Information Driven Price Jumps and Trading Strategy: Evidence from Stock Index Futures

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Abstract

In this paper we apply a relatively new nonparametric jump identification technique to examine the role of the 8:30am and 10:00am macroeconomic news announcements in explaining large and significant discontinuities in intraday futures prices on the Dow, Nasdaq and S&P 500 indices. We document a strong relationship between the two sets of morning economic news releases and "jumps" in equity index futures prices. We find that good (bad) economic news is followed by positive (negative) jumps and that the responses are asymmetric; bad news has a larger impact on returns than good news. Our results also provide insights into the speed of news absorption. Finally, we construct a high frequency trading rule to determine whether the observed relations can be used to generate trading profits. Using the 10:00 am announcement and after accounting for transaction costs, the returns from 1-minute holding positions aggregated over the 10-year sample period range between 16-29%.

Keywords: Macroeconomic News, Jumps, Index Futures, Trading Strategy

JEL Classification Codes: G10, G14

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I. Introduction

Researchers have long been interested in examining the distributional properties of asset price movements because of their important implications on risk measurement and management, portfolio allocation and rebalancing, and on the pricing of various derivative instruments. While most of the standard literature in finance assumes that prices follow a geometric Brownian motion, this assumption has come under scrutiny as empirical observations increasingly point to the presence of infrequent and large price movements (labeled as "jumps") that violate the Gaussian distribution in practice. Several studies such as Bates (2000), Eraker, Johannes, and Polson (2003), Zhou and Zhu (2009) document the importance of stochastic volatility and systematic jump risk when pricing returns. Maheu and McCurdy (2004) argue that price discontinuities are likely the result of uncertainty resolution associated with the release of new and relevant information, or "news". This argument is consistent with Clark's (1973) mixture of distribution hypothesis which postulates that prices change only in response to new information.

In this paper we apply a nonparametric jump identification technique recently proposed by Andersen et al. (2010) to examine the role of macroeconomic news announcements in explaining large and significant discontinuities in intraday equity futures prices in the Dow, Nasdaq and S&P 500 indices. Identifying the precise timing of the high-frequency price jump is important since several prior studies indicate that majority of price adjustments occur within a few minutes after important news events are announced (see Ederington and Lee, 1993, 1995; Balduzzi, Elton and Green, 2001, inter alia). Finally, we examine the profitability of a simple trading rule that exploits the predictability in the relationship between macro news and jump returns.

Previewing the results, we find that better than expected economic news is associated with positive jumps in equity futures prices, and bad news corresponds with negative jumps. Notably, about 48% to 56% of jumps between 10:00-10:01 am can be explained by U.S. macroeconomic announcements released at that time. Among the seven types of 10:00 am announcements, Consumer Confidence, NAPM, and Leading Economic Index (LEI) have the largest explanatory power. The impacts of premarket news releases at 8:30 am, which are evaluated using Globex trades, are even more impressive. Specifically, nearly three-quarters of all recorded jumps between 8:30-8:31 am are explained by macroeconomic announcements released at 8:30 am, with the most prominent announcements being Change in Nonfarm Payroll, GDP, PPI and CPI. Using the estimates relationship between announcements and jump returns, we operationalize a trading rule that triggers a "long" or "short" position in the futures market *immediately* after good or bad macro news, respectively. Based on this trading rule, the cumulative profits from 10:00 am announcement before transaction costs of 1-minute holding positions of the Dow Jones, the NASDAQ, and the S&P 500 index futures over the 2001-2010 sample period are about 26%, 37%, and 39%, respectively. The profits are lower, but still significant, after accounting for trading costs. In contrast, the profitability of equity index trading based on 8:30 am news is significantly lower. Possible reasons include: Globex trades are relatively illiquid compared to pit trades; and underlying assets are not traded during the Globex session at the time of the 8:30 am news release.

The contributions of the paper are twofold. First, by investigating only significant price movements following macroeconomic announcements, the paper identifies the relationship between macro news and equity prices movements more successfully than previous studies. The paper documents a strong relationship between the two sets of morning economic news releases and equity index futures prices. Second, we construct a high frequency trading rule to show how one can utilize pre-scheduled economic announcements to generate profits. In this regard, most empirical studies explain the impact (or lack thereof) of macro announcements, but rarely provide ways of translating these results into a possible trading rule. Our results provide insights into the speed of news absorption and highlight the market's asymmetry in responding to macro information.

The paper proceeds as follows. Section II motivates the current study in the context of the literature. Sections III and IV outlines the data relevant to this study and describes the jump detection methodology, respectively. Section V reports empirical evidence linking jumps with news. Section VI presents test results from the trading rule. Section VII concludes.

II. Motivation and Background

In order to motivate the study, consider the simple equity valuation equation:

(1) $$P_t = E\left[\sum_{t=1}^{\infty} \frac{C_{1+i}}{1+k_{1+i}}\right]$$

where P_t is the price of a security at time t, C_{t+i} is the expected future cash flows paid at time $t+i$, and k_{t+i} is the firm-specific discount rate that accounts for the risk-free rate and risk premium associated with the stock. News can potentially influence stock prices through two channels: (a) cash flows; and (b) discount rates. Holding the discount rate effect constant, news that convey an unexpected improvement in the economy would bode well for firms' future cash flows, and would have a positive effect on prices. On the same token, a better-than-expected economic growth can concomitantly raise discount rates which would push stock prices lower. Ultimately, the response of stock prices – which represents an amalgam of both cash flow and discount rate effects – to economic news remains an empirical question.

Numerous papers have examined the effect of news on the return generating process of various assets. Among the various sources of information the role of public information takes ascendant importance since they represent an easily available and closely followed news source, and they provide insights into the canonical model of weakly efficient markets which posits that security prices reflect all available information. Affirming the role of macro announcements in affecting returns would also support the notion that any variable that affects the investment opportunity set (Merton, 1973) or consumption level (Breeden, 1979) should be a priced factor in equilibrium. However, the theoretical relationship between news – both firm-specific and macroeconomic news items – and equity returns has found only limited, and often contradictory, support among empirical studies. Papers that report a weak relationship between stock market activity and news include Roll (1988), Cutler, Poterba, and Summers (1989), Mitchell and Mulherin (1994), and Berry and Howe (1994). In contrast, the influence of monetary and price variables are more consistent with theoretical predictions, but the effect of *real* sector macro variables has proven to be elusive (Flannery and Protopapadakis, 2002). In general, the failure of fundamental models to explain equity returns have led researchers to conclude that there exists an "embarrassing gap" (Chen, Roll and Ross, 1986) and a "poor showing" (Chan, Karceski and Lakonishok, 1998) in the empirical literature.

Given this backdrop, the central questions we seek to answer in this study are as follows: if economic state variables are not very helpful in explaining equity return movements, can they at least be used to explain dramatic price fluctuations? Furthermore, in the event macro announcements are found to be related to stock price movements in some predictable manner, can this predictability be used to generate a profitable trading strategy? In examining the price reaction, several other related questions arise: Are some economic news items more important than others to changes in stock prices? What is the nature and direction of the relationship? Finally, how fast do stock prices adjust to new information?

The empirical literature provides some guidance on all these questions. For instance, Flannery and Protopapadakis (2002) document the impact of inflation and real macroeconomic variables on the level and/or volatility of equity market portfolio returns. However, they find that popular measures of overall economic activity such as Industrial Production and GNP are not significant. Adams, McQueen, and Wood (2004) report that large stocks respond to inflation surprises "within 10-20 minutes or about six trades", and that small stocks response to inflation news is less significant. Fair (2002) identifies 69 events between 1982 and 1999 that were followed by large price changes (classified as a change greater than 0.75% in absolute value in the 1- to 5-minute frequency) in the S&P 500 futures. The author indicates that about 32% of these events were directly associated with money supply or interest rate announcements, and another 45% of changes were indirectly related to monetary policy announcements. Notably, several large price changes did not correspond with any events. Still other studies document the state dependent nature of the equity response (see, for instance, Veronesi, 1999, and Boyd et al., 2005).

More recently, jump detection methods are used to reexamine the news-returns relationship. Rangel (2011) examines ‘‘normal” and ‘‘surprising” news events and finds that jumps are more frequent on announcement days than on non-announcement days. Evans (2011) also reports that about one-third of the observed price jumps in the equity, bond and currency markets occur on days of macroeconomic news announcements. The sizes of the jumps are directly related to the “informational surprise” contained in the announcements and the market incorporates the news within about five minutes. However, elevated return volatility may persist for several more hours and, interestingly, the reactions of the S&P 500 E-Mini futures are “more dramatic” than the reactions of the T-bond and exchange rate futures. Jiang, Lo, and Verdelhan (2011) use 5-minute price data on Treasury notes and bonds to compare the impact of macroeconomic news announcements with the impact of liquidity shocks and conclude that liquidity shocks in addition to announcement shocks “play an important role” in the price discovery process.

Our study differs from prior studies in several aspects. First, the equity index futures products are very special. It differs from other futures products in that the trading hours of the floor and electronic exchange do not overlap. Second, a more recent jump identification technique is employed that is able to identify the precise timing of the jump during the day. Third, we use data sampled at 1-minute frequency that span an expansive time period between 2001 and 2010, consider price impact on both floor and electronic markets, and devise and test the profitability of a trading rule. Previous studies only examine the impact of macroeconomic news on financial products. To the best of our knowledge, this is the first study that shows how to generate profits based on economic news announcements. Fourth, our results indicate that even in those instances when the impacts of macroeconomic news announcements are clear and significant they do not translate into a profitable trading opportunity. For example, some of the 8:30 announcements are found to have very significant impacts, but when transaction costs are considered, the profit of the simple trading rule approaches zero.

III. Data Description

The *Chicago Mercantile Exchange* (CME) is the primary venue for trading equity index futures while NYSE and Nasdaq are the markets that price the underlying assets. Index futures can be traded either through open outcry in the "pit" or through GLOBEX, the electronic trading platform. Trading in the CME pit occurs on weekdays between 9:30 am-4:15 pm while trading on NYSE and Nasdaq is between 9:30 am-4:00 pm Monday through Friday. Trading on GLOBEX begins at 4:30 pm and ends at 9:15 am the following day on Monday through Thursday, and Sunday 6:00 pm to 9:15 am the next day, with the electronic market closed Friday night and all day Saturday.

We examine tick-by-tick index futures prices of the Dow Jones, the Nasdaq 100 and the S&P 500 indices. TickData Inc. is the source of the futures price data used in the study. TickData provides the price of each trade and the time of each trade to the nearest second. The period of the analysis runs from January 2001 through December 2010. The dataset contains all pit transactions from January 2001 through December 2010 and all Globex transactions beginning July 2003 to yearend 2010.

Following earlier studies, a continuous time series of transactions is developed using the contract with the greatest number of transactions. We begin with the front-month contract, but roll into the first back-month contract when the daily transactions of the current front month contract are exceeded by the first back-month contract.[1]

Table 1 presents summary statistics of 1-minute returns, calculated as price of the last trade in the current minute interval less the price of the last trade in the previous minute (in percentage terms), of the three index futures series for both pit (see Panel A) and electronic trades (see Panel B). Using data from pit trades, a 1-minute discrete interval sampling process results in about 660,000 return observations for the Dow, 690,000 observations for the Nasdaq, and 935,000 observations for the S&P 500. In relation to the pit market transactions, Globex trades at the 1-minute sampling interval results in substantially lower return observations for the Dow and Nasdaq (about 180,000 and 205,000, respectively). Overall, the S&P 500 futures contracts are the most active equity index futures contracts.

The average returns for all three indices are slightly negative, and that the standard deviations are substantially higher at 0.049% for the Dow, 0.084% for the Nasdaq, and 0.055% for the S&P 500. Two of the three series, the Dow and S&P 500, are slightly positively skewed at 0.116 and 0.175, respectively; the Nasdaq is more highly skewed with a value of 0.825. High kurtosis causes the rejection of the null hypothesis that the

[1] By following this procedure, we avoid the front-month contract stale prices that occur as it approaches expiration.

return distributions are normally distributed. The Nasdaq also exhibits the greatest kurtosis of 103.7. These statistics, along with the extreme maximum and minimum values, provide evidence that Nasdaq futures prices are much more volatile than either the Dow or the S&P 500. Evaluating Globex in Panel B, the returns of all three futures products are relatively less volatile (with lower standard deviations compared to the pit trading sessions), more highly skewed and with higher kurtosis.

Following Elder et al. (2011), for the jump identification process we eliminate days with relatively low trading volume to eliminate biases that can occur due to nonsynchronous trading or stale prices.[2] Specifically, for the pit trading sample we remove days that have less than 50% of the possible one-minute price observations in a regular trading day. Since there are 450 one-minute intervals in a normal 'pit' trading day, days with less than 225 observations are eliminated. Thus, we use one-minute returns for 1766 days for the Dow Jones, 1941 days for the Nasdaq 100, and 2484 days for the S&P 500.[3] On the other hand, due to the relatively illiquidity of the contracts in Globex, only trade-days with less than 50 transactions are removed from the sample. This results sample sizes of 1484, 1395 and 1899 "trade-days" for Dow Jones, Nasdaq 100 and S&P 500 futures.[4]

This study considers several different types of announcements released at 8:30 am and 10:00 am, similar to those used in Ederington and Lee (1993) to examine foreign

[2] For the trading strategy process discussed below, we use return observations from all days.
[3] For the Dow Jones, the Nasdaq and the S&P 500, a total of 766, 623 and 69 days were eliminated, respectively.
[4] If trade-days with less than 100 transactions were to be removed from the sample, then the number of days in the sample for both Dow Jones and Nasdaq would be less than 800 days compared to the total of more than 1900 days in the raw sample. Trade-days here are defined as Sunday 5:00 pm to Monday 9:15 am, and 4:30 pm to 9:15 am the next day from Monday through Thursday.

exchange rate and interest rate futures markets. *Bloomberg* is the source of both the pre-announcement consensus (median) forecast and the realized value for each monthly, pre-scheduled macroeconomic news release. Each news release is "standardized" by dividing the difference between the realized value and the consensus forecast by its standard deviation. This allows us to compare the impact across the different macroeconomic news announcements. That is,

(2) $$SA_{i,t} = \frac{A_{i,t} - E_{i,t}}{\sigma_i},$$

where $SA_{i,t}$ is the surprise element of the announcement of type i at time t, $A_{i,t}$ is the realized or actual value of an announcement, $E_{i,t}$ is the consensus forecast and σ_i is the sample standard deviation of the surprise component of the type i announcement, $A_{i,t} - E_{i,t}$. The standardization procedure does not affect the statistical significance of the estimated response coefficients and the fit of the regression model discussed below, because σ_i is constant for each announcement.

A brief set of descriptive statistics for the 17 pre-scheduled news releases at 8:30 and 10:00 am are shown in Table 2.[5] Note the 8:30 am announcements are released forty-five minutes before the opening of the CME pit market, and we measure their price impact using Globex transactions. With the exception of Business Inventories, each of the remaining 10 economic variables has 90 different news releases. The majority of Business Inventories are released at 10:00 am. The 10:00 am announcements are released thirty minutes after the opening of the CME futures pit market and the NYSE and Nasdaq markets. During the sample period the number of observations ranges from 74 for Business Inventories to 120 for Construction Spending, NAPM, and New Home

[5] Business Inventories was released at 8:30 am for some months and 10:00 am for other months .

Sales. The differences in the mean surprises and the standard deviations confirm that the data should be standardized in order to assess the impact of the different types of announcements.

IV. Jump Identification Methodology

The evolution of asset prices in jump-diffusion models is represented as a sum of a continuous sample path process and occasional discontinuous jumps with the following stochastic differential equation form:

$$dp_t = \mu_t dt + \sigma(t) dw_t + \kappa_t dq_t, \quad t \geq 0, \tag{3}$$

where p_t denotes the continuous-time log-price process, the mean process μ_t is continuous and locally bounded, the instantaneous volatility process σ_t is càdlàg, w_t is a standard Brownian motion independent of the drift, and q_t refers to a normalized counting process such that $dq_t = 1$ indicates a jump at time t, and $dq_t = 0$ otherwise, with the κ_t process describing the size of the jump if a jump actually occurs at time t.

The continuous-time expression in equation (3) is convenient for theoretical pricing arguments, but is of limited relevance in empirical studies that rely on discretely sampled prices. In practice, the discrete-time returns implied by equation (3) are defined as:

$$r_t = p_t - p_{t-1}, \quad t = 1,2, \ldots \tag{4}$$

where the unit time interval is usually referred to as a "day." With $M + 1$ observations per day of high-frequency data, the continuously compounded M intra-daily returns for day t are similarly denoted by,

$$r_{t,j} = p_{t,j} - p_{t,j-1}, \quad t = 1,2, \ldots, T, \tag{5}$$

where, $p_{t,j}$ denotes the j^{th} intra-day log-price for day t and T is the total number of days in the sample.

Following Andersen and Bollerslev (1998), Andersen et al. (2001a, 2001b) and Barndroff-Nielsen and Shephard (2002), realized volatility for day t is defined as:

(6) $$RV_t = \sum_{j=1}^{M} r_{t,j}^2, \qquad t = 1, \dots, T.$$

From the theory of quadratic variation, RV_t provides a consistent estimator of the daily increment to the quadratic variation for the underlying log-price process in equation (3). That is, for $M \to \infty$,

(7) $$RV_t \to_p \int_{t-1}^{t} \sigma_s^2 ds + \sum_{s=q_{t-1}}^{q_t} \kappa_s^2, \quad t = 1, \dots, T.$$

Clearly, the realized volatility measure includes the contributions of both integrated volatility (the first term) and total variation stemming from the squared jumps.

On the other hand, the bipower variation (BV) introduced by Barndorff-Nielsen and Shephard (2004) is defined as:

(8) $$BV_t \equiv \mu_1^{-2} \sum_{j=2}^{M} |r_{t,j}||r_{t,j-1}|, \qquad t = 1, \dots, T,$$

where $\mu_1$is the mean of the absolute value of the standard normally distributed random variable and $\mu_1 = \sqrt{2/\pi}$. It has been shown that, even in the presence of jumps, for $M \to \infty$,

(9) $$BV_t \to_p \int_{t-1}^{t} \sigma_s^2 ds, \quad t = 1, \dots, T.$$

Combining equations (7) and (8), we have, for $M \to \infty$,

(10) $$RV_t - BV_t \to \sum_{s=q_{t-1}}^{q_t} \kappa_s^2, \quad t = 1, \dots, T.$$

The difference between RV_t and BV_t would then provide a consistent estimate of the contribution of the jump component to the total variation.

Following Andersen et al. (2010), we only consider significant jumps defined as the most extreme price movements with the discontinuous jump component. To determine the significance of the daily jump component, the feasible logarithmic test statistic is utilized:

(11) $$Z_t \equiv \sqrt{M}\,\frac{lnRV_t - lnBV_t}{[(\mu_1^{-4}+2\mu_1^{-2}-5)TQ_t\ BV_t^{-2}]^{\frac{1}{2}}} \rightarrow_d N(0,1),$$

where the realized tripower quarticity measure in the denominator is defined by the equation:

(12) $$TQ_t \equiv \frac{1}{M}\mu_{\frac{4}{3}}^{-3}\sum_{j=3}^{M}\left|r_{t,j}\right|^{\frac{4}{3}}\left|r_{t,j-1}\right|^{\frac{4}{3}}\left|r_{t,j-2}\right|^{\frac{4}{3}}, \quad t = 1, \ldots, T,$$

and $\mu_{4/3} = 2^{\frac{2}{3}}\Gamma(\frac{7}{6})/\Gamma(\frac{1}{2})$, with $\Gamma(\cdot)$ denoting the *Gamma* function. The only values that are considered jump components are the statistically volatile positive values of the difference between RV_t and BV_t. Andersen et al. (2001a, 2001b) indicate that the conventional test statistic used to determine the significance of jump days is subject to bias. Therefore, Huang and Tauchen (2005) modify the jump test statistic (JS) to the following form:

(13) $$JS_t = \frac{RV_t - BV_t}{\sqrt{(\mu_1^{-4}+2\mu_1^{-2}-5)max[0,TQ_tBV_t^{-2}]}} \rightarrow N(0,1).$$

The high-frequency data-based measures discussed above provides a simple approach for determining days with jumps, or jump days, based on the test statistic in equation (13). However, this approach does not identify the individual jumps themselves.

Andersen et al. (2010) further modify the jump identification technique and we use their procedures to identify multiple intraday jumps and the exact timing and size of the jumps. Both RV_t and BV_t are computed for day *t* using equations (6) through (8) and the jump test statistic is determined from equation (13). If the jump test statistic is significant, there is at least one jump at day *t*. Thus, the first (largest) jump is the intra-daily return with the highest absolute value. The timing of the first jump is obtained by ordering the intra-daily absolute returns.

To identify a possible second jump, we recalculate $\mathrm{RV_t}$ by replacing the squared return of the first jump by the average of the remaining $\mathrm{M} - 1$ squared returns. If the new test statistic obtained by plugging in the recalculated $\mathrm{RV_t}$ in equation (13) is not rejected, we conclude that there is exactly one jump on day *t*, and the procedure is terminated. If on the other hand, the test statistic is rejected, there are at least two jumps, and the second jump is the intra-day return with the second largest absolute value. More generally, after having identified i jumps, we calculate the jump-corrected realized volatility using the remaining $M - i$ returns that are scaled by $M/(M - i)$. This procedure is continued until the test statistic can no longer be rejected.

V. Macroeconomic News and Jumps in Index Futures

A. Jumps in Index Futures Prices

The jump identification procedure described in Section 4 is used to identify price jumps for all trading days with sufficient returns for all three index futures in the Globex and pit trading session, separately.[6] Table 3 documents descriptive properties of jump returns that are significant at the 1% threshold at the 1-minute frequency.

[6] Days with fewer than 225 and 50 1-minute observations are omitted for the pit and Globex trading sessions, respectively.

Panel A of Table 3 reports statistics that pertain to the pit trading session. Several results are evident. First, the number of days with at least one significant jump occurs during 89%, 87% and 45% of the effective trading days in the Dow, Nasdaq and S&P 500 samples. On average, the S&P 500 index has the fewest number of jumps per day (about 1.95), as indicated by the E(#Jump|Jump Day) statistic. We surmise that more active trading in S&P 500 futures relative to the Dow and Nasdaq index futures may have contributed to its smoother price movements or fewer jumps. Second, we identify a total of 2172 jumps for S&P 500 which accounts for about 0.23% of the total number of observations. In comparison, there are 7055 and 7783 jumps in the Dow and Nasdaq series, respectively, and they each represent jump percentages of about 1.3%. Finally, the results indicate that there are slightly more negative jumps than positive jumps in all three futures return series. The mean absolute jump values are 0.14%, 0.22%, and 0.16% for the Dow Jones, Nasdaq and S&P 500, respectively. These values are significantly higher than the means of the absolute returns which are about 0.03%, 0.05%, and 0.03% for Dow Jones, the Nasdaq and the S&P 500, respectively.

An examination of Panel B indicates that, compared to pit trades, there is a higher jump propensity in Globex especially in the trading of S&P 500 futures. There is evidence of at least one jump in almost each trading day. The average numbers of jumps per jump day are 4.62, 6.98 and 7.89 for the Dow, Nasdaq and S&P 500, respectively. Interestingly, the jump sizes in Globex are substantially smaller in magnitude compared to the price jumps identified in pit trading. For example, for the S&P 500, the jump size in the pit is 0.17% versus 0.07% in the electronic market. This provides additional rationale for identifying jumps in the pit and Globex sessions separately. Although jump sizes are much smaller in Globex, they are still significantly higher than the "normal" returns since the means of the absolute returns are only 0.007%, 0.009%, and 0.011% for Dow, Nasdaq, and S&P 500, respectively. If trades in the two platforms are pooled together most of the price jumps in Globex would be washed away due to their relatively smaller sizes.[7]

B. Jumps and Macroeconomic News Releases

Having identified intraday jumps, we next match the 8:31 am and 10:01 am jumps (defined as the jump return between 8:30-8:31 am and 10:00-10:01 am) with news at 8:30 am and 10:00 am. Figure 1 reports the jump distributions for all three return series. It is clear that there are far greater numbers of jumps at 8:31am, and 10:01 am than at any other time during the trading day. For the Dow, Nasdaq and S&P500, there are 319, 275, and 473 significant jump events at 8:31 am; and additional 162, 163 and 149 jumps at 10:31 am.[8] These findings lead us to believe that some of these jumps may be associated with macroeconomic news released at those times. Table 4 provides additional results on this relationship.

Panel A presents the results for the 10:01am jumps. Specifically, about 48%-56% of the price jumps can be matched with the release of at least one 10:00 am macroeconomic news announcement. Notably, Consumer Confidence has the largest impact on jump returns – over one-fifth of these releases can be matched with index return jumps. In

[7] These results are available from the authors upon request.

[8] We also observe 100, 249 and 145 jumps at 9:31am for the Dow, Nasdaq and S&P 500, which corresponds to the immediate 1-minute time interval after the stock market open. There are also 324 jumps at 8:21am for the Dow Jones which corresponds to the fact that before the merger of the CME and CBOT, the Dow Jones index futures was traded on CBOT and the trading sessions starts at 8:20 am.

terms of importance, NAPM, New Home Sales, and Leading Economic Index (LEI) indicators are also prominently associated with price jumps across the three indices. Gilbert et al. (2006) document that a recurring release of already publicly available macroeconomic information, such as the LEI, has a significant impact on aggregate stock returns, volatility and volume.

Results from Globex, presented in Panel B of Table 4, document that there are several significant jumps at 8:31am (319 for the Dow, 275 for the Nasdaq, and 473 for the S&P 500). Notably, over 70% of these jumps occur right after the release of one or more pre-scheduled news releases at 8:30 am. A breakdown of the individual types of macroeconomic news announcements shows that Changes in Nonfarm Payroll, CPI and PPI are among the most influential macroeconomic news announcements. For example, out of the 90 total releases of PPI at 8:30 am, there are 38 (42%), 28 (31%) and 55 (61%) announcements that are followed by price jumps in the Dow, Nasdaq and S&P 500. The corresponding statistic for nonfarm payroll indicator is between 32-50%. Among all the different type of 8:30 am news Trade Balance is the least influential. Finally, the S&P 500 which is the most liquid among the three equity index futures products is found to be the most responsive to news.

Table 5 provides another perspective on the correspondence between jumps and news releases. This table documents the top twenty 10:01 am (see Panel A) and 8:31 (see Panel B) jumps based on the absolute values of the returns in the three index futures series and corresponding macro announcements. Examining Panel A, we observe that among the top twenty jumps in the Dow, 14 occur immediately after the release of at least one macroeconomic announcement. A closer examination reveals that among the top ten jumps, seven jumps can be tagged with the release of Consumer Confidence and one of them closely follows the release of LEI. The directional relationship is also highlighted by the fact that negative jumps follow worse-than-expected economic news and positive jumps follow better-than-expected news. Similarly for the Nasdaq, we find that 14 out of the top twenty jumps are associated with news releases, with Consumer Confidence accounting for 12 of these jumps. Finally, for the S&P 500, 16 out of the 20 jumps follow macroeconomic announcements with Consumer Confidence, NAPM, and LEI accounting for six, five and three jumps, respectively.

An examination in Panel B reveals that, strikingly, all the top twenty jumps at 8:31 in the Dow are connected to a macroeconomic news announcement. Equally impressive, 19 out of the 20 jumps for both Nasdaq and S&P 500 can be linked with one (or two) macroeconomic news announcements. Furthermore, the results confirm the importance of the nonfarm payroll statistics. Among the top twenty 8:31 am jumps in the Dow, Nasdaq and S&P 500, over 60% corresponds with the Change in Nonfarm Payroll.

Overall, results from both Panels A and B indicate a positive association between news and index return jumps and highlight several influential news announcements. This apparent relation is more formally investigated through regression analysis.

C. The Marginal Impact of Macroeconomic News on Return Jumps

The marginal impact of each time-stamped news surprise on the 8:31am and 10:01 am return jumps are examined by fitting a multivariate regression model of the following form:

(14) $$jp_{t_{j+1}} = c + \sum_{i=1}^{n} c_i^{+} \, SA_{i,t_j}^{+} + \sum_{i=1}^{n} c_i^{-} \, SA_{i,t_j}^{-} + \varepsilon_{t_{j+1}}.$$

The variable $jp_{t_{j+1}}$ refers to the 8:31 am or 10:01 am jump returns and SA^{+}_{i,t_j}, and SA^{-}_{i,t_j} are the positive and negative standardized surprises of the i^{th} macro news announcement. The regression model fits jumps following the release of at least one announcement. These results are reported in Table 6.

One of the goals of this study is to examine the profitability of a trading strategy that is based on the relationship between macroeconomic news announcements and stock index returns. Specifically, we anticipate that better-than-expected economic news (i.e., positive standardized surprises) leads to positive price jumps, and vice versa. We attempt to further clarify the trading rule by separating positive and negative standardized surprises, thus allowing for asymmetric responses of equity returns to news.

Panel A reports regression results for the 10:01am jumps. First, examining positive surprises, majority of the coefficients have a positive sign with Consumer Confidence and LEI having statistically significant impacts on all three index futures returns. For the S&P 500, the significant role of NAPM is also documented. Second, in the case of negative surprises, all coefficients that are significant carry a positive sign. Note, in interpreting the c_i^- coefficients a positive sign would indicate that bad news leads to negative jump returns. In addition to Consumer Confidence, announcements pertaining to Factory Orders, New Home Sales and NAPM have significant impacts. Therefore, there seems to be clear and compelling evidence that good economic news is followed by positive jumps and bad economic news is followed by negative jumps. Third, the results also indicate that, based on the magnitude of the coefficients, bad news has a larger impact than good news. Finally, support for the model's goodness-of-fit is provided by relatively large adjusted-R^2 values of 39%, 47% and 51% for the Dow Jones, the Nasdaq and the S&P 500, respectively.

Examining the 8:31am jumps in Panel B, we find that the majority of surprises are positively related with jumps. For instance, among the 22 different parameters estimated, 15, 16 and 18 of them are positive for the Dow, Nasdaq and S&P 500, respectively. It is interesting to note that Changes in Nonfarm Payroll is the only announcement for which the parameters of both positive and negative surprises are positive for all three indices. This is consistent with evidence documented by Andersen and Bollerslev (1998) who refer to the 'Employment Situation' report as the "king" of all announcements because of the significant sensitivity of most asset prices to its public release. Furthermore, the parameters of positive GDP surprises are positive and significant at the 5% level of significance. Equally important, the results show that several news releases are not significantly associated with jumps in the equity futures markets. Furthermore, results reveal a slight asymmetry in the response to positive and negative surprises. For example, in the 8:31 am jump regression model for the S&P 500, the Change in Non-farm Payroll and GDP are the only two types of news for which the parameter estimates for both the positive and negative surprises are statistically significant. However, the magnitudes of the estimates are different. A one standard deviation positive surprise of Change in Nonfarm Payroll leads to a return jump of size 0.25% on average, whereas an equal size negative surprise results in a return jump size that is about 56% higher. It is not unusual to observe asymmetric responses to news announcements in financial markets. For instance, Conrad, Cornell and Landsman (2002) report that stock prices are impacted more by bad news than good news (also see Skinner and Sloan, 1999) work. In the context of currency markets, Lobo, Darrat and Ramchander (2006) and Wang, Yang and Simpson (2008) show exchange rates are more affected with tightening of monetary policy (bad news) than by easing (good news). In general, research tends to show investors' are more sensitive to bad news than to good news.

VI. Trading Strategy

In this section we evaluate the profitability of a trading rule that is predicated on the direction of the relationship between macroeconomic surprises and equity index returns. A simple technical trading rule is devised where trades are initiated only on days when a macroeconomic news release is scheduled. Specifically, when there is a scheduled news release, an intraday 1-minute long or short position is initiated depending on the direction of the surprise. If the surprise is positive (negative), we open a long (short) position with the nearest index futures contract at the first transaction 1-minute after the announcement and close this out one minute later. In the event that there are two or more announcements that are released at the same time on the same day, a trade is triggered if and only if all the surprises at any given release time. are in the same direction. Finally, we do not trade in those instances when the surprise is zero.

The profitability (or excess returns) of the trading rule is measured by comparing the means and cumulative returns of trade periods versus a customized benchmark that comprises non-trade periods. The benchmark returns, which serve as the control sample, are computed by constructing a corresponding time-matched 1 minute returns when there are no trade signals. We refer to the benchmark returns as "nontrade" returns. The null hypothesis that excess returns are zero is tested with a z-statistic (see Taylor, 2000) given by $z = \frac{\bar{r}_T - \bar{r}_{NT}}{\sqrt{\frac{s_T^2}{n_T} + \frac{s_{NT}^2}{n_{NT}}}}$, where $\bar{r}_T$ and $\bar{r}_{NT}$ are the returns during trade and non-trade periods, and s_T, and s_{NT}, are the standard deviations of trade returns and nontrade returns, respectively.

A. The 10:00 am News and Trading Profits

Table 7 provides results from the trading rule without transaction costs (Panel A) and with transaction costs (Panel B) based on all trading days in the sample. A quick survey of the results indicates that the simple trading rule generates considerable profits. For example, Panel A shows that the mean return for the Dow Jones futures on trading days is about 0.05%, substantially higher than the nontrade returns of 0.0013%. This difference, or excess return, is statistically significant at the 1% level. To get a general sense of how large these profits are, the average daily returns, when cumulated over the entire 10-year sample period, are found to be 25.84% and 2.21% for the trading and non-trading days, respectively. In other words, the 1-minute trade returns which are generated from 516 transactions are found to be nearly 11 times as high as the benchmark returns. In comparison to the Dow, the cumulative trading returns for the Nasdaq and the S&P 500 are even larger – about 36.64%, and 38.95%, respectively. It would be important to note that the cumulative trading profits are generated about equally from both long and short positions. For instance, among the overall 516 trades in the Dow, there are 245 short positions with cumulative profits of 11.52% and 271 long positions with cumulative profits of 14.31%. Similar results are obtained for Nasdaq and S&P 500. To summarize, the results in Panel A show that excess returns are statistically significant, and also appear to be economically significant as suggested by the magnitude of the returns.[9]

We now examine trading profits after explicitly accounting for transactions costs. Although, transactions costs are quite low in equity index futures, one could argue that the relatively large numbers of transactions in the strategy would make this analysis relevant. Therefore, for the purpose of our analysis we assume that the trading cost is one tick for each one-way transaction. Compared to other studies in the literature this assumption is actually quite onerous. For instance, Fleming and Sarkar (1999) document that the interdealer estimates of bid-ask spreads on Treasury futures are between half a tick and one tick. Faust and Wright (2009) assume the trading cost is half a tick for the five and ten year futures contracts and a whole tick for the thirty-year contract. Examining Panel B, after adjusting for transaction costs, the cumulative returns across both long and short positions for the Dow Jones is 15.86% (25.84% without transactions costs); whereas, the cumulative returns for the benchmark non-trade days is -31.63% (2.21% without transaction costs). Thus, the relative advantage of the trading rule appears to have increased when transactions costs are factored in. Again, the results are qualitatively similar for the Nasdaq and S&P 500. In both cases, with and without transaction costs, the S&P 500 provides the greatest cumulative returns (38.95% without and 29.27% with transactions costs), followed by the Nasdaq (36.64% without and 19.42% with transactions costs) and the Dow provides the lowest cumulative returns. In

[9] Note these returns can be further amplified because of high amounts of leverage (about 10:1) that is common in futures market transactions. The initial margin requirements as of August 2011 are: $10,000 per Dow Jones contract (with an underlying value of about $110,000), $17,500 per Nasdaq contract (about $250,000), and $25,000 per S&P 500 contract (about $300,000).

summary, the inclusion of transactions costs reduces returns; however, the trading rule still generates economically significant excess returns.

Additional insights from the trading strategy are derived by examining trade and non-trade mean returns on a year-by-year basis. These results are shown in Figure 2 (without transaction costs) and Figure 3 (with transaction costs). These figures show that across all three indices the 10:00 am trading rule yields significant profits every single year with the notable exception of 2006.[10]

Next we investigate the temporal aspect of excess returns; or in other words, how quickly the market absorbs new information so as to preclude profitable opportunities. Figure 4 presents the plots of cumulative profits on trade days and the benchmark non-trade sample. As shown by the plot for the Dow Jones futures, the maximum cumulative profit is realized if both long and short positions are held until 10:17 am. The aggregate profit over the ten year sample period is 45.26%. For the Nasdaq futures, the maximum cumulative profit is observed at 10:02 am (43.82%) and the second highest cumulative profit is 40.81% which occurs at 10:09 am. For the S&P 500 futures, we observe the maximum cumulative profit of 51.12% at 10:16 am. It should be noted that although cumulative profits reach their apex at 10:17 am and 10:16 am for the Dow Jones and the S&P 500, the largest increases of profits occur in the first one minute after the announcement for all three markets. Beyond the first minute, cumulative profits only increase slightly and later decrease after roughly 20 minutes. Therefore, the

[10] For the sake of brevity, the corresponding z-statistics for the difference between trade and non-trade mean returns are not reported. They can be obtained from the authors upon request.

microstructure implication is that although the market absorbs macro news rapidly, it takes several minutes for the information to be fully impounded into prices.

The asymmetric response of markets to good news versus bad news in generating trading profits is provided in Figure 5. An overview of the results indicates that during the first one hour, the cumulative profits of short positions are higher than long positions. Since the number of long and short positions are approximately the same this corroborates our earlier finding that bad news has a larger impact on prices than good news.

B. The 8:30 am News and Trading Profits

All of the results reported thus far pertain to the 10:00 am announcements. There are several important U.S. news releases at 8:30 am when floor trading in the futures market and the stock markets are closed, but electronic trading is open. This trading feature offers a unique window to test the impact of the 8:30 am news, and also allows us to benchmark these findings with the 10:00 am results. Specifically, depending on the direction of the surprise, we enter into long or short position at the first transaction or immediately after 8:31 am and unwind this position on the pit at 9:30 am. We consider holding the position until the opening of the pit market for two reasons. First, equity index futures trading in Globex is not very liquid, thus it is not always possible to close the position in a pre-determined time window. Second, we are also interested in finding the response of the futures market when the underlying asset trades simultaneously with futures trading.

Figure 6 shows cumulative profits on trade and non-trade days assuming that the positions are closed at the plotted time points (minutes) after the stock market opens. The results show that it is possible to make profits, and that the maximum profits occur about 10 minutes after the opening of the stock exchange for both the Dow and the Nasdaq. The maximum profits are 20.88% for the Dow Jones with a total of 649 transactions, and 13.80% for the Nasdaq with 710 transactions. On the other hand, the maximum profit for the S&P 500 is only 6.37% with 756 transactions at 9:34 am. Comparing these results with the 10:00 am news, it is evident that the cumulative profits for 8:30 am news announcements are much lower. A breakdown of the profits associated with long and short positions in Figure 7 indicates that only the short positions, triggered by bad economic news, generate positive cumulative profits. In contrast, long positions triggered by better-than-expected economic news yields negative profits.

Finally, Figures 8 and 9 show yearly breakdowns of mean returns with and without transactions costs, respectively. It is observed that, when transactions costs are ignored, trade returns are positive in 8 out of 10 years for the Dow, and 6 out of 10 years for Nasdaq and S&P 500. By comparison, the excess returns (i.e., trade day returns *minus* the benchmark non-trade day returns) remain positive in 9 out of 10 years for the Dow and Nasdaq, and in 7 out of 10 years for the S&P 500. Once transactions costs are taken into consideration, we notice that cumulative profits from 8:30 am announcements are all but eliminated (see Figure 9).

VII. Concluding Remarks

This study uses high-frequency trading data to investigate the relationship between macroeconomic news announcements and stock index futures price movements of the

Dow Jones, the Nasdaq 100 and the S&P 500. High frequency index futures prices are used to examine to the extent to which intraday equity index price "jumps" are related to "surprises" in macroeconomic news announcements, and to determine if the information driven jumps can be used to generate trading profits. We find that price jumps are strongly related to macroeconomic news releases. Among all the announcements, Changes in Non-farm Payroll, Consumer Confidence and LEI are significantly related to jumps in all three indices. The influential role of GDP, PPI, CPI, NAPM, Factory Orders and New Home Sales is also evident. In general, our results confirm the pro-cyclical nature of the impact of macro news on equity markets – i.e., good economic news is positive for equities, and correspondingly bad economic news is negative for stocks. On a broader front, the results imply that the cash flow effect on firm value outweighs the discount rate effect. We also find that the market response to bad news is greater than the response to good news.

Although the impact of macroeconomic news on equity prices are found to dissipate quickly, we find that an intraday ultra-short term trading rule can still generate substantial excess returns (especially using the 10:00 am announcements). The most dramatic price changes occur within the first few minutes following the announcement and the information is completely absorbed by the markets within about 20 minutes. It remains to seen whether the increasing trends towards high frequency trading platforms would result in information being absorbed even more quickly thus reducing or eliminating any profitable trading opportunities.

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Table 1. Summary Statistics of One-Minute Returns

Panel A: Pit Trading (Sample period is from January 2001 through December 2010)

Statistics	Returns (%)		
	Dow Jones	**Nasdaq 100**	**S&P 500**
Mean	-0.0002	-0.0006	-0.0004
Std. Deviation	0.0493	0.0837	0.0553
Min	-2.2367	-4.0822	-1.9961
Max	2.1404	5.8269	2.5520
Skewness	0.1164	0.8251	0.1749
Kurtosis	58.28	103.70	39.54
Count	660,140	689,248	935,232
Days	2532	2554	2553

Panel B: Globex Trading (Sample period is from July 2003 through December 2010)

Statistics	Returns (%)		
	Dow Jones	**Nasdaq**	**S&P 500**
Mean	-0.0002	0.0000	-0.0001
Std. Deviation	0.0304	0.0335	0.0272
Min	-2.0608	-1.5137	-1.5734
Max	3.0330	2.6588	2.9772
Skewness	5.1327	3.7515	3.3876
Kurtosis	992.20	570.34	499.13
Count	181,174	204,598	794,492
Days	1911	1933	1933

Table 2. Statistics of Macroeconomic News Announcements

News	Obs.	Mean	Std. Dev.
8:30 News Announcements:			
Advanced Retail Sales (ARS)	90	0.0000	0.0057
Business Inventories (BI)	17	-0.0002	0.0024
Changes in Nonfarm Payrolls (CNP)	90	-16.1444	76.9932
Consumer Price Index (CPI)	90	0.0000	0.0015
Durable Goods Orders (DGO)	90	-0.0024	0.0238
Gross Domestic Product (GDP)	90	-0.0003	0.0048
Housing Starts (HS)	90	4.4222	91.3879
Personal Consumption (PC)	90	-0.0001	0.0036
Personal Income (PI)	90	0.0005	0.0032
Producer Price Index (PPI)	90	0.0006	0.0053
Trade Balance Goods and Services (TBGS)	90	0.1444	3.4473
10:00 News Announcements:			
Business Inventories (BI[1])	74	-0.0001	0.0022
Consumer Confidence (CC)	118	-0.2831	5.3733
Construction Spending (CS)	120	0.0011	0.0080
Factory Orders (FO)	119	0.0002	0.0071
Leading Economic Indicators (LEI)	119	0.0001	0.0018
National Association of Purchasing Management (NAPM)	120	0.2067	2.1174
New Home Sales (NHS)	120	5.6000	69.4272

Notes:

1. Before 2003, Business Inventories was released at 8:30 am. During 2003-2005, it was released at 8:30 am for some months and 10:00 am for other months. Specific, 3 announcements in 2003, 6 announcements in 2004 and 5 announcements in 2005 were made at 10:00 am and the others at 8:30 am. It has been released at 10:00 am since 2006.

Table 3. Descriptive Properties of Significant Return Jumps Sampled at 1-minute Frequency

Panel A: Pit Market

	Dow Jones	**Nasdaq**	**S&P 500**
Observations	544,759	588,695	926,271
E(|abs(return)|)	0.0270	0.0468	0.0337
Days	1766	1941	2484
Jump Days	1568	1683	1113
P(Jumpday) (%)	89	87	45
E(#Jump|Jump Day)	4.50	4.62	1.95
Jumps	7055	7783	2172
P(jump) (%)	1.30	1.32	0.23
E(|jumpsize||jump)	0.14	0.22	0.16
Std(|jumpsize||jump) (%)	0.11	0.14	0.12
Positive Jumps	3439	3783	1057
P(jump>0) (%)	0.63	0.64	0.11
E(jumpsize|jump>0)	0.14	0.22	0.17
Std(jumpsize|jump>0) (%)	0.12	0.15	0.12
Negative Jumps	3616	4000	1115
P(jump<0) (%)	0.66	0.68	0.12
E(jumpsize|jump<0)	-0.13	-0.21	-0.16
Std(jumpsize|jump<0) (%)	0.11	0.13	0.12
% of Negative Jumps	51.25	51.39	51.34

Panel B: Globex Market

<table>
<tr><th></th><th>Dow Jones</th><th>Nasdaq</th><th>S&P 500</th></tr>
<tr><td>Observations</td><td>167,668</td><td>187,658</td><td>794,299</td></tr>
<tr><td>E(|abs(return)|)</td><td>0.0070</td><td>0.0087</td><td>0.0107</td></tr>
<tr><td>Days</td><td>1484</td><td>1395</td><td>1899</td></tr>
<tr><td>Jump Days</td><td>1451</td><td>1371</td><td>1871</td></tr>
<tr><td>P(Jumpday) (%)</td><td>98</td><td>98</td><td>99</td></tr>
<tr><td>E(#Jump|Jump Day)</td><td>4.62</td><td>6.98</td><td>7.89</td></tr>
<tr><td>Jumps</td><td>6701</td><td>9571</td><td>14760</td></tr>
<tr><td>P(jump) (%)</td><td>4.00</td><td>5.10</td><td>1.86</td></tr>
<tr><td>E(|jumpsize||jump)</td><td>0.07</td><td>0.07</td><td>0.07</td></tr>
<tr><td>Std(|jumpsize||jump) (%)</td><td>0.10</td><td>0.09</td><td>0.09</td></tr>
<tr><td>Positive Jumps</td><td>3283</td><td>4655</td><td>7255</td></tr>
<tr><td>P(jump>0) (%)</td><td>1.96</td><td>2.48</td><td>0.91</td></tr>
<tr><td>E(jumpsize|jump>0)</td><td>0.07</td><td>0.07</td><td>0.07</td></tr>
<tr><td>Std(jumpsize|jump>0) (%)</td><td>0.11</td><td>0.10</td><td>0.10</td></tr>
<tr><td>Negative Jumps</td><td>3418</td><td>4916</td><td>7505</td></tr>
<tr><td>P(jump<0) (%)</td><td>2.04</td><td>2.62</td><td>0.94</td></tr>
<tr><td>E(jumpsize|jump<0)</td><td>-0.07</td><td>-0.07</td><td>-0.07</td></tr>
<tr><td>Std(jumpsize|jump<0) (%)</td><td>0.10</td><td>0.09</td><td>0.08</td></tr>
<tr><td>% of Negative Jumps</td><td>51.01</td><td>51.36</td><td>50.85</td></tr>
</table>

Table 4. Jumps Matched with Macroeconomic News Releases

Panel A: 10:01 am Jumps and 10:00 am Macroeconomic News Releases

	Dow Jones		Nasdaq		S&P 500	
News	**Obs.**	**%**	**Obs.**	**%**	**Obs.**	**%**
BI	4	5.41	5	6.76	2	2.70
CC	29	24.58	31	26.27	26	22.03
CS	15	12.50	10	8.33	17	14.17
FO	11	9.24	13	10.92	8	6.72
LEI	13	10.92	7	5.88	15	12.61
NAPM	19	15.83	13	10.83	17	14.17
NHS	19	15.83	14	11.67	17	14.17
Total jumps	162		163		149	
Jump match news	88	54.32	78	47.85	83	55.70

Panel B: 8:31 am Jumps and 8:30 am Macroeconomic News Releases

	Dow Jones		Nasdaq		S&P 500	
News	**Obs.**	**%**	**Obs.**	**%**	**Obs.**	**%**
ARS	29	32.22	30	33.33	53	58.89
BI	6	35.29	8	47.06	9	52.94
CNP	45	50.00	29	32.22	40	44.44
CPI	35	38.89	30	33.33	52	57.78
DGO	29	32.22	36	40.00	49	54.44
GDP	33	36.67	24	26.67	47	52.22
HS	27	30.00	20	22.22	40	44.44
PC	33	36.67	24	26.67	47	52.22
PI	17	18.89	16	17.78	43	47.78
PPI	38	42.22	28	31.11	55	61.11
TBGS	12	13.33	12	13.33	26	28.89
Total jumps	319		275		473	
Jump match news	229	71.79	199	72.36	353	74.63

Table 5. Top 20 Jumps and Corresponding Macroeconomic Announcements

Panel A: 10:00 am News Releases

	Dow Jones				Nasdaq				S&P 500			
Rank	Date	Return	News	Standard Surprise	Date	Return	News	Standard Surprise	Date	Return	News	Standard Surprise
1	10/16/08	-0.70			10/16/08	-1.43	--		07/29/03	-0.69	CC	-1.56
2	09/25/01	-0.64	CC	-1.38	11/27/02	1.07	--		02/25/03	-0.67	CC	-2.42
3	07/29/03	-0.61	CC	-1.56	07/30/02	-1.04	CC	-0.73	06/29/10	-0.67	CC	-1.79
4	08/27/02	-0.56	CC	-0.65	10/30/01	-0.97	CC	-1.86	09/24/02	0.63	CC	0.22
5	09/24/02	0.52	CC	0.22	10/09/01	-0.95	--		01/26/09	0.63	LEI	2.75
6	01/26/09	0.49	LEI	2.75	08/30/02	0.95	--		10/20/08	0.62	LEI	2.20
7	01/28/03	0.44	CC	0.11	09/25/01	-0.91	CC	-1.38	09/01/10	0.61	CS	-0.62
											NAPM	1.65
8	03/14/08	-0.42	--		07/29/03	-0.86	CC	-1.56	11/07/08	0.60	--	
9	04/29/03	0.41	CC	2.05	09/24/02	0.82	CC	0.22	09/29/09	-0.57	CC	-0.73
10	11/25/08	0.41	CC	1.28	10/29/02	-0.82	CC	-1.97	06/23/10	-0.55	NHS	-1.58
11	01/18/08	0.37	LEI	-0.55	08/27/02	-0.79	CC	-0.65	01/28/03	0.55	NHS	0.60
12	10/25/02	0.36	NHS	0.45	03/27/01	0.76	CC	2.23	08/19/10	-0.51	LEI	0.00
13	01/02/08	-0.36	CS	0.62	08/31/01	0.76	FO	0.85	10/01/09	-0.48	CS	1.12
13			NAPM	-1.32							NAPM	-0.66
14	09/30/03	-0.36	CC	-0.69	06/02/09	0.74	--		10/30/01	-0.45	CC	-1.86
15	12/05/01	0.35	--		01/26/09	0.67	LEI	2.75	04/03/09	-0.45	--	
16	11/07/08	0.34	--		12/28/01	0.67	CC	1.99	07/01/10	-0.44	CS	0.75
							NHS	0.71			NAPM	-1.32
17	08/05/03	0.33	--		06/25/02	0.66	CC	0.07	12/09/08	0.43	--	
18	02/28/07	-0.33	NHS	-2.06	09/07/01	0.65	--		06/02/09	0.42	--	
19	01/31/03	0.33	--		03/26/02	0.62	CC	2.27	08/02/10	0.42	CS	0.75
											NAPM	0.47
20	03/05/08	0.33	FO	0.00	11/27/01	-0.62	CC	-0.80	07/01/08	0.42	CS	0.25
											NAPM	0.80

Panel B: 8:30 am News Releases

	Dow Jones				Nasdaq				S&P 500			
Rank	Date	Return	News	Standard Surprise	Date	Return	News	Standard Surprise	Date	Return	News	Standard Surprise
1	08/06/04	-0.71	CNP	-2.70	09/05/08	-0.91	CNP	-0.12	12/05/08	-1.10	CNP	-2.57
2	01/04/08	-0.69	CNP	-0.68	10/03/03	0.89	CNP	1.07	06/04/10	-1.01	CNP	-1.36
3	09/05/08	-0.66	CNP	-0.12	11/05/04	0.75	CNP	2.10	01/04/08	-0.95	CNP	-0.68
4	11/06/09	-0.66	CNP	-0.19	05/07/04	-0.67	CNP	1.53	06/05/09	0.88	CNP	2.27
5	12/05/08	-0.64	CNP	-2.57	07/03/03	-0.65	CNP	-0.39	10/30/08	0.84	GDP	0.42
											PC	-1.97
6	02/13/08	0.60	ARS	1.05	05/02/08	0.64	CNP	0.71	09/05/08	-0.81	CNP	-0.12
7	06/06/08	-0.59	CNP	0.14	12/14/07	-0.63	CPI	1.35	03/14/08	0.76	CPI	-2.03
8	08/07/09	0.59	CNP	1.01	06/06/08	-0.62	CNP	0.14	05/02/08	0.75	CNP	0.71
9	10/03/03	0.58	CNP	1.07	07/31/03	0.59	PC	0.56	08/19/10	-0.73	--	
10	07/03/03	-0.55	CNP	-0.39	03/14/08	0.58	CPI	-2.03	11/07/08	-0.69	CNP	-0.52
11	06/05/09	0.54	CNP	2.27	11/02/07	0.55	CNP	1.05	01/30/09	0.69	PC	0.00
12	11/02/07	0.51	CNP	1.05	08/16/06	0.55	CPI	0.00	11/02/07	0.69	CNP	1.05
					08/16/06	0.55	HS	-0.14				
13	04/16/09	0.50	HS	-0.33	03/09/07	0.53	CNP	0.03	10/03/03	0.68	CNP	1.07
					03/09/07	0.53	TBGS	0.20				
14	01/30/09	0.49	GDP	3.54	06/02/06	0.52	CNP	-1.23	10/02/09	-0.63	CNP	-1.14
15	08/15/06	0.49	PPI	-0.57	12/05/03	-0.49	CNP	-1.21	08/07/09	0.62	CNP	1.01
16	05/02/08	0.47	CNP	0.71	10/30/03	0.49	GDP	2.50	02/13/08	0.57	ARS	1.05
					10/30/03	0.49	PC	0.84				
17	10/08/04	-0.47	CNP	-0.68	03/15/07	-0.47	PPI	1.51	12/04/09	0.56	CNP	1.48
18	08/01/08	0.45	CNP	0.31	02/13/08	0.46	ARS	1.05	03/11/08	0.54	TBGS	0.38
19	05/07/04	-0.44	CNP	1.53	06/04/10	-0.46	CNP	-1.36	09/03/10	0.54	CNP	0.66
20	07/31/03	0.43	GDP	1.87	10/02/08	-0.45	--		05/13/09	-0.54	ARS	-0.70

Table 6. Marginal Impact of Macroeconomic News on Jumps

This table reports panel regression results of the following form: $jp_{t_j} = c + \sum_{i=1}^{n} c_i^+ \, SA_{i,t_j}^+ + \sum_{i=1}^{n} c_i^- \, SA_{i,t_j}^- + \varepsilon_{t_j}$. Specifically, jumps that match at least one news announcement are regressed against the standardized surprises of news announcements one minute before the occurrence of the jump.

Panel A: 10:00 am News Releases

Variables		Dow Jones			Nasdaq			S&P 500		
	News	Estimate	t-stat	p-value	Estimate	t-stat	p-value	Estimate	t-stat	p-value
News	BI^+	-0.17	-0.88	0.38	-0.35	-1.09	0.28	0.02	0.05	0.96
	CC^+	0.12^{*}	2.01	0.05	0.22^{**}	3.26	0.00	0.12^{*}	2.18	0.03
	CS^+	-0.12^{c}	-1.84	0.07	-0.01	-0.04	0.97	0.03	0.50	0.62
	FO^+	0.03	0.31	0.76	0.26	1.61	0.11	0.08	0.63	0.53
	LEI^+	0.08^{c}	1.70	0.09	0.20^{c}	1.74	0.09	0.21^{**}	3.37	0.00
	$NAPM^+$	0.05	0.75	0.46	0.15	1.07	0.29	0.27^{*}	2.52	0.01
	NHS^+	-0.02	-0.32	0.75	-0.07	-0.74	0.46	0.00	0.02	0.99
	BI^-	0.46^{*}	2.10	0.04	0.66^{**}	2.58	0.01	0.00	--	--
	CC^-	0.25^{**}	5.11	0.00	0.44^{**}	5.86	0.00	0.37^{**}	6.06	0.00
	CS^-	0.09	1.38	0.17	0.21	1.58	0.12	0.08	0.39	0.70
	FO^-	0.20^{*}	2.27	0.03	0.03	0.38	0.71	0.21	1.35	0.18
	LEI^-	0.18	1.54	0.13	0.40	1.36	0.18	0.16	0.80	0.42
	$NAPM^-$	0.24^{*}	2.41	0.02	0.17	1.10	0.27	0.30^{*}	2.23	0.03
	NHS^-	0.12^{*}	2.06	0.04	0.06	0.72	0.47	0.19^{**}	2.91	0.00
Model	Obs		88			78			83	
	Adj-R^2(%)		39.08			46.93			51.95	
	F-Value		4.99			5.86			7.82	
	P-value		0.00			0.00			0.00	

Note: Superscripts "**", "*", and "c" represents significance at the 1%, 5% and 10% level, respectively.

Panel B: 8:30 am News Releases

Variables		Dow Jones			Nasdaq			S&P 500		
	News	Estimate	t-stat	p-value	Estimate	t-stat	p-value	Estimate	t-stat	p-value
	ARS^+	0.03	0.74	0.46	0.00	-0.03	0.98	0.05	1.20	0.23
	BI^+	0.09	0.73	0.47	0.02	0.15	0.88	0.09	0.91	0.37
	CNP^+	0.19^{**}	4.73	0.00	0.17^{*}	2.34	0.02	0.25^{**}	5.94	0.00
	CPI^+	-0.05	-1.27	0.21	-0.03	-0.38	0.71	-0.13^{**}	-3.24	0.00
	DGO^+	-0.01	-0.16	0.87	0.02	0.29	0.78	0.09	1.67	0.10
	GDP^+	0.09^{*}	2.36	0.02	0.19^{*}	2.31	0.02	0.11^{*}	2.45	0.02
	HS^+	0.03	0.46	0.64	0.01	0.18	0.86	0.06	1.06	0.29
	PC^+	0.04	0.50	0.62	0.00	0.00	1.00	0.04	0.86	0.39
	PI^+	0.00	-0.09	0.93	0.07	1.43	0.15	0.03	1.13	0.26
	PPI^+	-0.08^{*}	-1.99	0.05	-0.08	-1.32	0.19	-0.11^{*}	-2.97	0.00
News	$TBGS^+$	-0.02	-0.15	0.88	0.06	0.42	0.67	0.09	0.95	0.34
	ARS^-	0.14^{*}	2.47	0.01	0.01	0.13	0.90	0.14^{*}	3.33	0.00
	BI^-	0.03	0.41	0.68	0.01	0.12	0.91	-0.26	-0.85	0.40
	CNP^-	0.21^{**}	6.12	0.00	0.18^{**}	2.75	0.01	0.39^{**}	8.19	0.00
	CPI^-	-0.07	-1.30	0.20	-0.12^{*}	-2.09	0.04	-0.09^{*}	-2.29	0.02
	DGO^-	0.07	1.41	0.16	0.08	1.38	0.17	0.14^{**}	3.14	0.00
	GDP^-	0.09^{c}	1.68	0.09	0.10	1.35	0.18	0.17^{**}	2.99	0.00
	HS^-	0.03	0.25	0.80	-0.04	-0.52	0.60	0.03	0.58	0.56
	PC^-	0.10	1.03	0.30	0.00	-0.04	0.97	0.01	0.11	0.91
	PI^-	-0.06	-0.53	0.60	-0.09	-0.52	0.60	0.00	0.04	0.97
	PPI^-	-0.05	-0.87	0.39	-0.09	-0.72	0.47	0.01	0.29	0.77
	$TBGS^-$	0.06	0.49	0.62	0.08	0.85	0.40	0.07	1.19	0.23
Model	Obs		229			199			353	
	Adj-R^2(%)		26.67			9.06			33.23	
	F-Value		4.77^{**}			1.90^{*}			8.96^{**}	
	P-value		0.00			0.01			0.00	

Table 7. Profitability of Trading Rule

This table presents returns from trade and benchmark non-trade sample. Trade returns refer to returns from all trades at 10:01-10:02 am. Non-trade returns refer to returns from the corresponding time-matched sample where a trade signal is not triggered. The z-statistic tests for the difference between the means of trade and non-trade returns.

Panel A: Without Transaction Costs													
		Dow Jones				Nasdaq				S&P 500			
		Non-	Trade			Non-	Trade			Non-	Trade		
		Trade	Short	Long	Total	Trade	Short	Long	Total	Trade	Short	Long	Total
	Obs	1732	245	271	516	1846	250	280	530	1983	265	283	548
Return	Mean	0.0013	0.0470	0.0528	0.0501	-0.0004	0.0723	0.0663	0.0691	0.0002	0.0697	0.0724	0.0711
Stats(%)	Std. Dev	0.0827	0.1304	0.1140	0.1220	0.1403	0.2108	0.1731	0.1916	0.1055	0.1633	0.1340	0.1488
	Sum	2.2070	11.5264	14.3115	25.8379	-0.7535	18.0798	18.5598	36.6396	0.3358	18.4606	20.4889	38.9495
Test	Z-Stat		5.34	7.16	8.52		5.30	6.15	7.78		6.74	8.69	10.46
Diff.	P-value		0.00	0.00	0.00		0.00	0.00	0.00		0.00	0.00	0.00
Panel B: With Transaction Costs													
		Dow Jones				Nasdaq				S&P500			
		Non-	Trade			Non-	Trade			Non-	Trade		
		Trade	Short	Long	Total	Trade	Short	Long	Total	Trade	Short	Long	Total
	Obs	1732	245	271	516	1846	250	280	530	1983	265	283	548
Return	Mean	-0.0183	0.0277	0.0335	0.0307	-0.0335	0.0399	0.0338	0.0367	-0.0175	0.0520	0.0548	0.0534
Stats(%)	Std. Dev	0.0827	0.1298	0.1134	0.1214	0.1406	0.2085	0.1713	0.1896	0.1055	0.1628	0.1330	0.1480
	Sum	-31.6288	6.7933	9.0678	15.8611	-61.8433	9.9655	9.4644	19.4298	-34.7922	13.7684	15.5029	29.2713
Test	Z-Stat		5.3942	7.2152	8.60		5.3986	6.2615	7.92		6.7637	8.76	10.51
Diff.	P-value		0.0000	0.0000	0.00		0.0000	0.0000	0.00		0.0000	0.00	0.00

Figure 1. Jump Return Distribution Sampled at 1-minute Frequency

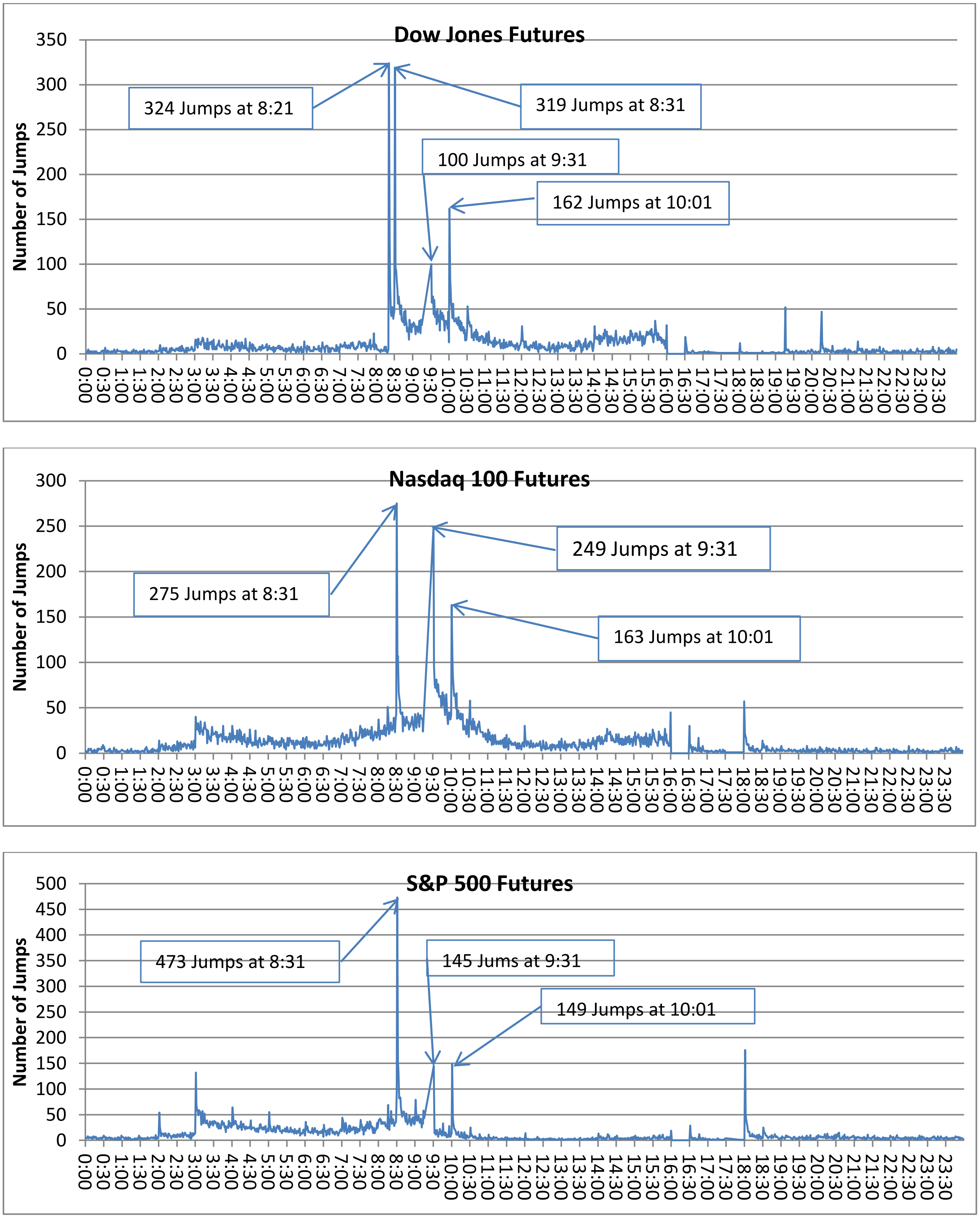


Figure 2. Year-by-year Comparison of 10:01-10:02 am Trade versus Non-Trade Returns from 10:00 am Announcements, without Transaction Costs

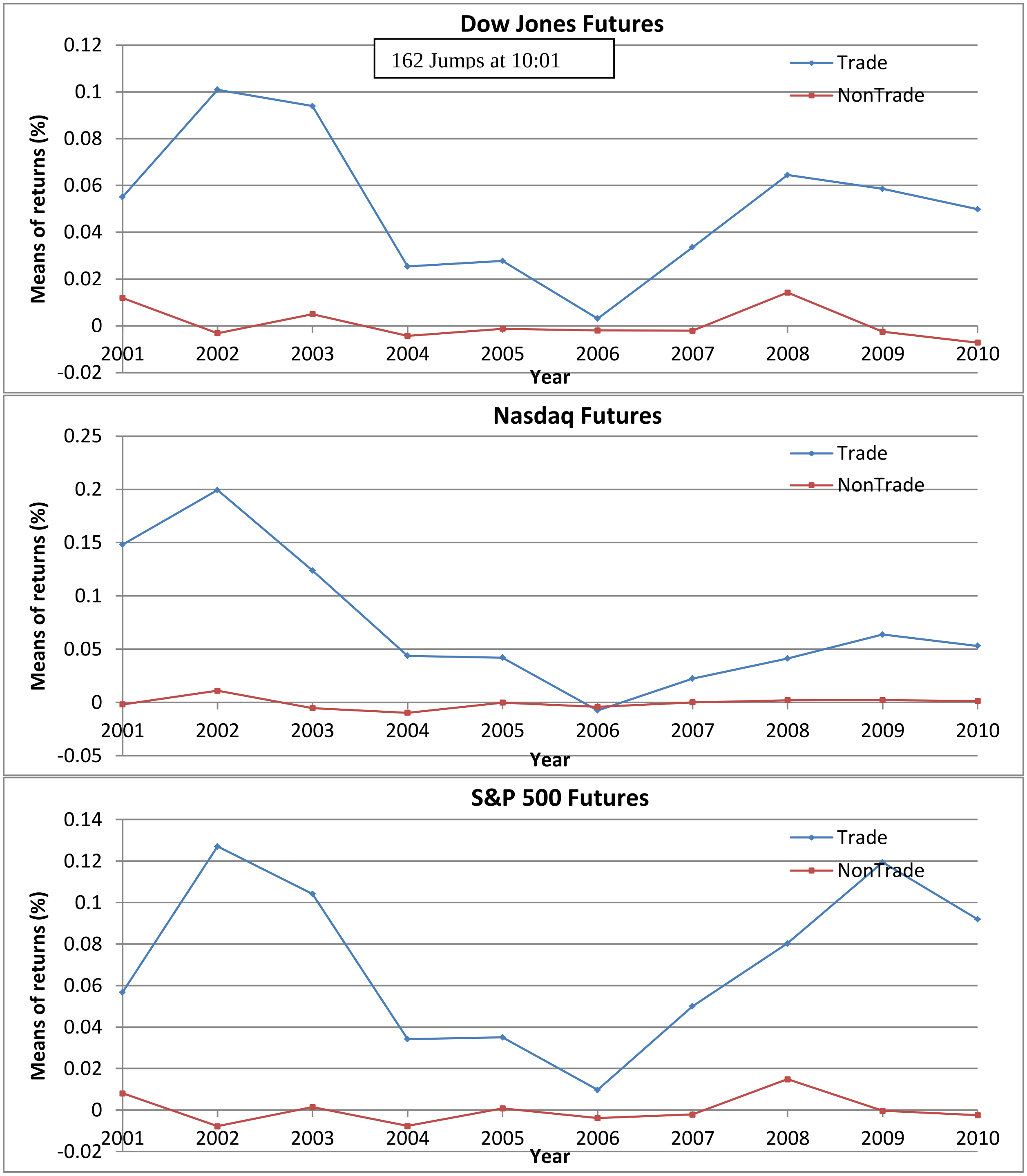


Figure 3. Year-by-year Comparison of 10:01-10:02 am Trade versus Non-Trade Returns from 10:00 am Announcements, with Transaction Costs

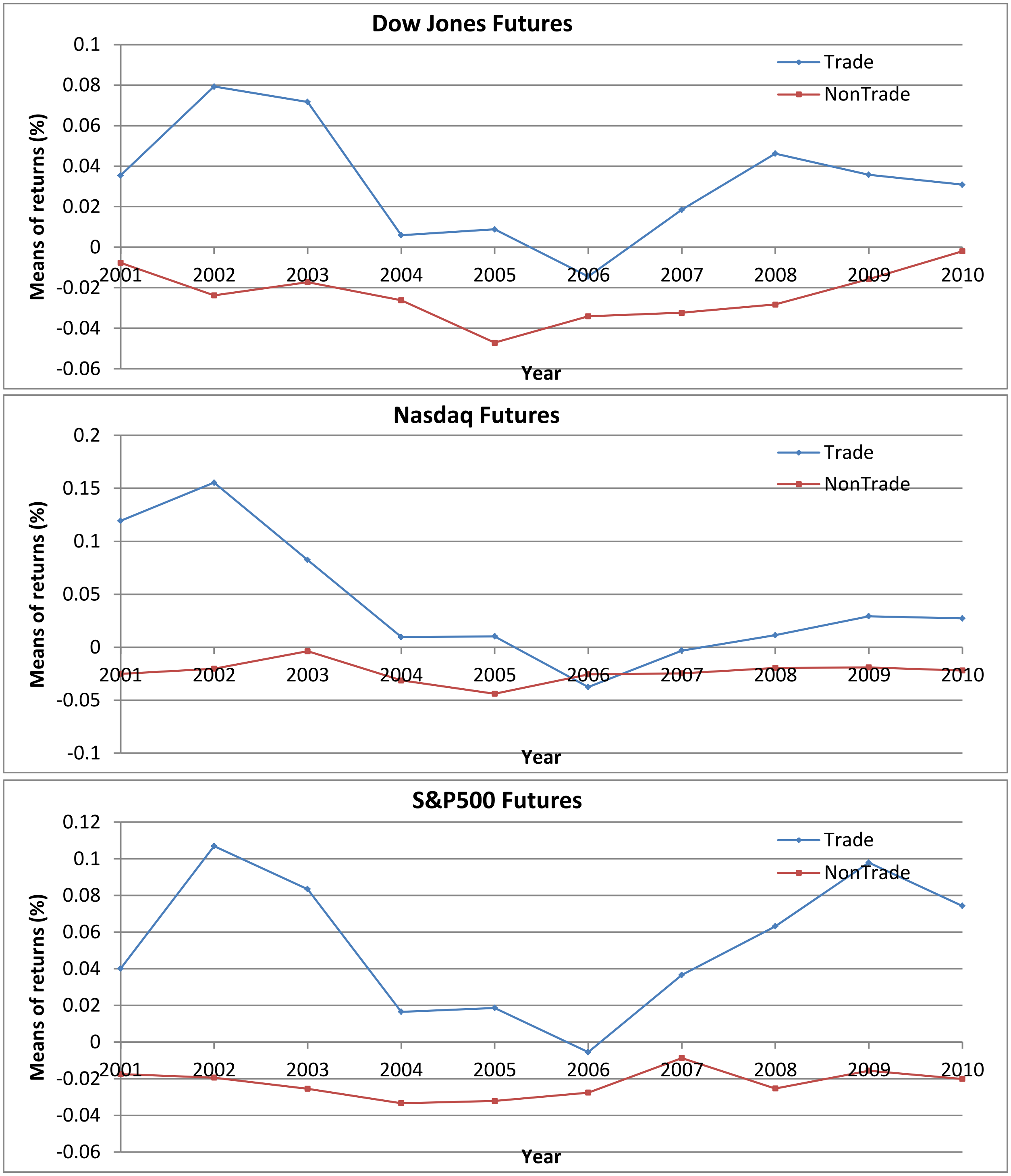
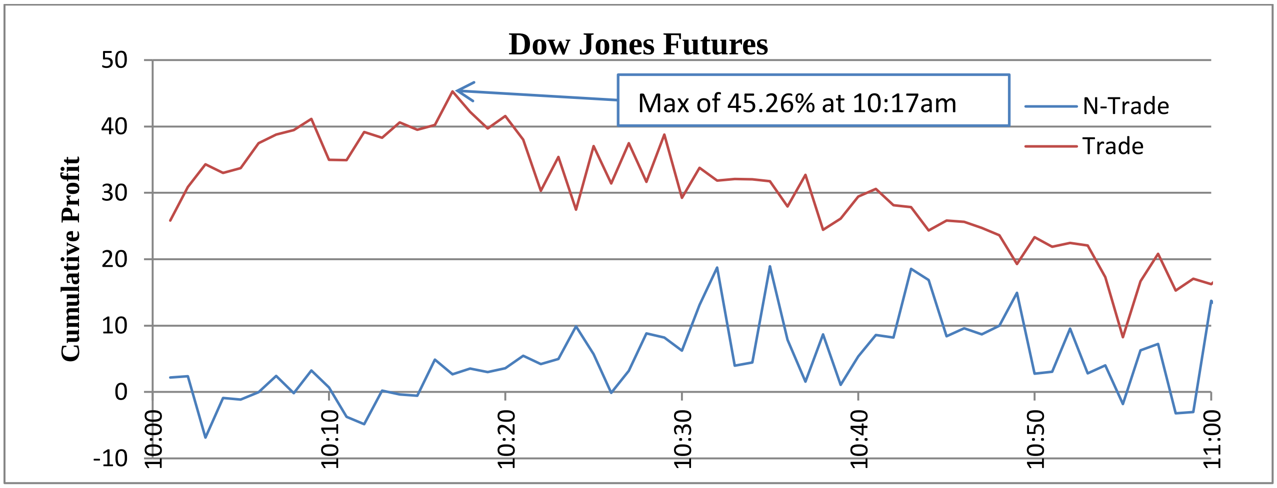
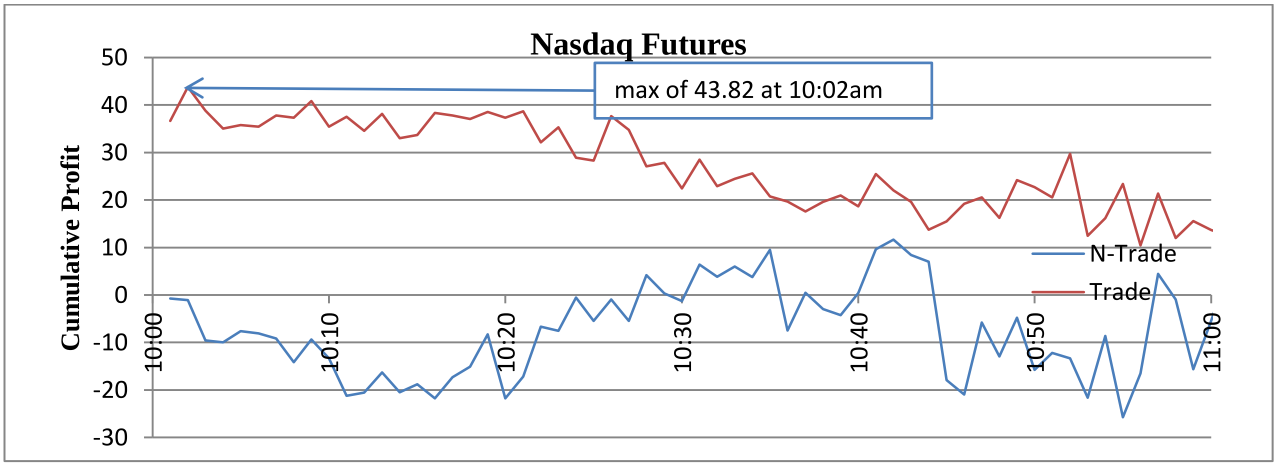


Figure 4. Minute-by-minute Cumulative Return Comparisons of Trade versus Non-trade Cumulative Returns (cumulated from the first transaction after 10:01 am) from 10:00 am Announcements, without Transaction Costs





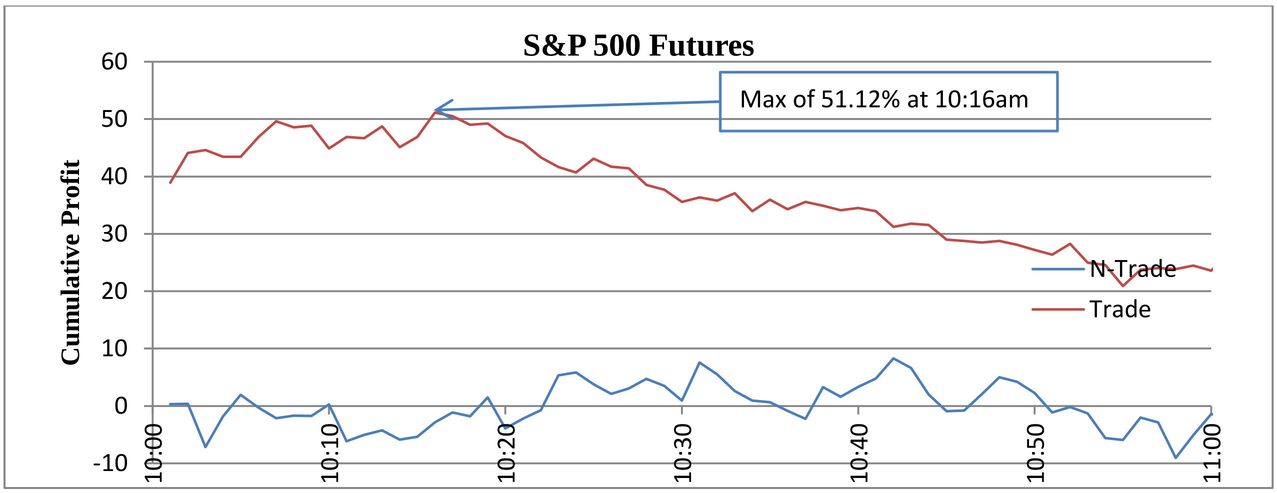


Figure 5. Cumulative Trading Profits (cumulated from the first transaction after 10:01 am) from Long and Short Positions Constructed from 10:00 am Announcements, without Transaction Costs

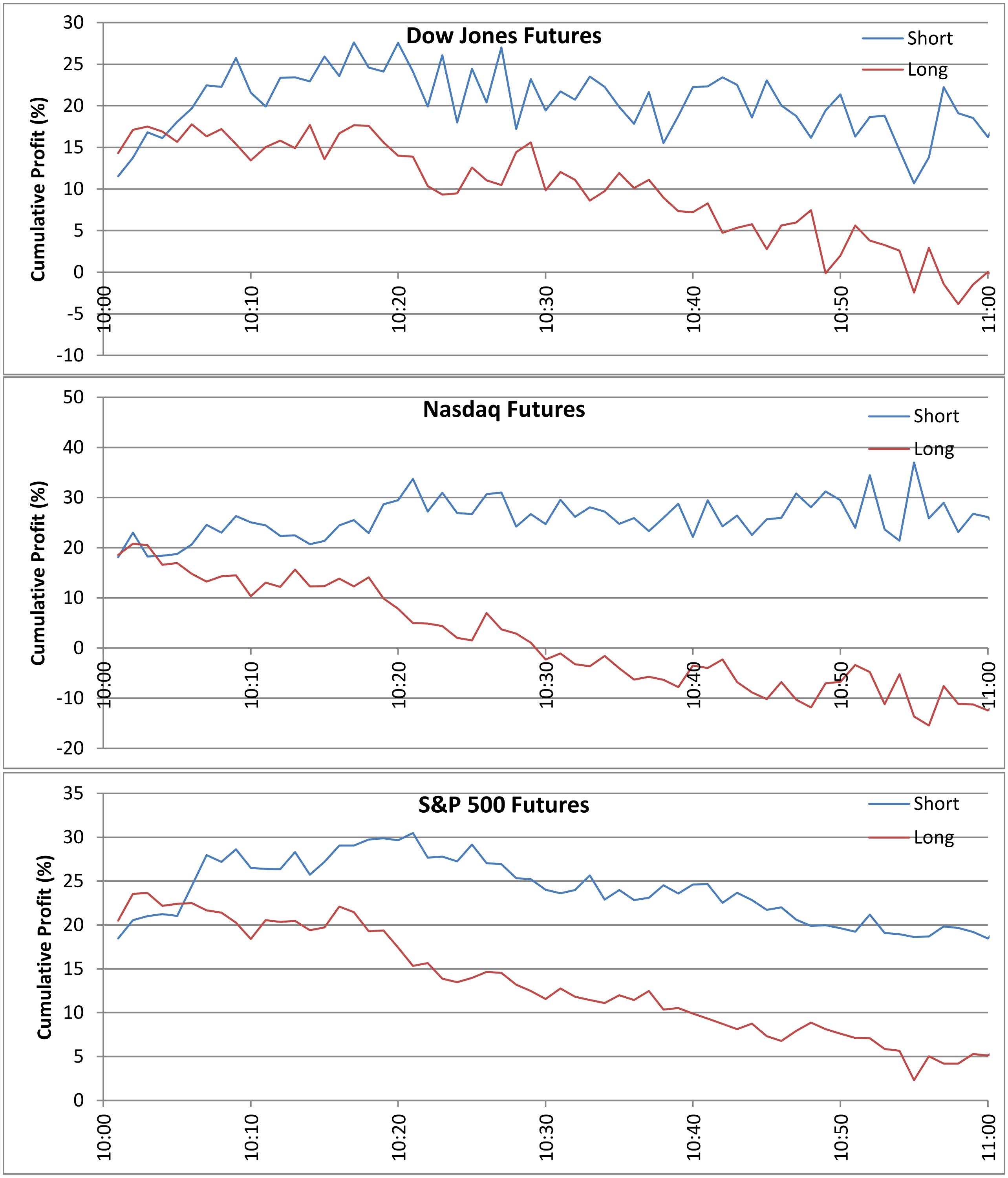


Figure 6. Minute-by-Minute Cumulative Return Comparison of Trade and Non-trade Cumulative Returns (cumulated from the first transaction after 8:31 am) from 8:30 am Announcements, without Transaction Costs

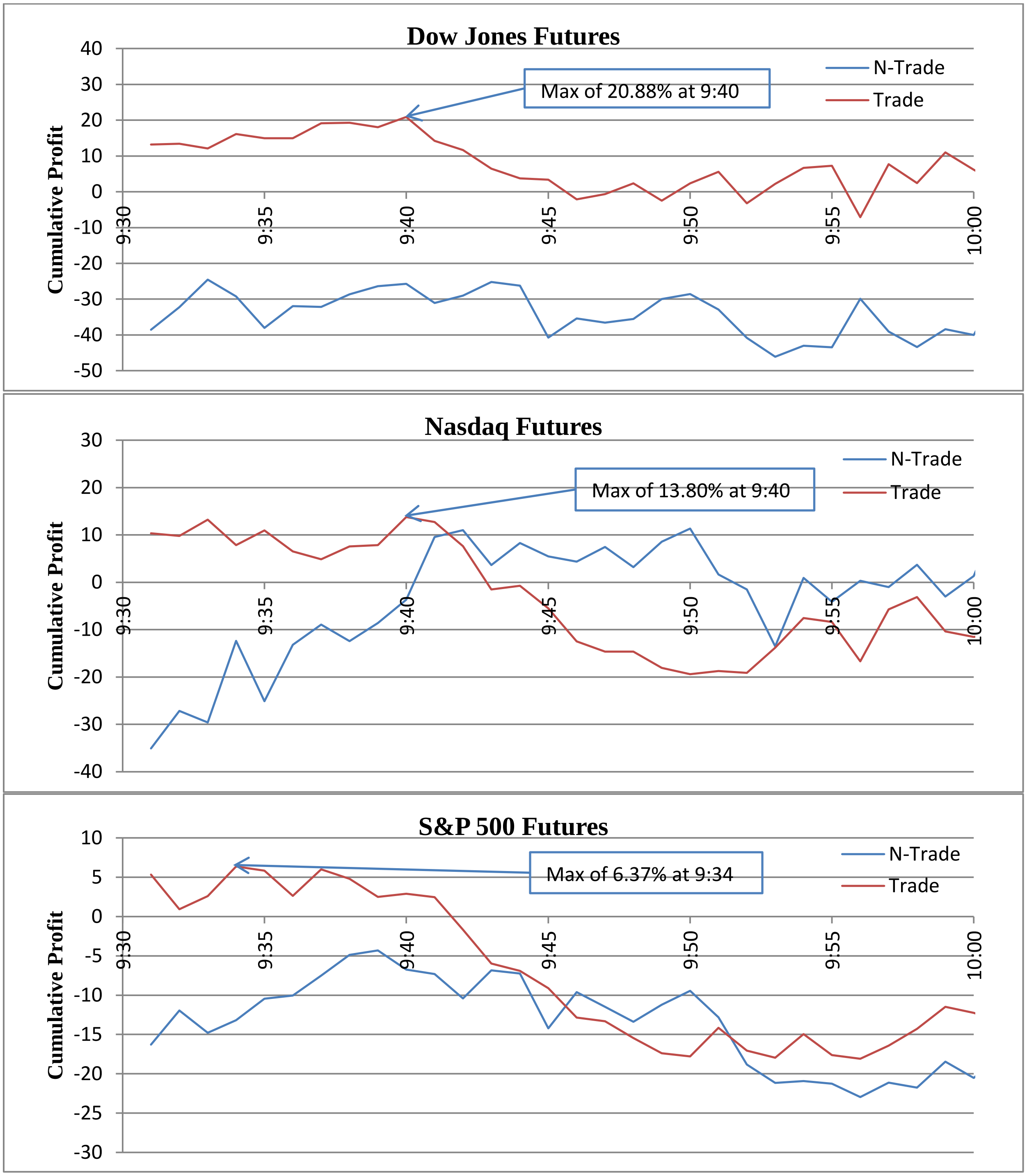


Figure 7. Minute-by-Minute Cumulative Return Comparison of Long versus Short Positions (cumulated from the first transaction after 8:31 am) from 8:30 am Announcements, without Transaction Costs

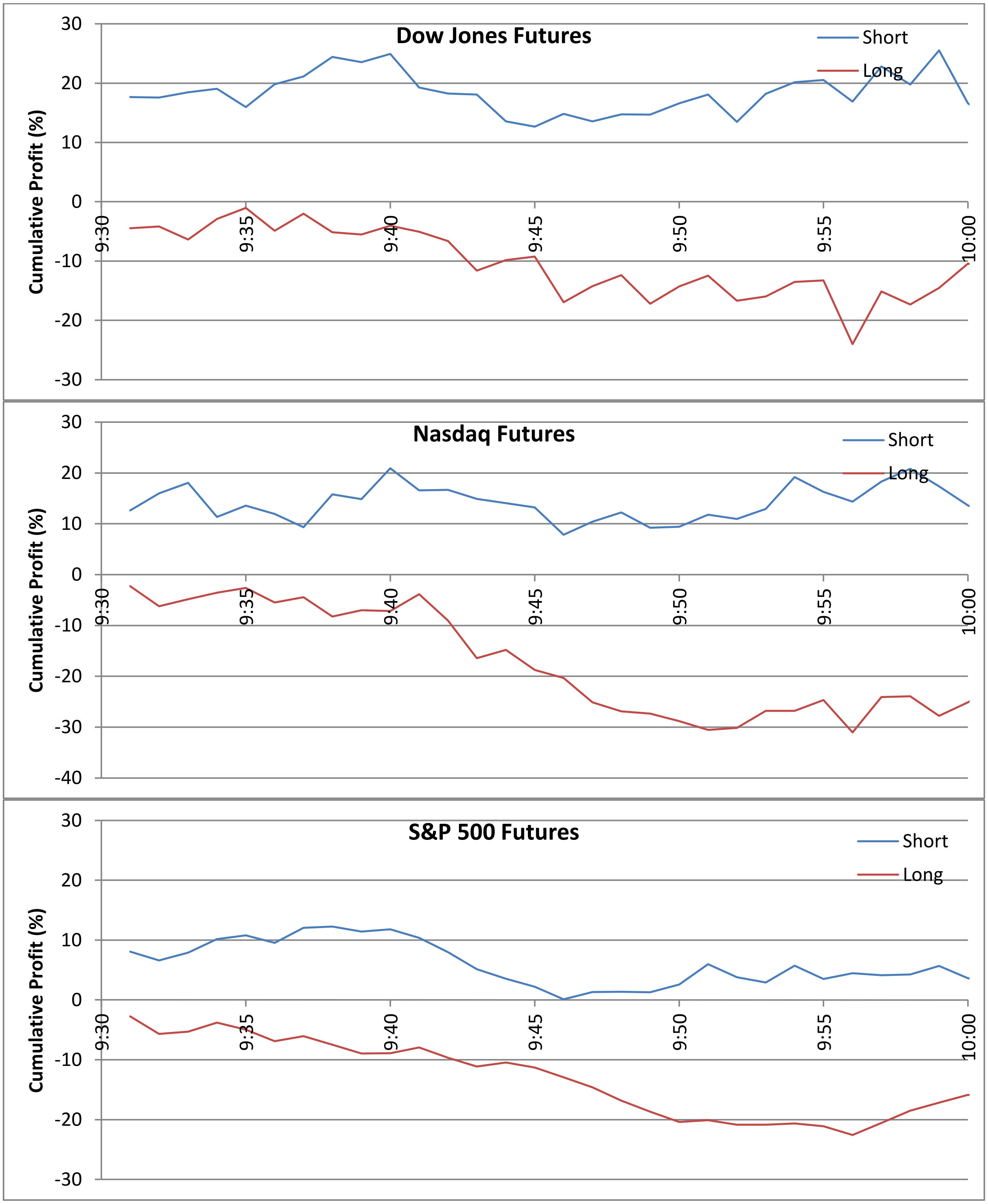


Figure 8. Year-by-Year Cumulative Comparison of Trade versus Non-Trade Mean Returns (cumulated from the first transaction after 8:31 am to the last transaction at 9:31am) from 8:30 am Announcements, without Transaction Costs

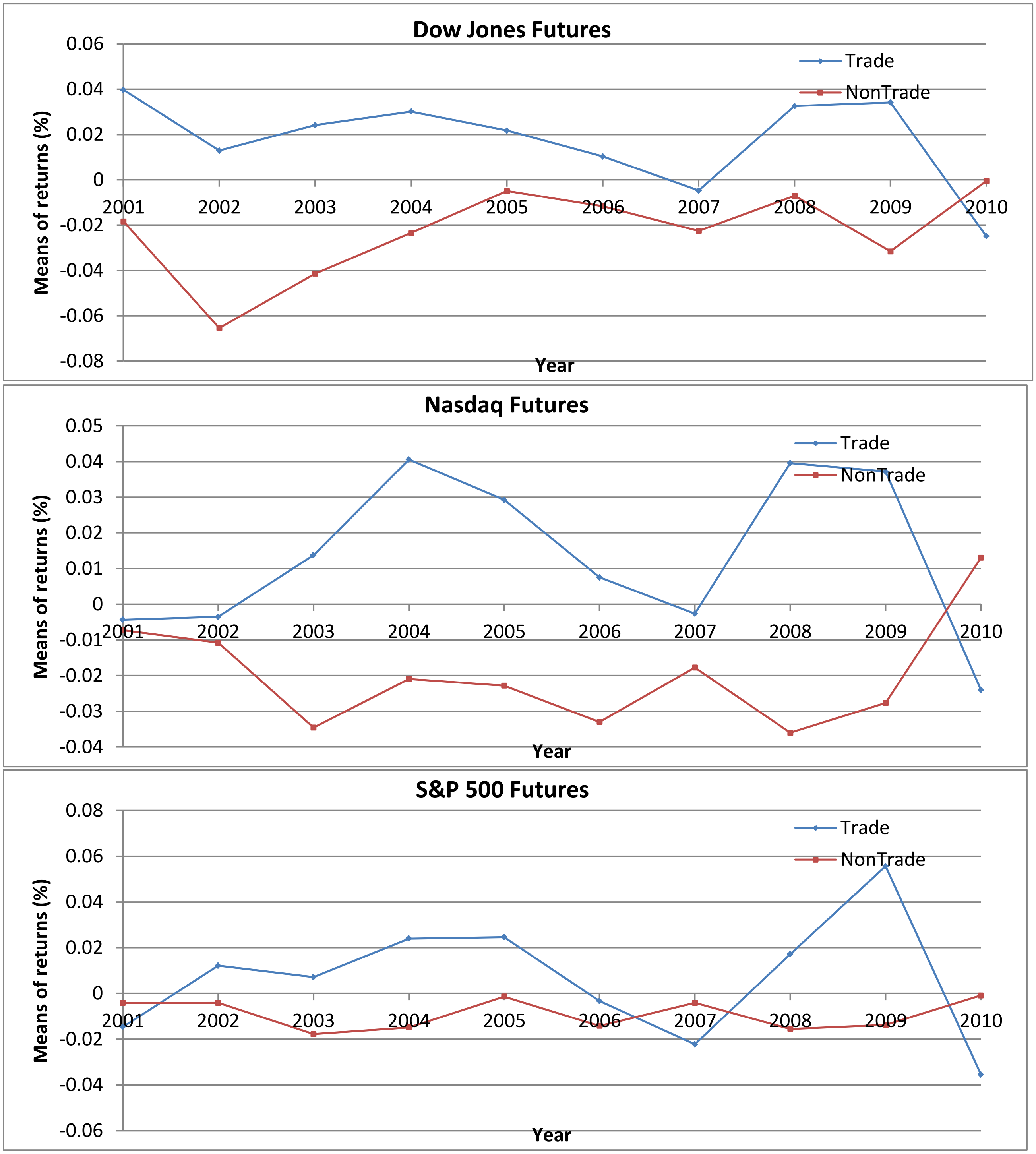


Figure 9. Year- by-Year Cumulative Return Comparisons of Trade versus Non-Trade Mean Returns (cumulated from the first transaction after 8:31 am to the last transaction at 9:31am) from 8:30 am Announcements, with Transaction Costs