

Macroeconomic News Announcements, Financial Market Volatility and Jumps*

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Abstract: This paper studies the financial market responses to macroeconomic news announcements, in the form of volatility and jumps. The traditional empirical literature using daily or lower-frequency data finds mixed or relatively weak evidence of big price movements during the announcement periods, which seems to falsify the efficient market hypothesis. However, with the advance of high frequency data, recent literature has discovered some links between macroeconomic news announcements and financial market responses. This paper extends the recent literature by separating market responses into continuous volatility and discontinuous jumps using some recent jump detection test statistics, and differentiating the market's disagreement based on survey data and uncertainty based on economic derivatives. Using more than a decade of high-frequency data, this paper finds that there are more large jumps on news days than on no-news days, with the fixed-income market being more responsive than the equity market, and nonfarm payroll employment being the most influential news. Surprises in forecasts impact the fixed-income market more than the equity market, while disagreement and uncertainty influence both markets with different effects on volatility and jumps.

Keywords: macroeconomic news announcements, market expectation, realized variance, bipower variation, jumps, economic derivatives.

JEL classification: C5, F3, F4, G14.

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1 Introduction

When macroeconomic news announcements bring new information to the financial market, will the market respond? If so, how does it respond? If not, what are the likely reasons? Answers to these questions not only are of great theoretical interest, as they can directly buttress or falsify the efficient market hypothesis in financial economics, and may be useful for studying various macroeconomic questions, but also have important practical implications.

This paper addresses the above questions by separating market responses into continuous volatility and discontinuous jumps, and differentiating the market's disagreement and uncertainty about the future news release values. I discover significant impacts of macroeconomic news announcements on financial markets, as well as different effects of disagreement and uncertainty on market volatility and jump responses to news announcements.

There is a vast literature studying macroeconomic news announcements and the financial market responses. For the equity market, the empirical evidence in the 1980s and early 1990s, based on monthly or daily data, is mixed and relatively weak. Cutler, Poterba and Summers (1989) find little evidence that the fifty largest daily S&P 500 index returns are linked to important announcements or events from 1946 to 1987, though they detect a negative effect of the inflation rate on the common stock returns. However, Schwert (1981), Pearce and Roley (1985), and Hardouvelis (1987) find a negative effect of monetary policy surprises on stock prices, while inflation surprise has a limited impact. Surprises in real activity announcements, such as industrial production and the unemployment rate, do not turn out to be significant in Pearce and Roley (1985), but the unemployment rate, trade deficit and personal income are significant in Hardouvelis (1987). In the joint study of market price, volatility, and economic events, Haugen, Talmor and Torous (1993) find negative and asymmetric responses of market price to volatility changes, but they can only identify 28 out of 217 volatility increase periods and 18 out of 224 volatility decrease periods associated with events. Similarly, Fair (2002) only identifies events for 69 days out of 220 days with at least one "large" 1- to 5-minute price change on S&P 500 futures, among which 53 days are related to monetary policy.

In contrast, Jain (1988) uses only the hourly data around the announcement time and shows both monetary and inflation surprises are significant. On the other hand, after controlling for different states of the economy, McQueen and Roley (1993) find a stronger relationship between stock prices and news based on daily stock and bond data. When real activity goes up, including higher industrial production and lower unemployment rate, stock price goes down in the strong economy while up in the weak economy. Other economic news, including trade deficit, inflation and money supply, has statistically the same negative impact on stock price across different states of the economy. Nevertheless, they can explain only a small fraction of the daily S&P 500 index variance.

More recently, in the joint study of stock, bond and foreign exchange markets using high frequency data, Andersen, Bollerslev, Diebold and Vega (2005) find similar asymmetric but stronger stock market responses to news announcement surprises. They attribute this phe-

nomenon to the competing impacts of “cash flow” and “discount rate” in the asset evaluation. This provides an explanation for the seemingly weak link between news announcements and stock market responses when averaging across the expansion and recession periods.

In terms of response speed, Pearce and Roley (1983, 1985) and Jain (1988) find that the stock price response essentially completes in the trading day or one hour after the announcements, consistent with the efficient market hypothesis, while Schwert (1981) shows small magnitudes of reaction in days following the announcements. In more recent literature, Wongswan (2005) finds that announcement surprises induces large but short-lived increases in volatility within thirty minutes of the announcements. This likely explains why it is hard to find a link between announcements and volatility using low-frequency data.

For the bond market, the empirical evidence is more affirmative. Grossman (1981), Urich and Wachtel (1981), Bradford (1982, 1983), Roley (1983), Hardouvelis (1988), and Strongin and Tarhan (1986) find significant impacts of surprises in money supply announcements during the 1970s and early 1980s period, while Harvey and Huang (1993) detect volatility increases within 15 minutes of the announcements. In more recent literature, Fleming and Remolona (1997) show that, for the five-year Treasury note, each of the 25 sharpest price changes from 8/23/1993 to 8/19/1994 is on an announcement day, among which 24 changes are within 15 minutes of announcement releases. Each of the 25 greatest trading volume surges is also on an announcement day. Moreover the surprise component of a given announcement affects price but not trading volume, while market uncertainty induces greater price movements and even stronger volume responses.

This paper extends the literature in two directions. First, it differentiates market responses into volatility coming from the continuous price movements often known as diffusion, and jumps from the discrete price movements, and studies them at the same time. In particular, jump in this paper is defined in the formal statistical sense, instead of price movements over certain threshold, as traditionally used in literature. As diffusion and jumps are two distinct dynamic processes, they exhibit quite different patterns in response to news releases.

Of course, when we model the price movement as a jump-diffusion process, both jumps and volatility are unobservable. The powerful toolkit of jump detection test statistics introduced by Barndorff-Nielsen and Shephard (2004, 2006) makes it possible to separate the jump component from the continuous volatility. Then using realized measures based on high-frequency data, we can turn the latent jumps and volatility into observable time series, and study their dynamics during the announcement periods.

The second direction is to differentiate the market’s disagreement based on survey data and uncertainty based on economic derivatives, which are options on the future values of some macroeconomic data releases. The traditional literature uncovers the market’s expectation about future announcement release values using survey data, mostly from Money Market Services (MMS). This data set also provides the variance of the surveys. However, such variance conveys only the disagreement among economic agents about the release values, rather than the uncertainty, that is, the second moment of a representative agent in the

market. The two concepts may be related, but can be quite different, too, because it is possible that the distribution of the representative agent is quite centered, but the surveyed forecasters are selected from very different points of the distribution curve, resulting in large survey variance. See Gürkaynak and Wolfers (2006) for further evidence on the difference between disagreement and uncertainty. Therefore, it will be interesting to see how these two different measures affect market responses.

To measure the uncertainty of a representative agent, this paper uses the economic derivatives, first introduced by Goldman Sachs and Deutsche Bank in October 2002, and now traded in Chicago Mercantile Exchange as well as some online markets. In fact, by taking the difference of put or call prices on adjacent strike prices, we can recover the whole risk-neutral forecast probability distribution curve of the possible outcomes of the future release value.

The empirical findings of this paper are based on more than a decade of high-frequency futures data for the S&P 500 index and US 30-Year Treasury Bond, together with MMS survey data and economic derivative data. This paper finds that there are statistically significantly more large jumps on news days than on no-news days, with the fixed-income market being more responsive than the equity market, and nonfarm payroll employment being the most influential news. Surprises in forecasts impact volatility and jumps in the bond market more than the equity market, while disagreement and uncertainty influence both markets with different effects on volatility and jumps.

The rest of this paper is organized as follows. Section 2 sets up the notation, and defines volatility and jumps studied in this paper. Section 3 describes the data used in this paper. Section 4 provides initial empirical evidence of market responses to news announcements. Section 5 compares the market volatility and jump responses to news surprises when market forecasts are measured by survey and economic derivative data respectively. Finally, Section 6 concludes the paper and provides some directions for future research.

2 Volatility and Jumps Definitions

To understand how market volatility and jump respond to news announcements, it is necessary to give proper definitions for these two components of the price process first. In this paper, the logarithmic asset price $p(\tau)$ is assumed to follow the jump-diffusion process defined by the following stochastic differential equation:

$$dp(\tau) = \mu(\tau)d\tau + \sigma(\tau-)dw(\tau) + \kappa(\tau)dq(\tau), \quad (1)$$

where $\tau \in \mathbb{R}^+$. The time scale is normalized such that one time unit corresponds to one trading day. $\mu(\tau)$ is the drift term with a continuous and locally finite variation sample path. $\sigma(\tau) > 0$ is the spot volatility process, assumed to be càdlàg. $w(\tau)$ is a standard Brownian motion. $\kappa(\tau)dq(\tau)$ refers to the pure jump part, where $dq(\tau) = 1$ if there is a jump at time τ and 0 otherwise, and $\kappa(\tau)$ represents the jump size.

Correspondingly, the within-day geometric returns are defined as

$$r_{t,j} = p(t - 1 + j/M) - p(t - 1 + (j - 1)/M), \quad j = 1, 2, \dots, M \quad (2)$$

where $t \in \mathbb{N}^+$ represents the trading day, and M refers the number of intraday returns over a trading day.

The volatility over the trading day t is measured by the quadratic variation of the price process

$$QV_t = \int_{t-1}^t \sigma^2(s)ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2. \quad (3)$$

The first term is the integrated variance term from the continuous-sample-path part, and the second term is the quadratic variation from the discrete jump part, with N_t equals the number of jumps on day t .

As QV_t and its different components are not directly observable, some model-free non-parametric consistent measures based on high frequency data are used in this paper. The first one is the now familiar realized variance, which consistently estimates the QV_t when the sampling interval goes to zero, as noted in Andersen and Bollerslev (1998), Comte and Renault (1998), Andersen, Bollerslev, Diebold and Labys (2001, 2003), and Barndorff-Nielsen and Shephard (2002a,b), among others.

$$RV_t(M) = \sum_{j=1}^M r_{t,j}^2 \xrightarrow[M \rightarrow \infty]{P} \int_{t-1}^t \sigma^2(s)ds + \sum_{j=1}^{N_t} \kappa_{t,j}^2. \quad (4)$$

To separately measure the volatility and the jump parts, Barndorff-Nielsen and Shephard (2004, 2006) introduce the realized bipower variation

$$RBV(M)_{1,t} = \mu_1^{-2} \left(\frac{M}{M-2} \right) \sum_{j=3}^M |r_{t,j-2}| |r_{t,j}| = \frac{\pi}{2} \left(\frac{M}{M-2} \right) \sum_{j=3}^M |r_{t,j-2}| |r_{t,j}|. \quad (5)$$

where

$$\mu_a = E(|Z|^a), \quad Z \sim N(0, 1), \quad a > 0.$$

There is an additional staggering term in the above bipower variation formula, relative to the one initially introduced by Barndorff-Nielsen and Shephard (2004). It helps to make the RBV measure together with the following jump detection test statistics robust under the influence of i.i.d. normal market microstructure noise. See Huang and Tauchen (2005) for some initial analytical investigations and Monte Carlo evidence. Under the assumption that the logarithmic price process is a continuous-time stochastic volatility semimartingale ($SVSM^c$) plus a finite-activity jump process, $RBV_{i,t}$ converges to the integrated variance as the sampling frequency goes to infinity

$$RBV_{1,t}(M) \xrightarrow[M \rightarrow \infty]{P} \int_{t-1}^t \sigma^2(s)ds. \quad (6)$$

Consequently, the difference between the realized variance and the realized bipower variation consistently estimates the quadratic variation of the jump component in the log price process

$$RV_t(M) - RBV_{1,t}(M) \xrightarrow[M \rightarrow \infty]{P} \sum_{j=1}^{N_t} \kappa_{t,j}^2. \quad (7)$$

Moreover, under the same regularity conditions, the test statistic

$$z_{RTQ,rm,t} = \frac{\frac{RV(M)_t - RBV(M)_{1,t}}{RV(M)_t}}{\sqrt{\left(\left(\frac{\pi}{2}\right)^2 + \pi - 5\right) \frac{1}{M} \max\left(1, \frac{RTQ(M)_t}{RBV(M)_{1,t}^2}\right)}}. \quad (8)$$

where

$$RTQ(M)_{1,t} = M \mu_{4/3}^{-3} \left(\frac{M}{M-6} \right) \sum_{j=1}^M |r_{t,j-4}|^{4/3} |r_{t,j-2}|^{4/3} |r_{t,j}|^{4/3}, \quad (9)$$

is asymptotically standard normally distributed under the null of no within-day jumps, and consequently may be used to test for significant jumps.¹

Based on the above jump detection test statistic, the realized quadratic variation of the jump components is measured by

$$J_t(M) = I(z_{RTQ,rm,t} > \Phi_\alpha) \cdot (RV_t(M) - RBV_{i,t}(M)), \quad (10)$$

where $I(\cdot)$ is the indicator function, equal to 1 if its argument is evaluated to be true, and 0 otherwise, while Φ_α refers to the critical value from the standard normal distribution in the upper α quantile. Accordingly, the realized measure for the integrated variance is defined as

$$C_t(M) = I(z_{RTQ,rm,t} \leq \Phi_\alpha) \cdot RV_t(M) + I(z_{RTQ,rm,t} > \Phi_\alpha) \cdot RBV_{i,t}(M), \quad (11)$$

which automatically ensures that the non-parametric measures for the jump and continuous components add up to $RV_t(M)$. This same decomposition of the within day variance is first studied by Andersen, Bollerslev and Diebold (2006). The actual implementation requires a choice of α . In most of the results reported below, I use the critical value of $\alpha = 0.99$, but very similar results were obtained for other critical values, which are available upon request.

3 Data

To study the market responses to news announcements, two types of data are needed. The first one is the market response data, and the second one is the news release values and the corresponding market forecasts or expectations.

¹Huang and Tauchen (2005) report extensive simulation evidence showing that the particular jump detection test statistic used here exhibits excellent size and power properties for a one-factor logarithmic stochastic volatility plus Compound Poisson jump process.

3.1 High-frequency Futures Data for Market Responses

This paper studies both the U.S. equity and fixed-income markets, and the corresponding market responses data are five-minutes returns on the S&P 500 index futures (SP, traded in Chicago Mercantile Exchange (CME)) and 30-year U.S. treasury bond futures (US, traded in Chicago Board of Trade (CBOT)).

The choice of five-minute sampling frequency is based on the balance between sampling as finely as possible for the asymptotic theory to work, and minimizing the impact of the market microstructure noise usually found in very high-frequency data. Tick data are converted into five-minute prices using the previous-tick method, that is, the last price observation in the previous five-minute interval is taken as the price of this five-minute mark; see Wasserfallen and Zimmermann (1985) and Dacorogna, Gencay, Müller, Olsen and Pictet (2001) for details on the previous-tick method.

As CME opens from 8:30 to 15:15 Central Time, or 9:30 to 16:15 Eastern Time, while many important news announcements, such as nonfarm payroll employment, are released at 8:30 Eastern Time, I extend the pit-traded price data by Globex to 8:25 Eastern Time. Hence there are 94 five-minute returns on each day for the S&P 500 index futures. Since Globex data became available from January 1994, the sample period for the S&P 500 index futures ranges from 1/3/1994 to 6/30/2005, for a total of $2857 \times 94 = 268558$ five-minute returns. On the other hand, as CBOT opens from 8:20 to 15:00 Eastern Time, the exchange-traded data is sufficient to cover the news announcements periods, so the sample period for US 30-year TB is relatively longer, from 11/7/1988 to 6/30/2005, for a total of $4108 \times 79 = 324532$ five minute returns. The data source for the exchange-traded data is Price-Data before February 2005, Globex and all the futures data from February 2005 on are from TickData.

Four different futures contracts mature every year, in March, June, September and December respectively, and each futures contract exists for no more than two years, so the different futures contracts have to be rolled over to construct a single futures price time series. I always use the most actively traded futures contracts, usually the one closest to its maturity, and roll over to the next contract five business days before the expiration day for the S&P 500 index futures, and the first business day in the delivery month for the US 30-Year treasury bonds. The same rollover method is also implemented in Andersen, Bollerslev and Huang (2006).

3.2 News Announcements and Market Forecast Data

Data on macroeconomic news announcement release values and the corresponding survey values are from the International Money Market Services (MMS). I collect 26 announcements as listed in Table 1, covering the 25 announcements studied in Andersen, Bollerslev, Diebold and Vega (2005), plus retail sales excluding autos, as it is one of the four major announcements that the economic derivatives are traded on. In this paper, different announcements have slightly different sampling periods, according to the availability of the

MMS survey data, but the four major announcements for the economic derivatives cover the full sample period of the 30-Year TB futures data.

Since the economic derivatives started trading only from October, 2002, their sample period is relatively short, ranging from 10/2002 to 6/2005. The four news announcements that the derivatives traded on are nonfarm payroll employment (NFPAY), the Institute of Supply Managements (formerly known as National Association of Purchasing Managers) manufacturing diffusion index (NAPM or ISM), percentage change in retail sales excluding autos (RSXAUT), and initial unemployment claims (ICLM). The economic derivatives data can be collected from the web page of Goldman Sachs, who initiated the auction trading of the economic derivatives together with Deutsche Bank.

4 Initial Evidence Linking Announcements and Jumps

To visualize the financial market responses to macroeconomic news announcements, figure 1 plots a typical announcement day. It is June 6, 1996, when the nonfarm payroll employment value was released at 340, while the survey expectation was only 170 with standard deviation 56.5. This news was quite out of the market expectation, and both S&P and US T-Bond reacted quickly and their price slumped right at the announcement time. Meanwhile, the jump detection test statistic discussed in Section 2 signals this day as a jump day for both markets. So we can be quite sure that the economic factor behind this jump day is the unexpected nonfarm payroll employment news release.

Of course, convincing evidence for the significant link between announcements and jumps comes from formal statistical tests. There are two directions we can approach this question, both of which have been used in the literature.

First, given each and all the news announcements, we can compute the proportion of the jump days. If news has no impact on jumps, then it is equally likely to observe jump days on news and no-news days. Consequently, we can use these two probabilities to form a test statistics. Specifically, let p_1 be the probability of jump days on the news days, and p_2 be the probability of jump days on the no-news days. Under the null of no link between news and jumps, $\hat{p}_1 - \hat{p}_2 \sim N(0, p_1(1 - p_1)/n_1 + p_2(1 - p_2)/n_2)$, where n_1 is the number of news days, and n_2 is the number of no news days, and the hat above p 's denotes estimated probabilities using sample proportions.

Table 2 reports the proportion of jump days in each of the news announcement days, as well as in the total news days and no-news days, together with the above test statistics computed from the two probability estimates, and one-sided p-values. The jump days are detected at the 99% significance level. It is apparent from the table that the proportions of jump days in many news announcement days are statistically significantly larger than those in no-news days for both S&P and US T-Bond markets, showing the significant impact of these news on jumps, especially nonfarm payroll employment, PPI, CPI, retail sales, initial unemployment claims, consumer credit and business inventories. Nonfarm payroll employment turns out to be the most influential news across different markets. The last

column in Table 2 is based on the cojump of S&P and US T-Bond, and the same significant impacts of news show up when the two markets jump together. Moreover, US T-Bond exhibits more sensitivity to news announcements than S&P does.

The second direction is to pick out the jump days, and find out how many of them can be associated with news announcement days. If news has no impact on jumps, then this proportion will be equal to the proportion of news days in the whole sample. Similar test statistics can be constructed as the above jump-on-news-days test. Table 3 reports such test statistics for jump days signaled at the 99% and 999% levels of significance. Again we can see strong evidence that there are statistically significantly larger proportions of news days in jump days than that in the whole sample, either for the individual equity or fixed-income market jumps, or for the co-jumps of the two markets.

5 News Surprises, Volatility and Jumps

It may be noticeable that although the news impacts on jumps are statistically significant, the proportions of jump days in the news announcement days are not very high in Table 2, and the proportions of news days in the jump days are not much larger than the overall proportions of news days in Table 3. This does not mean that the news impact is not economically significant. Rather, we have not fully explored the relationship between news and market responses.

There are a lot of news releases, around two-third of the days are news days, as can be seen from Table 3. However, many of them are within market expectations, and thus introduce not much new information to the market. As price is the discounted expected future cash flow, it is not supposed to move much at the expected news announcements. So we have to translate news announcements into surprises, and link surprises in news announcements to market responses, and see how volatility and jumps change during the announcement periods.

Following Balduzzi, Elton and Green (2006), and Andersen, Bollerslev, Diebold and Vega (2003, 2005), I define the standardized news surprise as

$$S_{kt} = \frac{A_{kt} - E_{kt}}{\hat{\sigma}_k} \quad (12)$$

where A_{kt} is the released value for news k on day t , E_{kt} is the mean of survey forecast or market-based forecast from the economic derivative, $\hat{\sigma}_k$ is the sample standard deviation of surprise $A_{kt} - E_{kt}$. The numerator translates announcements into surprises, while the denominator standardizes the surprises to ensure the comparability of coefficient estimates across different news and markets.

To study how volatility and jumps react to the surprises in news, the realized continuous volatility C_t and jump quadratic variation J_t discussed in Section 2 are regressed on the

standardized news surprises:

$$\begin{aligned}\log(C_t^h + 1) &= \alpha_{C,k}^h + \beta_{C,k}^h S_{kt}^{ED} + \gamma_{C,k}^h S_{kt}^S + \epsilon_{C,t}^h \\ \log(J_t^h + 1) &= \alpha_{J,k}^h + \beta_{J,k}^h S_{kt}^{ED} + \gamma_{J,k}^h S_{kt}^S + \epsilon_{J,t}^h\end{aligned}$$

I take logarithmic transformation of C and J so that the left-hand-side variables can cover the whole real line instead of only the positive quadrant, and their finite sample distribution can be better approximated by the normal distribution. The ED superscript means economic derivative, and S superscript means survey.

These regressions can be run on individual news as above. They can also be run on all the news jointly as follows:

$$\begin{aligned}\log(C_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{C,k}^h + \beta_{C,k}^h S_{kt}^{ED} + \gamma_{C,k}^h S_{kt}^S + \epsilon_{C,t}^h \\ \log(J_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{J,k}^h + \beta_{J,k}^h S_{kt}^{ED} + \gamma_{J,k}^h S_{kt}^S + \epsilon_{J,t}^h\end{aligned}$$

Table 4 reports the coefficient estimates together with their White heteroskedastic robust standard error for the individual news surprise regression. As economic derivatives were traded only on four economic news announcements in October 2002, I only compare the regression results on the four corresponding survey data. The last column of Table 4 reports the p-value of the joint test that all the news surprise coefficients are zero in the joint regression.

In line with the finding in Section 4, news surprises impact the bond market statistically significantly, both in terms of volatility and jumps, even though each individual news announcement may not always be significant. In comparison, the equity market is not very significantly affected by the news surprises, as any factor influencing either cash flow or discount rate can affect the equity market.

The above analysis uses the first moment of the market forecast for the news release values. However, market response to news surprise can be affected by the second moment, that is the disagreement among the individual economic agents measured by the standard deviation of the survey forecast, and the uncertainty of the representative agent measured by the standard deviation of the probability distribution recovered from the economic derivative prices. So I run similar individual regressions of C and J on these standard deviations. The individual regressions are:

$$\begin{aligned}\log(C_t^h + 1) &= \alpha_{C,k}^h + \beta_{C,k}^h SD_{kt}^{ED} + \gamma_{C,k}^h SD_{kt}^S + \epsilon_{C,t}^h \\ \log(J_t^h + 1) &= \alpha_{J,k}^h + \beta_{J,k}^h SD_{kt}^{ED} + \gamma_{J,k}^h SD_{kt}^S + \epsilon_{J,t}^h\end{aligned}$$

and the joint regressions are:

$$\begin{aligned}\log(C_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{C,k}^h + \beta_{C,k}^h SD_{kt}^{ED} + \gamma_{C,k}^h SD_{kt}^S + \epsilon_{C,t}^h \\ \log(J_t^h + 1) &= \sum_{k \in \text{Economic series}} \alpha_{J,k}^h + \beta_{J,k}^h SD_{kt}^{ED} + \gamma_{J,k}^h SD_{kt}^S + \epsilon_{J,t}^h\end{aligned}$$

where SD is the standard deviation from economic derivatives or survey.

Table 5 reports the coefficient estimates together with their White heteroskedastic robust standard error for the individual uncertainty and disagreement regressions. The last column of Table 5 reports the p-value of the joint test that all the coefficients are zero in the joint regression. Interestingly, uncertainty and disagreement turn out to be statistically significant for both equity and fixed-income markets, with slightly different roles for different markets' volatility and jumps. Uncertainty is significant for both volatility and jumps in the equity market, while uncertainty affects the fixed-income market's volatility, and disagreement significantly influences its jumps.

The impacts of disagreement or uncertainty on market responses make economic sense. When the news release values are different from market forecast expectation, but the representative economic agent is not very sure about his or her expectation, or the individual agents disagree quite a lot on their forecasts, then the news surprises are not likely to increase volatility or induce big jumps in the prices. The effect of news surprises is the biggest, when the market players are quite sure about their expectation or there is strong consensus among themselves, while the release value turns out to be different from the market forecast. Of course, different markets can exhibit different ways of responses, either in volatility or in jumps, depending on the characteristics of the particular markets.

6 Conclusion

This paper studies the financial market responses to macroeconomics news announcements. It extends the literature in two directions. First, it differentiates market responses into continuous volatility and discontinuous jumps, and studies them at the same time. Second, in addition to news surprises in the first moment of the market forecast, this paper introduces disagreement and uncertainty in the second moment of the market forecast.

Based on high-frequency futures data of the U.S. equity and fixed-income markets, this paper detects a statistically significant link between news announcements and financial market jump responses, with the fixed-income market being the more responsive one and nonfarm payroll employment being the most influential news. Surprises in news releases also affect the fixed-income market more, while disagreement and uncertainty influence both markets with different effects on volatility and jumps.

There are several directions for future research. First, jumps detected in this paper are on a daily basis. As jumps are defined to be short-lived events, it will be of both theoretical and practical interest to discover the particular interval(s) within the trading day in which jumps occur. The sequential test proposed by Andersen, Bollerslev, Frederiksen and Nielsen (2006) provides a good starting point. Discovering the jump interval can reaffirm the link between the news announcement and market jump response if the jump takes place right after the announcement time.

Second, as jumps are controlled by jump occurrence and jump size, it will be interesting to see how news surprises impact these two components separately. Will big surprises in

news announcements increase the jump hazard rate for the future jump occurrence? Are jump sizes positively related to the sizes of the news surprises? Answers to these questions will help portfolio hedging and other risk management applications.

Last but not least, understanding how financial markets respond to news surprises has important policy implications, too. From the results reported in this paper, it is obvious that different news announcements have different levels of impact on jumps and volatilities. Further analysis along this line, such as how the direction of market responses changes over the business cycle, will provide guidance for the policy makers as they choose different fiscal and monetary policies to affect the economy during different phases of the economy.

7 References

- Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2003). “Micro Effects of Macro Announcements: Real-Time Price Discovery in Foreign Exchange.” *American Economic Review* 93, 38-62.
- Andersen, T. G., T. Bollerslev, F. X. Diebold, and C. Vega (2004). “Real-Time Price Discovery in Stock, Bond, and Foreign Exchange Markets.” PIER Working Paper No. 04-028; Simon School Working Paper No. FR 04-13.
- Andersen, T. G. and T. Bollerslev (1998). “Deutschemark-Dollar Volatility: Intraday Activity Patterns, Macroeconomic Announcements, and Longer Run Dependencies.” *Journal of Finance* 53, 219-265.
- Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2001). “The Distribution of Realized Exchange Rate Volatility.” *Journal of the American Statistical Association* 96, 42-55.
- Andersen, T. G., T. Bollerslev, F. X. Diebold, and P. Labys (2003). “Modeling and Forecasting Realized Volatility.” *Econometrica* 71, 579-625.
- Andersen, T. G., T. Bollerslev, and F. Diebold (2006). “Roughing it Up: Including Jump Components in the Measurement, Modeling and Forecasting of Return Volatility.” Working Paper, Duke University.
- Andersen, T. G., T. Bollerslev, P. H. Frederiksen, and M. Ø. Nielsen (2006). “Continuous-Time Models, Realized Volatilities, and Testable Distributional Implications for Daily Stock Returns.” Presented in Conference on Realized Volatility, Montréal, Canada.
- Andersen, T. G., T. Bollerslev, and X. Huang (2006). “A Semiparametric Framework for Modeling and Forecasting Jumps and Volatility in Speculative Prices.” Working Paper, Duke University.
- Balduzzi, P., E. J. Elton, and T. C. Green (2001). “Economic News and Bond Prices: Evidence from the U.S. Treasury Market.” *Journal of Financial and Quantitative Analysis* 36, 523-544.
- Barndorff-Nielsen, O. E. and N. Shephard (2002a). “Econometric Analysis of Realised Volatility and its Use in Estimating Stochastic Volatility Models.” *Journal of the Royal Statistical Society* 64, 253-280.
- Barndorff-Nielsen, O. E. and N. Shephard (2002b). “Estimating Quadratic Variation Using Realized Variance.” *Journal of Applied Econometrics* 17, 457-478.

- Barndorff-Nielsen, O. E. and N. Shephard (2004). "Power and Bipower Variation with Stochastic Volatility and Jumps." *Journal of Financial Econometrics* 2, 1-37.
- Barndorff-Nielsen, O. E. and N. Shephard (2006). "Econometrics of Testing for Jumps in Financial Economics Using Bipower Variation." *Journal of Financial Econometrics* 4, 1-30.
- Cornell, B. (1982). "Money Supply Announcements, Interest Rates, and Foreign Exchange." *Journal of International Money and Finance* 1, 201-208.
- Cornell, B. (1983). "The Money Supply Announcements Puzzle: Review and Interpretation." *The American Economic Review* 73, 644-657.
- Comte, F. and E. Renault (1998). "Long Memory in Continuous Time Stochastic Volatility Models." *Mathematical Finance* 8, 291-323.
- Cutler, D. M., J. M. Poterba, and L. H. Summers (1989). "What Moves Stock Prices?" *The Journal of Portfolio Management* 15, 4-12.
- Dacorogna, M. M., R. Gencay, U. Müller, R. B. Olsen, and O. V. Pictet (2001). *An Introduction to High-Frequency Finance*. London: AP Professional.
- Fair, R. C. (2002). "Events that Shook the Market." *Journal of Business* 75, 713-732.
- Fleming, M. J. and E. M. Remolona (1997). "What Moves the Bond Market?" *Frbny Economic Policy Review* 3, 31-50.
- Grossman, J. (1981). "The "Rationality" of Money Supply Expectations and the Short-Run Response of Interest Rates to Monetary Surprises." *Journal of Money, Credit and Banking* 13, 409-424.
- Gürkaynak, R. S. and J. Wolfers (2006). "Macroeconomic Derivatives: An Initial Analysis of Market-Based Macro Forecasts, Uncertainty, and Risk." NBER Working Paper No. W11929.
- Hardouvelis, G. A. (1987). "Macroeconomic information and stock prices." *Journal of Economics and Business* 39, 131-140.
- Hardouvelis, G. A. (1988). "Economic News, Exchange Rates and Interest Rates." *Journal of International Money and Finance* 7, 23-35 .
- Harvey, C. R. and R. D. Huang (1993) "Public Information and Fixed Income Volatility." Unpublished paper, Duke University.
- Robert A. H., E. Talmor, and W. N. Torous (1991). "The Effect of Volatility Changes on the Level of Stock Prices and Subsequent Expected Returns." *Journal of Finance* 46, 985-1007.

- Huang, X. and G. Tauchen (2005). "The Relative Contribution of Jumps to Total Price Variance." *Journal of Financial Econometrics* 3, 456-499.
- Hillebrand, E., G. Schnabl, and Y. Ulu (2006). "Japanese Foreign Exchange Intervention and the Yen/Dollar Exchange Rate: A Simultaneous Equations Approach Using Realized Volatility." Presented in Conference on Realized Volatility, Montréal, Canada.
- Jain, P. C. (1988). "Response of Hourly Stock Prices and Trading Volume to Economic News." *The Journal of Business* 61, 219-231.
- Krueger, A. B. (1996). "Do Markets Respond More to More Reliable Labor Market Data? A Test of Market Rationality." Unpublished paper, Princeton University.
- McQueen, G. and V. V. Roley (1993). "Stock Prices, News, and Business Conditions." *The Review of Financial Studies* 6, 683-707.
- Pearce, D. K. and V. V. Roley (1983). "The Reaction of Stock Prices to Unanticipated Changes in Money: A Note." *Journal of Finance* 38, 1323-1333.
- Pearce, D. K. and V. V. Roley (1985). "Stock Prices and Economic News." *Journal of Business* 58, 49-67.
- Prag, J. (1994). "The Response of Interest Rates to Unemployment Rate Announcements: is there a Natural Rate of Unemployment?" *Journal of Macroeconomics* 16, 171-184.
- Roley, V. V. (1983). "The Response of Short-Term Interest Rates to Weekly Money Announcements: Note." *Journal of Money, Credit and Banking* 15, 344-354.
- Schwert, G. W. (1981). "The Adjustment of Stock Prices to Information About Inflation.." *Journal of Finance* 36, 15-29.
- Strongin, S. and V. Tarhan (1990). "Money Supply Announcements and the Market's Perception of Federal Reserve Policy." *Journal of Money, Credit and Banking* 22, 135-153.
- Urich, T. and P. Wachtel (1981). "Market Response to the Weekly Money Supply Announcements in the 1970s." *The Journal of Finance* 36, 1063-1072.
- Wasserfallen W. and H. Zimmermann (1985). "The Behavior of Intraday Exchange Rates." *Journal of Banking and Finance* 9, 557-572.
- Wongswan, J.(2005). "Transmission of Information across International Equity Markets." *The Review of Financial Studies*, forthcoming.

8 Tables

Table 1: List of Macroeconomics News Announcements

BUSINV:	Business Inventories	ICLM:	Initial Unemployment Claims
CAPA:	Capacity Utilization	INDPRD:	Industrial Production
CCONF:	Consumer Confidence	LDERS:	Leading Economic Indicators
CONST:	Construction Spending	NAPM:	National Association of Purchasing Managers
CPI:	Consumer Price Index	NFPAY:	Nonfarm Payroll Employment
CREDIT:	Consumer Credit	NHOMES:	New Home Sales
DGORD:	Durable Goods Orders	PCE:	Personal Consumption Expenditures
FACORD:	Factory Orders	PERINC:	Personal Income
FFR:	Average Fed Funds Rate	PPI:	Producer Price Index
GDPADV:	GDP Advance	RETLS:	Retail Sales
GDPFIN:	GDP Final	RSXAUT:	Retail Sales excluding Auto
GDPPRE:	GDP Preliminary	TRDBAL:	Trade Balance
HSTART:	Housing Starts	TREBUD:	Treasury Budget

Table 2: Proportion of Jump Days in Announcement Days

Announcement	SP	US	Cojump
BUSINV	0.181<116>(1.633)[0.051]*	0.339<174>(3.193)[0.001]**	0.061<115>(1.632)[0.051]*
CAPA	0.162<136>(1.250)[0.106]	0.316<193>(2.750)[0.003]**	0.045<133>(1.154)[0.124]
CCONF	0.139<137>(0.593)[0.277]	0.323<164>(2.727)[0.003]**	0.044<135>(1.133)[0.129]
CONST	0.104<134>(-0.545)[0.707]	0.263<194>(1.311)[0.095]*	0.030<132>(0.429)[0.334]
CPI	0.232<138>(2.982)[0.001]**	0.307<199>(2.534)[0.006]**	0.080<138>(2.379)[0.009]**
CREDIT	0.244<131>(3.181)[0.001]**	0.326<193>(3.020)[0.001]**	0.107<131>(3.034)[0.001]**
DGORD	0.150<133>(0.924)[0.178]	0.298<188>(2.242)[0.012]**	0.039<129>(0.858)[0.195]
FACORD	0.170<135>(1.476)[0.070]*	0.249<193>(0.901)[0.184]	0.052<134>(1.443)[0.074]*
GDPADV	0.143< 42>(0.414)[0.339]	0.435< 62>(3.385)[0.000]**	0.119< 42>(1.901)[0.029]**
GDPFIN	0.217< 23>(1.123)[0.131]	0.182< 22>(-0.446)[0.672]	0.000< 22>(-4.637)[1.000]
GDPPRE	0.091< 22>(-0.468)[0.680]	0.286< 21>(0.674)[0.250]	0.095< 21>(1.116)[0.132]
HSTART	0.176<136>(1.639)[0.051]*	0.221<195>(0.052)[0.479]	0.052<134>(1.443)[0.074]*
ICLM	0.179<581>(3.068)[0.001]**	0.258<705>(1.963)[0.025]**	0.064<575>(3.572)[0.000]**
INDPRD	0.162<136>(1.250)[0.106]	0.311<193>(2.614)[0.004]**	0.045<133>(1.154)[0.124]
LDERS	0.094<138>(-0.953)[0.830]	0.246<195>(0.830)[0.203]	0.029<137>(0.371)[0.355]
NAPM	0.119<134>(-0.021)[0.509]	0.243<181>(0.716)[0.237]	0.030<132>(0.429)[0.334]
NFPAY	0.356<132>(5.482)[0.000]**	0.547<192>(8.705)[0.000]**	0.200<130>(4.978)[0.000]**
NHOMES	0.118<136>(-0.081)[0.532]	0.241<191>(0.667)[0.253]	0.023<133>(-0.071)[0.528]
PCE	0.126<127>(0.189)[0.425]	0.267<187>(1.414)[0.079]*	0.049<123>(1.257)[0.104]
PERINC	0.125<128>(0.159)[0.437]	0.266<188>(1.378)[0.084]*	0.048<124>(1.247)[0.106]
PPI	0.228<136>(2.873)[0.002]**	0.411<192>(5.165)[0.000]**	0.137<131>(3.733)[0.000]**
RETLs	0.243<136>(3.200)[0.001]**	0.368<193>(4.080)[0.000]**	0.106<132>(3.025)[0.001]**
RSXAUT	0.250<136>(3.361)[0.000]**	0.364<184>(3.900)[0.000]**	0.114<132>(3.208)[0.001]**
TRDBAL	0.091< 33>(-0.569)[0.715]	0.232< 95>(0.284)[0.388]	0.030< 33>(0.223)[0.412]
TREBUD	0.138<130>(0.573)[0.283]	0.208<192>(-0.335)[0.631]	0.038<130>(0.847)[0.198]
FFR	0.108<120>(-0.386)[0.650]	0.270<248>(1.687)[0.046]**	0.042<118>(0.979)[0.164]
News	0.169<1949>	0.290<2783>	0.063<1924>
No-news	0.120< 908>	0.219<1325>	0.024< 892>
Total	0.154<2857>	0.267<4108>	0.051<2816>

The four elements in each cell are: the proportion of jump days in each of the news announcement days, the number of the news announcement or no-news days inside the angle brackets, the t-statistic inside the parentheses, and the one-sided p-value inside the square brackets. The t-statistic is computed under the null that news has no impact on jumps, thus the probability of the jump days in the respective news day is equal to the probability of the jump days in no-news days. Two asterisks mean the t-statistic is statistically significant at the 5% level, and one asterisk denotes statistical significance at the 10% level.

Table 3: Proportion of News Days in Jump Days

Asset	0.99 Sig. Jumps	0.999 Sig. Jumps	Overall
SP	0.752< 439>(3.106)[0.001]**	0.775< 231>(3.216)[0.001]**	0.682<2857>
US	0.735<1096>(3.815)[0.000]**	0.795< 575>(6.392)[0.000]**	0.677<4108>
Cojump	0.853< 143>(5.504)[0.000]**	0.939< 49>(7.228)[0.000]**	0.683<2816>

The four elements in each cell are: the proportion of the news days in the jump or co-jump days, the number of the jump or co-jump days inside the angle brackets, the t-statistic inside the parentheses, and the one-sided p-value inside the square brackets. The t-statistic is computed under the null that news has no impact on jumps, thus the probability of the news days in the jump days is equal to the overall probability of the news days. Two asterisks mean the t-statistic is statistically significant at the 5% level, and one asterisk denotes statistical significance at the 10% level.

Table 4: News Surprises, Volatility and Jumps

	NFPAY	NAPM	RSXAUT	ICLM	Joint
Panel 1: S&P 500, C					
Econ. Deriv.	0.481 (0.307)	-0.078 (0.245)	0.554 (0.272)	-0.013 (0.134)	p=0.381
Survey	-0.504 (0.301)	-0.073 (0.189)	-0.406 (0.224)	0.009 (0.124)	p=0.407
Panel 2: S&P 500, J					
Econ. Deriv.	-0.037 (0.171)	0.059 (0.106)	-0.120 (0.051)	0.014 (0.019)	p=0.448
Survey	-0.032 (0.189)	-0.043 (0.092)	0.138 (0.068)	-0.017 (0.021)	p=0.268
Panel 3: US 30-Year TB, C					
Econ. Deriv.	-0.199 (0.194)	-0.108 (0.126)	0.060 (0.130)	0.019 (0.046)	p=0.008**
Survey	0.187 (0.224)	0.127 (0.120)	-0.046 (0.109)	-0.027 (0.044)	p=0.027**
Panel 4: US 30-Year TB, J					
Econ. Deriv.	-0.614 (0.265)	0.006 (0.030)	-0.082 (0.040)	-0.015 (0.031)	p=0.000**
Survey	0.664 (0.270)	0.004 (0.027)	0.085 (0.036)	0.016 (0.029)	p=0.000**

This table reports the regression coefficients of C and J on standardized news surprise, together with the White standard deviations inside the parentheses. The p-value is from the joint test that all the news surprises coefficients are zero.

Table 5: Disagreement v.s. Uncertainty

	NFPAY	NAPM	RSXAUT	ICLM	Joint
Panel 1: S&P 500, C					
Econ. Deriv.	-1.126 (0.395)	0.639 (0.707)	-0.025 (0.539)	0.324 (0.251)	p=0.035**
Survey	0.744 (0.524)	-0.746 (0.348)	0.145 (0.349)	-0.108 (0.145)	p=0.238
Panel 2: S&P 500, J					
Econ. Deriv.	-0.454 (0.293)	0.358 (0.269)	0.132 (0.222)	0.002 (0.076)	p=0.001**
Survey	0.350 (0.453)	0.051 (0.088*)	-0.152 (0.145)	-0.009 (0.043)	p=0.057*
Panel 3: US 30-Year TB, C					
Econ. Deriv.	-0.616 (0.370)	0.284 (0.399)	-0.239 (0.145)	-0.108 (0.116)	p=0.000**
Survey	-0.455 (0.512)	-0.604 (0.383)	-0.012 (0.211)	-0.031 (0.060)	p=0.166
Panel 4: US 30-Year TB, J					
Econ. Deriv.	0.773 (0.466)	0.086 (0.148)	-0.115 (0.133)	0.104 (0.077)	p=0.727
Survey	-0.434 (0.793)	-0.006 (0.113)	0.014 (0.117)	0.025 (0.042)	p=0.003**

This table reports the regression coefficients of C and J on uncertainty from the economic derivative data, or disagreement from survey data, together with the White standard deviations inside the parentheses. The p-value is from the joint test that all the coefficients are zero.

9 Figures

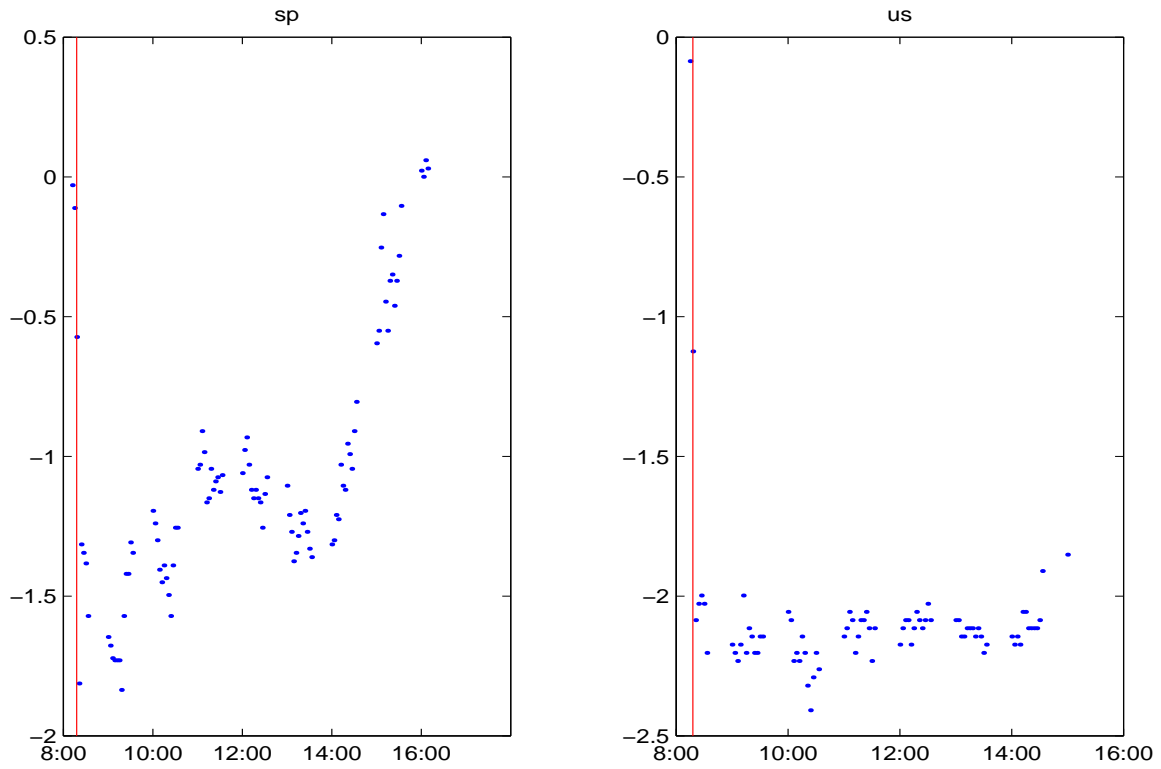


Figure 1: Logarithmic price plot on 6/7/1996. NFPAY: release value is 340, survey expectation is 170 with standard deviation 56.5. The dots are the prices, and the line is at 8:30 when the announcement was released.