Order Flow, Comovement, and Market Predictability

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If non-informational traders can cause changes in individual securities returns, can the same traders a ect market returns? This paper studies predictability of market returns using a mechanism | program trading on the NYSE | well suited for index traders to minimize trading costs. After a stock joins the S&P500 Index, we show the volume of program trading increases and program traders acquire a substantial fraction of shares. The stock's order imbalances and returns comove more with the order imbalances of other S&P500 stocks. Aggregate measure program trading order imbalances (buy minus sell volume) are positively correlated with contemporaneous S&P500 returns and negatively correlated with future S&P500 returns. Our results indicate these traders induce a common component in S&P500 returns and cause return predictability and cause excess volatility. Overall, our results are consistent with market frictions due to limited risk bearing capacity operating at the market-level.

Keywords: Return Predictability, Liquidity, Comovement

JEL Number: G1, G12

1 Introduction

Prior research shows that index membership, listing exchange, and the location of a firm's headquarters all impact individual stock returns. A common explanation is that buying and selling by certain groups of investors can induce a common component in individual stock returns. Thus, when a stock's index membership or location changes, the group of investors/traders changes, which changes the common components affecting the stock's return.

In markets with limited risk bearing capacity, non-informational trading can create excess volatility and return predictability. At the individual stock level, non-informational traders may have to compensate market makers (arbitrageurs) by selling below, or buying at price above, fundamental values. This paper moves beyond individual stocks by asking whether non-informational trading can cause excess volatility and predictability in market returns.

To establish a channel by which uninformed traders can impact security returns we begin by examining a commonly studied event: additions to the S&P500 Index. Consistent with index traders impacting stocks returns, we confirm that after a security is added to the S&P500 Index its return comoves more with other stocks already in the S&P500 as in Vijh (1994) and comoves less with stocks not in the index as in Barberis, Shleifer, and Wurgler (2005).

Unfortunately, identifying daily index trading is not directly possible with available data. However, program trading (PT) is a widely used, and natural way, for indexers to minimize trading costs.[1] We define program traders' daily order imbalance in a given stock ($\mathit{OIB}_{i,t}$) as the buy volume minus sell volume divided by the stock's market capitalization. We also define the daily order imbalance for all S&P500 Index stocks ($\mathit{OIB}_{sp500,t}$) as the market capitalization weighted average of order imbalance across all stocks in the index.

Just as a stock's return beta with S&P500 returns increases upon addition, a stock's order imbalance beta increases as well. In other words, after joining an index, PT order imbalances for the added stock comove more with PT order imbalances in the other S&P500 stocks. In addition, and as with returns, there is a decrease in the added stock's OIB beta with respect to non-S&P500 stocks. Also consistent with indexers using program trading, when

[1] Program trading is de ned by the New York Stock Exchange (NYSE) as the purchase or sale of 15 or more stocks having a total market value of $1 million or more. Brokers o er very low commissions for program trading. PT appeals more to traders who are less concerned about disguising their trading strategies. While these characterizations t index traders and our data exclude PT for index arbitrage, investors trading other types of portfolio use PT as well. See Section 2.2 for further discussion.

stocks are added to the S&P500 the program traders buy a significant fraction of shares outstanding (more than 1% of the company) and the volume of program trading in the stock also increases. Finally, consistent with PT being linked to a common component in the returns of S&P500 stocks, cross-betas of added stocks also increase—a stock's cross-beta is a measure of comovement that is estimated from a regression of stock i's returns on the market-wide order imbalance.

Having established an association between program trading and changes in returns of stocks recently added to the S&P500 Index, we turn to studying whether program trading causes excess volatility and predictability in market returns. If program trading affects market returns, we should observe a positive contemporaneous correlation between $OIB_{sp500,t}$ and market returns. We also expect program trading to represent a significant fraction of market volume. We find that $OIB_{sp500,t}$ has a 0.475 contemporaneous correlation with the market return and program trading represents 13.3% of NYSE trading volume on average.

We also find that program trading on day t has a -0.079 correlation with the market return on day $t+1$. This negative lag-lead correlation provides the first evidence of market predictability and excess volatility. We test whether $OIB_{sp500,t}$ predicts market returns more formally using vector autoregressions. We show that positive shocks to $OIB_{sp500,t}$ Granger-causes negative market returns the following day. Our results are consistent with index traders causing return predictability and excess volatility at the market-level. Because program trading imbalances are not publicly available, we do not necessarily interpret our findings as a violation of market efficiency, but rather as a statement about the limited risk-bearing capacity of markets.

Our results are related to recent research on trading activity affecting individual security returns and having a transitory impact on stock prices. Froot and Dabora (1999) study Siamese twin stocks—two stocks with claims on the same company but that are traded on different stock exchanges. They find that these stocks comove more with stocks on the exchange they are listed on. Chan, Hameed, and Lau (2003) extend these location of trade results by studying the de-listing of some Jardine Group stocks from the Hong Kong Stock Exchange (HKSE) and subsequent re-listing on the Stock Exchange of Singapore (SSE). After the move the stocks' returns comove less with HKSE stocks and comove more with SSE stocks. Pirinsky and Wang (2006) show that when firms move the location of their headquarters, the returns of their stocks comove more with firms headquartered in the new location and less with stocks headquartered in the old location.

By looking at a one-time change in the index weights of Nikkei 225 and the cross-sectional differences between the Nikkei 255's price weights and value weights, Greenwood (2005, 2008) examines how index investors can impact stock returns. These papers provide evidence consistent with non-informational trading by index investors causing transitory distortions in prices. Our results for program traders on the NYSE provide direct evidence of a trading channel that causes price distortions. We also extend Greenwood's results by showing that limits to arbitrage/limited risk-bearing extend to a market-wide scope.

There is also cross-sectional evidence on non-informational traders affecting individual stock returns. Coval and Stafford (2007) show that when mutual funds face redemptions, stocks they are heavily invested in decline and then recover. Andrade, Chang, and Seasholes (2008) show the order imbalances of a group of non-informational traders in Taiwan cause temporary price pressure in both the stocks with order imbalances and stocks most correlated with those stocks.

For order imbalances of groups of traders to have transitory effects on stock prices there must be frictions in the provision of liquidity. The transitory price effects can be thought of as compensation to the liquidity suppliers who take the other side of traders initiated by the non-informational traders.[2] See Hendershott and Seasholes (2007), Kaniel, Saar, and Titman (2008), and Boehmer and Wu (2008) for empirical cross-sectional and idiosyncratic evidence on return predictability due to liquidity supplier trading.[3]

The rest of this paper is as follows. Section 2 describes the data and provides summary statistics. Section 3 presents analyzes index additions and program trading. Section 4 studies market returns and program trading. Section 5 concludes.

2 Data

Our data draw on a number of sources. We use CRSP to obtain price, daily share volumes, and shares outstanding. For trading information we use the NYSE's Trades and Quotes (TAQ) and the Consolidated Equity Audit Trail Data (CAUD) databases. For stock returns we use TAQ to calculate returns based on the closing bid and ask quotes. The TAQ Master

[2] Microstructure models with inventory provide predictions that the inventory of a market maker should negatively predict future stock returns. For example, see Amihud and Mendelson (1980), Ho and Stoll (1981), Grossman and Miller (1988), and Madhavan Smidt (1993).

[3] Boehmer and Wu (2008) study all categories of trading on the NYSE and nd that program trading negatively predicts idiosyncratic returns at the individual stock level.

file provides CUSIP numbers that correspond to the symbols in the data on each date and are used to match with NCUSIP in the CRSP data. The use of midquote returns eliminates issues of bid-ask bounce that are present in transaction-based returns such as in CRSP.

We use TAQ to calculate daily spreads, i.e., the difference between the prices at which investors can sell and buy a given stock. The prices are typically referred to as the bid and ask prices and the difference between them is the quoted spread. On the floor of the NYSE, specialists and floor brokers can offer better prices than the bid and ask, and Chordia, Roll, and Subrahmanyam (2000) show that this often occurs. Therefore, we use the effective spread, which is the difference between an estimate of the true value of the security (the midpoint of the bid and ask) and the actual transaction price. We calculate the effective spread associated with each trade of a given stock on a given day. We then volume-weight the intra-day spreads to obtain a stock-day spread.

2.1 Index Addition Data

To begin our analysis of S&P500 stock returns and trading, we obtain S&P500 Index additions from January 2000 through December 2004 from Standard and Poor's website. For each addition, the website provides the stock's name, ticker, and last day of trading before change becomes effective. Announcement dates are originally obtained from Jeffrey Wurgler's website and then modified by searching news releases.

Throughout the paper we make a distinction between an addition's "announcement date" and its "effective date". The average difference between the two dates is 6.6 trading days. The standard deviation of the difference is 6.4 days. For one event in our sample, the two dates are the same. For thirteen of the events, the difference is more than ten trading days. The most frequent difference is four trading days.

[Insert Figure 1 About Here]

Figure 1 shows the periods of time we use in our event study analysis. Event returns, trading activity, *OIB*, and spreads are analyzed over the t-20 to t+20 interval. When calculating comovement of returns and *OIB*, we use the t-251 to t+251 interval while dropping the 100 days surrounding the addition. Requiring trading data a year before and after the addition requires the sample period for our event study of the additions to the S&P500 to be 2 years shorter than the period for which we have program trading data.

Table 1, Panel A shows there are 141 index additions between the 2000 and 2004. Because we only have program trading data for NYSE stocks, we focus on the 94 additions that are listed on the NYSE. Four of the stocks do not have trading data during the t-20 to t+20 interval leaving. Ten additional stocks do not have sufficient trading data during the t-251 to t+251 interval leaving us with a panel of 80 additions. The year 2000 has the most additions (27) the year 2003 has the fewest (5). Our events occur on 68 different days. Five days have two additions, one day has four additions, and one day has five additions. One stock, *CIT Group*, was added, dropped, and the added again during our sample period. Thus, the NYSE sample contains 79 unique tickers.

[Insert Table 1 About Here]

Our study includes [(Our71ed86dragout)-3282(ou(inc326(1)-327(Ab8(4227 0(1)S&P5(the) Td [(the)-39 futures prices—see Harris, Sofianos, and Shapiro (1994) and Hasbrouck (1996). In contrast to this prior emphasis on program trading, index arbitrage, and intraday volatility, our data is designed to filter out the index arbitrage component of program trading and we examine PT's impact at interday horizons.

Since 1987, program trading by index traders has increased as the value of exchange-traded funds and index-linked derivatives has grown by hundreds of billions and trillions of dollars. Contracts based on the S&P500 Index are the most heavily traded (ETFs and options). The advantages of program trading for index traders are its efficiency and low costs.[4] Program trades may be low cost because those trading a basket of securities can signal they have little or no information about the underlying stocks—Subrahmanyam (1991).

Our program trading data (non-index arbitrage) come from the NYSE's Consolidated Equity Audit Trail (CAUD) dataset from 1999-2005. The files contain detailed records of all trades that execute on the NYSE including transaction price and amount. Two of the data fields, labeled "Buyer Account Type" and "Seller Account Type", contain information about what type of trader is either buying or selling. There are account types for both Program Traders (PTs) and Program Index Arbitrages Traders. To minimize the influence of index arbitrage activity, we examine we use the Program Trader (PT) account code only.

Table 1, Panel B shows the aggregate average daily dollar volume (buy dollar volume + sell dollar volume). Over the entire sample period, program traders have an average volume of $11.9 billion per day. The program traders account for an average of 13.3% of market volume.[5] The fraction has been increasing from 8.4% in 2000 to 17.6% in 2004. While there is an increase in the volume of program trading over the sample period, we will later see that the magnitude of the PT OIB does not have such a time trend.

[4]Bloomberg, \Program Trades Dominate NYSE 18 Years After Crash: Taking Stock," October 19, 2005, quotes the head of equity trading at the biggest manager of ETFs, Barclays Global Investors, as using program trading because \it increases e ciency and reduces costs."

[5]When the NYSE reports program trading as a percentage it typically reports program trading buys plus sells divided by total volume. If all trading were program trading this would result in reporting that 200% of trading volume was program trading. Therefore, we calculate total volume as buy volume plus sell volume, which is twice as much as the trading volume reported in TAQ or CRSP. This results in our program trading percentages being half as large as the NYSE would report.

3 Index Additions

While program trading is a logical way for index investors to trade, to provide direct evidence on PT being used by index traders we study stocks added to the S&P500 Index. We start with a traditional event study and align events by announcement date (at t=0). The top-left graph of Figure 2 shows prices (cumulative returns) rise approximately 2% in the two trading weeks before the announcement. On the announcement date itself, prices jump up approximately 4% and then hold steady. This increase is comparable to Chen, Noronha, and Singal (2004) for their 1989 to 2000 sample period.

[Insert Figure 2 About Here]

Looking down the left-hand column of the figure, we see the average stock's turnover spikes noticeably on the announcement date (t=0). Turnover remains high for the next couple trading weeks and appears to be permanently higher at the end of a month. Spreads show a slight downward trend over the [-20,+20] event window. Consistent with Hegde and McDermott (2003), the increase in turnover and decline in spreads are statistically significant.

Figure 2 highlights the difference between aligning events on announcement dates and aligning events on effective dates. When using effective dates we use the convention that t=0 is the last trading day before a stock joins the index. Indexers who desire zero tracking error try to accumulate shares of a recently added stocks at the close of market on effective day t=0.

The top right graph of Figure 2 shows an interesting price pattern. Prices run-up more than 8% in the month before a stock joins the S&P500 Index. Prices "overshoot" by 2.25% in that they mean revert between t+1 and t+5. The final cumulative price effect is 6%. The permanent and transitory price changes are found in Chen, Noronha, and Singal (2004). The earlier paper finds a somewhat larger transitory price effect of 3.45% after additions using effective dates. The transitory price effect that is reversed is also referred to as price pressure.

Table 2, Panel A shows the average overshooting of 2.25% with 0.71 of all events experiencing some level of price pressure. The average price pressure of -2.25% is statistically significant with a 4.25 t-statistic. A liquidity supplier going short at the close of market on day t=0 has an average revenue of 2.25% when covering the short position at the close on day t=5.

However, the liquidity supplier faces short sale costs and may need to pay the bid-ask spread on both opening and closing the short position.

[Insert Table 2 About Here]

The negative return over effective dates $[+1, +5]$ suggests that index traders cause excess volatility and return predictability in the added stocks, at least around the time of index inclusion. The price pressure, high turnover, and increased spreads are consistent with limited risk-bearing capacity in the market.

3.1 Return Comovement and Index Additions

We next study return comovement around index additions. The analysis in this subsection replicates (for our sample period) the pre- and post-addition return comovement results of Vijh (1994) and Barberis et al. (2005). Vijh estimates the return comovement of a recently added stock from a univariate regression of its return on the market return:

$$R_{i,t} = \alpha_i + \beta_{sp500,i} \left(R_{sp500,t}\right) + \varepsilon_{i,t}. \tag{1}$$

This regression is performed separately for each stock added to the S&P500 Index using time periods before and after the addition. The R^2 and $\beta_{sp500,i}$ are recorded. We then compare the pre- and post-event R^2 and $\beta_{sp500,i}$ for each stock and calculate statistical significance using the cross-section of differences.

The left two columns in Table 2, Panel B show the results based on the univariate regression in Equations (1). The average R^2 is 0.132 pre-addition and is 0.256 post-addition. The 0.124 change in R^2 is statistically significant with a 7.10 t-statistic. The 0.124 increase is economically significant as well—the explanatory power of the regression almost doubles. Similarly the $\beta_{sp500,i}$ increases by almost 50% after joining the index with the increase having a 5.81 t-statistic.

The increases R^2 and β_{sp500} are greater than those found by Barberis et al. (2005) using data from 1988 to 2000. In their Table 1, Panel A, the authors found an increase in R^2 of 0.058 as compared to our 0.124 and an increase in β_{sp500} of 0.214 versus our increase of 0.315. Barberis et al. found that the comovement increases are stronger in the later parts of their sample and comparing their results to ours show that the higher comovement after inclusion in the S&P500 has continued to increase over time. The rise in comovement from 1988 to 2004 coincides with the increase in program trading shown in Table 1.

Index additions also have implications for the added stocks comovement with stocks ***not*** in the index. Barberis et al. (2005) extend the univariate framework to include the returns of non-S&P500 stocks:

$$R_{i,t} = \alpha_i + \beta_{sp500,i}\left(R_{sp500,t}\right) + \beta_{nonsp500,i}\left(R_{nonsp500,t}\right) + \varepsilon_{i,t}. \tag{2}$$

The right columns in Table 2, Panel B show the bivariate regression results for β_{sp500} and $\beta_{nonsp500}$. The increase in β_{sp500} is 0.341 with a 4.61 t-statistic. The return comovement with non-S&P500 stocks, $\beta_{nonsp500}$, shows a decrease of -0.124 which is not statistically different from zero.

3.2 Program Trading and Index Additions

To examine whether or not program trading is related to the increase in return comovement, we study program trading around index additions. We measure the total program trading volume (buy volume plus sell volume) and cumulative ***OIB*** (buy volume minus sell volume). To compare measures across stocks, we normalize both trading volume and ***OIB*** by shares outstanding and express all values in basis points. As is often done, we refer to the normalized trading volume as turnover. If program traders have a cumulative OIB of 100 basis points ("bp") of a stock over a set time period (say one week), then program traders as a whole own 1% more of the company at the end of the period than they did at the beginning of the period.

The left column of Table 3, Panel A shows that the amount of program trading (buys plus sells) increases from before the addition [-20,-6] to after the addition [+6,+20]. There is also a sharp spike in turnover on day t=0. The right column shows the cumulative program ***OIB***. We start at zero 21 days before a stock joins the S&P500 Index. Program traders accumulate an average of 110.35 bp of each stock between ***t***-20 and ***t***+20.

[Insert Table 3 About Here]

Figure 3 graphs the program trades around index additions. The top graphs shows daily turnover. Aligning events by effective dates shows a spike in program trading on the day before a stock joins the index. The lower graphs show cumulative order imbalances. Between t-20 and t-5, program traders accumulate about 15 bp of a company. Over the entire [t-20,t+20] window, program traders accumulate more than 1% of the newly-added stock.

[Insert Figure 3 About Here]

3.3 OIB Betas and Index Additions

We next link program trading to increases in return comovement after addition. We start by testing whether program trading in a recently added stock comoves more with program trading in other S&P500 stocks. Similar to the univariate return regression in Equation (1), we estimate the comovement of program trading with the regression:

$$OIB_{i,t} = \alpha_i + \beta^{oib}_{sp500,i} \left(OIB_{sp500,t}\right) + \varepsilon_{i,t}. \tag{3}$$

Regression (3) is performed separately for each of the event stocks both before and after the addition. We record the $\beta^{oib}_{sp500,i}$ and R^2 for each regression before comparing pre- and post-event values. $OIB_{sp500,t}$ is the market-capitalization weighted average of $OIB_{i,t}$ across the S&P500 stocks.

The left columns of Table 3, Panel B show the R^2 and β^{oib}_{sp500} increases are larger (in percentage terms) than those for the univariate return comovement regressions. The average ***OIB*** comovement increases are both statistically significant with 5.09 and 5.34 t-statistics respectively. The β^{oib}_{sp500} increases almost four-fold while the R^2 more than triples. We note the R^2 is relative low. This may be due to program trading in indices other than the S&P500, because quasi-index traders try to minimize their transaction costs by only trading some of the S&P500 stocks, or because program traders may be trading portfolios including non-index stocks.

We examine the cross-sectional dispersion of post-event increases in return comovement. We find a link with the increase in ***OIB*** comovement. The cross-sectional Pearson correlation of $\Delta R^2(returns)$ and $\Delta R^2(OIB)$ is 0.246 with 0.02 P-value. This cross-sectional result shows that stocks with larger increases in ***OIB*** comovement have larger increases in return comovement. Thus, there is both a time series and cross-sectional relationship between changes in return comovement and the ***OIB*** comovement.

The right columns of Table 3, Panel B show results of a bivariate ***OIB*** regression as seen in Equation (4) below. Similar to the bivariate return comovement regressions, the β^{oib}_{sp500} increases and the $\beta^{oib}_{nonsp500}$ decreases. Both the increase and decrease are statistically significant.

$$OIB_{i,t} = \alpha_i + \beta^{oib}_{sp500,i}\left(OIB_{sp500,t}\right) + \beta^{oib}_{nonsp500,i}\left(OIB_{nonsp500,t}\right) + \varepsilon_{i,t}. \tag{4}$$

Our ***OIB*** comovement results show that upon addition to the S&P500 Index, a stock's order imbalances start to comove more with the order imbalances of other S&P500 stocks. This, taken together with the increase in PT volume and the large positive cumulative PT ***OIB***), suggests that PT ***OIB*** may be a source of increased return comovement. To more directly establish a link, we estimate a "cross-β" from the regression:

$$R_{i,t} = \alpha_i + \beta^{r,oib}_{sp500,i}\left(OIB_{sp500,t}\right) + \varepsilon_{i,t}. \tag{5}$$

Table 3, Panel C provides more direct evidence of a link between return comovement being caused by program trading. The R^2 of the cross-regression more than doubles from 0.030 to 0.068 with a 4.65 t-statistic. The cross-beta almost doubles from 0.039 to 0.066 with a 3.89 t-statistic.

4 Returns and Program Trading at the Market Level

We test whether there is a systematic component to program trading that impacts returns of the market index. Our tests build on the prior section's results which establish that program trading affects individual S&P500 stock returns. After joining the index, in the added stock: program trading activity increases, PT order imbalances comove more with the order imbalance of other S&P500 stocks, and returns comoves more with the order imbalance of other S&P500 stocks.

Figure 4 graphs the aggregate PT ***OIB***. Only one day does the buy or sell imbalance exceed four basis points of the aggregate market capitalization of the S&P500 index stocks. The standard deviation of ***OIB*** is 0.739 basis points per day. The volatility of ***OIB*** appears somewhat higher at the beginning of the sample compared with at the end of the sample.

[Insert Figure 4 About Here]

We first examine the relationship of program tradings and market returns through simple contemporaneous and lead-lag correlations. Table 4 provides correlations of market-level variables including returns and order imbalances of stocks in the S&P500 Index. We also include returns and order imbalances of stocks ***not*** in the index. $\mathit{OIB}_{s}p500$ has a positive AR(1) coefficient of 0.186 while returns show no autocorrelation. The contemporaneous correlation between OIB and S&P500 returns is 0.475 and significant at all conventional levels. This indicates that PTs contemporaneously move prices or PTs engage in high-frequency (intra-day) positive feedback trading. OIB is contrarian at a one-day lag with a -0.064 correlation.

[Insert Table 4 About Here]

Most intriguingly, OIB negatively predicts market returns one day ahead as seen by the -0.079 correlation between $OIB_{sp500,t-1}$ and $R_{sp500,t}$. This is consistent with a limited-risk bearing operating at the S&P500-level. The only other evidence of such inventory effects are found in Chordia, Roll, and Subrahmanyam (2002). Their measure of OIB constructed using trade signing algorithms does not predict market returns in their entire sample, but does predict S&P500 returns the following day when OIB and returns are both very negative on the same day.

Market returns have a 0.483 correlation with non-S&P500 order imbalances. Trading of non-S&P500 stocks cannot forcast market returns. Not surprisingly, we see a high contemporaneous correlation of 0.861 between S&P500 and non-S&P500 returns. Consistent with work on large stocks leading small stocks, the S&P500 return on day ***t-1*** predicts the non-S&P500 on day t as can be seen by the 0.094 correlation coefficient. Consistent with some index investors using program trading to follow indices broader than the S&P500, e.g., the Russell 3000 or Wilshire 5000, OIB has a contemporaneous correlation of 0.334 across S&P500 and non-S&P500 stocks. There is weak positive evidence of cross autocorrelation in the OIBs. There is no evidence of PT OIB in non-S&P500 stocks predicting the next day's S&P500 return. OIB_{sp500} predicts $R_{nonsp500}$, although the simple correlations cannot tell us if this is distinct from the contemporaneous correlation between OIB_{sp500} and R_{sp500} and S&P500 stocks leading non-S&P500 stocks.

Order imbalances are positively autocorrelated and negatively correlated with future market returns, suggesting that to examine the effects of unexpected order imbalances we need to filter out these effects. The standard way of doing this is to estimate a vector autoregression

(VAR) that includes returns and OIB_{sp500}. In Equation 6, each of the $\mathbf{\Phi}$s is a two-by-two matrix of coefficients to be estimated. The errors are distributed: $\varepsilon_t \sim N[0, \mathbf{\Omega}]$. The HQIC criteria indicates we should include four lags.

$$Y_t = c + \mathbf{\Phi}_1 Y_{t-1} + \mathbf{\Phi}_1 Y_{t-1} + \mathbf{\Phi}_1 Y_{t-1} + \mathbf{\Phi}_1 Y_{t-1} + \varepsilon_t \tag{6}$$

$$Y_t = \begin{bmatrix} OIB_{sp500,t} \\ r_{sp500,t} \end{bmatrix} \qquad c = \begin{bmatrix} \alpha_{oib} \\ \alpha_r \end{bmatrix} \qquad \varepsilon_t = \begin{bmatrix} \varepsilon_{oib} \\ \varepsilon_r \end{bmatrix}$$

Table 5 presents the VAR coefficient estimates. As expected the OIB equation shows positive autocorrelation at all four lags. The negative feedback of returns on OIB at lag 1 is also evident, but is not present at longer lags. Consistent with OIB negatively predicting returns, in the return equation OIB at lag 1 has a coefficient of -0.019 with a t-statistic of 4.43. This along with OIB's standard deviation of 0.739 translates into returns falling roughly 13 basis points after a one standard deviation increase in OIB. Finally, the R^2 of the OIB equation is 0.103 and 0.013 for the return equation.

[Insert Table 5 About Here]

The bi-variate VAR gives insights into return autocorrelation at the market level. Table 4 shows the autocorrelation of raw returns is close to zero. Table 5 shows that when lagged OIB is included in the autocorrelation regression, returns at lag 1 have a 0.070 coefficient with 2.49 t-statistic. One way to interpret this result is that the VARs report return autocorrelation conditional on OIB.

In a Kyle (1985) setup, each period the informed trader continues to trade to push price to its fundamental value. The informed trader does this while disguising his order flow in the order flow of noise traders such that returns have zero autocorrelation. If the market maker could observe the noise traders' order flow, then the market maker could infer the informed trader's order flow. The informed order flow does predict subsequent price changes. If OIB_{sp500} represents noise or noninformational trades, then returns conditional on the noise traders' order flow are a measure of the informed order flow. Thus, returns conditional on OIB_{sp500} can positively predict future returns.

Granger causality tests show that there exists bi-direction causality between returns and OIB. Most importantly, we show OIB Granger causes returns. The relationship is significant at all conventional levels as the 20.67 χ^2 statistic shows. This result shows there is predictability of market returns. Also, we see that returns Granger cause OIB at all conventional levels of significance. This results shows positive feedback trading behavior by the program traders.

A parsimonious way of capturing the net effects of all the coefficients in the VAR is to follow Hamilton (1994) and form orthogonalized impulse response functions (IRFs). The unit-shock IRF at horizon $t+s$ comes from recursively solving for $\mathbf{\Psi}$ matrices:

$$\begin{aligned}
\mathbf{\Psi}_1 &= \mathbf{\Phi}_1 \\
\mathbf{\Psi}_2 &= \mathbf{\Phi}_1\mathbf{\Psi}_1 + \mathbf{\Phi}_2 \\
\mathbf{\Psi}_s &= \mathbf{\Phi}_1\mathbf{\Psi}_{s-1} + \mathbf{\Phi}_2\mathbf{\Psi}_{s-2} + \ldots + \mathbf{\Phi}_p\mathbf{\Psi}_{s-p}
\end{aligned}$$

The orthogonalized shock is obtained by factoring the covariance matrix of the error term $\mathbf{\Omega} = \mathbf{PP}'$ where $\mathbf{P}$ is lower diagonal. Denote the j^{th} column of $\mathbf{P}$ as P_j. The IRF, or change to Y_{t+s} in response to an orthogonalized shock at $t=0$, is given by $\mathbf{\Psi}_s P_j$.

Figure 5 has four sub-panels. The focus of this paper is the lower-left panel. We see that a one standard deviation shock to OIB_{sp500} leads to a -10 bp return the following day. The effect is short-lived and not significant after one day.

[Insert Figure 5 About Here]

Figure 5 shows the high autocorrelation of OIB_{sp500} in the top-left panel. The top-right panel gives evidence of the negative feedback trading. Although economically small, a one standard deviation shock to returns causes a -0.10 bp decrease in OIB_{sp500}.

Table 6 reports results from a quadravariate VAR that adds returns and order imbalances of non-S&P500 stocks. The coefficients on OIB_{sp500} and R_{sp500} in the first two equations are relatively unaffected by the inclusion of the non-S&P500 variables. OIB_{sp500} remains significant in the R_{sp500} equations at 1 lag. The lag 1 coefficient on R_{sp500} in the R_{sp500} equation falls from 0.070 to 0.065 and loses its statistical significance. Similarly, the lag 1 coefficient on R_{sp500} in the OIB_{sp500} equation falls slightly from -0.970 to -0.937, but its statistical significance falls appreciably.

[Insert Table 6 About Here]

The Granger causality tests show that the non-S&P500 returns and non-S&P500 OIB do not have statistically significant effects on either S&P500 returns or S&P500 OIB. Most importantly, S&P500 OIB continues to Granger cause S&P500 returns. The Granger causality running from S&P500 returns to S&P500 OIB is now weakly significant.

The market-level results in Table 5 and 6 extend the individual stock return results from the event study. We see that OIB_{sp500} causes predictability and excess volatility in the S&P500 return. Again, and because program trading imbalances are not publicly available, we do not interpret this as necessarily a violation of market efficiency. Rather, our results point to frictions operating at the market-level due to limited risk-bearing capacity.

5 Conclusions

If non-informational traders can cause changes in individual securities returns, can these traders affect market returns? We show that program traders induce a common component in the returns of the S&P500 Index. The order imbalances of program traders are positively correlated with contemporaneous index returns and negatively correlated with future returns. Thus, conditioning on trades today, allows us to (negatively) predict future market returns.

There a number of reasons to believe that program trading a good proxy for trading by index investors. Program trading is an efficient and low cost way for index investors to trade. Program trading activity increase after a stock is added to the S&P500 Index. After a stock joins the S&P500, its program trading order imbalances comove more with the order imbalances of other S&P500 stocks.

We are conservative when interpreting our results. Investors trading portfolios of stocks may also use program trading. While we prefer to interpret our results as showing that index traders cause predictability and excess volatility in the index/market returns, it is possible that other portfolio traders are responsible for this effect. Either interpretation is consistent with there being limited risk bearing capacity at the market-level.

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Table 1
Overview Statistics

Panel A shows the number of S&P 500 Index additions in our sample. Panel B shows trading statistics including: the average daily trading volume (in dollars) for the program traders in our sample; the average daily volume (in dollars) for the whole market, and average fraction of daily volume accounted for by the program traders. Trading volumes in dollars are measured as buy volume plus sell volume.

Panel A: Sample of S&P 500 Additions

	2000	2001	2002	2003	2004	All Years
All Events	58	30	24	9	20	141
NYSE Only	31	20	19	6	18	94
NYSE with Data for [-251,+251] Interval	27	16	16	5	16	80

Panel B: Aggregate Program Trading

	2000	2001	2002	2003	2004	All Years
Average Daily PT Volume in $ (billions)	7.72	10.00	11.60	13.00	17.20	11.90
Average Daily Market Volume in $ (billions)	92.40	88.30	86.90	82.30	98.20	89.60
Average PT Fraction of Daily Market Volume	8.4%	11.4%	13.4%	15.8%	17.6%	13.3%

Table 2
Stock Returns Around Index Additions

Stock price and comovement reactions around index additions. Panel A reports the cumulative abnormal returns (for the time periods shown) based on both announcement dates and effective dates. We consider additions to the S&P 500 Index from 2000 through 2004. Returns are based on the closing mid-point of the bid and ask. "Fraction" is the proportion of the events whose return has the same sign as the mean return. "*" and "**"indicates significance at the 5% and 1% levels. Panel B reports measures of return comovement prior to the addition, days [-250,-51], and following the stock's addition, days [+51,+250]. Univariate comovement measures come from a regression of a stock's returns on the returns of the S&P500. Bivariate comovement measures come from a regression on a stock's returns on the return of the S&P500 and the return of stocks not in the S&P500.

Panel A: Cumulative Abnormal Returns

	Announcement Dates			Effective Dates		
Time Window	**Mean**		**Fraction**	**Mean**		**Fraction**
[-20,-6]	0.0159		0.68	0.0389	**	0.76
[-20,-1]	0.0203		0.72	0.0731	**	0.84
[-20,0]	0.0546	**	0.81	0.0835	**	0.81
[+1,+5]	0.0009		0.49	-0.0225	**	0.71
[-20,+5]	0.0556	**	0.71	0.0610	**	0.71
[-20,+20]	0.0556	**	0.68	0.0611	**	0.66

Panel B: Changes in Return Comovement

	Univariate		Bivariate	
	R^2	β_{sp500}	β_{sp500}	$\beta_{nonsp500}$
Pre Event	0.132	0.697	0.085	0.828
Post Event	0.256	1.013	0.425	0.704
Δ Post-Event	0.124	0.315	0.341	-0.124
(T-Stat of Diff)	*(7.10)*	*(5.81)*	*(4.61)*	*(-1.27)*

Table 3
Program Trading Around Index Additions

Panel A shows program trading activity for time periods around the 80 index additions. For each event, turnover is program trading buy volume plus sell volume normalized by shares outstanding. Order imbalance (OIB) is program trading shares bought minus shares sold normalized by shares outstanding. Panel B reports measures of OIB comovement prior to the addition, days [-250,-51], and following the stock's addition, days [+51,+250]. Univariate measures come from regressions of each stock's OIB on the OIB of the S&P 500. Bivariate measures come from regressions of each stock's OIB on the OIB of the S&P 500 and the OIB of stocks not in the S&P 500. Panel C provides measures of cross comovement from regressions of each stock's returns on the OIB of the S&P 500.

Panel A: Turnover and Cumulative Order Imbalance (OIB) of Program Traders
OIB = Buys – Sells in b.p. of Shares Outstanding

Time Window	Turnover	Cumulative OIB
[-20,-6]	15.20	10.04
[-5,-1]	18.42	9.82
[0,0]	170.37	40.27
[+1,+5]	29.06	28.90
[+6,+20]	20.02	21.32
[-20,+20]	22.83	110.35

Panel B: Order Imbalance Comovement

	Univariate		Bivariate	
	R^2	β_{sp500}	β_{sp500}	$\beta_{nonsp500}$
Pre Event	0.012	0.266	-0.081	1.271
Post Event	0.035	0.907	0.772	0.322
Δ Post-Event	0.024	0.641	0.843	-0.948
(T-Stat of Diff)	*(5.09)*	*(5.34)*	*(7.07)*	*(-6.44)*

Panel C: Cross Comovement: Returns on Order Imbalance

	R^2	β_{sp500}
Pre Event	0.030	0.039
Post Event	0.068	0.066
Δ Post-Event	0.038	0.027
(T-Stat of Diff)	*(4.65)*	*(3.89)*

Table 4
Correlations of Market Variables

Pearson correlations of market-level returns and order imbalances on stocks in the S&P500 (subscripted sp500) and not in the S&P500 (subscripted nonsp500) on date t and date t-1. Returns are value-weighted. Order imbalance (OIB) for each stock is program trading shares bought minus shares sold normalized by shares outstanding. OIB is aggregated across stocks using market capitalization weighst. P-values are shown in parentheses.

	$R_{sp500,t}$	$R_{sp500,t-1}$	$OIB_{sp500,t}$	$OIB_{sp500,t-1}$	$R_{nonsp500,t}$	$R_{nonsp500,t-1}$	$OIB_{nonp500,t}$
$R_{sp500,t}$	1.000 ----						
$R_{sp500,t-1}$	0.005 *(0.84)*	1.000 ----					
$OIB_{sp500,t}$	0.476 *(0.00)*	-0.064 *(0.00)*	1.000 ----				
$OIB_{sp500,t-1}$	-0.079 *(0.00)*	0.477 *(0.00)*	0.179 *(0.00)*	1.000 ----			
$R_{nonsp500,t}$	0.861 *(0.00)*	0.094 *(0.00)*	0.344 *(0.00)*	-0.002 *(0.93)*	1.000 ----		
$R_{nonsp500,t-1}$	0.010 *(0.69)*	0.861 *(0.00)*	-0.057 *(0.02)*	0.344 *(0.00)*	0.092 *(0.00)*	1.000 ----	
$OIB_{nonsp500,t}$	0.483 *(0.00)*	-0.051 *(0.03)*	0.334 *(0.00)*	0.027 *(0.26)*	0.568 *(0.00)*	-0.062 *(0.01)*	1.000 ----
$OIB_{nonsp500,t-1}$	-0.006 *(0.82)*	0.483 *(0.00)*	0.046 *(0.06)*	0.335 *(0.00)*	0.028 *(0.24)*	0.568 *(0.00)*	0.070 *(0.00)*

Table 5
Vector Autoregression of Order Imbalances and S&P 500 Returns

Results are reported for a vector autogression on market-level returns and order imbalances on stocks in the S&P500 (subscripted sp500) with 4 lags. Returns are value-weighted. Order imbalance (OIB) for each stock is program trading shares bought minus shares sold normalized by shares outstanding. OIB is aggregated across stocks using market capitalization weights.

OIB_{sp500} Equation

		Coef	*(Z-Stat)*
OIB_{sp500}	Lag 1	0.190	*(6.80)*
	Lag 2	0.124	*(4.30)*
	Lag 3	0.076	*(2.67)*
	Lag 4	0.112	*(4.04)*
R_{sp500}	Lag 1	-0.970	*(-5.32)*
	Lag 2	0.137	*(0.74)*
	Lag 3	0.202	*(1.09)*
	Lag 4	-0.274	*(-1.51)*
Const.		0.0117	*(6.21)*

R_{sp500} Equation

		Coef	***(Z-Stat)***
OIB_{sp500}	Lag 1	-0.019	*(-4.43)*
	Lag 2	0.007	*(1.59)*
	Lag 3	-0.002	*(-0.37)*
	Lag 4	0.005	*(1.15)*
R_{sp500}	Lag 1	0.070	*(2.49)*
	Lag 2	-0.056	*(-1.95)*
	Lag 3	-0.004	*(-0.13)*
	Lag 4	-0.011	*(-0.40)*
Const.		0.0004	*(1.25)*

Granger Causality Tests

Var 1	**Causes**	**Var 2**	χ^2	**P-Value**
R_{sp500}	→	OIB_{sp500}	31.91	0.0000
OIB_{sp500}	→	R_{sp500}	20.67	0.0004

Table 6
Vector Autoregression of Order Imbalances and Returns for S&P 500 Stocks and Non-S&P 500 Stocks

Results are reported for a vector autogression on market-level returns and order imbalances on stocks in the S&P500 (subscripted sp500) and not in the S&P500 (subscripted nonsp500) with 4 lags. Returns are value-weighted. Order imbalance (OIB) for each stock is program trading shares bought minus shares sold normalized by shares outstanding. OIB is aggregated across stocks using market capitalization weights.

		OIB_{sp500} Equation Coef	*(Z-Stat)*			R_{sp500} Equation Coef	*(Z-Stat)*
OIB_{sp500}	Lag 1	0.179	*(6.26)*	OIB_{sp500}	Lag 1	-0.019	*(-4.28)*
	Lag 2	0.119	*(4.02)*		Lag 2	0.007	*(1.52)*
	Lag 3	0.072	*(2.44)*		Lag 3	-0.002	*(-0.51)*
	Lag 4	0.109	*(3.80)*		Lag 4	0.003	*(0.64)*
$OIB_{nonsp500}$	Lag 1	0.049	*(1.89)*	$OIB_{nonsp500}$	Lag 1	-0.001	*(-0.28)*
	Lag 2	0.013	*(0.51)*		Lag 2	-0.003	*(-0.72)*
	Lag 3	0.016	*(0.62)*		Lag 3	0.009	*(2.25)*
	Lag 4	0.013	*(0.48)*		Lag 4	0.002	*(0.49)*
R_{sp500}	Lag 1	-0.937	*(-2.72)*	R_{sp500}	Lag 1	0.065	*(1.23)*
	Lag 2	0.099	*(0.29)*		Lag 2	-0.039	*(-0.73)*
	Lag 3	0.230	*(0.67)*		Lag 3	-0.023	*(-0.44)*
	Lag 4	-0.320	*(-0.96)*		Lag 4	0.076	*(1.49)*
$R_{nonsp500}$	Lag 1	-0.246	*(-0.63)*	$R_{nonsp500}$	Lag 1	0.012	*(0.20)*
	Lag 2	0.054	*(0.14)*		Lag 2	-0.009	*(-0.16)*
	Lag 3	-0.101	*(-0.26)*		Lag 3	-0.017	*(-0.28)*
	Lag 4	0.022	*(0.06)*		Lag 4	-0.109	*(-1.87)*
Const		0.009	*(4.10)*	Const		0.000	*(0.65)*

Granger Causality Tests (Partial Results Shown)

Var 1	Causes	Var 2	χ^2	*P-Value*
$OIB_{nonsp500}$	→	OIB_{sp500}	5.83	*0.212*
R_{sp500}	→	OIB_{sp500}	8.82	*0.066*
$R_{nonsp500}$	→	OIB_{sp500}	0.45	*0.978*
OIB_{sp500}	→	R_{sp500}	19.36	*0.001*
$OIB_{nonsp500}$	→	R_{sp500}	5.80	*0.215*
$R_{nonsp500}$	→	R_{sp500}	3.78	*0.436*

Table 6
Continued

		$OIB_{nonsp500}$ Equation				$R_{nonsp500}$ Equation	
		Coef	***(Z-Stat)***			**Coef**	***(Z-Stat)***
OIB_{sp500}	Lag 1	0.003	*(0.08)*	OIB_{sp500}	Lag 1	-0.009	*(-2.33)*
	Lag 2	0.018	*(0.53)*		Lag 2	0.009	*(2.17)*
	Lag 3	-0.005	*(-0.14)*		Lag 3	-0.005	*(-1.35)*
	Lag 4	0.057	*(1.73)*		Lag 4	0.001	*(0.22)*
$OIB_{nonsp500}$	Lag 1	0.120	*(3.99)*	$OIB_{nonsp500}$	Lag 1	-0.004	*(-1.06)*
	Lag 2	0.104	*(3.43)*		Lag 2	-0.004	*(-1.15)*
	Lag 3	0.065	*(2.14)*		Lag 3	0.005	*(1.44)*
	Lag 4	0.046	*(1.55)*		Lag 4	0.000	*(0.11)*
R_{sp500}	Lag 1	0.051	*(0.13)*	R_{sp500}	Lag 1	0.096	*(2.07)*
	Lag 2	0.425	*(1.08)*		Lag 2	0.036	*(0.77)*
	Lag 3	-0.012	*(-0.03)*		Lag 3	0.035	*(0.75)*
	Lag 4	-0.105	*(-0.28)*		Lag 4	0.061	*(1.35)*
$R_{nonsp500}$	Lag 1	-1.130	*(-2.51)*	$R_{nonsp500}$	Lag 1	0.047	*(0.90)*
	Lag 2	-0.840	*(-1.87)*		Lag 2	-0.084	*(-1.59)*
	Lag 3	0.226	*(0.51)*		Lag 3	-0.027	*(-0.51)*
	Lag 4	-0.243	*(-0.56)*		Lag 4	-0.074	*(-1.45)*
Const		0.022	*(8.74)*	Const			

Figure 1
Time Periods

The figures show time periods used to calculate returns, mean-reversion, comovement, spreads, and trading around index additions. Cumulative returns and cumulative order imbalances use a [-20,+20] window. The mean-reversion measure compares returns from the [-3, -1] and [0, +2] windows. Pre-addition turnover is measured uses a [-20,-6] window. Post-addition turnover is measured uses a [+6,+20] window. Pre-addition comovement is measured using data from a [-250,-51] window. Post-addition comovement is measured using data from a [+51,+250] window.

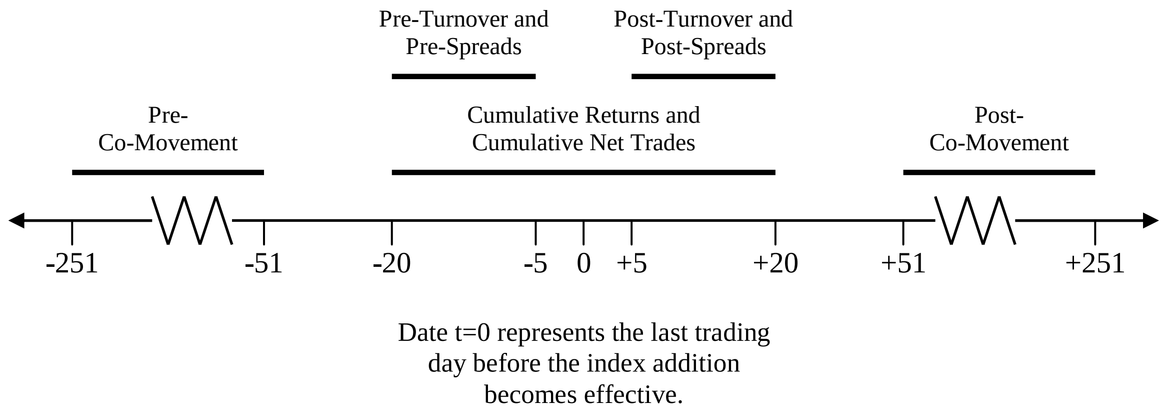


Figure 2
Reactions to Index Additions

The figures show cumulative abnormal returns, turnover, and spreads around stocks' addition in the S&P 500 Index. The left-hand figures align events by announcement dates. The right-hand figures align events by effective dates. The top two figures show the average cumulative return (in excess of the market) associated with being added to the index. The middle two figures show the average stock turnover. Turnover is share trading volume normalized by shares outstanding. The bottom two figures show the average stock spreads.

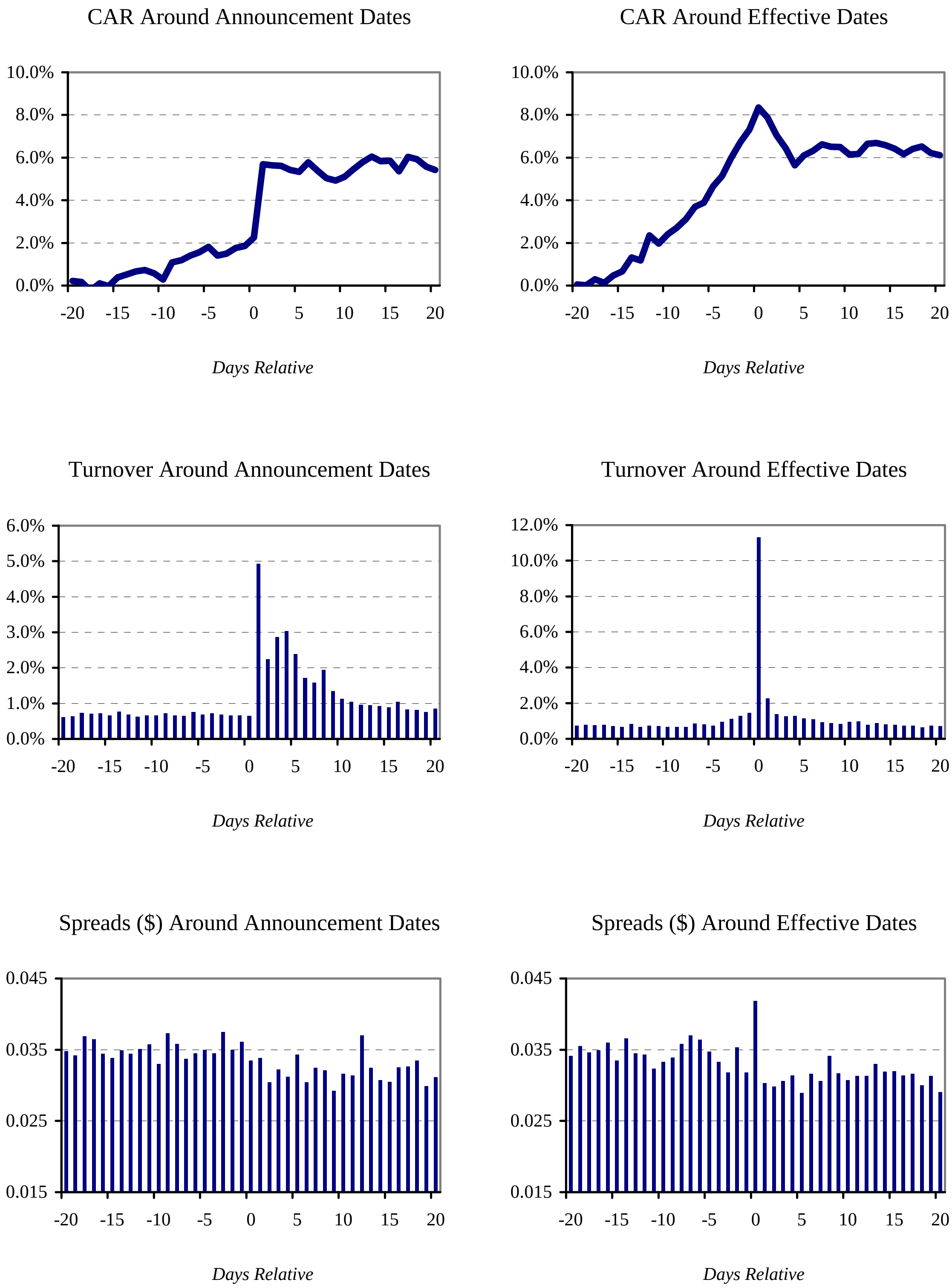
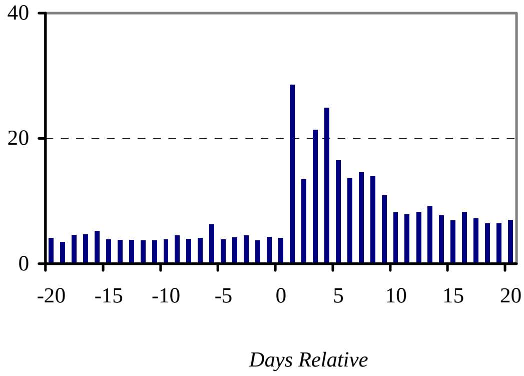


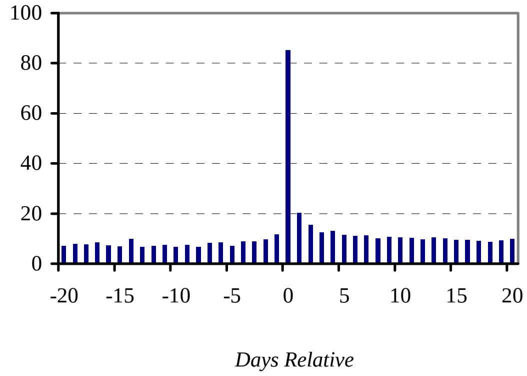
Figure 3
Program Trading Around Index Additions

The figures show program trading behavior around stocks' addition to the S&P 500 index. The left-hand column defines the announcement date as day zero. The right-hand column defines the effective date as day zero. We show shows turnover defined as shares bought plus shares normalized by shares outstanding.. We also show program traders' cumulative order imbalances defined as shares bought minus shares sold normalized by shares outstanding in basis points.

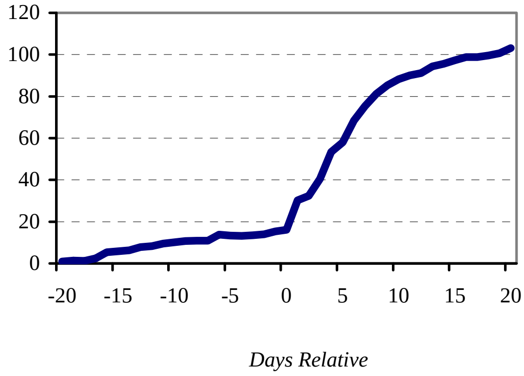
Program Traders
Turnover Around Announcement Dates



Program Traders
Turnover Around Effective Dates



Program Traders
Cumulative OIB (Buys – Sells)
Around Announcement Dates



Program Traders
Cumulative OIB (Buys – Sells)
Around Effective Dates

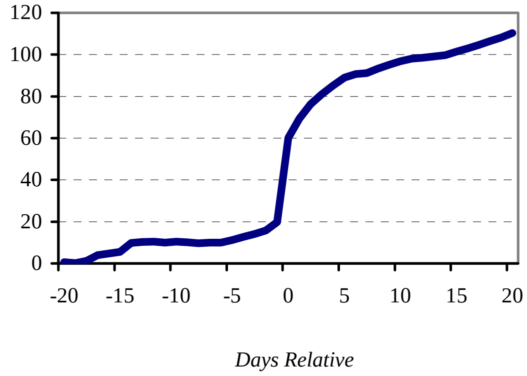


Figure 4
Market Order Imbalance

The figure shows the aggregate program trading order imbalances for S&P 500 stocks over our sample period. Order imbalance for each stock is program trading shares bought minus shares sold normalized by shares outstanding. Values are aggregated across stocks using market capitalization weights. Units shown are in basis points of market capitalization.

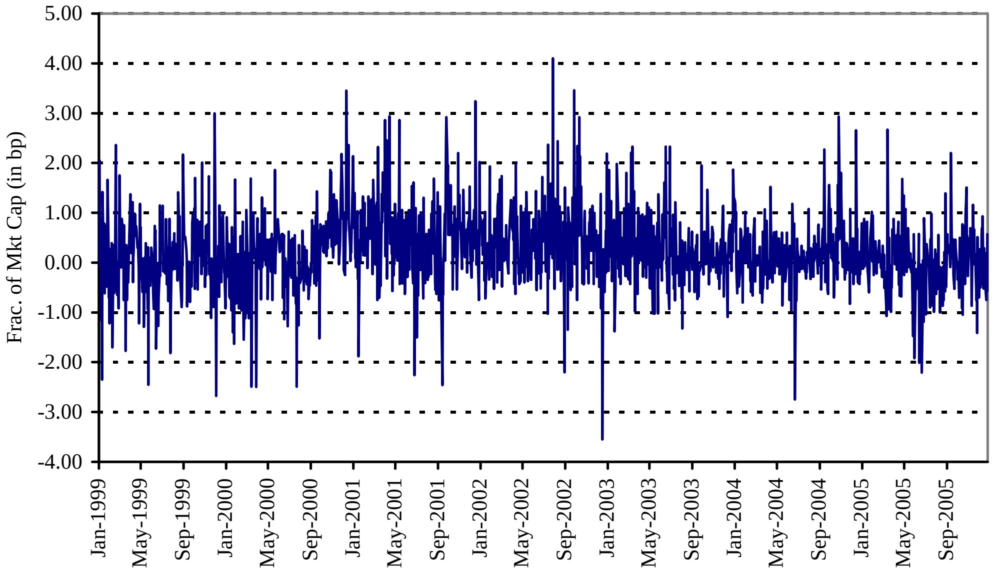


Figure 5
Impulse Response Function of the Response of Returns to a Shock in Order Imbalance

The figure shows the impulse response functions from a bivariate vector autogression on market-level returns and order imbalances on stocks in the S&P500 (subscripted sp500) with 4 lags. Returns are value-weighted. Order imbalance (OIB) for each stock is program trading shares bought minus shares sold normalized by shares outstanding. OIB is aggregated across stocks using market capitalization weights.