Do High Frequency Traders Need to be Regulated?

Evidence from Algorithmic Trading on Macroeconomic News

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Abstract

Stock index exchange traded funds and futures prices 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 relative 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 amongst high frequency 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 high frequency trading (HFT) 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 high frequency traders (HFTs) reduces trust in financial markets.

Theory points towards mixed welfare implications for HFT. Jovanovic and Menkveld (2015) argue that HFTs face lower adverse selection costs through their ability to quickly change quotes, and as a result HFTs 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 HFTs, as each firm expends greater resources to further reduce trade latency.

Although a welfare analysis from the perspective of a social planner is impossible, empirical studies have explored different welfare aspects of HFT. Brogaard, Hendershott and Riordan (2014) find evidence that HFTs facilitate price discovery by trading in the direction of permanent price changes and 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 HFT activity leads prices to more closely resemble a random walk, and Chaboud, Chiquoine, Hjalmarsson and Vega (2014) find that HFT improves price efficiency through lower return autocorrelations and fewer arbitrage opportunities.[1]

HFTs' improvements to price efficiency at the sub-second level carry considerable direct economic costs,[2] and they may also result in reduced trust in markets.[3] HFTs 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 HFTs' ability to trade ahead of slower investors allows them to earn profits in excess of the risks involved. For example, Hirschey (2013) finds HFTs' aggressive trades lead those of other investors, and Baron, Brogaard, and Kirilenko, (2012) find that aggressive (liquidity-taking) HFTs are highly profitable on a risk-adjusted basis. 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.

One channel by which HFTs are presumed to benefit from their technological advantage is through rapidly responding to public information releases. We contribute to the HFT debate by exploring the sub-second market response and the time series of trading profitability following the release of eighteen different macroeconomic (macro) news announcements. Macro news releases provide a clean setting in which 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. We study quote and transaction data around macro announcements for the highly liquid S&P500 ETF (SPY) from 2008-2014 and the E-mini S&P500 futures contract (ES) from July 2011-2014.

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[1] Other research suggests that the activities of HFTs improve market quality through increased liquidity and lower short-term volatility (Hendershott et al., 2011; Hasbrouck and Saar, 2013; Hendershott and Riordan, 2013).
[2] In one example of the HFT 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.
[3] Also, it is not clear whether by improving price efficiency at the millisecond level, HFTs have any impact on the allocational efficiency.

We find that the 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). The result is a remarkably efficient response to news as modeled by Holden and Subrahmanyam, (1992) and Martinez and Rosu, (2013). Prices react to announcement surprises within a tenth of a second and respond fully within five seconds.

Although HFTs respond swiftly and convincingly to macroeconomic news releases, we find 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 $80 million of notional value traded in the direction of the surprise, and 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, and bid-ask spreads are typically less than one basis point, which would seem to imply greater profit opportunities than we observe in the data. However, the posted quotes around news releases are not the stale, exploitable limit orders of slow investors but rather quickly changing quotes of HFTs. Supporting this view, in the first quarter of a second after the news releases we observe 500 changes to the best bid or offer quote in the ETF (across venues). These findings highlight the HFT'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, (2015) and Biais, Foucault and Moinas (2015).

In one controversial practice, Reuters began to sell access to the University of Michigan's Consumer Sentiment Index to HFTs two seconds before wide release, and media articles suggest market participants were not aware of the early release (Mullins et al., 2013). This provides us with a natural experiment to test whether HFTs 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 HFTs with incremental profits. While profits are lower after Reuters agreed to end the practice in July of 2013, this appears to be part of a general downward trend in trading profits across all macroeconomic announcements. A difference-in-difference approach reveals no statistically or economically significant changes in profits between Consumer Sentiment and other macroeconomic news announcements. The speed with which Consumer Sentiment information is incorporated into prices is consistent with a quick reaction among liquidity supplying HFTs. The results suggest that early access to consumer sentiment information did not lead to significant exploitation of slow traders.

Our findings are consistent with increasing competition over time among HFTs. 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. 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. The findings suggest an increasing ability for HFT quotes to respond directly to announcement surprises rather than responding indirectly through trading.

Our analysis has implications for calls to regulate HFT. Baron, Brogaard and Kirilenko (2012) find that new HFT entrants have a propensity to underperform and exit, which points towards an unlevel playing field even among HFTs and suggests that increased regulatory oversight may benefit financial markets. Brogaard and Garriott (2015), on the other hand, find evidence that new HFT entrants lead to crowding out, with reduced spreads and less informative incumbent order flow. Our evidence supports the view that high frequency 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 this setting, regulation should focus on increasing competition amongst HFTs rather than limiting their activity.

The remainder of the paper is organized as follows. Section 2 discusses the macroeconomic news releases we consider and the stock index ETF and futures examined in the analysis. Section 3 presents the empirical evidence regarding the effects of macro new announcements on the stock market at a millisecond level. Section 4 describes the profits obtained by algorithmic traders around macroeconomic announcements. Section 5 presents the effect of competition on profits and price discovery. Section 6 concludes.

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 allow 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 Eastern Standard Time), 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.[4] 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

[4] Each futures contract represents a contract size of 50 times the index value. For an S&P 500 index value of $2000, each contract represents a notional value of $100,000.

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 1 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 Claims (Weekly release). *Release Time* is the most common release time (changes in release time are rare in our 2008-2014 sample period). 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 algorithmic 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 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 final column of Table 1. It represents the change in price associated with a one standard deviation increase in 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 that firm-specific information released during market hours in 2000 is incorporated into prices within one minute. Speed of communication has since improved dramatically, leading to creation of a new class of algorithmic traders which strive to achieve low latency by investing in technology and co-locating their servers in same data centers as stock exchanges. Hasbrouck and Saar, (2013) note the fastest traders have 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 greater availability of machine readable news and the increased presence of HFTs in recent years has led to faster information assimilation.[5] In this section, we explore the role of algorithmic traders on the process by which macroeconomic news is incorporated into prices.

3.1 Speed of Information Incorporation

Table 2 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)[6]. Cumulative mid-quote returns for each period are computed relative to 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 2, 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 algorithmic trading. 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 participant at the release of

[5] A specialized industry has sprung up to deliver machine readable financial information to HFTs 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.

[6] 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).

macroeconomic news is a computer which interprets the announcement surprise and revises quotes or routes orders within a tenth of a second. The price reaction over the first two seconds of 5.4 (4.3) basis points on average 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 since the end of their sample in 2009.

The announcements of CPI, Factory Orders (in the case of the E-mini contract), and Leading Index exhibit significant surprise coefficients in Table 1, yet they do not exhibit a significant price reaction in the first 10 seconds after announcement, which suggests these announcements are either not available in machine readable format or not deemed important by algorithmic traders.[7] 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 the most of the sample period, early access subscribers were able to, for a fee, 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.[8] On the other hand, regardless of whether information is released exclusively to high

[7] 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.

[8] We more carefully analyze the incremental profitability of trading on early access to Consumer Sentiment information in section 5.4.

frequency traders or more widely, algorithmic traders are the primary agents for incorporating new (machine readable) information into prices.

Figure 1 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 2, 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. We see 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 2. 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

In this section, we analyze 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. Table 3 reports the results. We report volume, number of trades, and number of quote changes per second to facilitate comparisons across intervals.

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 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 3 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 relation between announcement surprise and order imbalance is similar when using the dollar value of purchases and sales (reported in Appendix Table A.1). The evidence suggests markets quickly incorporate new macroeconomic information, and part of the information is revealed through trading in the direction of the surprise.

4. Profitability of Algorithmic Trading on Macroeconomic News

The evidence in the previous section suggests that HFTs enhance market efficiency by swiftly and accurately responding to new information. This view is generally consistent with recent research on the effects of high frequency traders 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 HFTs to market efficiency come at the expense of reduced trust in financial markets. Conventional wisdom holds that algorithmic traders' speed advantage allows them to exploit slower market participants and earn profits that are disproportionate to the risks involved.[9] For example, Hirschey (2013) finds that HFT's aggressive purchases and sales lead those of other investors, and Baron et al., (2012) 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 algorithmic traders 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 algorithmic traders. We choose a two-second window based on the idea that human traders are

[9] 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

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.[10]

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 strategies: two to five seconds, five seconds to one minute, and one to five minutes after the event. We focus on short-term intervals as we are interested in measuring profits to fast trading, and we stop at five minutes after announcements to help avoid confounding information from other news. 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 4 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 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 HFTs during most of the sample period. Profits are $83,000 for ISM Manufacturing, however, suggesting quick reaction to this information was more profitable.

[10] 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).

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 midquotes we see in Panel B of Table 2 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.[11]

Figure 3 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.[12] 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 and an additional $1,500 for access to

[11] In appendix Table A.3 we report the profits for each *event per month* to make the profits across events comparable. This method of computing profits does not affect the relative importance of events considered here.

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

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 HFTs 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 4), which suggests the examples mentioned in media stories are outliers.[13]

Another potential concern is that we only consider two instruments, whereas algorithmic traders could conceivably submit orders in hundreds if not thousands of securities. We chose our instruments based on their high liquidity, where small price changes may potentially be profitable due to low quoted spreads and high depth.[14] As a robustness check, we also examine profits in three additional ETFs: a Nasdaq index (QQQ), a Russell 2000 index (IWM), and a Treasury Bond ETF (TLT). The dollar profits are considerably lower in these ETFs than those we find for SPY.

[13] 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.
[14] For example, according to State Street Global Advisors (the fund that manages SPY), average daily volume in SPY in 2014 was higher than the combined daily volume of the top 18 holdings in the S&P500.

While macro news may occasionally be significant enough to permit profits in less liquid securities, our evidence suggests these events are somewhat rare.

5. Effect of Competition on Profits and Price Discovery

Our findings suggest that stock index prices react near instantaneously to macroeconomic announcement surprises, yet profits to HFTs 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 HFTs a potential informational advantage following macroeconomic news releases, an increasing fraction of liquidity is also being provided by high speed traders who can post quotes confidently knowing they can update them quickly in light of new information. For example, Table 3 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

We conjecture that liquidity suppliers become increasingly adept at responding to information over time, either through subscribing to the machine readable news themselves or improving their ability to react to liquidity demanders.[15] Table 5 presents profits by year from trading in the first two seconds following macroeconomic surprises (as in Table 4). 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 fast algorithmic traders (e.g. Beschwitz, Keim and Massa, 2015). However,

[15] Anecdotal evidence suggests liquidity providers increasingly subscribe to real-time news "to keep from getting 'flattened '" by other traders. See, for example, Mullins, et al (2013).

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.

As a robustness check we also repeat the analysis by excluding certain events which do not move the prices by more than 3bps in the sample period (Factory Orders and Leading index for SPY and CPI, CPI ex Food and Energy, Consumption, Capacity Utilization, Industrial Production, Factory orders and leading index for Futures). Table A.2 in the Appendix presents the results. The pattern is similar with profits peaking in 2011 and declining thereafter. The pattern is similar in Appendix Table A.2, which repeats the analysis after filtering out events that are contemporaneous with other announcements (which could potentially lead to conflicting trading signals).

5.2 Effects of SEC Naked Access Ban

A potential alternative explanation for the reduction over time in HFT 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 HFTs that were not broker dealers, and Chakrabarty, Jain, Shkilko and Sokolov (2014) explore the effect of the ban of market quality. They find quoting activity falls by more than 33% after the implementation of the ban.

We test whether the HFTs who trade around macroeconomic news are affected by the ban by examining market activity in the six months around the ban (September 1, 2011 to February 29, 2012) after splitting it into pre- and post-ban periods. Table 6 presents the results of market activity in the two periods: trading volume per second, number of trades per second, and number of quote changes per second.

The evidence in Table 6 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 HFTs are likely to be most active. While the ban may have limited the activity of a subset of HFTs, 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 7 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 trade 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 Panel A, 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 25th and 75th 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 Panel B, 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 also include announcement fixed effects to allow for differences in average profitability across announcements, and we cluster the standard errors by month to account for possible cross sectional correlation in profits.

The evidence in Table 7 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 7 shows that high post-announcement quote-to-trade ratios lead uniformly to lower profits, which is consistent with more efficient response by liquidity providers who quickly move quotes towards the equilibrium price. The relation is significant for both the

[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.

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 (shown in Table 5) 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 evidence is consistent with active liquidity providers responding quickly to new information, which reduces profit opportunities for liquidity demanding algorithmic traders. Brogaard, Hagstomer, Norden and Riordan (2015) show that liquidity supplying HFTs take advantage of an optional colocation upgrade at the Nasdaq OMX Stockholm exchange to reduce their exposure to adverse selection. They argue that increasing the speed of market-making participants increases market liquidity.

Figure 4 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 (futures) 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 4 shows that the QT ratio has generally increased over time while quoted depths and trade sizes have declined.

Figure 5 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 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 0 and above by 1.

Higher values of the response speed measures imply that the reaction to the macroeconomic announcement is concentrated in the first milliseconds of release. Both under and overreaction in the first 100 milliseconds result in lower values of the measures, as reversals after the first 100 milliseconds result in negative values for *S1* and larger denominator for *S2*. Figure 5 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 HFT and faster response from liquidity-supplying HFT.

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. Although Reuters advertised its early access arrangement to high frequency traders, 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.[17]

In the previous subsection we found evidence that the decline in the profits associated with liquidity-demanding HFTs may be related to the quick updating of quotes by liquidity-supplying HFTs. The early access to the Consumer Sentiment news release provides us with a natural experiment to test whether liquidity-demanding HFTs 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 over time.

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 in the other announcements. After ending the early access practice, volume per second drops to just $44 million in the first quarter second, which suggests a huge effect of the change. However, average volume in all other announcements also falls considerably to $37 million after July 2013, which highlights the importance of using a difference-in-difference approach. Table 8 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

[17] See Hu, Pan, and Wang (2014) for more details.

incremental change in trading profit after Reuters ended early access is statistically insignificant. The evidence suggests early access had a modest impact on trading or profits.

Taken together, Reuter's practice of tiered release of information appears to have had little incremental impact on algorithmic trading 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 may help improve faith in financial markets.

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 trades executed within the first two seconds following macroeconomic news are initiated by liquidity demanding HFTs, and we examine whether their ability to trade in the direction of permanent price changes declines over time.

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 (1) and state equation (2) are described as follows:

$$p_t = m_t + s_t \tag{1}$$

$$m_t = m_{t-1} + w_t, \tag{2}$$

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 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. 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:

$$w_t = c + \alpha\, OIB_t + v_t \tag{3}$$

$$s_t = k + \mu\, s_{t-1} + \beta\, OIB_t + u_t. \tag{4}$$

We estimate the Unobserved Component Model in (1) and (2) and the regressions (3) and (4) separately for each announcement[18] 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 9. 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

[18] 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.

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 and 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 orders of magnitude lower. For the 2008-2014 period, the impact of order flow on the permanent component is statistically significant 0.224 basis points per unit of OIB. For the temporary component the impact is 0.004 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 HFTs 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 and 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.[19]

[19]Ravenpack, a provider of machine readable news, began its service in April of 2009 and has been continually upgrading its technology with the most recent upgrade on September 10, 2012.

The decrease in the informativeness of HFT 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 are very adept at quickly reacting to information in the order flow within the first two seconds after the announcement. This is consistent with Lyle, Naughton and Weller (2015), who note the technological improvements have helped to enhance the monitoring ability of market makers who efficiently update quotes and avoid being picked off on stale quotes.

6. Conclusion

Is HFT simply faster trading? The speed of trading has increased steadily for decades, and it is unclear whether HFT 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 HFTs and others market participants may have fundamentally changed markets in favor of those with resources to expend on latency decreasing technology. We contribute to the HFT 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 HFTs 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 HFTs. 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 HFTs. 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 HFT quotes to respond directly to announcement surprises rather than indirectly through trading.

The results suggest that HFT is maturing and becoming more competitive over time, with profits trending lower, possibly towards the marginal cost of obtaining information. One caveat to our analysis is that our approach focuses exclusively on macroeconomic announcements. Macro news releases provide a relatively clean setting for measuring the advantages of trading speed, as announcement times are known in advance and machine readable news is readily available. Baron, Brogaard and Kirilenko (2012) points towards increased competition amongst HFTs in general, which suggests that alternative sources of profit, such as predicting order flow, may also fall in response to competition from other fast market participants. In this setting, regulation should focus on preventing barriers to entry in order to increase competition rather than specifically limiting HFT trading.

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Figure 1: 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).

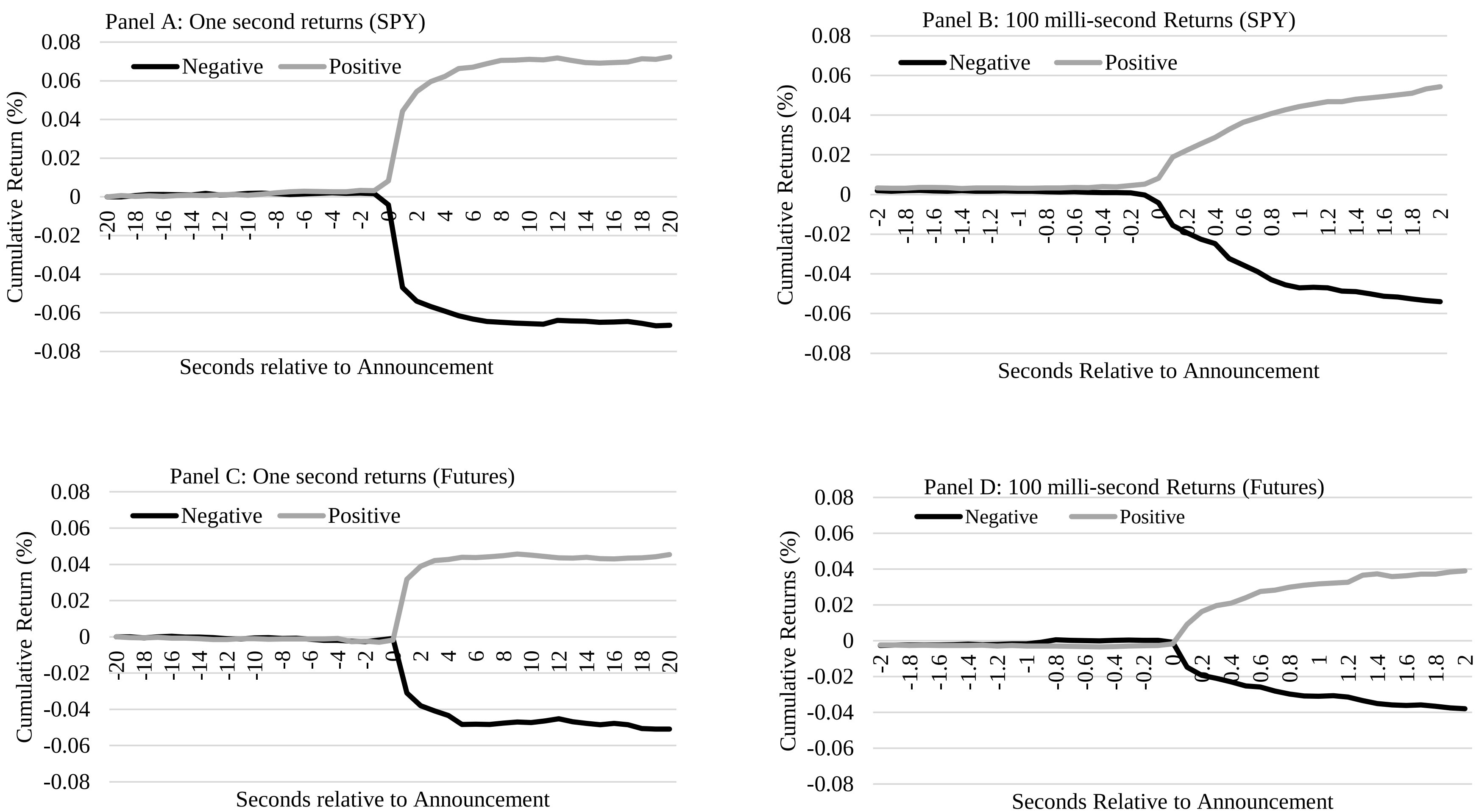
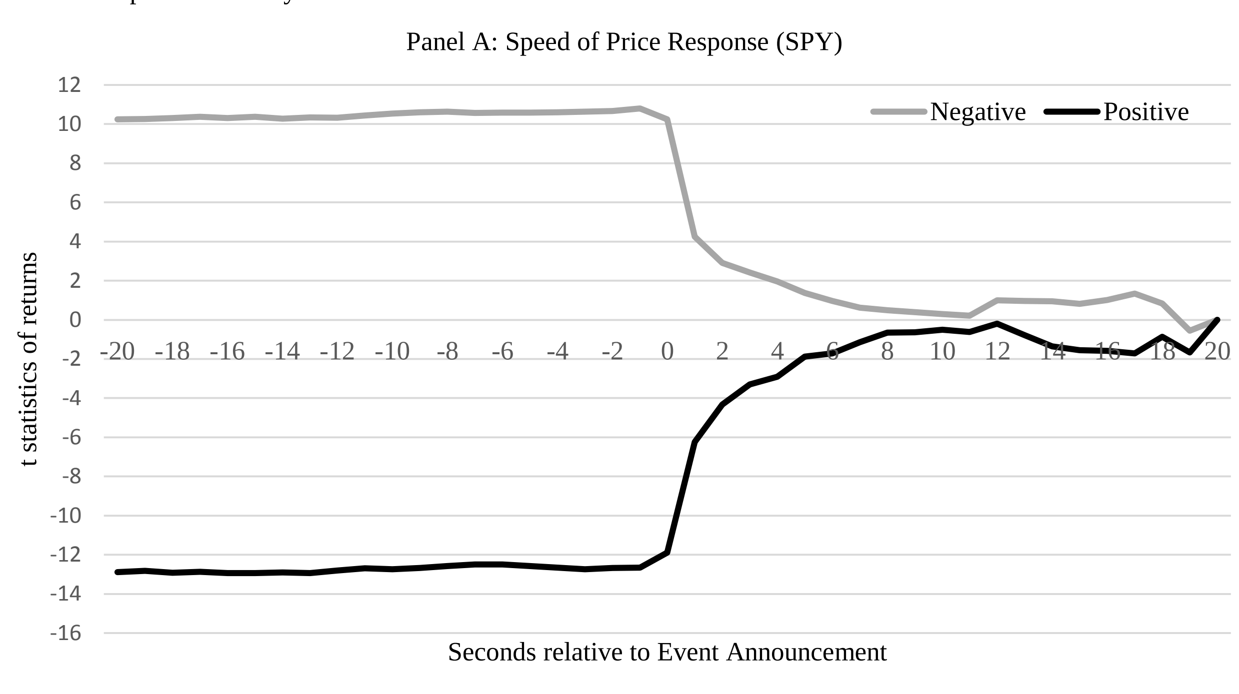


Figure 2: Speed of Stock Market Price Response to Macroeconomic News

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.



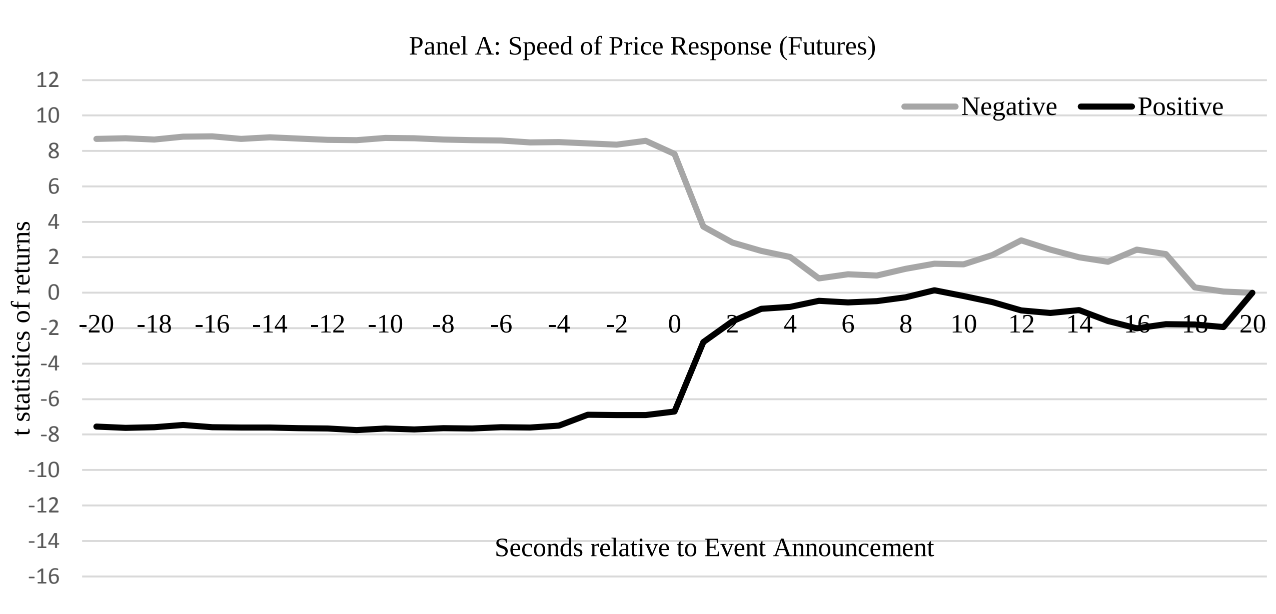
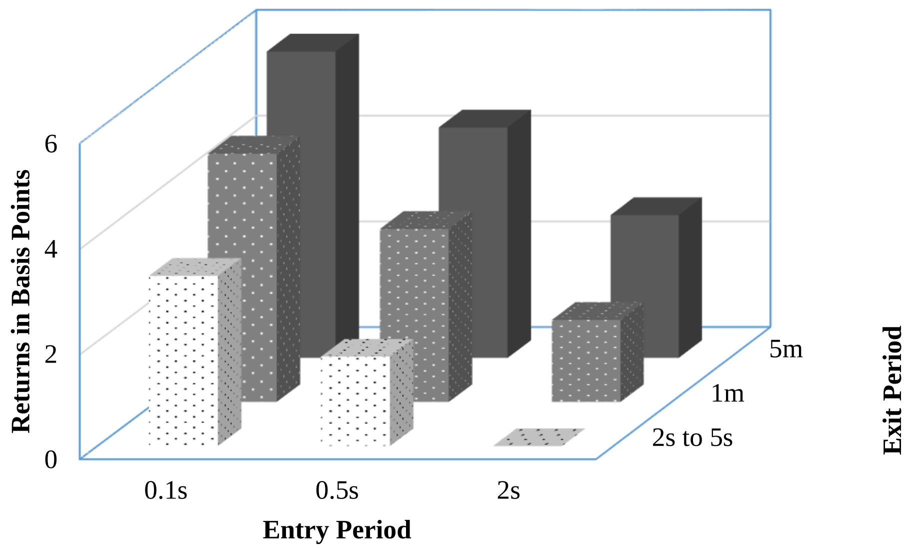


Figure 3: Profitability of Algorithmic Trading on Macroeconomic News Releases

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

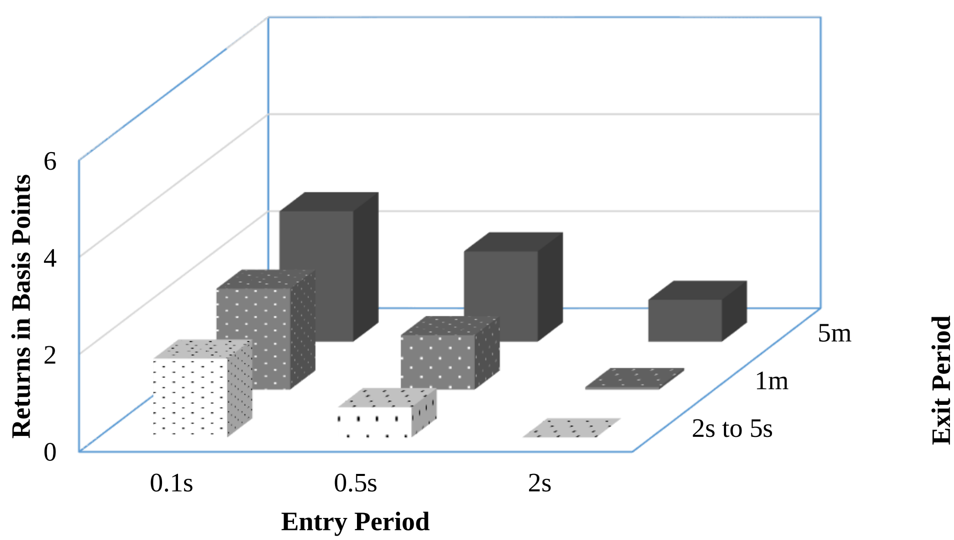


Figure 4: Trend in Quotes to Trades ratio, Quote Depth and Trade size

The figure plots the trend in average quotes to trades ratio, quoted depth and trade size around each macroeconomic announcements. *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 ends 2 seconds later. The numbers are averages across events for the year.

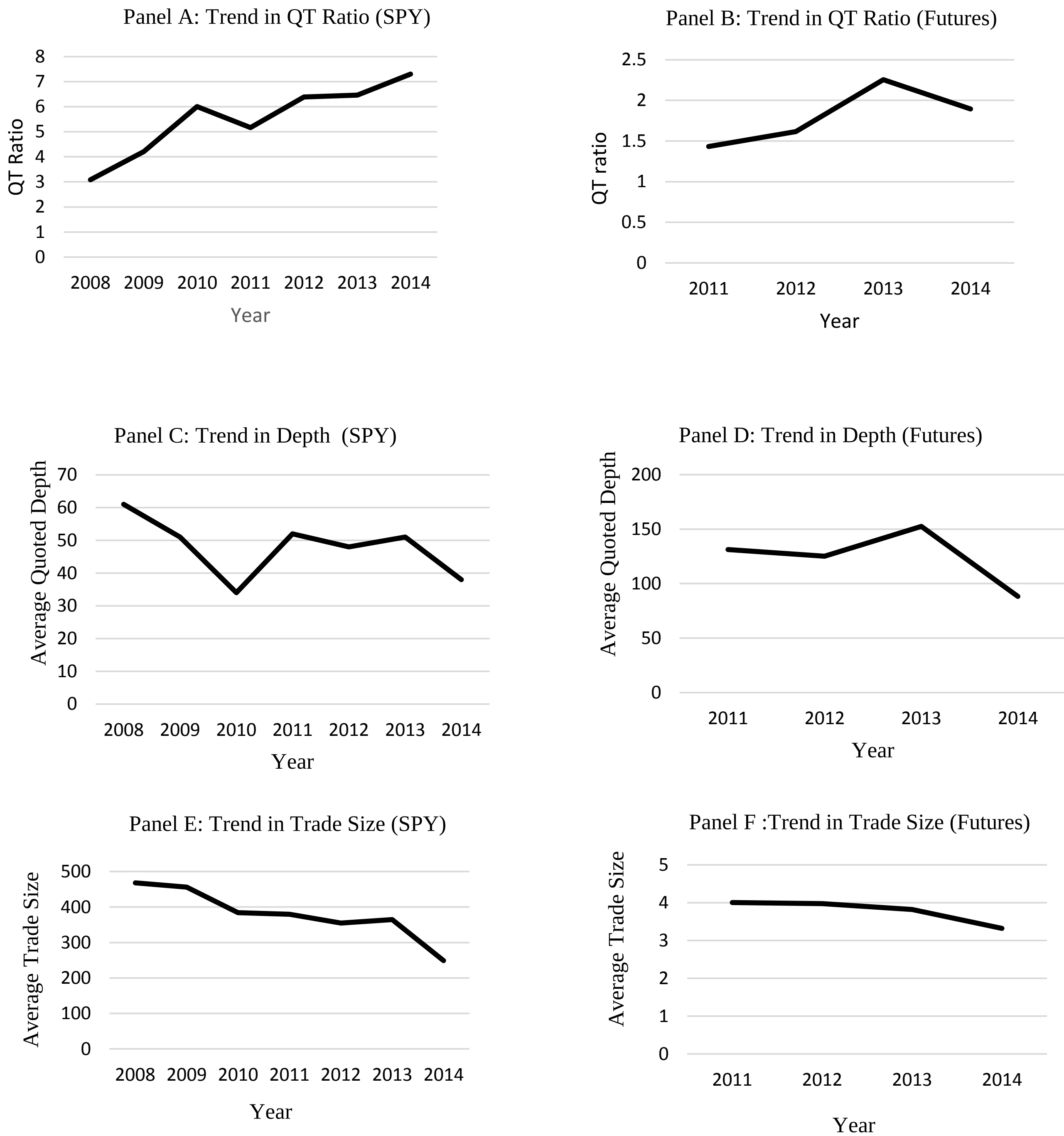
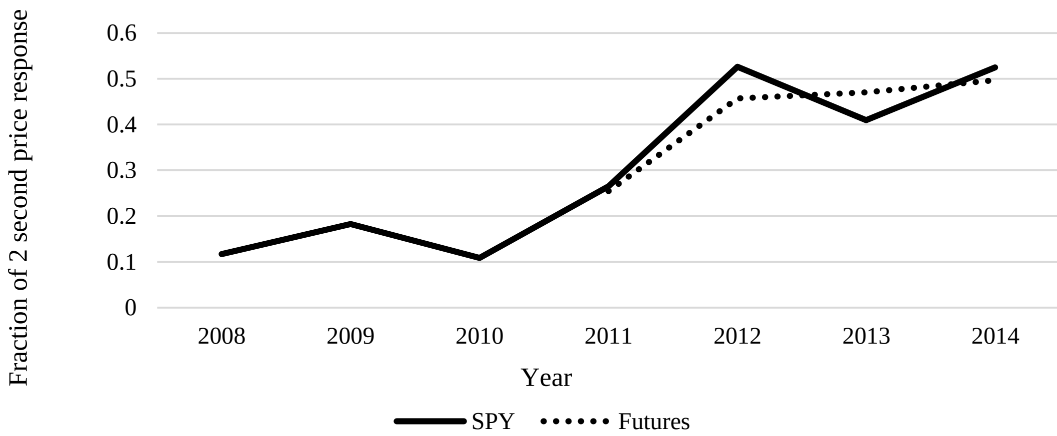


Figure 5: Trend in the Speed of Market Reaction
The figure plots the trend in speed of market reaction over time. In Panel A, the speed of market reaction (*S1*) is measured as the fraction of the 2-second price response that occurs in first 100ms after release, $S1 = r(t, t + 0.1)/r(t, t + 2)$, where $r(t, t + 0.1)$ 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 measure 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.

Panel A: Speed of market reaction (*S1*)



Panel B: Speed of market reaction (*S2*)

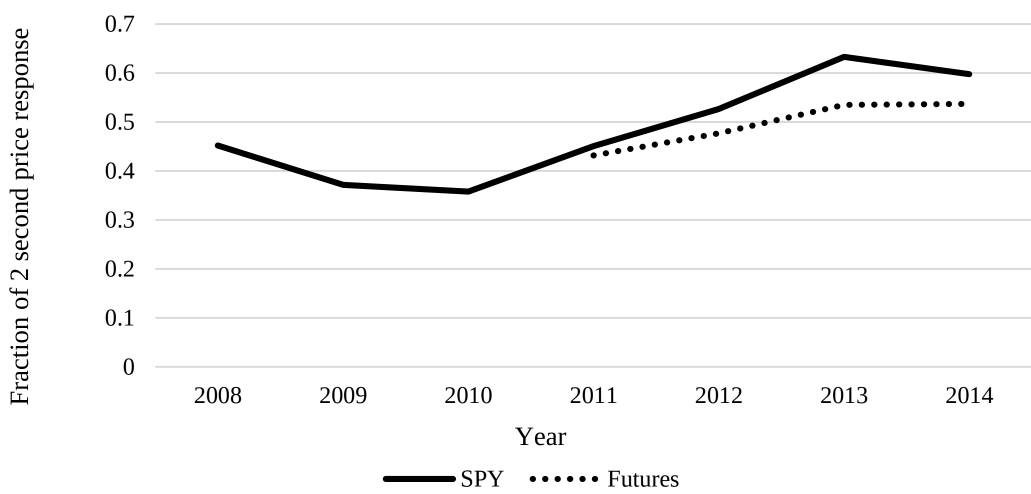


Table1: Macroeconomic Announcements Descriptive Statistics

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). For announcements after (before) 9.30am, we regress the change in SPY midquote (change in S&P 500 E-mini Futures midquote) from 5 minutes before to 5 minutes after the announcement on the standardized announcement surprise. 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 2: 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 and Energy	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 3: 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, number of quote changes per second, and average order imbalance during each measured interval. Order imbalance (OI) is computed as the (no of buys – no of sells)/(no of buys + no of sells), where buys(sells) represents buyer(seller) initiated trades. For negative surprises the negative of OI is used to compute average across events. The interval -5m to -5 captures activity from 5 minutes to 5 seconds before the announcement. Other rows reports the activity in the period beginning the time in the previous row and ending at the time reported in that row. 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. 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 4: 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 period covers 2008–2014 and the E-mini Futures sample is from July 2011- December 2014. t-statistics in parenthesis

	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 5: 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 6: Effect of SEC Naked Access Ban on Market Activity around Macroeconomic News Releases
This table compares the 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 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 7: Trading Profits around Macroeconomic News and Quote Intensity

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 5 minutes to 5 seconds before the announcement (denoted by Pre-Ann.) and 0 to 2 seconds after announcements (denoted by Post-Ann). 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. Panel A allows for events to have different responses to surprises at different stages of business cycle and Panel B for different levels of VIX. 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: 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: 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

Table 8: 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 9: Permanent and Temporary Effects of Order Imbalance on Prices Around Macroeconomic News

This table presents the results of state space model estimation. The log midquote 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 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 is from 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

Year	Permanent Impact of order flow (α)			Temporary Impact of order flow (β)		
	-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*****

APPENDIX

Table A.1: Order Imbalance around Macroeconomic News Releases

The table reports two different measures of order imbalance around macro news releases. Panel A reports order imbalance for the S&P500 ETF (SPY) and Panel B reports order imbalance for the S&P 500 E-mini Futures. *#OIB* is computed as the (no of buys – no of sells)/(no of buys + no of sells), where buys(sells) represents buyer(seller) initiated trades. *$OIB* is computed as the (total value of buys – total value of sells)/(total value of buys + total value of sells). *Corr* represents the correlation between the two measures. For negative surprises the negative of order imbalance is used to compute average across events. The interval -5m to -5s captures activity from 5 minutes to 5 seconds before the announcement. Other rows reports the imbalance in the period beginning the time in the previous row and ending at the time reported in that row. 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. The SPY sample period covers 2008–2014 and the Futures sample is from July 2011- December 2014.

Panel A: S&P500 ETF (SPY)

Time	#OIB	$OIB	Corr
-5m to -5s	0.00	0.00	0.59
-5s to 0	0.05*	0.07***	0.86
0.25s	0.22***	0.25***	0.94
0.5s	0.11***	0.13***	0.95
1s	0.07***	0.07***	0.92
2s	0.07***	0.06**	0.90
3s	0.07***	0.08***	0.91
3s to 5m	0.02	0.02	0.61

Panel B: S&P500 E-mini Futures

Time	#OIB	$OIB	Corr
-5m to -5s	0.00	0.00	0.88
-5s to 0	0.02	0.02	0.91
0.25s	0.19***	0.18***	0.95
0.5s	0.13***	0.13	0.96
1s	0.13***	0.12***	0.94
2s	0.14***	0.14**	0.91
3s	0.10***	0.11***	0.90
3s to 5m	0.03	0.03	0.91

Table A.2: Profitability of Algorithmic Trading on Macroeconomic News Releases by Year

The table reports average *per-event* dollar profits from trading on macroeconomic announcement surprises *excluding certain events*. 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. *Market Moving Events only* computes the average profits of all events in Table 5 with the exception of Factory Orders and Leading Index for SPY and CPI, CPI ex Food and Energy, Consumption, Capacity Utilization, Industrial Production, Factory Orders and Leading Index for S&P 500 Futures. *Excluding confounding events* reports average profits by excluding the announcements which were released contemporaneous with another announcement. 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
				Market moving events only				
2s to 5s	8,054***	7,407***	7,443***	10,929***	18,305***	7,709**	3,351**	1,206*
5s to 1m	14,202***	10,072***	17,754***	21,823***	33,700**	14,200**	690	942
1m to 5m	22,542***	13,233**	28,146***	34,876***	49,172**	25,878**	5,722*	349
				Excluding confounding events				
2s to 5s	6,904***	5,884***	6,025***	9,717***	14,652***	7,640**	2,815**	1,153*
5s to 1m	12,785***	8,882***	15,193***	19,083***	28,619**	14,609**	593	894
1m to 5m	19,974***	10,772**	24,136***	31,450***	39,709**	24,753**	6,310*	829

Panel B: S&P500 E-mini Futures

Exit Time	2011-2014	2011	2012	2013	2014
		Market moving events only			
2s to 5s	28,941***	90,042***	44,723***	7,974***	3,661*
5s to 1m	40,605***	133,067**	57,918***	12,725	5,022
1m to 5m	63,631***	215,183**	77,890***	28,242**	9,052
		Excluding confounding events			
2s to 5s	27,476***	81,179***	44,397	5,860**	3,810
5s to 1m	38,687***	118,200**	58,934***	10,611	4,593

1m to 5m	58,626***	182,670**	74,382***	27,396**	8,937

Table A.3: Profitability of Algorithmic Trading on Macroeconomic News Releases by Announcement
The table reports average *per-month* 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 period covers 2008–2014 and the E-mini Futures sample is from July 2011- December 2014. Profits are reported per month. Statistical significance at the 10%, 5%, and 1% level are denoted by *, **, and ***.

	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	13,231
CPI ex Food Energy				-4,088	-1,290	10,109
Housing Start				1,477	8,069**	16,282**
Jobless Claims				10,375	6,237	-4,146
Nonfarm Payroll				162,449***	221,196**	285,866**
Consumption				2,033	16,245	20,696
Retail Sales				2,140	8,584	25,472*
Capacity Utilization				134	423	2,516
Industrial Production				-116	733	3,988
Chicago PMI	$10,233***	$10,798***	$23,467***	40,166**	29,341*	105,328***
Consumer Sentiment	3,721***	9,050***	10,190*	-2,908	8,679	15,214
Consumer Confidence	15,430***	22,177***	24,546***	79,105***	51,096**	10,039
Existing Home Sales	6,562***	11,016**	22,331**	16,538	45,768	101,824
Factory Orders	267	741	-1,161	288	1,078	-3,694
ISM Manufacturing	16,490***	44,364***	83,044***	103,338***	228,663**	386,334**
ISM Non-Manufacturing	6,099***	5,994**	3,754	19,619	-9,329	8,150
Leading Index	-125	5,516	5,520	2,655	14,403	14,557
New Home Sales	5,924***	10,154***	12,820***	6,502	17,111**	15,325
All Events	7,399***	13,603***	21,043***	28,213***	40,574***	63,903***