Macroeconomic News Announcements, Systemic Risk, Financial Market Volatility and Jumps*

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April 2016

Abstract: This paper studies financial market volatility and jump responses to macroeconomic news announcements, incorporating the effect of financial systemic risk. Using high-frequency data, we finds that there are more jumps on news days than no-news days, with the bond market being more responsive than the equity market, and nonfarm payroll employment (NFPAY) being the most influential news. Uncertainty about news has stronger impact than disagreement. Equity market jumps and bond market volatility respond to NFPAY surprise, disagreement and their interactions with financial systemic risk. The zero-lower-bound (ZLB) policy constrains bond market responses. Financial systemic risk reduces bond market jump occurrences.

Keywords: macroeconomic news announcements, realized variance, jumps, disagreement and uncertainty, economic derivatives, financial systemic risk.

JEL classification: G12, G14, C5.

*I thank Tim Bollerslev, René Garcia, Clara Vega, Min Wei, Jon Wongswan, Jonathan H. Wright, and Hao Zhou, as well as participants of the 2006 NBER-NSF Time Series Conference in Montréal, the 2007 Conference on Volatility and High Frequency Data at the University of Chicago, the 2008 North American Summer Meeting of the Econometric Society, the Federal Reserve Board MFMA seminar, 19th SGF conference in Zürich for many helpful discussions of this paper. Will Kuchinski and Drew Pinta kindly provided support for news announcement release and survey data. The analysis and conclusions set forth are those of the author and do not necessarily represent those of the Board of Governors or its staff.

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1 Introduction

When macroeconomic news announcements bring new information to financial markets, will they respond? If so, how do they respond, in a continuous or discrete pattern? Do their responses change over time with different factors, such as business cycles, financial system stress level, or the monetary policy of zero lower bound?

Answers to these questions directly address the relationship between financial prices and economic fundamentals. For example, the answer to the first question can support or falsify the efficient market hypothesis. The answer to the second question not only contains theoretical interest, but also have important practical implications. Continuous price path allows for closed-form analytic solutions for many asset pricing and portfolio optimization problems, while discreteness in the price path, i.e. jumps, may render these solutions difficult. Moreover, jumps create discontinuities in the econometric objective functions, considerably increasing estimation difficulty. However, proper differentiation between the continuous component and jumps, if any, not only addresses the necessity of tackling the challenges imposed by jumps, but also may provide further insight into the first question. Different financial markets may respond to news in different patterns, and pattern separation can protect one type of response from being swamped by the other, so that we can observe the significant news impact, if any, more clearly. In view of the recent global financial and economic crisis, the level of financial systemic risk, which captures the stress level of the financial system, and the related monetary policy of zero lower bound could also be important in explaining market responses to macroeconomic news.

There has been a vast literature trying to address the first two questions, especially on market first-moment responses. Admittedly, detecting market responses to news announcements used to be a difficult task. Early empirical evidence based on monthly or daily data is mixed and relatively weak, especially for the equity market, which seems to falsify the efficient market hypothesis. Over time the literature discovers various factors contributing to such seemingly weak evidence and reveals more significant market responses to macroeconomic news announcements.

First, most of market responses are short-lived, so it can be hard to detect market responses using daily or other lower frequency data. For example, Jain (1988) finds that the stock price response essentially completes one hour after the announcements. Using intraday high-frequency data on interest rate spots and futures, and foreign exchange futures, Ederington and Lee (1993) find that most of the price adjustment to a major announcement occurs within the first minute, but volatility level can remain much higher than normal for fifteen minutes and slightly higher for several hours. Wongswan (2006) finds that announcement surprises induce large but short-lived increases in the volatility of the Korean and Thai equity markets within thirty minutes of the U.S. and Japanese announcements. The above evidence highlights the importance of using intraday data to study market responses to news.

Second, not all news announcements bring new information to markets. Markets should respond not to the expected announcements, but to the surprising component. So responses may look weak if we consider only the raw released value. Balduzzi, Elton, and Green (2001) propose using a z-type standardized measure to convert the raw released value into a news surprise value. They document significant and short-lived bond price responses to news surprises. This z-type measure has become popular in recent literature studying market responses to news.

Third, specific to the equity prices, there are two competing factors — cash flow and discount rate. The relative effects of a given news announcement on these two factors change over business cycles. For example, by controlling for different stages of the business cycle, and using the bond data to proxy the discount rate, McQueen and Roley (1993) find that higher industrial production and lower unemployment rate drive stock price down in a strong economy and up in a weak economy, because in a strong economy the discount rate increases more than the cash flow does, and the reverse happens in a week economy. Andersen, Bollerslev, Diebold, and Vega (2003, 2007) find similar results in their study of stock, bond and foreign exchange markets. The above findings explain the seemingly weak evidence in the early empirical study as the asymmetric responses of the equity market to news surprises can cancel each other if we average them over different business cycles.

Built upon the above wisdoms, this paper extends the literature in three directions. First, we separate market responses into a continuous component and a discrete component in a statistically rigorous way, as they have different theoretical and practical implications. This goal is accomplished through studying market second-moment responses — continuous volatility and discrete jumps, because rigorous statistical tests are based on the second instead of the first moment of the return processes. As jump detection and the measurement of volatility and jumps are nonparametric, we can study market second-moment responses independent of the first-moment.[1] Meanwhile, volatility and jumps are studied in the same framework so that their results are directly comparable. Second, to better explain market second-moment responses, we add, as explanatory variables, the second moments of news forecast to the first moment of news surprises commonly used in the literature, and differentiates between disagreement and uncertainty about the news. Finally, to incorporate the effect of the recent financial crisis, we introduce financial systemic risk of the recent global financial crisis into the framework, and consider the related monetary policy of zero lower bound (ZLB).

These extensions to the literature may not be easy, considering the latent nature of volatility, jumps, uncertainty and financial systemic risk. This paper draws on intraday high-frequency data, recent non-parametric jump detection tests, a special financial product, and a new systemic risk indicator to turn these latent processes into observable, and study market responses in a simple empirical framework.

As market responses to news are mostly short-lived, we need to go into intraday and detect these responses using high-frequency data. A number of studies have shown that futures markets lead cash markets in information discovery. See, for example, Kawaller, Koch, and Koch (1987). So this paper uses more than two decades of intraday data on S&P 500 index futures and 30-year U.S. Treasury bond futures to construct our measures of volatility and jumps.

In this paper, jump is defined in the formal statistical sense, instead of price movements over a certain threshold. In essence, both jumps and volatility are unobservable. The useful toolkit of jump detection test statistics proposed by Barndorff-Nielsen and Shephard (2004, 2006) makes it possible to separate discrete jumps from continuous volatility in the asymptotic setting when the price process can be observed continuously. Huang and Tauchen (2005) show that, under empirically realistic settings, the above asymptotic result works well in finite samples where we only observe discrete price processes. Then using realized measures based on high-frequency data, we can turn the latent jumps and volatility processes into observable time series, and study their dynamics during announcement days. Moreover, such

[1]This is helpful given the extensive study in the literature on market first-moment responses.

an event-study type of analysis also help to add economic intuition to the above statistically defined jumps and enhance our understanding of this potentially abstract concept.

Some recent papers have used similar jump test statistics to study the jumps or cojumps in financial market responses to news announcements. See, for example, Dungey, McKenzie, and Smith (2009), Jiang, Lo, and Verdelhan (2011), Lahaye, Laurent, and Neely (2011), and Lee (2012). As an extension to the literature , this paper studies both jumps and volatility responses to news announcement in the same framework, so that their results can be directly comparable.

In the study of news announcement impact on financial markets, a popular way in the literature to uncover the market's expectation for a future announcement value is to use survey data, such as those available from Money Market Services (MMS). The mean or median forecast is then compared to the released value to construct a measure of forecast error or news surprise. This is usually the news-related explanatory variable in the literature.

However, in addition to the forecast mean or median, MMS also provides the variance of the survey responses, which can also be utilized to explain the market volatility and jump responses. Of course, such a variance conveys only the disagreement among economic agents about the announcement value, rather than the uncertainty — the second moment of the forecast by a representative agent in the market. The two concepts may be related, but can be quite different: it is possible that the distribution of the representative agent's forecast is quite dispersed, but that the survey responses are selected from points on the distribution curve that are close to each other, resulting in a small survey variance. See Gürkaynak and Wolfers (2006) for further evidence on the difference between disagreement and uncertainty in this context. Therefore, it is interesting to see how these two different measures affect market responses separately.

To measure the uncertainty of a representative agent, this paper extracts information from a special financial product called economic derivatives. They were first introduced by Goldman Sachs and Deutsche Bank in October 2002, and were once traded in the Chicago Mercantile Exchange (CME) as well as in some online markets. They are mainly digital options on the future values of some important macroeconomic data releases, such as nonfarm payroll employment, retail sales excluding automobiles and initial unemployment claims. A trader take a position on whether the news announcement value will fall within a specific range (the strike range). On the exercise date when the official news is released, if the released value falls within the specific range, the option will pay the trader the face value. Otherwise, the option will expire valueless. By taking the difference of put or call prices on adjacent strike prices, we can recover the whole risk-neutral forecast probability distribution curve for the possible future announcement values. The standard deviation calculated from this distribution is our measure of uncertainty.

Since market's first-moment responses to news can vary over time, market's second-moment responses to news studied in this paper is also time-varying. In addition to the business cycle consideration as in McQueen and Roley (1993) and Andersen, Bollerslev, Diebold, and Vega (2007), this paper also incorporates the effect of the recent global financial crisis. Specifically, financial market responses to macroeconomic news can vary with macroeconomic conditions, but they can also change over time with financial system's own conditions. The business cycle effect captures the first aspect, while a financial systemic risk measure adapted in this paper captures the second aspect, which can be important given the recent global financial crisis. Goldberg and Grisse (2013) show that the first-moment responses of yield curves and exchange rates to news vary with the CBOE volatility index (VIX) and the Federal Fund rate. That is, both the risk level and the policy rate level affect market responses. Given that this paper studies how the equity and bond markets second-moment responses to news vary with different factors, to avoid the concern of putting the same variable on both sides of the regressions, we replace VIX by a systemic risk indicator that draws on the credit and equity markets information, instead of only on the equity or bond market information. Moreover, this indicator measures the left tail of the asset return distribution, instead of the second moment as captured by volatility or jumps.

The systemic risk indicator used in this paper is called Distress Insurance Premium (DIP). It is proposed and developed by Huang, Zhou, and Zhu (2009); Huang, Zhou, and Zhu (2012a); and Huang, Zhou, and Zhu (2012b). Conceptually, DIP is a hypothetical insurance premium against catastrophic losses in a financial system. Computationally, it is equal to the expected large default losses of a hypothetical portfolio consisting of all the liabilities of major financial institutions in the system. The higher the DIP value, the riskier or the more stressed the system is. As DIP is based on market data and can be updated at the weekly or even daily frequency, it can be easily incorporated into this study on the news announcement days, thus turning the latent systemic risk into an observable time series.[2]

To capture the effect of the policy rate level in the context of the recent global financial crisis, this paper incorporates the ZLB monetary policy. Swanson and Williams (2014) show that ZLB has different constraints on the responses of bond yields with different maturities. Since this paper studies both the equity and bond markets, and the bond maturity in this paper is much longer than those in Swanson and Williams (2014), it will be interesting to see whether the effect of the ZLB policy holds for a different type of market and for bonds with a longer maturity.

The main empirical findings of this paper are as follows. There are significantly more jumps on news days than no-news days, with the bond market being more responsive than the equity market, and NFPAY being the most influential news. Both volatility and jumps are affected by the first moment of news surprises and the second moments of disagreement and uncertainty. Their impact significance varies with different markets and different response styles. Relatively, uncertainty about news has stronger impact than disagreement. Market responses to news also vary with economic situations, financial systemic risk and the ZLB policy. In particular, equity market jumps and bond market volatility respond to NFPAY surprise, disagreement and their interactions with financial systemic risk. Bond market jumps also respond to NFPAY surprise. The ZLB policy constrains the bond market responses. Financial systemic risk reduces bond market jump occurrences.

The rest of this paper is organized as follows. Section 2 sets up the notation, and defines volatility and jumps. Section 3 describes the data used in this paper. Section 4 provides initial empirical evidence of market responses to news announcements. Section 5 studies market volatility and jump responses to news surprises, disagreement and uncertainty, and how they change over time. Finally, Section 6 concludes the paper and provides some directions for future research.

[2]We use DIP instead of the conventional risk indicators, such as the LIBOR-OIS spread, for two reasons. First, DIP draws on information from multiple markets, and explicitly accounts for the default risk of individual firms and the correlations among firms. Thus it is a more comprehensive measure and robust to the temporary malfunctions of one or two markets, such as a sudden liquidity dry-up. Second, Huang, Zhou, and Zhu (2012a,b) shows a significant and positive relationship between DIP and the LIBOR-OIS spread. So we believe the qualitative results will remain the same when DIP is replaced by other conventional risk indicators, but the results from DIP will be clearer.

2 Volatility and Jumps Definitions

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

$$p(t) = \int_0^t \mu(\tau)d\tau + \int_0^t \sigma(\tau)dw(\tau) + \sum_{i=0}^{N(t)} \kappa_i, \tag{1}$$

where $t \in \mathbb{R}^+$. 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. $\sum_{i=0}^{N(t)} \kappa_i$ refers to the pure jump component, where $N(t)$ is the number of jumps that have occurred between time 0 and time t, and κ_i represents the corresponding jump size for the ith jump.

Correspondingly, the within-day geometric returns are defined as

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

where $t \in \mathbb{N}^+$ represents the trading day, and M refers to 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

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

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, where N_t equals the number of jumps on day t.

As QV_t and its different components are not directly observable, 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.

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

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

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

where

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

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,

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

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

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

Moreover, under the same regularity conditions, the test statistic

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

where

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

is asymptotically standard normal under the null hypothesis of no within-day jumps, and consequently may be used to test for significant jumps.[3]

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

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

where $I(\cdot)$ is the indicator function, equal to 1 if its argument is evaluated to be true, and 0 otherwise, and 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

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

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, we use the critical value of $\alpha = 0.01$, but very similar results were obtained for other critical values, which are available upon request.

3 Data

To study market responses to news announcements and allow the responses to vary with the financial systemic risk level, three types of data are needed: (1) market response data, (2) news announcement values and the corresponding market forecasts, and (3) a measure for financial systemic risk.

[3] Huang 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 equity and the bond markets for the United States. The corresponding market responses data are five-minute returns on 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), acquired by CME on July 12, 2007).[4]

The choice of a 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, Gençay, Müller, Pictet, and Olsen (2001) for details on the previous-tick method.

As the pit trading hours for CME SP futures open outcry are from 8:30 to 15:15 Central Time, or 9:30 to 16:15 Eastern Time, while many important news announcements, such as NFPAY, are released at 8:30 Eastern Time, we extend the pit-traded price data by Globex electronic trading data to 8:20 Eastern Time, following Andersen, Bollerslev, Diebold, and Vega (2007). Dropping the noisy opening price, the first five-minute price for each trading day is taken at the 8:25 time stamp, thus the first return data point has the 8:30 time stamp. So there are 94 five-minute returns on each day for the SP futures. Since SP Globex trading started on September 21, 1993 and the data became available from January 1994, the sample period for the SP futures ranges from January 3, 1994 to September 30, 2014, for a total of $5276 \times 94 = 495{,}944$ five-minute returns.

In comparison, as the pit trading hours for CBOT US futures are from 8:20 to 15:00 Eastern Time, the exchange-traded data are sufficient to cover the news announcements periods. As a result, the sample period for US is longer, ranging from November 7, 1988 to September 30, 2014, for a total of $6545 \times 79 = 517{,}055$ five-minute returns. Notice that unlike SP, US Globex trading continues during the pit trading hours, and Globex trading

[4] From the start of U.S. Treasury bond futures in the 1980s until 2002 when the 30-year Treasury bonds was discontinued, the 30-year U.S. Treasury bond futures was the most liquid Treasury bond futures among all maturities. Its liquidity decreased somewhat since then, but has remained decent especially when the bonds were reintroduced in 2006. To ensure a sufficiently long time series, we choose the U.S. Treasury bond futures of the 30-year maturity, instead of other maturities.

has been more active than pit trading in recent years. So both pit and Globex (if available) information is used in the construction of US five-minute returns.

TickData provides most of the futures trading data studied in this paper. But due to their lack of corresponding data, the SP futures Globex data before July 1, 2003 is obtained directly from CME.

Four different futures contracts mature every year, in March, June, September and December, with the corresponding ticker symbols: H, M, U and Z, respectively. Each futures contract typically exists for no more than two years. So the different futures contracts have to be rolled over to construct a single price time series. We always use the most actively traded futures contracts, usually the one closest to its maturity, and roll over to the next contract when the daily day-session tick volume of the next contract exceeds that of the current contract. The resulting rollover days are very similar to those selected by the fixed-day practice as in Andersen, Bollerslev, and Diebold (2006): five business days before the expiration day for the SP futures, and the first business day in the delivery month for the US futures.

3.2 News Announcements and Market Forecast Data

Twenty-six macroeconomic news announcements are included in this study. They are listed in Table 1, covering the 25 announcements studied in Andersen, Bollerslev, Diebold, and Vega (2007), plus retail sales excluding automobiles, as it is one of the four major announcements that the economic derivatives were traded on.

There are two types of forecast data used in this study, coming from two different data sources. The first type is the survey data. Action Economics, which used to be known as International Money Market Services (MMS) in the literature, provides the survey data for all the 26 news announcements studied in this paper. MMS also supplements the survey data with the corresponding actual released values. Many of the news surveys go back as far as the 1980s, and so are long enough to cover the sample period of the high-frequency data.[5]

[5] Some recent papers also uses a second source of survey data: Bloomberg. Bloomberg's survey data may be more up to date than those from MMS, as Bloomberg collects the survey data all the way to the announcement dates. But 4 news releases data are not available from Bloomberg: business inventories (BUSINV), GDP 3rd report (GDPFIN), trade balance (TRDBAL) and treasury budget (TREBUD). Their

The second type is the forecast based on market prices of economic derivatives. This security was created by Goldman Sachs and Deutsche Bank. They initiated the auction trading of economic derivatives in October 2002. The market remained active from then until September 2006 when the trading was moved to CME.

Economic derivatives are, in essence, options, with underlying values equal to the future values of some important macroeconomic data releases. Accordingly, economic derivatives are settled when the underlying report is released.

The most popular form of economic derivative is digital (binary) options. For example, a call option with strike price 300 for NFPAY will pay off $1 to the buyer so long as the released value of NFPAY is above 300, and 0 otherwise. So the payoff can only take the value of either $1 or $0, and does not vary continuously with the precise released value. Typically, there are between 10 to 20 strike prices for each announcement.

From the option prices across different strikes, an implied probability distribution representing the market's forecast for the possible news announcement values can be recovered. Figure 1 provides an example. It shows the prices of the digital options from the auction conducted in the morning of June 3, 2005, right before the actual release of NFPAY. The auction traded on what the monthly change in non-farm payroll employment in May 2005 would be. The measurement unit is thousands of jobs. The auction data were released at 12:53 Eastern Time on the same day. The figure implies that investors estimated the probability that the announcement value would be between 150 and 175 thousand is about 9.5%. The probability that the announcement value would be higher than 174 thousand (forecast mean) is about 49%.

Considering both trading activity and sample length, economic derivative data on four news announcements are included in this study: NFPAY, the Institute for Supply Management (ISM)'s manufacturing index (formerly known as National Association of Purchasing Managers Index (NAPM) index) or Purchasing Managers' Composite Index (PMI), retail

data on the 1st and 2nd GDP reports (GDPADV and GDPPRE) are also sparse. Moreover, Bloomberg's survey data are no earlier than 1996, so they only cover part of the high-frequency data sample. Last but not least, Bloomberg does not provide the standard deviation of the survey data, which will be extensively studied in the following Subsection 5.2. So given the relatively incomplete coverage by Bloomberg, we use MMS survey data in this study. In an unreported study, we also use Bloomberg data on the partial empirical sample and find similar empirical results to those obtained using MMS mean or median data only on the same partial sample.

sales excluding automobiles (RSXAUT), and initial unemployment claims (ICLM). Detailed information about these four news announcements is provided in Table 2.[6]

3.3 Financial Systemic Risk Data

Financial market responses to macroeconomic news announcements are allowed to change over time in this paper, based on business cycles, the financial systemic risk level, or the monetary policy of zero lower bound. The data for business cycles are readily available from the NBER website, and the period of zero lower bound simply starts from December 16, 2008. But the level of financial systemic risk is not directly observable.

This paper uses Distress Insurance Premium (DIP) to turn the latent systemic risk level into an observable process. Conceptually, DIP is a hypothetical insurance premium against catastrophic losses in a financial system. Computationally, it is equal to the expected large default losses of a hypothetical portfolio consisting of all the liabilities of major financial institutions in the system.

To calculate DIP, we first form a portfolio that consists of all the liabilities of major financial institutions in the system. Then the credit default swap (CDS) spread is used to infer the risk-neutral probability of default (PD) for each institution. Estimated equity return correlation is used to capture the relationship between firms. Finally Monte Carlo simulations are run such that the joint default scenarios for the portfolio are consistent with both the PD and correlation inferred from the data. By the no-arbitrage condition, the insurance premium of this portfolio is equal to the expectation of default losses of this portfolio in excess of a certain threshold.

In this study, the financial institutions for the liability portfolio are the 14 recently designated systemically important financial institutions (SIFIs) that are either chartered or have a major presence in the U.S. They are Bank of America, Bank of New York Mellon, Barclays, Citigroup, Credit Suisse, Goldman Sachs, JPMorgan Chase, Morgan Stanley, State Street, Wells Fargo, Deutsche Bank, UBS, AIG and Prudential Financial.

Since DIP computation needs the input of CDS, while the quality of the CDS data for

[6] Fortunately, MMS data on all of these four news announcements cover the full sample period of our futures data, which enables us to conduct the empirical study over the longest possible sample in a consistent way later in Section 5.

the sample firms became sufficiently good only from January 2002, the empirical results involving DIP are restricted to this relatively short sample period. Fortunately there are still two expansions and one contraction in this period according to NBER criteria, so as a continuous control variable, DIP still has the support of varying discrete states.

Figure 2 provides a time series plot of DIP to show how the financial system stress evolved over the past 13 years. For easy comparison, the only NBER contraction in this period is shaded in grey.

For a long period of time before the subprime mortgage crisis in the summer of 2007, DIP remained at very low levels of less than 1 percentage point. It reached the first peak in March 2008 when Bear Sterns was acquired by JPMorgan Chase. After a short period of financial improvement in April and May of 2008 due to strong central bank interventions, DIP surged again in the fall of 2008 and reached the second peak when Lehman Brothers failed. The third peak occurred in March of 2009 when the stock market reached the bottom. The first three peaks in DIP corresponds to the U.S. financial crisis period. DIP trended downward temporarily since then, before moving upwards again in May 2010, when the Greek government accepted 110 billion euros of bailout loan from the European Commission, European Central Bank (ECB) and International Monetary Fund, signalling the start of the European sovereign debt crisis. The U.S. financial system was unavoidably affected by this foreign crisis, and DIP reached the fourth peak in November 2011, right before the ECB expanded liquidity provision for European banks using a dollar-swap line with the U.S. Federal Reserve and its first three-year Long-Term Refinancing Operations (LTRO). ECB president Mario Draghi's "courageous leap" and "whatever it takes" speeches in June and July 2012 also helped to reduced DIP further from its fifth peak. The U.S. financial system has been on the path of recovery since then.

The dynamics of the U.S. financial systemic risk depicted in Figure 2 corresponds nicely to major world-wide financial events and makes intuitive sense, so DIP may be a good control variable for studying the time-varying financial market responses to news announcements.

4 Initial Evidence Linking Announcements and Jumps

To visualize the financial market responses to macroeconomic news announcements, we plot a typical announcement day in Figure 3. It is June 6, 1996, when NFPAY value was released at 340, while the survey expectation was only 170 with a standard deviation of 56.5. This news was quite far from the market expectation, and both SP (equity) and US (bond) reacted quickly. 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 NFPAY news release.

Of course, convincing evidence for the significant link between announcements and jumps comes from formal statistical tests. We can approach this question from two directions, 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 statistic. Specifically, let p_1 be the probability of jump days on news days, and p_2 be the probability of jump days on 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 p's with a hat above them refer to the estimated probabilities by sample proportions.

Table 3 reports the proportion of jump days in each type of the news announcement days, as well as in all the news days and no-news days, together with the above test statistics and the one-sided p-values. The jump days are detected at the 1% 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 the equity and bond markets, showing the significant impact of these news on jumps, especially NFPAY, PPI, CPI, retail sales, initial unemployment claims, consumer credit and business inventories. NFPAY turns out to be the most influential news across different markets. The last column in Table 3 is based on the cojumps of the equity and bond markets, and the same significant impacts of news show up when the two markets jump together. Moreover, the bond market exhibits more sensitivity to news announcements than the equity market 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 jumps-on-news-days test. Table 4 reports such test statistics for jump days signaled at the 1% and 0.1% 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 bond market jumps, or for the cojumps of the two markets.

5 Impacts of News Announcements on Volatility and Jumps

5.1 News Surprises

Although the news impacts on jumps are statistically significant, the proportions of jump days in the news announcement days are not very high (Table 3), and the proportions of news days in the jump days are not much larger than the overall proportions of news days (Table 4). 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 4. However, many of the news releases are within the range of market expectations, and thus do not introduce much new information to markets. 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, link surprises in news announcements to market responses, and see how volatility and jumps behave during the announcement days.

Following Balduzzi, Elton, and Green (2001), we define the standardized news surprise as

$$S_{kt} = \frac{A_{kt} - E_{kt}}{\hat{\sigma}_k}, \tag{12}$$

where A_{kt} is the released value for news k on day t, E_{kt} is the median 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.

Literature studying market first-moment responses to news typically regresses returns on the above news surprise directly. In comparison, to study market second-moment responses to news, we need to adjust the above news surprise further. First, since second moments are never negative, we need to take the absolute value of the above surprise. Second, it is possible that positive and negative surprises may exert asymmetric impacts on the market. To allow for such an asymmetry, surprises are separated into positive and negative ones, with only their magnitudes showing up on the right-hand-side (RHS) of the regressions.

The regressions used in this paper are as follows. The realized continuous volatility C_t and jump quadratic variation J_t discussed in Section 2 are regressed on the news surprise variables on the news announcement days in an event-study style of setup:

$$\begin{aligned}
log(C_t+1) &= \alpha_{C,k} + \beta_{C,k,p}|S_{kt}^{ED}|1(S_{kt}^{ED} \geq 0) + \beta_{C,k,n}|S_{kt}^{ED}|1(S_{kt}^{ED} < 0) \\
&\quad + \gamma_{C,k,p}|S_{kt}^{S}|1(S_{kt}^{S} \geq 0) + \gamma_{C,k,n}|S_{kt}^{S}|1(S_{kt}^{S} < 0) + \epsilon_{C,k,t} \\
log(J_t+1) &= \beta_{J,k,p}|S_{kt}^{ED}|1(S_{kt}^{ED} \geq 0) + \beta_{J,k,n}|S_{kt}^{ED}|1(S_{kt}^{ED} < 0) \\
&\quad + \gamma_{J,k,p}|S_{kt}^{S}|1(S_{kt}^{S} \geq 0) + \gamma_{J,k,n}|S_{kt}^{S}|1(S_{kt}^{S} < 0) + \epsilon_{J,k,t}.
\end{aligned}$$

The above set of regressions are run on stock and bond markets separately. We take logarithmic transformation of C_t and J_t to temper their extreme values so that the finite sample distribution of the left-hand-side variables 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:

$$\begin{aligned}
log(C_t+1) &= \sum_{k \in \text{Economic series}} [\alpha_{C,k} + \beta_{C,k,p}|S_{kt}^{ED}|1(S_{kt}^{ED} \geq 0) + \beta_{C,k,n}|S_{kt}^{ED}|1(S_{kt}^{ED} < 0) \\
&\quad + \gamma_{C,k,p}|S_{kt}^{S}|1(S_{kt}^{S} \geq 0) + \gamma_{C,k,n}|S_{kt}^{S}|1(S_{kt}^{S} < 0)] + \epsilon_{C,t} \\
log(J_t+1) &= \sum_{k \in \text{Economic series}} [\beta_{J,k,p}|S_{kt}^{ED}|1(S_{kt}^{ED} \geq 0) + \beta_{J,k,n}|S_{kt}^{ED}|1(S_{kt}^{ED} < 0) \\
&\quad + \gamma_{J,k,p}|S_{kt}^{S}|1(S_{kt}^{S} \geq 0) + \gamma_{J,k,n}|S_{kt}^{S}|1(S_{kt}^{S} < 0)] + \epsilon_{J,t},
\end{aligned}$$

which is needed if we want to test for the joint significance of the individual news.

Tables 5 and 6 report the regression results. For the rows labeled with "Pos" and "Neg," the cells in the columns of individual news contain the coefficient estimates together with their White heteroskedastic robust standard errors for the individual news surprise regressions. As only four news announcements have relatively long time span of economic derivatives data, we only compare the regression results for them using both the economic derivatives and the corresponding survey data. The last column of these rows reports the p-values of the joint test that $\beta_{C,k,\cdot} = 0 \,\forall\, k$, $\gamma_{C,k,\cdot} = 0 \,\forall\, k$, $\beta_{J,k,\cdot} = 0 \,\forall\, k$, and $\gamma_{J,k,\cdot} = 0 \,\forall\, k$. That is, the coefficients in front of all the news surprises from both economic derivatives and surveys are zero in the joint regression.

For the rows marked with "Pos = Neg", the cells in the columns of individual news report the p-values of the Wald test for the null hypothesis that the impacts of the positive and negative news surprises are the same ($H_0 : \beta_{\cdot,\cdot,p} = \beta_{\cdot,\cdot,n}$ and $H_0 : \gamma_{\cdot,\cdot,p} = \gamma_{\cdot,\cdot,n}$). The last column of these rows reports the p-values of the joint test that the surprises, both positive and negative, in all the four news announcements are insignificant.

The results in Tables 5 and 6 show that the surprises in the four news announcements, computed using either the economic derivative data or the MMS survey data, jointly significantly affect the continuous volatility of the equity market. Positive surprises from survey data also jointly significantly affect both the volatility and jumps of the bond market. Meanwhile, each of the individual news turns out to be significant in explaining at least one instance of the volatility or jumps of the equity or bond market, showing the important role of these news announcements in influencing financial market activities.[7]

5.2 Disagreement and Uncertainty

The above analysis uses the first moment of market forecast for news announcement values. However, market responses to news announcements can also be affected by the second moments, which are the disagreement among individual economic agents as measured by the standard deviation of the survey forecast, and the uncertainty of the representative agent as measured by the standard deviation of the probability distribution recovered from economic derivative prices. We therefore run similar individual regressions of volatility and jumps on

[7] As a robustness check, we replace the median forecast by mean forecast. The results are qualitatively the same.

these standard deviations. The individual regressions are:

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

and the joint regressions are:

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

where SD is the standard deviation from economic derivatives or MMS surveys, standardized by $\hat{\sigma}_k$ in Equation (12) (as has been done for news surprises), to ensure the comparability of coefficient estimates across different news.

Table 7 reports the coefficient estimates together with their White heteroskedastic robust standard errors for the individual uncertainty and disagreement regressions. The last column of Table 7 reports the p-values of the joint test that all the slope coefficients are zero in the joint regressions.

Interestingly, uncertainty and disagreement are not only conceptually different, but also have different impacts on market activities. Uncertainties in the four news announcements jointly significantly affect the volatility and jumps of the bond market. In contrast, disagreement is only significant in explaining the jumps of the bond market. The relatively stronger impact of uncertainty than that of disagreement on the bond market make economic sense. When the representative agent is not very sure about his or her expectation, then the news surprises are not very 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, while the release value turns out to be different from the market forecast. In essence, price response is an aggregate behavior, so whether heterogeneous agents agree with each other or not (i.e. disagreement) plays a less role than the uncertainty of a representative agent does.

In comparison, for the equity market, the joint effect of disagreement and uncertainty from the four news series is insignificant in explaining the equity volatility and jumps. However, such insignificance may be due to the relatively short sample that economic derivatives existed, and the difficulty in discovering equity market responses as documented in the literature. If we extend to the longer sample that the survey data cover, and allow for time-varying effects, as will be shown in the following subsections, then we will observe more significant impacts of the forecast second moment on the markets.

5.3 Full Sample, Economic Expansions and Contractions

The above two subsections use both sources of market forecasts for news announcements, including MMS and economic derivatives. Due to the relatively short period during which economic derivatives were actively traded, 2002 to 2006, the evidence presented in the above two subsections is restricted to this short period, too.

If we rely on only one source of the news forecast, i.e. MMS, then we can extend our analysis to the full sample. Furthermore, we can divide the long sample into economic expansions and contractions, based on NBER definitions of "US business cycle expansions and contractions," to investigate possible cyclical patterns in market responses to news announcements.[8] Two points are worth mentioning before we proceed.

First, Section 4 shows that not all news announcements significantly impact the markets. To keep this subsection compact and comparable to the previous two subsections, only the four important news series studied in the previous two subsections are included in this subsection.

Second, since the second moment from the MMS data measures disagreement while that from economic derivatives measure uncertainty, by dropping economic derivatives, this section can only study the impact of news surprises and disagreement on the markets.

To keep the results compact, news surprises and disagreement are put together on the RHS of the regressions. The individual regressions are:

$$\begin{aligned} log(C_t+1) &= \alpha_{C,k} + \beta_{C,k,S,p}|S^S_{kt}|1(S^S_{kt} \geq 0) + \beta_{C,k,S,n}|S^S_{kt}|1(S^S_{kt} < 0) \\ &\quad + \beta_{C,k,D} SD^S_{kt} + \epsilon_{C,k,t} \\ log(J_t+1) &= \alpha_{J,k} + \beta_{J,k,S,p}|S^S_{kt}|1(S^S_{kt} \geq 0) + \beta_{J,k,S,n}|S^S_{kt}|1(S^S_{kt} < 0) \\ &\quad + \beta_{J,k,D} SD^S_{kt} + \epsilon_{J,k,t}, \end{aligned}$$

[8] NBER website (http://www.nber.org/cycles.html) provides the definitions of expansions and contractions, and classifies every month into one of these two categories.

and the joint regressions are:

$$\begin{aligned} log(C_t+1) &= \alpha_C + \sum_{k\in\text{Economic series}} [\beta_{C,k,S,p}|S^S_{kt}|1(S^S_{kt}\geq 0) + \beta_{C,k,S,n}|S^S_{kt}|1(S^S_{kt}<0) \\ &\quad +\beta_{C,k,D}SD^S_{kt}] + \epsilon_{C,t} \\ log(J_t+1) &= \alpha_J + \sum_{k\in\text{Economic series}} [\beta_{J,k,S,p}|S^S_{kt}|1(S^S_{kt}\geq 0) + \beta_{J,k,S,n}|S^S_{kt}|1(S^S_{kt}<0) \\ &\quad +\beta_{J,k,D}SD^S_{kt}] + \epsilon_{J,t}. \end{aligned}$$

All of the above regressions are run on the full sample, the subsamples of expansions and contractions, respectively. Tables 8 to 10 report the regression results. Some new interesting features emerge when we run the regressions on the much longer sample periods with the expansion and contraction classifications.

First, in terms of the joint effects of the four news announcements, the last column of Table 8 shows that for the full sample, both news surprises and disagreement significantly affect both the continuous volatility and discrete jumps of the equity and bond markets. When the full sample is separated into expansion and contraction subsamples, the last columns of Tables 9 and 10 show that the bond market remains significantly influenced by most variables in the two subsamples, while the equity market is less so.

Second, in terms of the effects of individual news surprises, some news surprises, though insignificant in the full sample, turn out to be significant in the subsamples. For example, NFPAY surprises are insignificant in explaining equity market volatility in the full sample. But its positive surprise significantly increases the equity volatility in the expansion subsample. This result shows the benefit of allowing news effects to change over the different business cycles in discovering the significance of news effects on financial markets. Moreover, in the same example, we can observe the asymmetric effects of positive and negative news surprises: the positive surprise of NFPAY is significant, while its negative surprise is insignificant. Of course, the significance of positive and negative surprises varies across different news announcements.

Third, in terms of the effects of disagreement about individual news, for volatility, Table 8 shows that disagreement, if significant, always increases the volatility of both markets over the full sample. This result is echoed by Table 10 over the contraction subsample. In comparison, for jumps, Tables 8 to 10 show that disagreement may either increase or decrease jump sizes. This seemly puzzling effect may be resolved in the next subsection when market responses are allowed to vary continuously over time with the financial systemic risk level.

5.4 Financial Stress and Time-Varying Responses

Results in Subsection 5.3 show that the responses of financial market volatility and jumps to news announcements vary over time. To further explore this feature, this subsection extends the previous subsection in two directions. First, instead of classifying market responses according to only two discrete states (expansion and contraction of the macroeconomy), this subsection uses a new continuous control variable to allow for continuously-changing responses. Second, it is understandable that the overall macroeconomic conditions affect financial market responses to macroeconomic news. But it is also possible that the financial system's own condition, such as its stress level, can directly affect financial market responses to news announcements.

To achieve the above goals, this subsection replaces the expansion/contraction classification in the previous subsection by DIP, a systemic risk indicator and a continuous measure of how stressed the financial system is.

Following Goldberg and Grisse (2013), we now set up a framework to study the continuously-changing responses formally. Assume y_t is the dependent variable, which can be either volatility or jumps in our settings. $x_{k,t}$ is the explanatory variables, which can be the intercept, news surprises, disagreement, or their interaction. z_t is the control variable that affects y_t response to $x_{k,t}$. In our settings z_t is DIP.

$$y_t = \sum_{k=1}^{K} \beta_{k,t} x_{k,t} + \epsilon_t \tag{13}$$

$$\beta_{k,t} = \tau_{0,k} + \tau_{1,k} z_t. \tag{14}$$

Equations (13) and (14) can be estimated separately in a two-step procedure, with the additional attention to adjusting the standard errors of the τ estimates in Equation (14) because of the estimated-dependent-variable problem.

More efficiently, we can substitute Equation (14) into Equation (13), and estimate the following nested model in one step:

$$y_t = \sum_{k=1}^{K} (\tau_{0,k} + \tau_{1,k} z_t) x_{k,t} + \epsilon_t = \sum_{k=1}^{K} \tau_{0,k} x_{k,t} + \sum_{k=1}^{K} \tau_{1,k} z_t x_{k,t} + \epsilon_t, \tag{15}$$

where $\tau_{1,k}$ measures how the response of y_t to $x_{k,t}$ varies over time depending on the z_t values.

Substituting in Equation (15) the notations we have used for volatility, jumps, news surprises, disagreement and the systemic risk indicator, we obtain the full model as follows. The individual regressions are:

$$\begin{aligned}
log(C_t + 1) \;=\;& \alpha_{C,k} + \beta_{C,k,S,p}|S_{kt}^S|1(S_{kt}^S \geq 0) + \beta_{C,k,S,n}|S_{kt}^S|1(S_{kt}^S < 0) + \beta_{C,k,D} SD_{kt}^S \\
&+ \beta_{C,k,SD,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot SD_{kt}^S + \beta_{C,k,SD,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot SD_{kt}^S \\
&+ \beta_{C,k,DIP} DIP_t + \tau_{C,k,S,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot DIP_t + \tau_{C,k,S,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot DIP_t \\
&+ \tau_{C,k,D} SD_{kt}^S \cdot DIP_t + \tau_{C,k,SD,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot SD_{kt}^S \cdot DIP_t \\
&+ \tau_{C,k,SD,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot SD_{kt}^S \cdot DIP_t + \epsilon_{C,k,t}
\end{aligned}$$

$$\begin{aligned}
log(J_t + 1) \;=\;& \alpha_{J,k} + \beta_{J,k,S,p}|S_{kt}^S|1(S_{kt}^S \geq 0) + \beta_{J,k,S,n}|S_{kt}^S|1(S_{kt}^S < 0) + \beta_{J,k,D} SD_{kt}^S \\
&+ \beta_{J,k,SD,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot SD_{kt}^S + \beta_{J,k,SD,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot SD_{kt}^S \\
&+ \beta_{J,k,DIP} DIP_t + \tau_{J,k,S,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot DIP_t + \tau_{J,k,S,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot DIP_t \\
&+ \tau_{J,k,D} SD_{kt}^S \cdot DIP_t + \tau_{J,k,SD,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot SD_{kt}^S \cdot DIP_t \\
&+ \tau_{J,k,SD,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot SD_{kt}^S \cdot DIP_t + \epsilon_{J,k,t},
\end{aligned}$$

and the joint regressions are:

$$\begin{aligned}
log(C_t + 1) \;=\;& \alpha_C + \sum_{k \in \text{Economic series}} [\beta_{C,k,S,p}|S_{kt}^S|1(S_{kt}^S \geq 0) + \beta_{C,k,S,n}|S_{kt}^S|1(S_{kt}^S < 0) + \beta_{C,k,D} SD_{kt}^S \\
&+ \beta_{C,k,SD,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot SD_{kt}^S + \beta_{C,k,SD,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot SD_{kt}^S] + \beta_{C,DIP} DIP_t \\
&\sum_{k \in \text{Economic series}} [\tau_{C,k,S,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot DIP_t + \tau_{C,k,S,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot DIP_t \\
&+ \tau_{C,k,D} SD_{kt}^S \cdot DIP_t + \tau_{C,k,SD,p}|S_{kt}^S|1(S_{kt}^S \geq 0) \cdot SD_{kt}^S \cdot DIP_t \\
&+ \tau_{C,k,SD,n}|S_{kt}^S|1(S_{kt}^S < 0) \cdot SD_{kt}^S \cdot DIP_t] + \epsilon_{C,t}
\end{aligned}$$

$$
\begin{aligned}
log(J_t+1) \;=\;& \alpha_J + \sum_{k\in \text{Economic series}} [\beta_{J,k,S,p}|S^S_{kt}|1(S^S_{kt}\geq 0) + \beta_{J,k,S,n}|S^S_{kt}|1(S^S_{kt}<0) + \beta_{J,k,D}SD^S_{kt} \\
& + \beta_{J,k,SD,p}|S^S_{kt}|1(S^S_{kt}\geq 0)\cdot SD^S_{kt} + \beta_{J,k,SD,n}|S^S_{kt}|1(S^S_{kt}<0)\cdot SD^S_{kt}] + \beta_{J,DIP}DIP_t \\
& \sum_{k\in \text{Economic series}} [\tau_{J,k,S,p}|S^S_{kt}|1(S^S_{kt}\geq 0)\cdot DIP_t + \tau_{J,k,S,n}|S^S_{kt}|1(S^S_{kt}<0)\cdot DIP_t \\
& + \tau_{J,k,D}SD^S_{kt}\cdot DIP_t + \tau_{J,k,SD,p}|S^S_{kt}|1(S^S_{kt}\geq 0)\cdot SD^S_{kt}\cdot DIP_t \\
& + \tau_{J,k,SD,n}|S^S_{kt}|1(S^S_{kt}<0)\cdot SD^S_{kt}\cdot DIP_t] + \epsilon_{J,t}.
\end{aligned}
$$

Since we allow for time-varying responses to news announcements, the hypothesis testings of this subsection change slightly from those in the previous subsections. The null hypotheses are now separated into the following two categories. First, $\beta_{\cdot,k,\cdot} = 0$. This category tests whether there are constant responses from either volatility or jumps to news surprises, disagreement or their interaction. Second, $\tau_{\cdot,k,\cdot} = 0$. This category tests whether the responses from either volatility or jumps to news surprises or disagreement or their interaction vary with the system stress level.

Tables 11 to 14 report the regression results. By disentangling the responses studied in Table 8 into a constant component and a time-varying component that depends on the financial system stress level, Tables 11 to 14 reveals some interesting patterns.

First, in terms of responsiveness of the two types of financial markets, these four tables confirms the findings in Table 8 that the bond market is more responsive to news announcements than the equity market, because more variables are jointly significant across all four news announcements for the bond market (last columns of Tables 13 and 14) than for the equity market (last columns of Tables 11 and 12).

Second, in terms of the effects of the individual news announcements, NFPAY turns out to be the most influential one. Recent high-frequency-data literature has repeatedly shown that NFPAY is the most important news announcement for market first-moment responses. Tables 11 to 14 support such a finding from a different angle. They show that, among the four news announcements that market participants care the most about, NFPAY is the only one that is significant across almost all the variables — surprises, disagreement or various interactions, in affecting market second-moment responses. In addition, NFPAY affects the equity and bond markets in different fashions: it moves the equity market mostly by discrete jumps while it moves the bond market mostly by continuous volatility, except that its surprises, including positive and negative surprises, are also significant in affecting bond market jumps.

These observations may partially explain the literature finding that the first-moment response of the bond market to new surprises is easier to detect than that of the equity market. We can roughly think of volatility as small but persistent (continuous) responses, while jumps as large but short-lived (discrete) responses. Huang and Tauchen (2005) document that volatility contributes a lot more to the total second moment than jumps do. So if we combine the small and large responses as in the first-moment response on the left-hand-side (LHS), and put only surprises on the right-hand-side (RHS), then the signal from the small continuous responses (i.e. the volatility-type) will dominate, resulting in insignificant equity responses and significant bond responses. However, if we properly separate the continuous and discrete responses by way of the second moment, then we can easily observe the significant relationship between NFPAY and the large responses of both the equity and the bond markets.

Third, in terms of the role of disagreement, Table 8 shows that disagreement on the individual news, if significant, always increases the volatility of the equity market. Table 11, by separating the effect of disagreement into a constant and a time-varying component, further reveals that the constant effect of disagreement can be negative, but the time-varying effect, if significant, is positive. Furthermore, though Tables 8 to 10 show that the effects of disagreement on jumps may be either positive or negative, Tables 12 and 14 show that the constant effect of disagreement on jumps may be negative, but the time-varying effect, if significant, is positive for both the equity and bond markets. That is, the more stressed the financial system is, and the more market participants disagree with each other, then the higher the equity market volatility is, and the larger the jumps are for both the equity and bond markets.

5.5 Effect of Zero Lower Bound

During the recent financial crisis, the Federal Reserve implemented the monetary policy of zero lower bound (ZLB), starting on December 16, 2008 and ending on December 15, 2015. Swanson and Williams (2014) study the effect of ZLB on the sensitivities of Treasury yields to news surprises. They find that ZLB constrained the short-maturity (six-month or less) yields since 2009, while it did not constrained the median-maturity (one- and two-year) yields until 2011, and never constrained the long-maturity (five- and ten-year) yields in their sample.

Since this paper uses the futures data on long-term bonds with maturity longer than those in Swanson and Williams (2014), it will be interesting to see whether the news impacts change with ZLB for this type of bonds. Also we study both the equity and bond markets to obtain a complete extension of the previous subsections.

Tables 15 to 18 report the full-model estimation results for the subsamples with ZLB. For the equity market, ZLB does not appear to constrain responses to news, in terms of either volatility or jumps. In contrast, ZLB does constrain the bond market volatility and jump responses to news. For example, when all news are considered jointly (last column of the tables), there are not as many significant variables in the ZLB subsample (Tables 17 and 18) as in the full sample (Tables 13 and 14). For individual news, there are fewer NFPAY-related variables that are significant in the ZLB subsample than in the full sample.

Overall, the evidence in this subsection for ZLB's effects on market second-moment responses to news is broadly in line with the observations in Swanson and Williams (2014) for ZLB's effects on market first-moment responses to news, even when the bond maturity in this paper is much longer than those in Swanson and Williams (2014). In addition, ZLB constrains the responses of the bond market more than those of the equity market.

5.6 Beyond Event Study — Jump Hazard Rate

The study up to now is based on an event-study style of analysis — that is, it focuses on news announcement days and explores how markets respond to various news-related explanatory variables. So only jump sizes on the news announcement days have been studied so far. It will make the analysis of financial market jump responses complete if we can also study how news announcements affect jump occurrences. As jump days differ from news days, we have to shift our domain from news days to business days to facilitate the study of jump occurrences. To ensure sufficient flexibility, our model allows for random jump arrivals with time-varying arrival rates.

The model we use here is called the autoregressive conditional hazard (ACH) model. It is proposed by Hamilton and Òscar Jordà (2002) to model the federal funds rate target changes, and later adapted by Andersen, Bollerslev, and Huang (2011) in a joint model for volatility and jump forecast. The ACH model is built upon the Autoregressive Conditional Duration (ACD) model proposed by Engle and Russell (1998) for modeling the durations (that is, time interval) between trades that arrive randomly. The ACD model is designed to capture time-varying and serially dependent arrival rates. The ACH model inherits this nice feature. Furthermore, by changing the modeling target from the durations to the hazard rate, the ACH model provides the additional convenience of continuously incorporating new information between two random arrivals. This additional feature is particularly helpful in our context as news may arrive between two jump days.

A quick review of the ACH model is as follows. Let $N(t)$ be the counting process that records the number of jump days up to day t. Then the hazard rate is defined as

$$h_t = P[N(t) \neq N(t-1)|\mathcal{F}_{t-1}],$$

where $\mathcal{F}_{t-1}$ is the filtration (information) up to day t-1. A simple ACH (1,1) model without incorporating news between jump days is

$$\begin{aligned} h_t &= \frac{1}{\psi_{N(t-1)}} \\ \psi_{N(t)} &= \omega + \alpha_1 d_{N(t)-1} + \beta_1 \psi_{N(t)-1}, \end{aligned}$$

where d_n is the number of days between the nth jump day and the $(n-1)$th jump day, ψ_n is the expectation of d_n. To allow for new information between jump days, the simple ACH(1,1) model is augmented as

$$h_t = \frac{1}{\alpha_1 d_{N(t)-1} + \beta_1 \psi_{N(t)-1} + \delta' z_{t-1}},$$

where z represents the explanatory variables other than past durations. As jumps are rare events, and the ACH model is highly non-linear, convergence is difficult to achieve if all the explanatory variables in Subsection 5.4 are included. It turns out that a sensible $\delta' z_t$ for optimization is as follows:

$$\delta' z_t = \delta_0 + \sum_{k \in \text{Economic series}} [\delta_{k,p}|S^S_{kt}|1(S^S_{kt} \geq 0) + \beta_{k,n}|S^S_{kt}|1(S^S_{kt} < 0)] + \delta_{DIP} DIP_t.$$

Disagreement is dropped mainly because of missing data. The issue of missing data is not a big concern for the regressions in previous subsections, but continuity in time is vital for the ACH model. The interaction terms are also dropped to facilitate convergence.

Table 19 reports the estimation results from both the simple and augmented ACH(1,1) models. As usual, the equity and bond markets show some similarities and differences in their hazard rate dynamics and responses to news variables.[9]

The similar features are the following. First, the durations for both markets are highly persistent, as the autoregressive coefficient $\alpha+\beta$ is very close 1 across both markets and both types of ACH models. Second, the positive surprises in NFPAY and RSXAUT significantly increase jump hazard rates for both markets, while only the negative surprise in NFPAY significantly decreases jump hazard rates for both markets.

The differences are the following. First, NAPM only affects the bond market, and only its positive surprise significantly increases the bond jump hazard rate. NAPM has no impact on the equity market jump hazard rate. Second, the financial systemic risk (DIP) does not affect the equity market jump hazard rate. However, the bond market jump durations do move in the same direction as the financial systemic risk in a statistically significant fashion. In other words, the more stressed the financial system is, the less likely the bond market is going to jump.

6 Conclusion

This paper studies financial market responses to macroeconomic news announcements. It extends the literature in three directions. First, it separates market responses into continuous volatility and discontinuous jumps, and studies them in the same settings so that their results are directly comparable. Second, in addition to the first moment of news surprises, this paper also introduces the second moments of disagreement and uncertainty in market forecasts. Third, this paper incorporates financial systemic risk into the framework of studying market responses to news announcements, so that the responses can vary with the stress level of the financial system.

Based on high-frequency futures data of the aggregate U.S. equity and bond markets, this paper finds that there are more jumps on news days than no-news days, with the bond market being more responsive than the equity market, and NFPAY being the most influen-

[9] Notice that the coefficients reflect the direct link between the explanatory variables and the expected duration, which is the inverse of the hazard rate. So when we interpret the relationship between the explanatory variables and the hazard rate, we need to flip the signs of the coefficients.

tial news. Both the first moment of news surprises and the second moments of disagreement and uncertainty affect financial market responses, with their significance changing over different markets and different response types. Relatively, uncertainty about news has stronger impact than disagreement. Meanwhile, market responses to news vary over time with economic situations, financial systemic risk and the ZLB monetary policy. In particular, equity market jumps and bond market volatility respond to NFPAY surprise, disagreement and their interactions with financial systemic risk. Bond market jumps also respond to NFPAY surprise. The ZLB policy constrains the bond market responses. Financial systemic risk reduces bond market jump occurrences.

There are several directions for future research. First, the markets studied in this paper are U.S. domestic equity and bond markets, and the news announcements mainly concern the domestic macroeconomic situations. If the data for foreign markets and news are available, the same framework can be readily applied to study how the equity and bond markets in foreign countries and regions respond to news. The empirical results will provide valuable information for policy makers around the world.

Second, the framework in this paper can also be extended from the aggregate markets to individual sectors in the economy. For example, energy suppliers and traders in energy related securities may be interested in how the volatility and jumps in the energy futures market react to various news announcements, including the aggregate macroeconomic news and the specific news related to the demand and supply of oil or natural gas.

Extensions along the above dimensions may be interesting for future research.

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8 Tables

Table 1: List of Macroeconomic 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 Index
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 Automobiles
GDPPRE:	GDP Preliminary	TRDBAL:	Trade Balance
HSTART:	Housing Starts	TREBUD:	Treasury Budget

Table 2: Details on Four Major News Announcements

News	Source[1]	Frequency	Release Date[2]	Time[3]	Sample Release Period
NFPAY	BLS	Monthly	First Friday	8:30	1/1993 – 1/2015
NAPM	NAPM	Monthly	First business day	10:00	1/1993 – 1/2015
RSXAUT	BC	Monthly	Mid-month Non-Monday	8:30	1/1993 – 1/2015
ICLM	ETA	Weekly	Thursday	8:30	12/17/1992 – 1/29/2015

[1] BLS: Bureau of Labor Statistics, http://www.bls.gov/news.release/empsit.toc.htm.
NAPM: National Association of Purchasing Managers until January 2, 2002. Now it is ISM: Institute of Supply Management, http://www.ism.ws/ismreport/mfgrob.cfm.
BC: Bureau of the Census, http://www.census.gov/retail/
ETA: Employment and Training Administration, http://www.dol.gov/ui/data.pdf.

[2] General rules with a few exceptions in history.
NFPAY refers to the level change from 2 months ago to the previous month.
NAPM refers to the change (increased/unchanged/decreased) from 2 months ago to the previous month in a diffusion index.
RSXAUT (Advance, seasonally adjusted) refers to the level of the previous month.
ICLM refers to the level of the previous week.

[3] Eastern Time.

Table 3: Proportion of Jump Days in Announcement Days

Announcement	SP	US	Cojump
BUSINV	0.220< 227>(1.657)[0.049]**	0.340< 288>(4.501)[0.000]**	0.088< 227>(2.793)[0.003]**
CAPA	0.203< 246>(1.139)[0.127]	0.282< 308>(2.726)[0.003]**	0.061< 246>(1.690)[0.046]**
CCONF	0.163< 246>(-0.383)[0.649]	0.275< 276>(2.362)[0.009]**	0.045< 246>(0.761)[0.223]
CONST	0.176< 245>(0.125)[0.450]	0.243< 305>(1.307)[0.096]*	0.049< 245>(1.025)[0.153]
CPI	0.245< 249>(2.532)[0.006]**	0.326< 310>(4.183)[0.000]**	0.096< 249>(3.240)[0.001]**
CREDIT	0.286< 241>(3.739)[0.000]**	0.333< 303>(4.383)[0.000]**	0.124< 241>(4.160)[0.000]**
DGORD	0.196< 245>(0.879)[0.190]	0.277< 307>(2.530)[0.006]**	0.053< 245>(1.263)[0.103]
FACORD	0.233< 245>(2.121)[0.017]**	0.248< 306>(1.519)[0.064]*	0.069< 245>(2.096)[0.018]**
FFR	0.151< 205>(-0.790)[0.785]	0.290< 338>(3.107)[0.001]**	0.049< 205>(0.934)[0.175]
GDPADV	0.195< 82>(0.512)[0.304]	0.467< 90>(4.841)[0.000]**	0.110< 82>(2.173)[0.015]**
GDPFIN	0.217< 60>(0.823)[0.205]	0.217< 60>(0.150)[0.440]	0.033< 60>(-0.034)[0.514]
GDPPRE	0.186< 59>(0.275)[0.392]	0.220< 59>(0.215)[0.415]	0.068< 59>(1.019)[0.154]
HSTART	0.204< 245>(1.166)[0.122]	0.232< 306>(0.914)[0.180]	0.069< 245>(2.096)[0.018]**
ICLM	0.221<1034>(3.060)[0.001]**	0.262<1163>(3.443)[0.000]**	0.074<1034>(4.263)[0.000]**
INDPRD	0.203< 246>(1.139)[0.127]	0.279< 308>(2.615)[0.004]**	0.061< 246>(1.690)[0.046]**
LDERS	0.141< 249>(-1.330)[0.908]	0.217< 309>(0.330)[0.371]	0.020< 249>(-1.417)[0.922]
NAPM	0.190< 247>(0.678)[0.249]	0.224< 294>(0.616)[0.269]	0.053< 247>(1.243)[0.107]
NFPAY	0.393< 247>(6.810)[0.000]**	0.526< 308>(10.661)[0.000]**	0.231< 247>(7.238)[0.000]**
NHOMES	0.155< 245>(-0.690)[0.755]	0.247< 304>(1.454)[0.073]*	0.037< 245>(0.203)[0.420]
PCE	0.201< 244>(1.050)[0.147]	0.266< 305>(2.130)[0.017]**	0.070< 244>(2.105)[0.018]**
PERINC	0.201< 244>(1.050)[0.147]	0.266< 305>(2.130)[0.017]**	0.070< 244>(2.105)[0.018]**
PPI	0.263< 247>(3.086)[0.001]**	0.344< 308>(4.765)[0.000]**	0.126< 247>(4.243)[0.000]**
RETLS	0.250< 248>(2.685)[0.004]**	0.330< 309>(4.317)[0.000]**	0.101< 248>(3.398)[0.000]**
RSXAUT	0.254< 248>(2.811)[0.002]**	0.327< 300>(4.150)[0.000]**	0.105< 248>(3.545)[0.000]**
TRDBAL	0.219< 160>(1.371)[0.085]*	0.261< 222>(1.713)[0.043]**	0.069< 160>(1.690)[0.046]**
TREBUD	0.204< 240>(1.158)[0.123]	0.219< 301>(0.421)[0.337]	0.063< 240>(1.747)[0.040]**
News	0.209<3546>	0.279<4397>	0.072<3546>
No-news	0.172<1730>	0.209<2148>	0.034<1699>
Total	0.197<5276>	0.256<6545>	0.034<1699>

Note: The jump days are detected at the 1% significance level. The four elements in each cell are: the proportion of jump days in each type of the news announcement days, as well as in all the news days and no-news 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 hypothesis that news has no impact on jumps, thus the probability of the jump days in the respective news days is equal to the probability of the jump days in no-news days. Two asterisks mean that the t-statistic is statistically significant at the 5% level, and one asterisk denotes statistical significance at the 10% level.

Table 4: Proportion of News Days in Jump Days

Asset	0.99 Sig. Jumps	0.999 Sig. Jumps	Overall
SP	0.713<1040>(2.679)[0.004]**	0.732< 552>(2.999)[0.001]**	0.672<5276>
US	0.732<1674>(4.933)[0.000]**	0.790< 875>(7.887)[0.000]**	0.672<6545>
CoJumps	0.814< 312>(6.014)[0.000]**	0.929< 99>(9.534)[0.000]**	0.676<5245>

Note: The jump days are detected at the 1% and 0.1% significance levels. The four elements in each cell are: the proportion of the news days in the jump or cojump days, the number of the jump or cojump 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 hypothesis 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 that the t-statistic is statistically significant at the 5% level, and one asterisk denotes statistical significance at the 10% level.

Table 5: News Surprises, Volatility and Jumps (SP)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 1: S&P 500, C				
Econ. Deriv.	Pos	0.381*	0.035	0.786**	0.241**	0.081*
		(0.200)	(0.074)	(0.318)	(0.063)	
	Neg	-0.384	-0.111	-0.064	0.085**	0.017**
		(0.481)	(0.170)	(0.149)	(0.038)	
	Pos = Neg	0.072*	0.386	0.016**	0.003**	0.006**
Survey	Pos	-0.253	-0.058	-0.634**	-0.177**	0.087*
		(0.166)	(0.077)	(0.305)	(0.057)	
	Neg	0.490	0.119	0.129	-0.044	0.002**
		(0.462)	(0.172)	(0.110)	(0.026)	
	Pos = Neg	0.077*	0.299	0.031**	0.011**	0.002**
		Panel 2: S&P 500, J				
Econ. Deriv.	Pos	0.184	-0.071	-0.138**	0.030	0.323
		(0.131)	(0.060)	(0.056)	(0.041)	
	Neg	-0.020	0.113*	0.045	-0.001	0.741
		(0.221)	(0.061)	(0.050)	(0.016)	
	Pos = Neg	0.423	0.021**	0.226	0.232	0.589
Survey	Pos	-0.016	0.066	0.202**	-0.020	0.816
		(0.117)	(0.063)	(0.085)	(0.037)	
	Neg	0.241	-0.099*	-0.031	-0.008	0.121
		(0.271)	(0.049)	(0.044)	(0.015)	
	Pos = Neg	0.306	0.041**	0.125	0.632	0.377

Note: This table reports the coefficient estimates of regressing volatility and jumps on standardized positive and negative news surprises, together with White standard errors inside the parentheses, for S&P 500 index futures. The p-values in the rows labeled with "Pos = Neg" and in each news column come from the Wald test that the impacts of positive and negative news surprises are the same (that is, no asymmetry). The p-values in the last column come from the Wald test that all the coefficients are zeros for the positive, negative or both types of surprises.

Table 6: News Surprises, Volatility and Jumps (US)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 3: US 30-Year TB, C				
Econ. Deriv.	Pos	-0.193	-0.120	0.214*	-0.006	0.922
		(0.176)	(0.088)	(0.125)	(0.020)	
	Neg	0.140	-0.244**	0.126	0.014	0.402
		(0.212)	(0.089)	(0.118)	(0.013)	
	Pos = Neg	0.298	0.278	0.635	0.319	0.750
Survey	Pos	0.333	0.135	-0.191*	0.039*	0.074*
		(0.218)	(0.096)	(0.109)	(0.022)	
	Neg	-0.081	0.225**	-0.098	-0.001	0.941
		(0.205)	(0.094)	(0.117)	(0.011)	
	Pos = Neg	0.190	0.435	0.616	0.055*	0.301
		Panel 4: US 30-Year TB, J				
Econ. Deriv.	Pos	-0.346*	0.038	-0.020	-0.022*	0.395
		(0.194)	(0.058)	(0.036)	(0.012)	
	Neg	0.103	0.054*	0.030	-0.015**	0.668
		(0.227)	(0.029)	(0.067)	(0.007)	
	Pos = Neg	0.251	0.853	0.565	0.548	0.571
Survey	Pos	0.695**	-0.023	0.022	0.021	0.000**
		(0.184)	(0.055)	(0.034)	(0.013)	
	Neg	0.042	-0.053	-0.050	0.008	0.981
		(0.268)	(0.041)	(0.060)	(0.005)	
	Pos = Neg	0.092*	0.712	0.410	0.299	0.000**

Note: This table reports the coefficient estimates of regressing volatility and jumps on standardized positive and negative news surprises, together with White standard errors inside the parentheses, for 30-year U.S. Treasury bond futures. The p-values in the rows labeled with "Pos = Neg" and in each news column come from the Wald test that the impacts of positive and negative news surprises are the same (that is, no asymmetry). The p-values in the last column come from the Wald test that all the coefficients are zeros for the positive, negative or both types of surprises.

Table 7: Disagreement v.s. Uncertainty

	NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 1: S&P 500, C			
Econ. Deriv.	-0.459*	0.386	-0.078	-0.019	0.537
	(0.249)	(0.256)	(0.380)	(0.039)	
Survey	0.371	0.120	-0.203	0.041	0.283
	(0.307)	(0.161)	(0.353)	(0.043)	
		Panel 2: S&P 500, J			
Econ. Deriv.	-0.261	0.058	0.114	0.002	0.533
	(0.239)	(0.118)	(0.169)	(0.003)	
Survey	0.201	0.038	-0.127	-0.008**	0.467
	(0.300)	(0.095)	(0.162)	(0.003)	
		Panel 3: US 30-Year TB, C			
Econ. Deriv.	-0.153	0.108	-0.113	0.018*	0.021**
	(0.329)	(0.186)	(0.152)	(0.011)	
Survey	-0.056	0.151	-0.228	-0.013	0.514
	(0.327)	(0.103)	(0.211)	(0.010)	
		Panel 4: US 30-Year TB, J			
Econ. Deriv.	0.718**	0.246	-0.003	-0.006	0.000**
	(0.341)	(0.184)	(0.074)	(0.004)	
Survey	-0.686	-0.097	0.041	0.002	0.030**
	(0.440)	(0.108)	(0.102)	(0.004)	

Note: This table reports the coefficient estimates of regressing volatility and jumps on uncertainty from the economic derivative data and disagreement from the survey data, together with White standard errors inside the parentheses. The p-values in the last column come from the Wald test that all the coefficients in the corresponding rows are zero.

Table 8: News Surprises and Disagreement — Full Sample

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 1: S&P 500, C				
News Surprises	Pos.	0.085	0.037	0.066	0.056**	0.043**
		(0.056)	(0.051)	(0.055)	(0.023)	
	Neg.	0.085	0.115**	0.147**	0.025	0.021**
		(0.061)	(0.058)	(0.057)	(0.028)	
	Pos = Neg	1.000	0.155	0.140	0.334	0.019**
Disagreement		0.468**	0.070	0.407*	0.085	0.016**
		(0.166)	(0.202)	(0.221)	(0.055)	
		Panel 2: S&P 500, J				
News Surprises	Pos.	0.120*	0.014	0.007	-0.005	0.043**
		(0.072)	(0.020)	(0.034)	(0.008)	
	Neg.	0.065	0.033	-0.012	-0.002	0.021**
		(0.048)	(0.024)	(0.033)	(0.014)	
	Pos = Neg	0.258	0.372	0.478	0.853	0.019**
Disagreement		0.167	0.059	0.073	0.003	0.016**
		(0.150)	(0.071)	(0.157)	(0.017)	
		Panel 3: US 30-Year TB, C				
News Surprises	Pos.	0.117**	0.044**	0.019	0.007	0.000**
		(0.039)	(0.022)	(0.017)	(0.008)	
	Neg.	0.068**	0.047**	0.028*	0.013	0.000**
		(0.027)	(0.020)	(0.017)	(0.009)	
	Pos = Neg	0.101	0.856	0.595	0.541	0.000**
Disagreement		0.048	0.056	0.164**	0.040**	0.000**
		(0.074)	(0.067)	(0.079)	(0.016)	
		Panel 4: US 30-Year TB, J				
News Surprises	Pos.	0.196**	0.029**	0.017	0.003	0.000**
		(0.052)	(0.011)	(0.011)	(0.003)	
	Neg.	0.063**	0.034*	0.019	0.009	0.000**
		(0.028)	(0.018)	(0.012)	(0.006)	
	Pos = Neg	0.000**	0.533	0.835	0.210	0.000**
Disagreement		-0.247**	-0.017	-0.045**	-0.000	0.000**
		(0.094)	(0.027)	(0.021)	(0.005)	

Note: This table reports the estimation results of regressing volatility and jumps on standardized positive and negative news surprises and disagreement from the survey data over the full sample.

Table 9: News Surprises and Disagreement — Expansions

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 1: S&P 500, C				
News Surprises	Pos.	0.146**	-0.000	0.004	0.018	0.198
		(0.055)	(0.042)	(0.049)	(0.015)	
	Neg.	0.032	0.088	-0.010	0.003	0.524
		(0.044)	(0.053)	(0.049)	(0.025)	
	Pos = Neg	0.071*	0.108	0.799	0.621	0.275
Disagreement		0.384**	-0.299*	-0.119	-0.033	0.287
		(0.153)	(0.172)	(0.131)	(0.023)	
		Panel 2: S&P 500, J				
News Surprises	Pos.	0.115	0.012	0.028	-0.010	0.198
		(0.073)	(0.021)	(0.036)	(0.007)	
	Neg.	0.085	0.038	-0.015	-0.019*	0.524
		(0.054)	(0.027)	(0.016)	(0.012)	
	Pos = Neg	0.564	0.262	0.141	0.546	0.275
Disagreement		0.240	0.001	-0.093	-0.007	0.287
		(0.155)	(0.067)	(0.083)	(0.016)	
		Panel 3: US 30-Year TB, C				
News Surprises	Pos.	0.126**	0.034	0.020	0.002	0.000**
		(0.040)	(0.022)	(0.018)	(0.006)	
	Neg.	0.063**	0.032	0.041**	0.012	0.000**
		(0.028)	(0.020)	(0.020)	(0.011)	
	Pos = Neg	0.039**	0.921	0.322	0.292	0.000**
Disagreement		0.048	0.009	0.068	0.019	0.000**
		(0.074)	(0.067)	(0.056)	(0.013)	
		Panel 4: US 30-Year TB, J				
News Surprises	Pos.	0.187**	0.034**	0.013	0.002	0.000**
		(0.053)	(0.013)	(0.012)	(0.003)	
	Neg.	0.068**	0.038*	0.023	0.009	0.000**
		(0.032)	(0.021)	(0.015)	(0.007)	
	Pos = Neg	0.001**	0.654	0.382	0.123	0.000**
Disagreement		-0.233**	-0.003	-0.063**	-0.001	0.000**
		(0.098)	(0.030)	(0.024)	(0.004)	

Note: This table reports the estimation results of regressing volatility and jumps on standardized positive and negative news surprises and disagreement from the survey data over the expansion subsample.

Table 10: News Surprises and Disagreement — Contractions

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 1: S&P 500, C				
News Surprises	Pos.	-0.624	0.173	-0.012	0.078	0.716
		(0.435)	(0.122)	(0.052)	(0.099)	
	Neg.	0.337	0.261**	0.173*	-0.050	0.254
		(0.218)	(0.086)	(0.087)	(0.067)	
	Pos = Neg	0.065*	0.559	0.158	0.225	0.211
Disagreement		-0.084	0.697	1.102**	0.427**	0.064*
		(0.927)	(0.513)	(0.231)	(0.191)	
		Panel 2: S&P 500, J				
News Surprises	Pos.	0.351	0.019	-0.162*	0.008	0.716
		(0.208)	(0.045)	(0.080)	(0.051)	
	Neg.	-0.013	0.022	-0.106	0.044	0.254
		(0.024)	(0.036)	(0.093)	(0.051)	
	Pos = Neg	0.054*	0.966	0.491	0.450	0.211
Disagreement		-0.866**	0.321*	0.559*	0.017	0.064*
		(0.393)	(0.168)	(0.319)	(0.087)	
		Panel 3: US 30-Year TB, C				
News Surprises	Pos.	-0.065	0.081*	-0.037	-0.005	0.662
		(0.154)	(0.042)	(0.028)	(0.031)	
	Neg.	0.088	0.123**	-0.047*	-0.017	0.038**
		(0.082)	(0.029)	(0.024)	(0.021)	
	Pos = Neg	0.434	0.477	0.687	0.635	0.173
Disagreement		-0.155	0.141	0.445**	0.120**	0.005**
		(0.374)	(0.198)	(0.097)	(0.055)	
		Panel 4: US 30-Year TB, J				
News Surprises	Pos.	0.330**	-0.004	0.026	0.013	0.662
		(0.113)	(0.008)	(0.030)	(0.013)	
	Neg.	0.047	0.011	0.006	0.008	0.038**
		(0.032)	(0.019)	(0.020)	(0.014)	
	Pos = Neg	0.000**	0.451	0.380	0.694	0.173
Disagreement		-0.248*	-0.056	-0.004	-0.011	0.005**
		(0.135)	(0.044)	(0.036)	(0.023)	

Note: This table reports the estimation results of regressing volatility and jumps on standardized positive and negative news surprises and disagreement from the survey data over the contraction subsample.

Table 11: Full Model (SP,C)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 1: S&P 500, C				
Surprises	Pos.	0.193	0.140	-0.192	0.074	0.537
		(0.268)	(0.222)	(0.252)	(0.052)	
	Neg.	0.136	0.424*	-0.695**	0.088	0.600
		(0.324)	(0.243)	(0.328)	(0.075)	
	Pos = Neg	0.901	0.429	0.132	0.878	0.790
Disagreement		-0.172	0.210	-1.145**	0.035	0.696
		(0.592)	(0.372)	(0.420)	(0.058)	
Surpr * Disagr	Pos.	-0.184	-0.214	0.527	-0.052	0.873
		(0.716)	(0.409)	(0.461)	(0.033)	
	Neg.	-0.090	-0.569	1.507**	-0.043	0.784
		(0.986)	(0.487)	(0.590)	(0.043)	
	Pos = Neg	0.942	0.616	0.118	0.924	0.956
Surprise * DIP	Pos.	-0.556	0.182	-0.110	-0.110	0.100*
		(0.547)	(0.436)	(0.298)	(0.132)	
	Neg.	0.016	-0.070	0.463	-0.079	0.653
		(0.598)	(0.280)	(0.322)	(0.123)	
	Pos = Neg	0.362	0.578	0.098*	0.826	0.342
Disagreement * DIP		1.067	1.522**	1.536**	0.462**	0.073*
		(0.979)	(0.699)	(0.385)	(0.209)	
Surpr * Disagr * DIP	Pos.	1.562	-0.438	-0.133	0.246	0.054*
		(1.436)	(0.828)	(0.421)	(0.164)	
	Neg.	0.210	0.248	-0.936*	-0.017	0.737
		(1.684)	(0.732)	(0.489)	(0.105)	
	Pos = Neg	0.423	0.452	0.136	0.115	0.205

Note: This table reports the full-model estimation results for the volatility of S&P 500 index futures over the full sample.

Table 12: Full Model (SP,J)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 2: S&P 500, J				
Surprises	Pos.	-0.328*	0.158	0.203	-0.002	0.055*
		(0.193)	(0.148)	(0.236)	(0.023)	
	Neg.	-0.705**	0.247	-0.063	-0.042*	0.333
		(0.187)	(0.174)	(0.089)	(0.024)	
	Pos = Neg	0.284	0.611	0.097*	0.179	0.077*
Disagreement		-1.174**	0.224	-0.314*	0.000	0.391
		(0.350)	(0.178)	(0.163)	(0.021)	
Surpr * Disagr	Pos.	1.151**	-0.324	-0.252	-0.002	0.378
		(0.488)	(0.252)	(0.398)	(0.012)	
	Neg.	2.694**	-0.466	0.113	0.023	0.112
		(0.625)	(0.307)	(0.165)	(0.018)	
	Pos = Neg	0.118	0.680	0.225	0.406	0.145
Surprise * DIP	Pos.	0.563*	-0.169	-0.108	-0.006	0.041**
		(0.289)	(0.182)	(0.221)	(0.032)	
	Neg.	0.892**	-0.213	0.219*	0.022	0.330
		(0.235)	(0.139)	(0.131)	(0.044)	
	Pos = Neg	0.492	0.841	0.049**	0.552	0.068*
Disagreement * DIP		1.485**	-0.256	0.793**	-0.022	0.021**
		(0.474)	(0.216)	(0.330)	(0.042)	
Surpr * Disagr * DIP	Pos.	-1.625**	0.399	0.026	-0.008	0.247
		(0.800)	(0.333)	(0.340)	(0.030)	
	Neg.	-2.642**	0.497	-0.375*	-0.014	0.291
		(0.743)	(0.326)	(0.214)	(0.030)	
	Pos = Neg	0.429	0.824	0.120	0.914	0.251

Note: This table reports the full-model estimation results for the jumps of S&P 500 index futures over the full sample.

Table 13: Full Model (US,C)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 3: US 30-Year TB, C				
Surprises	Pos.	0.749**	0.169	-0.107	0.016	0.000**
		(0.238)	(0.160)	(0.101)	(0.018)	
	Neg.	0.259	-0.105	-0.338**	0.043*	0.088*
		(0.165)	(0.138)	(0.113)	(0.024)	
	Pos = Neg	0.016**	0.086*	0.042**	0.325	0.000**
Disagreement		0.553**	0.141	-0.480**	-0.018	0.007**
		(0.269)	(0.251)	(0.137)	(0.013)	
Surpr * Disagr	Pos.	-1.547**	-0.252	0.275	0.011	0.001**
		(0.482)	(0.296)	(0.186)	(0.008)	
	Neg.	-0.579	0.150	0.685**	-0.017	0.354
		(0.444)	(0.274)	(0.211)	(0.014)	
	Pos = Neg	0.089*	0.201	0.055*	0.324	0.004**
Surprise * DIP	Pos.	-0.759**	-0.156	0.119	-0.055	0.005**
		(0.303)	(0.219)	(0.119)	(0.040)	
	Neg.	-0.150	0.101	0.310**	-0.061*	0.379
		(0.235)	(0.143)	(0.117)	(0.036)	
	Pos = Neg	0.028**	0.202	0.105	0.873	0.023**
Disagreement * DIP		-0.576*	0.192	0.744**	0.154**	0.003**
		(0.338)	(0.354)	(0.144)	(0.067)	
Surpr * Disagr * DIP	Pos.	2.323**	0.189	-0.280	0.028	0.003**
		(0.776)	(0.420)	(0.169)	(0.049)	
	Neg.	0.662	-0.086	-0.613**	0.006	0.957
		(0.568)	(0.373)	(0.185)	(0.030)	
	Pos = Neg	0.025**	0.498	0.070*	0.663	0.029**

Note: This table reports the full-model estimation results for the volatility of 30-year U.S. Treasury futures over the full sample.

Table 14: Full Model (US,J)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 4: US 30-Year TB, J				
Surprises	Pos.	0.814**	0.068	0.085	-0.002	0.000**
		(0.273)	(0.094)	(0.071)	(0.006)	
	Neg.	0.432*	0.134**	0.025	0.015	0.000**
		(0.234)	(0.059)	(0.061)	(0.013)	
	Pos = Neg	0.121	0.285	0.305	0.128	0.000**
Disagreement		0.013	0.038	0.045	0.001	0.140
		(0.396)	(0.092)	(0.091)	(0.006)	
Surpr * Disagr	Pos.	-0.962	-0.072	-0.165	-0.003	0.000**
		(0.674)	(0.161)	(0.135)	(0.003)	
	Neg.	-0.756	-0.224**	-0.085	-0.012*	0.003**
		(0.823)	(0.103)	(0.104)	(0.007)	
	Pos = Neg	0.767	0.214	0.465	0.430	0.000**
Surprise * DIP	Pos.	-0.271	-0.025	-0.019	0.027**	0.269
		(0.378)	(0.094)	(0.073)	(0.013)	
	Neg.	-0.181	-0.064	0.002	0.008	0.391
		(0.300)	(0.046)	(0.066)	(0.018)	
	Pos = Neg	0.790	0.618	0.728	0.271	0.327
Disagreement * DIP		0.101	-0.032	-0.054	0.051**	0.607
		(0.391)	(0.100)	(0.083)	(0.022)	
Surpr * Disagr * DIP	Pos.	0.024	0.039	0.113	-0.031*	0.897
		(0.891)	(0.163)	(0.114)	(0.016)	
	Neg.	0.247	0.110	0.066	-0.009	0.828
		(0.821)	(0.096)	(0.098)	(0.013)	
	Pos = Neg	0.805	0.652	0.623	0.271	0.961

Note: This table reports the full-model estimation results for the jumps of 30-year U.S. Treasury futures over the full sample.

Table 15: Full Model for the Subsample with Zero Lower Bound (SP,C)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 1: S&P 500, C				
Surprises	Pos.	-0.471	-0.834	0.219	0.028	0.589
		(0.753)	(0.523)	(0.476)	(0.180)	
	Neg.	-0.348	0.537	-0.132	-0.579**	0.461
		(0.420)	(0.794)	(0.310)	(0.266)	
	Pos = Neg	0.907	0.103	0.400	0.048**	0.552
Disagreement		-3.381**	-0.892	-0.624	-1.571**	0.083*
		(1.021)	(0.619)	(0.646)	(0.418)	
Surpr * Disagr	Pos.	2.263	2.253**	-0.019	0.209	0.556
		(3.585)	(1.084)	(0.732)	(0.360)	
	Neg.	2.478	-0.970	0.640	1.640**	0.559
		(1.626)	(1.961)	(0.530)	(0.660)	
	Pos = Neg	0.960	0.135	0.353	0.045**	0.584
Surprise * DIP	Pos.	0.599	1.084	-0.541	-0.083	0.459
		(0.921)	(0.752)	(0.538)	(0.203)	
	Neg.	0.549	-0.266	-0.126	0.496*	0.300
		(0.476)	(1.111)	(0.386)	(0.280)	
	Pos = Neg	0.964	0.189	0.272	0.047**	0.346
Disagreement * DIP		5.221**	2.252**	0.834	1.799**	0.002**
		(0.960)	(0.727)	(0.845)	(0.359)	
Surpr * Disagr * DIP	Pos.	-2.157	-2.456*	0.432	-0.068	0.648
		(3.795)	(1.355)	(0.741)	(0.307)	
	Neg.	-3.578**	0.725	-0.144	-1.484**	0.649
		(1.545)	(2.764)	(0.557)	(0.620)	
	Pos = Neg	0.730	0.235	0.306	0.025**	0.631

Note: This table reports the full-model estimation results for the volatility of S&P 500 index futures over the subsample with zero lower bound.

Table 16: Full Model for the Subsample with Zero Lower Bound (SP,J)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 2: S&P 500, J				
Surprises	Pos.	-1.109**	0.029	-0.028	0.033	0.422
		(0.326)	(0.207)	(0.079)	(0.062)	
	Neg.	-0.647*	0.571**	-0.086	0.061	0.514
		(0.359)	(0.284)	(0.081)	(0.103)	
	Pos = Neg	0.467	0.158	0.540	0.833	0.521
Disagreement		-0.546	-0.000	-0.137	0.203	0.441
		(0.734)	(0.213)	(0.099)	(0.148)	
Surpr * Disagr	Pos.	5.477**	-0.369	0.035	-0.088	0.103
		(1.419)	(0.503)	(0.106)	(0.109)	
	Neg.	2.271	-1.671**	0.052	-0.317	0.401
		(1.750)	(0.591)	(0.112)	(0.226)	
	Pos = Neg	0.212	0.187	0.917	0.462	0.172
Surprise * DIP	Pos.	1.193**	0.110	0.038	-0.027	0.328
		(0.398)	(0.258)	(0.074)	(0.069)	
	Neg.	0.759**	-0.637**	0.114	-0.062	0.451
		(0.372)	(0.303)	(0.077)	(0.106)	
	Pos = Neg	0.502	0.112	0.371	0.785	0.405
Disagreement * DIP		0.459	-0.030	0.091	-0.226*	0.193
		(0.675)	(0.236)	(0.094)	(0.136)	
Surpr * Disagr * DIP	Pos.	-5.201**	0.204	-0.036	0.075	0.093*
		(1.434)	(0.533)	(0.095)	(0.097)	
	Neg.	-1.485	2.191**	-0.090	0.294	0.410
		(1.736)	(0.739)	(0.098)	(0.211)	
	Pos = Neg	0.132	0.105	0.669	0.431	0.144

Note: This table reports the full-model estimation results for the jumps of S&P 500 index futures over the subsample with zero lower bound.

Table 17: Full Model for the Subsample with Zero Lower Bound (US,C)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 3: US 30-Year TB, C				
Surprises	Pos.	-0.145	0.234	0.096	-0.005	0.830
		(0.416)	(0.228)	(0.241)	(0.072)	
	Neg.	-0.302	0.471	-0.324*	-0.188**	0.145
		(0.281)	(0.322)	(0.170)	(0.080)	
	Pos = Neg	0.718	0.527	0.046**	0.120	0.313
Disagreement		-0.993**	0.351	-0.376	-0.335*	0.161
		(0.394)	(0.319)	(0.299)	(0.178)	
Surpr * Disagr	Pos.	1.396	-0.415	0.075	0.112	0.995
		(1.645)	(0.521)	(0.369)	(0.161)	
	Neg.	1.027	-1.537**	0.891**	0.564**	0.011**
		(0.971)	(0.746)	(0.376)	(0.208)	
	Pos = Neg	0.835	0.243	0.022**	0.099*	0.102
Surprise * DIP	Pos.	0.210	-0.247	-0.135	-0.048	0.817
		(0.455)	(0.302)	(0.257)	(0.075)	
	Neg.	0.350	-0.621	0.164	0.148*	0.453
		(0.296)	(0.450)	(0.179)	(0.080)	
	Pos = Neg	0.752	0.415	0.117	0.081*	0.602
Disagreement * DIP		1.069**	-0.186	0.500	0.424**	0.055*
		(0.368)	(0.431)	(0.406)	(0.154)	
Surpr * Disagr * DIP	Pos.	-0.734	0.467	-0.019	-0.062	0.992
		(1.846)	(0.629)	(0.357)	(0.139)	
	Neg.	-0.951	2.068*	-0.599*	-0.513**	0.027**
		(0.887)	(1.061)	(0.321)	(0.192)	
	Pos = Neg	0.898	0.180	0.041**	0.064*	0.170

Note: This table reports the full-model estimation results for the volatility of 30-year U.S. Treasury bond futures over the subsample with zero lower bound.

Table 18: Full Model for the Subsample with Zero Lower Bound (US,J)

		NFPAY	NAPM	RSXAUT	ICLM	Joint
		Panel 4: US 30-Year TB, J				
Surprises	Pos.	-0.205	-0.067	0.068	0.021	0.505
		(0.630)	(0.157)	(0.116)	(0.039)	
	Neg.	-0.079	0.080	0.100	-0.005	0.078*
		(0.393)	(0.100)	(0.083)	(0.039)	
	Pos = Neg	0.841	0.391	0.705	0.604	0.163
Disagreement		-0.914	0.035	0.172**	0.044	0.328
		(0.641)	(0.132)	(0.084)	(0.101)	
Surpr * Disagr	Pos.	2.329	0.196	-0.240	-0.088	0.888
		(2.243)	(0.389)	(0.192)	(0.081)	
	Neg.	0.716	-0.119	-0.164	-0.006	0.398
		(1.355)	(0.221)	(0.123)	(0.120)	
	Pos = Neg	0.525	0.473	0.596	0.482	0.701
Surprise * DIP	Pos.	0.714	0.092	-0.014	0.010	0.690
		(0.625)	(0.124)	(0.123)	(0.041)	
	Neg.	0.349	0.022	-0.078	0.028	0.900
		(0.446)	(0.147)	(0.092)	(0.035)	
	Pos = Neg	0.567	0.737	0.395	0.712	0.920
Disagreement * DIP		0.915	0.007	-0.232**	0.026	0.697
		(0.628)	(0.102)	(0.109)	(0.091)	
Surpr * Disagr * DIP	Pos.	-3.079	-0.186	0.188	0.029	0.566
		(2.140)	(0.275)	(0.172)	(0.068)	
	Neg.	-1.051	-0.060	0.169	-0.018	0.837
		(1.353)	(0.322)	(0.119)	(0.109)	
	Pos = Neg	0.406	0.817	0.869	0.649	0.771

Note: This table reports the full-model estimation results for the jumps of 30-year U.S. Treasury bond futures over the subsample with zero lower bound.

Table 19: ACH Model Estimates

	ACH(1,1)		Augmented ACH(1,1)	
	SP	US	SP	US
ω	0.018(0.019)	0.034(0.024)	–	–
α_1	0.056(0.013)**	0.056(0.014)**	0.058(0.014)**	0.020(0.011)
β_1	0.940(0.015)**	0.936(0.017)**	0.929(0.018)**	0.938(0.027)**
δ_0	–	–	0.899(0.368)**	2.048(0.301)**
NFPAY(+)	–	–	-1.976(0.609)**	-3.587(0.321)**
NAPM(+)	–	–	-0.157(0.721)	-0.618(0.050)**
RSXAUT(+)	–	–	-1.280(0.083)**	-0.838(0.079)**
ICLM(+)	–	–	-0.125(0.396)	-0.100(0.397)
NFPAY(-)	–	–	1.499(0.103)**	2.127(0.220)**
NAPM(-)	–	–	-0.109(0.824)	-0.054(0.964)
RSXAUT(-)	–	–	-0.787(1.401)	0.677(0.527)
ICLM(-)	–	–	0.282(0.473)	0.313(0.294)
DIP	–	–	-0.030(0.324)	2.472(0.504)**

This table reports the estimated coefficients from both the simple and augmented ACH(1,1) models. White standard errors are inside the parentheses.

9 Figures

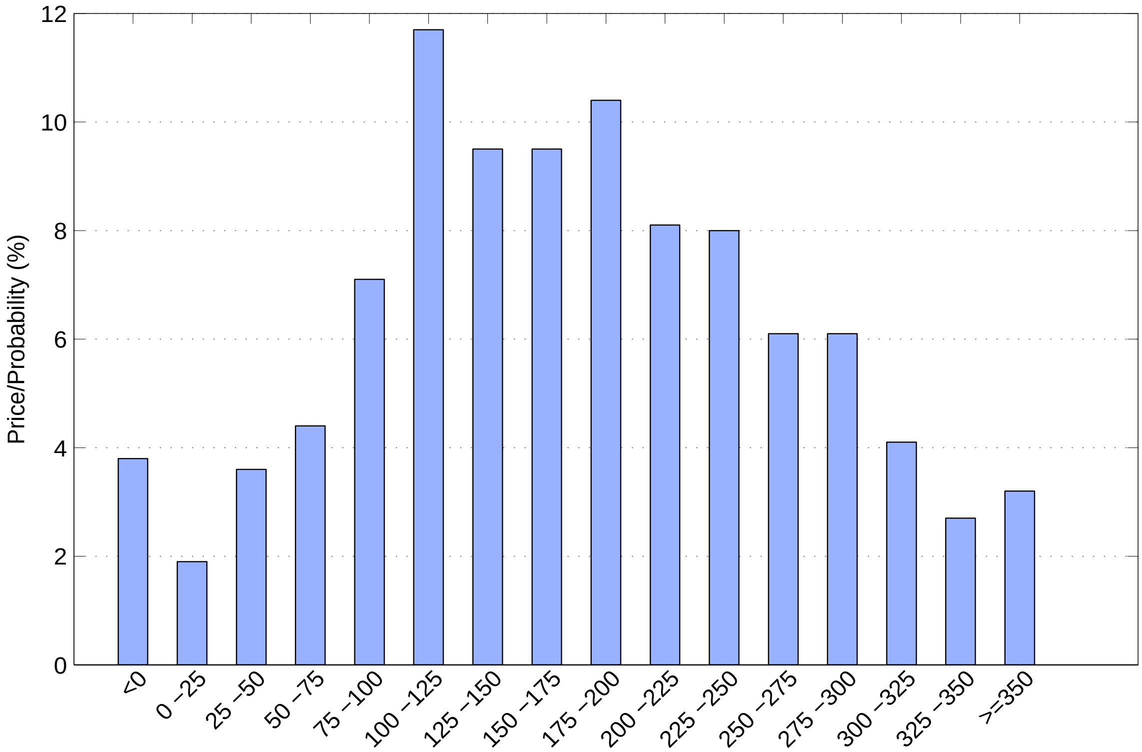

Figure 1: An Example of Economic Derivative Prices

Note: These are prices of the digital options on nonfarm payroll employment for May 2005. The auction was held on June 3, 2005.

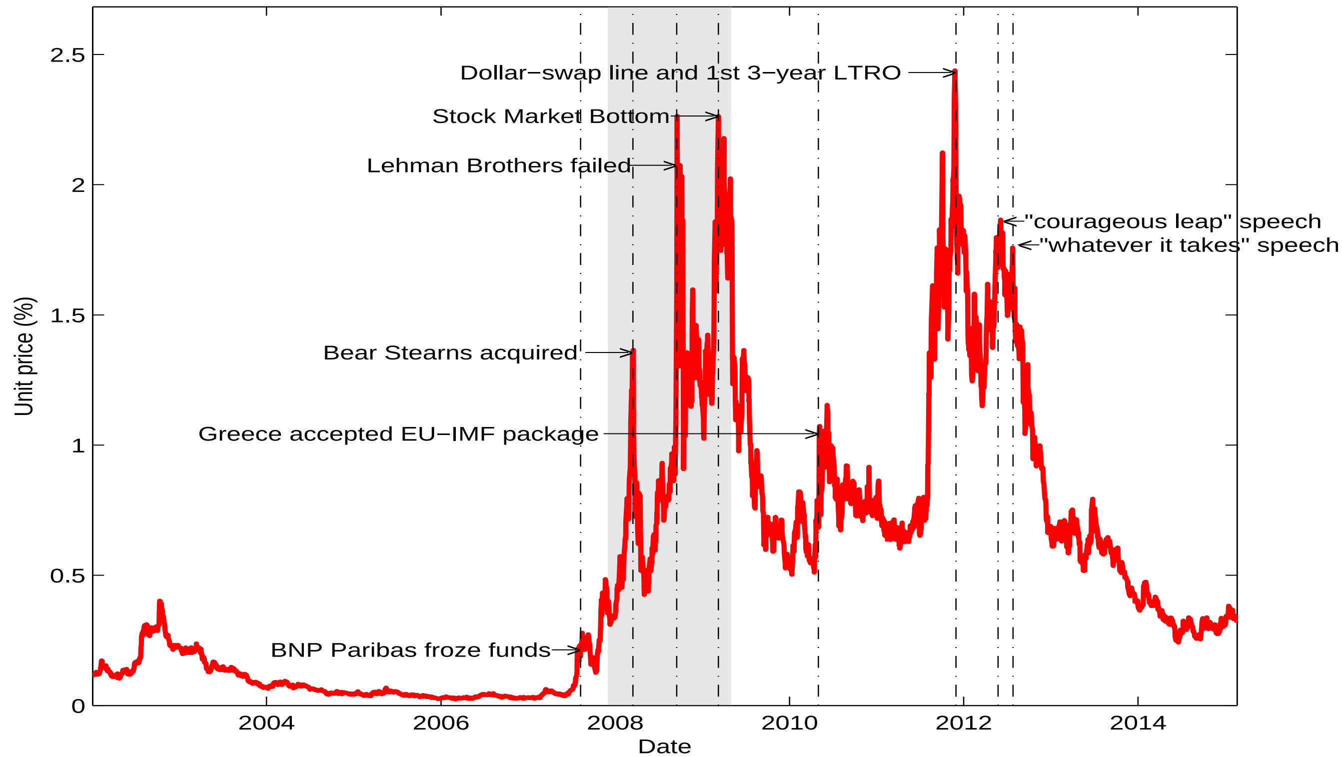

Figure 2: DIP from January 2002 to September 2014

Note: NBER contraction period is shaded in grey. The 14 SIFI sample firms are Bank of America, Bank of New York Mellon, Barclays, Citigroup, Credit Suisse, Goldman Sachs, JPMorgan Chase, Morgan Stanley, State Street, Wells Fargo, Deutsche Bank, UBS, AIG and Prudential Financial. The first 12 firms are in the banking sector and the last 2 firms are insurance companies.

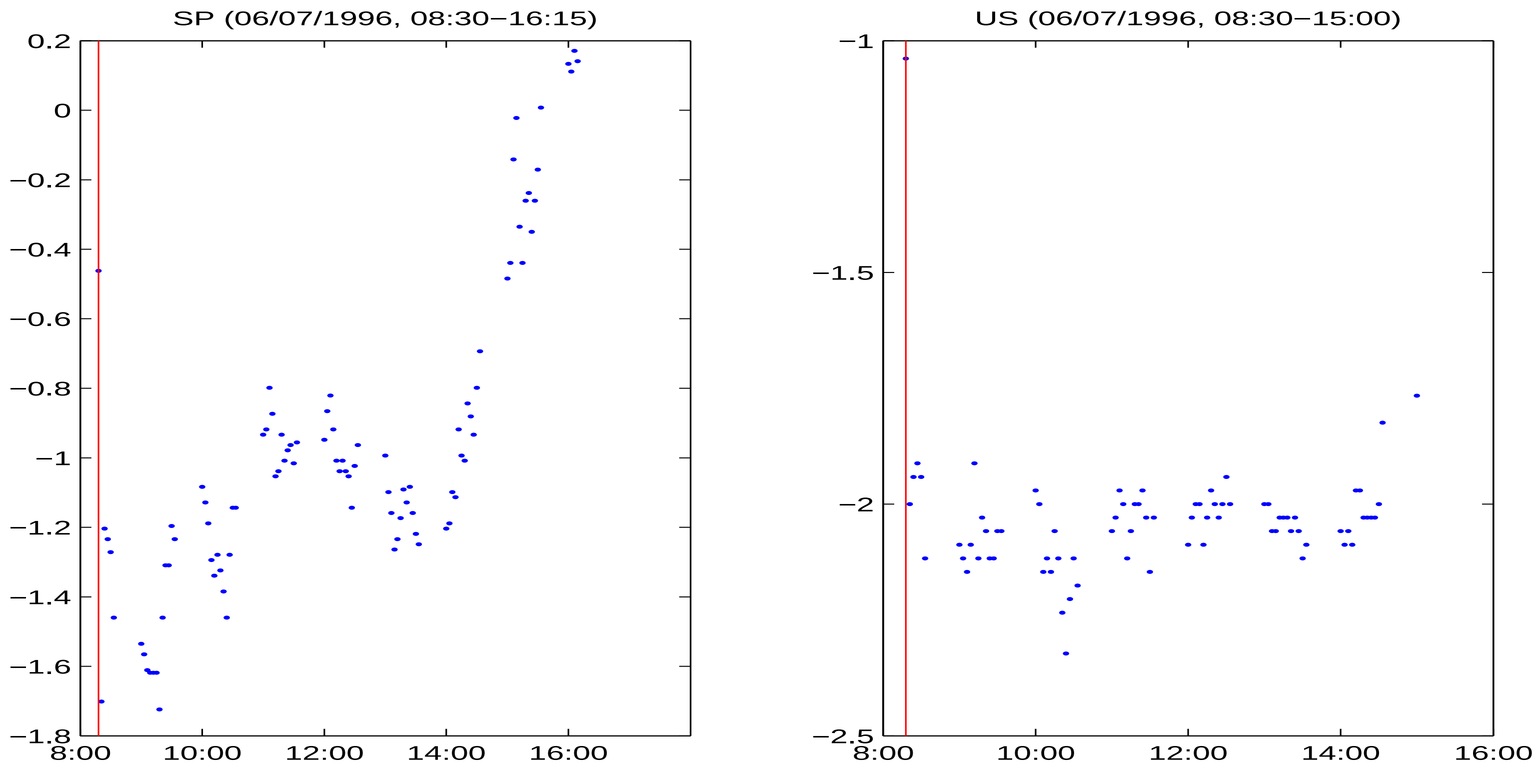

Figure 3: Logarithmic Prices on 6/7/1996

Note: Both series are shifted so that the first logarithmic prices for both SP and US on this day are 0 for easy comparison. NFPAY: released value is 340, survey expectation is 170 with a standard deviation of 56.5. The dots are the logarithmic prices, and the line is at 8:30 Eastern Time when the announcement was released.