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Abstract

We use recently proposed tests to extract jumps and cojumps from three types of assets: stock index futures, bond futures, and exchange rates. We then characterize the dynamics of these discontinuities and informally relate them to U.S. macroeconomic releases before using limited dependent variable models to formally model how news surprises explain (co)jumps. Nonfarm payroll and federal funds target announcements are the most important news across asset classes. Trade balance shocks are important for foreign exchange jumps. We relate the size, frequency and timing of jumps across asset classes to the likely sources of shocks and the relation of asset prices to fundamentals in the respective classes.

Keywords: exchange rates, futures, bonds, bipower variation, robust intraday periodicity, jumps, macroeconomic announcement.

JEL Codes: G14, G15, F31, C22

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1 Introduction

How markets process information and what determines asset return distributions are central issues in economics. Our study investigates jumps and simultaneous jumps in multiple markets (i.e., cojumps) and their relation to macroeconomic news releases. How big and frequent are jumps across asset classes and over time? Do jumps cluster in time? Are there more "cojumps" than one would expect if asset prices jumped independently? What causes (co)jumps and how do such causes vary across markets? Our study answers these questions.

Andersen, Bollerslev, Diebold and Vega (2003, 2007a) studied how macroeconomic news releases affect asset returns generally, but we focus on discontinuous price changes. Duffie, Pan and Singleton (2000), Liu, Longstaff and Pan (2003), Eraker, Johannes and Polson (2003), and Piazzesi (2005) discuss how knowledge of jumps influences financial management. Lee and Mykland (2008) and Tauchen and Zhou (2005) explain how characterizing the distribution and causes of jumps can improve asset pricing models, which motivates our study.

We use the non-parametric statistic of Andersen, Bollerslev and Dobrev (2007c) and Lee and Mykland (2008), modified by Boudt, Croux and Laurent (2008), to extract jumps and cojumps from three types of assets—exchange rates, stock index futures and U.S. bond futures—and then relate those jumps to macroeconomic news. The jump test compares returns to a local volatility measure to find returns that a diffusion is very unlikely to produce—jumps. Because our procedure identifies the precise timing of intraday jumps, it is especially useful in studying the effects of announcements on jumps and cojumps.

We define cojumps with univariate tests as simultaneous significant jumps, rather than using any of the multivariate tests proposed by Barndorff-Nielsen and Shephard (2006b), Jacod and Todorov (2009), and Bollerslev, Law and Tauchen (2008). Our approach is most appropriate for the present study because it permits straightforward estimates of precisely timed cojumps with a relatively narrow range of intraday data.

Researchers have evaluated the impact of macroeconomic news on assets returns in many ways. To the best of our knowledge, two other concurrent papers study the link between jumps and news besides the present paper. Huang (2007) estimates daily jumps with bipower variation on 10 years of S&P 500 and U.S. T-bonds data. Analyzing conditional distributions of jumps, and regressing continuous and jump components on measures of disagreement and uncertainty concerning future macroeconomic states, Huang (2007) finds a major role for payroll news and a relatively more responsive bond market. This is basically consistent with our findings. Dungey, McKenzie and Smith (2008) focus on the Treasury market, estimating jumps and cojumps across the term structure with bipower variation. Dungey et al. (2008) find that the middle of the yield curve often cojumps with one of the ends, while the ends of the curve exhibit more idiosyncratic jumps. Macro news is strongly associated with cojumps in the term structure.

Our paper differs from these concurrent papers in several respects. First, we estimate jumps at a very high frequency with the Andersen/Bollerslev/Dobrev and Lee/Mykland technique, modified by Boudt et al. (2008). These intraday estimates, which are much more precise than daily (bipower variation) jump measures, enable us characterize cojumps and to carefully link macro news to (co)jumps. Second, we implement Boudt et al. (2008)'s modification to the jump statistic, which improves jump detection in the presence of intraday patterns in volatility. The Lee/Mykland statistic overdetects (underdetects) jumps in periods of high (low) intraday volatility. Third, we consider a broad set of financial assets including exchange rates, stocks, and bonds. Fourth, we estimate Tobit-GARCH and probit models to formally assess the impact of macro surprises on jumps and cojumps.

To presage our results, we find that exchange rate jumps are frequent but small, fairly symmetric and highly interdependent. U.S. news releases are relatively less important to USD markets than to U.S. stock and bond markets. In contrast, bond markets are the most sensitive to our news releases, by some measures, and display significant asymmetry. Certain market combinations are more likely to cojump because shocks affect them similarly. The fed funds target, NFP and GDP announcements are important in all markets and the trade balance is important in forex. We conclude that (co)jump behavior varies across markets in a sensible fashion. The likely sources of jumps and the variation in market dependence on fundamentals explains how (co)jump behavior differs across markets.

The rest of the paper proceeds as follows: Section 2 explains our jump detection procedures while Section 3 characterizes (co)jumps and their joint distribution with our news releases. Section 4 formally evaluate the impact of news surprises on jumps/cojumps with Tobit-GARCH and probit models. Section 5 concludes.

2 Jump identification

We describe the original tests of Andersen et al. (2007c) and Lee and Mykland (2008) before explaining Boudt et al. (2008)'s modification that accounts for a deterministic volatility component.

2.1 First step towards intraday jumps detection

Andersen et al. (2007c) and Lee and Mykland (2008) assume a continuous time jump-diffusion data generating process. The log price process evolves as follows:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), \qquad 0 \leq t \leq T, \tag{1}$$

where $p(t)$ is a log asset price, $W(t)$ is a standard Brownian motion, $q(t)$ is a counting process, possibly a non-homogenous Poisson process, independent of $W(t)$, and $\kappa(t)$ $(= p(t) - p(t-))$ is the jump size. The Brownian motion, $W(t)$, jump sizes, $\kappa(t)$, and the counting process, $q(t)$, are independent of each other. In the absence of jumps, the drift $\mu(t)$ and instantaneous volatility $\sigma(t)$ are such that the underlying data generating process is an Itô process with continuous sample paths. The drift and diffusion coefficients may not change dramatically over short periods of time.

The intuition behind the jump test proposed simultaneously by Andersen et al. (2007c) and Lee and Mykland (2008) is straightforward: In the absence of jumps, instantaneous returns are increments of Brownian motion. Standardized returns that are too large to plausibly come from a standard Brownian motion must reflect jumps.[1] More formally, assume we have T days of $\lfloor 1/\Delta \rfloor \equiv M$ equally-spaced intraday returns and denote the i-th return of day t by $r_{t,i} \equiv p(t + i\Delta) - p(t + (i-1)\Delta)$, where $i = 1, \ldots, M$. Andersen et al. (2007c) and Lee and Mykland (2008) propose the following test statistic for jumps in $r_{t,i}$:

$$J_{t,i} \equiv \frac{\mid r_{t,i} \mid}{\sigma_{t,i}}. \tag{2}$$

One must estimate the unobserved volatility, $\sigma_{t,i}$, with a robust-to-jumps estimator. Barndorff-Nielsen and Shephard (2004, 2006a) show that, under weak conditions, realized bipower variation (RBV) converges to integrated volatility under the model described by Equation (1).

$$\operatorname*{plim}_{\Delta \to 0} RBV_t(\Delta) = \int_{t-1}^{t} \sigma^2(s)ds, \tag{3}$$

where

$$RBV_t(\Delta) \equiv \mu_1^{-2} \sum_{i=2}^{M} |r_{t,i}||r_{t,i-1}|, \tag{4}$$

with $\mu_1 \equiv \sqrt{2/\pi} \simeq 0.79788$.

Consequently, Andersen et al. (2007c) and Lee and Mykland (2008) propose estimating $\sigma^2_{t,i}$ as the average of the RBV computed over a local window of K observations preceding period t, i. They both explicitly assume that the spot volatility is approximately constant over that window. There is a clear tradeoff in choosing the window size K: K must be large enough to accurately estimate integrated volatility but small enough for variance to be approximately constant. For returns sampled at frequencies of 60, 30, 15, and 5 minutes, Lee and Mykland (2008) recommend using $K = 78, 110, 156$ and 270 observations, respectively.

Under the null of no jumps, the test statistic, $J_{t,i}$, follows the same distribution as the absolute value of a standard normal variable. Lee and Mykland (2008) propose inferring jumps from the distribution of the statistic's maximum over the sample size. Under the null of no jumps in $t, i-1$ to t, i, then, as $\Delta \to 0$, the sample maximum of the absolute value of a standard normal (i.e. $J_{t,i}$ in (2)) converges to a Gumbel distribution. We reject the null of no jump if

$$J_{t,i} > G^{-1}(1-\alpha)S_n + C_n, \tag{5}$$

where $G^{-1}(1-\alpha)$ is the $1-\alpha$ quantile function of the standard Gumbel distribution, $C_n = (2\log n)^{0.5} - \frac{\log(\pi)+\log(\log n)}{2(2\log n)^{0.5}}$ and $S_n = \frac{1}{(2\log n)^{0.5}}$, n being the total number of observations (i.e, $M \times T$). With a significance level of $\alpha = 0.1$, we reject the null of no jump if $J_{t,i} > S_n\beta^* + C_n$ with β^* such that $exp(-e^{-\beta^*}) = 1 - \alpha = 0.9$, i.e. $\beta^* = -log(-log(0.9)) = 2.25$. This conservative procedure can be expected to find only α spurious jumps in a given sample of n observations.

[1] The drift is nearly zero and can be ignored in practice.

2.2 The instantaneous volatility periodicity problem

Many financial time series display deterministic periodic variation within a day or a week (Andersen and Bollerslev, 1997). Estimating volatility using RBV rolling windows inappropriately smooths these periodic patterns, because such an estimator is necessarily slowly time varying. Boudt et al. (2008) show that such cyclical patterns might induce the $J_{t,i}$ statistic to spuriously detect jumps. To correctly infer jumps, we must estimate and remove this deterministic periodicity with a robust-to-jumps volatility estimator.

Following Boudt et al. (2008), we assume that instantaneous volatility in Equation (1) is the product of a slowly varying component, $\delta(t)$, and a deterministic circadian component, $f(t)$.

$$\sigma(t) = \delta(t) f(t). \tag{6}$$

We assume, without loss of generality, this deterministic variance process integrates to one on a daily basis,

$$\int_{t-1}^{t} f^2(s) ds = 1, \tag{7}$$

and standardize the estimates of intraday periodicity in volatility accordingly.

Boudt et al. (2008) propose modifying the jump statistic to account for the circadian component in volatility, i.e.,

$$FiltJ_{t,i} \equiv \frac{\mid r_{t,i} \mid}{\delta_{t,i} f_{t,i}}, \tag{8}$$

where $\delta_{t,i}$ is estimated as the average of the RBV over the K observations preceding $r_{t,i}$ and $f_{t,i}$, the circadian component, with Boudt et al. (2008)'s modification to Taylor and Xu (1997)'s estimator. This estimation scheme omits returns that might contain jumps to avoid biased estimates of the periodicity. Appendix A-1 describes the periodicity filters.

The pattern of intraday periodicity in volatility varies over time, enough to affect the jump estimation. So we reestimate it for each year, which provides a reasonable trade-off between permitting time variation and accurate estimation. For brevity, we do not describe the estimated volatility periodicity in this paper, but they are available upon request.

In the remainder of the text, $Jump_{t,i}$ denotes significant jumps based on the jump statistics given in Equation (8). It equals the tested return $r_{t,i}$ when there is a significant jump (i.e. $FiltJ_{t,i} > G^{-1}(1-\alpha)S_n + C_n$) and it equals 0 otherwise, i.e.,

$$Jump_{t,i} \equiv r_{t,i} \times I(FiltJ_{t,i} - G^{-1}(1-\alpha)S_n - C_n), \tag{9}$$

where $I(.)$ is the indicator function for a positive argument. Because we use the conservative Lee and Mykland (2008) procedure that is expected to find only α spurious jumps in the whole sample, we evaluate jumps with a significance level of $\alpha = 0.1$.

3 Jumps and cojumps

This subsection characterizes the jumping and cojumping behavior of 8 financial assets from 3 asset classes: four dollar exchange rates, denoted USD/EUR, USD/GBP, JPY/USD, and CHF/USD, respectively, three stock index futures, Nasdaq, Dow Jones, S&P 500, denoted as ND, DJ, and SP, respectively, and 30-year U.S. Treasury bond futures, denoted as US.

3.1 The Data

Table 1 summarizes the source, timing and sample lengths of the asset return series and Appendix A-2 further details these data. The sample lengths vary across assets, from 18 years for the exchange rates to about 6.5 to 7 years for bond and equity futures.[2] We consider 24-hour trading for exchange rates and approximately business hours for the bond and equity data: 8:30 to 15:00 or 16:15.[3] The Nasdaq and S&P 500 data include limited electronic trading, which enables these data to start at 8:30, the same starting time as the U.S. bonds and Dow Jones futures.[4] In choosing the trading hours, we sought to obtain the longest spans of data, the longest daily trading hours with liquid trading and similar trading hours within the bond and stock classes.

We use a sampling frequency of 15 minutes for all data. Our own unreported simulation results and those in Lee and Mykland (2008) show that the jump test has good power at the 15-minute frequency. Volatility signature plots —omitted for brevity— and results from the literature lead us to think that 15-minute returns are free of microstructure noise.

3.2 Jump sources and relation to fundamentals

The sources of news and relation of asset prices to fundamentals help us understand jump characteristics across markets. There are at least three sources of jumps: 1) Our set of U.S. news releases; 2) other news, not in our set, including foreign releases; and 3) idiosyncratic liquidity shocks from traders moving into and out of markets, perhaps revealing private information. Liquidity shocks are much more likely during periods of slow trading—as might be experienced on the 24-hour-a-day forex markets—and are likely to be specific to one market.

Different functions of fundamentals drive exchange rates, stocks and bond prices. Exchange rates reflect the discounted stream of expected relative fundamentals between the two currencies.

[2] We splice USD/DEM returns with USD/EUR returns on January 1, 1999, and call the resulting series the USD/EUR for simplicity.

[3] Exchange rates display known features: low volatility during Tokyo lunch at about 22:00 EST (3:00 GMT), higher volatility during the London segment starting at about 1:00 EST (6:00 GMT), and the highest variation during the London - New-York overlap, from 7:00 to 10:00 EST (12:00 to 15:00 GMT) (Andersen and Bollerslev 1998). The Nasdaq and S&P series display relatively low volatility during the E-platform trading, prior to 9:30 EST, and a U-shaped pattern of higher volatility during pit trading. The Dow Jones and U.S. T-bonds futures series also display U-shaped patterns during pit trading.

[4] We note that U.S. bonds and Dow Jones futures trade at the CBOT from 8:20 EST on. We sampled from 8:30 for ease of comparison with other series.

Equity prices reflect the discounted stream of expected future dividends in the domestic currency; bond prices reflect only the domestic discount factor. The fact that asset prices reflect changes in fundamentals in different ways will affect their jump characteristics.

3.3 Jump size and frequency

Figure 1 provides a bird's eye view on the time series of identified jumps, illustrating that jumping behavior varies by asset class. For example, the volatile ND futures exhibit fewer but larger jumps than exchange rates. Comparing jumps between markets, the size of detected jumps must be positively related to the underlying volatility of the market because jump detection procedures can only find jumps that are larger than the diffusion volatility, for a given data frequency. More volatile markets will tend to have larger jumps.

The $P(jumpday)$ statistics in the second horizontal panel of Table 2 show that stock indices and bond futures exhibit fewer jump days than on dollar exchange rates. US bonds and stock index futures jump on 6.62 to 8.43 % of sample days, while dollar exchange rates—with 24 hours of data per day—jump on about 25% of sample days. While foreign exchange rates jump on 3 or 4 times as many days as stock and bond markets, the 24-hour forex market also has about 3 times as many trading hours in the day. Per observation, foreign exchange markets jump about 50 percent more often than the SP or DJ markets but about as often as the very volatile ND or US Treasury bond futures ($P(jump)$). The Treasury bond futures market (column 4, US) also jumps frequently. It exhibits more jumps per observation ($P(jump) = 0.37\%$) than three of the four exchange rates but the exchange rates exhibit more jump days.

Table 2 shows that stock indices and bond futures exhibit relatively large jumps, which average between 0.51 and 1.61%, in absolute value ($E(|jumpsize|\ |jump)$). Exchange rates jumps are smaller, averaging between 0.27 and 0.36%, in absolute value. The coefficients of variation $\left(\frac{\sigma}{\mu}\right)$ for absolute jumps are similar across assets, ranging from 63 percent for the SP to 74 percent for the DJ.

Exchange rates experience more frequent jump days than stock or bond markets because they are subject to news from two countries, not just one, and probably because they experience more idiosyncratic liquidity shocks during slow trading in the 24-hour markets. Commonality in international business cycles (see Kose, Otrok and Whiteman, 2003, 2008) means that a shock to a U.S. or foreign fundamental will change the expected value of the relative fundamentals much less than the individual variable. And idiosyncratic liquidity shocks will tend to produce relatively small jumps. Thus, exchange rates will experience small but frequent jumps.

Equity prices depend on the expected discounted stream of future dividends while bond prices depend on the discount factor. That is, U.S. macro surprises—not relative surprises—matter for equities and bonds and their jumps tend to be larger than forex jumps, even relative to their larger return volatility. Mean bond, stock and forex jumps are about 5, 4 and 3 percent of their annual volatilities, respectively. Researchers have speculated that bond prices exhibit large jumps in response to news because bond prices depend only on the discount factor, while offsetting news effects on the discount rate and expected dividends might dampen the size of equity jumps, weakening the relation of macro surprises to equity jumps (Ederington and Lee, 1993; Fleming and Remolona, 1997, 1999). For example, a positive GDP shock will tend to increase dividend forecasts but it will also tend to raise expected interest rates. These effects will tend to offset each other in equity prices. We will show later that some of the bond market's jump frequency is due to its sensitivity to news.

3.4 Symmetry in jump frequency

Is there asymmetry in positive and negative jump frequency? While we analyze jumps rather than returns, previous theoretical and empirical results on returns suggest that markets respond more to negative surprises in good times.[5] Because surprises are mean zero and most of our sample covers expansions, we might expect more significant negative jumps, at least for bonds and equities.[6] The justification for asymmetry is less clear in other markets.

The last two rows of Table 2 show that forex markets show no evidence of consistent or sizable asymmetry, although the USD/EUR shows a modest—but statistically significant—preponderance of positive jumps.[7] Equity markets tend to show more negative jumps but the disparity is not statistically significant. Bond markets do display significant asymmetry, however: More than 58 percent of all bond jumps are negative and this figure is statistically significantly different than 50 percent.

Why are bond market jumps asymmetric? Figure 1 suggests that many of the negative bond price jumps came in late 1998 and the first half of 1999, during which 30-year Treasury bond yields rose from about 5 percent to 6 percent. About 75 percent of bond jumps were negative from July 1998 through June 1999, and one fails to reject bond jump symmetry in the whole sample without these observations. What happened during late 1998 and 1999? The Russian default in August 1998 led investors to seek safe returns, pushing up U.S. long bond prices considerably from July 1, 1998 to about October 1, 1998. For the next 15 months, long yields rose about 2 percentage points and bond futures prices fell substantially. This recovery from the flight-to-safety generated inordinately many negative jumps in bond futures prices.

[5] The literature has suggested both behavioral and rational expectations explanations for such asymmetric responses. Barberis, Shleifer and Vishny (1998) offer a behavioral approach, while Veronesi (1999) provides a rational expectations model. Moreover, practitioners commonly accept that markets strongly respond to bad news in good times, as Conrad, Bradford and Landsman (2002) and Andersen, Bollerslev, Diebold and Vega (2003) explain.

[6] NBER business cycle dating identifies only two periods covering about 18 months (July 1990 to March 1991 and March-to-November 2001) as contractions. These recession periods are only a small fraction of our longest samples that cover about 18 years of data.

[7] A positive jump means a dollar depreciation for the USD/EUR and USD/GBP markets and a dollar appreciation for the JPY/USD and CHF/USD.

3.5 Intraday jump timing and size

Figure 2 shows the estimated jumps frequency and mean absolute size, by time of day, for each series. On the equity and bond markets, jumps are most prevalent during the 8:45 a.m. return, the period spanning most macro news releases in our sample. Bond markets also experience many jumps near 14:00-15:00. The equity jumps are fairly small but the bond market jumps are the largest of the day. Examination of intraday volatility patterns—omitted for brevity—suggests that stock markets ordinarily experience relatively low volatility prior to 10:00 am Eastern time, which means that proper treatment of intraday volatility is necessary to discern these modestly sized jumps. In contrast, bond market volatility is substantial at announcement times, which means that the detection procedure can only identify fairly large jumps.

Exchange rate jumps are modestly more frequent around 8:30 a.m., 16:00 to 20:00 and 22:00-02:00, indicating links with major macro news, and during periods of known low volatility, i.e., Tokyo lunch and early Asian trading. The latter pattern suggests that illiquidity can cause jumps. Exchange rate jumps tend to get larger after the opening of European markets at about 2:00 Eastern time and appear to be especially large near announcements. In contrast, jumps that occur during purely Asian trading tend to be more frequent but smaller than those from European and North-American trading hours. These "small" jumps are still economically important, representing price moves of about one third of a percent over 15 minutes.

The contrasting results from equity, bond and forex markets illustrate the importance of proper treatment of intraday volatility. We find relatively small equity jumps around announcement times because we can compare them to the low equity market volatility during this period. In contrast, we find very large bond market jumps at announcement times because intraday bond volatility is very high around these times.

3.5.1 Markets interdependence: an analysis of cojumps

This section characterizes cojumps, simultaneous jumps on different markets. The cojump indicator on a set of markets, Mkt, at period t, i is defined as follows:

$$COJump_{t,i}^{Mkt} = \prod_{Mkt} I(|Jump_{t,i}^{m_j}|), \tag{10}$$

where $I(.)$ is the indicator function for a positive argument, $Jump_{t,i}^{m_j}$ refers to significant jumps detected at period t, i (as defined in Equation (9)) on market m_j in the set Mkt. For brevity, we denote the probability of a cojump simply as $P(coj)$.

Table 3 details the properties of cojumps found with a significance level of $\alpha = 0.1$. Cojumps are overwhelmingly more likely than one would expect under the null of independent jumps. For example, the observed proportion of cojumps on the ND-SP markets was 0.04%, but the expected probability under the null that the jumps are independent is essentially zero.[8] Formal tests of this

[8]The probability of cojumping under the null of independence is the product of the jump proportions in the respective markets. These are near zero for every market combination in Table 3. Thus, we do not report them.

hypothesis reject the null of independent jumps for all cases in which there are cojumps.

To study jump dependence, we examine the probability of cojumps conditional on jumps in individual markets ($P(coj|jump)$). In the third vertical panel of Table 3, the four columns, numbered from 1 to 4, show the conditional probabilities of a cojump in all markets, conditional on a jump in markets 1 to 4, respectively. For example, the first conditional probability on the second line of the table means that 11.76% of all jumps on the ND market are also cojumps with the DJ. Likewise, 16.53% of all DJ jumps are ND-DJ cojumps.

Stock-bond cojump probabilities, conditional on a jump in one of the markets range from 3.16% (P(ND-DJ-US cojump | ND jump)) to 35.38% for P(ND-SP cojump | SP jump). That is, over one third of SP jumps were also cojumps with the ND. Cojumps are somewhat more frequent on dollar exchange rate pairs than on stock-bond combinations, even accounting for the greater number of forex observations. For example, there are 313 cojumps on the USD/EUR and CHF/USD markets, or about one every three weeks. The conditional probability of a cojump on two dollar markets, given a jump on one of them, ranges between 8.26 % (USD/GBP and JPY/USD) to 37.74 % (USD/EUR and CHF/USD).

There are about 50 percent more exchange rate cojumps than stock-bond cojumps. That is, exchange rate jumps are strongly interdependent because shocks to U.S. fundamentals affect all 4 exchange rates in our study and European regional shocks directly affect 3 of the 4 exchange rates. The fact that the JPY/USD cojumps relatively infrequently with other exchange rates illustrates the importance of European regional shocks.

Certain pairs of exchange rates and stock-bond combinations cojump more than others. Two factors seem to generate disproportionate cojumps: 1) correlation between the fundamentals in the markets; and 2) ease of simultaneous trading in the markets. For example, the USD/EUR and USD/CHF cojump more often than any other exchange rate pair, probably due to the strong correlation in fundamentals between Germany and Switzerland, which have substantial trade, financial and monetary ties. Likewise, the ND-SP pair displays the most cojumps of any stock-bond pair. The fact that both ND and SP traded on the CME—while the DJ and US traded on the CBOT—might explain the strong relation. Traders could easily track the prices of both the ND and SP and rapidly eliminate any perceived mispricing.[9]

4 Macroeconomic announcements, jumps and cojumps: empirical analysis

This section analyzes the impact of 25 U.S. macroeconomic announcements on jumps and cojumps to determine the extent to which macroeconomic surprises cause cojumps. We assume that news surprises cause jumps but that jumps do not cause news. There is a long literature on asset market reactions to macroeconomic news. Flannery and Protopapadakis (1988) document day-of-the-week

[9]The CME and CBOT were independent entities during our sample period but merged as of July 12, 2007.

patterns in Treasuries and stock indices. Ederington and Lee (1993, 1995) did the seminal work with intraday bond data and macro announcements. Fleming and Remolona (1997, 1999) related the 25 largest price changes in the GovPX bond price data to macroeconomic announcements. Mizrach and Neely (2009) review the literature on bond market reactions to news in some detail. More recently, Andersen and Bollerslev (1998) have shown that macro news affects the continuous part of price variation through a periodic component. In this section, we complement Andersen and Bollerslev (1998) by formally showing that macro surprises significantly explain identified jumps. We describe the data before estimating limited dependent variable models for (co)jumps.

4.1 Descriptive analysis

4.1.1 Macroeconomic announcements

As is standard in the literature, we use the International Money Market Service data on surveyed and realized macroeconomic fundamentals. Macroeconomic news is almost always released at scheduled times, most often at 8:30 U.S. Eastern Time (12:30 or 13:30 GMT), secondarily at 10:00 U.S. Eastern Time, for the news considered in our study. Table 4 describes our announcement data. Of course, these 25 announcements are only a subset of all U.S. announcements and do not reflect all news or relevant announcements. To avoid cumbersome qualifications, we will sometimes refer to days of our 25 announcements simply as "announcement days".

As in Balduzzi, Elton and Green (2001) or Andersen et al. (2003), we standardize surprises to easily compare coefficients across surprises and series. The standardized surprise for announcement j, at time t, i, is $S^j_{t,i} = \frac{R^j_{t,i} - E^j_{t,i}}{\hat{\sigma_j}}$, where $R^j_{t,i}$ is the realization of announcement j at time t, i, $E^j_{t,i}$ is its survey expectation and $\hat{\sigma_j}$ is the standard deviation of that difference. Balduzzi et al. (2001) have shown that the survey median expectation is an unbiased predictor of the macro news.

4.1.2 Matching jumps and macroeconomic announcement

This subsection considers how closely asset price jumps match our announcements and which considered news are most likely to produce discontinuities. Table 5 reports the conditional probabilities of jumps and announcements. We emphasize that $P(jump|news)$ and $P(news|jump)$ convey two very different types of information about the relation between news and jumps. $P(jump|news)$ describes the likelihood that a news releases causes a jump while $P(news|jump)$ tells us what proportion of jumps are associated with a particular type of news. For example, consider a rare type of news—perhaps the outbreak of war—that nearly always causes jumps. In this case, $P(jump|news)$ would be very high but—because wars are infrequent—$P(news|jump)$ might be very, very low.[10]

The second horizontal panel of that table shows the probability of a jump, conditional on a generic announcement. In this case, $P(jump|news)$ ranges from 1.10 % (JPY/USD) to 4.17 %

[10] Because the probability of a jump simultaneous with an unrelated news release is very, very small, we think it reasonable to assume that news releases cause coincident jumps.

(U.S. bonds). A generic announcement from our set of news is unlikely to create a jump on any market, but it is most likely to do so on the bond futures market and least likely to do so for forex.

Our news appears to cause many jumps on equity and bond markets: $P(news|jump)$ reaches 32.21%, for DJ futures. That is, almost 1/3 of DJ jumps are associated with the release of one of our 25 macro news items. The corresponding $P(news|jump)$ figures for the SP, ND and US markets are very similar to those of the DJ market, at 29.23, 27.06 and 32.21 percent, respectively. In contrast, our news announcements precede only about 3 to 4% of USD jumps. Clearly, prices jump disproportionately near one of our macro news releases, especially in the equity and bond markets. However, the $P(news|jump)$ figures indicate that our announcements precede only a minority of equity and bond jumps and very few foreign exchange jumps. Other factors cause most jumps in our data.

Why is our news more closely associated with equity and bond jumps than with exchange rate discontinuities? Recall that there are at least three sources of jumps: our news, other news and liquidity shocks. Because foreign news and liquidity shocks cause many forex jumps, but not U.S. stock-bond jumps, our news set necessarily causes a lower proportion of forex jumps ($P(news|jump)$) than stocks and bond jumps. The fact that news about relative fundamentals matters for forex—rather than the shocks themselves—means that many shocks will not change expected relative fundamentals (much) and thus a given bit of news is less likely to cause forex jumps. That is, $P(jump|news)$ is also lower for forex.

As previously discussed, most research has found that bond markets react more strongly than equity markets to news. In contrast to previous research, we find that equity jumps are almost as closely associated with news as bond jumps. We believe that our careful modeling of intraday volatility, with the methods of Boudt et al. (2008), enables us to find relatively small equity jumps that previous researchers might have overlooked because they occur during a period of low intraday volatility.

What news announcements are most likely to create jumps? The third panel of Table 5 shows the $P(jump|news)$ for 8 types of news that are often coincident with jumps.[11] The federal funds target is important to all markets because it directly affects the yield curve and is forward looking. The NFP and GDP reports are likewise generally acknowledged as very important announcements for all asset markets because they summarize real activity. As a relative measure of U.S. and foreign fundamentals, the trade balance is important to forex markets. This importance might reflect expectations that unfavorable trade numbers will elicit a change in monetary or intervention policy. Both the United States and its trading partners practiced foreign exchange intervention for much of the sample.

Comparing the $P(jump|news)$ for PPI and CPI reveals a potentially interesting fact: Foreign exchange jumps correlate better with PPI announcements, while bond futures jumps respond more strongly to CPI news. This is intuitively appealing: Exchange rates should be more sensitive to

[11] We omit the statistics on the less relevant announcements for brevity. Full results are available on request.

tradeable goods prices—which the PPI better reflects— through goods market arbitrage, while the bond market should respond to broader price indices, such as the CPI, which reflect changes in domestic purchasing power. We will see later, however, that the Tobit estimation fails to confirm a relation between PPI shocks and foreign exchange jumps.

The last panel of Table 5 shows the importance of various types of news releases in generating jumps, $P(news|jump)$, revealing their importance for market expectations. If the release frequency for all the types of announcements were the same, then $P(news|jump)$ would be proportional to $P(jump|news)$. But the fact that federal funds rate is released only every 6 or 7 weeks, on average, means that although funds target announcements are very likely to cause jumps, they cause relatively fewer jumps than one might expect. A funds target announcement is more than 20 times as likely as one of the 17 "other" announcements to cause a jump in the Treasury bond futures market (39.47 versus 1.93%). But because the 17 "other" announcements are much more frequent, they cause about as many jumps as the federal funds target announcements (10.07%). Likewise, federal funds target announcements only cause about 1% of exchange rate jumps, on average although the conditional probability of an exchange rate jump after a target announcement ranges from 8.47 to 33.33 percent.

4.1.3 Cojumps and macroeconomic announcements

When do cojumps usually occur? Figure 3 illustrates that cojumps in the six bivariate dollar exchange rate combinations tend to cluster in the Asian segment (between 22:00 and 2:00 EST) and in the North American afternoon. The release of some Japanese news in the afternoon might explain the tendency of JPY jumps and cojumps at about midnight Eastern time, 13:00 Tokyo time. Liquidity shocks around that time might produce the cojumps in European pairs. But there is a pronounced spike in all cojump pairs around the time of many U.S. macro news releases, 8:30 EST. This suggests a strong relation between news and jumps.

The last column of Table 3 shows the proportions of cojumps that occur within 15 minutes of news arrival for various combinations of markets ($P(news|cojump)$). Equity and bond market cojumps are much more strongly associated with news releases than foreign exchange cojumps. News accompanies 73.33 % of ND-US jumps, for example. But cojumps on equity-bond or foreign exchange markets are much more likely to be associated with news than jumps on those respective markets. And cojumps in 3 forex markets are more likely to be associated with news than cojumps in 2 markets, which are more consistently associated with news than single jumps.

Our news set causes a lower proportion of jumps than cojumps because liquidity shocks and foreign shocks are more likely to be market-specific and so create more jumps than cojumps. Therefore, our set of announcements will drive a higher percentage of cojumps than jumps. Likewise, our news causes a lower proportion of forex cojumps than stock-bond cojumps because foreign news–not in our data set–is more likely to affect relative fundamentals than U.S. fundamentals and thus will cause more forex cojumps than U.S. stock-bond cojumps.

4.2 Modeling jumps and cojumps in Tobit-probit framework

The previous section described the conditional probabilities of (co)jumps and our macro announcements. One would expect jumps to depend on the surprise component of announcements, not on the mere announcement itself. To properly infer the link between (co)jumps and macro surprises, one must model (co)jumps formally as a function of such releases using Tobit-GARCH and probit models, respectively. The Tobit regression analysis of jumps includes all series. The probit analysis of cojumps focuses on dollar exchange rates, where cojumps are most frequent.

4.2.1 Modeling jumps to assess the impact of macro announcements

We estimate the impact of macroeconomic surprises on jump magnitudes with a Tobit regression model, because the dependent variable is constrained.[12] The announcement regressor list varies with the dependent variable because we can only include announcements that are coincident with jumps. Besides considering absolute macro surprises as jump determinants, we control for day-of-the-week effects and an intraday periodic component, which might be related to liquidity and trading volume.

$$|Jump_{t,i}| = \begin{cases} \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \varepsilon_{t,i} & if\ \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \varepsilon_{t,i} > 0 \\ 0 & otherwise \end{cases}$$

where $|Jump_{t,i}|$ is the magnitude of significant observed jumps ($\alpha = 0.1$) at period t, i (see Equation (9)), $\eta_{t,i}$ is a linear combination of day-of-the-week dummies and $\mu_{t,i}$ describes the impact of standardized U.S. news surprises.

$$\mu_{t,i} = \sum_{j=1}^{N} \lambda_j |S^j_{t,i}|,$$

where λ's are coefficients, $S^j_{t,i}$ is the standardized surprises magnitudes in market j and N denotes the number of announcements used as regressors. We also permit potential delayed response to news by testing for lagged news, $\mu_{t,i-1}$. $\xi_{t,i}$ represents an intraday periodic component—separate from announcement effects—that is based on a flexible Fourier form, in the spirit of Andersen and Bollerslev (1998). That is, we include

$$\xi_{t,i} = \gamma_1 n_{t,i} + \gamma_2 n^2_{t,i} + \sum_{i=1}^{p} (\gamma_{2+i} \cos \kappa_{i(t,i)} + \gamma_{2+p+i} \sin \kappa_{i(t,i)}), \tag{11}$$

where $n_{t,i}$ takes M (the number of intraday periods within a day) values in $\{1, ..., M\}$ according to the intraday position of the index t, i, $\kappa_{i(t,i)} = 2\pi \frac{1}{M} \times i \times n_{t,i}$, and p is fixed at 5 terms.

[12] The Tobit model can be motivated as the result of a two-step data generating process for jumps. A probit model first determines whether the asset price jumps and then–if there is a jump–a truncated regression model determines the magnitude of that jump. The probit and truncated regression models must have the same explanatory variables and proportional coefficients. The Tobit likelihood function can be written as the product of the probit and truncated normal likelihood functions.

Finally, following Andersen, Bollerslev and Huang (2007b), we correct for heteroskedasticity using the Tobit-GARCH model of Calzolari and Fiorentini (1998). In the GARCH(1,1) variant, for example, $\varepsilon_{t,i}|\mathcal{I}_{t,i-1}$ is $N(0, \sigma^2_{t,i})$ with $\sigma^2_{t,i} = \omega + \alpha_1 \varepsilon^2_{t,i-1} + \beta_1 \sigma^2_{t,i-1}$ and $\mathcal{I}_{t,i}$ is the information set up to time the i-th interval of day t.[13] We estimate this computationally demanding model with a forex sample starting in 1990 to match most announcement samples.

We note that both the (co)jumps and surprises are measured with some error. The error in the jumps will decrease the apparent amount of predictability in the Tobit-probit relations. The surprises are measured with error because the survey expectations are only approximately market expectations at the time of the announcement. The error in the exogenous variables (i.e., the surprises) will attenuate their coefficients toward zero and inflate their p-values. Therefore our Tobit and probit results present a conservative picture of the relation between these macro surprises and (co)jumps.

Model Selection We selected models by testing restrictions from general frameworks. We first determined what conditional variance specification—GARCH(1,1), ARCH(2), ARCH(1) or homoskedastic—best fits the data in models that allowed for day-of-the-week effects, a circadian component, as well as contemporaneous and lagged announcement effects. Likelihood ratio tests reject homoskedasticity in favor of the GARCH(1,1) model, except for the CHF/USD and ND series, where ARCH(2) and ARCH(1) are more appropriate, respectively. The periodic component parameters and day-of-the-week effects were each jointly significant on all series. Lagged announcement effects were significant only for U.S. bond prices.

Formal tests of asymmetry in the news/jump relation rejected that feature in both Tobit and probit models of jump reaction to news. That is, negative surprises are usually no more or less likely to produce cojumps than are positive surprises. This symmetry fails to confirm research such as Andersen et al. (2003), to cite one example.

Tobit results Table 6 reports Tobit-GARCH estimation results for effect of U.S. macro surprises on jumps. We omit coefficients associated with intraday periodicity and days-of-the-week to save space. The Tobit results formally confirm much inference from the coincidence of news and jumps. NFP, retail sales, advanced GDP, fed funds target announcements and the CPI often contribute significantly to equity and bond jumps. Exchange rates also respond significantly to NFP and the ubiquitous fed funds target announcements but also to trade balance reports, preliminary GDP, government fiscal announcements and consumer confidence. As with the previous results, NFP and fed funds target announcements most strongly explain jumps across all markets, followed by consumer confidence and the two types of GDP announcements.

Recall that the PPI news release events were associated with foreign exchange jumps. The

[13] In Tobit models, residuals are not directly observed. Calzolari and Fiorentini (1998) detail how to approximate the squared residuals $\varepsilon^2_{t,i-1}$ of censored values of the dependent variable with their expected values. Note also that for ease of notation, we use the conventions $\varepsilon^2_{t,0} = \varepsilon^2_{t-1,M}$ and $\sigma^2_{t,0} = \sigma^2_{t-1,M}$.

Tobit estimation finds, however, that PPI news surprises have no significant positive effect on jumps. There are at least three possible explanations for this. The first is that the coincidence between PPI announcements and forex jumps is simply a coincidence. The second is that the PPI expectations/surprises are measured with significant error, attenuating the value of the Tobit coefficients. The third possibility is that forex jumps depend only on the fact that there is a PPI announcement, not the size of the shock. It is not clear why an announcement, rather than the surprise, would produce a forex jump.

Aside from the PPI puzzle, our results are economically sensible. For example, trade balance news affects exchange rates more than other markets. One might reason that trade balance shocks affect expectations of future exchange rate policy, perhaps including interventions, trade or capital flow regulations or even monetary policy. The Tobit regressions confirm previous studies indicating that the bond market is very sensitive to news. Equity and some forex markets appear nearly as sensitive in terms of significant Tobit coefficients, however.

4.2.2 Modeling cojumps

Table 7 presents evidence on the link between macro news and cojumps from a probit model. We use probit estimation with a qualitative indicator for cojumps because there is no unambiguous way to attach a single magnitude to cojumps. That is, one could define the magnitude of a cojump as any number of increasing functions mapping the set of jump sizes into the real line: geometric or arithmetic averages, minimum, maximum, etc.

$$P(COjump_{t,i} = 1) = \Phi(\mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i}).^{14} \tag{12}$$

$COjump_{t,i}$ is the cojump indicator at a significance level $\alpha = 0.1$ (see Equation (10)), while $\Phi(*)$ is the cumulative normal distribution function. The remaining variables are defined as in the Tobit model: $\eta_{t,i}$ controls for weekly seasonality; $\mu_{t,i}$ includes macro surprises in absolute value; $\xi_{t,i}$ adjusts for intraday periodicity. The seasonal component and day-of-the-week regressors significantly improve the models' fit, as they do for the Tobit models. As with the Tobit results, we omit these coefficients to save space.

The relation between news surprises and cojumps is very strong and consistent. Almost all (18 of 19) of the announcement coefficients are positive and significant. The most important shocks for the exchange rate cojumps are the federal funds rate target shocks, NFP shocks and preliminary GDP. The federal funds target surprise, in particular, significantly explains every cojump pair. The pair USD/EUR - CHF/USD is sensitive to the widest variety of news, as six announcements have significant effects. Again, the close correlation between Swiss and German/euro area fundamentals

[14] Unlike that of the Tobit model, the variance of the error term of the Probit model is assumed to be constant. We tested for but did not find any evidence of ARCH effects for the cojumps. Time varying variance in the latent variable in Tobit models implies the same behavior in the latent probit models because the two latent variables are conceptually identical. In our case, however, we estimate the Tobit model on jumps while we estimate the probit on cojumps. Therefore, strictly speaking, the time varying variance need not carry over.

surely explains the fact that the USD/EUR and CHF/USD tend to respond very similarly to U.S. news releases. We obtain McFadden R^2s of about 4% for the exchange rate cojump models.

5 Conclusion

This paper has studied financial price discontinuities and macroeconomic announcements. We apply a modified version of the test for jumps, initially proposed by Andersen et al. (2007c) and Lee and Mykland (2008) and extended by Boudt et al. (2008), to characterize (co)jumps in USD exchange rates, U.S. Treasury bond futures and U.S. equity futures. Our analysis indicates that one must account for volatility periodicity in detecting jumps or risk size or power problems. Because we can almost exactly determine jump times, we can identify cojumps and associate (co)jumps with scheduled macro announcements.

Assets differ in how they depend on fundamentals and on the likely sources of shocks to those fundamentals. Considering this variation enables us to explain how (co)jump behavior varies across markets. Exchange rates experience frequent but relatively small jumps because they are subject to news from two countries and because they probably experience more idiosyncratic liquidity shocks during slow trading in the 24-hour markets. Forex jumps tend to be smaller than bond or equity jumps because national macro shocks produce much smaller changes in expected relative fundamentals between currencies. Therefore a generic U.S. announcement is less likely to create a jump in forex markets. Because a wider variety of shocks influence forex markets, our set of news announcements creates a smaller proportion of forex jumps than bond or equity jumps.

Bond price jumps are frequent and large relative to bond return volatility. Consistent with previous research, bonds respond very strongly to our set of news. In contrast to previous research, however, equities jump almost as often in response to news, but these jumps are relatively small and might have been overlooked because they occur during a period of low intraday volatility. Bond response to news might be larger than equity response because bonds do not depend on expected dividends, which might offset the effect of news on the discount factor.

Jump frequency appears to be fairly symmetric in most markets. The exception is the bond futures market, which experiences more negative jumps, largely as a result of the recovery from the Russian-default/LTCM flight-to-safety in late 1998. Without the July 1998 through June 1999 period, there would be little evidence of asymmetry on bond markets.

Certain pairs of exchange rates or stock-bond combinations cojump more than others, either because the fundamentals are highly correlated or because it is easy to simultaneously trade the assets. For example, exchange rate jumps are strongly interdependent because shocks to U.S. fundamentals change relative fundamentals for all 4 exchange rates in our study. Similarly, European regional shocks affect 3 of the 4 exchange rates. The correlation between European currencies means that the JPY/USD cojumps less often than other exchange rates.

Most of our news does not cause jumps. A generic announcement from our data set only produces an exchange rate jump about 1 to 2 percent of the time and a bond or equity jump only about 3 to 4 percent of the time. News creates a lower proportion of jumps than cojumps because liquidity shocks and foreign news tend to be market-specific and unlikely to create cojumps. Therefore, our set of announcements drives a higher percentage of cojumps than jumps.

Consistent with this, regression models indicate that macro announcement surprises are associated with cojumps even more consistently than with jumps. Almost all of the surprises in the probit estimations were statistically significant generators of exchange rate cojumps. NFP and federal funds target announcements strongly determine forex cojumps.

Certain announcements are much more likely to be coincident with jumps than others. Federal funds target, non-farm payroll and GDP announcements appear to be the most important. A federal funds target announcement, for example, produces a Treasury bond price jump almost 40 percent of the time. Tobit and probit analysis confirms the importance of NFP and federal funds target announcements for a wide range of markets.

Jumps and cojumps in foreign exchange markets are more strongly associated with PPI announcements, while jumps in bond prices coincide more often with CPI news. While this might seem consistent with foreign exchange markets responding more strongly to tradeables inflation (PPI) and bond markets reacting more strongly to overall inflation (CPI), Tobit models show no positive relation between PPI shocks and exchange rate jumps. The reason for this is not clear.

A-1 APPENDIX: Robust periodicity filter

To identify jumps, one first needs a robust-to-jumps periodicity estimator to determine which observations might contain jumps. One can use a robust scale estimator, such as the median absolute deviation (MAD) or the shortest half scale of Rousseeuw and Leroy (1988). This nonparametric approach to periodicity estimation, called weighted standard deviation (WSD), has at least two advantages in our context: 1) We remain fully agnostic on the relation between macro surprises and jumps; 2) Monte-Carlo simulation results in Boudt et al. (2008) suggest that the WSD approach is a good compromise between efficiency in the absence of jumps and robustness to the presence of jumps.

We permit the intraday periodicity to vary by the day of the week and thus compute 5 separate cyclical components. For ease of exposition, however, we present the periodicity filters for the simplest case where the length of the cycle is one day.

To compare returns across sample days, Boudt et al. (2008) suggest standardizing intraday returns with daily bipower variation. This is in line with Andersen and Bollerslev (1998) who show, that daily exchange rate volatility must be controlled for in order to isolate high-frequency periodic effects. The standardized intraday returns are computed as follows:

$$\overline{r}_{t,i} = \frac{r_{t,i}}{\sqrt{RBV_t(\Delta)}}, \tag{A-1}$$

where $RBV_t(\Delta)$ is given in Equation (4).

A first approximation of the intraday periodicity in volatility could be based on the robust scale measure given by the shortest half scale (SHS) estimator, proposed by Rousseeuw and Leroy (1988). To compute the Shortest Half scale estimator, we need the corresponding order statistics $\overline{r}_{(1);t,i}, \ldots, \overline{r}_{(n_{t,i});t,i}$ such that $\overline{r}_{(1);t,i} \leq \overline{r}_{(2);t,i} \leq \ldots \leq \overline{r}_{(n_{t,i});t,i}$. The shortest half scale is the smallest length of all "halves" consisting of $h_{t,i} = \lfloor n_{t,i}/2 \rfloor + 1$ contiguous order observations. These halves equal $\{\overline{r}_{(1);t,i}, \ldots, \overline{r}_{(h_{t,i});t,i}\}$, ..., $\{\overline{r}_{(n_{t,i}-h_{t,i}+1);t,i}, \ldots, \overline{r}_{(n_{t,i});t,i}\}$, and their length is $\overline{r}_{(h_{t,i});t,i} - \overline{r}_{(1);t,i}$, ..., $\overline{r}_{(n_{t,i});t,i} - \overline{r}_{(h_{t,i});t,i}$, respectively. The corresponding scale estimator—corrected for consistency under normality—equals the minimum of these lengths:

$$\text{ShortH}_{t,i} = 0.741 \cdot \min\{\overline{r}_{(h_{t,i});t,i} - \overline{r}_{(1);t,i}, \ldots, \overline{r}_{(n_{t,i});t,i} - \overline{r}_{(n_{t,i}-h_{t,i}+1);t,i}\}. \tag{A-2}$$

The Shortest Half estimator for the periodicity factor of $r_{t,i}$ (that satisfies the identifiability condition stated in Equation (7)) equals

$$\hat{f}_{t,i}^{\text{ShortH}} = \frac{\text{ShortH}_{t,i}}{\sqrt{\frac{1}{M}\sum_{j=1}^{M} \text{ShortH}_{t,j}^2}}. \tag{A-3}$$

The shortest half dispersion is highly robust to jumps, but it has only 37% efficiency with normally distributed $\overline{r}_{t,i}$'s. Boudt et al. (2008) show that the standard deviation applied to the returns, weighted as a function of their outlyingness under the SHS estimate, offers a better trade-off between the efficiency of the standard deviation under normality and the shortest-half-dispersion's robustness to jumps.

$$\hat{f}_{t,i}^{\text{WSD}} = \frac{\text{WSD}_{t,i}}{\sqrt{\frac{1}{M}\sum_{j=1}^{M} \text{WSD}_{t,j}^2}}, \tag{A-4}$$

where

$$\text{WSD}_{t,j} = \sqrt{1.081 \cdot \frac{\sum_{l=1}^{n_{t,j}} w[(\overline{r}_{l;t,j}/\hat{f}_{t,j}^{\text{ShortH}})^2]\overline{r}_{l;t,j}^2}{\sum_{l=1}^{n_{t,j}} w[(\overline{r}_{l;t,j}/\hat{f}_{t,j}^{\text{ShortH}})^2]}}.$$

The function $w(z)$ is an indicator function that equals one when $z \leq 6.635$, which is the $\chi^2(1)$ 99% quantile, and 0 otherwise. The function w selects jump-free returns, based on a first approximation of periodicity with the shortest half scale, to evaluate a Taylor and Xu (1997) type of periodicity.

A-2 APPENDIX: Asset price data

Olsen and Associates provide the exchange rate series, which cover about 18 years of data (1987-2004). The series denoted USD/EUR is the composition of USD/DEM returns, prior to January 1, 1999, and USD/EUR returns after January 1, 1999. We use the USD/EUR label for simplicity. The decentralized currency markets trade 24-hours a day. Thus, a trading day consists of 96 15-minute intervals. Consistent with the literature on intraday exchange rate patterns, we define trading day t to start at 21:15 GMT on day $t-1$ and end at 21:00 GMT on day t, as in Bollerslev and Domowitz (1993). Also consistent with the literature, we remove week-ends and a set of fixed and irregular holidays, from the intraday return series, as well as days where there are too many missing values, constant prices, and/or days with the longest constant runs activity. The regular holidays removed are December 24 through the 26, December 31 through January 2 and July 4. Irregular holidays include Good Friday, Easter Monday, Memorial Day, Labor Day, Thanksgiving and the day after. The first two lines of Table 2 report the number of observations and sample days for each asset.

We convert the original database times from GMT to Eastern time (EST) or Eastern time Daylight Saving Time (EST-DST), depending on the appropriate period of the year. We use U.S. time, rather than GMT, because the macro announcements and most other trading regularities—e.g., the start of North American trading—create periodic patterns in U.S. time, rather than in GMT. For simplicity, we simply call the U.S. time scale EST. So the first exchange rate of trading day t is the last price of the 16:00-16:15 EST interval (of calendar day t-1).

The Dow Jones and 30-year U.S. T-bonds futures contracts series trade on the Chicago Board of Trade (CBOT), while the Nasdaq and S&P 500 futures trade on the Chicago Mercantile Exchange (CME). We augment the regular trading hours data of Nasdaq and S&P 500 with the GLOBEX electronic platform data, which extends the trading day to 8:30 to 16:15. The Dow Jones and US Treasury futures from the CBOT trade from 8:20 to 16:15 and 8:20 to 15:00, respectively. We sampled the CBOT series from 8:30 on for ease of comparison with other series, however. The availability of the off-hours electronic trading data limits the useful GLOBEX-augmented S&P and Nasdaq sample to about 6.5 years. Trading on this Globex platform before the retained dates is rather thin and contains many missing values.

We construct continuous futures series in the usual way by splicing contracts with liquid trading. We roll-over contracts 6 business days before maturity for most futures and 15 business days for U.S. T-bonds.

We note that we cannot identify jumps in the long overnight futures return, because it cannot be directly compared to a local volatility estimate and the noise in the long return would obscure the presence of jumps. Thus, our futures calculations omit the overnight return.

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Table 1: Description of the raw original series used in the study

Asset	**Source**	**Original Freq.**	**Trading Hours***	**Period retained**
NASDAQ 100 Futures (ND)	CME/GLOBEX	tick	8:30-16:15 EST	07/01/1998 - 12/30/2004
$S\&P$ 500 Futures (SP)	CME/GLOBEX	tick	8:30-16:15 EST	07/01/1998 - 12/30/2004
US Treasury bonds Futures (US)	CBOT	5-min	8:30-15:00 EST	07/01/1998 - 11/29/2004
Dow Jones Futures (DJ)	CBOT	5-min	8:30-16:15 EST	07/01/1998 - 07/22/2005
USD/EUR	O&A	5-min	24 hours a day	01/01/1987 - 10/01/2004
USD/GBP	O&A	5-min	24 hours a day	01/01/1987 - 10/01/2004
JPY/USD	O&A	5-min	24 hours a day	01/01/1987 - 10/01/2004
CHF/USD	O&A	5-min	24 hours a day	01/01/1987 - 09/30/2004

* CBOT futures (Dow Jones and U.S. bonds) trading actually starts at 8:20 EST. We sampled from 8:30 on for ease of comparison with other series.

Table 2: Descriptive statistics on significant jumps using the $FiltJ$ statistics

	SP	ND	DJ	US	USD/EUR	USD/GBP	JPY/USD	CHF/USD
# obs.	49135	49662	53909	40560	419616	423072	418272	424128
annualized std. dev.	18.15	35.84	17.81	8.99	11.38	10.20	12.06	12.15
# days	1585	1602	1739	1560	4371	4407	4357	4418
# jump days	105	135	116	130	1062	1184	1092	1143
$P(jumpday)$ (%)	6.62	8.43	6.67	8.33	24.30	26.87	25.06	25.87
$E(\#jump \vert jumpday)$	1.24	1.26	1.12	1.15	1.33	1.38	1.35	1.34
# jumps	130	170	130	149	1408	1636	1471	1531
$P(jump)$ (%)	0.26	0.34	0.24	0.37	0.34	0.39	0.35	0.36
$E(\vert jumpsize\vert \vert jump)$	0.89	1.61	0.74	0.51	0.32	0.27	0.36	0.30
$\sqrt{Var(\vert jumpsize\vert \vert jump)}$	0.56	1.22	0.55	0.35	0.23	0.18	0.25	0.20
# jumps > 0	59	84	57	62	744	802	701	745
$P(jump > 0)$ (%)	0.12	0.17	0.11	0.15	0.18	0.19	0.17	0.18
$E(jumpsize \vert jump > 0)$	0.87	1.66	0.82	0.53	0.32	0.27	0.36	0.30
$\sqrt{Var(jumpsize \vert jump > 0)}$	0.61	1.33	0.71	0.37	0.23	0.18	0.26	0.20
# jumps < 0	71	86	73	87	664	834	770	786
$P(jump < 0)$ (%)	0.14	0.17	0.14	0.21	0.16	0.20	0.18	0.19
$E(jumpsize \vert jump < 0)$	-0.90	-1.57	-0.68	-0.49	-0.33	-0.27	-0.36	-0.31
$\sqrt{Var(jumpsize \vert jump < 0)}$	0.51	1.10	0.36	0.32	0.23	0.19	0.25	0.20
% of negative jumps	54.62	50.59	56.15	58.39	47.16	50.98	52.35	51.34
standard error	4.37	3.83	4.35	4.04	1.33	1.24	1.30	1.28

Note: The table displays, from top to bottom the number of sample points ($\#obs.$), the annualized standard deviation of intraday returns, the number of sample days ($\#days$), the total number of jump days (# jump days, i.e. days with at least one jump), the probability (in %) of a jump day (P(jump day)=100(# jump days / # days)), and the number of jumps per jump day (E(# jumps|jump day)=# jumps/#jump days). We further give the total number jumps ($\#jumps$), their proportion (in %) over sample observations ($P(jump) = 100(\#jumps/\#obs.)$), as well as their absolute mean size and standard deviation ($E(|jumpsize||jump)$ and $\sqrt{Var(|jumpsize||jump)}$). The next two panels split the jumps in two sets: positive and negative jumps. Proportions ($P(jump > 0)$ and $P(jump < 0)$), mean ($E(jumpsize|jump > 0)$ and $E(jumpsize|jump < 0)$) and std. dev. ($\sqrt{Var(jumpsize|jump > 0)}$ and $\sqrt{Var(jumpsize|jump < 0)}$) are reported, as for the full set of jumps in absolute value. Finally, the last panel reports the percentage of jumps that are negative ($100\frac{\#jumps<0}{\#jumps}$) and the associated standard error ($100\sqrt{(1-\frac{\#jumps<0}{\#jumps})\frac{\#jumps<0}{\#jumps}/\#jumps}$). The chosen significance level for jumps estimation is $\alpha = 0.1$. The sampling frequency is 15 minutes. The sample period is given in Table 1.

Table 3: Cojumps

	# obs.	# coj.	$P(coj)$ (%)	$P(coj\|jump)$ (%) 1	2	3	4	# coj. match. news	$P(news\|coj)$
ND - DJ	49600	20	0.04	11.76	16.53	-	-	11	55.00
ND - SP	49135	46	0.09	27.54	35.38	-	-	16	34.78
ND - US	40482	15	0.04	9.49	10.07	-	-	11	73.33
DJ - SP	49073	22	0.04	18.97	16.92	-	-	8	36.36
DJ - US	40508	9	0.02	9.09	6.04	-	-	5	55.56
SP - US	40040	10	0.02	8.47	6.71	-	-	7	70.00
ND - DJ - SP	49073	16	0.03	9.58	13.79	12.31	-	8	50.00
ND - DJ - US	40456	5	0.01	3.16	5.05	3.36	-	3	60.00
DJ - SP - US	40014	5	0.01	5.32	4.24	3.36	-	3	60.00
ND - SP - US	40040	9	0.02	5.81	7.63	6.04	-	6	66.67
ND - DJ - SP - US	40014	5	0.01	3.23	5.32	4.24	3.36	3	60.00
USD/EUR - USD/GBP	419424	313	0.07	22.28	19.25	-	-	15	4.79
USD/EUR - JPY/USD	417792	214	0.05	15.24	14.58	-	-	17	7.94
USD/EUR - CHF/USD	418848	531	0.13	37.74	35.21	-	-	24	4.52
USD/GBP - JPY/USD	417984	134	0.03	8.26	9.11	-	-	12	8.96
USD/GBP - CHF/USD	422304	266	0.06	16.29	17.45	-	-	14	5.26
JPY/USD - CHF/USD	417504	172	0.04	11.69	11.46	-	-	17	9.88
USD/EUR - USD/GBP - JPY/USD	417600	89	0.02	6.35	5.49	6.06	-	11	12.36
USD/GBP - JPY/USD - CHF/USD	417216	74	0.02	4.57	5.03	4.94	-	10	13.51
USD/EUR - USD/GBP - CHF/USD	418656	186	0.04	13.25	11.46	12.36	-	12	6.45
USD/EUR - JPY/USD - CHF/USD	417024	129	0.03	9.19	8.79	8.60	-	15	11.63
USD/EUR - USD/GBP - JPY/USD - CHF/USD	416832	62	0.01	4.43	3.83	4.22	4.14	9	14.52
USD/EUR - ND	46080	9	0.02	7.44	5.66	-	-	3	33.33
USD/EUR - SP	45570	12	0.03	10.08	9.92	-	-	3	25.00
USD/EUR - DJ	46050	9	0.02	7.44	8.04	-	-	4	44.44
USD/EUR - US	39442	7	0.02	7.29	5.00	-	-	1	14.29

Note: Cojumps are defined as an indicator variable equal to one when significant jumps (at $\alpha = 0.1$, and a 15-minute sampling frequency occur exactly at the same time on different markets. The table displays, the number of observations, the number of cojumps, the cojump probability ($P(coj)$, in %). Columns 5 to 8 ($P(coj|jump)$ in %, numbered 1 to 4) report the probability of a cojump on the considered markets, given a jump on the market designated by the number of the column (1 to 4). This number refers to the order of the markets in which they appear on the first column. For example, the values in the 5th and 6th columns of row 2 (ND-SP) indicate that 27.54% (35.38) of all jumps on the ND (SP) market are also ND-SP cojumps. The last two columns report the number of cojumps matching exactly news arrival and the probability of a type of news, given a cojump ($P(news|coj)$), respectively. The sample period is given by the common sample between the considered assets.

Table 4: Scheduled macroeconomic announcement

Announcement	Variable Name	Starting Date	Time (EST)	Freq.
Real Activity				
Real GDP Advance	GDPADV	4/27/1990	8:30	Q
Real GDP Preliminary	GDPPRE	5/24/1990	8:30	Q
Real GDP Final	GDPFIN	6/21/1990	8:30	Q
Employees on Non-farm Payrolls	NFPAYROL	1/8/1986	8:30	M
Retail Sales	RETSALES	2/11/1980	8:30	M
Industrial Production	INDPROD	2/15/1980	9:15	M
Capacity Utilization	CAPUTIL	4/18/1988	9:15	M
Consumer Credit	CONSCRED	1/11/1996	15:00	M
Personal Income	PERSINC	3/17/1981	8:30/10:00	M
Prices				
Producer Price Index	PPI	1/10/1986	8:30	M
Consumer Price Index	CPI	1/22/1986	8:30	M
Investment				
Durable Good Orders	DURABLE	1/24/1986	8:30	M
Business Inventories	BINVENT	3/14/1988	8:30/10:00	M
Construction Spending	CNSTRSPEND	4/1/1988	10:00	M
New Orders at Factories	ORDERFACT	3/30/1988	10:00	M
Consumption				
Personal Consumption Expenditures	PCE	7/17/1985	8:30/10:00	M
New Home Sales	HOMESALES	3/29/1988	10:00	M
Net Exports				
Trade Balance	TRADEBAL	1/30/1986	8:30	M
Government Deficit				
Government Fiscal Surplus - Deficit	GVFISCDEF	2/22/1988	14:00	M
Forward Looking				
Manufacturing Composite Index	MFGIND	2/1/1990	10:00	M
Housing Starts	HOUSING	1/17/1986	8:30	M
Consumer Confidence	CONSCONF	7/30/1991	10:00	M
Index of Leading Economic Indicators	LEADINGI	1/30/1986	8:30	M
FOMC				
Federal Funds Target	FFRTARGET	9/21/1994	14:15	6-weeks

Table 5: Further descriptive statistics on jumps

	SP	ND	DJ	US	$\frac{USD}{EUR}$	$\frac{USD}{GBP}$	$\frac{JPY}{USD}$	$\frac{CHF}{USD}$
# days	1585	1602	1739	1560	3668	3675	3660	3670
# obs.	49135	49662	53909	40560	352128	352800	351360	352320
P(news) (%)	2.53	2.53	2.52	2.84	0.78	0.78	0.78	0.78
# news days	991	1004	1085	934	2213	2219	2208	2216
# jumps	130	170	130	149	1136	1330	1190	1200
Aggregated news								
# jump-news match	38	46	42	48	35	40	30	50
$P(jump\|news)$ (%)	3.06	3.66	3.09	4.17	1.28	1.46	1.10	1.82
	(0.49)	(0.53)	(0.47)	(0.59)	(0.21)	(0.23)	(0.2)	(0.26)
$P(news\|jump)$ (%)	29.23	27.06	32.31	32.21	3.08	3.01	2.52	4.17
	(3.99)	(3.41)	(4.1)	(3.83)	(0.51)	(0.47)	(0.45)	(0.58)
P(jump,news) (%)	0.077	0.093	0.078	0.118	0.010	0.011	0.009	0.014
	(0.013)	(0.014)	(0.012)	(0.017)	(0.002)	(0.002)	(0.002)	(0.002)
Disaggregated news - $P(jump\|news)$ (%)								
PPI	3.90	3.90	3.57	1.33	0.00	1.14	1.14	0.57
	(2.21)	(2.21)	(2.02)	(1.32)	(0)	(0.8)	(0.8)	(0.57)
CPI	6.58	5.13	5.95	7.79	0.57	0.00	0.57	0.57
	(2.84)	(2.5)	(2.58)	(3.05)	(0.57)	(0)	(0.57)	(0.57)
NFPAYROL	12.00	23.38	9.52	14.47	5.20	0.00	1.73	5.20
	(3.75)	(4.82)	(3.2)	(4.04)	(1.69)	(0)	(0.99)	(1.69)
TRADEBAL	1.30	2.56	1.18	1.30	0.56	1.13	1.13	0.56
	(1.29)	(1.79)	(1.17)	(1.29)	(0.56)	(0.79)	(0.79)	(0.56)
GDPADV	16.00	16.00	18.52	0.00	0.00	1.82	0.00	0.00
	(7.33)	(7.33)	(7.48)	(0)	(0)	(1.8)	(0)	(0)
GDPPRE	0.00	0.00	3.70	4.17	1.85	0.00	1.85	1.85
	(0)	(0)	(3.63)	(4.08)	(1.83)	(0)	(1.83)	(1.83)
RETSALES	4.23	12.68	6.41	7.25	0.62	0.00	0.00	0.62
	(2.39)	(3.95)	(2.77)	(3.12)	(0.62)	(0)	(0)	(0.62)
FFRTARGET	5.41	7.89	7.89	39.47	22.03	30.00	8.47	33.33
	(3.72)	(4.37)	(4.37)	(7.93)	(5.4)	(5.92)	(3.63)	(6.09)
Other	1.87	0.81	1.60	1.95	0.59	0.86	0.81	0.86
	(0.46)	(0.3)	(0.41)	(0.5)	(0.18)	(0.21)	(0.21)	(0.21)
Disaggregated news - $P(news\|jump)$ (%)								
PPI	2.31	1.76	2.31	0.67	0.00	0.15	0.17	0.08
	(1.32)	(1.01)	(1.32)	(0.67)	(0)	(0.11)	(0.12)	(0.08)
CPI	3.85	2.35	3.85	4.03	0.09	0.00	0.08	0.08
	(1.69)	(1.16)	(1.69)	(1.61)	(0.09)	(0)	(0.08)	(0.08)
NFPAYROL	6.92	10.59	6.15	7.38	0.79	0.00	0.25	0.75
	(2.23)	(2.36)	(2.11)	(2.14)	(0.26)	(0)	(0.15)	(0.25)
TRADEBAL	0.77	1.18	0.77	0.67	0.09	0.15	0.17	0.08
	(0.77)	(0.83)	(0.77)	(0.67)	(0.09)	(0.11)	(0.12)	(0.08)
GDPADV	3.08	2.35	3.85	0.00	0.00	0.08	0.00	0.00
	(1.51)	(1.16)	(1.69)	(0)	(0)	(0.08)	(0)	(0)
GDPPRE	0.00	0.00	0.77	0.67	0.09	0.00	0.08	0.08
	(0)	(0)	(0.77)	(0.67)	(0.09)	(0)	(0.08)	(0.08)
RETSALES	2.31	5.29	3.85	3.36	0.09	0.00	0.00	0.08
	(1.32)	(1.72)	(1.69)	(1.48)	(0.09)	(0)	(0)	(0.08)
FFRTARGET	1.54	1.76	2.31	10.07	1.14	1.35	0.42	1.67
	(1.08)	(1.01)	(1.32)	(2.47)	(0.32)	(0.32)	(0.19)	(0.37)
Other	12.31	4.12	11.54	10.07	0.97	1.20	1.26	1.33
	(2.88)	(1.52)	(2.8)	(2.47)	(0.29)	(0.3)	(0.32)	(0.33)

Note: The table gives the matching between announcements and jumps computed at a 15-minutes frequency with significance level $\alpha = 0.1$. The table's upper panel shows, from top to bottom, the number of sample days (# days), the number of observations (# obs.), the probability (in %) of an announcement (i.e. the probability that at least one announcement occurs in an intra-day interval), the number of announcement days and the number of jumps (# news days and # jumps). Next panel (Aggregated news) shows the number of jumps occurring within one hour after announcement arrival (# Jump-news match), the probability (in %) of a jump given a release ($P(jump|news)$ = 100(# Jump-news match / # news)), the probability (in %) of an announcement given a jump ($P(news|jump)$ = 100(# Jump-news match / # jumps)), the probability (in %) of an announcement and a jump ($P(jump, news)$ = 100(# Jump-news match / # obs.)). Jump-news matches are very similar with a half-hour window. In the second panel, reported quantities are based on a news indicator equal to one when at least one of our sample announcement occurs, and 0 otherwise. The last two panels (Disaggregated news, $P(jump|news)$ and $P(news|jump)$) split previous panel (Aggregated news) information. They provide detailed results for most important news and displays $P(jump|news)$ and $P(news|jump)$ in percent. The last line of the "disaggregated panels" (called "Other") is based on a news indicator equal to one when one of our sample announcement occurs, excluding those detailed above in the corresponding panel. The exchange rate samples start in January 1990. The other series samples period is given in Table 1.

Table 6: Tobit-GARCH models for jumps

	S&P futures		Nasdaq futures		Dow jones futures		U.S. bond futures		USD/EUR		JPY/USD		USD/GBP		CHF/USD	
	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$
CONSCONF	-	-	-	-	0.71	0.88	-	-	-	-	0.74	0.00	0.38	0.08	0.43	0.02
CONSCONF (-1)	-	-	-	-	-	-	0.96	0.01	-	-	-	-	-	-	-	-
CONSCRED	-	-	-	-	0.98	0.10	-	-	-	-	-	-	0.06	0.99	-0.13	0.99
CPI	2.13	0.00	1.90	0.59	0.81	0.68	1.20	0.00	0.01	1.00	0.09	0.99	-	-	-0.06	0.99
FFRTARGET	1.06	0.49	1.39	0.63	1.65	0.00	0.74	0.05	0.88	0.00	0.72	0.00	0.66	0.00	0.57	0.00
FFRTARGET (-1)	-	-	-	-	-	-	0.66	0.02	-	-	-	-	-	-	-	-
GDPADV	2.19	0.01	3.47	0.01	2.09	0.00	-	-	-	-	-	-	0.40	0.83	0.48	0.81
GDPPRE	-	-	-	-	1.17	0.51	-	-	0.81	0.00	0.84	0.01	-	-	0.58	0.04
GVFISCDEF	0.97	0.69	-	-	-	-	0.30	0.88	-0.55	0.17	-0.72	0.08	-0.32	0.66	-0.62	0.08
MFGIND	-	-	-	-	2.61	0.00	1.69	0.74	0.24	0.81	-0.21	1.00	-0.04	1.00	0.54	0.12
NFPAYROL	2.28	0.00	4.75	0.00	1.78	0.00	1.52	0.00	0.98	0.00	0.35	0.25	0.16	0.94	0.43	0.00
PPI	1.05	0.14	-0.12	0.96	0.49	0.70	0.55	0.10	-0.70	0.99	-0.82	0.99	-0.15	0.58	-1.02	0.67
RETSALES	0.78	0.04	1.37	0.05	0.59	0.27	0.41	0.27	-0.21	0.99	-	-	-	-	-1.18	0.99
TRADEBAL	-10.09	0.79	-	-	0.10	0.92	-3.99	0.81	0.43	0.05	0.02	1.00	0.17	0.89	0.47	0.02
ω	1.65	0.03	11.58	0.00	0.90	0.10	0.69	0.06	0.30	0.00	0.26	0.00	0.25	0.00	0.52	0.00
α_1	0.27	0.02	0.34	0.00	0.11	0.01	0.19	0.02	0.19	0.00	0.18	0.00	0.28	0.00	0.26	0.00
α_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.09	0.00
β_1	0.46	0.01	-	-	0.72	0.00	0.46	0.04	0.49	0.00	0.60	0.00	0.28	0.00	-	-
Function value	-877.44	0.00	-1204.57	0.00	-924.59	0.00	-917.35	0.00	-7090.68		-7542.77		-7727.96		-7331.87	
# obs	49135.00	0.00	49662.00	0.00	53909.00	0.00	40559.00	0.00	352127.00		351359.00		352799.00		352319.00	

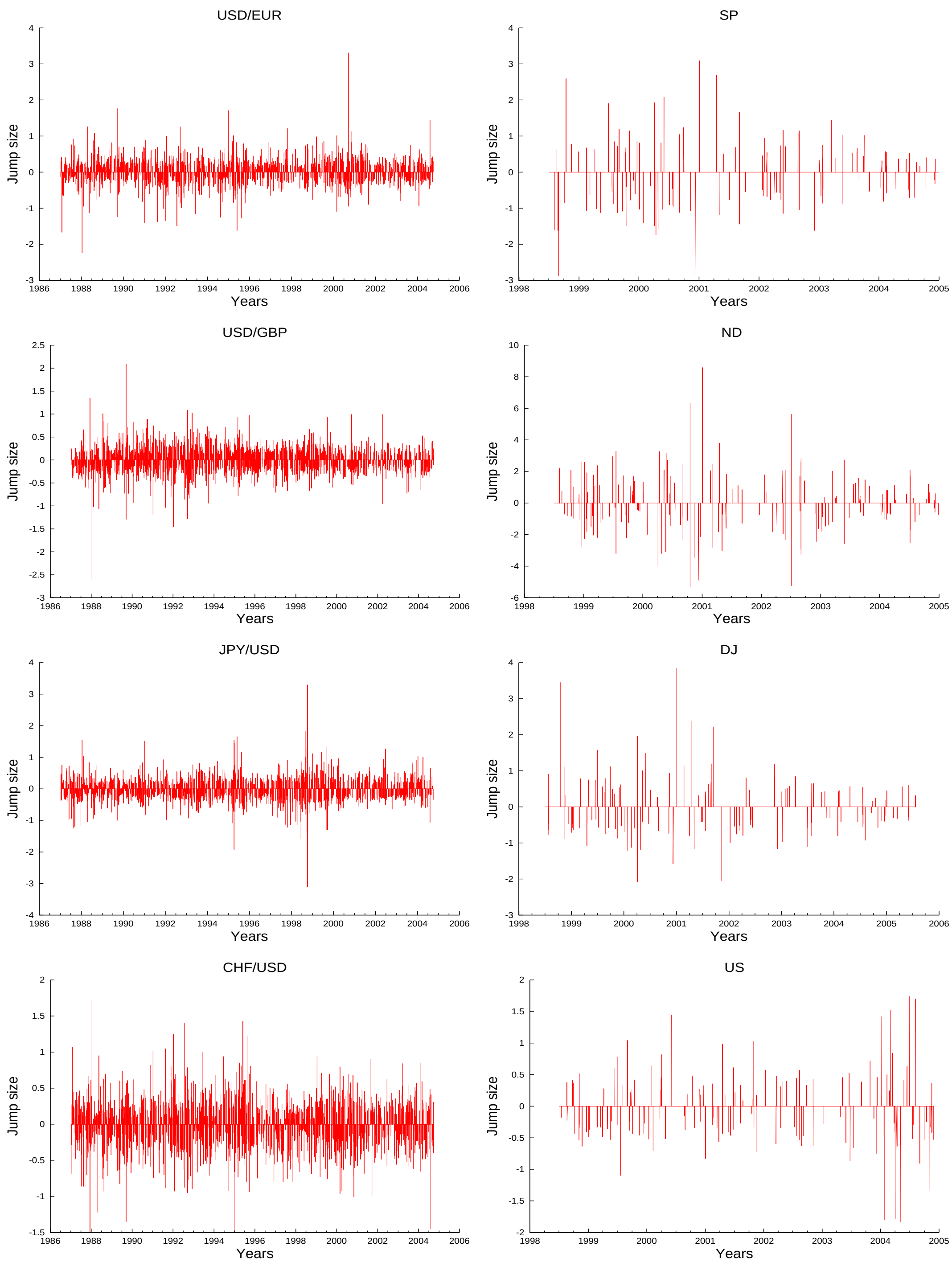
Note: The latent Tobit jump variable is given by $Jump^*_{t,i} = \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \varepsilon_{t,i}$, where $|Jump_{t,i}| = Jump^*_{t,i}$ if $Jump^*_{t,i} > 0$ and $|Jump_{t,i}| = 0$ if $Jump^*_{t,i} \leq 0$, $\varepsilon_{t,i}|\mathcal{I}_{t,i-1}$ is $N(0, \sigma_t^2)$. The variance σ_t^2 is assumed to follow an ARCH or GARCH process. $|Jump_{t,i}|$ represents significant jumps ($\alpha = 0.1$) as defined in the theoretical part. $\eta_{t,i}$ controls for day of the week effects (not reported) and $\mu_{t,i}$ includes surprises concerning macro announcements. For each series, we regress jumps in absolute value on surprises in absolute value. $\xi_{t,i}$ controls for intradaily periodicity (not reported). Estimates and robust p-values ($2 \times (1 - Prob(X < |tstat|))$, X being a $t-$distributed random variable with $N - K$ (# obs. - #parameters) degrees of freedom, and $tstat$ being the estimated coefficient over its std. error) are reported for surprise coefficient (if it is significant at 10% in at leats one series), as well as the ARCH and GARCH coefficients. Regressors with no contemporaneous match with significant jumps are excluded from the model. We further report the maximized log-likelihood function value. The exchange rate samples start in January 1990. The other series samples period is given in Table 1.

Table 7: Probit models for cojumps

	USD/EUR - USD/GBP		USD/EUR - JPY/USD		USD/EUR - CHF/USD		USD/GBP - JPY/USD		USD/GBP - CHF/USD		JPY/USD - CHF/USD	
	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$	Coef.	$P > \|t\|$		
CNSTRSPEND	-	-	-	-	-7.41	0.00	-	-	-	-	-	-
CONSCONF	-	-	-	-	-	-	-	-	-	-	0.73	0.00
FFRTARGET	1.08	0.00	0.86	0.00	0.83	0.00	0.90	0.00	0.89	0.00	0.74	0.01
GDPPRE	-	-	0.87	0.00	0.60	0.02	-	-	-	-	0.83	0.00
GVFISCDEF	-	-	0.23	0.07	0.17	0.18	-	-	-	-	0.25	0.05
MFGIND	-	-	-	-	1.50	0.00	-	-	-	-	-	-
NFPAYROL	-	-	0.65	0.00	0.79	0.00	-	-	-	-	0.61	0.00
TRADEBAL	-	-	-	-	0.76	0.02	-	-	-	-	-	-
Function value	-1842.90		-1181.87		-3130.59		-742.60		-1610.76		-933.24	
Pseudo R^2	0.04		0.04		0.03		0.05		0.04		0.05	
# obs	349355		348967		349557		348593		349542		348619	

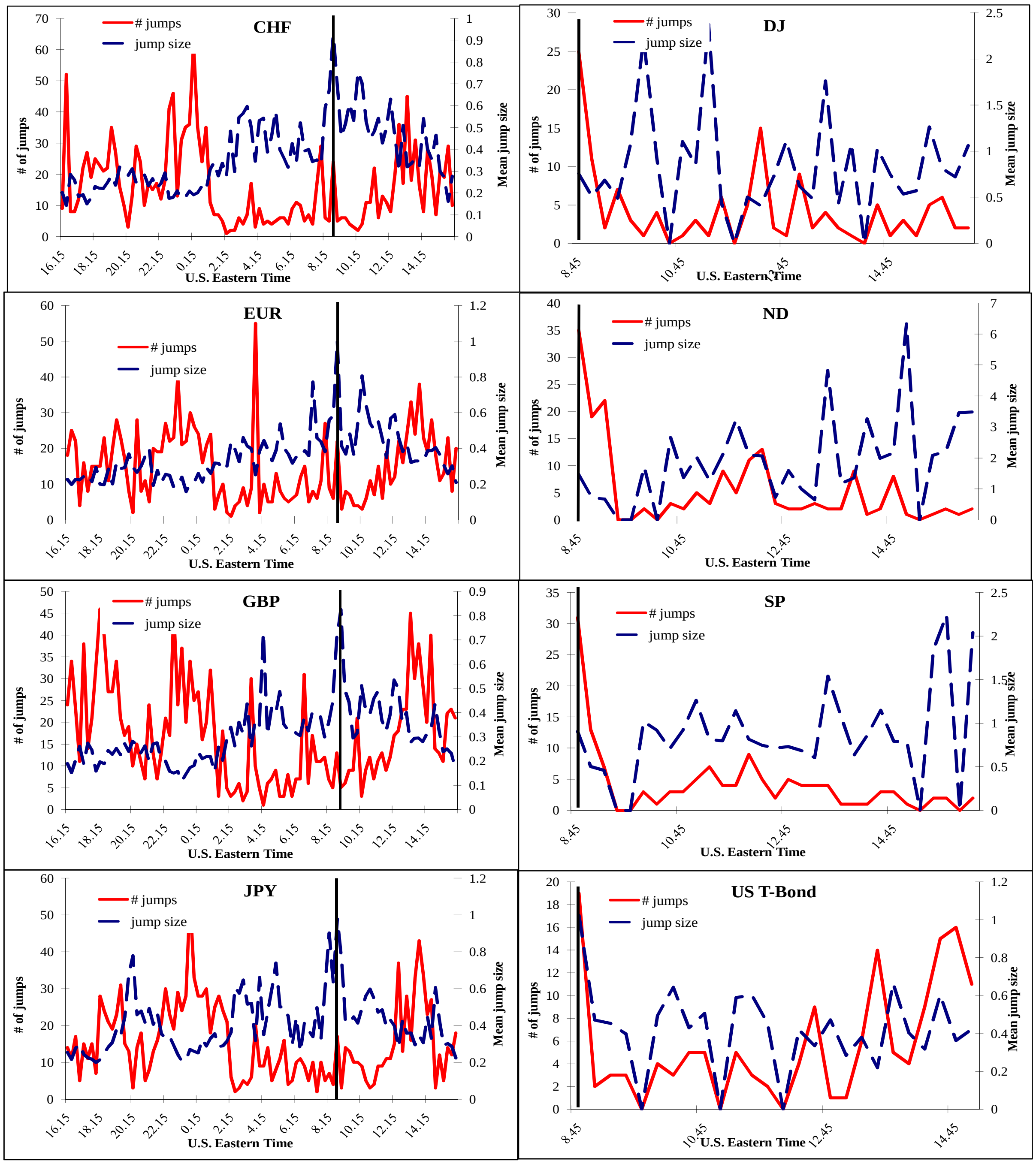
Note: The latent probit cojump variable is given by $COJump^*_{t,i} = \mu + \eta_{t,i} + \mu_{t,i} + \xi_{t,i} + \varepsilon_{t,i}$, where $COJump_{t,i} = 1$ if $COJump^*_{t,i} > 0$ and $COJump_{t,i} = 0$ if $COJump^*_{t,i} \leq 0$. $\varepsilon_{t,i}$ is $NID(0,1)$. $COJump_{t,i}$ is the cojump indicator (see Equation (10)). $\eta_{t,i}$ controls for day of the week effects (not reported) and $\mu_{t,i}$ includes surprises concerning macro announcements. For each series, we regress cojumps on surprises in absolute value. $\xi_{t,i}$ controls for intradaily seasonality (not reported). Estimates and robust p-values $(2 \times (1 - Prob(X < |tstat|))$, X being a $t-$distributed random variable with $N - K$ (# obs. - #parameters) degrees of freedom, and $tstat$ being the estimated coefficient over its std. error) are reported for each surprise coefficient. Regressors with no contemporaneous match with significant cojumps are excluded from the model. We further report the maximized log-likelihood function value, and the McFadden R^2 (defined as $1 - \frac{LogLik_1}{LogLik_0}$, i.e. 1 minus the ratio of the log likelihood function value of the full model to the constant only model one). The exchange rate samples start in January 1990.

Figure 1: Time series of significant jumps



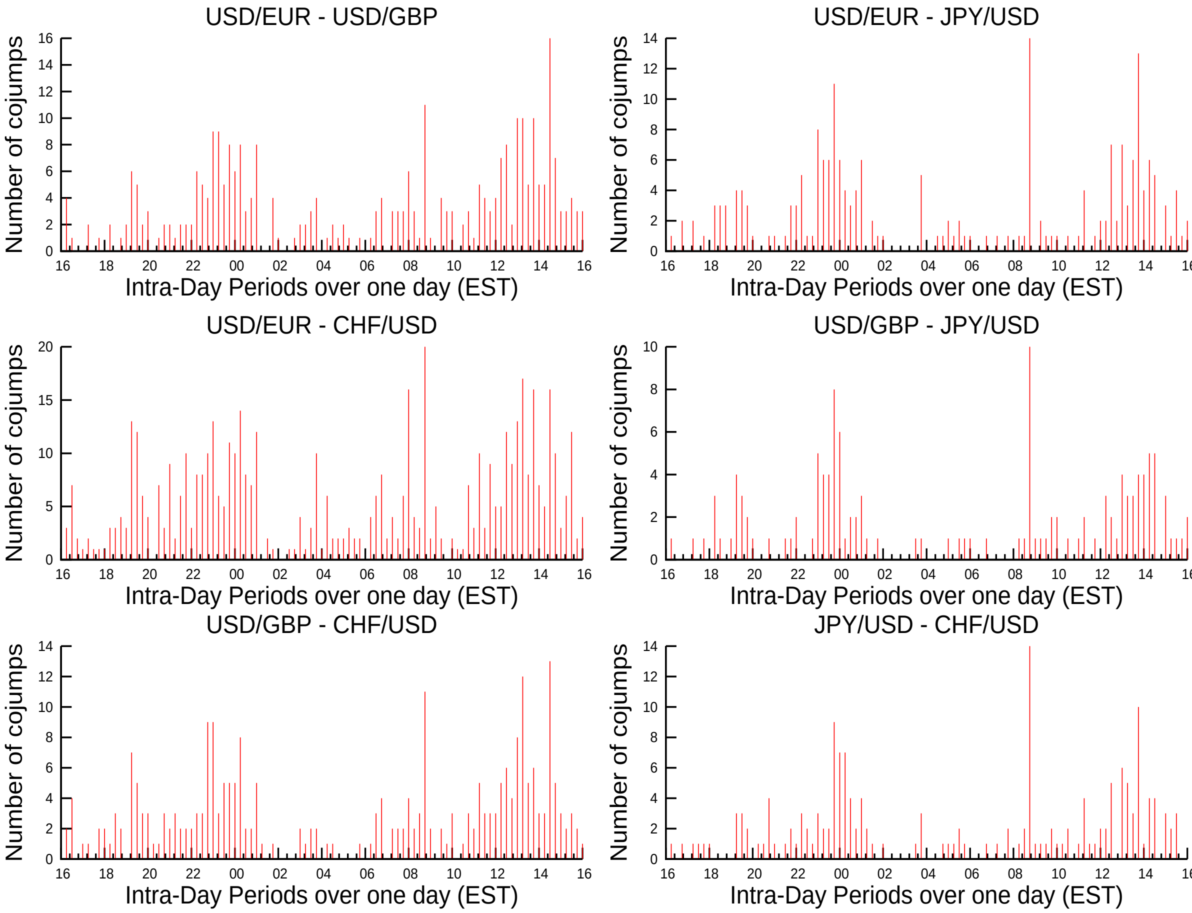
Note: The figure illustrates significant jumps based on the $FiltJ_{t,i}$ statistics given in Equation (8). The significance level is $\alpha = 0.1$ and the sampling frequency is 15 minutes. The X-axis displays time in years, while the Y-axis displays identified jumps (in %), i.e. the variable $Jump_{t,i}$ given in Equation (9). The sample period is given in Table 1.

Figure 2: Count of significant jump occurrences and mean of absolute jumps conditional on the intraday period



Note: the X-axis represents intraday time (U.S. eastern time). The left side Y-axis displays the number of significant jumps ($\alpha = 0.1$), while the right side Y-axis displays the mean of absolute values of significant jumps. Solid lines denote the number of jumps and dashed lines denote mean jump size. Vertical lines denote the interval containing 8:30, the time of most news arrival. The sample period is given in Table 1.

Figure 3: Cojump occurrences per intra-day period



Note: The graphs display the cojump count ($\alpha = 0.1$) for different exchange rates combinations. The X-axis displays intraday periods over 24 hours in EST time. The sample period is given in Table 1.