portfolio is the average percentage change in abnormal buying for each stock in the benchmark, excluding the index change stock.

5.2 New Household Purchases Following Index Composition Changes

Table 18 presents the results for new household purchases for added/deleted firms and the benchmark portfolios. In the 20 trading days after the announcement, both added and deleted stocks experience a significant increase in new household purchases (15% for additions and 13% for deletions). The changes are of similar magnitude and generally remain significant after controlling for the various benchmarks. The symmetric increase in buying for both added and deleted stocks in the short-term is consistent with attention-based trading as in Barber and Odean (2008). For example, news regarding recently added stocks may draw the attention of growth or momentum investors, whereas news of index deletion may attract value or contrarian investors. However, the symmetric response is not consistent with the investor recognition hypothesis driving the inclusion effect, which argues that being added to the index increases investor awareness, whereas being deleted from the index does not similarly reduce investor awareness.

Over longer horizons, added stocks do experience a greater increase in household buying than deleted stocks. Newly included stocks experience a 152% increase in new household buying in the 240 trading days after index recomposition, compared to a statistically insignificant 28% for removed stocks. However, much of the increase for added stocks can be explained by firm characteristics. Controlling for size and book-to-market reduces the increase to 129%. Controlling for operational performance and changes in liquidity reduces the number to 86%, and further controlling for announcement period returns reduces the number to 65%, which is not reliably different from zero. The fact that simple firm controls are able to explain more than half of the increase in new household purchases for added stocks suggests that the increase in investor awareness following index composition changes may be related changes in firm fundamentals.

Chen, Noronha, and Singal (2004) find that the cumulative abnormal return from the announcement date to 60 days after the effective date is negatively related to a proxy for Merton's (1987) investor recognition shadow cost. They further note that the change in the number of shareholders is the main reason for the relationship between shadow cost and abnormal returns. They interpret these findings as evidence consistent with the investor recognition hypothesis. Our results cast doubt on the conclusion that the permanent price impact following index inclusion is driven by the investor recognition hypothesis. First, the majority of household buying occurs more than 120 days after the effective date. The increase in abnormal purchasing is 1.2% for days 21-120 vs. 54.6% for days 121-240, although the difference is not statistically significant. The 6-month delay in investor response to index addition suggest suggests that changes in fundamentals may be driving both the increase in investor awareness and the permanent abnormal return of added stocks. For example, Denis et al. (2003) find improvements in analyst forecasts of operating performance as well as positive earnings surprises (relative to control firms) for included stocks in the year of addition and the following year.[35]

We further explore this hypothesis using regressions similar to Chen et al. (2004). The dependent variable captures the permanent effect of inclusion and is measured as the cumulative abnormal return for an added stock from the announcement date to 60 days after the effective date. We regress inclusion returns on the percentage increase in new household buying over the contemporaneous period as well as longer horizons. If the inclusion effect is driven by changes in breadth of ownership as suggested by previous work, then we would expect a positive relation between contemporaneous changes in breadth of ownership and abnormal returns. If, on the other hand, new investors are responding to the announcement returns themselves or realized improvements in firm fundamentals, then we would expect the relation to occur with a delay. For

[35] The fact that operating performance improves within the current fiscal year of the inclusion makes it difficult to fully explain by improvements in monitoring, which would likely take longer to have an effect. One potential explanation is that customers of the firm perceive index membership as a signal of quality which leads to greater revenues. Alternatively it is possible that the Standard and Poor's has superior analytical ability, and chooses to add companies with stronger future prospects.

example, Hvidkjaer (2006) finds that retail investors are contrarian traders over short horizons (the past 3 months) and momentum traders over longer horizons (6 to 24 months), in which case event period abnormal returns should be positively related to changes in ownership measured over longer horizons.

We also include the number of retail shareholders before the event to help control for any level effects. As in Chen et al. (2004), we include relative size and a NYSE dummy variable. Moreover, to help control for the informational environment of the firm, we include the number of analysts who cover the stock, based on the idea that analysts serve a monitoring role (e.g. Chung and Jo, 1996 and Moyer, Chatfield, and Sisneros, 1989). Finally, to control for improvements in fundamentals we include the change in liquidity, measured as the difference in share turnover between the 60 days before and after the announcement, and the number of analysts who cover the firm.[36] T-statistics are computed using heteroskedasticity-robust standard errors.

Table 19 reports the results of the regression for each independent variable separately as well as the multivariate regression that includes all the independent variables. The first four columns confirm our conjecture. Abnormal returns over the 60 days after the announcement are insignificantly related to the increase in household buying in days 1-60 or 61-120 after the announcement, but returns are significantly related to new purchases 121-240 days after the announcement with an R-squared of 15.2%. The fact that changes in breadth of ownership is related to event period returns yet only after a considerable lag suggests that investors may be reacting to the returns themselves or the improvements in fundamentals that take place after inclusion rather than driving the inclusion effect.[37]

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[36] Using dollar volume or the Amihud illiquidity measure produces similar results.

[37] It is possible that event period returns anticipate later improvements in investor awareness, but the fact that there is no contemporaneous relation suggests investors are responding to prior returns rather than the other way around.

The last column includes additional controls. The relation between returns and new household buying 6 to 12 months after inclusion remains. Moreover, we find a statistically positive relation between contemporaneous changes in liquidity and abnormal returns which is consistent with part of the inclusion effect being related to improvements in liquidity. In addition, the coefficient on number of analysts is significantly negative, which provides indirect evidence that firms experience improvements in monitoring following inclusion. Firms with higher analyst coverage are arguably better monitored, so they respond less to inclusion.[38] Taken together, our evidence supports the view that the permanent part of the inclusion effect is driven primarily by improvements in fundamentals which in turn leads to increases in breadth of ownership.

6. Conclusion

S&P 500 index composition changes have a large effect on the prices of added and deleted stocks. Previous research suggests the effect may be related to downward-sloping demand curves, while others argue that index inclusion has a material effect on the fundamentals of the firm. In this study, we examine the transactions of index funds and individual investors to shed light on the effects of index composition changes on stock prices.

We find convincing evidence that index funds trade strategically around composition changes. Index funds purchase added stocks and sell deleted stocks beginning with the announcement and do not fully establish their positions until weeks after the effective date. Large index funds are more likely to trade strategically, and strategic trading is also more evident for large, illiquid stocks. The results suggest index funds react to the anticipated price pressure associated with composition changes. Consistent with strategic trading by index funds, we find the effective date price return for included stocks is no longer significantly different from zero in recent years.

[38] We also examine improvements in operating performance as measured by the change in analysts' forecasts of EPS. The regression coefficient is not statistically significant, and requiring that firms be covered by sell-side analysts reduces the sample size and diminishes the statistical significance of the other regressors (the coefficients themselves remain similar in sign and magnitude).

Index fund trading around the effective date suggests part of the announcement price effect is driven by the price pressure hypothesis of Harris and Gurel (1986). However, price pressure due to short-term downward sloping demand curves is not able to explain the asymmetric response for additions and deletions. Chen, Noronha, and Singal (2004) show added stocks experience a more permanent price response than deleted stocks, which they attribute to the investor recognition hypothesis. On the other hand, the asymmetric price response could also be related to changes in firm fundamentals. For example, Denis, McConnell, Ovtchinnikov, and Yu (2003) find evidence that stocks added to the index experience higher operating performance which they argue may be explained by better monitoring. Our analysis of individual investor trading in the weeks and months following composition changes helps clarify the effects of index inclusion on investor awareness.

We find the number of new households that purchase the stock increases for both added and deleted stocks in the month after composition changes, which is consistent with attention-based trading but inconsistent with the asymmetric predictions of the investor recognition hypothesis. Over longer horizons, new household purchases are greater for added stocks, but this result appears largely driven by improvements in liquidity and operating performance following inclusion. In the cross-section, we find no relation between the event period returns of added stocks and short-term increases in breadth of ownership, but a relation does exist over longer horizons. The results suggest new investors are responding to the information contained in index membership, rather than causing the inclusion effect. Taken together, the pattern of individual investor purchases suggests that improvements in fundamentals, rather than changes in investor recognition, are the primary force behind both the increase in breadth of ownership and the permanent abnormal returns associated with inclusion in the S&P 500.

Third Essay: Retail Investor Industry Herding

1. Introduction

There is growing evidence that investors often group stocks into categories or "styles" based on shared commonalities. For example, Barberis, Shleifer and Wurgler (2005) find that stocks added to the S&P 500 index begin to covary more with other members of the index, and Greenwood (2008) provides similar evidence for the Nikkei 225. Similarly, Green and Hwang (2008) document that stocks that undergo stock splits experience an increase in comovement with low-priced stocks and a decrease in comovement with high-priced stocks. These results are consistent with investors categorizing stocks based on index membership and price. Another potentially important category is industry. For example, Microsoft, Google, and Yahoo are often categorized as "technology stocks", while Merck, Pfizer, and Eli Lilly are often grouped together as "pharmaceutical stocks". Moreover, industry-wide categories appear important enough to merit institutional investors offering sector oriented mutual funds such as "Vanguard Utilities" or "Fidelity Wireless Portfolio".

If investors categorize stocks by industry membership, then their investment decisions will have an industry-wide component. This implies that industry-level reallocations should occur with greater intensity than reallocations across stocks grouped randomly. There are at least two reasons to expect that these industry-level reallocations will be particularly strong amongst retail investors. First, retail investors tend to have more limited resources than institutional investors. Thus, retail investors seem more susceptible to simplifying complex investment decisions by categorizing stocks by industry. Indeed, processing information on 50 different industries is far less time consuming than processing information on thousands of different stocks. Second, prior research has found strong evidence that the trading of retail investors is systematically correlated (see e.g. Kumar and Lee (2006), and Barber, Odean, and Zhu (2009b)).[39] Thus, if retail investors do categorize stocks by industry, it seems likely that the industry-wide investment decisions of individuals will aggregate into large industry-wide demand shocks.

In this paper, we explore three main questions about retail investor industry herding. First, do retail investors herd across industries? Second, how does retail investor industry herding impact industry-level prices? Third, to what extent is the poor performance of retail investor trading driven by their industry-wide investment decisions?

To answer these questions, we calculate the proportion of all trades in an industry that are buys (industry proportion bought) using the Trade and Quotes (TAQ) and Institute for the Study of Security Markets (ISSM) transaction data over the period of 1983-2000. We find strong and persistent herding by small traders (hereafter retail investors) at the industry-level. For example, the cross-sectional correlation between small trade proportion bought in week t and week $t+1$ averages over 60%. Moreover, retail investor industry herding is highly persistent. The cross-sectional correlation between industry-level proportion bought at week t and week t+52 averages 16%. In addition, we show that industry herding is distinct from firm-level herding and persists even after controlling for herding into stocks with similar market capitalizations and book-to-market ratios. Consistent with the style investing model of Barberis and Shleifer (2003), we find that retail investors tend to chase industries that have performed well over the past two years. In fact, prior industry returns can forecast retail investor firm-level proportion bought, even after controlling for prior firm-level returns.

Next, we examine the impact of retail investor industry herding on industry prices. The Barberis and Shleifer (2003) style investing model posits that style-level demand is not entirely

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[39] Prior research has also found that institutional investor trading is correlated; however the magnitude of retail investor herding is generally much larger than institutional herding. For example, Lakonishok, Shleifer, and Vishny (1992) report a herding measure of 2.7% amongst pension funds and Grinblatt, Titman, and Wermers (1995) report a herding measure of 2.5% amongst mutual funds managers. In constrast, Barber, Odean, and Zhu (2008b) find that herding ranges from 6.8% amongst retail investors at a discount brokerage and 12.8% amongst retail investors at a full service brokerage.

driven by fundamentals. The model predicts that style-level demand will push prices away from fundamentals in the short run and lead to long-term reversals. However, other models theorize that herding is driven by investors receiving correlated signals about fundamentals. (e.g Froot, Scharfstein, and Stein (1992) or Hirshleifer, Subrahmanyam, and Titman (1994)).[40] These models argue that herding simply reflects the process in which value-relevant information is impounded into prices. Thus these models do not predict long-run reversals.

We find that weekly retail investor industry proportion bought positively forecasts industry returns over the subsequent week. We also find that retail investor industry proportion bought over the prior quarter (6 months or year) negatively forecast industry returns over the subsequent quarter (6 months or year). A portfolio that went short the value-weighted quintile of industries most heavily bought over the prior quarter and went long the value-weighted quintile of industries most heavily sold would earn an average five-factor alpha of 41 basis points per month over the subsequent quarter. These results support the style investing model of Barberis and Shleifer (2003) and are inconsistent with rational explanations of industry herding.

Barber, Odean, and Zhu (2009) and Hvidkjaer (2008) find that small trade proportion bought also forecasts firm-level returns. Stocks heavily bought by retail investors, measured over the past year, significantly underperform stocks heavily sold by retail investors. To assess the extent to which the poor performance of retail investor trading is driven by industry-wide sentiment, we decompose retail investor performance into a firm-specific component and an industry-wide component. Our results indicate that industry selection is responsible for roughly 60% of the poor performance documented by Barber, Odean, and Zhu (2009) and Hvidkjaer (2008). Moreover, after controlling for industry selection, we find that the stock picking ability of retail investors is not significantly different from zero. The results suggest that industry sentiment explains a significant portion of the poor performance of retail trades.

[40] These models were designed to explain herding into specific stocks, not industries. However, it is equally plausible that investors can receive correlated signals about value-relevant industry information.

Lastly, we compare our findings of small trade industry herding with the results based on large trade ("institutional") industry herding. Consistent with prior work on institutional industry herding (e.g. Choi and Sias (2008) and Froot and Teo (2008)), we find statistically significant evidence of industry herding by institutions. However, the magnitude of institutional industry herding is roughly half the magnitude of retail investor industry herding. Moreover, we find no significant relationship between institutional industry proportion bought and longer-horizon industry returns.

This paper contributes to the growing empirical literature on style investing. To our knowledge, this is the first paper that examines the industry-wide investment decisions of retail investors. Kumar (2009) finds that retail investors herd into similar size and book-to-market styles and finds some evidence of style-level momentum. We show that even after controlling for size and book-to-market, retail investors herd at the industry level. Moreover, we are able to document both style-level momentum at weekly horizons, and style-level reversals at quarterly to yearly horizons. Choi and Sias (2008) and Froot and Teo (2008) examine industry herding, but focus exclusively on institutional investors. We show that relative to institutions, retail investors exhibit significantly greater industry herding and have a substantially different impact on industry prices. Our comparison suggests that industry herding by retail investors is more motivated by sentiment, while institutional industry herding is more motivated by informational reasons.

This paper also adds to the literature that investigates the relationship between investor sentiment and subsequent returns. Baker and Wurgler (2006) show that when economy wide sentiment is high, subsequent returns for stocks that are difficult to value (i.e. small stocks, growth stocks, young stocks, etc) are low. Similarly, Hvidkjaer (2008) and Barber, Odean, and Zhu (2009) find that when sentiment is high for a specific stock, subsequent returns for that stock are low. We extend this literature by documenting that when sentiment for an industry is high, subsequent returns for that industry are low. Moreover, our results suggest that firm-specific sentiment is driven largely by industry-wide sentiment.

The remainder of this paper is organized as follows. Section 2 discusses the data and presents descriptive statistics. Section 3 examines whether investors herd at the industry level. Section 4 investigates the relationship between industry proportion bought and subsequent industry returns. Section 5 decomposes the poor performance of retail investors into an industry-component and firm-specific component. Section 6 concludes.

2. Data

The data for this study come from several sources. We obtain data on returns, market capitalization, and industry classifications (SIC codes) from the Center for Research and Security Prices (CRSP). We obtain book value of equity form Compustat. We include all ordinary shares (CRSP share code 10 or 11) with adequate data. We assign each stock to one of 49 Fama and French (1997) industries.[41] Lastly, we obtain transaction data from the Institute for the Studies of Securities Market (ISSM) and the Trade and Quote database (TAQ). The ISSM dataset includes all transactions made on the NYSE and AMEX from 1983-1992 and covers NASDAQ stocks from 1987-1992. TAQ data includes all transactions from 1993 to present.

The data do not specify whether the executed trade was a buy or sell. We use the Lee and Ready (1991) algorithm to classify trades as either buyer or seller initiated. Specifically, if a trade is executed above (below) the quoted midpoint, the trade is classified as a buy (sell). If the trade is executed at the quoted midpoint, the executed trade price is compared to the preceding trade; the trade is considered a buy (sell) if the executed price was above (below) the last executed trade price. Thus all trades are classified as either a buy or a sell.

The data do not distinguish between trades made by retail investors and institutional investors. Instead, we use trade size as a proxy for individual and institutional trading. Following Barber, Odean, and Zhu (2009), trades less than $5,000 (small trades) are used to proxy for retail investor trading. Trades greater than $50,000 (large trades) are used to proxy for

[41] We use the updated industry definitions available on Ken French's website.

institutional investors.[42] Barber, Odean, and Zhu (2009) provide evidence that small trade order imbalance is positively correlated with order imbalance of retail investors at a large discount broker and a large retail full-service broker. Moreover, large trade order imbalance is negatively correlated with order imbalance from both the large discount and large retail broker, suggesting that trade size is a reasonable proxy for investor type. However, Hvidkjaer (2008) finds that many of the patterns associated with small trades disappear after 2000, presumably because it became more common for institutions to break up large orders into smaller trades after the introduction of decimalization in 2001. Consequently, this paper limits its analysis to data from 1983-2000.

In each week (month or year), from January 1983 to December 2000, for each industry, we calculate the industry proportion bought amongst retail and institutional investors. We define industry proportion bought as the number of buyer initiated trades in a given industry divided by the number of total trades in that industry. Results are very similar if we value weight each trade by the dollar volume traded.

Table 20 provides the time-series mean of cross-sectional monthly descriptive statistics. Panel A presents industry statistics. The average industry includes 98 firms, with the minimum industry containing only 5 firms and the maximum industry containing over 500 firms. The largest industry represents, on average, 10.78% of the market portfolio, while the smallest industry account for 0.08% of the market portfolio. The largest stock in an industry typically accounts for a substantial percentage of the industry's total valuation. Specifically, the largest firm accounts for roughly 30% of the average industry's market capitalization.

Panel B provides descriptive statistics on retail investor and institutional investor trading across industries. In the average industry, retail investors execute over 58,000 trades, although this ranges from 321,243 trades in the most heavily traded industries to 3,278 in the least heavily traded industries. Institutional investors execute roughly 48,000 trades in the average industry.

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[42] Hereafter, we will use the term "small trader" and "retail investor" synonymously. Similarly, we will use the term "large trader" and "institutional investor" interchangeably.

Industry proportion bought exhibits substantial cross-sectional variation. Retail investors are net buyers 65% of the time in their most favored industries and only 37% of the time in their least favored industries. Similarly, institutional investor industry proportion bought ranges from 60% to 43%. The fact that retail investor industry proportion bought has a greater cross-sectional standard deviation than institutional investor industry proportion bought is consistent with our conjecture that industry herding is likely to be stronger amongst retail investors.

One concern is that retail and institutional investor trading are simple complements. Since all non-institutional investors are retail investors, and since every trade is both a buy and a sell, it seems to follow that if retail investors are herding into an industry, institutions must be herding out of the same industry. To examine this, we calculate the correlation between retail investor and institutional investor industry proportion bought. We find that the time-series average of monthly cross-sectional correlations is -0.03. This indicates that small and large trade industry order imbalances are not simple complements.

There are at least two explanations for the relatively low negative correlation between small and large trade industry proportion bought. First, our measure of small and large trade proportion bought only considers active trading through market orders. Thus passive traders who provide liquidity, either as market makers or though limit orders, are not included. This distinction is important, because a sizeable fraction of retail investor trading is done through limit orders.[43] We believe that active trades are a better measure of investor sentiment than limit orders, because whether a limit order is executed depends on the actions of others. For example, suppose retail investors have no strong belief about the technology sector and submit an equal amount of buy and sell limit orders. If institutional investors become bullish on the technology sector, then the sell limit orders of retail investors will be executed, while the buy limit orders

[43] Linnainmaa (2010), using discount brokerage data from October 2004 to September 2005, finds that limit orders account for roughly 70% of all orders placed by retail investors.

will not. In this case, the heavy sell order imbalance of retail investors simply reflects the preferences of institutional investors.[44]

The second reason our results are not complementary is because our small trading measure is meant to capture the trading of small retail investors, rather than all non-institutional investors. For example, our small trading measure is probably not very representative of the trades of very wealthy individuals. These individuals make up a sizeable portion of non-institutional trading. Wolff (2004) reports that the wealthiest 1% of households are responsible for over one-third of all US household ownership in stocks. Moreover, recent empirical evidence suggests that the trading behavior of these wealthy individuals is motivated by different considerations than the small retail traders who are the focus of this study. For example, Koirnoitis and Kumar (2010) finds that the trading behavior of retail investors with high cognitive ability (which they find is highly correlated with wealth) tends to be more motivated by information reasons, while the trading behavior of retail investors with low cognitive ability is more motivated by psychological biases.

3. Tests for industry herding

3.1 Do Investors Herd Across Industries?

In this section we examine whether the industry-wide trading of retail investors and institutional investors is systematically correlated. We first examine contemporaneous correlations. Each month we compute the proportion bought in each industry. We then calculate the Lakonishok, Shleifer, and Vishny (1992) herding measure. Let pb_{it} be equal to the proportion bought in industry *i* in month *t* and let $E[pb_{it}]$ be the expected proportion bought in month *t*. The herding measure for industry *i* in month *t* is computed as follows:

$$H_{it} = |pb_{it} - E[pb_{it}]| - E\left|[pb_{it} - E[pb_{it}]]\right|$$

[44] Consistent with this reasoning, Linnainmaa (2010) finds that the use of limit orders significantly alters inferences about individuals trading intentions and investment abilities.

The first term measures the difference between the proportion bought in industry i and the average proportion bought across all industries. Since the difference is an absolute value, the first term will always be non-negative. The second term in this equation is the expected value of this herding measure under the null hypothesis of no herding.[45] In essence, this equation, examines whether the realized industry proportion bought is "fat-tailed" relative to the expected industry proportion bought under the null of no industry herding.

Each month we calculate this industry herding measure for both retail and institutional investors. We average the herding measure across all 49 industries and then we take the time-series average. We find that the average industry herding measure amongst retail investors is 4.01%, while the average industry herding amongst institutional investors is 2.09%. Both measures are significantly greater than zero (p-value < .001). To get a sense of the economic importance of this effect, the 4.01% herding measure implies that if the average proportion bought was 50%, then in the average industry, 54.01% of retail trades would be on one side of the market (e.g. buying), while the remaining 45.99% of retail trades volume would be on the other side of the market (e.g. selling).

An alternative measure of herding, proposed by Sias (2004), is to examine the cross-sectional correlation between the proportion bought in period t and period $t+1$.This measure allows us to examine the persistence of investor's industry-wide preferences. Specifically, we examine the cross-sectional correlation between retail investor (institutional) industry proportion bought in week t and retail investor (institutional) industry proportion bought in week $t + x$, where x ranges from 1 week to 104 weeks. Figure 2 reports the time-series average of the cross-sectional correlations across all time periods. The correlation between retail investor industry demand this week and the prior week is over 60%. This correlation gradually declines to roughly 45% after four weeks, 34% after 12 weeks, 16% after 52 weeks, and 8% after 104 weeks. All

[45] Since pb_{it} follows a binomial distribution, the expected value of this measure can be computed for any given average proportion bought (i.e. the probability of success) and the number of trades.

estimates are significantly greater than zero.[46] Thus retail investor industry trading is not only contemporaneously correlated but also highly persistent. Moreover, across all horizons, the cross-sectional correlation between retail industry herding is typically 2 to 3 times as large as the cross-sectional correlation of institutional industry herding.

3.2 Is Industry Herding Driven by Stock Herding or Size and Book-to-Market Herding?

Table 20 indicates that, on average, the largest firm in an industry accounts for roughly 30% of the industry's market capitalization and roughly 27.5% of retail investors total trades. Thus, one concern is that our industry-level results are being driven by investors herding into the largest stock in the industry. An additional concern is that industry herding may be due to the fact that stocks in the same industries tend to have similar characteristics such as size and book-to-market ratios. For example, technology stocks tend to be growth oriented, while utility stocks tend to be value stocks. Teo and Woo (2004) and Kumar (2009) provide evidence that investors tend to categorize stocks based on size and book-to-market. Thus, it is worth examining whether industry herding persists after controlling for firm-level herding and herding into stocks with similar size and book-to-market ratios.

To examine this issue, we run Fama-Macbeth regressions where the dependent variable is the proportion bought in stock *i* in week t. We then include three independent variables. The first is the proportion bought in stock *i* in week *t-x*. This variable captures industry herding that is due to firm-level herding. We then assign all other stocks in the same industry to one of six size and book-to-market styles based on the Fama and French (1993) methodology. The second variable is the average industry proportion bought amongst stocks in the same industry and size and book-to-market styles in week *t-x*. The third variable is the average industry proportion bought amongst stocks in the same industry but in a different size and book-to-market style in week *t-x*. Thus, this

[46] Standard errors are computed from the time-series average. We find that the estimates are significantly serially correlated for the first few lags but that this correlation declines quickly. For example, at one lag, the serial correlation is 0.36, but this declines to 0.09 at lag 6. To adjust for this serial correlation, we use Newey-West standard errors with six lags. Using additional lags does not significantly alter the standard errors.

last variable reflects industry herding that is distinct from firm-level herding and size and book-to-market style herding.

Panel A of Table 21 reports the time-series average of the cross-sectional estimates for retail investors. The t-statistics are computed using the Newey-West (1987) correction.[47] The first column reports results based on the proportion bought over the prior week. Retail investor demand for a stock this week is strongly related to their demand for the stock last week. A 10% increase in the proportion bought of a stock in the prior week will increase the expected proportion bought of the stock by 2.8% in the following week. Retail investor demand for a stock this week is also related to their demand for stocks with similar size and book-to-market styles in the same industry. However, even after controlling for these effects, we see that retail investor demand for a stock is strongly related to its demand for other stocks in the same industry with different size and book-to-market styles. The second, third, and fourth column indicates that retail investor demand for a stock is positively related to their industry-wide demand measures over the prior 2 months, 6 months, or a year. The results indicate that industry herding is distinct from firm-level herding and size and book-to-market style herding and provide further evidence that retail investor industry herding is highly persistent.

Panel B of Table 21 repeats the analysis for institutional investors. Like retail investors, institutional investors demand for a stock is positively related to their demand for the stock in the prior week, along with their demand for other stocks in the same industry in the prior week. However, the relationship is weaker amongst institutional investors. The adjusted R^2 from the institutional regressions is roughly half the adjusted R^2 from the retail investor regressions. Moreover, the coefficients for institutional investors are always less than half the magnitude of those for retail investors. Institutional investor industry herding is also less persistent. There is no

[47] Unless otherwise specified, Newey-West standard errors are computed using six lags. Using more than six lags does not significantly alter the standard errors in Table 2.

significant relationship between institutional demand for a stock and its demands for other stocks with in the same industry over the past 6 months to 1 year.

3.3 Prior Returns and Industry Proportion Bought

The previous results establish that retail investors have strong and persistent preferences for certain industries. The style investing model of Barberis and Shleifer (2003) posits that these preferences may be related to prior returns. Specifically, Barberis and Shliefer (2003) model an economy in which there are fundamental traders and "switchers". These switchers move their wealth out of poorly performing styles and into styles that have performed well. This implies that industry proportion bought will be positively related to past industry returns. To examine this implication, each month, from January 1983 to December 2000, we run the following cross-sectional regression:

$$IND\_PB_{it} = a_o + b_1 IndSize_{it} + b_2 IndBM_{it} + b_3 IndRet_{it-1} + b_4 IndRet_{it-3,t-2} + b_5 IndRet_{it-6,t-3} + b_6 IndRet_{it-12,t-7} + b_7 IndRet_{it-24,t-12} + b_8 Ind\_PB_{it-1} + b_9 Ind\_PB_{it-3,t-2} + b_{10} Ind\_PB_{it-6,t-3} + b_{11} Ind\_PB_{it-12,t-7} + b_{12} Ind\_PB_{it-24,t-12}$$

The dependent variable is the industry proportion bought. The independent variables include IndSize and IndBM which are equal to the industry average size and the industry average book-to-market ratio (both in natural logs). We then include several measures of prior industry returns, ranging from the prior one month return to the return over the prior 12 to 24 months. In addition, we include lagged levels of industry proportion bought.

Panel A of Table 22 reports the time-series average of the cross-sectional results. Standard errors are computed using the Newey-West correction. The first column of panel A reports the results for retail investors. Industry proportion bought is negatively related to industry returns over the prior 3 months. This suggests that retail investors do not immediately withdraw assets from poorly performing styles and invest in recent winning styles. However, industry proportion bought is positively related to prior industry returns over the past 4 to 6 months, 7 to

12 months, and 13 to 24 months. The impact of prior industry returns on industry proportion bought is both statistically and economically significant. For example, a 10% increase in the industry return over the prior 13 to 24 months would increase the industry proportion bought by 6.5%. We also examine whether prior industry returns can forecast industry proportion bought, after controlling for lagged industry proportion bought. The results of column 3 indicate that both prior industry return and prior industry proportion bought are significantly related to industry proportion bought.

Columns 5 and 7 repeat the analysis for institutional investors. Unlike retail investors, institutional investors are significant short-term industry momentum traders. The industry return over the prior month positively forecasts institutional industry proportion bought. This result persists even after controlling for institutional industry proportion bought over the prior month. However, there is no significant relationship between institutional industry proportion bought and industry returns over the prior 2 to 12 months.

A question of interest is whether style-level momentum trading is distinct from firm-level momentum trading. To address this question, we examine whether prior industry returns can forecast firm-level proportion bought after controlling for firm-level prior returns. Thus, the dependent variable of this regression is the firm-level proportion bought and all the independent variables are firm-level variables with the exception of industry returns. Panel B of Table 22 reports the time-series average of the monthly coefficients for this regression. Consistent with Hvidkjaer (2006), we find that retail investors tend to be firm-level contrarians over short horizons, but firm-level momentum traders over longer horizons. Moreover, after controlling for firm-level returns, industry returns now positively forecast firm-level proportion bought across all horizons. Thus over shorter horizons both firm-level and industry-level returns can forecast firm-level proportion bought but in opposite directions. The results suggest that prior industry performance and prior firm-level performance influences the investment decisions of retail investors in a fundamentally different way.

The fifth column of Panel B analyzes the firm-level and industry-level momentum trading of institutional investors. Consistent with many prior studies on institutional investors, our result indicate that institutional investors are firm-level momentum traders.[48] In addition, firm level proportion bought is significantly positively related to prior one month industry returns. However, firm-level proportion bought is significantly negatively related to industry returns over the prior 6 to 24 months. Thus, unlike retail investors, institutional investors are not industry-level momentum traders.

4. Industry Herding and Industry Returns

The results suggest that retail investors herd into winning industries and herd out of losing industries. The style investing model posits that this herding is motivated, at least in part, by investor sentiment. Moreover, it argues that this sentiment related demand cannot be completely offset by the actions of rational arbitragers. Consequently, the style investing model predicts that style-level sentiment pushes prices away from fundamentals in the short run, leading to long-term reversals. These predictions are in sharp contrast to the rational herding models of Froot, Sharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam and Titman (1994) which argue that herding is driven by investors receiving correlated signals about fundamental information. These rational herding models argue that herding pushes price towards fundamentals, and therefore, do not predict subsequent price reversals.

4.1 Industry Herding and Industry Return*s*

To explore these competing explanations, we sort industries into quintiles based on retail investor (or institutional investor) industry proportion bought and examine their subsequent returns. The first trading strategy we consider is to sort on prior 3 month industry proportion bought and hold that portfolio for 3 months (3m-3m strategy). For example, from April 1983 to June 1983, portfolio 1 (5) would consist of the quintile of industries most heavily sold (bought)

[48] Studies that provide evidence of institutional momentum trading include Lakonishok, Shleifer and Vishny (1992), Grinblatt, Titman, and Wermers (1995) and Badrinath and Wahal (2002).

by retail investors from January 1983 to March 1983. For each portfolio, we first compute the value-weighted performance of each industry in the portfolio.[49] We then take the equally weighted average of each industry's return in that portfolio.[50] This gives us a time series of monthly returns starting in April of 1983 and ending in December of 2000.

Panel A of Table 23 reports the average monthly market-adjusted returns for each quintile. Market-adjusted returns are the difference between the portfolio return and the value-weighted market index. Interestingly, the industries most heavily bought by retail investors in the prior quarter underperform the industries most heavily sold by retail investors over the subsequent 3 months by roughly 48 basis points (bps) per month. This is estimate is highly statistically significant and translates into an annual outperformance of nearly 6%. In contrast, the industries most heavily bought by institutional investors outperform the industries most heavily sold by about 16 bps per month; however this estimate is not significantly different from zero.

To see if the poor performance of retail investors is driven by retail investors loading on factors with poor performance, we also compute five-factor alphas for each portfolio. We compute five-factor alphas using a time-series regression. The dependent variable is the monthly return on a given portfolio less the risk-free rate, and the independent variables represent factors related to market, firm size, book-to-market, firm-level momentum, and industry momentum. The first four factors are taken from Ken French's data library.[51] The fifth factor is included to control for the industry momentum effect documented by Moskowitz and Grinblatt (1999).[52] The five-factor alpha results indicate that a portfolio that went long the industries most heavily bought by retail investors and short the industries most heavily sold by retail investors, would earn a

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[49] Equally weighting each stock in the industry yields stronger results.

[50] We equal weight each industry. Value weighting each industry leads to very similar conclusions.

[51] See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html for more details on the construction of these factors.

[52] To construct the industry momentum factor, we use six value weighed portfolios formed on average industry size and prior 12 month industry returns. The portfolios, which are formed monthly, are the intersection of 2 portfolios formed on size and 3 portfolios formed on prior industry returns. Industry momentum is the average return on the two high prior return portfolios minus the average return of the two low prior return portfolios.

monthly alpha of -41 bps. This estimate remains highly significant and indicates that factor loadings cannot explain the poor industry selection of retail investors. The five-factor alpha for the long-short portfolio based on institutional industry proportion bought is 11 basis points, and is not statistically significant.

We explore several other strategies. Panel B of Table 23 presents results for a trading strategy that sorts on prior 6 month industry proportion bought and then holds the portfolio for 6 months (6m-6m). Similarly, Panel C shows the results of a trading strategy that sorts on prior 12 month industry proportion bought and then holds the portfolio for 12 months (12m-12m). The results from these strategies are very similar to the 3m-3m strategy. In both cases, the industries most heavily bought by retail investors significantly underperform the industries most heavily sold by retail investors. The long-short portfolio for the 6m-6m strategy earns a five-factor alpha of roughly -39 bps per month, and the long-short portfolio for the 12m-12m strategy earns a five-factor alpha of roughly -34 bps per month. In unreported results, we also consider strategies shorter than 3 months and longer than 12 months. We find that a 1m-1m strategy earns a five-factor alpha of roughly -33 bps which is marginally significant (t-stat = -1.89) and that a 24m-24m strategy earns a five-factor alpha of -10 bps which is not significantly different from zero. For all holding periods and formation periods, the long short portfolio based on institutional industry proportion bought does not earn returns that are significantly different from zero. These results seem most consistent with retail investor industry demand being driven, at least in part, by sentiment; while institutional industry demand is more driven by fundamentals.

4.2 Industry Herding and Weekly Returns

The style investing model of Barberis and Shleifer (2003) not only predicts long-term reversals but also short-term style-level momentum. This section investigates whether there is any evidence of style-level momentum at shorter horizons. First, however, we examine the relationship between industry proportion bought and contemporaneous returns. Each week, from 1983-2000, we sort industries into quintiles based on small and large trade industry proportion bought. For each industry, we compute the value-weighted return for each day during the sorting week. We then calculate the performance of each quintile by taking the average of each industry's return within the quintile. We compound the daily returns to obtain a monthly return series. Panel A of Table 24 presents the results of this analysis. Industry returns are strongly related to both small and large trade proportion bought, although the magnitude is significantly larger for institutional proportion bought. This is consistent with the larger trades of institutional investors having significantly greater price impact than the smaller trades of retail investors. However, this is also consistent with institutional investors being significantly greater short-term industry momentum traders. We do not attempt to determine the causality of this relationship.[53]

Next we examine whether industry proportion bought can forecast the subsequent week's industry returns. Each week we sort industries into quintiles based on the retail investors (or institutional investor) proportion bought. The value-weighted return for each industry is computed over the subsequent five trading days. Each day, we calculate the performance of each quintile by taking the average of each industry's return in that quintile. Thus, we obtain a time series of daily returns. We compound these daily returns into monthly returns.

Panel B of Table 24 reports the market-adjusted and five-factor alphas for the portfolios sorted on prior week industry proportion bought. Consistent with Barberis and Shleifer (2003), amongst retail investors, we find strong evidence of industry-level continuations. A portfolio that went long the industries most heavily bought by retail investors in the prior week and short the industries most heavily sold by retail investors would earn a five-factor alpha of 62 basis points a month. This effect is highly statistically and economically significant and runs counter to the typical pattern of short-term reversals documented by Jegadeesh (1990) and Lehman (1990). These short-term continuations (in conjunction with long-term reversals) are consistent with

[53] Prior research that investigated the relationship between order imbalance and contemporaneous returns has found evidence that supports both explanations (see e.g Griffin, Harris, and Topalogu (2003) and Sias, Starks, and Titman (2006)).

persistent retail investor industry-wide sentiment pushing prices away from fundamental values in the short run.

Table 24 also reports the results for institutional industry herding. In contrast to our retail investor results, here we find strong evidence of industry reversals. Specifically, a portfolio that went long the industries most heavily bought by institutional investors over the prior week and short the industries most heavily sold would earn a five-factor alpha of -45 basis points. The magnitude of this reversal is relatively small compared to the contemporaneous price effects associated with institutional industry proportion bought (roughly 858 bps). This result is consistent with large institutional traders requiring short-term liquidity. This price pressure temporarily pushes prices up leading to short-term reversals. An alternative explanation is that institutional investors overreact.

4.3 Fama-Macbeth Weekly Regressions

As an additional test, we examine how weekly industry returns are a function of industry proportion bought over the prior two years. For both retail and institutional investors, each week, we estimate the following cross-sectional regression:

$$\begin{aligned} IndRet_{it} = a_o + \; & b_1 Ind\_PB_{it-1} + b_2 Ind\_PB_{i,t-4,t-2} \\ & + b_3 Ind\_PB_{i,t-8,t-5} \sum_{w=9}^{97\ by\ 8} b_{t-w,t-w-7}\, Ind\_PB_{it-w,t-w-7} + c_1 MVE_{it} \\ & + d_1 BM_{it} + \sum_{w=1}^{4} e_{t-w,}\, Ind\_Ret_{it-w,} + f_1 Ind\_Ret_{it-52,t-5} \\ & + g_1 Ind\_Ret_{it-104,t-53} + \varepsilon_i \end{aligned}$$

The dependent variable is the industry return in week *t.* The independent variables include the industry proportion bought over the prior week, prior two to four weeks, prior 5 to 8 weeks, and subsequent 8 week periods, beginning with the prior 9 to 16 weeks and ending over the prior 97 to 104 weeks. We also include controls for factors that are known to influence industry returns. We include the average industry market cap (the natural log of the market value of equity) and the average industry book-to-market ratio (in natural logs). Lastly, to control for the industry momentum, we include variables to capture past industry returns over different horizons.

Figure 3A plots the coefficient estimates for lagged industry proportion bought by retail investors. The coefficients are based on the time-series average of the cross-sectional estimates. Standard errors are based on the time-series standard deviation of the weekly estimates. The stanrdard errors are adjusted for serial correlation using the Newey-West (1987) correction. The figure indicates that the industry proportion bought by retail investors over the prior 4 weeks positively forecasts returns. In contrast, industry proportion bought over the past 9 week to the past 72 weeks consistently negatively forecasts returns. The results provide additional support for the style investing model of Barberis and Shleifer (2003).

Figure 3B graphs the results for prior industry proportion bought by institutional investors. Consistent with our weekly results, industry proportion bought over the prior week is negatively related to industry returns. However, over longer horizons there is no consistent relationship between prior industry proportion bought and industry returns.

5. Industry Sentiment vs. Firm Sentiment

Barber, Odean, and Zhu (2009) and Hvidkjaer (2008) document that the stocks bought by retail investors underperform the stocks sold by retail investors. This section investigates to what extent the poor firm-level performance of retail investors is driven by their poor industry selection. To examine the issue, we repeat the industry analysis of Tables 23 and 24, but substitute stock proportion bought for industry proportion bought. In other words, for each strategy we sort stocks based on retail investor firm-level proportion bought over the past n months (where n can equal 1 week, 3 months, 6 months, or 12 months) and then hold that portfolio for n months. The return on that portfolio is the value-weighted return of each stock in that portfolio. We then decompose the performance of this portfolio into industry performance and firm-level performance. Following Busse and Tong (2009), we compute industry performance by replacing each stock in the quintile with its value-weighted industry return. The industry return receives the same weight as the stock it represents in the portfolio. This measure is a proxy for the performance of retail investors that is due to their industry selection. The difference between their total performance and this industry performance is a measure of retail investor's performance due to their stock selection.

For example, suppose Microsoft made up 80% of quintile 1 and Goldman Sachs made up the remaining 20% of quintile 1. Suppose Microsoft earned 3%, Goldman Sachs earned 2%, the tech industry earned 1%, and the financial industry earned 4%. Under this scenario, quintile 1's total performance would be 2.8%, its industry return would be 1.6% and its firm return would be 1.2%.

Table 25 reports the results of this decomposition. Panel A reports the results for the 1w-1w strategy. Consistent with Barber, Odean, and Zhu (2009) the total performance of retail investors is significantly positive over this horizon. A portfolio that went long the stocks most heavily bought by retail investors and short the stocks most heavily sold by retail investors would earn an average monthly five-factor alpha of 79 bps. The decomposition indicates that the industry selection is responsible for roughly 43 bps (54%), while the stock selection is responsible for 37 bps (46%). Both the industry component and stock level component contribute significantly to the short-term momentum.

Consistent with both Hvidkjaer (2008) and Barber, Odean, and Zhu (2009), Panels B, C, and D all document a negative relationship between retail investor firm-level proportion bought over the prior quarter, six months, or a year, and subsequent firm-level returns. For example, Panel C indicates that a portfolio that went long the stocks most heavily bought by retail investors and short the stocks most heavily sold by retail investors over the prior six months, would earn an average monthly five-factor alpha of -54 bps over the subsequent six months. The decomposition indicates that roughly 63% (34 bps) of total underperformance is due to retail investors' industry-wide selection, while 37% (20) bps is due to their firm-level selection. Moreover, the industry component remains reliably different from zero indicating that the industry selection of retail investors contributes significantly to their overall poor performance. In contrast, the firm-level component is no longer significantly different from zero. The 3m-3m and 12m-12m decomposition results yield similar conclusions.

6. Conclusion

This paper examines the industry-wide investment decisions of retail and institutional investors. We find that the industry-wide trading behavior of retail investors is consistent with the style investing model of Barberis and Shleifer (2003). Specifically, we find that retail investors herd into and out of the same industries and that their herding is highly persistent. Retail investors prefer industries with high returns over the past two year. Retail investor herding has a strong impact on contemporaneous prices and also positively forecasts returns over the subsequent week. Over longer horizons, however, retail investors' industry proportion bought negatively forecasts industry returns. Thus, retail investors appear to behave very much like the "style switchers" described in Barberis and Shleifer (2003). They chase industries that have done well in the past, pushing prices away from fundamentals.

Our finding that retail investor industry proportion bought forecasts industry returns are similar to the findings of Barber, Odean, and Zhu (2009) and Hvidkjaer (2008) who document that retail investor firm-level proportion bought forecasts firm returns. To assess the extent to which the poor performance of retail investor trading is driven by their industry-wide investment decisions, we decompose the performance of retail traders into an industry component and a firm-specific component. Our industry decomposition reveals that roughly 60% of the poor performance is driven by the poor industry selection of retail investors. Moreover, this industry component remains significantly negative, while the firm-specific component is no longer reliably different from zero. Taken together, our findings suggest that retail investors categorize stocks by industry and that industry-wide sentiment accounts for a substantial portion of the poor performance of retail investors.

We also find that institutional investors exhibit industry herding. However, the magnitude and persistence of institutional industry herding is smaller than that of retail investor industry herding. Moreover, institutional industry herding does not seem to be well described by the style investing model. Institutional industry herding is associated with very large contemporaneous price increases, a small portion of which reverses in the subsequent week. Over longer horizons, institutional industry proportion bought is not significantly related to industry returns. The fact that institutional industry herding does not generate long run reversals, suggests that unlike retail investors, institutional investor herding is not motivated by sentiment. Institutional industry herding seems better described by rational herding models such as Froot, Sharfstein, and Stein (1992) and Hirshleifer, Subrahmanyam and Titman (1994).

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Table 1
Descriptive Statistics for Aggregate Institutional Trading

This table presents descriptive statistics for Abel Noser institutional trading data. The sample includes all the institutional clients of Abel Noser Corp. who are likely to be actively managed funds benchmarked to the S&P 500. Panel A reports aggregated sums across all institutions (or all pension funds/mutual funds) over the sample period of January 1, 1999 to December 31, 2005. Panel B reports the cross-sectional distribution of fund manager trading. For each month, the distribution for each variable is computed for mutual funds and pension funds. The coefficients reported are the time-series average based on 84 monthly observations.

Panel A: Aggregate Trading

	All Funds	Pension Funds	% of Sample	Mutual Funds	% of Sample
Total Number of Managers	2161	1984	91.8%	177	8.2%
Total Executed Trades	18.07	6.98	38.6%	11.09	61.4%
Total Dollar Volume Traded ($trillions)	4.56	1.55	34.0%	3.01	66.0%
Dollar Volume of Buys ($trillions)	2.27	0.76	33.5%	1.51	66.5%
Dollar Volume of Sells ($trillions)	2.29	0.79	34.5%	1.5	65.5%
Total Shares Volume Traded (billions)	139.5	44.74	32.1%	94.76	67.9%
Share Volume of Buys (billions)	68.78	21.78	31.7%	47	68.3%
Share Volume of Sells (billions)	70.73	22.96	32.5%	47.77	67.5%

Panel B: Cross-Sectional Distribution of Monthly Trading

	Mean	Median	Std. Dev	95th	5th
PF No. of Trades Executed	111	53	290	358	4
MF No. of Trades Executed	4058	967	8083	22074	44
PF No. of Stocks Trades	40	24	60	128	3
MF No. of Stocks Traded	183	123	170	522	14
PF Ave $ Vol Per Trade (thousands)	337	148	611	1276	19
MF Ave $ Vol Per Trade (thousands)	445	254	600	1370	29
PF Total $ Volume (millions)	22	8	54	87	1
MF Total $ Volume (million)	1314	224	2864	7257	7
PF Pct Monthly Roundtrip Trades	3.86%	0.02%	8.78%	17.76%	0.00%
MF Pct Monthly Roundtrip Trades	24.94%	20.10%	21.71%	66.15%	0.51%

Table 2
A Decomposition of Pension Fund and Mutual Fund Active Management

This table measures the degree of active management amongst. Active management is defined as the percentage of aggregate pension fund or mutual fund monthly trading that generates active long-short positions. This table decomposes active management into the portion that is due to trading S&P 500 and non-S&P 500 stocks and reports results for four size groups based on beginning of month market cap: Large stocks- 500 largest stocks; medium stocks – next 500 largest stocks, small stocks - next 2000 largest stocks, and microcaps - all remaining stocks. The coefficients are the average of 84 monthly estimates. Standard errors are based on the variance of monthly estimates. *,**,and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

	ALL Stocks	**S&P 500 Stocks**	**Non-S&P 500 Stocks**
Panel A: All Stocks			
Pension Funds	39.54	27.07	12.47
	(0.56)	(0.37)	(0.28)
Mutual Funds	48.19	30.45	17.74
	(0.63)	(0.41)	(0.37)
PF - MF	-8.65***	-3.38***	-5.28***
	(0.66)	(0.52)	(0.37)
Panel B: Large Stocks (Largest 500)			
Pension Funds	27.41	23.90	3.51
	(0.37)	(0.32)	(0.16)
Mutual Funds	31.66	27.18	4.48
	(0.58)	(0.43)	(0.28)
PF - MF	-4.25***	-3.28***	-0.96***
	(0.62)	(0.52)	(0.20)
Panel C: Medium Stocks (501-1000)			
Pension Funds	6.45	2.71	3.74
	(0.16)	(0.09)	(0.09)
Mutual Funds	7.83	2.82	5.01
	(0.18)	(0.12)	(0.10)
PF - MF	-1.38***	-0.10	-1.27***
	(0.12)	(0.07)	(0.09)
Panel D: Small Stocks (1001-3000)			
Pension Funds	4.92	0.45	4.47
	(0.22)	(0.02)	(0.20)
Mutual Funds	7.25	0.44	6.81
	(0.23)	(0.02)	(0.22)
PF - MF	-2.33***	0.01	-2.34***
	(0.18)	(0.02)	(0.18)
Panel E: Microcaps (<3000)			
Pension Funds	0.76	0.00	0.76
	(0.05)	(0.00)	(0.05)
Mutual Funds	1.46	0.00	1.46
	(0.06)	(0.00)	(0.06)
PF - MF	-0.70***	0.00	-0.70***
	(0.05)	(0.00)	(0.05)

Table 3
The Determinants of Pension Fund and Mutual Fund Trading

This table presents the results of panel regressions over the sample period of January 1999 to December 2005. The dependent variable is either PF TILT, MF TILT, or DIF. PF TILT measures the extent to which pension funds tilt their total trading (i.e. buys + sells) towards a given stock in a given month. MF TILT is defined analogously and DIF = PF TILT – MF TILT. The independent variables are defined in the text. The regression coefficient and standard errors are derived from monthly Fama Macbeth (1973) regressions. The standard errors (in parentheses) are adjusted for serial correlation using the Newey-West standard errors with 12 lags. *,**,and *** denote statistical significant at the 10, 5, and 1 percent level, respectively.

	PF TILT			MF TILT			DIF		
	1	2	3	4	5	6	7	8	9
INT	6.88***	11.86***	8.20***	9.80***	14.17***	24.16***	-2.92***	12.31***	-15.96***
	(0.39)	(2.19)	(2.47)	(0.34)	(2.18)	(2.25)	(0.21)	(1.95)	(2.10)
SP	4.66***	4.66***	12.17***	0.51	1.25***	1.56*	4.16***	3.41***	10.60***
	(0.35)	(0.21)	(1.44)	(0.47)	(0.20)	(0.82)	(0.51)	(0.25)	(1.21)
VOL		-1.03	-1.52**		1.34***	1.33***		-2.36***	-2.85***
		(0.65)	(0.72)		(0.27)	(0.28)		(0.70)	(0.63)
SP*VOL			1.75***			0.10			1.66***
			(0.35)			(0.63)			(0.28)
SIZE		-0.39***	-0.33***		-0.52***	-0.52***		0.13	0.19*
		(0.09)	(0.10)		(0.14)	(0.14)		(0.11)	(0.11)
TURN		3.56***	3.58***		3.81***	3.81***		-0.25	-0.23
		(0.52)	(0.52)		(0.26)	(0.26)		(0.39)	(0.39)
BM		1.03***	0.98***		-0.76***	-0.75***		1.79***	1.74***
		(0.21)	(0.21)		(0.08)	(0.08)		(0.22)	(0.22)
PRC		0.16	0.25		0.62***	0.63***		-0.46**	-0.38*
		(0.18)	(0.16)		(0.09)	(0.09)		(0.22)	(0.21)
AGE		-0.55*	-0.52*		-0.41***	-0.41***		-0.14	-0.11
		(0.29)	(0.27)		(0.08)	(0.08)		(0.28)	(0.56)
CR		0.00	0.02		0.00	0.00		0.00	0.02
		(0.01)	(0.01)		(0.01)	(0.01)		(0.01)	(0.01)
D/P		-13.77***	-13.67***		-13.43***	-13.27***		-0.34	-0.39
		(2.03)	(2.03)		(2.84)	(2.84)		(2.88)	(2.83)
DIV		0.70*	0.71*		-2.00***	-2.00***		2.70***	2.71***
		(0.43)	(0.44)		(0.24)	(0.24)		(0.54)	(0.54)
R^2	4.08%	11.65%	12.03%	0.37%	22.71%	22.80%	2.52%	9.87%	10.13%

Table 4
Momentum Trading by Pension Funds and Mutual Funds

This table presents the prior performance of the stocks bought and sold by pension funds and mutual funds over the sample period of January 1, 1999 to December31, 2005. For each trade, I calculate the gross return over the prior 60, 120, or 240 trading days. Each day, I separately compute the value-weighted (by dollar traded) average return for pension fund buys and sells and mutual fund buys and sells. Finally, I take the difference between buys and sells and the difference between pension funds and mutual funds across all measures. This table reports the time-series average across the 1760 trading days in the sample. All returns are in basis points. Standard errors, in parentheses, are computed using the Newey-West correction. *,**,and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

	Pension Funds			**Mutual Funds**			**PF-MF**		
Holding Period	Buys	Sells	Buys-Sells	Buys	Sells	Buys-Sells	Buys	Sells	Buys-Sells
-60	352.5***	375.45***	-22.95	680.12***	383.45**	296.67***	-327.62***	-7.99	-319.62***
	(133.20)	(133.96)	(22.18)	(202.70)	(168.90)	(71.48)	(97.57)	(53.02)	(78.96)
-120	847.85***	860.54***	-12.69	1441.44***	1092.75***	348.69***	-593.59***	-232.21**	-361.38***
	(232.39)	(231.31)	(29.81)	(392.67)	(321.77)	(126.83)	(194.68)	(113.08)	(127.64)
-240	2154.37***	2056.64***	97.74	3307.87***	2921.33***	386.53*	-1153.49***	-864.49***	-288.80
	(448.69)	(441.98)	(116.33)	(760.73)	(639.21)	(214.97)	(353.91)	(270.23)	(208.00)

Table 5
The Performance of the Stocks Traded by Pension Funds and Mutual Funds

This table summarizes the performance of the stocks bought and sold by pension funds and mutual funds over the sample period of January, 1, 1999 to December 31, 2005. For each trade, I calculate the gross return from the execution price until 5, 20, 60, 120, 180, or 240 trading days have passed. Each day, I separately compute the value-weighted (by dollars traded) average return for pension fund buys and sells and mutual fund buys and sells. Finally, I take the difference between buys and sells and the difference between pension fund and mutual funds across all measures. This table reports the time-series average across the 1760 trading days in the sample. Panel A reports the gross returns and Panel B reports the DGTW-adjusted returns. All returns are in basis points. Standard errors, in parentheses, are computed using the Newey-West correction. *,**,and *** denote statistical significant at the 10, 5, and 1 percent level, respectively

Panel A: Gross Returns

	Pension Funds			Mutual Funds			PF – MF		
Holding Period	Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells
5	18.47	15.56	2.90	44.34**	5.95	38.40***	-25.88***	9.62**	-35.49***
	(12.87)	(12.60)	(2.87)	(14.90)	(14.76)	(4.56)	(5.06)	(4.53)	(5.08)
20	54.84	52.59	2.25	88.21*	33.04	55.17***	-33.36*	19.55	-52.92***
	(44.71)	(42.71)	(7.28)	(52.64)	(50.42)	(13.09)	(18.49)	(15.58)	(13.65)
60	132.47	130.99	1.48	167.05	113.98	53.07**	-34.58	17.01	-51.59**
	(119.07)	(117.69)	(12.80)	(149.87)	(142.86)	(25.85)	(49.82)	(42.54)	(23.80)
120	233.41	233.58	-0.18	268.00	194.15	73.85**	-34.59	39.43	-74.02**
	(191.48)	(186.19)	(22.64)	(240.49)	(232.96)	(36.53)	(75.03)	(73.52)	(31.74)
180	337.59	330.22	7.37	381.70	300.24	81.46*	-44.10	29.99	-74.09*
	(250.88)	(241.09)	(24.20)	(315.91)	(309.06)	(44.68)	(103.06)	(103.47)	(43.02)
240	467.93	476.01	-8.08	511.98	453.56	58.42	-44.06	22.45	-66.51
	(307.56)	(291.57)	(31.06)	(387.75)	(375.53)	(67.22)	(125.24)	(126.62)	(63.03)

Panel B: DGTW-Adjusted Returns									
	Pension Funds			**Mutual Funds**			**PF – MF**		
Holding Period	Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells	Buys	Sells	Buys - Sells
5	8.32***	4.77*	3.54	29.40***	-2.26	31.67***	-21.08***	7.03**	-28.12***
	(2.74)	(1.72)	(2.45)	(3.94)	(3.81)	(3.52)	(3.51)	(3.05)	(4.11)
20	13.23**	9.60	3.63	38.83***	0.96	37.87***	-25.60**	8.64	-34.24***
	(6.43)	(6.47)	(5.53)	(10.61)	(8.86)	(8.92)	(11.12)	(9.28)	(3.52)
60	14.99	12.89	2.10	33.98	9.39	24.59	-18.99	3.50	-22.49
	(13.57)	(16.40)	(9.75)	(25.90)	(21.62)	(16.79)	(24.90)	(20.62)	(15.42)
120	11.42	18.18	-6.76	26.28	-0.66	26.94	-14.86	18.84	-33.69
	(21.86)	(26.30)	(14.13)	(44.52)	(38.07)	(23.66)	(38.57)	(36.29)	(23.12)
180	86.86	91.97	-5.11	105.47	65.11	40.36	-18.60	26.86	-45.46
	(118.37)	(110.64)	(18.61)	(161.47)	(157.78)	(28.14)	(67.44)	(71.09)	(30.40)
240	15.39	23.67	-8.28	27.05	-12.95	40.00	-11.67	36.62	-48.29
	(34.10)	(31.62)	(22.50)	(73.84)	(60.35)	(32.04)	(63.00)	(61.57)	(33.38)

Table 6

The Performance of Pension Funds and Mutual Funds in S&P 500 and Non-S&P 500 Stocks

This table reports the net performance (i.e buys- sells) of pension funds and mutual funds in Non-S&P 500 stocks (NSP) and S&P 500 stocks (SP). For each trade, , I calculate the gross return from the execution price until 5, 20, 60, 120, 180, or 240 trading days have passed. Each day, from January 1, 1999 to December 31, 2005, I separately compute the value-weighted (by dollars traded) average return for pension fund buys and sells and mutual fund buys and sells amongst the subset of NSP and SP stocks. I then compute the net returns as the returns on stocks bought less the returns on the stocks sold. Finally, I take the difference between NSP and SP performance and the difference between pension fund and mutual funds across all measures. This table reports the time-series average across the 1760 trading days in the sample. Panel A reports the gross returns, Panel B reports the DGTW-adjusted returns, and Panel C reports DGTW-adjusted returns for the subset of the largest 1000 stocks. All returns are in basis points. Standard errors, in parentheses, are computed using the Newey-West correction. *,**,and *** denote statistical significant at the 10, 5, and 1 percent level, respectively.

Panel A: Gross Returns

	Pension Funds			**Mutual Funds**			**PF – MF**		
Holding Period	NSP	SP	NSP - SP	NSP	SP	NSP - SP	NSP	SP	NSP - SP
5	-1.97	4.69	-6.67	51.97***	30.69***	21.28***	-53.95***	-26.00***	-27.94***
	(5.09)	(3.13)	(5.84)	(6.22)	(4.58)	(6.44)	(7.21)	(5.48)	(8.32)
20	16.89	-1.96	18.85	68.48***	45.99	22.49	-51.59***	-47.95***	-3.64
	(14.99)	(7.35)	(16.16)	(17.23)	(10.84)	(15.78)	(17.47)	(13.61)	(0.18)
60	24.80	-6.38	31.19	84.77*	33.08**	51.69	-59.96	-39.46**	-20.50
	(38.60)	(13.97)	(44.55)	(49.08)	(16.46)	(52.14)	(37.01)	(19.73)	(42.82)
120	35.18	-12.50	47.68	153.58*	35.88	117.60	-118.30*	-48.38	-69.92
	(51.78)	(20.81)	(54.52)	(90.87)	(25.43)	(93.36)	(71.27)	(30.93)	(83.17)
180	131.69*	-28.54	160.23**	246.60**	-6.43	253.03***	-114.91	-22.11	-92.79
	(69.28)	(23.35)	(75.82)	(100.58)	(43.86)	(115.88)	(85.43)	(42.38)	(95.96)
240	115.84*	-44.62	160.46**	283.01**	-51.52	334.52**	-167.17	6.90	-174.06
	(70.16)	(30.26)	(76.84)	(144.04)	(68.92)	(164.82)	(117.47)	(65.21)	(133.68)

Panel B: DGTW-Adjusted Returns									
	Pension Funds			Mutual Funds			PF – MF		
Holding Period	NSP	SP	NSP - SP	NSP	SP	NSP - SP	NSP	SP	NSP - SP
5	-3.63	5.65**	-9.28*	47.47***	23.92***	23.58***	-51.10***	-18.27***	-32.83***
	(4.70)	(2.67)	(5.26)	(5.78)	(3.59)	(6.06)	(6.92)	(4.44)	(7.73)
20	9.74	2.15	7.59	60.94***	27.40***	33.54**	-51.21***	-25.25**	-25.96
	(13.21)	(5.73)	(13.99)	(15.19)	(8.15)	(14.86)	(16.97)	(10.08)	(18.60)
60	11.26	-0.05	11.31	68.19*	8.24	59.95	-56.94*	-8.29	-48.64
	(30.48)	(11.61)	(34.40)	(36.12)	(17.63)	(42.78)	(34.00)	(19.20)	(43.52)
120	12.69	-13.47	26.17	104.77**	-2.45	107.21	-92.07	-11.02	-81.05
	(34.28)	(17.54)	(40.85)	(61.71)	(24.91)	(71.01)	(59.50)	(27.87)	(73.22)
180	97.58*	-33.28	130.86**	200.33***	-36.69	237.02**	-102.75	3.40	-106.16
	(54.05)	(21.25)	(60.88)	(71.74)	(34.34)	(91.52)	(1.43)	(32.91)	(84.74)
240	114.95**	-39.19	154.13***	198.38**	-26.72	225.10*	-83.44	-12.47	-70.97
	(51.82)	(25.94)	(58.26)	(99.48)	(31.22)	(115.33)	(92.85)	(32.99)	(107.08)

Panel C: DGTW-Adjusted Returns (Largest 1000 Stocks)									
	Pension Funds			Mutual Funds			PF – MF		
Holding Period	NSP	SP	NSP - SP	NSP	SP	NSP - SP	NSP	SP	NSP - SP
5	5.59	6.27**	-0.67	47.07***	23.44***	23.63***	-41.47***	-17.17***	-24.30***
	(5.80)	(2.68)	(6.17)	(6.99)	(3.59)	(7.21)	(8.48)	(4.45)	(9.05)
20	30.66*	3.10	27.57*	62.18***	27.42***	34.76**	-31.53	-24.32**	-7.21
	(1.93)	(5.73)	(15.90)	(16.39)	(3.36)	(16.66)	(19.47)	(10.01)	(21.28)
60	58.80*	0.53	58.27	94.35**	9.05	85.29*	-35.55	-8.52	-27.02
	(35.34)	(11.46)	(38.36)	(43.51)	(17.40)	(47.95)	(39.04)	(19.24)	(45.71)
120	66.49	-12.44	78.93*	156.79**	-0.92	157.71*	-90.29	-11.52	-78.78
	(40.92)	(17.28)	(47.94)	(75.78)	(24.73)	(82.75)	(67.13)	(27.96)	(78.91)
180	174.99***	-32.94	207.93***	270.75***	-33.91	304.66**	-95.76	0.96	-96.72
	(65.01)	(20.99)	(71.03)	(87.48)	(34.84)	(106.05)	(81.64)	(33.45)	(93.91)
240	215.69***	-39.45	255.14***	261.93**	-22.35	284.28**	-46.24	-17.10	29.14
	(63.66)	(25.81)	(69.98)	(108.68)	(31.88)	(124.20)	(96.15)	(33.44)	(111.50)

Table 7

Pension Fund and Mutual Fund Performance by Firm Characteristics

This table reports the average performance (i.e. buys- sells) of the trades of pension funds and mutual funds in various firm characteristics. Each month, I rank the largest 1000 firms on the following characteristics: Marketcap – beginning of month share price times total shares outstanding. Book-to-Market – book value of equity divided by market value of equity. Turnover – the average monthly turnover over the prior three months. Volatility – the standard deviation of monthly gross returns over the previous two years. Age – the number of month since first returns appear in CRSP. I split stocks based on the median breakpoint of the firm characteristic. Then, within each breakpoint I dived stocks in non-S&P 500 stocks (NSP) and S&P 500 stocks (SP). Each day, from January 1, 1999 to December 31, 2005, I compute the value-weighted DGTW-adjusted performance for each of these groups over a 240 day holding period. This table reports the time-series average across the 1760 trading days in the sample. All returns are in basis points. Standard errors, in parentheses, are computed using the Newey-West correction. *,**,and *** denote statistical significant at the 10, 5, and 1 percent level, respectively.

	Pension Funds			**Mutual Funds**		
	NSP	SP	DIF	NSP	SP	DIF
Panel A: Marketcap						
Large	356.05***	-44.70*	400.75***	367.00***	-35.74	402.74***
	(114.99)	(25.93)	(118.56)	(121.42)	(35.06)	(129.83)
Small	16.29	-16.02	32.31	77.81	24.23	53.58
	(60.91)	(67.04)	(92.29)	(134.42)	(68.41)	(159.00)
Large - Small	339.76**	-28.68	368.44**	289.19***	-59.97	349.15**
	(145.08)	(71.03)	(172.72)	(124.42)	(63.77)	(136.56)
Panel B: Book-to-Market						
Value	116.68	-17.52	134.19	112.80	37.60	75.21
	(79.23)	(35.96)	(88.12)	(91.12)	(35.90)	(103.45)
Growth	233.61***	-57.09*	290.70***	283.86**	-54.05	337.91**
	(70.14)	(32.73)	(77.33)	(121.37)	(44.40)	(143.54)
Value - Growth	-116.94	39.57	-156.51	-171.06	91.65*	-262.71*
	(94.22)	(47.03)	(106.35)	(142.09)	(54.23)	(159.02)
Panel C: Turnover						
Liquid	232.40***	-59.41	291.81***	263.90**	-61.44	325.38**
	(63.77)	(37.70)	(71.17)	(119.11)	(58.78)	(157.45)
Illiquid	136.26**	-29.16	165.41**	223.74***	10.26	213.48***
	(65.07)	(28.32)	(74.01)	(47.24)	(26.77)	(81.08)
Liquid - Illiquid	96.14	-30.25	126.40	40.15	-71.70	111.86
	(73.35)	(48.16)	(87.03)	(0.32)	(67.30)	(161.40)

	Pension Funds			Mutual Funds		
	NSP	SP	DIF	NSP	SP	DIF
Panel D: Volatility						
High	181.49**	-98.64**	280.13***	268.74**	-59.15	327.89**
	(76.89)	(46.28)	(87.08)	(109.29)	(67.5)	(159.64)
Low	172.57***	-18.59	191.17***	236.45**	-22.39	258.84**
	(55.93)	(21.32)	(61.82)	(105.12)	(34.66)	(105.39)
Value - Growth	8.92	-80.04	89.96	32.29	-36.76	69.05
	(95.49)	(50.62)	(97.14)	(121.68)	(79.86)	(154.77)
Panel E: Age						
Old	124.05	-18.51	142.56	211.99	-20.25	232.46
	(79.12)	(29.34)	(94.37)	(1.44)	(41.89)	(149.13)
Young	204.57**	-100.09**	304.67***	265.59**	-56.11	318.70**
	(82.22)	(40.86)	(104.40)	(109.08)	(74.24)	(162.06)
Old – Young	-80.52	81.59	-162.10	-50.59	35.86	-86.45
	(132.50)	(51.26)	(162.92)	(127.29)	(91.44)	(154.54)

Table 8
The DGTW Implied Performance of Pension Funds and Mutual Funds

This table estimates the hypothetical, or implied, DGTW-adjusted net performance (i.e. buys – sells) of pension funds trades under the assumption that pension funds traded S&P 500 stocks to the same extent as mutual funds. The table also estimates the implied performance of mutual fund trades under the assumption that they traded S&P 500 stocks to the same extent as pension funds. I obtain hypothetical returns by scaling the dollar volume of all trades in S&P 500 and non-S&P 500 stocks by the appropriate factor. I account for differences in transaction costs by applying the execution cost regression of Keim and Madhavan (1997). For each hypothetical trade, I calculate the return from the execution price until 5, 20, 60, 120, 180, or 240 trading days have passed. Each day, I separately compute the value-weighted (by dollars traded) average DGTW-adjusted return for pension fund buys and sells and mutual fund buys and sells. Net performance is the difference between buys – sells. This table reports the time-series average of net performance across the 1760 trading days in the sample. For reference, the actual returns (from table 5) are also reported. All returns are in basis points. Standard errors, in parentheses, are computed using the Newey-West correction. *,**,and *** denote statistical significant at the 10, 5, and 1 percent level, respectively

	Pension Funds			**Mutual Funds**			**PF – MF**		
Holding Period	Implied	Actual	Implied - Actual	Implied	Actual	Implied - Actual	Implied	Actual	Implied – Actual
5	1.27	3.54	-2.27***	28.30***	31.67***	-3.37***	-27.03***	-28.13***	1.10
	(2.56)	(2.45)	(0.70)	(3.43)	(3.52)	(0.67)	(4.01)	(4.11)	(1.36)
20	4.34	3.63	0.71	33.22***	37.87***	-4.65***	-28.87***	-34.23***	5.36***
	(6.25)	(5.53)	(1.79)	(8.38)	(8.92)	(1.70)	(8.91)	(8.99)	(1.70)
60	5.65	2.10	3.55	16.21	24.59	-8.38	-10.56*	-22.49	11.93
	(11.48)	(9.75)	(4.13)	(14.78)	(16.79)	(5.41)	(15.87)	(15.42)	(11.47)
120	-0.95	-6.76	5.81	12.63	26.94	-14.31	-13.58	-33.70	20.12
	(14.84)	(14.13)	(5.16)	(20.63)	(23.66)	(8.04)	(21.16)	(23.12)	(15.01)
180	22.30	-5.11	27.41***	20.37	40.36	-19.99**	1.93	-45.57	47.40**
	(23.17)	(18.61)	(7.71)	(21.22)	(28.14)	(9.68)	(34.77)	(30.40)	(22.10)
240	14.89	-8.28	23.17***	12.64	40.00	-27.36**	2.25	-48.28	50.33**
	(24.61)	(22.50)	(7.73)	(26.73)	(32.04)	(12.31)	(31.41)	(33.38)	(24.08)

Table 9

The Performance of the Stocks Traded by Pension Funds and Mutual Funds: Thomsons Data

This table reports the performance of pension fund and mutual fund trades using the Thomson (CDA/Spectrum) database. Each quarter, from the first quarter of 1980 to the fourth quarter of 2007, I compute the total net asset weighted performance of the net trades (i.e. buys- sells) of pension funds and mutual funds. Buys and sells are inferred from changes in quarterly holdings. The period in which the trade occurred is labeled "Qtr 0". I report the average (across all quarters) portfolio return during event quarters -2, -1, 0, 1, and 2. Qtr 1(Qtr 2) is the return of the stocks bought less the return on the stocks sold over the subsequent 1 (2) quarters. Panel A reports the gross returns, Panel B reports the DGTW-adjusted returns. All returns are in basis points. Standard errors, in parentheses, are computed using the Newey-West correction. *, **, and *** denote statistical significance at the 10, 5, and 1% level, respectively.

Panel A: Gross Returns

	Qtr -2	Qtr -1	Qtr 0	Qtr 1	Qtr 2
Pension Funds	286.90***	64.79	2.76	3.42	29.48
	(102.83)	(79.99)	(46.00)	(48.86)	(73.70)
Mutual Funds	547.15***	337.35***	770.52***	91.68*	181.11***
	(97.88)	(62.94)	(65.91)	(48.25)	(67.83)
PF - MF	-260.25***	-272.56***	-767.76***	-88.26	-151.63*
	(88.82)	(64.43)	(65.85)	(63.50)	(90.80)

Panel B: DGTW-Adjusted Returns

	Qtr -2	Qtr -1	Qtr 0	Qtr 1	Qtr 2
Pension Funds	303.60***	14.34	20.85	-21.16	-12.56
	(91.72)	(62.34)	(52.15)	(55.68)	(89.71)
Mutual Funds	557.83***	314.14***	703.00***	77.07*	103.00*
	(86.36)	(52.80)	(67.02)	(41.44)	(58.52)
PF - MF	-254.23**	-299.80***	-682.15***	-98.23	-115.56
	(104.62)	(70.38)	(75.56)	(66.82)	(97.93)

Table 10
The Performance of the Stocks Held by Pension Funds and Mutual Funds

The table reports the performance of the stocks held by pension funds and mutual funds. The sample period is the first quarter of 1980 to the fourth quarter of 2007, and includes all funds in the Thomson/CDA database. Each quarter I compute the total net asset weighted gross returns on the stocks held by pension funds and mutual funds. In addition, I compute the DGTW-adjusted return, the Fama and French (1993) three factor (3F) alpha, and the Carhart (1997) four factor (4F) alpha for the total net asset weighted holdings of pension funds and mutual funds. In Panel A, I assume that all trades were made at the end of the quarter. Thus, any trade made during the quarter would not be included in the fund holdings. In Panel B, I assume that all trades were made at the beginning of the quarter. Thus, any trade made during that quarter would be included in fund holdings. All returns are in basis points per quarter. Standard errors are reported below in parentheses. *,**, and *** denote statistical significance at the 10, 5, and 1 percent level, respectively.

Panel A: If Trades Occur at End of Quarter

	Gross Return	DGTW	3F Alpha	4F Alpha
Pension Funds	343.33***	5.01	5.66	0.23
	(76.98)	(5.96)	(12.04)	(11.50)
Mutual Funds	355.50***	6.97	18.10*	-0.42
	(83.45)	(5.45)	(10.97)	-10.5
PF - MF	12.16	1.96	12.3	-0.66
	(13.51)	(5.30)	(10.97)	(11.00)

Panel B: If Trades Occur at Beginning of Quarter

	Gross Return	DGTW	3F Alpha	4F Alpha
Pension Funds	347.60***	8.37**	7.47	-1.14
	(77.54)	(4.19)	(11.32)	(12.67)
Mutual Funds	422.97***	32.03***	81.60***	52.80***
	(84.59)	(5.24)	(14.24)	(14.43)
PF - MF	75.36***	23.66***	74.13***	53.90***
	(13.93)	(5.06)	(12.01)	(14.37)

Table 11
Summary Statistics for Trading Data and S&P 500 Index Changes

Panel A shows descriptive statistics for the samples of institutional and individual investor transaction data. The institutional trading data is from Abel Noser Corporation and spans the period from January 1, 1999 to December 31, 2005. Individual transaction data is from a large discount brokerage firm and spans January 1991 to December 1996. Panel B shows descriptive statistics for the sample of S&P 500 index changes. Data on index changes is obtained from Jeff Wurgler's website and Standard & Poor's website. The table also shows the number of index addition and deletion observations where the effective date was greater than one day after the announcement date, and where return data from CRSP was available for 60 days prior and 90 days after the effective date.

Panel A: Summary Statistics for Trading Data

Investor Type	Number	Ave. Daily Number of Trades	Ave. Daily Share Volume (Millions)	Ave. Daily Dollar Volume ($Millions)	Ave. Share Volume Per Trade	Median Share Volume per Trade	Ave. Dollar Volume Per Trade	Median Dollar Volume Per Trade
Index Funds	56	480	2.69	105.84	5,624	1,300	220,557	51,475
Institutional Investors	2,562	52,466	420.01	127,000.00	7,992	882	241,734	24,112
Households	78,000	2,055	2.46	23.06	1,197	200	11,224	4,600

Panel B: Summary Statistics for S&P 500 Index Changes

	Total		Institutional Investor Sample (1999-2005)		Individual Investor Sample Sample (1991-1996)	
	Additions	Deletions	Additions	Deletions	Additions	Deletions
Total	306	306	196	196	110	110
Date Difference >1	261	260	166	165	95	95
Return Data Criteria	215	127	145	64	70	63
Price > $5	215	87	145	46	70	41

Table 12
Abnormal Returns Surrounding Changes to the S&P 500 Index

The table presents abnormal returns for stocks added to or removed from the S&P 500 index. Abnormal returns are calculated by subtracting the return on a matching portfolio based on size and book-to-market. Announcement Date is the first trading day after the announcement date. Between Announcement and Effective Date is the buy and hold abnormal return starting two trading days after the announcement date until the day prior to the effective date. Effective Date is the abnormal return on the effective date. Effective Date (1 to 20) is the abnormal return starting one trading days after the effective date and ending 20 trading days after the effective date. Announcement Date to Effective Date is the abnormal return starting the first trading day after the announcement date and ending on the effective date. Announcement to Effective Date (+60) is the buy and hold abnormal return starting the first trading day after the announcement date and ending 60 trading days after the effective date.

	Index Additions		Index Deletions	
	Abnormal Return (%)	t-stat	Abnormal Return (%)	t-stat
Panel A: Full Sample (1991-1996, 1999-2005)				
Announcement Date	3.76	15.54	-4.02	-8.82
Announcement to Effective Date (-1)	2.44	4.53	-1.72	-2.87
Effective Date	1.17	3.69	-2.22	-4.49
Effective Date (1 to 20)	-2.69	-3.48	2.34	1.27
Effective date (21 to 60)	0.69	0.50	5.11	2.43
Announcement to Effective	7.35	10.28	-7.56	-7.80
Announcement to Effective Date (+60)	4.95	2.65	-0.53	-0.17
Panel B: Later Sample (1999-2005)				
Announcement Date	3.92	11.80	-4.22	-6.80
Announcement to Effective Date (-1)	2.76	3.57	0.16	0.21
Effective Date	0.71	1.68	-1.52	-2.85
Effective Date (1 to 20)	-2.27	-2.21	-1.51	-0.49
Effective date (21 to 60)	1.37	0.70	7.83	2.62
Announcement to Effective	7.35	7.28	-5.49	-4.87
Announcement to Effective Date (+60)	6.05	2.31	0.50	0.10
Panel B: Early Sample (1991-1996)				
Announcement Date	3.42	12.28	-3.81	-5.59
Announcement to Effective Date (-1)	1.78	4.29	-3.80	-4.59
Effective Date	2.13	5.09	-3.01	-3.52
Effective Date (1 to 20)	-3.54	-3.41	6.68	3.97
Effective date (21 to 60)	-0.67	-0.45	2.06	0.70
Announcement to Effective	7.36	10.72	-9.89	-6.37
Announcement to Effective Date (+60)	2.67	1.43	-1.69	-0.45

Table 13

Trading of Index Funds and Other Institutions Surrounding Index Changes

The table presents the percent of a stock bought or sold by index funds and by other institutions. All figures are in percent and are multiplied by 100. Thus, 24.43 = 0.24%. The mean (median) represents the average (median) net percentage traded across all additions or deletions. P-values from t-tests and signed rank tests are used to test whether the mean and median are significantly different from zero. The transaction sample is from Abel Noser and spans 1999-2005.

	Sample Size	Announcement to Effective Date -1	Effective Date	5 Days After Effective Date
Panel A: Trading Behavior of Investor Group for Stocks Added to S&P 500				
Index Funds				
Mean	145	24.43	58.61	33.42
T-stat p-Value		(<0.01)	(<0.01)	(<0.01)
Median		12.44	52.40	17.23
Sign p-Value		(<0.01)	(<0.01)	(<0.01)
Institutions				
Mean	145	-26.59	-24.77	-32.86
T-stat p-Value		(<0.01)	(<0.01)	(<0.01)
Median		-11.24	-8.10	-12.07
Sign p-Value		(<0.01)	(<0.01)	(<0.01)
Panel B: Trading Behavior of Investor Group for Stocks Deleted to S&P 500				
Index Funds				
Mean	46	-31.80	-57.00	-36.60
T-stat p-Value		(<0.01)	(<0.01)	(<0.01)
Median		-11.40	-34.80	-14.80
Sign p-Value		(<0.01)	(<0.01)	(<0.01)
Institutions				
Mean	46	1.50	23.90	18.30
T-stat p-Value		(0.90)	(0.05)	(0.26)
Median		-6.20	0.00	-8.90
Sign p-Value		(0.58)	(0.44)	(0.68)

Table 14

Index Fund Trading of Newly Included Stocks Following Index Changes

The table reports the total net order flow across index funds for newly added stocks to the S&P 500 index (in percent traded *100). The table also reports total net order flow for a benchmark stock, chosen to be the next largest stock in the index. Difference is the incremental trading in the newly added stock over the benchmark. The transaction sample is from Abel Noser and spans 1999-2005.

Period	Added Stock	t-stat	Benchmark	t-Stat	Difference	t-stat
Ann. Date to Effective Date	24.43	8.97	0.19	2.35	24.23	8.90
Effective Date	58.61	14.10	-0.01	-0.01	58.62	14.09
1 – 5 Days Post Effective Date	33.42	10.15	0.18	-0.14	33.23	10.09
6 – 15 Days Post Effective Date	11.18	8.83	0.23	3.14	10.94	8.51
16 – 30 Days Post Effective Date	4.56	5.94	0.01	0.08	4.55	5.87
31 – 60 Days Post Effective Date	3.55	5.70	0.48	2.89	3.07	4.78
61 – 120 Days Post Effective Date	1.35	3.17	1.03	5.93	0.32	0.71

Table 15

Performance Implications of Strategic Trading by Index Funds Around Composition Changes

The table reports the performance implications for index funds trading away from the closing price on the effective date for S&P 500 Index composition changes. Pre-Event trading is defined as transactions that take place between the announcement date and effective date. The Effective Date period describes transactions that take place on the effective date, and the Post-Event period is defined as 1-5 days after the effective date. Actual Dollar Value Traded is the total amount traded by index funds in $Millions. Value Using Effective Date Closing Price is an implied cost under the assumption that index funds bought rebalanced their holdings entirely on the effective date. Total Dollar Savings and Savings Per Index Change show the total and average savings in $Millions across the sample of 145 index additions and 45 deletions. Equal-weighted Percentage Savings is the (across event) average percentage difference between index funds' value-weighted transaction price and closing price on the effective date less the S&P 500 return over the same period.

	Index Additions			Index Deletions		
	Pre-Event	Effective Date	Post-Event	Pre-Event	Effective Date	Post-Event
Actual Dollar Value Traded ($M)	5,036	11,446	4,925	686	1,861	497
Value Using Effective Date Closing Price	5,377	11,513	5,057	670	1,852	495
Total Dollar Savings	341	66	132	16	9	2
Average Savings Per Index Change ($M)	2.34	0.46	0.91	0.35	0.20	0.05
t-statistic	(2.18)	(1.71)	(3.40)	(0.83)	(1.59)	(0.45)
Equal-weighted Percentage Savings (%)	2.10	0.22	1.54	0.44	0.02	0.55
t-statistic	(3.22)	(1.65)	(4.11)	(0.69)	(0.05)	(0.06)

Table 16

Strategic Trading around Index Composition Changes and Tracking Error

This table reports the abnormal returns and tracking error volatility associated with different trading strategies around index inclusion. Trading strategies range from buying an added stock the day after the announcement (an date (+1)), to waiting to buy the added stock until 20 days after the effective date (EF(+20)). For event days prior to the effective date, abnormal returns are defined as the return on the added stock from the event day to the effective date less the return on the S&P 500 index. For event days after the effective date, abnormal returns are computed as the S&P 500 return from the effective date to the event date, less the return on the added stock over the same period. In both case, the returns of the added stock are computed using the value-weighted execution price on the event day. To assess the impact of the return savings on total fund performance, each abnormal return is scaled by its weight in the S&P 500 index. These abnormal returns are then summed across all index additions in a given year. Average refers to the equally weighted average abnormal returns of a given trading strategy across the 7 years in the sample. Std Dev is the standard deviation of the yearly abnormal returns, a measure of tracking error volatility. Ratio is the information ratio defined as the average yearly abnormal return divided by the standard deviation of these returns.

	N	Ann. Date (+1)	Eff. Date (-1)	Eff. Date (0)	Eff. Date (+1)	Eff. Date (+5)	Eff. Date (+10)	Eff. Date (+20)
1999	35	28.43	18.37	3.03	4.39	1.08	-7.58	-3.36
2000	43	21.82	7.75	1.77	18.73	16.13	31.07	16.78
2001	19	0.01	-0.81	0.00	0.46	1.60	3.75	-0.18
2002	14	13.29	7.79	2.56	3.44	7.81	8.94	7.45
2003	6	-0.52	-0.40	-0.14	-0.47	-0.39	-0.56	-0.39
2004	16	7.50	2.78	2.04	0.02	1.01	1.70	4.53
2005	12	2.61	1.76	1.71	-0.57	-1.61	-2.63	0.47
Average		10.45	5.32	1.57	3.71	3.66	4.96	3.61
Std. Dev.		11.25	6.73	1.21	6.90	6.26	12.62	6.80
Ratio		0.93	0.79	1.30	0.54	0.59	0.39	0.53

Table 17

Determinants of Strategic Trading by Index Funds Surrounding Composition Changes

The table reports the results from logit regressions on whether index funds purchase recently included stocks before or after the effective date. Pre-Event trading is defined as trading between the announcement date and the effective date, and Post-Event trading is defined as abnormal purchases of the included stock 1 to 5 days after the effective date. The dependent variable is 1 if the fund traded strategically before or after the inclusion. Lagged Strategic Trading is a dummy variable equal to 1 if the index fund previously traded strategically in the past. Fund Volume is the sum and Trade Size is the average of the dollar volume of all trades made by the index fund in the month prior to the announcement date. Illiquidity is Amihud's (2002) measure of illiquidity for the added stock measured one month prior to the announcement date. Ln Market Cap is the natural log of a firm's market equity. NYSE listed is one if the stock is listed on the New York Stock Exchange. Arbitrage risk is the root mean squared error from a market model regression 250 to 20 days prior to announcement. Announcement Date Return is the abnormal announcement date return. Both regressions include year dummy variables. Z-scores based on standard errors clustered by index fund. Marginal effects are evaluated at the mean of the independent variables.

Coefficients	Determinants of Pre- and Post-Event Trading		
Lagged Strategic Trading	1.14	1.08	
Z score	(4.64)	(4.38)	
Marginal Effect	0.28	0.26	
Fund Volume ($B)	2.63	2.56	
Z score	(5.32)	(5.10)	
Marginal Effect	0.65	0.64	
Trade Size ($M)	-0.21	-0.20	
Z score	(-2.12)	(-1.98)	
Marginal Effect	-0.05	-0.05	
Illiquidity ($B)	0.21		0.16
Z score	(2.03)		(1.79)
Marginal Effect	0.05		0.04
Market Capitalization	0.48		0.34
Z score	(5.63)		(3.52)
Marginal Effect	0.12		0.08
NYSE listed	-0.21		-0.13
Z score	(-1.86)		(-1.40)
Marginal Effect	-0.05		-0.03
Arbitrage Risk	-4.83		-2.50
Z score	(-0.67)		(-0.42)
Marginal Effect	-1.20		-0.62
Announcement Date Return	2.53		1.82
Z score	(2.61)		(2.23)
Marginal Effect	0.63		0.45
Pseudo R-squared	21.95	20.69	9.25

Table 18
Changes in Retail Investor Buying for Additions and Deletions to the S&P500 Index

The table reports the average percentage abnormal buying by new households for added or deleted stocks over a given period. Percentage abnormal buying is defined as the number of new households who purchase a stock after the announcement date less the number of new households who purchase the stock during the same interval before the announcement date, scaled by the number of new households who owned the stock prior to the interval before the announcement period. New investor buying is presented for different periods after the announcement day 0 up to 240 days after the announcement. For each index change we also report percentage abnormal buying for all other stocks (i.e. non-index change stocks), size and book-to-market matched control firms, and earnings and liquidity matched portfolios over the same period. The last three columns report the difference between the percentage abnormal buying for the index change stock and the benchmarks, respectively. The data analysis includes index changes between February, 1991 and November, 1996 in which the firm being added/deleted has retail transaction data for the intervals under consideration. The sample includes 78,000 households who have an account at a large discount broker during the period of 1991-1996. Numbers in parentheses are t-statistics.

		Abnormal Buying: Alternative Benchmarks			
	S&P 500 Stocks	All Stocks	Size & BTM	EPS & Liquidity	EPS, Liq., & Returns
Panel A: Index Additions					
Days 1 to 20	15.27	15.11	13.52	12.97	10.97
t-statistic	(2.28)	(2.27)	(1.98)	(1.96)	(1.63)
Days 21 to 120	32.27	24.42	23.14	9.89	1.23
t-statistic	(2.05)	(1.58)	(1.23)	(0.65)	(0.08)
Days 121 to 240	108.03	91.20	91.64	67.85	54.56
t-statistic	(2.68)	(2.28)	(2.17)	(1.77)	(1.39)
Days 1 to 240	151.50	127.62	129.36	86.15	64.64
t-statistic	(2.78)	(2.37)	(2.25)	(1.70)	(1.23)
Panel B: Index Deletions					
Days 1 to 20	12.75	13.00	11.54	12.35	11.99
t-statistic	(2.72)	(2.80)	(2.58)	(2.60)	(2.50)
Days 21 to 120	-21.07	-25.75	-27.99	-29.70	-32.33
t-statistic	(-1.19)	(-1.42)	(-1.26)	(-1.88)	(2.12)
Days 121 to 240	33.30	15.08	14.66	12.14	1.89
t-statistic	(1.05)	(0.48)	(0.40)	(0.40)	(0.06)
Days 1 to 240	27.64	5.06	-1.88	-3.23	-16.18
t-statistic	(0.78)	(0.15)	(-0.04)	(-0.11)	(-0.54)

Table 19

Abnormal Returns, Changes in Household Buying, and Changes in Firm Fundamentals

The table presents the results of regressions of cumulative abnormal returns following S&P 500 Index changes on changes in household buying and firm characteristics.

$$CAR_i = \gamma_0 + \gamma_1 Hshd\_Buy_i + \gamma_2 Num\_Shrhldr_i + \gamma_3 Rel\_Size_i + \gamma_4 Num\_Anlyst_i + \gamma_5 Chng\_Liq_i$$

The dependent variable is the return on added stock *i* measured from the announcement date to 60 days after the effective date less the return on a matching portfolio based on size and book-to-market. Abnormal returns are in basis points. $Hshd\_Buy_i$ is the number of new households who purchased stock *i* over the period 1-60, 61-120, or 121-140 days after announcement date less the number who purchased the stock during the same period before the announcement date. $Num\_Shrhldr$ is the number of shareholders at the time of the announcement. Rel_Size_i is the natural log of market capitalization the firm, divided by the average size for the S&P 500. Num_Anlyst_i is the number of analysts who covered the stock at the time of announcement, and $Chng\_Liq_i$ is the difference between share turnover in the 60 days before and after the announcement. Heteroskedasticity-adjusted t-statistics are reported in parentheses.

Intercept	2.63	2.35	-0.70	-0.3	5.54
	(1.30)	(1.25)	(-0.34)	(-0.15)	(0.48)
Household Buying: Days 1-60	0.78			-1.12	-7.47
	(0.13)			(-0.15)	(-0.87)
Household Buying: Days 61-120		-0.43		-3.92	-3.11
		(-0.13)		(-0.15)	(-0.98)
Household Buying: Days 121-240			2.40	3.15	3.77
			(2.00)	(2.47)	(2.74)
Number of Shareholders					-0.04
					(-0.02)
Relative Size					0.60
					(0.18)
Number of Analysts					-3.29
					(-2.14)
NYSE Dummy					-5.47
					(-1.01)
Change in Liquidity					25.93
					(2.47)
Adjusted R-squared	-1.56%	-1.79%	15.16%	14.94%	17.70%

Table 20

Industry Trading Descriptive Statistics

Each month, from January 1983 to December 2000, we classify stocks into one of the Fama and French (1997) 49 industries. Panel A reports the time-series average of the cross-sectional descriptive statistics for the number of firms in each industry, the percentage of total market capitalization accounted for by each industry, and the fraction of industry capitalization accounted for by the largest firm in the industry. Panel B provides reports the time-series average of the cross-sectional descriptive statistics for number of small and large trades made in each industry, the proportion bought by small and large traders in each industry, and the percentage of total small and large trader industry trading accounted for by the largest firm in the industry.

	Mean	Median	Minimum	Maximum	Std Dev
Panel A: Industry Statistics					
No. of firms in industry	98	61	5	526	83
Industry capitalization/Market capitalization	2.04%	1.32%	0.08%	10.78%	2.17%
Largest firm in industry/Industry capitalization	30.56%	23.21%	4.98%	78.23%	9.34%
Panel B: Industry Trading Statistics					
No. of Small Trades in an Industry	58,456	51,327	3,278	321,243	48,239
No. of Large Trades in an Industry	47,987	42,340	2,861	265,397	37,309
Small trades proportion bought	51.06%	51.02%	36.55%	64.61%	3.03%
Large trades proportion bought	52.72%	52.89%	42.97%	59.89%	2.25%
No. of Small Trades Largest Firm/ No. of Small Trades Industry	27.45%	20.12%	2.87%	69.23%	12.10%
No. of Large Trades Largest Firm/ No. of Large Trades Industry	23.23%	18.13%	3.85%	65.45%	11.65%

Table 21

Firm Herding, Size and Book-to-Market Herding, and Industry Herding

Each year, from 1983 to 2000, all stocks are assigned to one of 49 Fama and French (1997) industry portfolios and one of 6 Fama and French (1993) size and book-to-market portfolios. Each week we run cross-sectional regressions, where the dependent variable is the firm-level proportion bought and the independent variables include lagged firm-level proportion bought, lagged proportion bought from all other stocks in the same industry and the same size and book-to-market portfolio, and lagged proportion bought from all other stocks in the same industry but in a different size and book-to-market portfolio. Proportion bought is lagged 1 week, 2 to 8 weeks, 9 to 24 weeks, 25 to 52 weeks, and 53 to 104 weeks. Panel A reports the results based on retail investor (small trade) proportion bought and Panel B reports the results based on institutional (large trade) proportion bought. The coefficients reported are the time-series averages of the cross-sectional estimates. The standard errors are computed using the Newey-West adjustment. T-statistics are in parentheses.

	Weeks				
	-1	-2 to -8	-9 to -24	-25 to -52	-53 to -104
Panel A: Retail Investors					
Firm Proportion Bought	0.28	0.22	0.06	0.03	0.01
	[28.45]	[17.19]	[9.11]	[5.55]	[1.24]
Size and BM Proportion Bought	0.18	0.15	0.05	0.02	0.01
	[15.34]	[11.22]	[5.39]	[3.89]	[0.98]
Industry Proportion Bought	0.16	0.14	0.05	0.03	0.01
	[19.32]	[14.78]	[7.65]	[4.07]	[0.28]
Adjusted R^2	0.10	0.06	0.04	0.03	0.03
Panel B: Institutional Investors					
Firm Proportion Bought	0.138	0.128	0.027	0.005	0.001
	[14.08]	[5.19]	[2.11]	[1.11]	[0.11]
Size and BM Proportion Bought	0.082	0.054	0.012	0.003	0.001
	[11.39]	[4.21]	[1.78]	[0.19]	[0.78]
Industry Proportion Bought	0.072	0.042	0.008	0.001	0.002
	[10.77]	[3.79]	[1.45]	[0.32]	[0.39]
Adjusted R^2	0.06	0.03	0.02	0.01	0.01

Table 22

Proportion Bought and Prior Industry Returns

This table presents the results from industry-level (Panel A) and firm-level (Panel B) Fama-Macbeth cross-sectional regression estimated monthly from January 1983 to December, 2000. In Panel A, retail investor (institutional) industry proportion bought are regressed on lagged industry returns, lagged retail investor (institutional) industry proportion bought, industry average values of ln (Size) and industry average values of ln(BM). In Panel B, retail investor (institutional) firm-level proportion bought are regressed on lagged industry returns, lagged retail investor (institutional) firm proportion bought, lagged firm returns, firm ln(size) and firm ln(bm). Time-series average values of the monthly regression coefficients are reported blow. Standard errors are adjusted using the Newey-West correction. T-statistics are in brackets.

Panel A: Industry Proportion Bought

	Retail Investor Industry Proportion Bought				Institutional Industry Proportion Bought			
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
$Intercept$	47.70	[33.16]	36.75	[29.16]	45.20	[58.65]	37.56	[46.34]
$LN\ (Size)$	-0.01	[-0.08]	0.00	[0.05]	0.61	[10.19]	0.69	[8.32]
$LN\ (BM)$	-2.64	[-6.85]	-2.24	[-5.25]	-0.43	[-3.51]	-0.37	[-2.54]
IND_RET_{t-1}	-6.92	[-1.68]	-6.24	[-1.01]	3.87	[3.35]	2.88	[2.65]
$IND\_RET_{t-3,t-2}$	-6.32	[-1.17]	1.34	[0.34]	2.41	[1.53]	2.20	[1.34]
$IND\_RET_{t-6,t-4}$	14.78	[3.77]	11.34	[2.32]	2.35	[1.28]	2.01	[1.38]
$IND\_RET_{t-12,t-7}$	44.19	[5.77]	40.23	[4.23]	3.26	[1.27]	3.02	[1.02]
$IND\_RET_{t-24,t-13}$	65.47	[7.83]	62.34	[5.32]	-5.38	[-1.44]	-4.33	[-1.02]
IND_PB_{t-1}			2.23	[3.92]			1.33	[2.54]
$IND\_PB_{t-3,t-2}$			1.99	[5.34]			0.79	[3.43]
$IND\_PB_{t-6,t-4}$			4.23	[4.28]			-0.36	[-0.73]
$IND\_PB_{t-12,t-7}$			2.03	[5.34]			0.29	[1.78]
$IND\_PB_{t-24,t-13}$			0.68	[2.49]			0.11	[0.23]
$Adjusted\ R^2$	0.26		0.35		0.20		0.28	

Panel B: Firm Proportion Bought								
	Retail Investor Firm Proportion Bought				Institutional Firm Proportion Bought			
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
$Intercept$	36.33	[46.05]	25.60	[20.48]	33.82	[53.55]	24.21	[22.24]
$LN\ (Size)$	0.76	[5.87]	1.13	[5.66]	1.29	[12.22	1.57	[16.09]
$LN\ (BM)$	-2.41	[-6.40]	-1.98	[-2.14]	0.01	[0.23]	0.00	[0.19]
RET_{t-1}	-8.61	[-12.31]	-5.74	[-3.10]	2.83	[5.17]	3.30	[8.35]
$RET_{t-3,t-2}$	-8.03	[-9.94]	-5.20	[-4.19]	3.58	[4.29]	3.91	[8.01]
$RET_{t-6,t-4}$	-0.46	[-0.70]	2.13	[2.85]	3.06	[3.34]	3.53	[6.21]
$RET_{t-12,t-7}$	11.65	[12.63]	10.79	[10.00]	1.69	[2.09]	1.79	[2.24]
$RET_{t-24,t-13}$	18.85	[15.83]	13.89	[9.97]	-3.73	[-3.85]	-2.74	[-3.13]
IND_RET_{t-1}	6.43	[3.42]	5.87	[2.27]	5.12	[4.06]	4.66	[2.69]
$IND\_RET_{t-3,t-2}$	4.72	[2.40]	1.27	[0.35]	-0.38	[-0.21]	2.23	[1.1]
$IND\_RET_{t-6,t-4}$	6.71	[2.77]	9.59	[2.48]	-3.38	[-1.45]	-4.18	[-2.19]
$IND\_RET_{t-12,t-7}$	24.85	[3.90]	23.69	[4.33]	-5.78	[-2.10]	-6.39	[-2.67]
$IND\_RET_{t-24,t-13}$	19.88	[4.20]	12.41	[2.39]	-21.14	[-5.61]	-23.01	[-4.89]
PB_{t-1}			9.30	[5.87]			3.56	[2.96]
$PB_{t-3,t-2}$			6.90	[3.37]			1.79	[2.65]
$PB_{t-6,t-4}$			2.41	[4.80]			2.05	[1.8]
$PB_{t-12,t-7}$			4.53	[3.37]			2.14	[2.73]
$PB_{t-24,t-13}$			6.62	[2.21]			1.59	[2.35]
$Adjusted\ R^2$	0.08		0.12		0.04		0.10	

Table 23
Returns on Portfolios Sorted on Past Industry Proportion Bought

This table sorts industries into portfolios based on the past n month industry proportion bought for both small and large trades. The industries most heavily sold (bought) over the prior n months are placed into portfolio 1 (5). We then examine the average monthly return on each portfolio over the subsequent n months. For each industry, we compute a value-weighted return. The portfolio returns is the average return across all the industries in the portfolio. Market-adjusted returns are the return on the portfolio less the value-weighted market return. Five-factor alphas are the intercept from a time-series regression where the dependent variable is the monthly return on the portfolio less the risk-free rate and the independent variables are the market, size, book-to-market, momentum, and industry momentum factors. The differences in return between quintile 5 and 1 is also reported, along with t-statistics in parentheses. The formation and holding period is 3 months in Panel A, 6 months in Panel B, and 12 months in Panel C.

Panel A: Three Months – Three Months

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Retail Traders	Institutions	Difference	Retail Traders	Institutions	Difference
1 (sold)	0.375	-0.056	0.431	0.324	-0.017	0.341
2	0.282	0.249	0.033	0.162	0.148	0.014
3	0.102	0.189	-0.087	0.210	0.269	-0.059
4	0.023	0.179	-0.156	0.002	0.139	-0.137
5 (bought)	-0.101	0.107	-0.208	-0.090	0.093	-0.183
B-S (5-1)	-0.476	0.163	-0.639	-0.414	0.110	-0.524
	(-3.46)	(1.30)	(-4.36)	(-3.19)	(1.03)	(-3.79)

Panel B: Six Months – Six Months

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Retail Traders	Institutions	Difference	Retail Traders	Institutions	Difference
1 (sold)	0.249	-0.021	0.270	0.245	-0.005	0.260
2	0.299	0.290	0.009	0.202	0.125	0.077
3	0.190	0.186	0.004	0.174	0.302	-0.128
4	0.100	0.193	-0.093	0.118	0.175	-0.057
5 (bought)	-0.162	0.045	-0.207	-0.142	0.015	-0.157
B-S (5-1)	-0.411	0.066	-0.477	-0.387	0.020	-0.407
	(-2.59)	(0.59)	(-2.49)	(-2.31)	(0.18)	(-2.47)

Panel C: One Year – One Year

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Retail Traders	Institutions	Difference	Retail Traders	Institutions	Difference
1 (sold)	0.342	-0.032	0.374	0.274	-0.020	0.314
2	0.103	0.321	-0.218	0.135	0.359	-0.224
3	0.217	0.219	-0.002	0.263	0.242	0.021
4	0.066	0.142	-0.076	0.102	0.152	-0.050
5 (bought)	-0.043	0.082	-0.125	-0.070	-0.010	-0.060
B-S (5-1)	-0.385	0.114	-0.499	-0.344	0.010	-0.354
	(-2.22)	(0.97)	(-2.75)	(-2.12)	(0.45)	(-2.00)

Table 24
Returns on Portfolios Sorted on Past Week Industry Proportion Bought

Each week from January 4, 1983 to December 27th 2000, portfolios are formed on the basis of prior week retail investor (institutional) industry proportion bought. Panel A reports the returns on the portfolio during the ranking period. On each day of the ranking period, the value-weighted return for each industry is computed. The portfolio return is the average of the industry returns in the portfolio. Daily returns are compounded to yield a monthly return series. Market-adjusted returns are the difference between the portfolio return and the value-weighted market return. Five-factor alphas are the intercept from a time-series regression where the dependent variable is the monthly return on the portfolio less the risk-free rate and the independent variables are the market, size, book-to-market, momentum, and industry momentum factors. Panel B reports the returns on each portfolio over the subsequent one week. The returns for each portfolio are computed analogously. The differences in return between quintile 5 and 1 is also reported, along with t-statistics in parentheses.

Panel A: Contemporaneous Returns

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Retail Traders	Institutions	Difference	Retail Traders	Institutions	Difference
1 (sold)	-1.991	-3.543	1.552	-1.830	-3.279	1.449
2	-1.302	-2.320	1.018	-1.434	-2.283	0.849
3	0.021	1.203	-1.182	-0.109	1.403	-1.512
4	1.219	2.932	-1.173	1.432	3.232	-1.800
5 (bought)	2.721	5.439	-2.718	2.630	5.299	-2.669
B-S (5-1)	4.712	8.932	-4.270	4.460	8.578	-4.118
	‘(27.38)	‘(45.83)	-(23.39)	(24.79)	(42.43)	(-20.74)

Panel B: Subsequent Returns

	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Retail Traders	Institutions	Difference	Retail Traders	Institutions	Difference
1 (sold)	-0.286	0.423	-0.709	-0.147	0.328	-0.475
2	-0.181	0.389	-0.570	-0.253	0.349	-0.602
3	0.323	-0.29	0.613	0.195	-0.092	0.287
4	0.121	-0.212	0.333	0.102	-0.232	0.334
5 (bought)	0.438	-0.129	0.567	0.495	-0.121	0.616
B-S (5-1)	0.724	-0.552	1.276	0.642	-0.449	1.091
	(5.30)	(-5.04)	(6.89)	(4.29)	(-3.42)	(5.73)

Table 25 Retail Investor Industry and Stock Selection

This table decomposes the performance of retail investor trading into two components: industry selection and stock selection. Portfolios are formed on the basis of prior retail investor firm-level proportion bought. The return of the portfolio (total return) is the value-weighted average of the stocks return in that portfolio. The industry return is computed by substituting the return of the stock in the portfolio by the value-weighted return of the industry to which that stock returns. Stock return is defined as the difference between the total return and the industry return. Market-adjusted returns are the difference between the portfolio return and the value-weighted market return. Five-factor alphas are the intercept from a time-series regression where the dependent variable is the monthly return on the portfolio less the risk-free rate and the independent variables are the market, size, book-to-market, momentum, and industry momentum factors. The differences in return between quintile 5 and 1 is also reported, along with t-statistics in parentheses. The formation and holding period is 1 week in Panel A, 3 months in Panel B, 6 months in Panel C, and 12 months in Panel D.

Panel A: One Week – One Week						
	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	-0.326	-0.192	-0.134	-0.289	-0.153	-0.136
2	-0.239	-0.089	-0.150	-0.293	-0.131	-0.162
3	0.149	-0.054	0.203	0.123	-0.081	0.204
4	0.189	-0.015	0.204	0.201	0.012	0.189
5 (bought)	0.480	0.262	0.218	0.502	0.272	0.230
B-S (5-1)	0.806	0.454	0.352	0.791	0.425	0.366
	(6.49)	(3.47)	(2.39)	(6.21)	(3.18)	(2.76)
Panel B: Three Months – Three Months						
	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	0.426	0.301	0.125	0.440	0.323	0.117
2	0.229	0.153	0.076	0.203	0.129	0.074
3	0.119	0.029	0.090	0.020	-0.021	0.041
4	-0.062	-0.025	-0.037	-0.123	-0.012	-0.111
5 (bought)	-0.103	-0.006	-0.097	-0.150	0.021	-0.171
B-S (5-1)	-0.529	-0.307	-0.222	-0.590	-0.302	-0.288
	(-3.45)	(-2.12)	(-1.53)	(-3.89)	(-2.03)	(-1.73)
Panel C: Six Months – Six Months						
	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	0.486	0.302	0.184	0.502	0.248	0.254
2	0.186	0.199	-0.013	0.142	0.172	-0.030
3	-0.035	-0.002	-0.033	-0.065	0.029	-0.094
4	0.019	-0.015	0.034	0.002	0.071	-0.069
5 (bought)	-0.013	0.005	-0.018	-0.034	-0.091	0.057
B-S (5-1)	-0.499	-0.297	-0.202	-0.536	-0.339	-0.197
	(-2.98)	(-2.00)	(-1.47)	(-3.19)	(-2.10)	(-1.25)
Panel D: One Year – One Year						
	Market-Adjusted Returns (%)			Five-Factor Alphas (%)		
Portfolio	Total Ret.	Industry Ret.	Stock Ret.	Total Ret.	Industry Ret.	Stock Ret.
1 (sold)	0.402	0.298	0.104	0.391	0.285	0.106
2	0.135	0.177	-0.042	0.119	0.159	-0.040
3	0.089	-0.002	0.091	-0.020	-0.021	0.001
4	-0.008	-0.015	0.007	-0.020	0.012	-0.032
5 (bought)	0.009	0.050	-0.041	-0.015	0.021	-0.002
B-S (5-1)	-0.393	-0.248	-0.145	-0.405	-0.264	-0.141
	(-2.09)	(-1.76)	(-1.07)	(-2.31)	(-1.81)	(-0.97)

Figure 1.
Index Fund Trading Around Changes to the S&P 500 Index.

The figure shows the average index fund net trading around the 145 additions and 46 deletions in our sample from 1999-2005. The horizontal axis depicts the event day, where day 0 is the effective date. The vertical axis is average net percentage traded where percentage traded is computed as the net share volume traded in a stock scaled by the stock's shares outstanding. The transaction data is from Abel Noser Corporation.

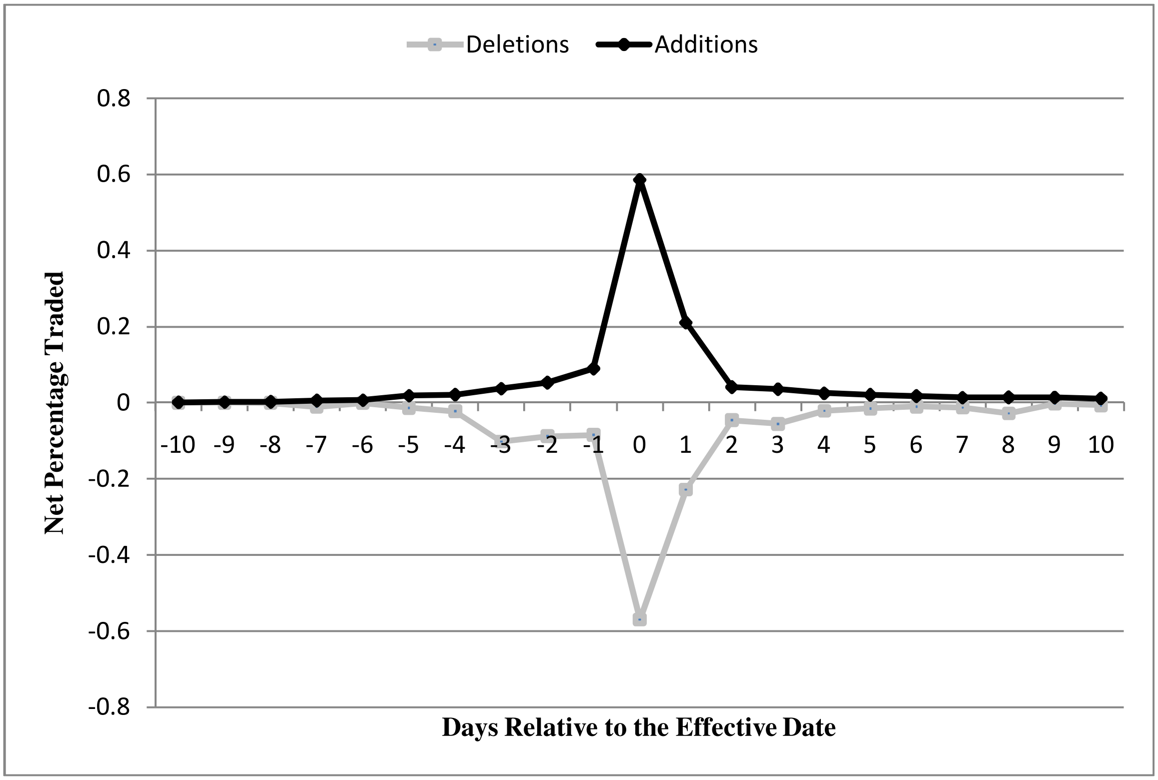


Figure 2

Cross-Sectional Correlation of Industry Proportion Bought

Each week from January 4, 1983 to December 27, 2000 we compute retail investor (institutional) industry proportion bought. This figure reports the time-series average of the cross-sectional correlations between retail investor (institutional) industry proportion bought in week *t,* and week *t+x.* The x axis represents different horizons.

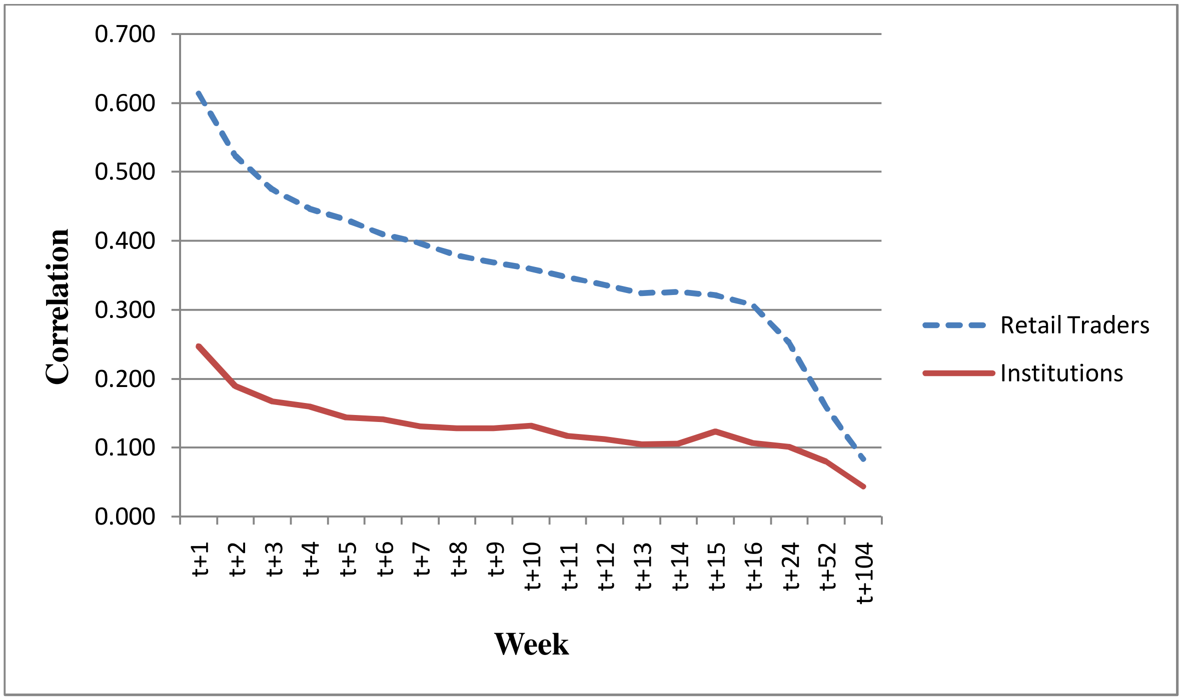


Figure 3

The Effect of Past Industry Proportion Bought on Industry Returns

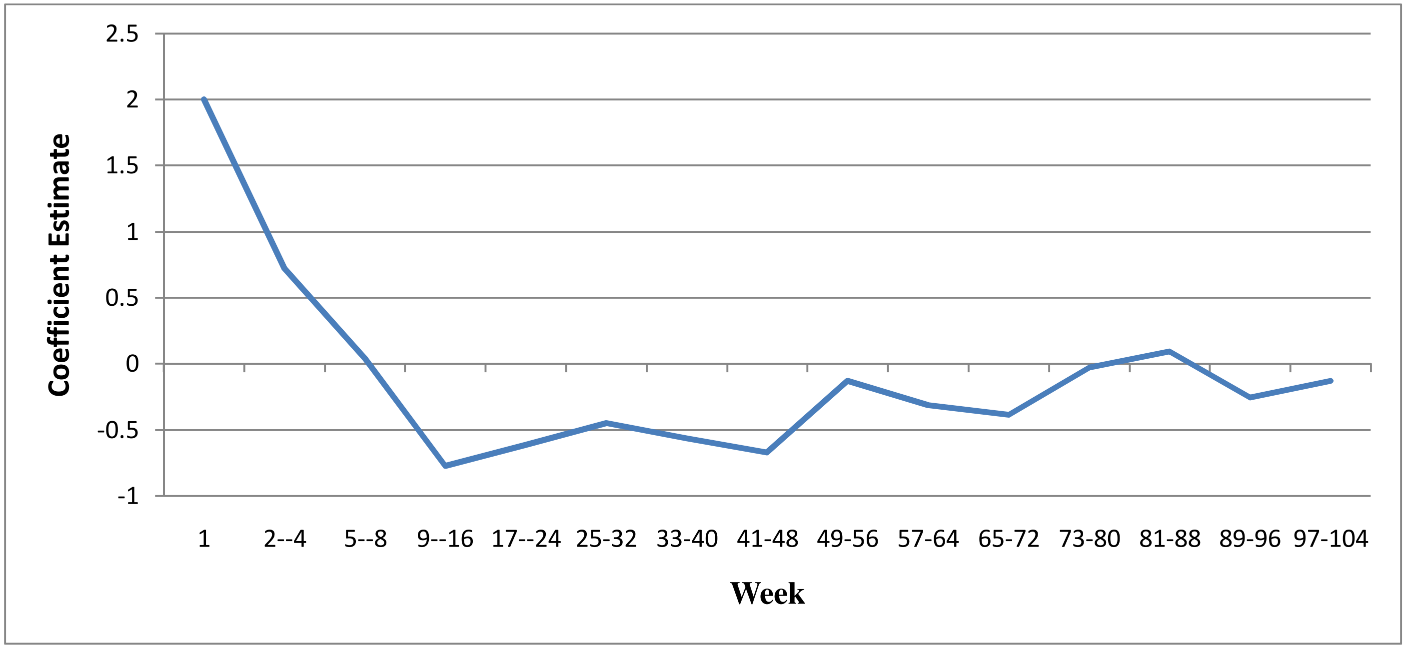
Each week from January 4, 1984 to through December 27, 2000 we fun the following cross-sectional regression:

$$IndRet_{it} = a_o + b_1 Ind\_PB_{it-1} + b_2 Ind\_PB_{i,t-4,t-2} + b_3 Ind\_PB_{i,t-8,t-5} \sum_{w=9}^{97\ by\ 8} b_{t-w,t-w-7}\, Ind\_PB_{it-w,t-w-7} + c_1 MVE_{it} + d_1 BM_{it}$$

$$+ \sum_{w=1}^{4} e_{t-w,}\, Ind\_Ret_{it-w,} + f_1 Ind\_Ret_{it-52,t-5} + g_1 Ind\_Ret_{it-104,t-53} + \varepsilon_i$$

The dependent variable is the industry return in week *t*. The independent variables includes the industry proportion bought over the prior week, prior two to four weeks, prior 5 to 8 weeks, and subsequent 8 week periods, beginning with the prior 9 to 16 weeks and ending over the prior 97 to 104 weeks. Other control variables include the average industry market cap, the average industry book to market, and prior industry returns. The figure presents the mean coefficient estimates on the lagged industry proportion bought variables. The coefficients and t-statistics are based on the time-series mean and time-series standard deviation of the cross-sectional estimates. Panel A reports the results for retail investor industry proportion bought. Panel B reports the results for institutional industry proportion bought.

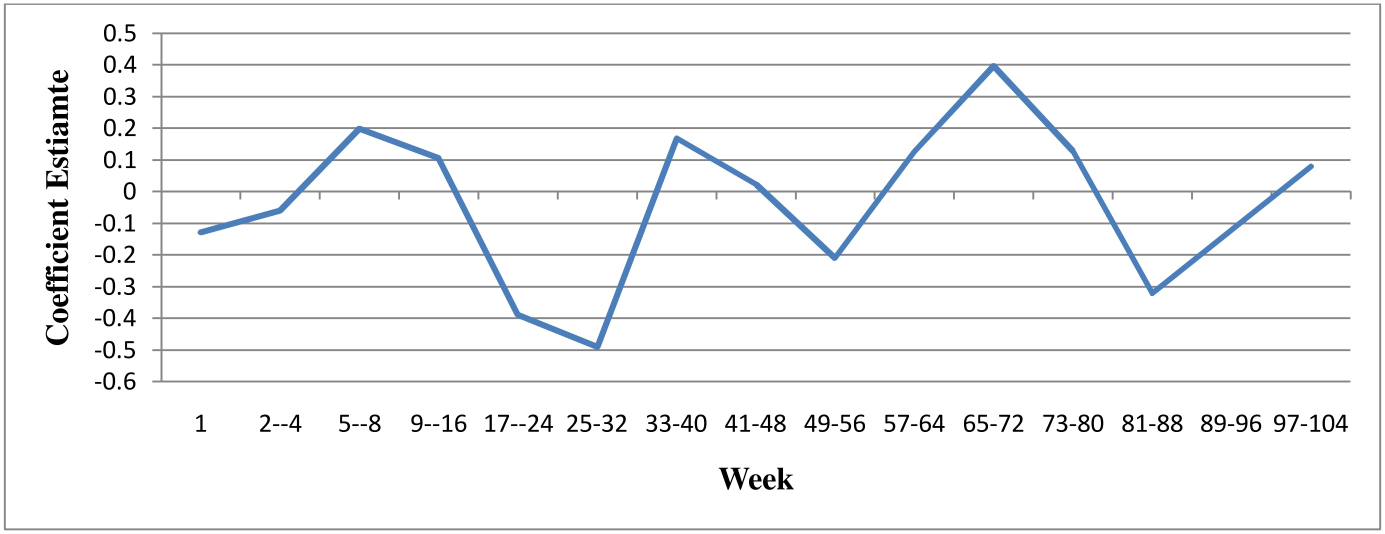
Panel A: Coefficient Estimates on Lagged Industry Proportion Bought of Retail Investors



	1	2--4	5--8	9--16	17--24	25-32	33-40	41-48	49-56	57-64	65-72	73-80	81-88	89-96	97-104
coef	2.002	0.716	0.038	-0.772	-0.612	-0.448	-0.562	-0.67	-0.126	-0.312	-0.383	-0.026	0.092	-0.254	-0.126
t-stat	12.32	3.36	0.68	-6.32	-4.12	-3.32	-4.42	-3.96	-1.36	-2.57	-2.02	-0.19	1.31	-2.38	-0.58

	$SIZE$	BM	Ind_Ret_{t-1}	Ind_Ret_{t-2}	Ind_Ret_{t-3}	Ind_Ret_{t-4}	$Ind\_Ret_{t-52,t-5}$	$Ind\_Ret_{t-104,t-53}$
coef	0.011	0.125	0.017	0.015	0.012	0.002	0.020	0.050
t-stat	1.39	3.15	2.95	2.32	2.48	1.07	3.39	1.59

Panel B: Coefficient Estimates on Lagged Industry Proportion Bought of Institutions



	1	2--4	5--8	9--16	17--24	25-32	33-40	41-48	49-56	57-64	65-72	73-80	81-88	89-96	97-104
coef	-0.129	-0.06	0.199	0.106	-0.39	-0.491	0.169	0.023	-0.209	0.126	0.397	0.128	-0.321	-0.121	0.08
t-stat	-2.16	-1.09	1.39	1.09	-2.75	-2.32	1.03	0.36	-1.15	0.78	2.49	1.68	-2.67	-1.10	0.98

	$SIZE$	BM	Ind_Ret_{t-1}	Ind_Ret_{t-2}	Ind_Ret_{t-3}	Ind_Ret_{t-4}	$Ind\_Ret_{t-52,t-5}$	$Ind\_Ret_{t-104,t-53}$
coef	0.015	0.116	0.015	0.012	0.010	0.005	0.022	0.008
t-stat	1.58	2.77	2.69	2.51	2.28	1.45	3.64	1.79