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Badrinath Kottimukkalur Date

Essays in Financial Economics

By

Badrinath Kottimukkalur
Doctor of Philosophy

Business

Tarun Chordia, Ph.D
Advisor

Jeff Busse, Ph.D
Committee Member

Ilia Dichev, Ph.D
Committee Member

T.Clifton Green, Ph.D
Committee Member

Narasimhan Jegadeesh, Ph.D
Committee Member

Accepted:

Lisa A. Tedesco, Ph.D.
Dean of the James T. Laney School of Graduate Studies

Date

Essays in Financial Economics

By

Badrinath Kottimukkalur
B.E., Anna University, 2003
PGPM, Great Lakes Institute of Management, 2005

Advisor: Tarun Chordia, Ph.D

An abstract of
A dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
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Abstract

Essays in Financial Economics

By Badrinath Kottimukkalur

My dissertation studies the behavior of investors in financial markets. My first essay investigates whether attention constraints lead investors to underreact to earnings news on days with large market movements (market moving days). Investors are less likely to trade on earnings announcements on market moving days compared to other days. Earnings on market moving days are accompanied by a lower immediate price and volume response, as well as a higher post-earnings announcement drift. Additionally, analysts are slow to revise estimates following earnings on market moving days. Prices respond slowly to earnings when macroeconomic announcements are surprising. The findings are consistent with investors paying more attention to market information as compared to firm-specific information. The second essay, co-authored with Tarun Chordia and Clifton Green, studies High Frequency Trading around macro releases. Prices of stock index exchange traded funds and index futures respond to macroeconomic announcement surprises within a tenth of a second, with trading intensity increasing ten-fold in the quarter second following the news release. Profits from trading quickly on announcement surprises are relatively small and decline in recent years. Trading profits also decrease with quote intensity. The speed of information incorporation increases in recent years and order flow becomes less informative, consistent with prices responding to news directly rather than indirectly through trading. Our evidence is consistent with increasing competition among low latency traders, which mitigates concerns about their speed advantage. The third essay investigates whether turnover volatility (TURNVOL) limits arbitrage. Mispricing is severe in the high TURNVOL stocks. Among overpriced (underpriced) stocks, the high TURNVOL stocks are the most overpriced (underpriced). Overpricing in high TURNVOL stocks is severe during high investor sentiment periods. The findings are consistent with TURNVOL limiting arbitrage. Further, the negative relationship between TURNVOL and average return is present only in difficult-to-short stocks. TURNVOL as a deterrent to arbitrage and arbitrage asymmetry together explain the negative TURNVOL-return relation documented in prior literature.

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Attention to Market Information and

Underreaction to Firm Earnings on Market Moving Days

Badrinath Kottimukkalur

Abstract

I investigate whether attention constraints lead investors to underreact to earnings news on days with large market movements (market moving days). Investors are less likely to trade on earnings announcements on market moving days compared to other days. Earnings on market moving days are accompanied by a lower immediate price and volume response, as well as a higher post-earnings announcement drift. Additionally, analysts are slow to revise estimates following earnings on market moving days. Prices respond slowly to earnings when macroeconomic announcements are surprising. The findings are consistent with investors paying more attention to market information as compared to firm-specific information.

1. Introduction

There are limits to cognitive abilities of humans. One such limit is the difficulty in attending to multiple tasks at the same time. As Pashler (1998) notes, "two activities that a person can easily carry out one at a time often pose tremendous problems when attempted simultaneously, even when these activities are in no way physically incompatible." People resolve attention constraints in a number of ways. Studies in psychology show that when presented with multiple stimuli, subjects can deliberately direct attention to a specific task (Yantis, 1998). This active allocation of attention to one task delays the completion of other unattended tasks.

Attention constraints are relevant to financial markets. Multiple events occur in a given day, including company earnings releases, macroeconomic news, brokerage reports, product announcements, and deal rumors. Given the attention constraints, it is important to identify the event that attracts investors' attention and to consider pricing implications of other unattended information. Peng and Xiong (2006) present a model where an investor chooses to allocate attention between market information, industry news, and firm news. The model predicts that the investor will pay more attention to market information as compared to firm news. In the extreme scenario, when attention is severely constrained, firm-specific news will be completely ignored. Intuitively, market information has a higher impact on an investor's wealth and therefore attracts more attention relative to firm-specific information. This leads to the delay in processing firm-specific information.

Finance literature has documented the existence of arbitrage costs including transaction costs, holding costs, idiosyncratic volatility, and noise trader risk. When such limits to arbitrage exist, delay in processing could result in underreaction of prices to information. In this paper, I empirically test whether attention to market information results in underreaction to firm-specific information on days with important market information.

The reaction of the Finish Line (FINL) stock to its earnings, released on the day of the Brexit result, provides anecdotal evidence of underreaction on a day with important market information. The Brexit result was announced on 24 June 2016. The result surprised the markets. The British Pound dropped from $1.50 to $1.37 and the S&P 500 index declined by 3.6%. On the same day, Finish Line, a shoe and apparel retailer, reported its first quarter (1Q17) earnings, 4.5% better than expectations. Figure 1 plots the cumulative returns in Finish Line and S&P500 from the Brexit result to two months following the result.

In the announcement period, Finish Line earned excess returns of 20.8% in response to the big positive surprise. If investors had paid complete attention to Finish Line earnings and fully reacted to the surprise a delayed reaction in the stock price post-earnings is less likely. If instead, investors were paying attention to Brexit result and were inattentive to Finish Line earnings, there would be a noticeable upward drift in the stock. In the two months following the announcement period, FINL earned excess returns of 16.2%, indicating that the stock did not completely price the information in the earnings during the announcement period.

The Finish Line example therefore provides compelling indications that important market information can affect attention to earnings. My study empirical tests this using magnitude of market return (market movement) as a measure of significance of market information. Each quarter, I sort trading days first by the day of the week to control for weekday variation in attention. Then I sort trading days within each day of the week into terciles on magnitude of market returns. Market moving days (slow market days) are the trading days in the tercile with highest (lowest) market movement.

To study the investors' trading behavior I use retail investor trading data.[1] I find that investors are less likely to trade on earnings announcements if the announcement happens on a market moving day as compared to a slow market day.

In price response tests, I study the reaction of stock prices to earnings surprise. Each quarter, following DellaVigna and Pollet (2009), I sort stocks into 11 groups based on earnings surprise. Cumulative abnormal return (CAR) is the buy and hold stock return over the beta-adjusted buy and hold market return. In volume response tests, abnormal volume (AVOL) is the ratio of volume in the stock relative to aggregate market volume in the announcement period, to the relative volume 7 to 46 days before earnings announcement. Consistent with underreaction, announcement period cumulative abnormal return (CAR[0,1]) and abnormal volume (AVOL[0,1]) are lower for firms releasing earnings on market moving days. Post-earnings announcement drift (CAR[2,90]) is higher for those firms.

Earnings surprise is persistent. This is due to the sluggish response of analysts' forecasts to past news (Chan, Jegadeesh, and Lakonishok, 1996). I find that the surprise is more persistent if the previous earnings occurred on a market moving day. Analysts are more sluggish in responding to earnings and do not adequately adjust their estimates on market moving days.

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[1] I am grateful to Terrance Odean for providing the data.

The slow responsiveness of analysts to earnings is another channel through which underreaction to firm news occurs (Zhang, 2008). I use two measures of analyst responsiveness: the average number of working days between the earnings date and the first revision by an analyst, and the proportion of firms with at least one revision within two days of the earnings release. I find that analysts take longer to revise following announcements on market moving days. The proportion of firms with on-time revision is lower for market moving day announcements. The results suggest that analysts are also inattentive to firm news during market moving days.

While macroeconomic announcements provide important market information, not all of them move markets equally. The ones that arrive in line with expectations rarely move the markets. The impact of macroeconomic announcements on prices is dependent on announcement surprise (Balduzzi, Elton, and Green, 2001). I consider a set of important macroeconomic announcements (Nonfarm Payrolls, GDP announcement, FOMC Rate Decision, ISM Manufacturing, ISM Non-Manufacturing, Construction Spending, New Home Sales, and ADP Employment) and study how the attention to firm news varies with the magnitude of macroeconomic surprise. I find that a firm's stock price underreacts to earnings on days with large magnitude of surprise in a major macroeconomic announcement.

Stocks with certain characteristics receive lower level of attention to their announcements. These stocks are typically small in size, have lower analyst following and high book-to-market ratio. These stocks also tend to have lower arbitrage participation. Post-earnings drift is generally higher in these stocks. I find that the drift is even higher when these stocks announce earnings on market moving days. The results provide evidence that the underreaction is severe in stocks with lower arbitrage participation.

Lower attention to firm earnings on market moving days provides an incentive for the managers to strategically time poor earnings. This behavior is typically found in earnings released on Fridays (DellaVigna and Pollet, 2009). While there is an incentive, I do not find evidence of managers timing poor earnings release on market moving day. This is due to the difficulty in predicting daily market returns.

I also study the response of aggregate mutual funds flows to market returns. Investors who are attentive to the market are likely to respond either by increasing or decreasing exposure to equities. Weekly aggregate equity mutual fund flow is positively related to contemporaneous returns (contemporaneous response) and lagged returns (delayed response). For large market movements, the contemporaneous response of flows is stronger and the delayed response is weaker. Attention to the market results in a quicker response of flows to returns when market movement is large.

Prior studies have documented *distraction* as the primary cause of inattention to firm news. DellaVigna and Pollet (2009) note that investors do not pay as much attention to earnings on Fridays as they are distracted by the coming weekend. Hirshleifer, Lim, and Teoh (2009) show that investors are distracted on days with large number of other earnings announcements. I contribute to the literature by highlighting that *active attention* to market information results in underreaction to firm-specific information.

Hirshleifer, Lim, and Teoh (2009) document that the *number of simultaneous announcements* affect attention to a news release. I highlight that the ability of *importance of simultaneous release* in affecting attention as well. My results provide empirical support to the model in Peng and Xiong (2006). Additionally, I show that analysts are slow to respond to firm-specific information on market moving days.

The remainder of the paper is organized as follows. Section 2 discusses the related literature on attention and develops hypotheses, Section 3 describes the data and methodology, Section 4 presents the results, and Section 5 concludes.

2. Literature and Hypothesis Development

Finance literature has investigated how the limits of human cognitive abilities affect asset prices. Theoretical work has shown that inattention can explain anomalies. Hirshleifer and Teoh (2003) and DellaVigna and Pollet (2009) use inattention to explain underreaction to accounting information. Similarly, Peng and Xiong (2006) use inattention to explain co-movement in Barberis, Shleifer, and Wurgler (2005) and further note this behavior can lead to "style investing" in Barberis and Shleifer (2003). In addition, Hong and Stein (1999) show that underreaction to information due to cognitive limits can explain momentum in Jegadeesh and Titman (1993). As a final example, Duffie (2010) uses inattention as a factor in explaining slow moving capital. Moreover in empirical work, Cohen and Frazzini (2008) cite inattention as a reason for underreaction to information from economic links.

Empirical literature has explored the factors affecting attention. Seasholes and Wu (2007) show that investors tend to buy stocks with attention grabbing events like stocks hitting upper price limits. Barber and Odean (2008) note investors are net buyers of stocks mentioned in the media. Other studies have examined whether extraneous events distract investors from paying attention to firm earnings. DellaVigna and Pollet (2009) find that investors are inattentive to Friday earnings due to weekend distractions.

Hirshleifer, Lim, and Teoh (2009) show that large number of other announcements can distract investors from paying attention to firm earnings. These studies focus on distracting effects. The potential for investors to actively allocate attention to a specific type of information has not received much attention.

Studies in psychology show that when presented with multiple stimuli, people can deliberately direct their attention to a specific task. It is important to understand which event, among the multiple events that occur in a day, would attract the investor's attention and the implications for other events which do not draw attention. Peng and Xiong (2006) present a model to explain how an investor will actively allocate attention among market information, industry information, and firm news. They follow Sims (2003) and employ entropy to study information-processing constraints. In the model, investors pay more attention to information that reduces the variance of their beliefs about next period dividends. The model predicts that attention constrained investors will focus on market information compared to firm-specific information. Intuitively, market information has a higher impact on an investor's wealth as compared to other types of information. Due to its consequences on wealth, an investor is more likely to be attentive to market information. In the presence of attention constraints, this would lead to a delay in processing firm-specific information that is released concurrent with a major market information.

There are limits to arbitrage. Transaction costs, short sale constraints (Miller, 1977 and Nagel, 2005), idiosyncratic volatility (Pontiff, 2006), and noise trader risk (Shleifer and Vishny, 1997) are examples of costs that hinder arbitrage. In the presence of limits to arbitrage, the tendency to pay attention to market information could result in underreaction of stock prices to firm news.

I empirically test the hypothesis by studying the reaction of firm stock price to earnings on days with important market information. Macroeconomic announcements are an important source of market information. For example, Liu and Peng (2015) study google search activity (Da, Engelberg, and Gao , 2011) for a firm ticker on days with a scheduled macroeconomic event. They find that the increase in searches is lower if a firm announces earnings on the day of scheduled macroeconomic event. However, jump literature shows that macro releases explain less than one-third of the jumps in S&P500 (Dungey, McKenzie and Smith, 2009 and Prokopczuk and Wese Simen, 2016). A large proportion of jumps are due to unscheduled events. Studying only scheduled macroeconomic announcements misses out on important events like the Brexit. These important market events are accompanied by a large shift in prices. For example, on the day of the Brexit, the indices declined by 3.6%. To capture events like Brexit, I directly use the magnitude of market returns as a measure of importance of news. I study the reaction of stock price to earnings announcements as it is the primary source of information on firm prospects.

I hypothesize that due to their attention to market information:

1) Investors are less likely to trade on earnings on days with large market movements.

Those earnings would be accompanied by:

2) A smaller immediate price response to earnings surprise
3) A larger post-earnings announcement drift
4) A smaller volume response to earnings

Investors attentive to the market are likely to respond either by increasing or decreasing exposure to equities. I also study the implications for aggregate mutual fund flows and aggregate volume.

3. Data and Methodology

3.1 Data

I obtain daily market returns from Kenneth French Website[2]; analyst estimates, actual quarterly EPS, and earnings dates from IBES; macroeconomic announcement dates, estimates, and actual values from Bloomberg; stock price and shares outstanding from CRSP; book values from COMPUSTAT; and weekly aggregate domestic equity mutual fund flows from Investment Company Institute.

I consider all firms with at least one analyst estimate of quarterly EPS available 90 days before earnings announcement. I exclude stocks with a price less than the absolute value of quarterly EPS, consensus EPS estimate, or the difference between the estimate and actual, as these are likely to be data errors. I also exclude penny stocks and firm quarters with earnings announcements on Saturdays or Sundays. I only consider stocks with market cap and book value information.

To accurately identify earnings release date, I use the procedure in DellaVigna and Pollet (2009). I exclude announcements where the IBES and COMPUSTAT release dates differ by more than five days. If IBES and COMPUSTAT have different earnings dates for the same fiscal quarter, the earliest date is the reporting date. DellaVigna and Pollet (2009) note that the identification procedure is accurate beginning in 1995. The sample period for price response tests is from 1995 to 2014. Due to data availability the

[2] I thank Kenneth French for providing the data.

sample period is restricted for tests involving macroeconomic announcements (1999 to 2014), aggregate mutual fund flows (2007 to 2014), and individual investor trades (1991-1996).

For the tests on analyst responsiveness, following Zhang (2008), I only retain earnings announcements that have at least one estimate of next quarter EPS before the current quarter earnings and one revision after the earnings. I only retain the first forecast revision by each analyst.

3.2 Variables

I define the earnings surprise of firm i in quarter t as

$$Surprise_{it} = \frac{Actual_{it} - Estimate_{it}}{Price_{it}}$$

where $Actual_{it}$ is the actual quarterly EPS reported by the firm i in quarter t, $Estimate_{it}$ is the corresponding median estimate and $Price_{it}$ is the stock price on the day before the earnings announcement. Only analyst estimates that were provided 90 days before the earnings announcement are used to compute the median consensus estimate. This effectively filters out any stale estimates.

I compute the beta of a stock using daily returns from 300 days to 45 days before the announcement. Cumulative abnormal return (CAR) is the buy and hold return of the stock less the beta adjusted buy and hold return of the market

$$\mathrm{CAR}[t_1, t_2] = \prod_{\tau=t+t_1}^{\tau=t+t_2} (1 + R_{i\tau}) - 1 - \hat{\beta}_1 \left[\prod_{\tau=t+t_1}^{\tau=t+t_2} (1 + R_{m\tau}) - 1\right]$$

where $R_{i\tau}$ is the return of the stock i on day τ, $R_{m\tau}$ is the corresponding market return, and t is the earnings announcement date.

The announcement period price response is given by CAR[0,1] where 0 and 1 represent the days relative to the announcement, 0 being day of the announcement and 1 the next trading day. CAR[2,90] gives the post earnings announcement drift. I exclude observations in the top and bottom 0.05% of CAR distributions.

The announcement period abnormal volume response is

$$\mathrm{AVOL}[0,1] = \frac{RVOL[0,1]}{RVOL[-7,-46]}$$

where RVOL is volume in the stock relative to aggregate market volume computed as

$$\mathrm{RVOL}[t_1,t_2] = \frac{\sum_{\tau=t+t_1}^{\tau=t+t_2} \mathrm{VOL}_{i\tau}}{\sum_{\tau=t+t_1}^{\tau=t+t_2} \mathrm{VOL}_{m\tau}}$$

where $VOL_{i\tau}$ is the dollar volume in stock i on day τ, and $VOL_{m\tau}$ is the corresponding market volume and t is the announcement day.

Size is the market value of equity at the end of the previous June. Book-to-Market (*B/M*) calculated at the end of June, is the book equity for last fiscal year-end in the previous calendar year divided by market equity as of December of the previous year. Size and B/M decile ranks are used as controls in the regressions. *Reporting lag* is the number of days between the fiscal quarter end date and the earnings announcement date. *Number of estimates* is the number of EPS estimates available for the current quarter. Monthly turnover is the ratio of shares traded in a month to the total shares outstanding. *Turnover* is the average of the previous 12 months' turnover. Revision Lag for an analyst in a firm quarter is the number of weekdays between the earnings announcement date and the date of first revision by the analyst for the next quarter. *Mean revision lag* is the mean of the revision lag for a firm-quarter. To control for the distraction effect due to the number of announcements each quarter, I sort announcement days into deciles based on the number of announcements that occur on that day. *NRANK* is the corresponding decile ranking variable.

3.3 Methodology

3.3.1 Market Movement Groups

Table 1 presents the number of announcements by day of the week. Most earnings releases occur on Thursdays (31%). Very few firms release earnings on Fridays (6%). To understand if large market movements are concentrated on certain days of the week, each quarter I sort trading days into three groups based on the magnitude of market returns. Panel B of Table 1 presents the percent of slow market days and market moving days by days of the week. There are relatively more market moving days as compared to slow market days in the middle of the week (Tuesday/Wednesday/Thursday). The proportion of market moving days compared to slow market days is 6% higher for days in the middle of the week. The reverse is true for Mondays and Friday, with proportion of market moving days being 9% lower.

DellaVigna and Pollet (2009) provide evidence that there is weekday variation in attention. In unreported results, I find that the level of underreaction to firm news is higher in the middle of the week and lower on Mondays and Fridays. The correlation between day of the week and market movements would bias the tests against finding underreaction to firm earnings on market moving days.

To break the correlation, I sort trading days first by day of the week and then into three groups (MMRANK) based on market movement. Panel C of Table 1 reports the percent of market moving days after controlling for the day of the week. After the control, the proportion of market moving days on a particular day of week is similar to the proportion of slow market days on the same day of the week. From the last two columns, the mean absolute market return and its standard deviation are largely similar after controlling for the day of the week. This provides comfort that the control has not artificially reduced the size of market returns across different groups.

3.3.2 Surprise Groups

Following DellaVigna and Pollet (2009), to ensure that there are equal number of groups for positive and negative surprises each quarter, I sort stocks into 11 groups (SRANK) based on announcement surprises. Quantiles 1 to 5 have stocks with negative surprise, Quantile 6 has stocks with zero surprise and Quantiles 7 to 11 have stocks with positive surprise.

Table 2 provides the descriptive statistics of surprise groups by slow market and market moving days. Firms with extreme surprises are typically small firms with high book to market. Large firms and firms with low book to market have smaller magnitude of earnings surprises. The mean market capitalization is below $1 billion for extreme negative surprises (Quantile 1) and below $1.5 billion for extreme positive surprises (Quantile 11). The mean book-to-market ratio for extreme surprise groups is above 1. There is no sizable difference in size or book-to-market ratio for a given surprise group on a market moving day or a slow market day.

4. Results

4.1 Individual Investor Trading

I study the trading behavior of individual investors around earnings on market moving days. If investors are paying attention to market information, when the market movement is large, they are unlikely to be fully attentive to a firm announcing its earnings on the same day. Hence, they are less likely to trade on earnings that occur on market moving days.

In this section, I test the effect of market movement on the likelihood of trade, using trading data of retail investors from an online brokerage in the period from Jan 1991- Nov 1996. This is the same dataset used in Barber and Odean (2008).

Investors need not be attentive to all stocks. To filter out stocks that the demand least attention from an investor, I only consider the account-stock pairs with at least 5 trades in the sample period. I consider all stocks with quarterly earnings dates available in IBES actuals detail file during the sample period. The filtered data contains 19,790 unique accounts and 4,655 stocks.

I test if investors are more or less likely to trade on an earnings release using the specification:

$$Trade_{i,j,t} = a_0 + a_1\ Earnings_{j,t} + a_2\ MMRANK_t + \ a_3\ Earnings_{j,t}\ x\ MMRANK_t + e_{i,j,t} (1)$$

where $Trade_{i,j,t}$ is a dummy variable which takes the value of 1 if the investor *i* traded stock *j* on day *t*, and 0 otherwise. $Earnings_{j,t}$ is a dummy variable that takes the value of 1 if the stock *j* announced quarterly earnings result on day *t* or day *t*-1, and 0 otherwise. $MMRANK_t$ is the ranking of the market movement group for the trading day *t*. If investors are less likely to trade on firm-earnings on market moving days, then the coefficient on the interaction term a_3 should be negative and significant.

I estimate the specification for investor-days where the investor has at least one trade in any security. By doing this, I only consider the days in which the investor was active on the market. I estimate the specification using ordinary least squares. I cluster the standard errors by account and trading day. Clustering by trading day is to account for any cross sectional correlation in the likelihood of trading.

Table 3 presents the results. In the first column, the coefficient on earnings dummy is positive and significant. Investors are more likely to trade on a stock on earnings day. On earnings day a firm releases it financials, holds a conference call, and provides guidance. Investors learn more about the financial performance of the firm and trade on the news.

In the second column, the coefficient on the interaction term is negative and significant. Investors are less likely to trade if the earnings release occurs on a market moving day. The probability of investors trading on earnings on a slow market day is 9.9%. On a market moving day the probability is 9.3%, a 0.6% decline from the slow market day.

The lower probability of trading is likely due to the investors paying attention to market information.

4.2 Price Response

In this section, I test whether the attention to the market leads to underreaction in stock price response to earnings. In the main tests I use the following specification.

$$CAR = b_o + b_1 SRANK + b_2 MMRANK + b_3(SRANK\ x\ MMRANK) + b_4\ R_m^2 + b_5(SRANK\ x\ R_m^2) + \sum_{i=1}^{n} c_i\ X_i + \sum_{i=1}^{n} d_i(SRANK\ x\ X_i) + \epsilon \qquad (2)$$

where SRANK is the surprise rank, MMRANK is the market movement rank and X_i represents the controls. Controls included are size, book-to market, and number of announcements, turnover, report lag and number of analysts providing estimates. I use decile ranks for size, book-to market, and number of announcements. I also include the interaction of controls with surprise ranks.

If investors underreact to earnings news on market movement days, then b_3 should be negative in the immediate response specification where the dependent variable is CAR[0,1], and b_3 should be positive in the post-earnings announcement drift specification where the dependent variable is CAR[2,90]. I cluster the standard errors by report date to account for cross sectional correlation in returns.

4.2.1 Immediate Price Response

Figure 2 plots the immediate price response measured by (CAR[0,1]) against surprise groups on market moving days and slow market days. I use surprise ranks instead of surprises since prior literature has shown that the response of prices to surprises is not linear (Kothari, 2001). Using surprise rank gives a linear response. The slope is flatter on market moving days compared to slow market days. Lower sensitivity is visible primarily in the extreme positive surprises group but the sensitivity is almost the same for negative surprises. This is similar to the results in DellaVigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2009), who find that the lower sensitivity on high-distraction announcement days is primary visible in extreme positive surprise groups.

Table 4 presents the results of regressing CAR[0,1] on surprise ranks (SRANK), market movement rank (MMRANK), the interaction of market movement rank and surprise ranks (MMRANK x SRANK), and controls in (2). In the first column, the coefficient on SRANK is positive. If the earnings have unexpected positive (negative) information, the stock prices react positively (negatively). The coefficient on the interaction term MMRANK x SRANK is negative and significant. In terms of economic magnitude this represents 42bps (-0.021*2*10) lower reaction to the extreme surprise group long-short portfolio (SRANK11 – SRANK1) on market moving days compared to slow market days.

To check whether the results are affected by other factors, in the second column, I run the specification in (2) with controls. The interaction term is unchanged and is negative and significant. The results show that the sensitivity to earnings surprises is lower on market moving days.

4.2.2 Delayed Price Response

Figure 3 plots the delayed price response measured by (CAR[2,90]) against surprise groups on market moving days and slow market days. The stocks with positive (negative) surprises continue to earn positive (negative) returns after the announcement day. This is the post-earnings announcement drift documented in Bernard and Thomas (1989). The drift is stronger on market moving days. Earnings with positive (negative) surprises on market moving days have more positive (negative) drift compared to slow market days.

I formally test the delayed price response by regressing CAR[2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and the interaction of market movement rank and surprise ranks (MMRANK x SRANK) and controls in (2). Table 5 presents the results. In the first column, the coefficient on SRANK is positive. Large positive surprises are accompanied by positive drift. The interaction term MMRANK x

SRANK is positive and significant. The economic magnitude amounts to 1.4% (0.07*2*10) difference in post earnings announcement reaction between market moving days and slow market days for the extreme surprise long-short portfolio. This amounts to approximately 4% excess returns on an annualized basis (1.4 * 250/ 90). The r-squares are an order of magnitude lower than the immediate price response, a result that is consistent with other studies on post-earnings announcement drift. When the return window is smaller, a specific news release does a better job of explaining stock returns. Similar pattern can be found when regressing market returns on macroeconomic announcements surprises, where r-squares increase at shorter return intervals.

In the second column, I run the specification in (2) with controls. Addition of controls do not affect the results as the interaction term is still positive and significant. The results show that post-earnings announcement drift is higher for releases on market moving days.

4.3 Volume Response

The response of trading volume to announcement surprises is non-linear. Kandel and Pearson (1995) show that the trading volume response to the announcement day price reaction is v-shaped. Considering the non-linearity, I sort the stocks into deciles each quarter on the magnitude of announcement surprises (ASRANK). For abnormal volume response, I use volume relative to the market. Scaling by market volume becomes important as the identification of important news in this paper depends on market returns. On market moving days, trading volume will be higher across stocks. Not controlling for the effect, then, will bias the trading volume response positively on market moving days. I define relative volume as the dollar volume in a stock in the period over the aggregate trading volume in the period. Abnormal volume (AVOL) is defined as the ratio of relative volume in the announcement period over the relative volume in the period 7 to 46 days before earnings. Table 6 reports the results.

ASRANK is positively related to announcement day trading volume. Kandel and Pearson (1995) argue that trading volume will increase after earnings announcements as investors update their priors with the new information. This increases the heterogeneity of beliefs and leads to more trading. If investors are inattentive to earnings, the beliefs will not be as heterogeneous as the investors will not update their priors, resulting in lower volume response. Table 6 supports the argument. In the first column (without controls), MMRANK coefficient is negative and significant. The addition of controls in the second column does not affect the sign or the significance of the coefficient. The results show that the abnormal volume is lower on market moving days compared to slow market days.

4.4 Analyst Behavior

4.4.1 Adequacy of Revision

One reason why post earnings announcement drift occurs is that analysts are not using the information in current quarter earnings to fully update their expectation for the future quarters. In Table 7, I regress the surprise ranking of a stock on its previous four lags. There is auto-correlation in surprises with the first lag being the strongest. Stocks that have positive surprises continue to have positive surprises in the future. This is because analysts do not adequately revise their estimates using information in the release (Chan, Jegadeesh and Lakonishok, 1996). If investors are inattentive to previous quarter earnings that occurred on a market moving day, then the persistence in this surprise will be higher. In the second column, I test this by regressing the interaction of market movement rank of the previous quarter announcement and lagged surprise. The interaction is positive and significant at the 10% level, suggesting that analysts are not adequately revising their estimates.

4.4.2 Analyst Responsiveness

I test if analysts are slow to react to company earnings on market moving days. A typical analyst covers 15-20 stocks. On a market moving day, if the analyst is processing the impact of market information on other stocks under coverage, there would be a delay in the responding to the company releasing earnings. I analyze the effect of market information on analyst attention by testing how analyst responsiveness varies on market moving days.

For the tests in this section, following Zhang (2008), I only consider firm earnings announcements that have at least one estimate for the next quarter before the current quarter earnings and one revision after the earnings. Only the first forecast revision by each analyst for the next quarter after current quarter earnings announcement is considered. I define two measures of analyst responsiveness: mean analyst lag, and the percent of firms with at least one on-time revision.

Table 8 presents the results of regressing measures of analyst responsiveness on the ranking of market movement groups. From the first column, if the earnings release occurs on a market moving day, then the mean lag increases. From the second column, on market moving days there are fewer firms with on-time revision. The results suggest that analysts also underreact to earnings information on market moving days due to attention constraints.

4.5 Attention around Macro Announcements

In this section, I test if investors are inattentive to firm earnings around important macroeconomic announcements. Many macroeconomic announcements do not move the markets. The impact of macroeconomic announcement on prices is dependent on announcement surprise (Balduzzi, Elton, and Green, 2001). I account for this by considering a set of important macroeconomic announcements (Nonfarm Payrolls, GDP announcement, FOMC Rate Decision ISM Manufacturing, ISM Non-Manufacturing, Construction Spending, New Home Sales, and ADP Employment) and sorting each macro announcements into 10 groups (MACRORANK) on magnitude of announcement surprise. This automatically controls for weekday variation in attention as macroeconomic announcements are released consistently on a specific day of the week. For example, Non-farm payroll data is released on Fridays.

I run the specification (2) with MACRORANK instead of MMRANK. Results are provided in Table 9. From the first column, there is lower immediate price reaction and the coefficient is significant at the 10% level. From the second column, the interaction term is positive and significant, indicating that post-earnings announcement drift is higher. The results are consistent with investors underreacting to earnings on days with big surprises in major macroeconomic announcements.

4.6 Firm Characteristics

Small stocks, stocks with lower analyst following and value stocks receive lower attention. These stocks also have lower arbitrage participation. I test whether the underreaction on market moving days is severe in these stocks. Each quarter, I sort the stocks into two groups based on market capitalization before the announcement. I repeat the post-earnings drift specification separately for small firms (market capitalization below median) and large firms (market capitalization above median). Table 10 presents the results. First column reports the results for small firms and second column reports the results for large firms. The coefficient on SRANK is higher for small firms than large firms. Small firms have higher drift following earnings. The interaction term is positive and significant in the first column. Small firms tend to have event higher drift following earnings on market moving days. The economic magnitude is annualized returns of 6.2%. Large firms do not exhibit such behavior.

I repeat the analysis with Book-to-Market in Table 11 and Analyst Coverage in Table 12. The higher drift on market moving days is found primarily in value stocks and stocks with low analyst following. The results suggest that the underreaction on market moving days is concentrated in stocks that tend to have low arbitrage participation.

4.7 Robustness

I check whether the results are influenced by same quarter breakpoints for market movement groups. I test for this by computing breakpoints from the previous quarter. Table 13 reports the results. In the first column, which reports the results of immediate price response the interaction term, MMRANK x SRANK is negative and significant. The coefficient is similar to the coefficient in Table 4. In the second column, the interaction term MMRANK x SRANK is positive and significant. Immediate response is lower and drift is higher on market moving days even when previous quarter breakpoints are used.

I choose 90 days post-earnings announcement drift horizon to capture the next quarter earnings announcement. Figure 4 plots the difference in delayed response for the extreme surprise groups. The post earnings drift increases over time as investors slowly price the information from previous earnings. The drift for releases on market moving days increases faster than the drift on slow market days.

The figure also plots the difference in drift between market moving days and slow market days. The difference in drift increases around the 90^{th} trading day following the earnings and is largely flat after that. This rules out another explanation for the drift, which is overreaction due to feedback trading to earnings on market moving days. If the drift is due feedback trading on proper immediate response to earnings, we would see reversals. But the flat response after 90 days provides support that the drift is due to inattention.

Table 14 reports the post earnings announcement drift results for CAR[2,75], CAR[2,90] and CAR[2,120]. The coefficient on SRANK is significant in all specifications and increases with the length of the post earnings window. The drift continues beyond a quarter. The coefficient on the interaction term is positive and increasing with the horizon, similar to Figure 4. For the 75 day horizon, it is positive and significant at the 10% level. For the 90 day and 120 day horizons, it is positive and significant at the 5% level. Figure 4 and Table 14 show that the post-earnings drift results reported in the paper are not heavily influenced by the choice of horizon.

I also test whether the results documented so far has been influenced by the grouping procedure. The choice of 11 surprise groups was to ensure there was equal number of quantiles for positive surprises and negative surprises. In Table 15, I repeat the analysis by forming surprise deciles instead of 11 surprise groups. From the first column we find that for the immediate response coefficient on the interaction term is negative and significant and is similar to Table 3. In the second column we find the coefficient on the interaction term is positive and significant at the 10% level. The lower significance is due to the lower power of this grouping which reduces the number of quantiles for negative surprises while increasing the number of quantiles for zero surprises.

I had used 3 market movement groups so far. To see if the results are influenced by the grouping procedure I repeat the analysis in Table 16 with 2 market movement groups. The interaction term is negative and significant in the first column for immediate response and positive and significant for delayed response in the second column. Using 2 groups for market movement doesn't affect the results. In Table 17, I repeat the analysis using 6 groups instead of 3 groups. The interaction term for the immediate response is negative and significant. For delayed response the interaction term is positive and significant at 10% level. The lower significance is due to lower power because the number of stocks in each portfolio is lower each quarter. Overall, the robustness suggest that the primary results reported in the paper is not heavily influenced by the grouping choice.

4.8 Strategic Scheduling of Poor Earnings

Literature has documented prevalence of companies announcing poor earnings on Fridays. DellaVigna and Pollet (2009) note that this behavior is could be due to strategic scheduling of poor earnings on Fridays by managers. When poor earnings is released when attention is low, the stock price would not react as negatively as it would have when attention is high. I investigate if managers time poor earnings on market moving days. In Table 18, I regress the surprise ranking of a stock on its market movement rank, Friday dummy and controls. Consistent with prior literature the surprise rank for Fridays releases is lower. The coefficient on market movement rank is insignificant. Managers do not time poor earnings on market moving days. This could be due to the difficulty in predicting daily market returns at the time of scheduling.

4.9 Response of Aggregate Mutual Fund Flows

I obtain the weekly aggregate mutual fund flow data from Investment Company Institute, which gives the flows for the week ending on Wednesday. I compute the market returns for the week ending on Wednesday. In Table 19, I regress the aggregate flows on three lags of flows and market return in the current week and previous week. From the first column, the flows are positively auto-correlated. Inflows into mutual funds are followed by more inflows. Similar to Warther (1995), I find that the flows and contemporaneous market returns are positively related. I also find that flows respond positively to lagged market returns. Investors shift capital to equities following market increases and away from equities following market decreases.

Attention to market information should result in a stronger response of aggregate flows to contemporaneous market returns and a weaker response of flows to lagged market returns, on market moving weeks. On the other hand, if investors are not acting on market information the contemporaneous response will be weaker and the delayed response will be stronger. Each year, I sort the weeks into two groups on magnitude of market returns. Controlling for day of the week variation in attention is not required here as the flows are weekly. The second column reports the results. The interaction term of market movement and contemporaneous returns is positive and significant, and the interaction term with lagged returns is negative and significant. The response of flows to contemporaneous returns is stronger during market moving weeks and the response of flows to lagged returns is weaker. The flow results suggest that flows to equities responds quickly following a major event.

4.10 Aggregate Trading Volume

On an important market moving day like the Brexit result, we see sizable movement in market returns. However, if investors are not acting on the market information, market volume need not increase. I define aggregate relative volume as the ratio of aggregate dollar trading volume scaled by the average trading volume in the previous 10 trading days. Table 20 presents the results of regressing aggregate relative volume on market movement ranks. I adjust the standard errors using Newey-West using 10 lags to control for any serial correlation. The coefficient on market movement rank is positive and significant. It represents a 6.2% (0.031 x 2) increase in volume on market moving day compared to a slow market day. In the second column, I check if the results are robust by adding 5 lags of relative volume and volatility. There is a significant increase in r-squares as the lagged aggregate relative volume has a higher ability to predict current volume. The market movement remains positive and significant. The results provide evidence that investors act on market information on market moving days.

5. Conclusion

I study the response of stock prices to earnings released on market moving days. Prices are slow to respond to earnings on market moving days, leading to higher post-earnings announcement drift. The difference in drift between market moving days and slow market days is annualized returns of 4%. Prices are slow in responding to earnings when major macroeconomic announcements are very surprising. Analysts are slow to revise estimates following earnings on market moving days. There is underreaction to earnings on days with large market movement.

The aggregate trading volume and the aggregate mutual fund flows are higher on market movement days. The aggregate results show that investors are acting on major market information.

Attention is not an unlimited cognitive resource. Due to the difficulty in processing multiple pieces of information simultaneously, investors pay more attention to market information and this results in underreaction to firm news on days with important market information.

Inattention to new information is a leading explanation for many asset pricing puzzles that involve underreaction in prices. Previous research shows how *distraction* can lead to inattention to firm news. I contribute to the literature by highlighting how attention to market can result in underreaction to firm news.

Rent Seeking by Low Latency Traders:
Evidence from Trading on Macroeconomic Announcements

Tarun Chordia, T. Clifton Green, and Badrinath Kottimukkalur*

Abstract

Prices of stock index exchange traded funds and index futures respond to macroeconomic announcement surprises within a tenth of a second, with trading intensity increasing ten-fold in the quarter second following the news release. Profits from trading quickly on announcement surprises are relatively small and decline in recent years. Trading profits also decrease with quote intensity. The speed of information incorporation increases in recent years and order flow becomes less informative, consistent with prices responding to news directly rather than indirectly through trading. Our evidence is consistent with increasing competition among low latency traders, which mitigates concerns about their speed advantage.

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1. Introduction

Financial information is increasingly being released to, interpreted by, and traded on by computers. Dramatic improvements in technology have allowed computer algorithms to dynamically monitor multiple trading venues and strategically execute orders. These algorithms emphasize speed, and as a result trade latency has been reduced to milliseconds. The increasing prevalence of low latency trading (LLT) has led to two main concerns: the welfare implications of investing huge sums to achieve sub-second speeds, and the broader issue of whether the presence of low latency traders (LLTs) reduces trust in financial markets.

Theory points towards mixed welfare implications for LLT. Jovanovic and Menkveld (2016) argue that LLTs face lower adverse selection costs through their ability to quickly change quotes, and as a result LLTs improve gains from trade through their greater willingness to provide liquidity to intertemporally separated buyers and sellers. On the other hand, Biais, Foucault, and Moinas (2015) and Budish, Cramton, and Shim (2015) point to the socially wasteful arms race between LLTs, as they expend greater resources to further reduce latency.[3]

Although a welfare analysis from the perspective of a social planner is impossible, empirical studies have explored different welfare aspects of LLT. Brogaard, Hendershott, and Riordan (2014) find evidence that high frequency traders (HFTs)[4] facilitate price discovery by trading in the direction of permanent price changes and

[3] In one example of the LLT arms race, Spread Networks constructed a $300 million high-speed fiber optic cable between Chicago and New York to reduce the round-trip time for messages by 0.003 seconds.

[4] HFTs are a subset of LLTs, as specifically defined by the Security and Exchange Commission's (SEC's) concept release on equity market structure (https://www.sec.gov/rules/concept/2010/34-61358.pdf). In the rest of the paper, we will use the term HFTs only for LLTs that fit the SEC definition. We study the Nasdaq HFT data in Section 3.2.

against transitory pricing errors. Carrion (2013) finds that prices incorporate market-wide return information more quickly on days with high HFT participation. Conrad, Wahal and Xiang (2015) find that LLT activity leads prices to more closely resemble a random walk, and Chaboud, Chiquoine, Hjalmarsson and Vega (2014) find that LLT improves price efficiency through lower return autocorrelations and fewer arbitrage opportunities. Other research suggests that the activities of LLTs improve market quality through increased liquidity and lower short-term volatility (Hendershott, Jones and Menkveld, 2011; Hasbrouck and Saar, 2013; Hendershott and Riordan, 2013).

Does the increase in liquidity and market efficiency at the sub-second level improve the allocational efficiency enough to outweigh the explicit cost of the arms race as well as the potential cost of market failures and reduced trust in markets? LLTs have attracted the scrutiny of regulators due to concerns that their technological advantages create an unlevel playing field among market participants (Baer and Patterson, 2014). Some argue that LLTs' ability to trade ahead of slower investors allows them to earn profits in excess of the risks involved. Bias, Foucault, and Moinas (2015) have argued that fast traders observe market information before slow traders, thus generating adverse selection and negative externalities. This short-lived monopoly access to information is deemed a market failure that allows LLTs to earn excessive rents.[5] These developments have led to arguments in the popular press that markets are "rigged" in favor of high-speed traders (Lewis, 2014), which erodes faith in financial markets and could raise firms' cost of capital. Calls for regulating LLTs abound.

[5] Anecdotal evidence abounds of high and remarkably consistent profits for high-speed trading firms. For example, the IPO prospectus for Virtu Financial noted that it had but one losing trading day over the course of four years. http://www.sec.gov/Archives/edgar/data/1592386/000104746914002070/a2218589zs-1.htm

One channel by which LLTs are presumed to benefit from their technological advantage is through rapidly responding to public news releases; we contribute to the LLT debate by exploring the sub-second market response to the release of eighteen different macroeconomic (macro) news announcements. Macro news releases provide a clean experimental setting where the timing of the release is known in advance, information is distributed in machine-readable form, and announcement surprises are relatively easy to interpret. Trading profits therefore depend critically on speed, making this the ideal setting for studying LLT. We analyze quote and transaction data for the highly liquid S&P500 ETF (SPY) and the E-mini S&P500 futures contract (ES).

Trading intensity increases ten-fold during the quarter-second following the release of macro news, and there is a significant shift in order imbalances in the direction of the announcement surprise (based on the Bloomberg consensus forecast). This is consistent with the theoretical model of Foucault, Hombert and Rosu (2016) who argue that LLT trades are more correlated with short-run price changes and that they account for a large fraction of the trading volume around news events. Prices react to announcement surprises within a tenth of a second and respond fully within five seconds.

Although LLTs respond swiftly and convincingly to macro news releases, profits from fast trading are relatively modest compared to descriptions in the media (e.g. Mullins, et al, 2013). Trading in the direction of the announcement surprise results in average dollar profits (across market participants) of $19,000 per event for the S&P500 ETF. Profits are larger for index futures, roughly $50,000 per event, yet this dollar amount translates to just two basis points of return relative to the approximately $80 million of notional value traded in the direction of the surprise. Moreover, our measured profits do not account for commissions or the expense incurred in subscribing to real-time data services.

The average price response for our sample of macroeconomic news events is roughly seven basis points (bps), and bid-ask spreads are typically less than one basis point, which would imply larger profit opportunities than what is observed in the data. However, the evidence suggests that the posted quotes around news releases are not the stale, exploitable limit orders of slow investors but rather quickly changing quotes of the liquidity-supplying LLTs. In the first quarter of a second after a news release, we observe 500 changes to the best bid or offer quote in the ETF (across venues). These findings highlight the LLT's lower adverse selection costs when supplying liquidity due to their ability to quickly update quotes in light of new information, consistent with the models of Jovanovic and Menkveld (2016).[6]

In one controversial practice, Reuters sold access to the University of Michigan's Consumer Sentiment Index to LLTs two seconds before wide release, and media articles suggest that market participants were not aware of the early release (Mullins et al., 2013, also see Hu, Pan, and Wang, 2016). The practice ended in July 2013 at the request of the New York attorney general. This provides us with a natural experiment to test whether LLTs who receive early information are able to exploit slower traders to earn excess profits.

We find no evidence that purchasing the two-second early access to Consumer Sentiment data provides LLTs with incremental profits. While profits are lower after Reuters ended the practice, this appears to be part of a general downward trend in trading

[6] Scholtus, van Dijk, and Frijns (2014) document that LLTs improve market quality following macro news releases.

profits across all macro announcements. A difference-in-difference approach reveals no statistically or economically significant changes in profits between Consumer Sentiment and other macro announcements. This is consistent with a quick reaction among liquidity-supplying LLTs. Thus, liquidity supplying and demanding LLTs are likely to be the marginal market participants following news releases. The practice of selling early access to macro news appears more consistent with a profit seeking behavior among information providers rather than the exploitation of slow traders.

Our findings are consistent with increasing competition over time amongst the LLTs. In particular, average profits for the S&P500 ETF fall from $38,000 per event in 2011, to $24,000 in 2012, $5,000 in 2013, and are non-existent in 2014. The corresponding profits in the E-mini futures are $165,000, $62,000, $21,000 and $9,000, respectively.[7] Supporting the view that declining profits reflect increased competition among market participants, we find a negative relation between announcement profits and the relative intensity of quote activity following the announcement. Moreover, the quote-to-trades ratio has increased over time while the available depth and trade sizes have decreased. We also observe that the speed of market reaction to macro announcements increases during the sample period.

We next analyze the informativeness of order flow using a state space approach similar to Brogaard, Hendershott and Riordan (2014). We observe a decrease over time in the informativeness of the post-announcement order flow, which suggests an increasing ability for LLT quotes to respond directly to announcement surprises rather than

[7] We also find evidence of intertemporally declining arbitrage opportunities between the S&P 500 ETF and futures.

responding indirectly through trading. The evidence is consistent with the increasing importance of LLTs as liquidity providers, as suggested by Menkveld (2013).

Our analysis has implications for calls to regulate LLT. Baron, Brogaard, Hagströmer, and Kirilenko (2016) find that new HFT entrants have a propensity to underperform and exit, which points towards an unlevel playing field even among LLTs and suggest that increased regulatory oversight may benefit financial markets. Brogaard and Garriott (2016), on the other hand, find evidence that new LLT entrants lead to crowding out, with reduced spreads and less informative incumbent order flow. Our evidence supports the view that low latency trading is maturing and becoming more competitive, with profits trending down, possibly towards the marginal cost of obtaining information (e.g. Grossman and Stiglitz, 1980). In an environment of increased competition amongst LLTs, the need to regulate their behavior is mitigated.

2. Data and descriptive statistics

2.1 Financial market data: S&P500 ETF and E-Mini Futures

We study the financial market response to macroeconomic announcements using two of the most liquid stock market instruments: the largest and most heavily traded S&P 500 ETF (SPY), and the S&P 500 E-Mini Futures (ES). Both instruments have been studied extensively in previous work (e.g. Hasbrouck, 2003). For these securities we obtain quote and trade data from Tick Data (now OneMarketData) that is time-stamped to the millisecond. The data allows us to capture price movements and to accurately assign the direction of trade at the millisecond level, which allows us to measure the profitability of trading on announcement surprises.

Our sample covers 2008-2014 for the ETF and July 2011-2014 for the E-mini Futures contract. Although the ETF sample is longer, ETFs do not begin trading each day until 9:30 am. E-mini futures trade 24 hours (except for a break from 4:15-4:30 pm and from 5:15-6:00 pm EST), and therefore the futures sample allows us to examine a number of important macroeconomic announcements that are released at 8:30 am. The notional traded value of the E-mini futures contract is higher than the dollar trading volume in the ETF.[8] For example, in 2012 the average daily notional value traded was \$142 billion for the futures versus a trading volume of \$18.5 billion for SPY. On the other hand, quoted spreads are smaller in the ETF, between 0.5-1.0 basis points for SPY versus 1-2 basis points for the futures, due to the smaller tick size (\$0.25 for the E-Mini futures contract vs \$0.01 for the ETF). In our analysis, we explore the market response and profitability of trading in both securities.

2.2 Macroeconomic Announcements

We obtain information about macro announcements from Bloomberg, including the release date and time, reported value, the median consensus estimate, number of estimates, and the standard deviation across estimates. We consider the macroeconomic series studied in Balduzzi, Elton and Green (2001) and/or Brogaard, Hendershott and Riordan (2014) for which Bloomberg reports consensus estimates and the actual announced values. We also consider the University of Michigan Consumer Sentiment Index and the Chicago Purchasing Mangers' (PMI) Index, which were released to certain subscribers prior to their wider release to the public.

Table 21 presents descriptive information for the twenty-seven announcements considered in our study. All occur at a monthly frequency with the exception of the University of Michigan Consumer Sentiment Index (bi-weekly release) and Initial Jobless

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[8] Each futures contract represents a contract size of 50 times the index value. For an S&P 500 index value of \$2,000, each contract represents a notional value of \$100,000.

Claims (weekly release). *Release Time* is the most common release time (changes in release time are rare in our 2008-2014 sample period).[9] We report the earliest time of access for Consumer Sentiment and Chicago PMI. Each of the macroeconomic series we consider is well covered with large numbers of analysts providing estimates for each release. The lowest average number of estimates is 20 for Personal Consumption and the highest is 90 for Nonfarm Payrolls. The coverage suggests that these are highly watched, market moving events. We also observe a reasonable number of positive and negative surprises during the sample period.

2.3 Market Moving Events

The twenty-seven macroeconomic releases that we consider may not all impact financial markets in a significant way. We begin by objectively assessing which releases are potentially important to low latency traders. Specifically, we follow Balduzzi, Elton and Green (2001) and regress percentage mid-quote price changes, measured from 5 minutes before to 5 minutes after the release, on the standardized announcement surprises. Surprises are measured as the difference between the actual value of the release and its median estimate, standardized by its time series standard deviation. For releases before (after) 9:30 ET we use price changes for the S&P 500 E-mini Futures (SPY ETF). The coefficient on the standardized surprise is reported in the final column of Table 21. It represents the change in price associated with a one standard deviation increase in

[9] Here are the exceptions to the release times during our sample period: (i) Personal Income was usually released at 08:30 am with the exception on Dec 23, 2014 when it was released at 10:00 am; (ii) 10:00am was the most common release time for ISM Non-Manufacturing with the exception of Feb 5, 2008 when it was released at 08:55 am; (ii) University of Michigan consumer sentiment scheduled release time was 09:55 am. But when early access was available, it was released to subscribers at 09:54:58am.

announcement surprise. The largest price impact is 30 basis points for a one standard deviation change in Nonfarm Payrolls.

Eighteen different types of macroeconomic news have a statistically significant impact on stock prices at the 5% level, and we restrict our attention to these eighteen releases for the rest of our analysis. The coefficients on CPI, CPI excluding food and energy, and initial jobless claims are negative, as higher-than-expected inflation and unemployment had negative implications for the stock market. For ease of interpretation, we multiply these surprises by negative one so that all positive surprises are associated with good news for the stock market.

3. Market Response to Macroeconomic News

The pace of trading in financial markets has increased rapidly in recent years. In 2000, Busse and Green (2002) find that firm-specific information released during market hours is incorporated into prices within one minute. Speed of communication has since improved dramatically, leading to LLTs who strive to achieve low latency by investing in technology and co-locating their servers in the same data centers as stock exchanges. Hasbrouck and Saar (2013) note that the fastest traders have an effective latency of 2-3 milliseconds. Brogaard, Hendershott and Riordan (2014) find that in 2008 and 2009, it took several seconds for macroeconomic news to be incorporated in stock prices. We conjecture that the greater availability of machine readable news and the increased presence of LLTs in recent years has led to faster information assimilation.[10] In this

[10] A specialized industry has sprung up to deliver machine readable financial information to LLTs in milliseconds. For example, RavenPack is a news analytics firm that provides tradeable information to subscribers with a latency of 300 milliseconds, and Beschwitz, Keim, and Massa (2015) document increases in market response speed following coverage by RavenPack.

section, we explore the role of LLTs in the process by which macroeconomic news is incorporated into prices.

3.1 Speed of Information Incorporation

Table 22 presents the cumulative mid-quote returns for two liquid stock market index securities in the sub-seconds around eighteen macroeconomic news releases. We calculate the mid-quote price for the S&P500 Index ETF (SPY) at the beginning of each time period (second or tenth of a second) using the average of the National Best Bid and Offer (NBBO)[11]. Cumulative mid-quote returns for each period are computed relative to the mid-quote that prevailed 20 seconds before the event. The returns for the S&P500 E-mini futures are calculated in a similar manner. Negative Surprises are releases in which the actual was below the consensus median, (above the consensus for CPI, CPI ex Food and Energy and Jobless Claims). Following positive (negative) surprises, we expect the cumulative mid-quote returns to be positive (negative). In Table 22, we combine positive and negative surprises together and report the mean absolute cumulative returns. Panel A reports the price response of the ETF to macro announcements released after 9:30am ET, and Panel B reports the results for the E-mini futures for the full set of eighteen announcements.

Prices respond significantly to announcement surprises within the first 100 milliseconds (ms) following the release, which points towards LLT. Kosinski (2008) surveys the literature on reaction time and notes that human reaction (single response to single stimulus) is of the order of 200ms. The evidence suggests that the marginal market

[11] We thank Joel Hasbrouck for providing code to compute NBBO. See Hasbrouck (2010) for details. Holden and Jacobsen (2014) suggest that with extremely low latencies (as response times accelerate), the NBBO may not exist from the perspective of a trader as the best quote information from distant exchanges may not be time synchronized. See also Angel (2014).

participant at the release of macroeconomic news is a computer which interprets the announcement surprise and revises quotes or routes orders within a tenth of a second. The average price reaction over the first two seconds of 5.4 (4.3) basis points for the ETF (futures) accounts for 78% (84%) of the 10-second price reaction. This fraction is considerably larger than the roughly 50% two-second price reaction documented in Brogaard, Hendershott and Riordan (2014), which is consistent with broader adoption of machine readable news after the end of their sample in 2009.

The announcements of CPI, Factory Orders (in the case of the E-mini contract), and Leading Index have significant surprise coefficients in Table 21, yet they do not exhibit a significant price reaction in the first 10 seconds after announcement, which suggests that these announcements are either not available in machine readable format or not deemed important by LLTs.[12] In untabulated results, we find that dropping these events increases the average reaction in S&P 500 ETF and S&P 500 E-mini futures by roughly one basis point (the results are otherwise similar).

The Consumer Sentiment announcement also merits special attention, as for most of the sample period, early access subscribers were able to obtain information in machine readable form two seconds prior to wider release. Using the early access time (9:54:58) as the information release time during this period of the sample, we find ETF prices incorporate roughly 73% of the ten-second price response within a half-second and futures prices react as quickly if not more so.[13] On the other hand, regardless of whether

[12] Table 1 uses a five-minute time window rather than 10 seconds, and it also relies on a continuous measure of announcement surprise rather than grouping surprises into positive and negative categories. We continue to find an insignificant 10-second price response if we use the continuous surprise measure as in Table 1.

[13] Section 5.4 analyzes the incremental profitability of trading on early access to Consumer Sentiment in more detail.

information is released exclusively to LLTs or more widely, LLTs are the primary agents for incorporating new (machine readable) information into prices.

Figure 5 disaggregates positive and negative announcement surprises and plots the average cumulative price response for the ETF (Panels A and B) and the E-mini Futures (Panels C and D) across announcements. The figures show that the speed of price reaction to negative surprises is similar to the price reaction to positive surprises. Consistent with Table 22, Panels A and C reveal that most of the price reaction happens within the first couple of seconds. Panels B and D focus on the two-second sub-period and more finely partition price changes into 100 millisecond intervals. A large portion of the price reaction occurs within the first second.

In order to statistically test for the speed of price response, we calculate price changes relative to the mid-quote measured twenty seconds *after* the announcement. In this setting, price changes should generally be statistically significant when measured before the event and gradually become insignificant as information is incorporated into prices. The resulting t-statistics are presented in Figure 6. For the ETF, negative news is priced in within four seconds and positive surprises are incorporated within five seconds. For the futures, the analogous numbers are five seconds and two seconds. Taken together, the evidence suggests that machine readable news and high-speed algorithms have diminished the role of humans while greatly increasing the speed with which prices incorporate new information.

3.2 Trading and Quoting Activity

This section analyzes trading and quoting activity around macroeconomic announcements. In particular, we examine the total dollar volume of trades per second (notional value for futures), number of trades per second, number of quote changes per second, and order imbalances in the S&P500 ETF and E-mini Futures. We use the period five minutes to five seconds before the release time as a benchmark. We report volume, number of trades, and number of quote changes per second to facilitate comparisons across intervals.

Table 23 reports the results. The index instruments are highly liquid. In the benchmark period, there are more than 30 trades per second and 350 quote changes in the ETF (across all market venues), accompanied by dollar volume of roughly $2 million per second. We find no changes in trading or quoting activity in the five seconds prior to the release.

In the first quarter of a second after the announcement, quoting activity increases six-fold and trading increases twenty-fold to 2000 quotes and 650 trades per second, with volume jumping to $43 million per second. The E-mini contract experiences an even larger jump in notional volume, rising from $3 million during the benchmark period to about $200 million per second in the quarter-second after the release. Trading and quoting activity in both instruments remain significantly elevated for several seconds after the announcement.

We examine whether trading activity is oriented in the direction of announcement surprises by analyzing order imbalances. We assign transactions using the Lee and Ready (1991) algorithm. In particular, trades that are executed at a price higher (lower) than the prevailing mid-quote are treated as buys (sells). If a trade occurs at the mid-quote then we compare the traded price to the previous traded price, and upticks (downticks) are classified as buys (sells). We then calculate order imbalance as (number of buys –

number of sells)/(number of buys + number of sells). We expect positive order imbalance for positive surprises and the opposite for negative surprises.

The last column of Table 23 reports mean order imbalances aggregated across positive and negative surprises, where we multiply negative surprise order imbalances by negative one. The evidence is consistent with traders reacting to announcement surprises. In the ETF (E-mini), order imbalance is zero (zero) during the benchmark period and 0.22 (0.19) and highly significant in the first quarter second after the news release. Order imbalance remains statistically significant for three seconds but falls considerably and loses significance afterwards. The evidence suggests that markets quickly incorporate new macroeconomic information, and part of the information is revealed through trading in the direction of the surprise.

4. Profitability of LLTs on Macroeconomic News

The evidence in the previous section suggests that LLTs enhance market efficiency by swiftly and accurately responding to new information. This view is generally consistent with recent research on the effects of LLTs on financial markets (e.g. Brogaard et al., 2014; Carrion, 2013; Chaboud et al., 2014). However, the concern of regulators and other market watchdogs is that the contributions of LLTs to market efficiency come at the expense of reduced trust in financial markets. Conventional wisdom holds that LLTs' speed advantage allows them to exploit slower market participants and earn profits that are disproportionate to the risks involved. For example, Hirschey (2016) finds that HFT's aggressive purchases and sales lead those of other investors, and Baron et al., (2016) find that aggressive (liquidity-taking) HFT is highly profitable on a risk-adjusted basis. In this section, we explore whether low latency translates into outsized profits for LLTs following macroeconomic announcements.

In computing profits, we assume that all trades in the direction of the announcement surprise and executed within two seconds of the release are initiated by liquidity demanding LLTs. We choose a two-second window based on the idea that human traders are unlikely to be able to respond to information within two seconds, and we note that Reuters also chose a two-second window for its early access arrangement for Consumer Sentiment information. The precise timing of the information release is also important for determining profits, and we include trades that occur up to 0.5 seconds before the official release time to allow for imprecision in the measurement of the release times.[14]

We calculate the volume-weighted average transaction price during the entry period, i.e. purchases following positive surprises and sales following negative surprises, and compare it to the offsetting volume-weighted average transaction prices measured during three post-announcement exit periods: two to five seconds, five seconds to one minute, and one to five minutes after the announcement. We measure profits in short time intervals to focus on fast trading. We stop at five minutes after announcements to avoid the impact of other confounding information. Finally, we calculate aggregate dollar profits by multiplying the total dollar volume of trades in the direction of surprise during the entry period by the percentage price change.

Table 24 reports the average profits. In the ETF, the average total dollar profits across events when exiting two to five seconds after the event (at the volume-weighted

[14] Although we find no evidence of timing inaccuracy for the futures, for the ETF the half-second return prior to the official release time is a significant 0.6 basis points across announcements (Table 2).

offsetting price) are below $7,000. Using a one to five minute exit window increases aggregate profits to $12,000, suggesting some price drift after the first five seconds. The profits from trading on Consumer Sentiment surprises do not exceed $6,000 ($8,000 in the case of the E-mini futures) per event on average for any exit window despite being provided early to subscribing LLTs during most of the sample period. Profits are $83,000 for ISM Manufacturing, however, suggesting quick reaction to this information was more profitable.

Notional values are considerably higher in the E-mini futures contract, which leads to dollar profits that are an order of magnitude higher. For example, average profits from trading on announcement surprises for Nonfarm Payrolls, Chicago PMI, Existing Home Sales, and ISM Manufacturing all exceed $100,000. Profits are the highest using the later exit window. For example, the drift in mid-quotes we see in Panel B of Table 22 Panel B for Nonfarm Payrolls and ISM manufacturing after the first two seconds contributes to the profits for these announcements. Across all events, aggregate profits in the futures contract are roughly $50,000 per event.

Figure 7 plots the percentage change in volume-weighted transaction prices surrounding the releases to provide a sense of scale for the dollar profits. We also partition the two-second entry window into smaller increments. We observe returns of about six basis points in the ETF if positions are entered within the first tenth of a second and unwound one to five minutes after the announcement. However, these high returns translate to relatively low aggregate dollar profits due to the limited trading in the first tenth of a second. Wider spreads for the futures contract lead to lower returns, just over two basis points, but dollar profits are higher due to larger notional values traded. A half-second delay greatly reduces returns.

Aggregate dollar profits of $19,000 per event in the ETF and $50,000 per event in the futures contract appear modest in light of the costs involved in subscribing to real-time access to machine readable news. For example, AlphaFlash (part of Deutsche Börse Group) charges roughly $10,000 per month for machine readable access to several macroeconomic series (including inflation and employment announcements), plus an additional $1,500 for access to the ISM announcements and $1,000 per month for Chicago PMI. Separately, Reuters charged up to $6,000 per month for early access to Consumer Sentiment information. Moreover, these expenses do not include initial setup fees and other monthly product fees or take into account commissions on trading. Thus, it would appear that subscribing to machine readable news and trading on announcement surprises in the ETF and E-mini would be routinely profitable only for a relatively few LLTs with the lowest latencies.

Our findings are somewhat at odds with descriptions of highly profitable "event-jumping" algorithmic trading in the media. For example, Mullins, et al., (2013) highlight the March 15, 2013 release of Consumer Sentiment that led SPY prices to fall by $0.27 over five minutes, with 310,000 shares traded in the first second (of which they suggest 2/3 were sales). Their numbers suggest a profit of ($2/3 \times 310{,}000 \times 0.27$) = $55,800, which is larger but on the same order of magnitude as the $31,578 profit we obtain using volume-weighted average transaction prices for a -0.5 to two second entry window and a one to five minute exit window. Both numbers are several multiples of the $5,200 we calculate on average for Consumer Sentiment announcements (in Table 24). Similarly, the March 15, 2013 Consumer Sentiment aggregate profit we measure when trading in the E-mini futures contract is $352,643, which is many times larger than the average Consumer Sentiment futures profit of $7,699. Thus, the examples mentioned in media stories seem to be outliers.

An important caveat here is that we do not know the exact trading strategy of the LLTs. It may be the case they are able to optimize their trades along some dimension, so as to earn higher profits than those we compute. On the other hand, our analysis focuses only on announcements types that have a significant impact on returns.

5. Effect of Competition on Profits and Price Discovery

Stock index prices react near instantaneously to macroeconomic announcement surprises, yet profits to LLTs are relatively modest. We focus on profits available to liquidity demanders who trade on announcement surprises, which suggests that they profit at the expense of slower and therefore less informed liquidity suppliers. Although speed gives LLTs a potential informational advantage following macroeconomic news releases, an increasing fraction of liquidity is also being provided by fast traders who can post quotes confidently knowing they can update them quickly in light of new information. For example, Table 23 shows that both the number of trades and quotes increase dramatically in the second after the announcement. In this section, we explore the effect of competition on price discovery and trading profits.

5.1 Trend in Profits

Anecdotal evidence suggests that liquidity providers may subscribe to real-time news “to keep from getting ‘flattened’” by other traders (Mullins, et al, 2013). We conjecture that liquidity suppliers become increasingly adept at responding to information over time, either by subscribing to the machine readable news themselves or by improving their ability to react to liquidity demanders. Table 25 presents profits by year from trading in the first two seconds following macroeconomic surprises (as in Table 24).[15] For the ETF, profits display a hump shape. Profits generally grow from 2008 to 2011, which is consistent with increased availability of machine readable news, generally increasing market liquidity, and a greater presence of LLTs (e.g. Beschwitz, Keim and Massa, 2015). However, profits peak in 2011 and fall steadily in 2012, 2013 and 2014. Although the sample is shorter for futures, the decline since 2011 is also evident, with average profits from trading on macroeconomic news in 2014 being just $9,000 for the futures. The decline in profitability is consistent with increased competition among high speed market participants and in particular the ability of liquidity providers to react quickly to new public information.

5.2 Effects of the SEC Naked Access Ban

A potential alternative explanation for the reduction over time in LLT trading profits is the SEC's ban on naked market access. Naked Access is a practice where traders bypass broker controls and gain direct access to the exchanges. Concerned about the lack of oversight, the SEC began implementing a ban on naked access on November 30, 2011. The ban altered market access for a large group of LLTs that were not broker dealers, and Chakrabarty, Jain, Shkilko and Sokolov (2016) explore the effect of the ban on market quality. They find quoting activity falls by more than 33% after the implementation of the ban.

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[15] In unreported results, we find that measuring profits from trades during the first second following announcement releases results in smaller profits in general, but produces a similar pattern across years.

We test whether the LLTs who trade around macroeconomic news are affected by the ban by examining market activity during three-month pre- and post-ban (September to November of 2011, and December 2011 to February 2012). Table 26 presents the following measures of market activity during the pre- and post-ban periods: trading volume per second, number of trades per second, and number of quote changes per second.

The evidence in Table 26 suggests that there is no discernable drop in quoting or trading activity around macroeconomic release times. In unreported results, we also find that the difference in trading and quoting activity between the pre-ban and post-ban periods is not statistically significant in the first two seconds after release when LLTs are likely to be most active. While the ban may have limited the activity of a subset of LLTs, it does not appear to have a material effect on the liquid securities we consider. Therefore, the gradual decline in profits we observe in recent years appears unlikely to be driven by the ban on Naked Access.

5.3 Effect of Competition on Profits

If observed profits are low due to the presence of quickly reacting liquidity providers, we would expect to see a relation between profits and quote intensity. Specifically, if quotes are slow to update and become stale in light of new information, we would expect greater profit opportunities. On the other hand, rapid quote changes alone could be sufficient to incorporate new information with trading being less profitable. We explore this relation formally in Table 27 by regressing profits on measures of quote intensity.

Quoting and trading are positively correlated and both generally signal a liquid market which could improve profits. By scaling quote intensity by trading intensity, we focus on the relative ability of liquidity providers to react to information. Our variable of interest is the ratio of quotes to trades (QT ratio), measured during the two-second entry window. We also include the ratio of quotes to trades measured during a benchmark period five minutes to five seconds before the event to control for possible time of day effects or longer-term trends. All variables are standardized to facilitate interpretation.

Price reaction to macro news depends on the surprise component, and we therefore control for the magnitude of the announcement surprise in the profit regression. We also allow for the impact of the surprise to vary over time. In Panels A and C, we follow the methodology in McQueen and Roley (1993) and allow price reactions to announcement surprises to vary with the business cycle. In particular, we measure the time trend in monthly industrial production (log seasonally-adjusted) and compute upper and lower trend values using the 25^{th} and 75^{th} percentiles. The dummy High State (Low State) is equal to 1 if industrial production for the month is above (below) the upper (lower) bound, and 0 otherwise (where the dummy Medium State takes a value 1). We multiply the stage of business cycle dummies with the absolute value of the announcement surprise and include them in the regression. In Panels B and D, we consider an alternative approach and allow the effect of announcement surprises on prices to vary with the level of the VIX (an index of implied volatility of S&P 500 index options).

We include announcement fixed effects to control for differences in average profitability across announcements (Table 24). It is possible that market-wide news shocks (such as the start or cessation of quantitative easing by the Federal Reserve) could impact the information content and LLT trading profits across all the macro announcements, thus leading to cross-sectional correlation of residuals around the news event. We therefore base our inferences on standard errors clustered by month.

The evidence in Table 27 indicates that profits do increase with the magnitude of the announcement surprise. For example, when unwinding the position one to five minutes after the announcement, a one standard deviation increase in surprise (during the Medium state) leads to about $39,000 in higher ETF profits and $111,000 in higher futures profits. There is also evidence that the effect of surprises varies with the state of the economy.[16]

More importantly, Table 27 shows that high post-announcement quote-to-trade ratios lead uniformly to lower profits. This is consistent with more efficient response by liquidity providers who quickly move quotes towards the equilibrium price. The relation is significant for both the ETF and the E-mini futures. For the futures in particular, a one standard deviation increase in the quotes-to-trade ratio reduces profits by more than half of the average profits in Table 24 for the three different exit strategies. The results in Panel B are similar when the impact of the surprise is allowed to vary with the level of the VIX. Profits decrease with the post-announcement quote to trade ratio but not with the pre-announcement ratio. The findings suggest that active liquidity providers respond quickly to new information, which reduces profit opportunities for liquidity-demanding LLTs. The evidence is consistent with Brogaard, Hagstromer, Norden, and Riordan

[16] For the E-mini-futures, there is no coefficient reported for surprise in the Low State as no low state observations occur during the futures sample period.

(2015) who argue that increasing the speed of market-making increases market liquidity through reduced adverse selection.

Figure 8 provides further evidence of competition in the two-second period after the announcements. The figure plots quoted depth, average trade size, and the quotes-to-trade ratio (QT) by year. Depth is measured following each quote change during the two second period after the announcement as the average of shares (for the SPY) or the number of contracts (for the E-mini) offered for trade at the best bid and offer prices. Trade size is the average trade size in shares (number of contracts) for the SPY (ES) traded during the two-second period after the announcement. The measures are first computed for each event, then averaged for each announcement type (e.g., non-farm payroll or consumer sentiment, etc.,) each year and finally averaged across events each year. Consistent with an increase in competition, Figure 8 shows that the QT ratio has generally increased over time while quoted depths and trade sizes have declined.[17]

Figure 9 plots the trend over time in the speed of market response to macro news. Our first measure of response speed is the fraction of market reaction in the first 2 seconds after a macroeconomic release that occurs in the first 100ms, $S1 = r(t, t + 0.1)/r(t, t + 2)$, where $r(t, t + 0.1)$ is the return in the first 100 milliseconds after the release and $\mathrm{r}(t + 2)$ is the return in the first 2 seconds after the release. *S1* is unbounded and less intuitive when the numerator and denominator have conflicting signs. Therefore, similar to Beschwitz, Keim, and Massa (2015), we also calculate the ratio of the absolute return in the first 100ms after the release to the sum of

[17] Our quotes-to-trades ratio measure is generally lower than the ratio of order submissions to order executions for the median firm reported in Hasbrouck and Saar (2013). While their measure is based on all displayed order messages for a particular stock, our measure uses only quote changes at the top of the order book.

the absolute return in the first 100ms and the absolute return in the subsequent 1.9 seconds, $S2 = |r(t, t+0.1)|/(|r(t, t+0.1)| + |r(t+0.1, t+2)|)$. $S2$ is bounded below by zero and above by one.

Higher values of the response speed measures imply that the reaction to the macroeconomic announcement is concentrated in the first few milliseconds of release. Both under and overreaction in the first few 100 milliseconds result in lower values of the measures, as reversals after the first 100 milliseconds result in negative values for *S1* and larger denominators for *S2*. Figure 9 documents an increase in the speed of trading over time using both measures for the SPY as well as the E-mini futures contract. The increased speed of response is consistent with tougher competition among liquidity-demanding LLT and faster response from liquidity-supplying LLT.

In Panels C and D of Table 27, we consider an alternative measure of competition based on the speed of price adjustment. Since profits and adjustment speed are likely mechanically related for a given event, we use the average of speed (S1) across events in the previous month as a proxy for speed of adjustment. We find evidence that trading profits are significantly negatively related to adjustment speed for the E-mini futures in Panel C. In the other specifications, the coefficients are generally negative albeit they are statistically insignificant.

5.4 Impact of Early Access to Macroeconomic News

In 2007 Reuters began compensating the University of Michigan for the exclusive right to distribute their Consumer Sentiment survey. Reuters created a two-tiered access system for their customers: standard clients would have access to the information at 9:55 am (five minutes before wide distribution), and premium subscribers could access the information in machine readable form an additional two seconds early at 9:54:58 am.[18] Although Reuters advertised its early access arrangement to LLTs, the practice was not widely known among other market participants until a former employee filed a lawsuit against the company suggesting it was illegal. In July of 2013, Reuters agreed to end the practice at the request of the New York Attorney General.[19]

In the previous subsection we found evidence that the decline in the profits associated with liquidity-demanding LLTs may be related to the quick updating of quotes by liquidity-supplying LLTs. The early access to the Consumer Sentiment news release provides us with a natural experiment to test whether liquidity-demanding LLTs are able to profit from slow traders who may be unaware of their informational disadvantage. The timing of the suspension of early access is exogenous, and we use a difference-in-difference approach to control for changes in trading activity before and after the suspension of the practice.

We focus on the sample period near the change, January 2013–June 2013 for the early access period and July 2013–December 2013 for the no-early-access period. During the early access period, the E-mini futures had a volume per second of $552 million in the first quarter-second following Consumer Sentiment information, compared to an average of $296 million following the other announcements. After ending the early access practice, the volume per second drops to just $44 million in the first quarter second, which suggests a huge effect due to the change. However, average volume in all other announcements also falls considerably to $37 million after July 2013, which

[18] Baer and Patterson (2014) notes that the NY attorney general's office sent subpoenas to more than a half-dozen HFTs, and the brief filed against Reuters describes their premium subscribers as "ultra low-latency," which is consistent with HFTs being active market participants following macro news.
[19] See Hu, Pan, and Wang (2016) for more details.

highlights the importance of using a difference-in-difference approach. Table 28 reports the difference-in-difference estimates for trading volume for the first quarter second (e.g. [(44 – 552) – (37 – 296)] = –$249 million), as well as for other time intervals.

There is modest evidence of a shift in trades and quotes from the first quarter-second to later in the first couple of seconds for Consumer Sentiment relative to the other announcements. However, the shift in quoting intensity does not translate into a significant change in profits. The incremental change in trading profit after Reuters ended early access is statistically insignificant. Relative to other macro announcements, early access to Consumer Sentiment had a modest impact on trading or profits.

Overall, the practice of tiered release of information appears to have had little incremental impact on LLT profits or more generally on the process by which information is incorporated into prices. Whether information is released exclusively to algorithmic traders or distributed more broadly, the marginal market participant in the first couple of seconds following the release of machine readable news is very likely to be a computer. The evidence suggests that regulations that constrain data gathering firms to release information to clients at a single time may be unnecessary, although requiring transparency among information distributors regarding when information is available to various client groups would likely help improve faith in financial markets.

In general, the practice of selling early access to market news is consistent with profit-seeking behavior by information providers. With a two-second head start, it would be possible for the slowest LLT to trade on new information more quickly than the fastest LLT. Therefore, the only way for LLTs to ensure that their costly investment in trade speed is not undercut is to invest in early access to information. In this way, information providers "force" LLTs to pay for early access. This type of profit-seeking behavior also applies to exchange access (co-location) fees, which puts a downward pressure on LLT profits.

5.5 Effect of Competition on Price Discovery

If liquidity providers are increasingly able to react to new public information, we would expect to see a reduction over time in the information contained in the post-announcement order flow. We test this conjecture using the state space model approach of Brogaard, Hendershott, and Riordan (2014). They explore a sample of HFT trades and find that the liquidity-demanding trades facilitate price discovery by trading in the direction of permanent price changes and in the opposite direction of transitory pricing errors. In our setting, we assume that trades executed within the first two seconds following macro news releases are initiated by liquidity-demanding LLTs, and we examine the impact of their order imbalances on the permanent price changes.

For each event day, we sample the mid-quote price at the beginning of each 100-millisecond interval from two minutes before to two minutes after event. We then estimate an Unobserved Component Model to extract the change in permanent and temporary price components. In particular, following Brogaard, Hendershott, and Riordan (2014) and Menkveld, Koopman, and Lucas (2007), the observation equation (3) and state equation (4) are described as follows:

$$p_t = m_t + s_t \qquad (3)$$

$$m_t = m_{t-1} + w_t, \qquad (4)$$

where p_t refers to the log of mid-quote at the end of each tenth of a second, m_t is the unobserved true or efficient price, w_t is the permanent component and s_t is the transitory component. In the first stage, we estimate the two components for each event day. In the second stage, we regress the change in permanent component (w_t) and the temporary component (s_t) on the order imbalance (OIB) during that 100-millisecond interval, in the first two seconds after the event, as follows:

$$w_t = c + \alpha\, OIB_t + v_t \qquad (5)$$

$$s_t = k + \mu\, s_{t-1} + \beta\, OIB_t + u_t. \qquad (6)$$

We estimate the Unobserved Component Model in (3) and (4) and the regressions (5) and (6) separately for each announcement[20] and then average α and β coefficients across announcements each year and calculate the corresponding standard errors, which are clustered by month.

The results are presented in Table 29. The coefficient estimates of α and β are presented over the periods -120 to -60 seconds, 0 to 2 seconds, and for 60 to 120 seconds, with time zero being the announcement. The table reports statistical significance for each coefficient estimate using one, two, or three stars to denote significance at the 0.1, 0.05, and 0.01 levels. We also test whether parameters estimated during the 0 to 2 second interval are statistically different from estimates from the periods before and after. We display significance for these tests at the 5% level with bold font (for the -120 to -60 or 60 to 120 seconds periods).

Over the whole sample, we see that the post-announcement ETF order imbalance (labeled 0 to 2 seconds) positively predicts movement in the permanent price component, consistent with Brogaard et al., (2014). The coefficient on the transitory component is

[20] Brogaard, Hendershott, and Riordan (2014) estimate Equations 1-4 in one step using a Kalman filter and maximum likelihood. We opt for a two-step approach due to our small estimation samples. Stock and Watson (1989) point out that a two-step approach helps prevent misspecification in (3) and (4) from inducing inconsistency in (1) and (2), but at the cost of potential inefficiency.

orders of magnitude lower. For the 2008-2014 period, the impact of order flow on the permanent component is a statistically significant 0.224 basis points per unit of OIB. For the temporary component the impact is 0.005 basis points per unit of OIB. In the case of the E-mini futures contract, over the 2011-2014 sample period, the impact of order flow on the permanent component is 0.408 basis points per unit of OIB and on the temporary component it is a statistically insignificant 0.02 basis points. While the impact of OIB is positive for the temporary component in the case of the ETF, it is orders of magnitude smaller than that for the permanent component.

The impact of order flow on the permanent price movements declines in recent years. The coefficient α, which measures the impact of liquidity-demanding LLTs on the permanent component of price changes, is the highest in 2011 for both the ETF the E-mini futures. For the ETF, α is 0.668 in 2011 and 0.587 in 2012 but declines to 0.229 in 2013 and -0.027 in 2014. In the case of the E-mini futures, α is 1.06 in 2011 but declines to 0.64 in 2012, 0.22 in 2013 and 0.01 in 2014. In both the instruments, the difference in α between 2011 and either 2013 or 2014 is statistically significant.

The decrease in the informativeness of LLT order flow over time is consistent with the hypothesis that prices respond to news with little trading, either because liquidity providers also have access to the announcement information or they have become increasingly adept at quickly reacting to information in the order flow within the first two seconds after the announcement. Table 29 shows that in 2014, post-announcement order flow is not related to the permanent component of prices. The evidence that order flow no longer contains information following macroeconomic announcements is consistent with liquidity-supplying LLTs subscribing to news in digital form and adjusting prices rather than reacting to order flow. This is consistent with Lyle and Naughton (2016), who note that technological improvements have helped to enhance the monitoring ability of market makers who efficiently update quotes and avoid being picked off on stale quotes.

Why don't the liquidity supplying LLTs exit the market around macro announcements? Brogaard, Carrion, Moyaert, Riordan, Shkilko and Sokolov (2016) show that, on average, HFTs profit from supplying liquidity even during periods with extreme price movements, which may help explain their continuing participation. Also, Jovanovic and Menkveld (2016) argue that LLTs ability to quickly change quotes makes them more willing to provide liquidity. Consistent with this view, we find that quotes react more quickly to macro news surprises over time.

5.6 Trend in ETF-Futures Arbitrage Profits

Our tests thus far examine profits from trading around macroeconomic announcements. In this section, we consider profits from a separate strategy that involves temporary price deviations between S&P 500 ETF and futures prices. If the decline in profitability from trading quickly on macro news reflects increased competition among LLTs, we would also expect to see a decline in other types of speed-based arbitrage profits. Budish, Cramton, and Shim (2015) (BCS) study trading profits from ETF (SPY) and E-mini Futures (ES) arbitrage during 2005-2011. Whenever the observed price spread differs from the average spread due to fundamental factors (the cost of carry for ES, quarterly dividends in SPY, and ETF tracking error) an arbitrage opportunity is created for LLTs.

We compute the ES-SPY arbitrage profits as in BCS. The ES-SPY spreads at the midquote, bid, and ask, at millisecond *t* are computed as:

$$S_t^{mid} = P_{ES,t}^{mid} - 10\ P_{SPY,t}^{mid},$$

$$S_t^{bid} = P_{ES,t}^{bid} - 10\ P_{SPY,t}^{ask},$$

$$S_t^{ask} = P_{ES,t}^{ask} - 10\ P_{SPY,t}^{bid},$$

where $P_{ES,t}^{mid}$ is the ES midquote at *t*. We assume that the fundamental spread between the instruments at time *t* can be approximated by the average S_t^{mid} over the previous minute, denoted by $\bar{S}_t$. When a price change in one of the instruments at time *t* leads to a violation in the inequality $S_t^{bid} < \bar{S}_t < S_t^{ask}$, then we consider it an arbitrage opportunity. Arbitrage profits (in index points) are measured as the difference between $S_t^{bid} - \bar{S}_t$ or $\bar{S}_t - S_t^{ask}$, depending on the direction of the violation. The dollar arbitrage profits are calculated as the profit in index points multiplied by the depth that can be profitably traded.

ES trades on CME, and SPY trades primarily on Nasdaq and NYSE, and we therefore exclude arbitrage opportunities that last less than 4 milliseconds to account for information travel time between Chicago and New York. Similar to BCS, we also exclude potential ‘bad’ arbitrage opportunities, which may reflect shifts in the fundamental spread rather than temporary price deviations, by excluding arbitrage opportunities that do not revert within one minute. We calculate arbitrage profits separately for ETF inside quotes on Nasdaq and NYSE, and inside quotes for ES on CME.

Table 30 reports the evidence regarding arbitrage opportunities arising from price discrepancies between SPY and ES. The average profit per arbitrage opportunity is 0.07 index points and remains constant throughout the sample period. However, the profits per day have decreased considerably from 2011 to 2014, from \$9,305 to \$1,650 for Nasdaq and \$7,251 to \$2,653 for NYSE.[21] The decline in profits per day is attributable to the reduction in the number of arbitrage opportunities, from over 100 on each exchange in 2011 to roughly 50 in 2014.

BCS note that the number of ES-SPY arbitrage opportunities is related to market volatility. In Panel B, we control for changes in market volatility using the VIX, and we test for whether the number of arbitrage opportunities has declined over time using monthly and annual time trends. The regression coefficients on the trend variables are negative and significant, consistent with an intertemporal decline in arbitrage profits in ES-SPY. The evidence in Table 30 is consistent with greater competition among LLTs leading to lower futures-ETF arbitrage profits.

5.7 Discussion

In the context of the macro announcements, we find that the profits of the liquidity demanding LLTs decline over time as the liquidity suppliers, who are also LLTs, quickly adjust their quotes in the direction of the surprise. Our findings suggest that liquidity-supplying LLTs are becoming increasingly adept at reacting to order flow shocks in recent years possibly by subscribing to machine readable news. We do not find evidence consistent with liquidity demanding LLTs exploiting slow retail traders, which mitigates concerns that markets are “rigged” in favor of HFTs (Lewis, 2015).

However, one concern is that in a world with LLTs, other liquidity providers are driven out and often liquidity is not available when needed as in the case of the flash

[21] We calculate profits using the available depth at the inside quotes, whereas BCS have access to the full order book for NYSE. Our approach results in lower profit estimates than in BCS, although this should not affect the trend provided the structure of order book has not materially changed (i.e. a relative shift in depth from inside to just outside).

crash.[22] Does this mean that LLTs should face regulation? Our response is that the rules should not be changed to eliminate the speed advantage of the LLTs for three broad reasons. First, our evidence suggests that competition is working to reduce the benefits of LLTs' speed advantage. Moreover, since prices adjust to information shocks in milliseconds, it is unlikely that the slow individual investors will trade at prices far from the equilibrium price. Second, for a proper welfare comparison, it is important to consider a world with LLTs and a counter-factual world without LLTs. The literature provides no evidence that market quality would be better in a world without LLTs, notwithstanding the flash crash. Also, note that in the pre-LLT world, NYSE specialists would often call market halts (the equivalent of circuit breakers) when the order imbalances became large. And third, while it is true that a social planner may not choose to spend the vast fortunes on reducing trading latency, one has to be mindful of unintended consequences of introducing regulations that eliminate LLT incentives to develop technologies that increase communication speeds. For example, technologies that increase communication speeds may have other important and, as yet, undiscovered applications (for instance, self-driving cars that communicate with each other, telesurgery etc.).

6. Conclusion

Is LLT simply faster trading? The speed of trading has increased steadily for decades, and it is unclear whether LLT represents a fundamental shift in how markets operate. On the other hand, the introduction of many different trading venues, fragmentation of trading, and the large disparity in the speed of trading between LLTs and others market participants may have fundamentally changed markets in favor of

[22] Kirilenko, Kyle, Samadi and Tuzun (2016) show that while the HFTs did not cause the flash crash, they exacerbated the decline in prices by becoming liquidity demanders themselves.

those with resources to expend on latency-decreasing technology. We contribute to the LLT debate by exploring the profitability of fast trading following the release of macroeconomic news.

Our evidence suggests that the marginal investor immediately following the release of macroeconomic information is a computer algorithm. Trading intensity in the stock index ETF and the E-mini futures increases ten-fold during the quarter-second following the release of macroeconomic news. The result is a remarkably efficient response to news with prices responding to announcement surprises within milliseconds. Although LLTs respond swiftly and convincingly to macroeconomic news releases, we find that the trading profits on announcement surprises are far smaller than those reported in the popular press.

The findings are consistent with increasing competition over time among LLTs. We find no evidence that the controversial practice of selling two-second early access to Consumer Sentiment information leads to incremental profits possibly because both the liquidity demanders and suppliers around macroeconomic announcements are LLTs. Trading profits decrease with quote intensity and are lower in recent years. Quoted depths and trade sizes decrease while the speed of trading has increased over time. We also observe a reduction in the informativeness of the post-announcement order flow over time. The findings suggest an increasing ability for LLT quotes to respond directly to announcement surprises rather than indirectly through trading.

The results suggest that LLT is maturing and becoming more competitive over time, with profits trending lower, possibly towards the marginal cost of obtaining information. Our results suggest that the market failure due to the fast traders' monopolistic access to information before other traders is being addressed by competition amongst the LLTs. While we focus mainly on macroeconomic announcements, increased competition amongst LLTs in general, suggests that alternative sources of profit, such as from predicting order flow, may also decrease in response to competition from other fast market participants. In a competitive environment, the need to regulate LLTs is mitigated.

Does Turnover Volatility Affect Arbitrage?

Badrinath Kottimukkalur

Abstract

Uncertainty about future turnover is higher in stocks with high turnover volatility. I investigate whether this uncertainty limits arbitrage. Limited arbitrage, in turn, results in mispricing. I find that mispricing is severe in stocks with high turnover volatility (TURNVOL). Among overpriced (underpriced) stocks, the high TURNVOL stocks are the most overpriced (underpriced). Overpricing, in high TURNVOL stocks, is severe during high investor sentiment periods. The findings are consistent with TURNVOL limiting arbitrage. Further, the negative relationship between TURNVOL and average return is present only in difficult-to-short stocks. TURNVOL as a deterrent to arbitrage and arbitrage asymmetry together explain the negative TURNVOL-return relation documented in prior literature.

1. Introduction

Whether or not prices reflect all available information is of interest to asset pricing literature. If information is not immediately incorporated, the price would deviate from the fundamentals. In a frictionless world, rational arbitrageurs will trade on such profitable opportunities and eliminate mispricing. However, in reality, arbitrageurs are risk-averse and will not completely eliminate mispricing in stocks with higher arbitrage risks. Idiosyncratic volatility is an example of arbitrage risk (Pontiff, 2006). In addition, market frictions such as transaction costs make arbitrage costly. While factors hindering arbitrage such as transaction costs (bid-ask spreads), idiosyncratic risk, and short sale constraints have been extensively studied, the effect of turnover volatility on arbitrage has not received much attention.

Volatility in turnover could affect arbitrage. Consider an arbitrageur who spots a mispricing in a stock. For a trade in the stock to be profitable, the arbitrageur must be able to initiate and exit a position without moving the price. If the position has to be held for a while, the arbitrageur would not only be concerned about the execution cost at initiation but also the potential cost at exit. There is uncertainty about future execution cost because it is unknown at initiation. This uncertainty is higher in stocks with large variation in turnover. These stocks have a higher probability of thin trading in the future which increases the cost of exiting the position. Due to this uncertainty arbitrageurs might shy away from eliminating mispricing completely in stocks having high turnover volatility (TURNVOL).

In this paper, I empirically test whether arbitrage is hindered in high TURNVOL stocks. If arbitrage is affected, high TURNVOL stocks would be more prone to mispricing. I test the hypothesis using monthly data from 1966 to 2013. I define turnover as the trading volume in a stock scaled by total shares outstanding. TURNVOL is computed as the standard deviation of monthly turnover. Stambaugh, Yu, and Yuan (2015) mispricing scores, the composite score of a stock's ranking in 11 different anomalies, identify mispricing in a stock. Each month, stocks are first sorted into quintiles based on mispricing scores as of previous month. Then within each mispricing quintile, stocks are sorted into quintiles based on TURNVOL as of previous month. The Fama-French five factor model is used for risk adjustment.

I find that high TURNVOL stocks earn the lowest risk adjusted returns among overpriced stocks (stocks with high mispricing scores) and highest risk adjusted returns among underpriced stocks (stocks with low mispricing scores). The difference in returns between the underpriced stocks and overpriced stocks increases monotonically with TURNVOL. The results are consistent with turnover volatility hindering arbitrage.

TURNVOL computed using monthly data assumes that arbitrageurs have a monthly holding horizon. If most arbitrageurs close their trades within a month, then using daily turnover volatility (DTURNVOL) measure will be more appropriate. I repeat the analysis using daily turnover volatility and find that the mispricing is also severe in high DTURNVOL stocks.

I study whether arbitrageurs worry about variation in other liquidity measures as well. For this purpose I use the illiquidity measure proposed by Amihud (2002). I find that stocks with higher volatility in the Amihud (2002) illiquidity measure are also prone to mispricing. The findings suggest that the variation in liquidity affects the ability of arbitrageurs to correct mispricing.

Prior studies have documented other factors that limit arbitrage. I test whether turnover volatility limits arbitrage over and above the other measures. I find that mispricing continues to be severe in high TURNVOL stocks after accounting for other factors: idiosyncratic volatility, level of turnover, and Amihud (2002) illiquidity measure.

When arbitrage is hindered, investor sentiment drives mispricing. I test how the mispricing in high TURNVOL stocks varies with investor sentiment. For the sentiment tests, I use the Baker and Wurgler (2006) investor sentiment measure. I find that in high TURNVOL stocks, overpricing is stronger after high sentiment periods and underpricing is stronger after low sentiment periods. This provides additional support for TURNVOL affecting arbitrage.

Chordia, Subrahmanyam, and Anshuman (2001) document a negative relationship between variation in volume and average returns. I test whether this is due to arbitrage asymmetry. Arbitrage asymmetry arises due to the difficulty in correcting overpricing due to short sale constraints. Due to the constraints, more arbitrage capital flows to correct underpricing in high TURNVOL stocks. This results in overpricing in difficult-to-short stocks with high TURNVOL. Supporting the argument, I find the negative TURNVOL-average return relation only in difficult-to-short stocks.

In individual stock Fama-Macbeth regressions, negative TURNVOL stocks earn lower average returns. But the relationship disappears after accounting for the mispricing in high TURNVOL stocks due to limited arbitrage. TURNVOL hindering arbitrage and arbitrage asymmetry together explain the negative TURNVOL-average return relation.

The paper adds to the literature on arbitrage risk by introducing turnover volatility as a factor limiting arbitrage. I present evidence that turnover volatility is different from idiosyncratic volatility, Amihud (2002) illiquidity measure and turnover.

The remainder of the paper is organized as follows: Section 2 discusses the literature and develops the hypotheses tested in the paper, Section 3 discusses the data and methodology, Section 4 presents the results and Section 5 concludes the paper.

2. Literature and Hypothesis Development

Prior literature has investigated the factors limiting arbitrage. Shleifer and Vishny (1997) discuss how noise trader sentiment could limit arbitrage. Pontiff (2006) argues that idiosyncratic volatility is an important holding cost for arbitrageurs. Stambaugh, Yu, and Yuan (2015) combine the arbitrage risk due to idiosyncratic volatility and arbitrage asymmetry to explain the negative idiosyncratic volatility and return relationship initially found by Ang, Hodrick, Xing, and Zhang (2006). Korajczyk, and Sadka (2004) investigate whether transactions costs explain the momentum returns reported by Jegadeesh and Titman (1993). Hong and Stein (2002), and Nagel (2005) investigate the impact of short sale constraints on returns. Diether, Malloy, Scherbina (2003) and Stambaugh, Yu, and Yuan (2012) provide support to Miller (1977) by showing that in the presence of short sale constraints stocks with higher difference of opinion have lower returns. Hou and Moskowitz (2005) investigate the frictions affecting a stock price using delayed response of price to information. However, the potential for turnover volatility to limit arbitrage has not received much attention.

Uncertainty about future execution cost could make arbitrage costly. This uncertainty arises since, when initiating a trade, the arbitrageur does not know the exact cost that will be incurred when closing the position. The uncertainty is higher in high TURNVOL stocks where the probability of thin trading is higher in the future. Thin trading increases the cost of executing large trades.

If arbitrage is limited in high TURNVOL stocks, then mispricing will be severe. Among overpriced stocks, high TURNVOL stocks will be more overpriced in the current period and earn lower returns in the next period. The opposite will be true for underpriced stocks.

Mispricing will vary with investor sentiment in the presence of arbitrage constraints (Stambaugh, Yu, and Yuan, 2015). Overpricing is higher during high sentiment periods and underpricing is higher during low sentiment periods. The relationship between sentiment and mispricing implies that high TURNVOL stocks will be more overpriced during periods of high investor sentiment and more underpriced during periods of low investor sentiment.

Chordia, Subrahmanyam and Anshuman (2001) investigate how the variation in trading volume is priced in a cross section of stocks. They find that it is negatively priced. I test whether this effect is due to arbitrage asymmetry. Given the difficulty in eliminating overpricing due to short sale constraints, more arbitrage capital will be deployed to correct underpricing. The resulting overpricing in difficult-to-short and high TURNVOL stocks results in lower returns. I address this by studying how the TURNVOL-return relation varies with the difficulty in shorting.

3. Data

Returns, trading volume, total shares outstanding, and stock price are from CRSP and book value is from COMPUSTAT. Stambaugh, Yu, and Yuan (2015) mispricing scores are from Yu Yuan's website, Fama and French (2015) factor returns are from Kenneth French's website and Baker and Wurgler (2006) investment sentiment series is from Jeffrey Wurgler's website[23].The sample period used in this paper is from January 1966 to December 2013.

Only stocks listed on NYSE/AMEX and NASDAQ are considered. NASDAQ volume is not comparable to NYSE. To make them comparable, I follow the volume adjustment proposed by Ritter and Gao (2010). I exclude penny stocks.

3.1 Variables

The following variables are used in the empirical analysis in the paper.

SIZE: Market capitalization of a stock as of the previous month.

BM: Book-to-market for stocks from July of year t to June of year t+1 is the book value for the fiscal reported in calendar year t-1 divided by market capitalization of stock as of year end t-1. This follows Fama and French (1992). BM values are winsorized at 1% and 99% levels.

TURN: Monthly turnover of a stock as of previous month. Turnover is defined as the trading volume in a stock divided by total shares outstanding.

TURNVOL: Standard deviation of monthly turnover computed using the previous 60 months of turnover. A stock should have at least 18 months of turnover data in the previous 60 months.

DTURNVOL: Standard deviation of daily turnover computed using previous 3 months of daily turnover. A stock should have at least 18 days of daily turnover data in the previous 3 months.

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[23] I thank Jeffery Wurgler, Kenneth French and Yu Yuan for making providing data on sentiment, factor returns and mispricing scores respectively.

AMIHUD: Amihud (2002) illiquidity measure as of the previous month computed using daily return and volume data in the month. AMIHUD illiquidity for the month t for stock i is calculated as

$$AMIHUD_{it} = \frac{1}{T}\sum_{d=1}^{T}\frac{|R_{id}|}{DVOL_{id}}$$

Where $|R_{id}|$ is the absolute return of the stock i on day d of the month t. DVOL is the dollar volume in the stock for that day.

AMIHUDVOL: Volatility in AMIHUD illiquidity measure computed using the previous 60 months of data. A stock should have a minimum of 18 months of AMIHUD illiquidity data in the previous 60 months.

1/PRICE: Reciprocal of the price of a stock as of previous month.

IVOL: Standard deviation of residuals obtained by regressing daily returns each month on Fama and French 3 factors. This methodology follows Stambaugh, Yu, and Yuan (2015). IVOL is computed only for stocks with at least 18 return observations in a month.

MISPRICING: Stambaugh, Yu and Yuan (2015) construct a measure of mispricing based on a stock's composite ranking in the following 11 anomalies.

(a) Net stock issues
(b) Composite equity issues
(c) Accruals
(d) Net Operating Assets
(e) Asset Growth
(f) Investment-to-Assets
(g) Distress
(h) O-score
(i) Momentum
(j) Gross Profitability Premium
(k) Return on Assets

RET23: For the month t, RET23 is the cumulative return in t-2 and t-3.

RET46: For the month t, RET46 is the cumulative return from t-4 to t-6.

RET712: RET712 is the cumulative return in the months from t-7 to t-12.

4. Results

Each month, I sort the stocks into quintiles on the mispricing score as of the previous month. The stocks in the quintile with lowest mispricing score are the most underpriced stocks and stocks in the highest mispricing score quintile are the most overpriced stocks. If TURNVOL limits arbitrage, then among underpriced stocks the high TURNVOL stocks will be most underpriced and earn higher returns than low TURNVOL stocks. To test this, within each mispricing quintile I sort stocks in turn into quintiles on TURNVOL and form value weighted portfolios. To compute risk-adjusted returns, I use the Fama and French (2015) five factor model with investment and profitability as new factors in addition to market, size and value factors

Table 31, Panel A presents the average market capitalization of the stocks in each group. Underpriced stocks are relatively larger and overpriced stocks are relatively smaller in size. This is due to the difficulty in shorting small stocks (D'avolio, 2002). Within each mispricing quintile, the high TURNVOL stocks are smaller in size than the low TURNVOL stocks since large stocks have relatively stable turnover compared to small stocks.

Table 31, Panel B presents the average standard deviation of monthly turnover in each group. Turnover volatility is high in overpriced stocks compared to underpriced stocks. In overpriced stocks, short sale constraints prevent pessimistic investors from trading. When price is below fundamentals investors will be less pessimistic and trading will not be affected as much. However, when the stock price is above fundamentals trading short sale constraints will be binding resulting in thin trading. Hence the stocks with a tendency to be overpriced have higher TURNVOL.

4.1 Turnover Volatility and Mispricing

Table 33 presents the risk adjusted returns of the value weighted portfolios formed by sorting first on mispricing and then on TURNVOL. The first row reports the risk-adjusted returns of the stocks in the most underpriced group. Underpriced stocks earn higher returns the next period as the mispricing is corrected. The returns increase with TURNVOL suggesting that underpricing increases with TURNVOL. The high TURNVOL stocks earn the highest returns consistent with them being most underpriced. The last column reports the risk-adjusted returns of long-short portfolios formed by buying high TURNVOL stocks and shorting low TURNVOL stocks within each mispricing group. The difference is 60 basis points a month and is statistically significant.

Among the most overpriced stocks, the risk-adjusted returns decrease with TURNVOL. The high TURNVOL stocks, since they are most overpriced earn the lowest returns next period. In the last column, the long-short TURNVOL portfolio alpha is negative and statistically significant. The last two rows report the difference between alphas and respective t-statistics of the most overpriced stocks and the most underpriced stocks within each TURNVOL quintile. This is a measure of mispricing. The magnitude of mispricing increases with TURNVOL. The results are consistent with mispricing being severe in high TURNVOL stocks.

4.2 Other measures of turnover volatility

In the previous tests I use monthly turnover volatility measure following Chordia, Subrahmanyam and Anshuman (2001) who use monthly variation in trading volume to test whether variation in trading volume is priced in the cross-section of returns. In limits to arbitrage tests, it is important that the period used to compute TURNVOL is comparable to the arbitrageurs holding period. Active mutual funds turnover stocks about once a year. But some hedge funds can flip holdings faster. To check whether the results are sensitive to the period used to compute turnover volatility, I repeat the tests using a daily turnover volatility measure (DTURNVOL). Table 34, reports the risk-adjusted returns of portfolios sorted on mispricing and DTURNVOL. Among underpriced stocks the Fama and French 5 factor alpha increases with DTURNVOL and among overpriced stocks the alpha decreases with turnover but is not monotonic. The long-short DTURNVOL portfolio has positive and significant alpha in underpriced stocks and negative alpha in overpriced stocks significant at the 10% level. The findings provide evidence that high DTURNVOL stocks are also prone to mispricing.

Do arbitrageurs also care about variation in liquidity? To test this, I use the variation in Amihud (2002) illiquidity measure (AMIHUDVOL). From Table 32, TURNVOL and AMIHUDVOL are not highly correlated. As liquidity is multi-dimensional both measures could be capturing different aspects of variation in liquidity. In Table 35, I repeat the analysis using AMIHUDVOL. Among underpriced stocks the alpha increases with AMIHUDVOL and among overpriced stocks the alpha decreases with AMIHUDVOL. The long-short AMIHUDVOL portfolio has positive and significant alpha in underpriced stocks and negative alpha in overpriced stocks significant at the

10% level. From the last two rows, we find that the magnitude of mispricing increases monotonically with AMIHUDVOL. The results are consistent with variation in liquidity affecting arbitrage.

4.3 Effect of TURNVOL on arbitrage after controlling for other limiting factors to arbitrage

For turnover volatility to be an additional factor limiting arbitrage it must explain the mispricing after controlling for previously documented limiting factors. First, I test whether TURNVOL impacts arbitrage over and above illiquidity. Each month, I sort stocks into three groups on mispricing scores. Then within each mispricing tercile, I sort stocks into three groups on Amihud (2002) illiquidity measure. Then within each mispricing AMIHUD group, I sort stocks into three groups based on TURNVOL.

Table 36 reports the risk-adjusted returns of the value weighted portfolios. In the most underpriced group, across all the AMIHUD terciles, alphas increase with TURNVOL. We find that the long-short TURNVOL alphas are higher among very liquid stocks with lower levels of AMIHUD illiquidity. The difference in alpha between TURNVOL groups within the highest AMIHUD group which contains most illiquid stocks is not significant. The last row provides the alpha of TURNVOL terciles after controlling for illiquidity. The long-short TURNVOL portfolio alpha across all stocks after accounting for AMIHUD is positive and significant. In the most overpriced group, we find that alpha decreases with TURNVOL across all AMIHUD terciles with the decrease being strongest among the most illiquid stocks.

Table 37 repeats the analysis using Turnover (TURN) as a measure of liquidity. In the most underpriced group, across all the TURN terciles, alphas increase with

TURNVOL. We find that the long-short TURNVOL alphas are higher among very liquid stocks with high turnover. The difference in alpha between TURNVOL groups within the lowest turnover group which contains most illiquid stocks is not significant. The last row provides the alpha of TURNVOL terciles after controlling for turnover. The long-short TURNVOL portfolio alpha across all stocks after controlling for turnover is positive and significant.

In the most overpriced group, we find that alpha decreases with TURNVOL across all liquidity terciles with the decrease being strongest in the most illiquid stocks and insignificant among the most liquid stocks. Across all stocks, in the overpriced group, after controlling for turnover, alpha decreases with TURNVOL and the long-short TURNVOL portfolio returns are statistically significant. The results suggest that TURNVOL makes arbitrage costly over and above illiquidity.

Pontiff (2006) argues that idiosyncratic volatility is an important holding cost incurred by the arbitrageurs. In Table 38, I test whether high TURNVOL stocks are mispriced after accounting for IVOL. In the most underpriced group, the alphas increase with TURNVOL across all idiosyncratic volatility groups. In the most overpriced group, the alphas decrease with TURNVOL across all idiosyncratic volatility groups. Across all stocks, after controlling for IVOL, the long-short TURNVOL portfolios earn positive and significant returns in the underpriced group and negative and significant returns in the overpriced group. The results suggest that TURNVOL limits arbitrage over and above IVOL.

4.4 Sentiment and Mispricing

In this section, I investigate how the relationship between TURNVOL and mispricing is affected by investor sentiment.

I use Baker and Wurgler (2006) sentiment (BW) as a measure of investor sentiment. In the presence of arbitrage costs, as arbitrageurs are unable to eliminate mispricing, sentiment will drive the mispricing. When sentiment is high overpricing will be larger. Because high turnover volatility stocks is where arbitrageurs will be hindered the most, we should see high TURNVOL stocks in the most overpriced quintile having lower returns following high sentiment periods. Similarly the most underpriced stocks with high TURNVOL should earn higher returns following low sentiment periods.

Table 39 reports the results. I classify months as high and low sentiment if BW sentiment measure was higher or lower than median in the prior month respectively. Following high sentiment months high TURNVOL stocks in the most overpriced quintile earn lower returns. Following low sentiment months, high TURNVOL stocks in the most underpriced quintile earn higher returns. Considering only the highest TURNVOL stocks, we find that they earn lower returns following high sentiment months than low sentiment months generally. For example the alpha of the high TURNVOL stocks in the most underpriced group is 0.43% following low sentiments, but is only 0.24% following high sentiments.

4.5 Arbitrage Asymmetry and negative TURNVOL-return relation

Arbitrage asymmetry is the difficulty in correcting overpricing due to short-sale constraints. It is easier to correct underpricing as there are no constraints on the long side.

Stambaugh, Yu, and Yuan (2015) note that due to the arbitrage asymmetry, more arbitrage capital will be deployed to correct underpricing. As a result overpricing will continue to exist in stocks with short-sale constraints.

Chordia, Subrahmanyam, and Anshuman (2001) document that stocks with high variation in volume earn low returns. I investigate whether the relation could be due to arbitrage asymmetry. If the relationship is due to arbitrage asymmetry we should find the relation to be stronger in difficult-to-short stocks.

I use institutional ownership (IO) as a measure of short sale constraints (Nagel, 2005). I sort stocks first into quintiles based on institutional ownership as of the previous month. Then within each IO quintile, I sort the stocks into quintiles based on TURNVOL. Table 40 presents the results. From the first row we find in the lowest IO group that, stocks with high TURNVOL earn negative risk-adjusted returns. In TURNVOL quintiles 3 and 4 the negative risk-adjusted return are significant. This is not monotonic since the highest TURNVOL quintile in the lowest IO group earns less negative return compared to group 4. The high TURNVOL stocks in other IO groups do not show the negative-return relation. The findings are consistent with arbitrage asymmetry. In the next section, I perform a Fama-Macbeth analysis with individual stocks to provide additional support for the arbitrage limiting nature of TURNVOL.

4.6 Individual stocks Fama-Macbeth analysis

Table 41 reports the results of the Fama-Macbeth regression of individual stock returns on characteristics. I follow Brennan, Chordia and Subrahmanyam (1998) and use the individual stocks risk adjusted returns. The characteristics considered are SIZE, BM, 1/PRICE, RET23, RET46, RET712, Mispricing and Mispricing interacted with

TURNVOL. I use the natural logarithm of all variables with the exception of mispricing and other return based variables to control for skewness. MISPRICING is a continuous variable with high value suggesting overpricing.

From the first column of Table 41 we find that TURNVOL has a negative coefficient. This is consistent with the findings in Chordia, Subrahmanyam, and Anshuman (2001). High TURNVOL stocks earn lower risk adjusted returns. In the second column, mispricing and the interaction of mispricing and TURNVOL are added. The coefficient on TURNVOL becomes insignificant. The coefficient on the interaction term is negative and significant suggesting that only the high TURNVOL stocks that are overpriced earn negative returns. This is due to the arbitrage asymmetry discussed in the previous section. TURNVOL as a limiting factor to arbitrage and arbitrage asymmetry together explain the negative TURNVOL-average return relation.

5. Conclusion:

This paper highlights an important holding cost faced by the arbitrageurs: uncertainty in future turnover. I find that mispricing is more pronounced in high TURNVOL stocks. Among overpriced stocks, high TURNVOL stocks are more overpriced and earn lower returns subsequently. In high TURNVOL stocks, overpricing is severe during periods of high investor sentiment and underpricing is severe during periods of low sentiment. The relationship holds after accounting for illiquidity, idiosyncratic volatility, different risk adjustments and other characteristics. The results are consistent with turnover volatility limiting arbitrage.

I also provide an arbitrage based explanation for the negative TURNVOL – return relation documented in the prior literature. I find that the negative TURNVOL – return relationship documented in prior literature is found only in stocks with short sale constraints. This is due to the presence of arbitrage asymmetry. TURNVOL deterring arbitrage and arbitrage asymmetry together explain the negative TURNVOL – return relationship.

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Figures

Figure 1. Price Response to Finish Line Earnings Following Brexit Vote

The figure plots Finish Line, Inc. (FINL) cumulative stock returns from Brexit vote result to two months following the result. Brexit result was announced on the morning of June 24, 2016. Finish Line (FINL) reported fiscal year 2017 first quarter results at 7.00am ET on June 24, 2016. S&P 500 cumulative returns are provided for comparison. Horizontal axis reports the trading days relative to Finish Line 1Q2017 earnings / Brexit result with 0 being June 24, 2016.

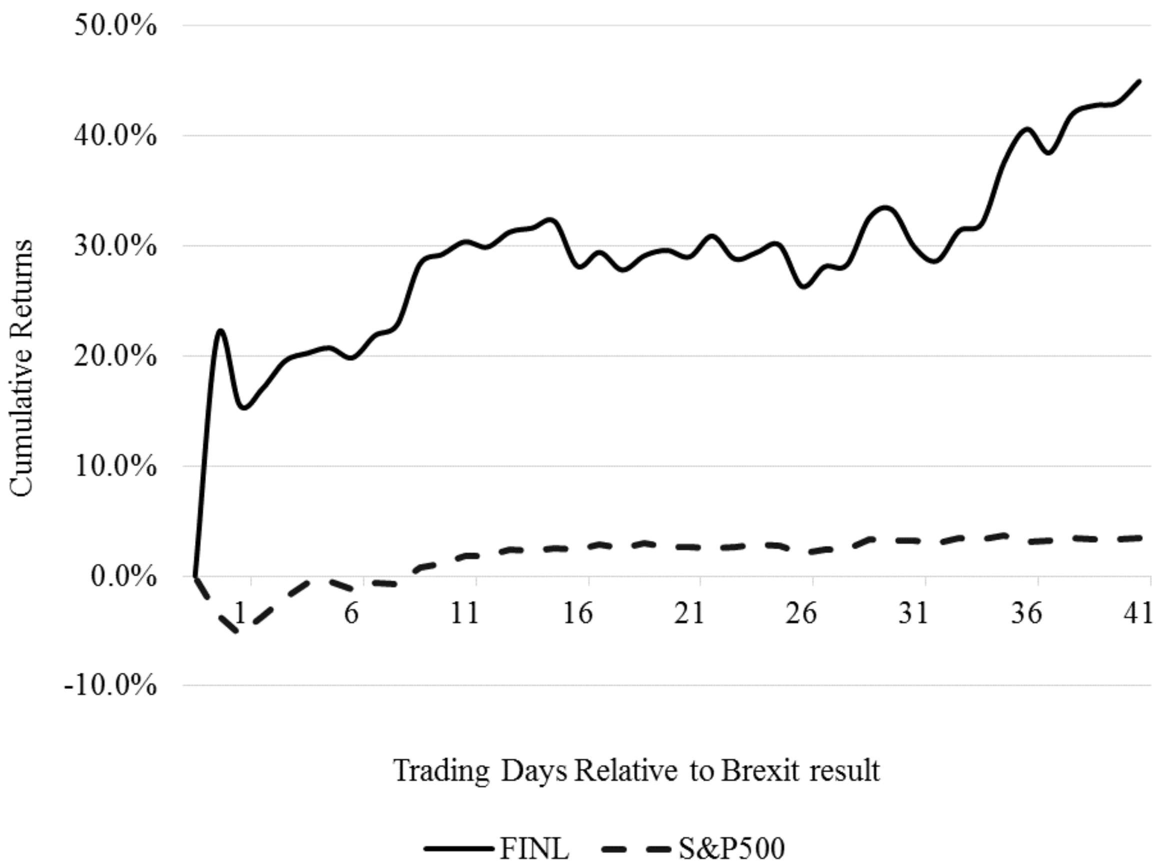


Figure 2. Immediate Price Response by Market Movement on Announcement Day

The figure plots the average announcement period cumulative abnormal returns (CAR[0,1]) against earnings surprise groups for announcements on market moving days and slow market days. Earnings surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted first by day of the week. Trading days within each day of the week are then sorted into terciles on the magnitude of market returns. *Market moving days* is the tercile with highest absolute market returns and s*low market days* is the tercile with lowest absolute market returns. Sample is from 1995-2014.

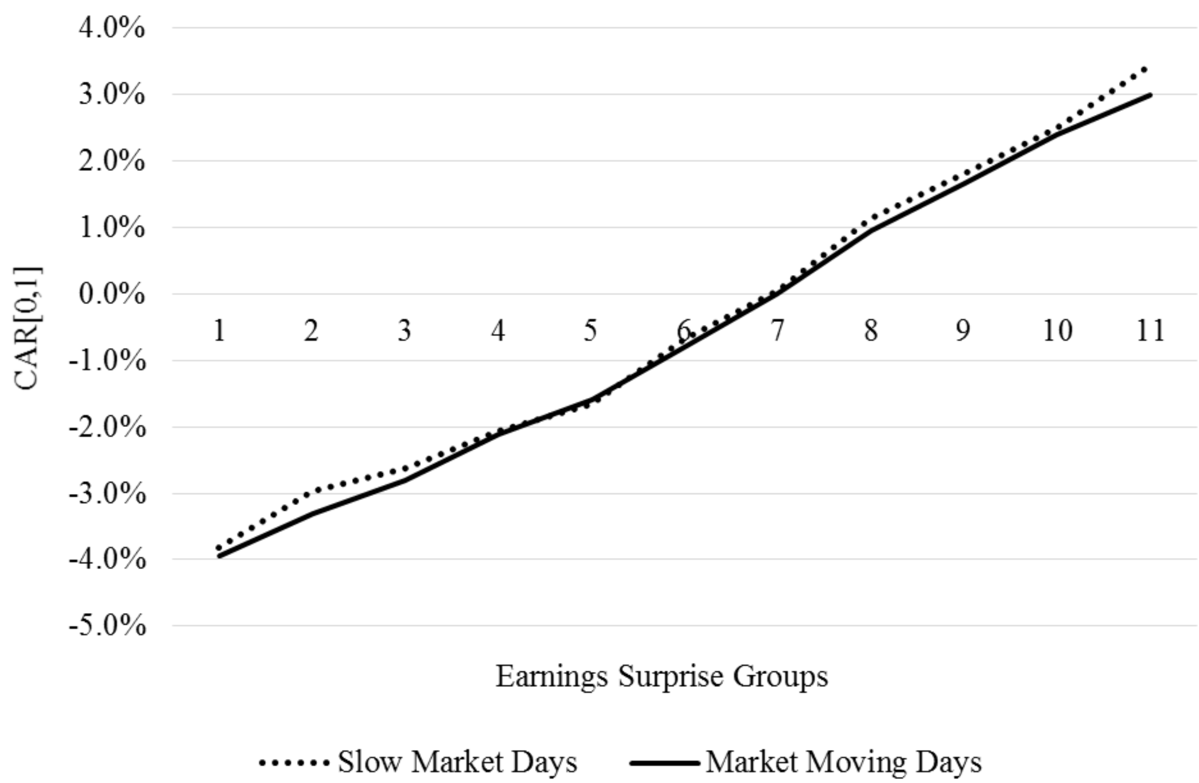


Figure 3. PEAD by Market Movement on Announcement Day

The figure plots the average post-earnings announcement cumulative abnormal returns (CAR[2,90]) against the earnings surprise groups for announcements on market moving days and slow market days. Earnings surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted first by day of the week. Trading days within each day of the week are then sorted into terciles on the magnitude of market returns. *Market moving days* is the tercile with highest absolute market returns and s*low market days* is the tercile with lowest absolute market returns. Sample is from 1995-2014.

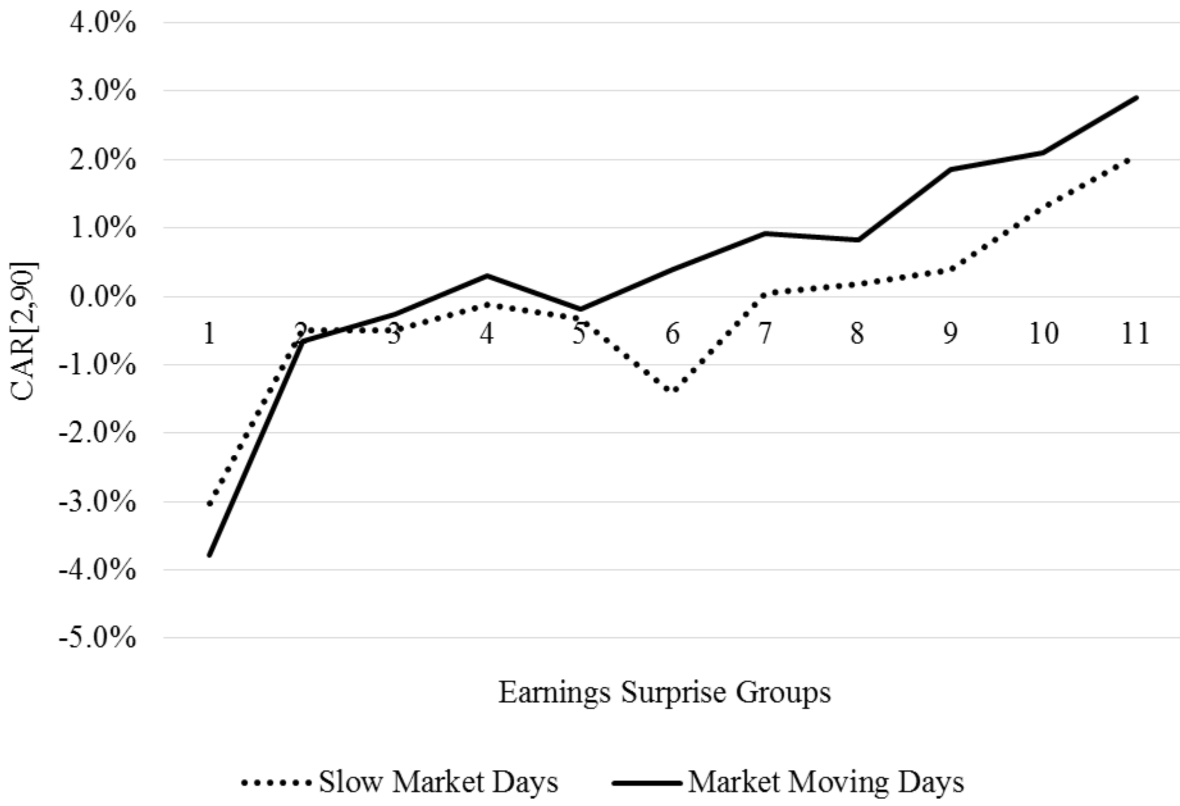


Figure 4. PEAD at Different Horizons.

The figure plots the difference in post-earnings announcement drift (CAR[2,h]) between extreme surprise groups at different horizons(h). Earnings surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings surprise (SRANK). Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. The figure plots the difference in CAR[2,h] for Quantiles 11 and Quantile 1 (SRANK11 – SRANK1). Each quarter, the trading days are sorted first by day of the week. Trading days within each day of the week are then sorted into terciles on the magnitude of market returns. Market moving days is the tercile with highest absolute market returns and slow market days is the tercile with lowest absolute market returns. Sample is from 1995-2014.

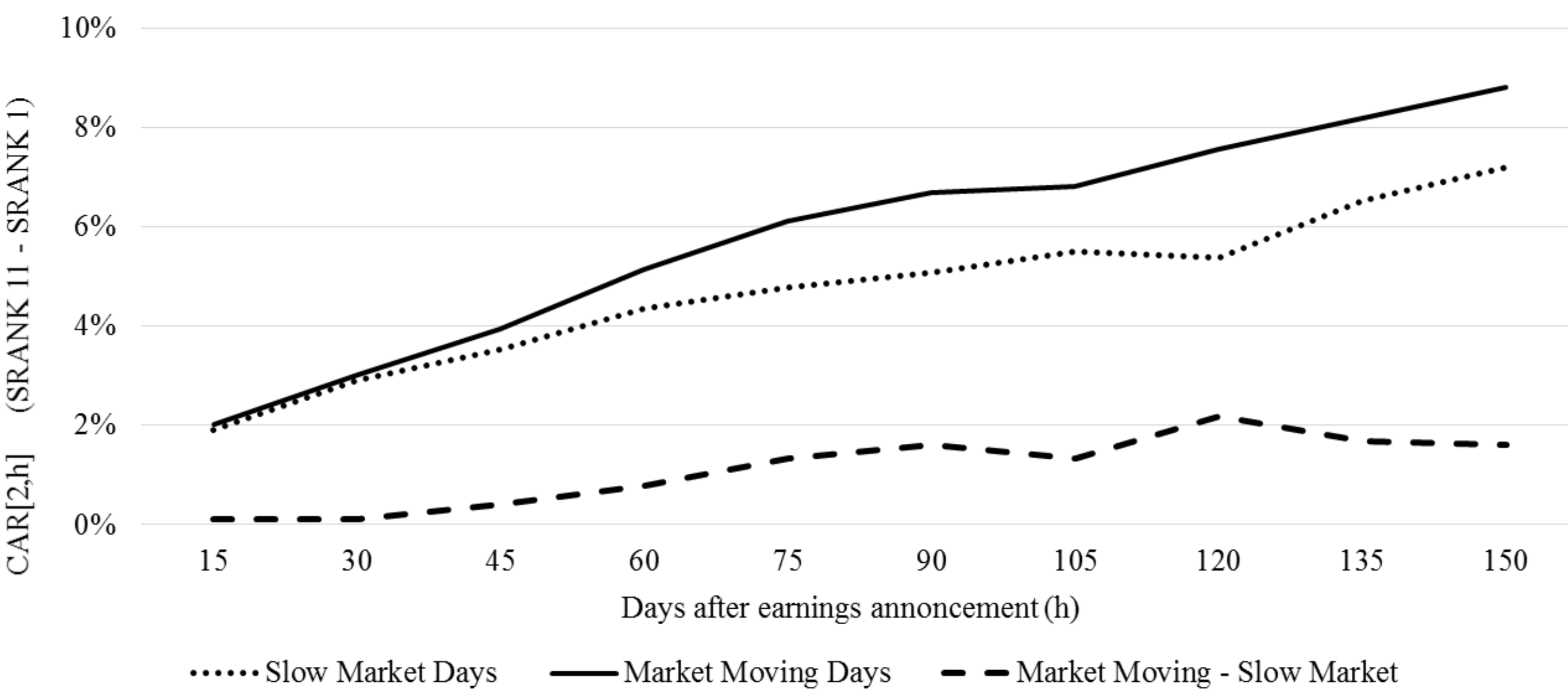


Figure 5. Stock Market Price Response to Macroeconomic News Releases

The figure plots the average cumulative mid-quote returns for the S&P500 ETF (SPY) and S&P500 E-mini Futures (Futures) around macro news releases. In Panel A and C, returns are measured each second relative to mid-quote 20 seconds before the event. In Panel B and D, returns are measured every 100 milliseconds relative to 20 seconds before the event. The SPY sample period covers 2008–2014 and the Futures sample is from July 2011- December 2014.The numbers in the horizontal axis represent the time in seconds relative to event announcement. Negative (Positive) surprises are events in which the announcement was below (above) the consensus median forecast (the opposite is true for CPI, CPI ex Food and Energy and Jobless claims announcements).

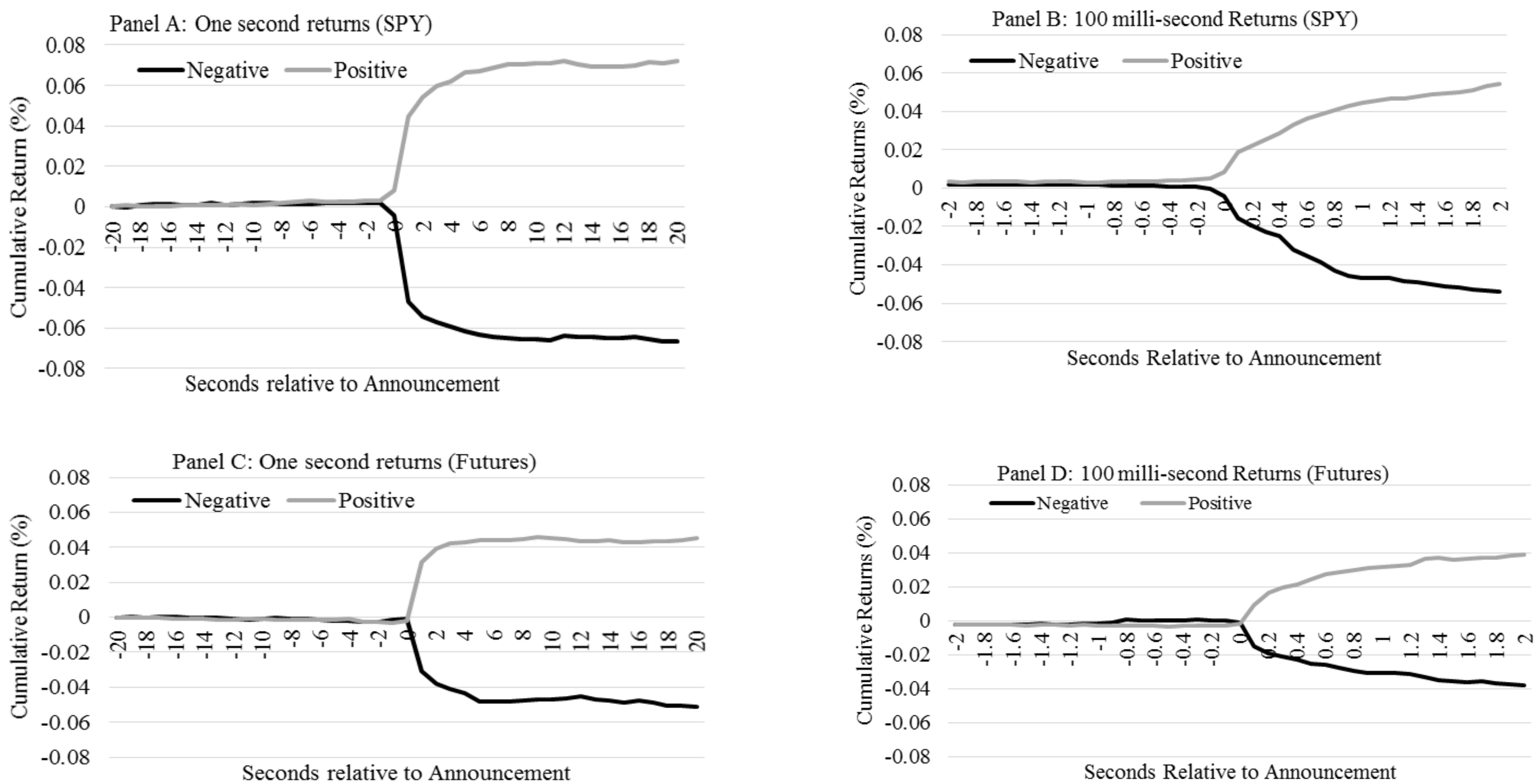
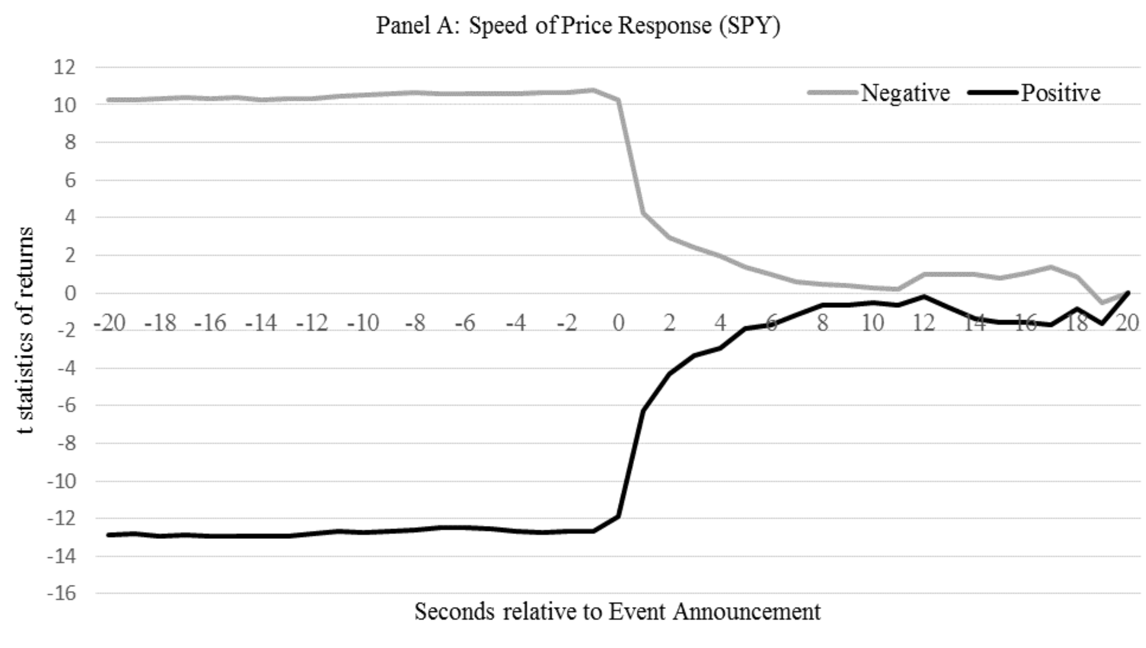


Figure 6. Speed of Stock Market Price Response to Macroeconomic News

The figure plots the t-statistics of mid-quote returns for the S&P500 ETF (SPY) and the S&P500 E-mini Futures (Futures) around macro news. Returns are measured each second relative to mid-quote 20 seconds *after* the event. The numbers in the horizontal axis is the time in seconds relative to event announcement. Negative (Positive) surprises are events in which the announcement was below (above) the consensus median forecast (the opposite is true for CPI, CPI ex Food and Energy and Jobless claims announcements). The SPY sample period covers 2008–2014 and the Futures sample is from July 2011- December 2014.



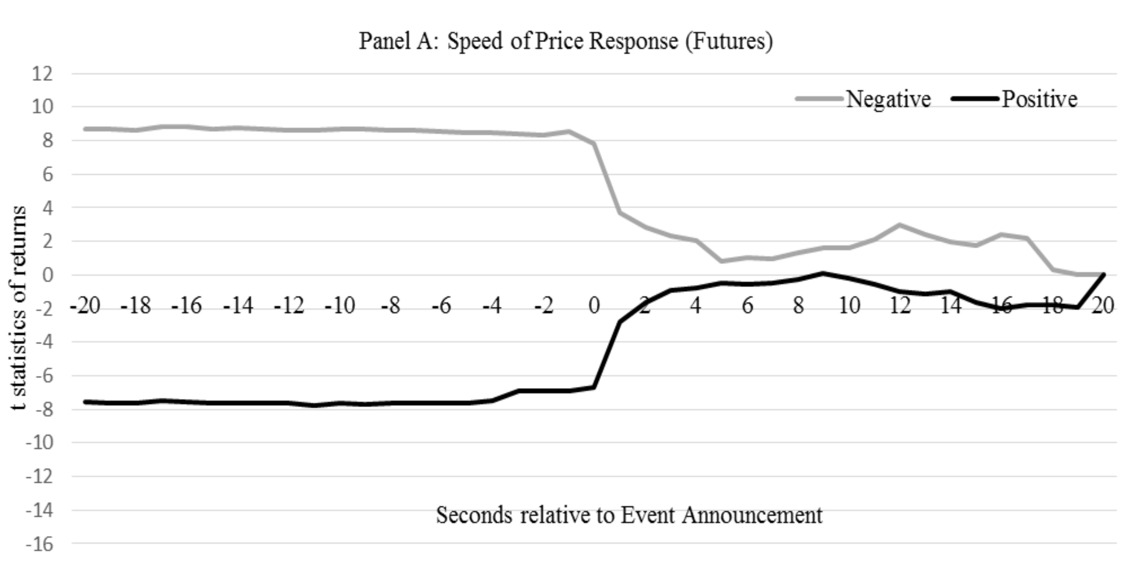
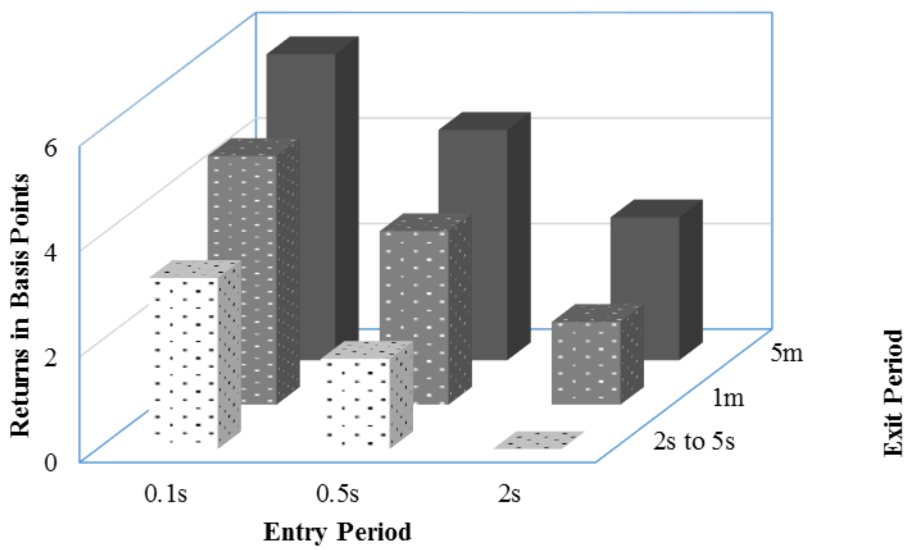


Figure 7. Profitability of Algorithmic Trading on Macroeconomic News Releases

The figure shows average percentage profits (in basis points) from trading on macroeconomic announcement surprises. Positions are assumed to be entered into at the volume-weighted average purchase (sale) price for positive (negative) announcements and unwound later at the volume-weighted average (offsetting) transaction price. The plot shows profits for various entry and exit periods. For example, the entry interval labeled 0.1s refers to the period 0.5 seconds before to 0.1 second after the event, and the exit period labeled 5m refers to the period 1 to 5 minutes after the event. The S&P500 ETF (SPY) sample period covers 2008–2014 and the E-mini Futures sample is from July 2011- December 2014.

Panel A: S&P500 ETF (SPY)



Panel B: S&P500 E-mini Futures

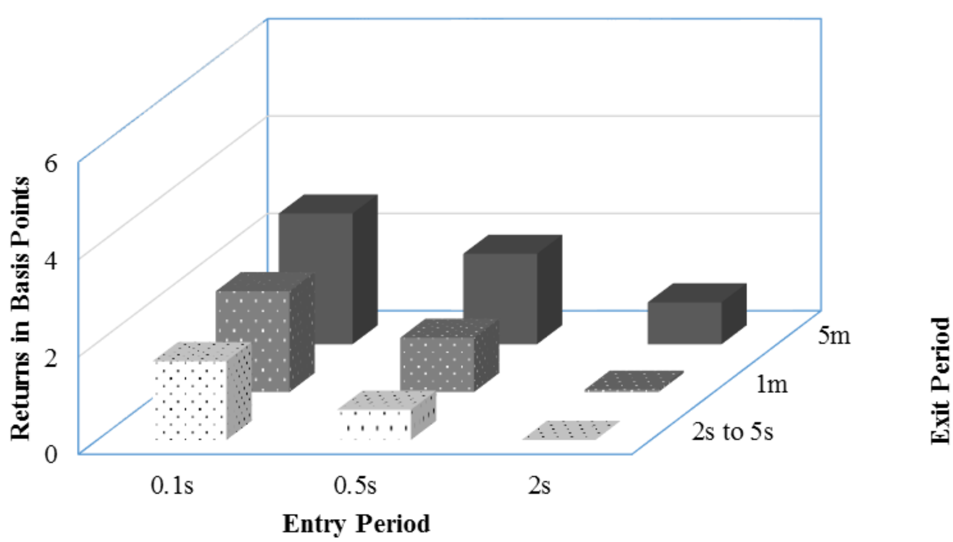


Figure 8. Trend in Quotes to Trades ratio, Quote Depth and Trade size

The figure plots the trend in average quotes to trades ratio, quoted depth and trade size around each macroeconomic announcement. *QT Ratio* is the ratio of number of quotes to number of trades in a given period. *Quoted Depth* is the average of number of shares at Best Bid Price and number of shares at Best Ask Price. *Trade Size* is the average volume per trade (for futures it is the number of contracts per trade). Reported are the average values for the period beginning with the announcement and ending 2 seconds later. The numbers are averages across events for the year.

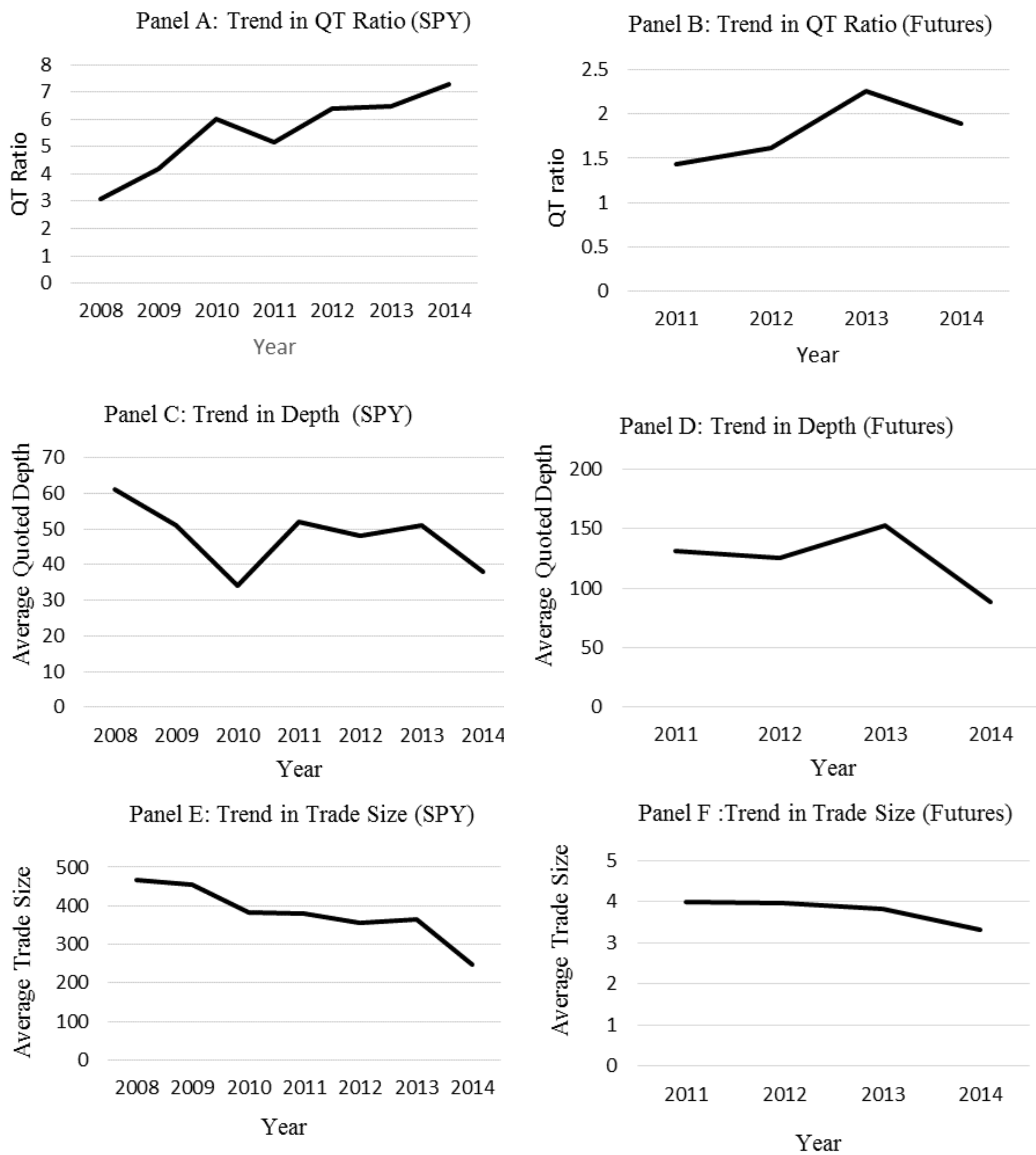
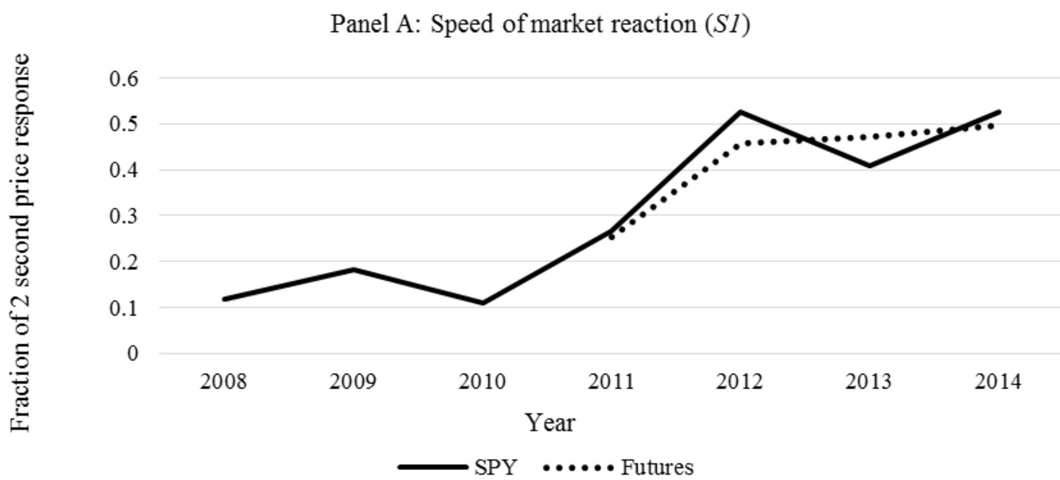
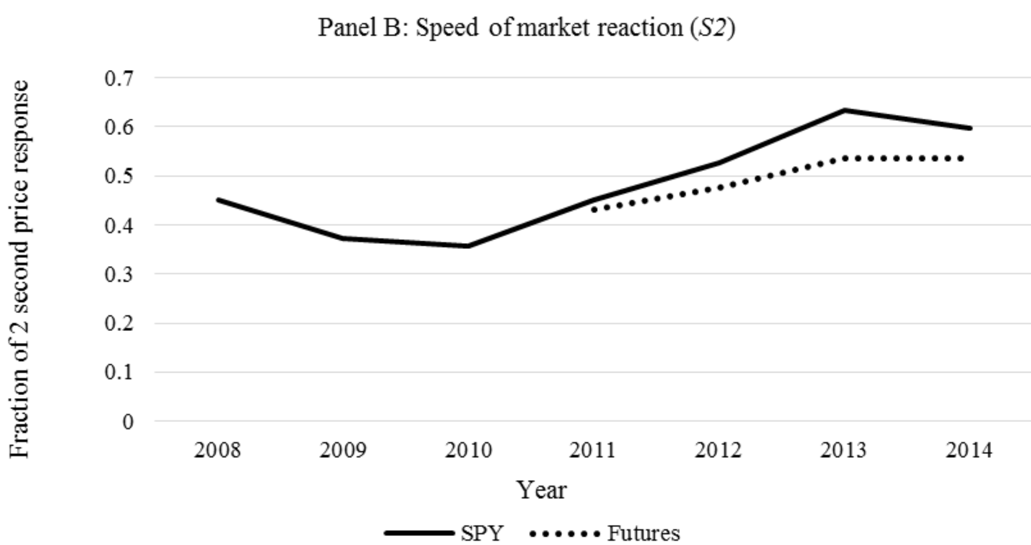


Figure 9. Trend in the Speed of Market Reaction

The figure plots the trend in speed of market reaction over time. In Panel A, the speed of market reaction (*S1*) is measured as the fraction of the 2-second price response that occurs in first 100ms after release, $S1 = r(t, t + 0.1)/r(t, t + 2)$, where $r(t, t + 0.1)$ is the return in the first 100 milliseconds after the release for the S&P 500 ETF (solid line) or S&P 500 e-mini futures (dotted line) and $r(t, t + 2)$ is the return in the first 2 seconds after the release. In Panel B, the speed of reaction (*S2*) is expressed as the ratio of absolute return in first 100ms after release to the sum of absolute return in first 100ms and the absolute return in the subsequent 1.9 seconds, $S2 = |r(t, t + 0.1)|/(|r(t, t + 0.1)| + |r(t + 0.1, t + 2)|)$. Each speed measurement is computed from mid-quotes each event day and averaged across the event type for a given year. The plot shows averages across events each year.





Tables

Table 1. Earnings Announcements and Market Movements by Day of the Week

The table presents the number of earnings announcements and market moving days by days of the week. Trading days within a quarter are sorted into three market moving groups on absolute market returns during the day. In Panel B, trading days are directly sorted into market movement terciles without adjusting for day of the week. In Panel C, trading days are sorted first by day of the week and within the day of the week into terciles on absolute market returns. The tercile with the lowest market movements is denoted as slow market days and the tercile with largest market movements is called market moving days. Mean |Rm| is the mean of absolute return of the market movement group and Std Dev |Rm| is its standard deviation. Sample is from 1995-2014.

	Mondays	Tuesdays	Wednesdays	Thursdays	Fridays	Total	Mean |Rm|	Std Dev |Rm|
Panel A: No of earnings Announcements by days of the week								
No of earnings announcements	32,362	57,274	60,990	72,870	14,412	237,893		
% of total earnings announcements	13.6%	24.1%	25.6%	30.6%	6.1%			
Panel B: Market moving days by days of week (Unadjusted)								
% of slow market days	20.6%	19.4%	20.2%	19.7%	20.2%		0.20%	0.17%
% of market moving days	18.9%	22.2%	19.2%	21.6%	18.1%		1.62%	1.07%
Panel C: Market moving days by days of the week (Adjusted for Day of the week)								
% of slow market days	19.2%	20.6%	20.7%	20.5%	19.1%		0.22%	0.22%
% of market moving days	19.7%	20.3%	20.3%	20.4%	19.3%		1.60%	1.11%

Table 2. Earnings Surprise and Firm Characteristics by Market Movement on Announcement Day

The table presents the earnings surprise, immediate and delayed price response for the surprise groups by the magnitude of the market movement on announcement day. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement. Panel A reports the results for lowest absolute market returns tercile and Panel B reports the results for highest absolute market returns tercile. Sample is from 1995-2014.

	Surprise Groups										
	1	2	3	4	5	6	7	8	9	10	11
Panel A: Slow Market Days											
Surprise	-4.9%	-0.7%	-0.3%	-0.1%	0.0%	0.0%	0.0%	0.1%	0.2%	0.4%	1.8%
CAR[0,1]	-3.8%	-3.0%	-2.6%	-2.1%	-1.7%	-0.7%	0.1%	1.1%	1.8%	2.5%	3.4%
CAR[2,90]	-3.0%	-0.5%	-0.5%	-0.1%	-0.3%	-1.4%	0.0%	0.2%	0.4%	1.3%	2.1%
Market Cap	982	1,568	2,423	3,668	7,205	5,370	9,892	5,930	4,155	2,876	1,401
B/M	1.26	0.91	0.91	0.79	0.60	0.63	0.46	0.57	0.90	1.02	1.09
N	4,281	4,372	4,311	4,333	4,436	7,929	8,097	8,113	7,797	7,814	7,713
Panel B: Market Moving Days											
Surprise	-5.2%	-0.7%	-0.3%	-0.1%	0.0%	0.0%	0.0%	0.1%	0.2%	0.4%	1.8%
CAR[0,1]	-3.9%	-3.3%	-2.8%	-2.1%	-1.6%	-0.8%	0.0%	0.9%	1.7%	2.4%	3.0%
CAR[2,90]	-3.8%	-0.7%	-0.3%	0.3%	-0.2%	0.4%	0.9%	0.8%	1.9%	2.1%	2.9%
Market Cap	865	1,597	2,296	3,926	7,085	5,609	9,844	5,671	4,619	3,032	1,417
B/M	1.21	1.07	0.98	0.90	0.58	0.62	0.49	0.56	0.71	0.86	1.05
N	4,969	4,984	5,029	5,055	5,153	9,406	9,542	9,301	9,272	9,260	9,266

Table 3. Retail Investor Trading Around Earnings

The table examines how earnings announcements, market movements and their interaction influence the likelihood that an investors trades in a stock. The dependent variable Trade is a dummy variable which takes the value of 1 if the investor traded the stock, and 0 otherwise. Independent variables are earnings dummy (Earnings) that takes the value of 1 if the stock announced quarterly earnings result on that day or the day before, and 0 otherwise, market movement ranking (MMRANK) of the day, and the interaction term. Sample is restricted to stocks in which the investor traded at least 5 times during the sample period. Only observations for the dates when at least one asset was traded in the account are considered. Sample period is from Jan 1991 to Nov 1996. The standard errors clustered by account and date are reported in parenthesis. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

	Trade	Trade
Constant	0.055***	0.054***
	(0.002)	(0.002)
Earnings	0.044***	0.047***
	(0.002)	(0.002)
MMRANK		0.001***
		(0.000)
MMRANK* Earnings		-0.003**
		(0.001)
R^2	0.001	0.001
N	8,073,706	8,073,706

Table 4. Immediate Price Response

The table reports the results of regressing Cumulative Abnormal Returns CAR[0,1] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *,**,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[0,1]	CAR[0,1]
Constant	-4.865***	-6.732***
	(0.090)	(0.227)
SRANK	0.738***	1.063***
	(0.012)	(0.031)
MMRANK	0.096	0.084
	(0.071)	(0.069)
MMRANK x SRANK	-0.021**	-0.021**
	(0.010)	(0.009)
Controls, Controls x SRANK	No	Yes
R^2	0.090	0.080
N	237,893	237,893

Table 5. Delayed Price Response

The table reports the results of regressing the Cumulative Abnormal Returns CAR [2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[2,90]	CAR[2,90]
Constant	-2.189***	-5.821***
	(0.390)	(0.905)
SRANK	0.348***	1.000***
	(0.040)	(0.110)
MMRANK	-0.221	-0.235
	(0.314)	(0.315)
MMRANK x SRANK	0.070**	0.068**
	(0.032)	(0.032)
Controls, Controls x SRANK	No	Yes
R^2	0.002	0.006
N	237,893	237,893

Table 6. Volume Response

The table reports the results of regressing the abnormal volume AVOL[0,1] on absolute surprise decile rank and market movement rank. Abnormal volume is computed as the ratio of relative volume RVOL[0,1] over RVOL[-7,-46]. RVOL is the dollar volume in a stock in a period divided by the aggregate dollar volume in the same period. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter firms are sorted into deciles on absolute value of announcement surprise (ASRANK). Each quarter, the trading days are sorted within each day of the week into terciles on the magnitude of market movement (MMRANK). Controls included are Size, Book to Market and Number of announcement decile rank, Turnover, No of Analysts, squared market returns and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	AVOL[0,1]	AVOL[0,1]
Constant	1.782***	2.249***
	(0.017)	(0.033)
ASRANK	0.047***	0.041***
	(0.002)	(0.002)
MMRANK	-0.086***	-0.028***
	(0.012)	(0.012)
Controls	No	Yes
R^2	0.004	0.016
N	237,821	237,821

Table 7. Persistence in Surprise and Market Movement

The table reports the results of regressing surprise rank of a firm in a quarter on its previous 4 lags of surprise, previous quarter market movement and the interaction between previous quarter market movement rank and surprise rank. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 comprise of stocks with negative earnings surprise, Quantile 6 has stocks that meet the expectations and Quantiles 7-11 has stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Standard errors are clustered by firm. *,**, *** indicate statistical significance at the 10%, 5% and 1% level respectively

	SRANK(t)	SRANK(t)
Constant	4.304***	4.075***
	(0.035)	(0.097)
SRANK(t-1)	0.159***	0.196***
	(0.003)	(0.012)
SRANK(t-2)	0.087***	0.084***
	(0.003)	(0.003)
SRANK(t-3)	0.061***	0.058***
	(0.003)	(0.003)
SRANK(t-4)	0.058***	0.056***
	(0.003)	(0.003)
MMRANK(t-1)		-0.048*
		(0.027)
MMRANK(t-1)xSRANK(t-1)		0.006*
		(0.004)
Controls, Controls x SRANK		Yes
R^2	0.054	0.056
N	196,907	196,907

Table 8. Analyst Responsiveness and Market Movement

The table reports the results of regressing measures of analyst responsiveness on the ranking of magnitude of market returns on the reporting day. Analyst responsiveness is measured by the mean lag (Analyst Lag), which is the mean of number of working days between the first analyst revision from the previous quarter report date, percent of firms with at least one analyst (% On time) who revises within two days of earnings report. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Controls included are squared market returns on the announcement day, Size, Book to Market and Number of announcements decile ranks, Turnover, Number of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *,**,*** denotes statistical significance at 10%,5% and 1% levels respectively.

	Analyst Lag	% On Time
Constant	9.248***	0.434***
	(0.232)	(0.007)
MMRANK	0.150*	-0.004**
	(0.0914)	(0.002)
Controls	Yes	Yes
R^2	0.018	0.037
N	118,732	118,732

Table 9. Attention around Important Macroeconomic events

The table reports the results of regressing the Cumulative Abnormal Returns CAR[0,1] and CAR [2,90] on surprise ranks (SRANK), absolute macroeconomic surprise rank (MACRORANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 comprise of stocks with negative earnings surprise, Quantile 6 has stocks that meet the expectations and Quantiles 7-11 has stocks with positive earnings surprise. Macroeconomic events considered are Nonfarm Payrolls, GDP announcement, FOMC Rate Decision ISM Manufacturing, ISM Non-Manufacturing, Construction Spending, New Home Sales, and ADP Employment. Announcements of each macroeconomic event type are sorted into deciles on the absolute surprise (MACRORANK). Coefficients are multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[0,1]	CAR[2,90]
Constant	-8.253***	-1.874
	(0.496)	(1.837)
SRANK	1.237***	0.403***
	(0.072)	(0.254)
MACRORANK x SRANK	-0.009*	0.033**
	(0.005)	(0.014)
Controls, Controls x SRANK	Yes	Yes
R^2	0.094	0.005
N	67,319	67,319

Table 10. Post-Earnings Drift By Firm Size

The table reports the results of regressing the Cumulative Abnormal Returns CAR [2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Small Firms are the firms with market cap below the median and Large Firms have market capitalization above the median in a quarter. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	Small Firms	Large Firms
Constant	-6.216***	-6.382***
	(1.189)	(1.564)
SRANK	1.162***	0.893***
	(0.144)	(0.210)
MMRANK	-0.414	0.235
	(0.404)	(0.360)
MMRANK x SRANK	0.112***	-0.013
	(0.042)	(0.042)
Controls, Controls x SRANK	Yes	Yes
R^2	0.009	0.003
N	118,927	118,966

Table 11. Post-Earnings Drift By Book-to-Market

The table reports the results of regressing the Cumulative Abnormal Returns CAR [2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Low B/M are the firms with Book-to-Market below the median and High B/M have Book-to-Market above the median in a quarter. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	Low B/M	High B/M
Constant	-7.460***	-5.353***
	(1.280)	(0.930)
SRANK	1.152***	0.926***
	(0.169)	(0.191)
MMRANK	0.289	-0.577
	(0.421)	(0.389)
MMRANK x SRANK	-0.020	0.127***
	(0.054)	(0.039)
Controls, Controls x SRANK	Yes	Yes
R^2	0.005	0.007
N	118,924	118,969

Table 12. Post-Earnings Drift By Analyst Coverage

The table reports the results of regressing the Cumulative Abnormal Returns CAR [2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Low Following are firms with analyst following below the median and High Following have analyst following above the median. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	Low Following	High Following
Constant	-6.196***	-4.871***
	(1.180)	(1.408)
SRANK	1.080***	0.807***
	(0.149)	(0.183)
MMRANK	-0.365	0.015
	(0.366)	(0.418)
MMRANK x SRANK	0.099**	0.019
	(0.004)	(0.048)
Controls, Controls x SRANK	Yes	Yes
R^2	0.009	0.003
N	117,741	120,152

Table 13. Immediate and Delayed Price Response using Previous Quarter Breakpoints for Market Movement Ranking

The table reports the results of regressing the Cumulative Abnormal Returns CAR[0,1] and CAR [2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 comprise of stocks with negative earnings surprise, Quantile 6 has stocks that meet the expectations and Quantiles 7-11 has stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK) using previous quarter breakpoints. Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[0,1]	CAR[2,90]
Constant	-6.892***	-4.284***
	(0.247)	(1.012)
SRANK	1.090***	0.900***
	(0.033)	(0.121)
MMRANK	0.119*	-0.883***
	(0.065)	(0.302)
MMRANK x SRANK	-0.023***	0.083***
	(0.009)	(0.030)
Controls, Controls x SRANK	Yes	Yes
R^2	0.080	0.006
N	237,893	237,893

Table 14. Different Post Earnings Horizons

The table reports the results of regressing the Cumulative Abnormal Returns CAR [2,75] , CAR [2,90] , and CAR [2,120] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 contain stocks with negative earnings surprise, Quantile 6 has the stocks that meet the expectations, and Quantiles 7-11 contain stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[2,75]	CAR[2,90]	CAR[2,120]
Constant	-6.117***	-5.821***	-6.962***
	(0.857)	(0.905)	(1.064)
SRANK	0.983***	1.000***	1.216***
	(0.104)	(0.110)	(0.132)
MMRANK	-0.159	-0.235	-0.601
	(0.278)	(0.315)	(0.379)
MMRANK x SRANK	0.050*	0.068**	1.018**
	(0.029)	(0.032)	(0.040)
Controls, Controls x SRANK	Yes	Yes	Yes
R^2	0.006	0.006	0.008
N	237,893	237,893	233,278

Table 15. 10 Surprise Groups

The table reports the results of regressing the Cumulative Abnormal Returns CAR[0,1] and CAR[2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter, firms are sorted into deciles based on the earnings announcement surprise. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[0,1]	CAR[2,90]
Constant	-4.394***	-3.634***
	(0.165)	(0.715)
SRANK	1.098***	1.006***
	(0.032)	(0.113)
MMRANK	0.048	-0.028
	(0.052)	(0.260)
MMRANK x SRANK	-0.022**	0.056*
	(0.010)	(0.033)
Controls, Controls x SRANK	Yes	Yes
R^2	0.080	0.006
N	237,893	237,893

Table 16. 2 Market Movement Groups

The table reports the results of regressing the Cumulative Abnormal Returns CAR[0,1] and CAR[2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 comprise of stocks with negative earnings surprise, Quantile 6 has stocks that meet the expectations and Quantiles 7-11 has stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into 2 groups on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[0,1]	CAR[2,90]
Constant	-6.708***	-5.834***
	(0.224)	(0.884)
SRANK	1.059***	1.010***
	(0.031)	(0.109)
MMRANK	0.113	-0.432
	(0.109)	(0.489)
MMRANK x SRANK	-0.029**	0.112**
	(0.015)	(0.049)
Controls, Controls x SRANK	Yes	Yes
R^2	0.080	0.006
N	237,893	237,893

Table 17. 6 Market Movement Groups

The table reports the results of regressing the Cumulative Abnormal Returns CAR[0,1] and CAR[2,90] on surprise ranks (SRANK), market movement rank (MMRANK) and their interaction. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 comprise of stocks with negative earnings surprise, Quantile 6 has stocks that meet the expectations and Quantiles 7-11 has stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into 6 groups on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	CAR[0,1]	CAR[2,90]
Constant	-6.777***	-5.912***
	(0.231)	(0.930)
SRANK	1.071***	1.001***
	(0.031)	(0.112)
MMRANK	0.049	-0.054
	(0.033)	(0.154)
MMRANK x SRANK	-0.011**	0.027*
	(0.005)	(0.015)
Controls, Controls x SRANK	Yes	Yes
R^2	0.080	0.006
N	237,893	237,893

Table 18. Strategic Scheduling of Poor Earnings

The table reports the results of regressing surprise ranks (SRANK) on the market movement rank (MMRANK), Friday dummy and controls. Earnings announcement surprise is the difference between actual EPS and median consensus estimate scaled by the stock price before the announcement. Each quarter firms are sorted into 11 groups on the earnings announcement surprise. Quantiles 1-5 comprise of stocks with negative earnings surprise, Quantile 6 has stocks that meet the expectations and Quantiles 7-11 has stocks with positive earnings surprise. Each quarter, the trading days are sorted within the day of the week into 3 groups on the magnitude of market movement (MMRANK). Coefficients multiplied by 100. Controls include Size, Book to Market and Number of announcement deciles, Turnover, No of Analysts, and Reporting Lag. Sample is from 1995-2014. Standard errors are clustered by the reporting date. *, **,*** denote statistical significance at 10%, 5% and 1% levels respectively.

	SRANK
Constant	7.044***
	(0.034)
MMRANK	0.010
	(0.107)
Friday	-0.396***
	(0.033)
Controls	Yes
R^2	0.011
N	237,893

Table 19. Response of Aggregate Mutual Fund Flows to Market Returns

The table reports the results of regressing aggregate weekly mutual fund flows on lagged flows, contemporary and lagged market returns, and contemporary and lagged weekly market movement rank (MMRANKW) and market movement ranks interacted with market returns. Up to three lags of weekly aggregate mutual fund flows are used. Each year, weeks (ending Wednesday) are sorted into two groups on magnitude of market returns (MMRANKW). Standard errors are Newey-West corrected with 4 lags. *, **, *** denote statistical significance at the 1%, 5% and 10% levels respectively

	Flow(t)	Flow(t)
Constant	-1.08***	-0.73***
Flow(t-1)	0.32***	0.31***
Flow(t-2)	0.14**	0.14***
Flow(t-3)	-0.01	-0.01
Rm(t)	31.80***	-16.70
Rm(t-1)	41.52***	76.12***
MMRANKW(t)		-0.13
MMRANKW(t-1)		-0.55**
Rm(t) x MMRANKW(t)		50.85**
Rm(t-1) x MMRANKW(t-1)		-36.35**
R^2	0.35	0.36
N	411	411

Table 20. Aggregate Trading Volume by Market Movement

The table reports the results of regressing aggregate relative trading volume on the ranking of market movement. Aggregate relative trading volume (AGGTVOL) is the ratio of aggregate dollar trading volume in a trading day over the average trading volume in the previous 10 days. Each quarter, the trading days are sorted within the day of the week into terciles on the magnitude of market movement (MMRANK). In the second specification squared of market returns and the aggregate relative trading volume in the previous 5 days are used as controls. Standard errors are Newey-West adjusted with 10 lags. *,**, *** indicate statistical significance at the 10%, 5% and 1% levels respectively.

	AGGTVOL	AGGTVOL
Constant	0.983***	0.286***
	(0.005)	(0.018)
MMRANK	0.031***	0.022***
	(0.004)	(0.003)
Controls		Yes
R^2	0.015	0.390
N	5036	5036

Table 21. Macroeconomic Announcements Descriptive Statistics

The table presents descriptive statistics for the sample of announcements. Release time is the most common release ET time (to subscribers) during the sample period. The sample period covers 2008-2014 for announcements released after 9.30am and July 2011 through December 2014 for announcements released before 9.30am. Obs is the number of announcement observations during the sample period. Announcement surprises are measured as the reported value less the median Bloomberg estimate. Surprise Std Dev denotes the standard deviation of announcement surprises, Num. of Estimates is the mean number of estimates, and Positive (Negative) Surprises is the fraction of announcements that are positive (negative). Surprise Coefficient is the resulting coefficient, with *, **, and *** indicating significance at the 10%, 5%, and 1% levels.

Announcement	Release Time	Frequency	Obs	Surprise Std Dev	Num. of Estimates	Positive Surprises	Negative Surprises	Surprise Coefficient
CPI MoM (% change)	8:30	Monthly	42	0.12%	83	21%	40%	-0.06***
CPI MoM ex- Food and Energy (% change)	8:30	Monthly	42	0.08%	81	21%	33%	-0.05**
Durable Goods Orders (% change)	8:30	Monthly	42	3.22%	78	64%	31%	0.03
Housing Starts (thousands)	8:30	Monthly	40	61.9	80	45%	55%	0.05**
Initial Jobless Claims(thousands)	8:30	Weekly	183	15.6	48	44%	55%	-0.05***
Nonfarm Payrolls (change in thousands)	8:30	Monthly	42	56.3	90	50%	50%	0.30***
Personal Consumption (% change)	8:30	Monthly	42	0.45%	20	48%	48%	0.06**
Personal Income (% change)	8:30	Monthly	42	0.37%	74	26%	48%	0.01
PPI Mom (% change)	8:30	Monthly	42	0.27%	74	36%	50%	0.03
PPI MoM ex- Food and Energy (% change)	8:30	Monthly	42	0.15%	69	36%	29%	0.02
Retail Sales (% change)	8:30	Monthly	42	0.30%	82	43%	43%	0.10***
Trade Balance ($ billions)	8:30	Monthly	42	3.8	71	48%	52%	-0.02
Unemployment Rate (% level)	8:30	Monthly	42	0.14%	85	24%	57%	-0.05
Capacity Utilization (% level)	9:15	Monthly	42	0.36%	65	45%	45%	0.04***
Industrial Production (% change)	9:15	Monthly	42	0.40%	82	43%	48%	0.04**
Chicago PMI (index value)	9:42	Monthly	84	4.0	53	58%	40%	0.15***
Consumer Sentiment (index value)	9:54:58	Bi-Weekly	168	2.9	64	54%	45%	0.06***
Business Inventories (% change)	10:00	Monthly	84	0.21%	48	40%	43%	0.01
Construction Spending (% change)	10:00	Monthly	83	0.99%	49	51%	47%	0.02
Consumer Confidence (index value)	10:00	Monthly	84	5.4	71	48%	51%	0.22***
Existing Home Sales (thousands)	10:00	Monthly	84	216.2	73	49%	48%	0.13***
Factory Orders (% change)	10:00	Monthly	83	0.70%	62	49%	47%	0.06***
ISM Manufacturing (index value)	10:00	Monthly	84	1.9	77	64%	35%	0.23***
ISM Non-Manufacturing (index value)	10:00	Monthly	84	2.1	72	57%	43%	0.06**
Leading Indicators (% change)	10:00	Monthly	84	0.20%	53	51%	29%	0.07**
New Home Sales (thousands)	10:00	Monthly	83	36.0	73	45%	53%	0.14***
Wholesale Inventories (% change)	10:00	Monthly	85	0.57%	31	54%	40%	-0.02

Table 22. Stock Market Price Response to Macroeconomic News

The table reports mean cumulative mid-quote returns for the S&P500 ETF (SPY) and S&P500 E-mini Futures around macroeconomic news announcements. Returns are reported in basis points and time is labeled in seconds. Cumulative returns are measured relative to the prevailing mid-quote 20 seconds before the announcement. Negative (Positive) surprises are events in which the announcement was below (above) the consensus median forecast (the opposite is true for CPI, CPI ex Food and Energy and Jobless claims announcements). The returns for negative surprises are multiplied by -1 and averaged with positive surprises. Panel A reports the results for the S&P500 ETF (SPY) and Panel B reports the results for S&P 500 E-mini Futures. The SPY sample period covers 2008-2014 and the E-mini sample is from July 2011 through December 2014. Statistical significance at the 10%, 5%, and 1% level are labeled with *, **, and ***.

Panel A: S&P500 ETF (SPY)

Time	Chicago PMI	Consumer Sentiment	Consumer Confidence	Existing Home Sales	Factory Orders	ISM Manu.	ISM Non-Manu.	Leading Index	New Home Sales	All Events
-5.0	-0.2	0.1	0.4	0.0	-0.4	0.0	0.7	0.0	-0.1	0.1
-1.0	0.0	0.0	0.4	0.2	-0.4	0.4	0.6	-0.4	0.0	0.1
-0.5	-0.1	0.1	0.5	0.3	-0.3	0.5	0.6	-0.6	0.2	0.1
0.0	0.6	0.4	2.8***	1.2**	-0.4	0.6	0.7	-0.3	0.2	0.6***
0.1	2.7***	2.0***	4.9***	1.7***	-0.2	2.0***	1.4**	-0.2	0.5	1.7***
0.2	2.9***	2.6***	5.9***	2.4***	0.0	2.0***	1.3**	0.0	0.8	2.1***
0.3	3.2***	3.0***	6.4***	3.0***	0.4	2.0***	1.3**	0.1	1.5***	2.4***
0.4	3.5***	3.2***	6.7***	3.6***	0.4	2.3***	1.5**	-0.1	2.0***	2.7***
0.5	3.7***	3.5***	7.4***	4.4***	0.6	3.2***	2.4***	0.5	2.7***	3.3***
1.0	4.5***	4.0***	9.0***	5.9***	1.6***	6.6***	4.6***	-0.4	4.7***	4.6***
2.0	5.1***	4.2***	10.5***	7.2***	1.9***	8.0***	6.1***	-0.2	6.0***	5.4***
5.0	6.0***	4.4***	12.6***	8.2***	1.9**	10.0***	7.8***	0.4	7.3***	6.4***
10.0	7.1***	4.8***	12.3***	8.8***	2.4***	10.7***	7.8***	1.2	7.6***	6.9***

Table 2 (continued): Stock Market Price Response to Macroeconomic News

Panel B: S&P 500 E-mini Futures

Time	CPI	CPI ex Food	Housing Starts	Jobless Claims	Nonfarm Payrolls	Personal Consump.	Retail Sales	Capacity Utilization	Industrial Production
-5.0	0.4	0.1	0.1	0.1	0.1	-0.3	0.2	0.1	-0.1
-1.0	0.3	-0.1	-0.1	0.0	-1.2	0.0	0.1	0.1	0.0
-0.5	0.3	0.2	0.0	-0.1	-3.3	0.0	0.2	0.1	0.0
0.0	0.4	0.3	0.0	0.0	-4.0	0.1	0.1	0.1	0.3
0.1	0.3	0.6	-0.2	0.2	0.4	0.1	-0.1	1.0**	1.3***
0.2	0.3	1.1	-0.1	1.2***	5.5	0.3	0.1	1.0**	1.3***
0.3	0.2	1.2	0.2	2.1***	6.6	0.6	0.4	0.9**	1.3***
0.4	0.6	1.1	0.2	2.3***	7.4*	0.9	0.5	0.9**	1.2***
0.5	0.6	1.0	0.3	2.3***	7.4*	0.9	2.2*	0.9**	1.3***
1.0	0.6	1.9**	1.7**	2.4***	9.3**	2.4*	3.8***	1.0**	1.4***
2.0	0.6	2.2*	3.0***	3.0***	14.6***	2.0	5.6***	0.9**	1.4***
5.0	0.7	2.7*	3.7***	3.6***	21.0***	2.4	5.7***	1.3***	1.7***
10.0	1.6	2.2*	3.7***	3.1***	20.4***	2.5	6.0***	1.7***	2.0***

Time	Chicago PMI	Consumer Sentiment	Consumer Confid.	Existing Home Sales	Factory Orders	ISM Manu.	ISM Non-Manu.	Leading Index	New Home Sales	All Events
-5.0	-0.4	-0.1	0.0	0.2	-0.6*	-0.1	0.3	0.0	0.0	0.0
-1.0	-0.3	-0.1	-0.3	0.2	-0.6*	0.2	0.3	0.1	0.1	-0.1
-0.5	-0.2	0.0	-0.2	0.2	-0.5*	0.0	0.5	0.0	0.1	-0.2
0.0	0.1	0.3	0.9	0.5	-0.7**	0.2	0.4	0.1	0.0	-0.1
0.1	4.1***	2.9***	5.0***	0.8	-0.7**	3.5***	1.4**	0.2	0.1	1.2***
0.2	4.0***	3.2***	5.6***	1.0**	-0.7*	3.3***	1.4**	0.5	-0.1	1.9***
0.3	4.3***	3.0***	5.4***	1.4***	-0.3	2.9***	1.2**	0.4	0.0	2.1***
0.4	4.4***	3.0***	5.6***	1.5***	-0.4	3.8***	1.6***	0.4	0.0	2.3***
0.5	4.5***	3.0***	5.5***	2.2***	-0.6	5.2***	3.1***	0.5	0.3	2.7***
1.0	5.5***	3.2***	6.0***	3.1***	0.3	7.9***	4.2***	0.1	1.1	3.5***
2.0	5.7***	3.1***	6.8***	3.6***	0.3	8.1***	4.7***	0.1	2.2**	4.3***
5.0	5.2***	3.2***	7.7***	4.0***	0.4	10.4***	5.4***	0.1	2.3***	5.1***
10.0	5.9***	3.2***	7.2***	4.5***	0.3	11.2***	4.8***	0.2	3.2***	5.1***

Table 23. Stock Market Activity around Macroeconomic News Releases

The table reports measures of trading activity around macro news releases. Panel A reports activity for the S&P500 ETF (SPY) and Panel B reports activity for the S&P 500 E-mini Futures. Average dollar trading volume and Notional Value are reported in $Millions for each reported interval. Also reported are the number of trades per second, the number of quote changes per second, and the average order imbalance during each measured interval. Order imbalance (OI) is computed as the (# of buys – # of sells)/(# of buys + # of sells), where buys(sells) represents buyer(seller)-initiated trades. For negative surprises the negative of OI is used to compute the average across events. The interval -5m to -5 captures activity from 5 minutes to 5 seconds before the announcement. The other rows report the activity in the period beginning at the time in the previous row and ending at the time reported in that row. Statistical significance for a difference in means compared to a benchmark period measured -5 minutes to -5 seconds before the event, is denoted by *, **, and *** for significance at the 10%, 5%, and 1% levels. The SPY sample period covers 2008–2014 and the Futures sample is from July 2011- December 2014.

Panel A: S&P500 ETF (SPY)

Time	Dollar Volume $Millions (per second)	Number of Trades (per second)	Number of Quote changes (per second)	Order Imbalance
-5m to -5s	2	33	350	0.00
-5s to 0	2	47	247	0.05*
0.25s	43***	655***	2048***	0.22***
0.5s	29***	467***	1433***	0.11***
1s	21***	406***	1464***	0.07***
2s	11***	246***	1015***	0.07***
3s	8***	196***	853***	0.07***
3s to 5m	3	63	618***	0.02

Panel B: S&P500 E-mini Futures

Time	Notional Value $Millions (per second)	Number of Trades (per second)	Number of Quote changes (per second)	Order Imbalance
-5m to -5s	3	11	37	0.00
-5s to 0	4	13	22	0.02
0.25s	196***	601***	312***	0.19***
0.5s	78***	267***	209***	0.13***
1s	53***	191***	194***	0.13***
2s	33***	106***	146***	0.14***
3s	21**	70***	123***	0.10**
3s to 5m	8	27	83***	0.03

Table 24. Profitability of Algorithmic Trading on Macroeconomic News Releases

The table reports average per-event dollar profits from trading on macroeconomic announcement surprises. Positions are assumed to be entered into at the volume-weighted average purchase (sale) price for positive (negative) announcements measured during the half-second before to two seconds after the event. Positions are unwound at the volume-weighted average (offsetting) transaction price during different intervals after the event. For example, 5s – 1m indicates unwinding the position five seconds to 1 minute after the event. The S&P500 ETF (SPY) sample is from 2008–2014 and the ES sample is from July 2011- Dec 2014. t-statistics in parentheses.

	S&P500 ETF (SPY)			S&P500 E-mini Futures		
Announcement	2s - 5s	5s - 1m	1m - 5m	2s - 5s	5s - 1m	1m - 5m
CPI				-$616	$2,709	$13,232
				(-0.16)	(0.40)	(0.87)
CPI ex Food Energy				-4,088	-1,290	10,109
				(-1.10)	(-0.23)	(0.92)
Housing Start				1,477	8,069	16,282
				(0.86)	(2.31)	(2.49)
Jobless Claims				2,408	1,447	-982
				(1.51)	(0.51)	(-0.18)
Nonfarm Payroll				162,449	221,196	285,866
				(3.16)	(2.49)	(2.36)
Consumption				1,982	15,839	20,179
				(0.24)	(1.27)	(0.87)
Retail Sales				2,140	8,584	25,472
				(0.45)	(1.60)	(2.03)
Capacity Utilization				134	423	2,516
				(0.15)	(0.27)	(0.58)
Industrial Production				-116	733	3,988
				(-0.13)	(0.47)	(0.92)
Chicago PMI	$10,233	$10,798	$23,467	40,166	29,341	105,328
	(3.00)	(2.81)	(3.58)	(2.14)	(1.89)	(3.19)
Consumer Sentiment	1,894	4,607	5,188	-1,472	4,392	7,699
	(2.78)	(2.63)	(1.68)	(-0.43)	(0.33)	(0.38)
Consumer Confidence	15,244	21,910	24,251	77,176	49,850	9,794
	(3.84)	(4.01)	(3.45)	(2.93)	(2.25)	(0.27)
Existing Home Sales	6,562	11,016	22,331	16,538	45,768	101,824
	(3.82)	(2.21)	(2.63)	(1.49)	(1.08)	(1.24)
Factory Orders	257	714	-1,117	281	1,050	-3,599
	(0.26)	(0.48)	(-0.44)	(0.05)	(0.21)	(-0.31)
ISM Manufacturing	16,490	44,364	83,044	103,338	228,663	386,334
	(3.16)	(2.78)	(3.32)	(3.20)	(2.30)	(2.58)
ISM Non-Manufacturing	6,099	5,994	3,754	19,619	-9,329	8,150
	(2.68)	(2.31)	(0.77)	(1.41)	(-0.65)	(0.38)
Leading Index	-123	5,433	5,438	2,582	14,003	14,152
	(-0.07)	(1.25)	(0.87)	(0.28)	(0.66)	(0.43)
New Home Sales	5,851	10,028	12,662	6,340	16,683	14,942
	(4.07)	(3.17)	(3.03)	(1.52)	(2.24)	(1.32)
All Events	6,600	12,134	18,801	21,936	31,547	49,685
	(7.53)	(6.05)	(5.96)	(5.61)	(4.09)	(4.25)

Table 25. Profitability of Algorithmic Trading on Macroeconomic News Releases by Year

The table reports average per-event dollar profits from trading on macroeconomic announcement surprises. Positions are assumed to be entered into at the volume-weighted average purchase (sale) price for positive (negative) announcements measured during the half-second before to two seconds after the event. Positions are unwound at the volume-weighted average (offsetting) transaction price during different intervals after the event. For example, 5s to 1m indicates unwinding the position five seconds to 1 minute after the event. The S&P500 ETF (SPY) sample period covers 2008–2014 and the E-mini Futures sample is from July 2011- December 2014. Profits are reported by year. Statistical significance at the 10%, 5%, and 1% level are denoted by *, **, and ***.

Panel A: S&P500 ETF (SPY)

Exit Time	2008-2014	2008	2009	2010	2011	2012	2013	2014
2s to 5s	6,600***	6,370***	5,826***	9,177***	14,574***	6,849***	2,474**	950*
5s to 1m	12,134***	7,643***	14,606***	19,718***	27,369**	14,284***	705	382
1m to 5m	18,771***	10,145**	22,403***	31,796***	38,183**	23,901***	4,936*	-374

Panel B: S&P500 E-mini Futures

Exit Time	2011-2014	2011	2012	2013	2014
2s to 5s	21,936***	70,267***	34,682***	4,969**	2,326
5s to 1m	31,547***	102,131**	47,199***	9,153	3,438
1m to 5m	49,685***	165,478**	61,748***	20,995**	8,933*

Table 26. Effect of SEC Naked Access Ban on Market Activity Around Macroeconomic News Releases

This table compares market activity around the macro-economic news releases in the three months after SEC imposed naked access ban (December 2011 to February 2012) relative to the three-month period before the ban (September 2011 to November 2011). Panel A reports the estimates for Stock Market Activity in the S&P500 ETF (SPY) and Panel B reports the estimates in the S&P500 E-mini Futures. Number of Trades and Quotes are per second, and Dollar Volume and Notional Contract Value are given in $millions per second. Statistical significance for a difference in means test with the benchmark period, measured -5 minutes to -5 seconds before the event, is denoted by *, **, and *** for significance at the 10%, 5%, and 1% levels.

Panel A: S&P500 ETF(SPY)

	Pre-Ban Period			Post-Ban Period		
Time	Dollar Volume $Millions (per second)	Number of Trades (per second)	Number of Quote changes (per second)	Dollar Volume $Millions (per second)	Number of Trades (per second)	Number of Quote changes (per second)
-5m to -5s	2	52	643	2	34	531
-5s to 0	3	66	395	3	44	281
0.25s	58***	839***	3344***	58***	932***	4529***
0.5s	53***	631***	1889***	69***	924***	2763***
1s	42***	639***	2158***	32*	584***	3143***
2s	16	334**	1428**	11	280	2103**
3s	12	313**	1344**	11	238	1459
3s to 5m	5	119	1191	3	56	828

Panel B: S&P 500 E-mini Futures

	Pre-Ban Period			Post-Ban Period		
Time	Notional Value $Millions (per second)	Number of Trades (per second)	Number of Quote changes (per second)	Notional Value $Millions (per second)	Number of Trades (per second)	Number of Quote changes (per second)
-5m to -5s	4	20	64	3	12	43
-5s to 0	5	22	32	4	16	24
0.25s	187***	771***	432***	226***	791***	417***
0.5s	124***	483***	268***	151***	538***	324***
1s	89***	351***	321***	51*	210*	277***
2s	25	105	196***	26	99	171***
3s	26	105	186**	26	91	153**
3s to 5m	9	43	120	6	24	73

Table 27. Trading Profits around Macroeconomic News and Measures of Trade Competition

The table presents the coefficient estimates from regressing trading profits on quote and trading activity around macroeconomic news announcements. Surprise is the absolute value of the standardized announcement surprise, with the standard deviation of surprise computed using time series of surprises for each event. Trades and Quotes are computed from 5 minutes to 5 seconds before the announcement (denoted by Pre-Ann.) and from 0 to 2 seconds after announcements (denoted by Post-Ann). The Quote/Trade ratio is the number of quote changes over the number of trades. The three different models represent different exit times for the trading strategy. For example, 5s to 1m indicates unwinding the position five seconds to 1 minute after the event. All strategies use an entry window of 0.5 seconds before to 2 seconds after announcements. The S&P500 ETF (SPY) sample covers 2008–2014, and the E-mini Futures sample is from July 2011-December 2014. Panels A and C allow for events to have different responses to surprises at different stages of business cycle (Low, Medium, and High) and Panel B and D for different levels of the VIX. In Panels C and D, we repeat the analysis in Panels A and B by using the speed of adjustment as the measure of competition instead of the quotes to trades ratio. Speed of Adjustment is measured as the average speed across events in the previous month, where the speed for each event is the fraction of two second price reaction that occurs within the first 100ms. Event fixed effects are included in the regression and standard errors are clustered by month. Statistical significance is denoted by *, **, *** for significance at the 10%, 5%, and 1% levels.

Panel A: Quote Intensity, Stages of Business Cycle

	S&P500 ETF(SPY)			S&P500 E-mini Futures		
Coefficients	2s to 5s	5s to 1m	1m to 5m	2s to 5s	5s to 1m	1m to 5m
Surprise (Low)	5,397***	8,525	15,387**			
Surprise (Medium)	11,792***	23,532***	38,562***	46,481***	74,047***	111,306***
Surprise (High)	4,583***	5,772**	7,502*	4,021	4,670	13,158
Pre-Ann Quote/Trade	-1,187*	-2,442	-4,635*	7,377*	-917	-9,992
Post-Ann Quote/Trade	-2,373***	-5,591***	-6,363**	-15,366***	-25,681***	-38,170***
Adjusted R-squared	0.11	0.09	0.11	0.20	0.13	0.13

Panel B: Quote Intensity, Adjusting for VIX

	S&P500 ETF(SPY)			S&P500 E-mini Futures		
Coefficients	2s to 5s	5s to 1m	1m to 5m	2s to 5s	5s to 1m	1m to 5m
Surprise	8,269***	16,573***	29,547***	-65,923***	-154,979***	-239,149**
VIX	376**	669	1,091**	-497	-3,231*	-5,356*
VIX * Surprise	-21	-91	-240	6,012***	12,377***	19,014***
Pre-Ann Quote/Trade	1,826	3,239	3,998	6,890	-1,781	-11,250
Post-Ann Quote/Trade	-1,848**	-4,469***	-4,601*	-12,700***	-21,641***	-32,081***
Adjusted R-squared	0.11	0.08	0.10	0.25	0.17	0.17

Panel C: Speed of Adjustment, Stages of Business Cycle

	S&P500 ETF(SPY)			S&P500 E-mini Futures		
Coefficients	2s to 5s	5s to 1m	1m to 5m	2s to 5s	5s to 1m	1m to 5m
Surprise (Low)	7,394***	12,644***	21,042***			
Surprise (Medium)	11,680***	23,304***	37,978***	45,840***	71,802***	104,967***
Surprise (High)	5,579***	7,729**	9,691**	6,255	7,451	16,200
Speed of Adjustment	-1,106	-5,013	-8,537	-63,777**	-141,152**	-177,730**
Adjusted R-squared	0.10	0.08	0.11	0.17	0.11	0.10

Panel D: Speed of Adjustment, Adjusting for VIX

	S&P500 ETF(SPY)			S&P500 E-mini Futures		
Coefficients	2s to 5s	5s to 1m	1m to 5m	2s to 5s	5s to 1m	1m to 5m
Surprise	8,683***	17,545***	30,458***	-46,737**	-117,540***	-175,668**
VIX	339***	597**	956**	-527	-3,864	-5,405
VIX * Surprise	-19	-89	-231	4,903***	10,192***	15,175***
Speed of Adjustment	1,694	77	-817	-8,972	-69,415	-66,018
Adjusted R-squared	0.11	0.08	0.10	0.19	0.12	0.13

Table 28. Effect of Advanced Access to Consumer Sentiment Information on Market Activity and Profits

The table compares market activity and trading profits for Consumer Sentiment announcements relative to other macroeconomic news. We measure the incremental effect of Consumer Sentiment during the period in which Thomson Reuters sold two-second early access to Consumer Sentiment information, and we compare this difference to the analogous measure calculated after Reuters ended the practice in July 2013. The difference-in-difference estimates below are the post-advanced-feed period difference less the advanced-feed period difference. The advanced-feed sample is from Jan 2013–June 2013 and post-advanced-feed sample is from July 2013-December of 2013. Panel A reports the estimates for Stock Market Activity in the S&P500 ETF (SPY) and the S&P500 E-mini Futures, and Panel B reports the estimates for aggregate per event dollar Profits. Number of Trades and Quotes are per second, and Dollar Volume and Notional Contract Value are given in $Millions per second. Statistical significance is denoted by *, **, and *** for significance at the 10%, 5%, and 1% levels.

Panel A: Stock Market Activity

	S&P500 ETF (SPY)			S&P500 E-mini Futures		
Time	Volume $M	Number of Trades	Number of Quotes	Value $M	Number of Trades	Number of Quotes
-5m to -5s	0	3	-1	1	3	7
-5s to 0	0	1	39	-1	-8	-5
0.25s	4	-273	-1,356	-249	-720	-443***
0.5s	2	-14	303	8	-3	-120
1s	35	316	699	46	144	29
2s	8	91	173	39	113	52
3s	2	47	426	15	20	39
3s to 5m	1	15	97	1	4	16

Panel B: Trading Profits

Exit Time	S&P500 ETF (SPY)	S&P500 E-mini Futures
2s-5s	$5,003	$9,589
5s-1m	-2,364	3,574
1m-5m	-85	-43,164

Table 29. Permanent and Temporary Effects of Order Imbalance on Prices Around Macroeconomic News

This table presents the results of state space model estimation. The log mid-quote price p_t is modeled to have a permanent component m_t and a transitory component s_t. The permanent component m_t is modeled as a random walk and the transitory component is modeled as a stationary process as followed:

$$P_t = m_t + s_t$$

$$m_t = m_{t-1} + w_t$$

$$w_t = c + \alpha\ OIB_t + v_t$$

$$s_t = k + \mu\ s_{t-1} + \beta\ OIB_t + u_t$$

The two components for each event day are estimated using an Unobserved Component Model with log of mid-quotes observed every 100 milliseconds in the interval from two minutes before to two minutes after the event. Then the components in the following three intervals, 120 seconds to 60 seconds before the announcement (-120s to -60s), the first two seconds after the event (0 to 2s), and 60 seconds to 120 seconds after the announcement (60s to 120s), are regressed on the order imbalance (OIB_t) during the interval. The coefficient is the change to the corresponding component of price in basis points for unit change in order imbalance. The reported results are time series average across events of the estimates, and standard errors are clustered by month. Statistical significance is denoted by *, **, and *** for significance at the 10%, 5%, and 1% levels. The S&P500 ETF (SPY) sample in Panel A covers 2008–2014, and the E-mini Futures sample in Panel B covers July 2011- December 2014. Numbers in bold font indicate that the mean for corresponding year is statistically different from the mean during the interval 0 to 2 seconds after announcement at the 5% level.

Panel A: S&P500 ETF (SPY)

	Permanent Impact of order flow (α)			Temporary Impact of order flow (β)		
Year	-120s to -60s	0 to 2 s	60s to 120s	-120s to -60s	0 to 2 s	60s to 120s
2008	-0.040	-0.189*	-0.023	-0.0003*	-0.0004*	-0.0002
2009	0.017**	0.007	0.037***	-0.0003	-0.0028*	-0.0003*
2010	**0.038*****	0.283***	**0.065*****	-0.0005**	-0.0011	-0.0006**
2011	**0.050*****	0.668***	**0.084*****	-0.0021***	0.0089	-0.0017**
2012	**0.039*****	0.587***	**0.067*****	**-0.0019*****	0.0098***	**-0.0020*****
2013	**0.020*****	0.229**	**0.047*****	-0.0025***	0.0134	-0.0026***
2014	0.021***	-0.027	0.051***	-0.0012***	0.0039	-0.0013***
2008-2014	**0.021*****	0.224***	**0.047**	**-0.0012*****	0.0045**	**-0.0012*****

Panel B: S&P500 E-mini Futures

	Permanent Impact of order flow (α)			Temporary Impact of order flow (β)		
Year	-120s to -60s	0 to 2 s	60s to 120s	-120s to -60s	0 to 2 s	60s to 120s
2011	**0.014***	1.064***	**0.056****	**-0.032*****	0.070	**-0.029*****
2012	**-0.003**	0.643***	**0.008*****	**-0.030*****	0.039***	**-0.032*****
2013	**0.003**	0.220***	**-0.002**	-0.015***	0.053	-0.025***
2014	-0.010***	0.01	-0.013***	-0.021***	-0.054*	-0.030***
2011-2014	**-0.001**	0.408***	**0.006**	**-0.023*****	0.021	**-0.029*****

Table 30. Trend in S&P 500 ETF-Futures Arbitrage Profits
The table reports the trend in arbitrage profits from trading on price deviations between the S&P500 ETF (SPY) and the E-mini futures (ES). Arbitrage profits are computed from the midquote spread differential between SPY and ES, compared to the average spread in the previous minute. Profits are computed separately using SPY quotes from the Nasdaq and NYSE markets, and quotes for ES are from CME. In Panel A, Profit/Opp denotes the average profit per arbitrage opportunity in index points, $Profit/Day represents the average arbitrage profits per day in dollars, and # of Opps/Day is the average number of arbitrage opportunities per day. Panel B presents the results of regressing the number of arbitrage opportunities per day on VIX and a monthly or an annual trend. The sample period covers 2011-2014 and t-statistics are reported below in parenthesis.

Panel A: Profits over time

	NASDAQ			NYSE		
Year	Profit/Opp	$ Profit/Day	Number of Opps/Day	Profit/Opp	$Profit/Day	Number of Opps/Day
2011	0.07	9,305	113	0.07	7,251	112
2012	0.07	8,203	44	0.07	8,229	46
2013	0.07	1,803	37	0.07	2,116	42
2014	0.07	1,650	44	0.07	2,653	53

Panel B: Trend in opportunities

	NASDAQ		NYSE	
Coefficients	Number of Opportunities/Day		Number of Opportunities/Day	
Intercept	15,360	-8.67	10,147	-3.78
	(2.98)	(-0.78)	(1.99)	(-0.34)
VIX	4.39	4.63	4.16	4.33
	(9.50)	(10.50)	(9.06)	(9.89)
Year	-7.64		-5.06	
	(-2.99)		(-2.00)	
Month		-0.48		-0.32
		(-2.46)		(-1.62)
R-Square	0.17	0.17	0.14	0.14

Table 31. Average Size and Turnover Volatility of Stocks sorted on Mispricing and Turnover Volatility

The table presents the average market capitalization (in $ Millions) and standard deviation of monthly turnover (TURNVOL) of stocks in the mispricing and turnover volatility quintiles. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of monthly turnover as of the previous month. Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. Standard deviation is computed using previous 60 months of turnover data. Sample period is from January 1966 to December 2013.

	Lowest TURNVOL	2	3	4	Highest TURNVOL
Panel A : Market Cap (in $ Millions)					
Most Underpriced	7,705	5,614	3,260	1,909	1,495
2	3,304	3,376	2,403	1,813	1,680
3	1,529	2,336	1,824	1,534	1,358
4	1,254	1,755	1,444	1,174	1,100
Most Overpriced	1,002	1,371	1,002	908	942
Panel B : Standard Deviation of Monthly Turnover					
Most Underpriced	0.010	0.020	0.030	0.047	0.107
2	0.009	0.020	0.031	0.048	0.111
3	0.008	0.019	0.031	0.050	0.120
4	0.008	0.020	0.034	0.054	0.132
Most Overpriced	0.011	0.026	0.043	0.067	0.159

Table 32. Correlations

The table reports the correlation between the variables used in the paper. TURNVOL is the standard deviation of monthly turnover computed using the turnover from previous 60 months. DTURNVOL is the standard deviation of daily turnover computed using previous 3 months of daily data. AMIHUD is the monthly Amihud (2002) illiquidity measure. AMIHUDVOL is the volatility in AMIHUD Illiquidity measure computed using the monthly AMIHUD measure from previous 60 months. IVOL is the standard deviation of return residuals from Fama and French 3 factor model computed using daily returns in the previous month. TURN is the ratio of trading volume in the previous month and total shares outstanding. SIZE is the market capitalization of the stock as of the previous month. Reported numbers are cross sectional averages of individual stock correlations. Sample period is from January 1966 to December 2013.

	TURNVOL	DTURNVOL	AMIHUDVOL	IVOL	AMIHUD	TURN	SIZE
TURNVOL	1.00	0.35	-0.13	0.03	-0.14	0.33	0.19
DTURNVOL	0.35	1.00	-0.05	0.12	-0.19	0.65	0.19
AMIHUDVOL	-0.13	-0.05	1.00	0.14	0.34	-0.10	-0.28
IVOL	0.03	0.12	0.14	1.00	0.29	0.26	-0.19
AMIHUD	-0.14	-0.19	0.34	0.29	1.00	-0.27	-0.39
TURN	0.33	0.65	-0.10	0.26	-0.27	1.00	0.25
SIZE	0.19	0.19	-0.28	-0.19	-0.39	0.25	1.00

Table 33. Risk-Adjusted Returns of Portfolios sorted on Mispricing and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and TURNVOL. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of *monthly turnover* as of the previous month(TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. Sample period is from January 1966 to December 2013. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Lowest TURNVOL	2	3	4	Highest TURNVOL	Highest - Lowest TURNVOL
Most Underpriced	-0.05%	-0.02%	0.24%	0.46%	0.55%	0.60%
	(-0.64)	(-0.26)	(2.60)	(4.02)	(3.49)	(3.39)
2	-0.08%	-0.13%	-0.04%	0.21%	0.49%	0.57%
	(-0.90)	(-1.61)	(-0.56)	(1.96)	(3.16)	(3.23)
3	-0.20%	0.00%	-0.16%	-0.04%	0.33%	0.52%
	(-1.74)	(0.02)	(-1.79)	(-0.36)	(2.23)	(2.55)
4	-0.15%	-0.31%	-0.07%	-0.29%	0.06%	0.21%
	(-1.28)	(-2.85)	(-0.76)	(-2.43)	(0.39)	(1.03)
Most Overpriced	-0.25%	-0.19%	-0.51%	-0.79%	-0.85%	-0.60%
	(-2.03)	(-1.37)	(-3.93)	(-5.73)	(-5.00)	(-3.05)
Most Overpriced - Most Underpriced	-0.20%	-0.17%	-0.75%	-1.25%	-1.40%	-1.20%
	(-1.27)	(-0.92)	(-4.29)	(-6.59)	(-6.19)	(-4.92)

Table 34. Risk-Adjusted Returns of Portfolios sorted on Mispricing and DTURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and DTURNVOL. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of daily turnover as of the previous month(DTURNVOL). Daily Turnover is defined as the ratio of daily trading volume and total shares outstanding in a stock. DTURNVOL is computed from 3 months of prior daily turnover data. Sample period is from January 1966 to December 2013. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Lowest DTURNVOL	2	3	4	Highest DTURNVOL	Highest - Lowest DTURNVOL
Most Underpriced	-0.07%	0.02%	0.27%	0.33%	0.63%	0.69%
	(-0.83)	(0.27)	(2.86)	(3.21)	(4.23)	(3.90)
2	-0.01%	-0.06%	-0.02%	0.13%	0.22%	0.23%
	(-0.13)	(-0.74)	(-0.21)	(1.41)	(1.44)	(1.36)
3	-0.30%	-0.11%	-0.03%	0.06%	0.22%	0.52%
	(-2.64)	(-1.29)	(-0.31)	(0.60)	(1.66)	(2.84)
4	-0.20%	-0.19%	-0.19%	-0.04%	-0.20%	0.00%
	(-1.73)	(-1.97)	(-2.04)	(-0.42)	(-1.51)	(-0.02)
Most Overpriced	-0.40%	-0.39%	-0.53%	-0.40%	-0.77%	-0.37%
	(-3.30)	(-3.00)	(-4.28)	(-3.04)	(-4.76)	(-1.90)
Most Overpriced - Most Underpriced	-0.33%	-0.42%	-0.80%	-0.73%	-1.40%	-1.06%
	(-2.22)	(-2.37)	(-4.54)	(-4.17)	(-6.63)	(-4.44)

Table 35. Risk-Adjusted Returns of Portfolios sorted on Mispricing and AMIHUDVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing and AMIHUDVOL. At the beginning of each month, stocks are sorted into quintiles based on their mispricing scores as of the previous month. Within each mispricing quintile, the stocks are in turn sorted into quintiles on the standard deviation of monthly Amihud(2002) Illiquidity measure(AMIHUDVOL). AMIHUDVOL is computed from previous 60 months of AMIHUD measure. Sample period is from January 1966 to December 2013. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Lowest AMIHUDVOL	2	3	4	Highest AMIHUDVOL	Highest - Lowest AMIHUDVOL
Most Underpriced	0.09%	0.19%	0.34%	0.34%	0.60%	0.51%
	(1.74)	(2.53)	(4.33)	(3.40)	(5.50)	(4.32)
2	0.01%	0.11%	0.21%	0.27%	0.32%	0.31%
	(0.18)	(1.32)	(2.37)	(2.90)	(2.47)	(2.25)
3	-0.05%	0.26%	0.28%	0.24%	0.07%	0.12%
	(-0.92)	(2.14)	(2.78)	(2.38)	(0.59)	(0.90)
4	-0.21%	0.07%	0.06%	-0.15%	0.13%	0.33%
	(-2.95)	(0.66)	(0.65)	(-1.47)	(0.85)	(1.86)
Most Overpriced	-0.42%	-0.38%	-0.49%	-0.66%	-0.76%	-0.33%
	(-3.63)	(-3.06)	(-5.41)	(-5.98)	(-5.23)	(-1.88)
Most Overpriced - Most Underpriced	-0.51%	-0.58%	-0.82%	-1.00%	-1.36%	-0.86%
	(-3.38)	(-3.60)	(-6.56)	(-6.37)	(-8.11)	(-4.01)

Table 36. Risk-Adjusted Returns of Portfolios sorted on Mispricing , AMIHUD and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing, AMIHUD and TURNVOL. At the beginning of each month, stocks are sorted into three groups based on their mispricing scores as of the previous month. Within each mispricing groups, the stocks are in turn sorted into terciles on the monthly Amihud (2002) measure(AMIHUD) as of the previous month. Within each mispricing and AMIHUD groups, the stocks are in turn sorted into terciles on the standard deviation of *monthly turnover* as of the previous month (TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. In the table TURNVOL is reported as TVOL. Sample period is from January 1966 to December 2013. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Most Underpriced				2				Most Overpriced			
	Low TVOL	2	High TVOL	High -Low TVOL	Low TVOL	2	High TVOL	High - Low TVOL	Low TVOL	2	High TVOL	High -Low TVOL
Low AMIHUD	-0.12%	0.28%	0.53%	0.65%	-0.14%	0.00%	0.35%	0.13%	-0.07%	-0.48%	-0.41%	-0.34%
	(-2.31)	(3.93)	(4.48)	(4.82)	(-2.07)	(0.06)	(3.15)	(3.35)	(-0.76)	(-4.64)	(-3.06)	(-2.15)
2	-0.04%	0.17%	0.48%	0.53%	-0.12%	-0.01%	0.04%	0.16%	-0.28%	-0.54%	-0.67%	-0.39%
	(-0.64)	(2.62)	(5.51)	(4.95)	(-1.68)	(0.10)	(0.44)	(1.37)	(-2.97)	(-5.77)	(-5.41)	(-2.65)
High AMIHUD	0.15%	0.38%	0.28%	0.12%	-0.04%	-0.16%	-0.29%	-0.25%	-0.50%	-0.84%	-1.12%	-0.63%
	(1.75)	(4.67)	(2.79)	(1.01)	(-0.41)	(-1.72)	(-2.71)	(-1.95)	(-4.06)	(-7.59)	(-8.58)	(-4.33)
High - Low AMIHUD	0.27%	0.10%	-0.26%		0.10%	-0.16%	-0.64%		-0.42%	-0.37%	-0.71%	
	(2.75)	(0.94)	(-1.56)		(0.88)	(-1.28)	(-4.09)		(-3.39)	(-2.60)	(-4.10)	
All Stocks	-0.11%	0.28%	0.54%	0.65%	-0.14%	0.00%	0.31%	0.44%	-0.11%	-0.50%	-0.47%	-0.37%
	(-2.30)	(4.30)	(4.97)	(5.22)	(-2.18)	(0.06)	(3.09)	(3.32)	(-1.17)	(-5.32)	(-3.88)	(-2.58)

Table 37. Risk-Adjusted Returns of Portfolios sorted on Mispricing , TURN and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing, TURN and TURNVOL. At the beginning of each month, stocks are sorted into three groups based on their mispricing scores as of the previous month. Within each mispricing groups, the stocks are in turn sorted into terciles on the monthly turnover(TURN) as of the previous month. Within each mispricing and TURN groups, the stocks are in turn sorted into terciles on the standard deviation of *monthly turnover* as of the previous month (TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. In the table TURNVOL is reported as TVOL. Sample period is from January 1966 to December 2013. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Most Underpriced								Most Overpriced			
	Low TVOL	2	High TVOL	High - Low TVOL	Low TVOL	2	High TVOL	High - Low TVOL	Low TVOL	2	High TVOL	High -Low TVOL
Low TURN	-0.17%	-0.26%	0.01%	0.18%	-0.13%	-0.14%	-0.24%	-0.11%	-0.21%	-0.52%	-0.97%	-0.76%
	(-1.72)	(-2.64)	(0.11)	(1.35)	(-1.10)	(-1.37)	(-2.10)	(-0.68)	(-1.68)	(-4.40)	(-7.57)	(-4.73)
2	-0.07%	0.21%	0.23%	0.30%	-0.13%	-0.25%	-0.13%	0.00%	-0.10%	-0.33%	-0.63%	-0.53%
	(-0.94)	(2.28)	(2.14)	(2.38)	(-1.56)	(-2.71)	(-1.11)	(-0.02)	(-0.85)	(-2.62)	(-4.15)	(-3.27)
High TURN	0.16%	0.29%	0.66%	0.50%	-0.07%	0.20%	0.28%	0.35%	-0.35%	-0.55%	-0.60%	-0.25%
	(1.81)	(2.38)	(3.94)	(3.12)	(-0.80)	(1.64)	(1.67)	(1.87)	(-2.94)	(-4.14)	(-3.40)	(-1.49)
High - Low TURN	0.33%	0.56%	0.65%		0.06%	0.34%	0.51%		-0.14%	-0.03%	0.37%	
	(2.28)	(3.40)	(3.24)		(0.37)	(1.94)	(2.42)		(-0.83)	(-0.18)	(1.79)	
All Stocks	-0.01%	0.16%	0.53%	0.54%	-0.11%	-0.01%	0.24%	0.35%	-0.20%	-0.42%	-0.57%	-0.37%
	(-0.33)	(2.36)	(5.16)	(4.88)	(-1.94)	(-0.14)	(2.41)	(2.74)	(-2.23)	(-4.61)	(-4.39)	(-2.74)

Table 38. Risk-Adjusted Returns of Portfolios sorted on Mispricing , IVOL and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on mispricing, IVOL and TURNVOL. At the beginning of each month, stocks are sorted into three groups based on their mispricing scores as of the previous month. Within each mispricing groups, the stocks are in turn sorted into terciles on the idiosyncratic volatility (IVOL) as of the previous month. Within each mispricing and IVOL groups, the stocks are in turn sorted into terciles on the standard deviation of *monthly turnover* as of the previous month (TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. In the table TURNVOL is reported as TVOL.Sample period is from January 1966 to December 2013. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Most Underpriced								Most Overpriced			
	Low TVOL	2	High TVOL	High - Low TVOL	Low TVOL	2	High TVOL	High - Low TVOL	Low TVOL	2	High TVOL	High -Low TVOL
Low IVOL	-0.10%	-0.06%	0.34%	0.44%	-0.02%	-0.13%	-0.06%	-0.04%	-0.15%	-0.22%	-0.63%	-0.48%
	(-1.38)	(-0.74)	(3.54)	(3.53)	(-0.24)	(-1.51)	(-0.56)	(-0.24)	(-1.31)	(-2.00)	(-5.60)	(-3.15)
2	-0.08%	0.24%	0.40%	0.48%	-0.41%	-0.04%	0.35%	0.76%	-0.14%	-0.32%	-0.53%	-0.39%
	(-0.89)	(2.37)	(3.11)	(3.05)	(-3.16)	(-0.45)	(2.90)	(3.98)	(-0.93)	(-2.40)	(-3.60)	(-2.18)
High IVOL	0.12%	0.35%	0.48%	0.36%	-0.05%	-0.05%	-0.07%	-0.02%	-0.55%	-0.90%	-1.13%	-0.58%
	(1.03)	(2.62)	(2.63)	(1.82)	(-0.32)	(-0.34)	(-0.40)	(-0.09)	(-3.29)	(-5.84)	(-5.49)	(-2.40)
High - Low IVOL	0.22%	0.41%	0.14%		-0.02%	0.08%	-0.01%		-0.40%	-0.69%	-0.50%	
	(1.48)	(2.60)	(0.71)		(-0.13)	(0.46)	(-0.04)		(-2.06)	(-3.72)	(-2.40)	
All Stocks	- 0.07%	0.09%	0.43%	0.49%	-0.13%	-0.06%	0.16%	0.29%	-0.16%	-0.29%	-0.57%	-0.41%
	(-1.25)	(1.42)	(4.43)	(4.24)	(-1.72)	(-0.93)	(1.95)	(2.25)	(-1.57)	(-3.32)	(-5.28)	(-2.92)

Table 39. Risk Adjusted Returns of portfolios sorted on Mispricing and TURNVOL in High-Sentiment and Low-Sentiment
The table presents the Fama French three factor alpha of portfolios ranked on mispricing and TURNVOL for High Sentiment and Low Sentiment months. Each month, stocks are sorted into quintiles based on their mispricing scores as of previous month. Within each mispricing quintile, they are sorted in turn into quintiles on the standard deviation of monthly turnover (TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock and is computed using 60 months of previous turnover data. Sample period is from January 1966 to December 2013. Reported numbers are a_H and a_L in the regression below. $d_{H,t}$ is a dummy variable that takes value of 1 if the Baker and Wurgler(2006) investment sentiment measure was above median previous month and $d_{L,t}$ is the dummy variable that takes value of 1 if the sentiment in the previous month was below median . Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

$$R_{i,t} = a_H d_{H,t} + a_L\, d_{L,t} + b\, MKT_t + c\, SMB_t + d\, HML_t + e\, CMA_t + f\, RMW_t + \epsilon_{i,t}$$

	High Sentiment months			Low Sentiment months		
	Lowest TURNVOL	Highest TURNVOL	Highest - Lowest	Lowest TURNVOL	Highest TURNVOL	Highest - Lowest
Most Underpriced	0.13%	0.24%	0.10%	-0.12%	0.43%	0.55%
	(0.84)	(0.89)	(0.32)	(-1.23)	(2.09)	(2.39)
2	-0.09%	-0.08%	0.02%	-0.04%	0.54%	0.57%
	(-0.59)	(-0.29)	(0.06)	(-0.33)	(2.44)	(2.32)
3	-0.28%	-0.18%	0.10%	-0.06%	0.41%	0.47%
	(-1.45)	(-0.72)	(0.29)	(-0.38)	(2.09)	(1.69)
4	0.19%	-0.07%	-0.26%	-0.23%	0.09%	0.32%
	(0.85)	(-0.24)	(-0.66)	(-1.44)	(0.44)	(1.15)
Most Overpriced	0.28%	-0.55%	-0.82%	-0.37%	-0.58%	-0.21%
	(1.26)	(-1.79)	(-2.21)	(-2.34)	(-2.61)	(-0.77)
Most Overpriced - Most Underpriced	0.14%	-0.78%	-0.93%	-0.26%	-1.01%	-0.76%
	(0.50)	(-1.91)	(-2.00)	(-1.30)	(-3.59)	(-2.39)

Table 40. Risk-Adjusted Returns of Portfolios sorted on Institutional Ownership and TURNVOL

The table presents the Fama and French five factor alpha of portfolios ranked on Institutional Ownership (IO) and TURNVOL. At the beginning of each month, stocks are sorted into quintiles based on institutional ownership as of the previous month. Within each short interest quintile, the stocks are in turn sorted into quintiles on the standard deviation of *monthly turnover* as of the previous month(TURNVOL). Monthly Turnover is defined as the ratio of monthly trading volume and total shares outstanding in a stock. TURNVOL is computed from 60 months of prior monthly turnover data. Sample period is from January 1966 to December 2013. Returns are value weighted. All t-statistics in parenthesis are computed using the heteroscedasticity-consistent standard errors of White (1980).

	Lowest TURNVOL	2	3	4	Highest TURNVOL	Highest - Lowest TURNVOL
Lowest IO	-0.06%	0.45%	-0.48%	-0.61%	-0.36%	-0.30%
	(-0.28)	(1.45)	(-1.97)	(-2.77)	(-1.10)	(-0.78)
2	0.08%	0.02%	-0.12%	0.04%	0.35%	0.27%
	(0.44)	(0.13)	(-0.61)	(0.19)	(1.18)	(0.73)
3	0.14%	0.30%	0.18%	0.22%	0.39%	0.25%
	(0.82)	(1.39)	(0.92)	(1.18)	(1.48)	(0.82)
4	-0.15%	-0.04%	0.46%	0.15%	0.37%	0.52%
	(-1.76)	(-0.32)	(3.30)	(0.95)	(1.85)	(2.24)
Highest IO	-0.30%	-0.31%	-0.10%	0.21%	0.12%	0.42%
	(-2.83)	(-2.88)	(-0.93)	(1.50)	(0.78)	(2.19)
Highest – Lowest IO	-0.24%	-0.76%	0.39%	0.82%	0.48%	0.72%
	(-1.12)	(-2.34)	(1.39)	(2.98)	(1.35)	(1.79)

Table 41. Fama-Macbeth Regression of Individual Risk Adjusted Returns on Characteristics

The table reports the Fama Macbeth Regression coefficients of individual risk adjusted stock return on Characteristics. Individual stock excess return is risk adjusted using Fama- French five factors. Factor loadings are allowed to vary over time and are computed from previous 60 months of returns. Natural logarithm of all variables is used with the exception of mispricing, RET23, RET46, RET712. SIZE refers to market capitalization, BM refers to the book to market, 1/PRICE is the reciprocal of price, and TURNVOL is the standard deviation of turnover. Mispricing is the Stambaugh, Yu, and Yuan(2015) mispricing score. RET23 refers to the return in the second and third month previous to current month. RET46 is the buy and hold return of the stocks from six month to four months before the current month. RET712 refers to the buy and hold return of the stock from twelve month to seven month before the current month. Sample period is from Jan 1966 to Dec 2013. Fama-Macbeth t-statistics in parenthesis.

Variable	Coefficient	Coefficient
Constant	1.420	3.724
	(3.66)	(9.26)
SIZE	-0.060	-0.053
	(-2.83)	(-2.62)
BM	0.162	0.091
	(4.46)	(2.58)
1/PRICE	0.086	0.199
	(1.25)	(3.36)
RET23	0.397	0.210
	(1.62)	(0.82)
RET46	0.607	0.268
	(3.08)	(1.36)
RET712	0.287	0.287
	(1.94)	(1.94)
TURNVOL	-0.151	0.107
	(-4.48)	(1.55)
Mispricing		-0.038
		(-7.03)
Mispricing * TURNVOL		-0.004
		(-3.15)