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Jumps, cojumps, and efficiency in the spot foreign exchange market☆

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ABSTRACT

I identify intraday jumps and cojumps in exchange rates controlling for volatility patterns and relate these events to pre-scheduled macroeconomic news and market conditions. Event study results show that preceding jump and cojump events, exchange rate quote volume, illiquidity, signed order flow, and informed trades are at heightened levels revealing that jump events are consistent with rational dealer quoting behavior. Following jump and cojump events, quote volume and return variance remain at heightened levels while illiquidity, informed trade, and signed order flow remain at depressed levels providing evidence that order flow following jump events is largely uninformed liquidity provision.

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1. Introduction

Jumps are rare discontinuous events in asset prices that have important implications for risk management (Boes et al., 2007; Christoffersen et al., 2012; Eraker, 2004; Jiang et al., 2011; Johannes, 2004; Kim et al., 1994; Maheu and McCurdy, 2004; Merton, 1976), optimal portfolio allocation (Das and Uppal, 2004; Jin and Zhang, 2012; Liu and Pan, 2003; Liu et al., 2003), and the equity risk premium (Jiang and Yao, 2014; Maheu et al., 2013; Ornthanalai, 2014; Yan, 2011). Despite the advances that the extant literature has made on the implications of jumps for portfolio *theory*, there have been relatively few empirical studies looking at the nature of jump events, the sources of jumps, and their effects on market efficiency. I fill this gap in the literature by examining market efficiency and market conditions surrounding jump and cojump[1] events, which include (Amihud, 2002) price impact illiquidity, quote volume, return variance, (Hasbrouck, 1991) informed trade, and currency order.

Prior literature examining financial markets has shown that in the moments surrounding pre-scheduled macroeconomic news releases, treasury prices experience jumps (Dungey et al., 2009; Jiang et al., 2011), many stocks experience significant increases in jump intensity (Lee, 2012), and foreign exchange rates experience jumps (Andersen et al., 2003; Chatrath et al., 2014). The foreign exchange market is ideal for studying the nature of jump events due to its twenty-four hour high-frequency trading environment which allows markets to trade freely with minimal frictions. These lower frictions greatly reduce the potential for erroneous jump identification (Aït-Sahalia et al., 2005; Zhang et al., 2005; Andersen et al., 2007). I identify jump events at the 5-minute frequency using the intraday jump identification methodology of Andersen et al. (2007) and Lee and Mykland (2008). I control for intraweek patterns in volatility by using the Boudt et al. (2011) weighted standard deviation (WSD) estimator, which they show is a robust estimator of patterns in the diffusion term of returns in the presence of jumps, so that the jump identification is not biased by the normal intraweek return volatility pattern in exchange rates.

Since previous literature has shown that foreign exchange rates follow intraweek patterns in volatility (Andersen and Bollerslev, 1998; Baillie and Bollerslev, 1991; Harvey and Huang, 1991) that is largely unrelated to the flow of public information (Andersen and Bollerslev, 1998),[2] controlling for these patterns is important so as to avoid falsely identifying a normal increase in volatility as a jump event. Similar to Lahaye et al. (2011), after controlling for intraweek patterns in volatility,[3] I find that the probability of a jump event in an individual exchange rate, conditional on a pre-

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[1] A cojump event of order n is defined as n exchange rates experiencing jump events simultaneously.

[2] In Section IA.B of the Internet Appendix, I show that in my sample the intraday volatility pattern is also largely unrelated to the release of pre-scheduled news (as well as unrelated to the arrival intensity of jumps). Berry and Howe (1994) and Mitchell and Mulherin (1994) find that volatility patterns in the stock market are also unrelated to the flow of public information

[3] Intraweek pattern refers to the intraday patterns that volatility follows over all 5 business days. In Section IA.A of the Internet Appendix, I present plots of the intraweek patterns in Δ-period return volatility, quote volume, order flow, informed trading intensity, and illiquidity.

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scheduled news event occurring, ranges from a low of 3.05% to a high of 15.42% . The lack of explanatory power that pre-scheduled macroeconomic news releases have for predicting exchange rate jump arrivals motivates the need to identify other causes for their occurrences.

I advance the jump literature by examining the market conditions surrounding jump and cojump events versus normal times. The market condition variables that I examine include: Amihud (2002)'s illiquidity (*PI*) measure, quote volume (*QV*), order flow (*OF*), Hasbrouck (1991)'s information content of trade (*S2XW*) measure (the component of changes in the efficient exchange rate that is trade correlated), return variance (*VAR*), and cumulative abnormal returns (*CAR*s). I find that preceding jumps and cojumps, exchange rates have greater jump-signed *CAR*s, greater quote volume, greater illiquidity, greater jump-signed order flow, and greater (Hasbrouck, 1991) information content of trades. Specifically, jumps occur with greater probability when the market becomes increasingly one-sided with informed order flow, which is consistent with rational quoting behavior by Glosten and Milgrom (1985) and Kyle (1985) market makers.

News jumps (a jump which coincides with the release of pre-scheduled news) and no-news jumps display differing characteristics. Prior to a news jump, relative to no-news jumps, liquidity is higher, quote volume is lower, and the return variance is lower. Following a news jump, relative to no-news jumps, liquidity is higher, quote volume is higher, informed trade is lower, and jump-signed order flow is higher.[4] The pattern following news jumps is consistent with the post-news patterns documented by Tetlock (2010), suggesting that information asymmetries are resolved by public news releases. Further, the lack of jump return reversal indicates that jumps represent permanent innovations to investors' information sets.

Similar to Lahaye et al. (2011), I also find that very few cojumps in exchange rates coincide with pre-scheduled macroeconomic news releases. I find that, ex-ante, the probabilities of a pre-scheduled news event generating a cojump event range from zero percent for a cojump of 11 exchange rates to 1.13% for a cojump of 2 exchange rates. Ex-post, the likelihood of a pre-scheduled news event having occurred with a cojump event ranges from a low of zero percent for a cojump of 11 exchange rates to a high of 35.71% for a cojump of 8 exchange rates.[5] These ex-ante and ex-post probabilities suggest that pre-scheduled macroeconomic news releases have limited power to explain jump and cojump events. My cojump event studies in the foreign exchange market reveal that illiquidity, quote volume, and jump-signed order flow are increasing in cojump order, while the information content of trade is decreasing in cojump order. This suggests that cojump events are the result of broad discount rate shocks in exchange rates.

Finally, I test for the effects that jump and cojump events have on triangular arbitrage pricing errors. Since jump events only create market incompleteness if they are purely discontinuous in nature, I test how discontinuous the identified jumps are. Christensen et al. (2014), using high-frequency data, shows that identified jump events are in fact largely continuous in nature. In order to compare the relative discontinuity in quotes during jump event times versus normal times, I examine the maximum quote revision during jump return times versus non-jump return times. I find that, on average, the maximum absolute quote revision during a jump event represents 20.61% of the jump return magnitude with the maximum absolute quote revision during cojumps being 50% greater than the magnitude attained in the full jump sample. The maximum absolute quote revisions vary during news jumps and no-news jumps where, on average, the maximum absolute quote revision, as a fraction of the jump return magnitude, is 19.22% for no-news jumps and it is 29.75% for news jumps.

I further find that the maximum quote revision magnitudes during jump events represent an illiquidity cost that significantly limits triangular arbitrage. My tests reveal, however, that identified jump events that are primarily driven by an increased demand to trade are associated with smaller arbitrage errors. Therefore, it is not the jump event per-se that leads to a limit to arbitrage, but rather the increased illiquidity cost associated with jump events that leads to a limit to arbitrage.

The study that is most similar to mine is Lahaye et al. (2011). While their paper also examines the relationship between jumps, cojumps, and pre-scheduled macroeconomic news in the foreign exchange market, my study differentiates itself from theirs in that I use event studies to examine the market conditions surrounding jump events. Therefore, I advance the jump literature by revealing how liquidity and price informativeness affect and are affected by jump events as well as by shedding light on dealer quoting behavior.

The remainder of the paper is organized as follows. Section 2 presents the dataset. Section 3 presents results from jump and cojump event studies. Section 4 presents results for jump and cojump determinants. Section 5 examines quote discontinuity and market efficiency during jump events. Section 6 contains concluding remarks.

2. Data

I obtain the tick-by-tick quote data for spot exchange rates from Gain Capital,[6] which is a retail aggregator. Retail forex volume makes up 3.63% (a daily average volume of $60 billion in April, 2016) of the total spot forex volume (BIS, 2016) and Gain Capital represents 9.16% of the volume by the largest 10 forex retail aggregators.[7] The exchange rates that I examine include: AUD/JPY, AUD/USD, EUR/GBP, EUR/USD, GBP/JPY, GBP/USD, USD/CHF, USD/JPY, USD/CAD, NZD/USD, CHF/JPY, EUR/AUD, EUR/CHF, and NZD/JPY covering the sample period of January 1, 2007–December 31, 2010.

Exchange rates are quoted such that they represent the price of one unit of the first currency in units of the second currency. Therefore, the second currency is viewed as the domestic currency and the first one is viewed as the foreign currency. Cross-rate quotes are those provided by Gain Capital and are not imputed using triangular arbitrage arguments. Since the quoted spread is adjusted by Gain Capital, I use the mid-quotes as the exchange rate price series in order to have a cleaner estimate of the representative exchange rates.

While Gain Capital is a forex retail aggregator, the quote data is representative of the aggregate spot foreign exchange market through arbitrage arguments. If the quotes were not in line with the rest of the market, then there would be risk-free arbitrage opportunities across dealers. Each observation contains an exchange rate identifier, date, time-stamp (to the second), bid rate, and ask rate. The bid and ask rates are firm which means that if an order arrives, then the dealer must transact at the posted rates. Therefore, quote spoofing is not a problem in my dataset. Since there is a negligible amount of foreign exchange activity during the weekend period, I drop observations from 17:00 ET on Friday to 22:00 ET on Sunday from the sample. I also drop observations on days containing a bank holiday in the United States, United Kingdom, or Japan from the sample.

[4] Similar post-news dynamics have recently been found in the stock market by Vega (2006) and Savor (2012).

[5] Ex-post conditional news event probabilities, however, are generally increasing in cojump order.

[6] http://ratedata.gaincapital.com/

[7] See http://fairreporters.net/economy/largest-forex-brokers-by-volume-in-2015/.

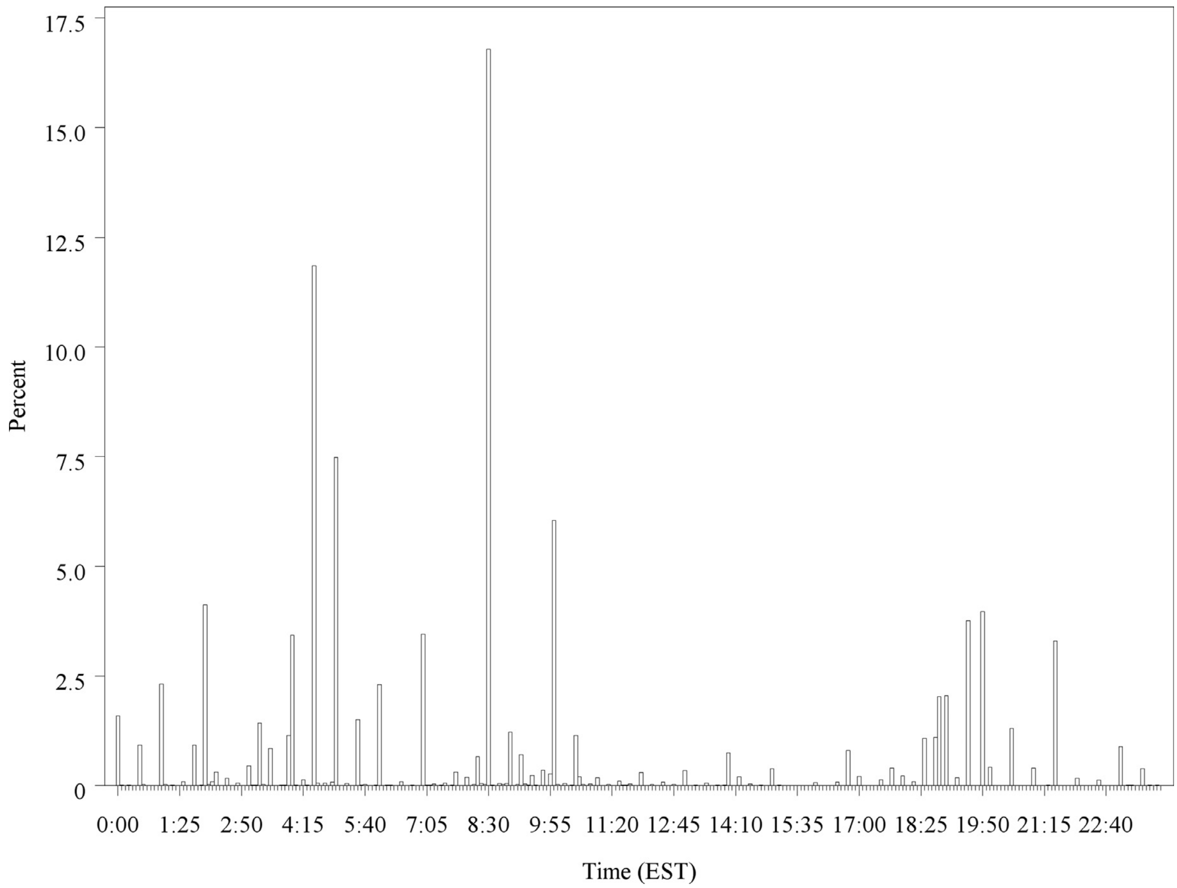

Fig. 1. Distribution of news release times. This figure plots the intraday distribution of pre-scheduled macroeconomic news release times. Times are in Eastern Standard Time. The sample period is January 1, 2007–December 31, 2010.

I obtain data on pre-scheduled macroeconomic news events from FXStreet.com.[8] The news observations contain the time of release (the date and intraday time), country of origin, and the name of the economic indicator or event. If the news release is an economic indicator, then there are further fields stating the actual value, the consensus estimated value, and the economic indicator's previously recorded value. In addition to economic indicators, pre-scheduled publicized speeches of key economic personnel are included, since these events often provide insight to future economic policy that the market pays close attention to.[9] In total, there are 14,764 pre-scheduled news observations from eleven nations for the January 1, 2007–December 31, 2010 period. Table A1 of Appendix A presents summary statistics on the sample of pre-scheduled macroeconomic news releases and Table IA.E1 in the Internet Appendix presents a sample of observations from the news dataset. The largest number of pre-scheduled news releases originates in the United States at 3763, representing 25.49% of the sample, while the fewest number originates in France at 6, representing 0.04% of the sample. No single indicator makes up more than 2.55% of the news sample. In many cases multiple economic indicators are released by a country simultaneously leading to a total of 8,551 *unique* pre-scheduled news release times.

Fig. 1 plots the intraday distribution of news releases. Approximately 17.5% of pre-scheduled news releases occur at 08:30 ET, which represents the largest volume. Notable pre-scheduled news release volumes also cluster at 10:00 ET, 04:00–05:00 ET, and 19:00–21:30 ET. The 04:00–05:00 ET and 19:00–21:30 ET periods are concurrent with the openings of European and Asian financial trading centers, respectively. Between 11:00 ET and 18:00 ET is largely absent of pre-scheduled news releases. Since many of the pre-scheduled news releases occur concurrently with other releases by the same country, for the remainder of the paper, I only use *unique* pre-scheduled news release times by each country.

3. Jump and cojump events

3.1. Jump events

I use the jump detection methodology of Andersen et al. (2007) and Lee and Mykland (2008) to detect intraday jumps at the 5-min frequency. A jump is identified if a 5-min period's standardized absolute return is in excess of the 99.9% critical level of the standard normal distribution.[10] Using a 5-min frequency provides a good compromise between retaining the information content of high-frequency data and avoiding microstructure biases that sampling more frequently would result in (Aït-Sahalia et al., 2005; Zhang et al., 2005; and Andersen et al., 2007). Appendices B and Appendix C outline the jump detection methodology. All jump and cojump statistics which I present are stochastic volatility (SV) robust estimates. I control for intraweek patterns in volatility, the diffusive component of exchange rate returns, by using the weighted standard deviation (WSD) estimator of Boudt et al. (2011). They show that the WSD

[8] http://www.fxstreet.com/fundamental/economic-calendar/

[9] These pre-scheduled speeches represent only 1.89% of the total pre-scheduled news sample.

[10] Under the null hypothesis of the jump detection test, there is a 0.1% unconditional probability of a jump occurring.

Table 1
Jump statistics. This table presents spot foreign exchange rate jump statistics. Jump events are defined as: $\kappa_{t+j\triangle} = r_{t+j\triangle} \cdot \mathbf{1}\left(\frac{|r_{t+j\triangle}|}{\hat{f}^{WSD}_{t+j\triangle}\hat{v}^{WSD}_{t+j\triangle}} > \Phi_{1-\beta/2}\right)$, where $\Phi_{1-\beta/2}$ is the critical value from the standard normal distribution at the $1-\beta/2$ confidence interval and $\beta = 1-(1-\alpha)^{\triangle}$. $\alpha = 0.1\%$. $\hat{f}^{WSD}_{t+j\triangle}$ and $\hat{v}^{WSD}_{t+j\triangle}$ are defined in Appendix C. FX Rate, N, and # DAYS denote the foreign exchange rate, the number of 5-min periods in the sample period, and the number of trading days in the sample period, respectively. JUMPS and J DAYS denote the total number of jumps that are identified and the number of days that had at least one jump occur, respectively. J MEAN is the mean jump return and J SD is the standard deviation of jump returns. Abs(J) is the mean absolute jump size, $\mathbf{P}\{J\}$ is the unconditional probability that a jump occurs during a 5-min period, $\mathbf{P}\{JD\}$ is the unconditional probability that at least one jump occurs during a trading day, and $\mathbf{E}[\#J|JD]$ is the expected number of intraday jumps that occur, conditional on at least one jump occurring during a trading day. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. The sample period is January 1, 2007–December 31, 2010.

FX rate	N	# DAYS	JUMPS	J DAYS	J MEAN	J SD	abs(J)	$P\{J\}$	$P\{JD\}$	$E[\#J\|JD]$
AUD/JPY	258,852	1,139	367	298	−0.0009	0.0052	0.0042	0.0014	0.2616	1.2315
AUD/USD	258,852	1,139	433	338	−0.0007	0.0041	0.0033	0.0017	0.2968	1.2811
EUR/GBP	258,852	1,139	470	376	0.0001	0.0024	0.0018	0.0018	0.3301	1.2500
EUR/USD	258,852	1,139	510	404	−0.0003	0.0024	0.0021	0.0020	0.3547	1.2624
GBP/JPY	258,852	1,139	358	283	−0.0007	0.0044	0.0034	0.0014	0.2485	1.2650
GBP/USD	258,852	1,139	505	382	−0.0003	0.0025	0.0020	0.0020	0.3354	1.3220
USD/CHF	258,852	1,139	532	410	−0.0001	0.0029	0.0024	0.0021	0.3600	1.2976
USD/JPY	258,852	1,139	465	358	−0.0007	0.0033	0.0027	0.0018	0.3143	1.2989
USD/CAD	258,852	1,139	496	381	−0.0002	0.0025	0.0020	0.0019	0.3345	1.3018
NZD/USD	258,852	1,139	454	361	−0.0006	0.0038	0.0033	0.0018	0.3169	1.2576
CHF/JPY	258,852	1,139	331	271	−0.0008	0.0037	0.0031	0.0013	0.2379	1.2214
EUR/AUD	258,852	1,139	367	302	0.0001	0.0035	0.0028	0.0014	0.2651	1.2152
EUR/CHF	258,852	1,139	656	455	−0.0001	0.0020	0.0014	0.0025	0.3995	1.4418
NZD/JPY	258,852	1,139	369	295	−0.0007	0.0052	0.0044	0.0014	0.2590	1.2508

estimator is a robust measure of the diffusive component of returns in the presence of jumps.

In Section IA.B of the Internet Appendix, I examine how patterns in the diffusive component of returns affects jump identification when there is also a pattern in the jump arrival intensity. First, I show that the intraday pattern in volatility remains relatively unchanged after removing all of the pre-scheduled macroeconomic release time observations and jump observations (Fig. IA.B1), which suggests that the news arrival pattern is not driving the intraday pattern in volatility. Next, through simulations (Fig. IA.B2), I show that in the cases where there is no pattern in the diffusion term and where the jump arrival intensity is positively related to the diffusion pattern, jumps are identified precisely. However, in the case where the diffusion term is large relative to the jump arrival intensity, a small percentage of jumps are not identified. Therefore, in the case of my study, there is only expected to be at most a small loss in jump identification power surrounding times of large pre-scheduled news release volumes.

3.1.1. Jump events and news

Table 1 presents the jump summary statistics. The number of identified jumps ranges from 331 to 656 jumps over the sample period. Unconditional jump probabilities range from 0.13% for the CHF/JPY pair to 0.25% for the EUR/CHF pair. Exchange rates experience jumps on 271–455 days, presented in column five, or on 23.79–39.95% of the trading days. The CHF/JPY has the fewest number of jump days at 271 and the EUR/CHF has the greatest number of jump days at 455. The expected number of intraday jumps, conditional on at least one jump having occurred on a given day, ranges from 1.2152 for the EUR/AUD to 1.4418 for the EUR/CHF currency pair. The mean jump return ranges from a low of 0.14% in magnitude for the EUR/CHF to a high of 0.44% in magnitude for the NZD/JPY and jump returns are distributed approximately symmetrically around zero.

A number of previous studies have shown that jumps largely tend to occur with pre-scheduled news events, without explicitly controlling for intraweek patterns in volatility. Recent studies among these include Jiang et al. (2011) in the market for treasury securities, Lee (2012) and Maheu and McCurdy (2004) in the stock market, and Chatrath et al. (2014) in the foreign exchange market. Fig. 2 contains plots of the intraday distribution of identified jump events without controlling for intraweek volatility patterns in the left panel and controlling for intraweek volatility patterns using the WSD estimator in the right panel. The figure reveals that failing to control for intraweek volatility patterns severely biases the identification of jump events to occur surrounding the release of pre-scheduled macroeconomic news. Once intraweek volatility patterns are controlled for, the intraday distribution of identified jumps appears to be more uniformly distributed.

Table 2 presents the probabilities of a jump occurring in response to a pre-scheduled news announcement in each exchange rate, controlling for the bias in jump identification that intraweek volatility patterns create. These probabilities are the ex-ante probabilities that pre-scheduled news events will generate jumps. Generally, contrary to previous findings in the literature, the probability of a jump occurring in an individual exchange rate in response to a pre-scheduled news event is less than one percent. The final column shows that the total ex-ante probability of a pre-scheduled news event for any of the economic regions generating a jump ranges from a low of 3.05% for the USD/JPY to a high of 15.42% for the NZD/USD. These small probabilities suggest that pre-scheduled news events have limited explanatory power for the arrival of jumps.[11]

Andersen et al. (2003) shows that pre-scheduled macroeconomic news may not be a good predictor of jump events, since many pre-scheduled news releases provide redundant information based on the time of the month in which they are released. Table 3 presents ex-post accounts of how likely a pre-scheduled news event is to occur, conditional on a jump event occurring. These probabilities reveal ex-post how important pre-scheduled news events are in generating jumps, in contrast to Table 2 which shows ex-ante how well pre-scheduled news events predict jumps. The ex-post likelihoods take into consideration that not all pre-scheduled news is important, since the ex-post likelihood fraction equals 1 if the most important pre-scheduled news always leads to a jump even if all other pre-scheduled news never leads to a

[11] Notable exceptions are the impacts that U.K. and Australian pre-scheduled news have on GBP and AUD exchange rates, respectively.

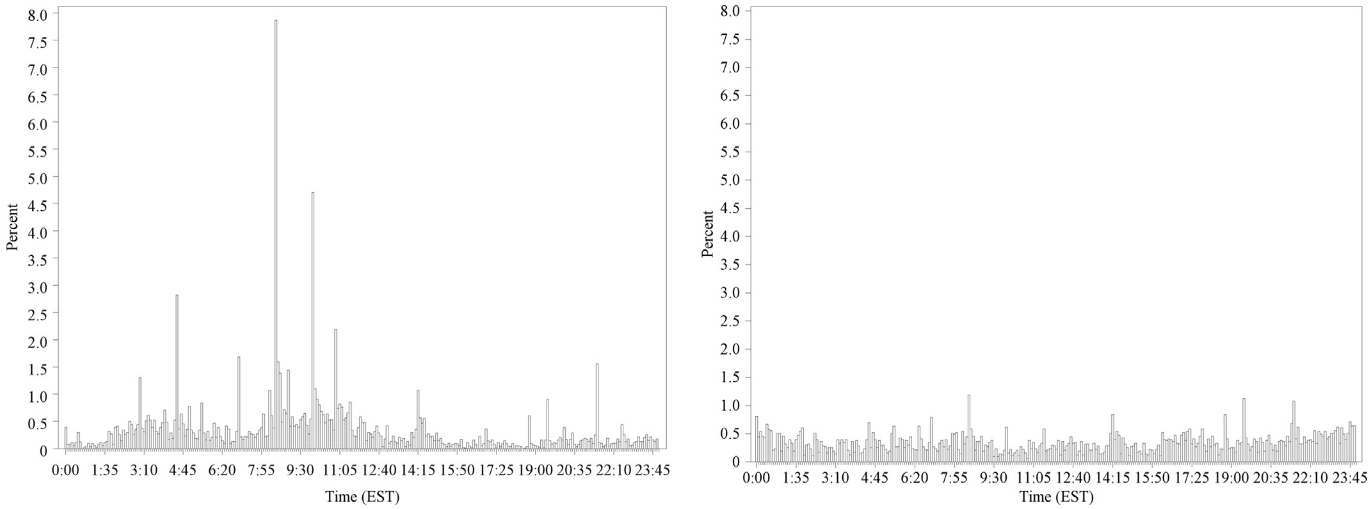

Fig. 2. Distribution of jump event times. This figure plots the intraday distribution of identified exchange rate jump events without controlling for intraweek volatility patterns in the left panel and controlling for intraweek volatillity patterns using the WSD estimator of Boudt et al. (2011) in the right panel. Jump events are defined as: $\kappa_{t+j\triangle} = r_{t+j\triangle} \cdot \mathbf{1}\left(\frac{|r_{t+j\triangle}|}{\hat{f}^{WSD}_{t+j\triangle}\hat{v}^{WSD}_{t+j\triangle}} > \Phi_{1-\beta/2}\right)$, where $\mathbf{1}(x)$ is the indicator function, which is equal to one if x is true and equal to zero otherwise, $\Phi_{1-\beta/2}$ is the critical value from the standard normal distribution at the 1-$\beta/2$ confidence interval, and $\beta = 1-(1-\alpha)^{\triangle}$. $\alpha = 0.1\%$. $\hat{f}^{WSD}_{t+j\triangle}$ and $\hat{v}^{WSD}_{t+j\triangle}$ are defined in Appendix C. Times are in Eastern Standard Time. The sample period is January 1, 2007–December 31, 2010.

Table 2
Jump probabilities conditional on news. This table presents jump probabilities in exchange rates, conditional on a pre-scheduled macroeconomic news event occurring in the same 5-min period in the country column. The conditional probability of a jump in the i'th exchange rate, given a news event in the h'th country, is given by: $\mathbf{P}\{JUMP_i|NEWS_h\} = \frac{\sum_{n=1}^{N}\mathbf{1}(\kappa_{i,n}\neq 0)\cdot\mathbf{1}(NEWS_{h,n}=1)}{\sum_{n=1}^{N}\mathbf{1}(NEWS_{h,n}=1)}$, where N is the total number of 5-min periods in the sample period, $\mathbf{1}(x)$ is an indicator variable equal to one if x is true and equal to zero otherwise, $\kappa_{i,\,n}$ is defined as in Table 1 and Appendix B, and $NEWS_{h,\,n}$ is a dummy variable equal to one if a pre-scheduled macroeconomic news event occurred in the h'th country in the n'th 5-min interval and equal to zero otherwise. The final column presents the cumulative probability of a jump occurring in an exchange rate conditional on any news event occuring. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. The sample period is January 1, 2007–December 31, 2010.

FX rate	U.S.	U.K.	Japan	E.M.U.	Australia	Germany	Canada	Switz.	N.Z.	Sweden	France	Total
AUD/JPY	0.0076	0.0012	0.0023	0.0000	0.0595	0.0000	0.0066	0.0000	0.0032	0.0000	0.0000	0.0803
AUD/USD	0.0056	0.0012	0.0000	0.0000	0.0757	0.0018	0.0051	0.0000	0.0095	0.0000	0.0000	0.0989
EUR/GBP	0.0067	0.0314	0.0012	0.0027	0.0083	0.0127	0.0000	0.0047	0.0032	0.0000	0.0000	0.0710
EUR/USD	0.0121	0.0013	0.0011	0.0027	0.0049	0.0091	0.0000	0.0023	0.0000	0.0000	0.0000	0.0336
GBP/JPY	0.0089	0.0190	0.0068	0.0000	0.0099	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0445
GBP/USD	0.0094	0.0341	0.0011	0.0027	0.0082	0.0000	0.0000	0.0023	0.0096	0.0000	0.0000	0.0674
USD/CHF	0.0111	0.0038	0.0023	0.0027	0.0033	0.0055	0.0025	0.0251	0.0000	0.0000	0.0000	0.0562
USD/JPY	0.0116	0.0025	0.0056	0.0000	0.0066	0.0018	0.0000	0.0023	0.0000	0.0000	0.0000	0.0305
USD/CAD	0.0061	0.0025	0.0012	0.0027	0.0120	0.0037	0.0395	0.0000	0.0033	0.0000	0.0000	0.0710
NZD/USD	0.0072	0.0013	0.0000	0.0000	0.0198	0.0000	0.0025	0.0000	0.1234	0.0000	0.0000	0.1542
CHF/JPY	0.0039	0.0013	0.0045	0.0014	0.0066	0.0018	0.0025	0.0160	0.0000	0.0000	0.0000	0.0379
EUR/AUD	0.0072	0.0025	0.0011	0.0000	0.0659	0.0055	0.0000	0.0000	0.0095	0.0000	0.0000	0.0917
EUR/CHF	0.0061	0.0038	0.0023	0.0014	0.0000	0.0018	0.0025	0.0457	0.0000	0.0588	0.0000	0.1223
NZD/JPY	0.0094	0.0013	0.0034	0.0000	0.0165	0.0018	0.0025	0.0000	0.0946	0.0000	0.0000	0.1295

jump. U.S. pre-scheduled news is revealed to be the most likely news to generate a jump with a likelihood ranging from 1.68% to 4.61% of jump events. The final column of Table 3 shows that even conditioning ex-post on a jump event occurring, pre-scheduled news is unlikely to be the generator of the jump. News jumps (a jump coinciding with the release of pre-scheduled news), as a fraction of the full jump sample, range from a low of 6.86% for the EUR/USD exchange rate to a high of 17.07% for the NZD/JPY exchange rate. Together, Tables 2 and 3 motivate the need to identify other sources for the occurrences of jumps in exchange rates.

3.1.2. Jump event studies

This section presents event studies for market conditions surrounding jump events where the event is the occurrence of an exchange rate jump. The previous twelve 5-min periods and the following twelve 5-min periods are included for a total event window size of twenty-five 5-min periods. The market conditions that I examine include cumulative abnormal returns (*CAR*), (Amihud, 2002) price impact illiquidity (*PI*), quote volume (*QV*), return variance (*VAR*), Hasbrouck's (1991) contribution of informed trade to return variance (*S2XW*), and order flow (*OF*). Formal definitions of *PI*, *S2XW*, and *OF* are provided in Appendix D. These variables are chosen, since they have been documented to have important effects on market efficiency (Piccotti, 2016) and price discovery.

OF and *S2XW* are included, since Evans and Lyons (2008) and Love and Payne (2008) show that order flow in the foreign exchange market contributes significantly to price discovery.[12] Greater *OF* and *S2XW* are expected to increase the likelihood of a jump event as the market becomes one-sided, which leads to discrete quote adjustments that can result with Bayesian dealers, as in the model of Glosten and Milgrom (1985). *QV* and *PI* are included to test how trading activity and illiquidity vary around

[12] Menkveld et al. (2012), Pasquariello and Vega (2007) and Locke and Onayev (2007) also find that order flow plays an important role for price discovery in the U.S. Treasury bond market and S&P 500 futures prices, respectively.

Table 3
Ex-post likelihoods of news jumps. This table presents probabilities of pre-scheduled macroeconomic news releases in the same 5-min period as a jump, conditional on a jump occurring. The conditional probability of a news event in the h'th country, given a jump in the i'th exchange rate, is given by: $\mathbf{P}\{NEWS_h|JUMP_i\} = \frac{\sum_{n=1}^{N}\mathbf{1}(\kappa_{i,n}\neq 0)\cdot\mathbf{1}(NEWS_{h,n}=1)}{\sum_{n=1}^{N}\mathbf{1}(\kappa_{i,n}\neq 0)}$, where N is the total number of 5-min periods in the sample period, $\mathbf{1}(x)$ is an indicator variable equal to one if x is true and equal to zero otherwise, $\kappa_{i,n}$ is defined as in Table 1 and Appendix B, and $NEWS_{h,n}$ is a dummy variable equal to one if a pre-scheduled macroeconomic news event occurred in the h'th country in the n'th 5-min interval and equal to zero otherwise. The final column presents the cumulative probability of a news event occurring in any nation, conditional on a jump occurring in an exchange rate. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. The sample period is January 1, 2007–December 31, 2010.

FX rate	U.S.	U.K.	Japan	E.M.U.	Australia	Germany	Canada	Switz.	N.Z.	Sweden	France	Total
AUD/JPY	0.0354	0.0027	0.0054	0.0000	0.0981	0.0000	0.0082	0.0000	0.0027	0.0000	0.0000	0.1526
AUD/USD	0.0231	0.0023	0.0000	0.0000	0.1062	0.0023	0.0046	0.0000	0.0069	0.0000	0.0000	0.1455
EUR/GBP	0.0255	0.0532	0.0021	0.0043	0.0106	0.0149	0.0000	0.0043	0.0021	0.0000	0.0000	0.1170
EUR/USD	0.0431	0.0020	0.0020	0.0039	0.0059	0.0098	0.0000	0.0020	0.0000	0.0000	0.0000	0.0686
GBP/JPY	0.0447	0.0419	0.0168	0.0000	0.0168	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.1201
GBP/USD	0.0337	0.0535	0.0020	0.0040	0.0099	0.0000	0.0000	0.0020	0.0059	0.0000	0.0000	0.1109
USD/CHF	0.0376	0.0056	0.0038	0.0038	0.0038	0.0056	0.0019	0.0207	0.0000	0.0000	0.0000	0.0827
USD/JPY	0.0452	0.0043	0.0108	0.0000	0.0086	0.0022	0.0000	0.0022	0.0000	0.0000	0.0000	0.0731
USD/CAD	0.0222	0.0040	0.0020	0.0040	0.0141	0.0040	0.0323	0.0000	0.0020	0.0000	0.0000	0.0847
NZD/USD	0.0286	0.0022	0.0000	0.0000	0.0264	0.0000	0.0022	0.0000	0.0859	0.0000	0.0000	0.1454
CHF/JPY	0.0211	0.0030	0.0121	0.0030	0.0121	0.0030	0.0030	0.0211	0.0000	0.0000	0.0000	0.0785
EUR/AUD	0.0354	0.0054	0.0027	0.0000	0.1090	0.0082	0.0000	0.0000	0.0082	0.0000	0.0000	0.1689
EUR/CHF	0.0168	0.0046	0.0030	0.0015	0.0000	0.0015	0.0015	0.0305	0.0000	0.0588	0.0000	0.1183
NZD/JPY	0.0461	0.0027	0.0081	0.0000	0.0271	0.0027	0.0027	0.0000	0.0813	0.0000	0.0000	0.1707

jump events, since Mancini et al. (2013) shows that illiquidity shocks can be significant in the foreign exchange market. If buy and sell orders follow Poisson processes with an equal probability of occurring and with only 1 share bought or sold, then quote volume is the variance of order flow. With dealers that behave as Kyle (1985) market makers, greater QV and PI are expected to increase the likelihood of a jump occurring, since they increase the market maker's quoted price variance.

When calculating abnormal returns, I use a constant-mean return model. Let T_j denote the total number of 5-min observations which occur at the intraweek time $j\triangle$ and let T denote the total number of 5-min observations in the sample. Abnormal returns for exchange rate i are defined to be:

$$AR_{i,t+j\triangle} = r_{i,t+j\triangle} - \mathbf{E}_{T,j}[r_i], \tag{3.1}$$

where $r_{i,t+j\triangle}$ is the 5-min log mid-quote revision and $\mathbf{E}_{T,j}[\cdot]$ denotes the expected value, conditioned on the full sample of data (i.e. the sample mean return for the exchange rate at intraweek time $j\triangle$ is $\mathbf{E}_{T,j}[r_i] = T_j^{-1}\sum_{t=1}^{T_j} r_{i,t+j\triangle}$). $\triangle$ is the frequency of discretely observed intraweek returns ($\triangle$=1/1,392),[13] t denotes the week, and $j = \{1, 2, \ldots, \triangle^{-1}\}$. Since PI, QV, VAR, $S2XW$, and OF display intraweek patterns, I standardize each variable to have a mean of zero and a variance of one for each intraweek period:

$$x_{i,t+j\triangle} = \frac{\left(x_{i,t+j\triangle} - \mathbf{E}_{T,j}[x_{i,j}]\right)}{\sqrt{\mathbf{V}_{T,j}[x_{i,j}]}}, \tag{3.2}$$

where $x \in \{PI, QV, VAR, S2XW, OF\}$ and $\mathbf{V}_{T,j}[\cdot]$ denotes the variance, conditioned on the full sample of data (i.e. the sample variance of $x_{i,j}$ at intraweek time $j\triangle$ is $\mathbf{V}_{T,j}[x_{i,j}] = \left(T_j - 1\right)^{-1}\sum_{t=1}^{T_j}\left(x_{i,t+j\triangle} - \mathbf{E}_{T,j}[x_{i,j}]\right)^2$). While the results that follow do not use standardized returns in order to show the economic significance of their magnitudes, the results which use standardized returns are included in Section IA.C of the Internet Appendix.

The jump event study results are presented in Table 4. $CAR^{\pm}$ and $OF^{\pm}$ denote the jump-signed CAR and the jump-signed OF (i.e. $CAR^{\pm}_{i,t+j\triangle} = sign\left(\kappa_{i,t+j^*\triangle}\right)CAR_{i,t+j\triangle}$ and $OF^{\pm}_{i,t+j\triangle} = sign\left(\kappa_{i,t+j^*\triangle}\right)OF_{i,t+j\triangle}$, where $t + j^*\triangle$ is the intraweek jump time and $t + j\triangle$ is within an hour before or after the intraday jump time) where CARs in the jump event window are defined as:

$$CAR_{i,t+j\triangle} = \sum_{m=j^*-12}^{j} AR_{i,t+m\triangle},$$
$$\text{for } j \in \{j^* - 12, \ldots, j^* - 1, j^*, j^* + 1, \ldots, j^* + 12\} \tag{3.3}$$

and where $\kappa_{i,t+j\triangle}$ is the jump return and is defined in Eq. (B.4) in Appendix B. Bold-faced print denotes statistical significance at the 10% level or better using a difference-in-means (between jump values and no-jump values) t-test assuming unequal sample variances. Serving as the control sample, the standardized variables are approximately equal to zero at all event window dates when there is not a jump event. At the intraday jump time, PI increases to 1.6287, QV increases to 1.9939, VAR increases to 6.2958, $S2XW$ decreases to −0.1063, and $OF^{\pm}$ increases to 3.2270, each of which is significantly different from the no-jump value. All variables except for PI display significant pre-jump drifts. QV increases monotonically from the start of the event window to the intraday jump time, increasing from −0.0234 to 0.5003. VAR increases from 0.0130 at the beginning of the event window to 0.4715 in the period prior to the intraday jump time. From the start of the event window to the period prior to the intraday jump time, $OF^{\pm}$ increases from 0.0660 to 0.1739. $S2XW$ has a mild pre-jump drift, decreasing from 0.0658 to −0.0076. These results are consistent with jumps resulting from the rational price setting behavior of Glosten and Milgrom (1985) and Kyle (1985) market makers.

Both QV and VAR mean-revert to normal levels slowly following a jump and continue to remain at heightened levels at the end of the event window. In the moments following a jump event, PI decreases to −0.1358 and remains lower than normal for the remainder of the event window, indicating that there is improved liquidity following a jump. $OF^{\pm}$ and $S2XW$ are −0.4362 and −0.1863 in the period following the intraday jump time and both also remain at lower than normal levels for the remainder of the event window, which provides further evidence that order flow tends to originate from uninformed liquidity providers following jumps.

There is statistically significant evidence of a mild pre-jump drift in $CAR^{\pm}$s which suggests that jump events may be anticipated. $CAR^{\pm}$s increase from 0.00% to 0.07% immediately prior to a jump event. While this may be a small amount in other financial markets, this is an economically meaningful amount in the for-

[13] 1,392 is equal to the 2,016 5-min periods in a 7-day 24-hour per day week minus the 5-min periods that I drop from weekends in my sample.

Table 4

Jump event studies. This table presents results from event studies of market state variables surrounding jump events. Normal returns are assumed to follow a constant-mean process. DATE is the intraday event time, $CAR^{\pm}$ is the cumulative abnormal return in the direction of jump sign, *PI* is standardized Amihud (2002) price impact per quote revision, *QV* is standardized quote volume, *VAR* is standardized return variance, *S2XW* is standardized (Hasbrouck, 1991) informed trade contribution, and $OF^{\pm}$ is standardized order flow in the direction of jump sign. Precise definitions for *PI*, *S2XW*, and *OF* are given in Appendix D. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. Bold-faced print denotes statistical significance at the 10% level or better using a difference-in-means (between jump and no jump values) *t*-test assuming unequal sample variances. The sample period is January 1, 2007–December 31, 2010.

DATE	Jump						No jump					
	CAR±	PI	QV	VAR	S2XW	OF±	CAR±	PI	QV	VAR	S2XW	OF±
−12	**0.0000**	−0.0063	−0.0234	0.0130	**0.0658**	**0.0660**	0.0000	0.0000	−0.0001	0.0000	0.0000	−0.0001
−11	**0.0001**	0.0127	−0.0177	0.0089	**0.0617**	**0.0614**	0.0000	0.0000	−0.0001	0.0000	0.0000	−0.0001
−10	**0.0001**	0.0129	0.0002	**0.0280**	**0.0663**	**0.0537**	0.0000	0.0000	−0.0001	0.0000	0.0000	−0.0001
−9	**0.0001**	−0.0076	0.0183	**0.0597**	**0.0538**	**0.0628**	0.0000	0.0000	−0.0001	−0.0001	0.0000	−0.0001
−8	**0.0002**	0.0063	**0.0504**	**0.0769**	**0.0401**	**0.0466**	0.0000	0.0000	−0.0002	−0.0001	0.0000	−0.0001
−7	**0.0002**	−0.0147	**0.0658**	**0.0661**	**0.0370**	**0.0720**	0.0000	0.0000	−0.0002	−0.0001	0.0000	−0.0001
−6	**0.0003**	−0.0176	**0.0892**	**0.0615**	**0.0339**	**0.0634**	0.0000	0.0000	−0.0002	−0.0001	0.0000	−0.0001
−5	**0.0004**	−0.0165	**0.1264**	**0.1222**	**0.0316**	**0.0757**	0.0000	0.0000	−0.0003	−0.0002	0.0000	0.0000
−4	**0.0004**	−0.0013	**0.1795**	**0.1560**	**0.0375**	**0.0603**	0.0000	0.0000	−0.0004	−0.0002	0.0000	−0.0001
−3	**0.0005**	0.0126	**0.2418**	**0.1970**	0.0205	**0.0883**	0.0000	0.0000	−0.0005	−0.0003	0.0000	−0.0001
−2	**0.0006**	0.0136	**0.3233**	**0.2873**	0.0085	**0.1362**	0.0000	0.0000	−0.0006	−0.0005	0.0001	0.0000
−1	**0.0007**	**0.0335**	**0.5003**	**0.4715**	−0.0076	**0.1739**	0.0000	−0.0001	−0.0009	−0.0008	0.0001	0.0000
0	**0.0033**	**1.6287**	**1.9939**	**6.2958**	−0.1063	**3.2270**	0.0000	−0.0028	−0.0035	−0.0110	0.0002	0.0004
1	**0.0031**	−0.1358	**1.6515**	**0.7916**	−0.1863	−0.4362	0.0000	0.0002	−0.0029	−0.0014	0.0004	−0.0002
2	**0.0032**	−0.1077	**1.0838**	**0.5028**	−0.2012	−0.0858	0.0000	0.0002	−0.0019	−0.0009	0.0004	−0.0002
3	**0.0031**	−0.0817	**0.8563**	**0.4526**	−0.1926	−0.0932	0.0000	0.0001	−0.0015	−0.0008	0.0004	−0.0002
4	**0.0031**	−0.0810	**0.6950**	**0.3500**	−0.1795	−0.0142	0.0000	0.0001	−0.0012	−0.0006	0.0004	−0.0001
5	**0.0031**	−0.0524	**0.5673**	**0.2997**	−0.1651	−0.0181	0.0000	0.0001	−0.0010	−0.0005	0.0003	−0.0002
6	**0.0031**	−0.0651	**0.4682**	**0.2008**	−0.1493	−0.0466	0.0000	0.0001	−0.0008	−0.0003	0.0003	−0.0002
7	**0.0031**	−0.0458	**0.3949**	**0.2005**	−0.1367	−0.0152	0.0000	0.0001	−0.0007	−0.0003	0.0003	−0.0002
8	**0.0032**	−0.0374	**0.3384**	**0.1940**	−0.1259	−0.0156	0.0000	0.0001	−0.0006	−0.0003	0.0003	−0.0002
9	**0.0031**	−0.0268	**0.2946**	**0.1636**	−0.1086	−0.0661	0.0000	0.0000	−0.0005	−0.0003	0.0002	−0.0002
10	**0.0031**	−0.0353	**0.2517**	**0.1021**	−0.1011	−0.0327	0.0000	0.0001	−0.0004	−0.0002	0.0002	−0.0001
11	**0.0031**	−0.0048	**0.2098**	**0.1199**	−0.0919	−0.0192	0.0000	0.0000	−0.0003	−0.0002	0.0002	−0.0002
12	**0.0031**	−0.0165	**0.1684**	**0.0936**	−0.0847	−0.0579	0.0000	0.0000	−0.0002	−0.0001	0.0002	−0.0002

eign exchange market where bid-ask spreads are very small and heavy leverage is often used[14] (common maximum leverage levels offered range from 20:1 to 50:1). Evidence that jumps represent permanent innovations to traders' information sets is provided by the absence of post-jump reversals in $CAR^{\pm}$s. The mean $CAR^{\pm}$s mildly decline from 0.33% at the intraday jump time to 0.31% at the end of the event window.

A pre-jump drift in $CAR^{\pm}$s can occur for information-reasons, such as private information about an upcoming news announcement, as well as for information-unrelated reasons, such as market one-sidedness. Market conditions are expected to differ between news jumps and no-news jumps, since pre-scheduled macroeconomic news releases resolve asymmetric information in exchange rates. Tetlock (2010) shows that following the resolution of asymmetric information, returns are serially correlated, high volume news is a better predictor of returns than low volume news, trading volume and return variance are higher, and lastly that illiquidity and informed trade decrease. Vega (2006) and Savor (2012) provide empirical evidence that when public news has less impact on resolving asymmetric information and when large price changes are not information-related, the less information-related price changes display no drift to a modest return reversal. Based on this extant evidence, following a news jump, relative to a no-news jump, there is expected to be a larger post-jump drift in $CAR^{\pm}$s, *QV* will be higher, $OF^{\pm}$ will be higher, *VAR* will be higher, *PI* will be lower, and *S2XW* will be lower.

Comparisons of news jumps and jumps that occur in the absence of pre-scheduled news, denoted as no-news jumps, are presented in Table 5. Jumps are conditioned on pre-scheduled news originating from any country in the sample, since Tables 2 and 3 show that jumps in exchange rates occur in association with pre-scheduled news, regardless of the nation of origin. Bold-faced print denotes statistical significance at the 10% level or better using a difference-in-means (between news jump values and no-news jump values) *t*-test assuming unequal sample variances. News jump magnitudes are significantly greater than no-news jump magnitudes by 17 pips (1 pip = 0.0001), or 70.83% greater, on average. The pre-jump drift in $CAR^{\pm}$s prior to news jumps is generally statistically insignificantly different from that of no-news jumps, which rejects the hypothesis that traders possess private information about pre-scheduled news. $CAR^{\pm}$s following news jumps increase from 0.42% at the intraday jump time to 0.47% at the end of the event window, which indicates that news jumps do not fully adjust to innovations in the public information set. This post-event drift is consistent with information continuing to be impounded into prices indirectly through order flow (Evans and Lyons, 2008; Love and Payne, 2008) with dealers that are Bayesian updaters as in Glosten and Milgrom (1985). A slight negative post-jump drift in $CAR^{\pm}$s is observed following no-news jumps, which provides evidence that the return to liquidity provision following a no-news jump is approximately 0.03% for a one hour holding period.

PI levels at the intraday jump time for news jumps and no-news jumps are insignificantly different from one another; however, pre-jump *PI* for news jumps is significantly lower than pre-jump *PI* for no-news jumps. Whereas *PI* is −0.1437 in the five minutes prior to a news jump, *PI* is 0.0551 in the five minute period prior to no-news jumps. *QV* is significantly larger during news jumps (2.5033) than no-news jumps (1.9319), indicating that there is a greater shock to the demand to trade during news jumps. *QV*, however, is significantly lower prior to news jumps than no-news jumps. Traders appear to take a wait-and-see approach prior to pre-scheduled news. News jumps also have a significantly smaller

[14] Section IA.A presents the current maximum leverage levels offered by Gain Capital for the exchange rates in my sample.

Table 5

News jump events. This table presents results from event studies of the market state surrounding jump events. Normal returns are assumed to follow a constant-mean process. DATE is the intraday event time, $CAR^{\pm}$ is the cumulative abnormal return in the direction of jump sign, *PI* is the Amihud (2002) standardized price impact per quote revision, *QV* is standardized quote volume, *VAR* is standardized return variance, *S2XW* is standardized (Hasbrouck, 1991) informed trade contribution, and $OF^{\pm}$ is standardized order flow in the direction of jump sign. Precise definitions for *PI, S2XW*, and *OF* are given in Appendix D. A news event is assumed to occur with a jump if any nation releases a pre-scheduled macroeconomic news release during the same 5-min period that a jump occurs. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. Bold-faced print denotes statistical significance at the 10% level or better using a difference-in-means (between news jump and no-news jump values) *t*-test assuming unequal sample variances. The sample period is January 1, 2007–December 31, 2010.

DATE	News jump						No-news jump					
	$CAR^{\pm}$	PI	QV	VAR	S2XW	$OF^{\pm}$	$CAR^{\pm}$	PI	QV	VAR	S2XW	$OF^{\pm}$
−12	0.0001	−0.0784	−0.2072	−0.1217	0.0510	0.0853	0.0000	0.0024	−0.0010	0.0294	0.0676	0.0636
−11	0.0001	−0.0581	−0.1622	−0.1572	0.0442	0.0399	0.0001	0.0213	−0.0001	0.0291	0.0639	0.0640
−10	0.0001	−0.1155	−0.1386	−0.1693	0.0672	0.0948	0.0001	0.0286	0.0171	0.0520	0.0662	0.0487
−9	0.0001	−0.1056	−0.1350	−0.1407	0.0726	−0.0062	0.0001	0.0044	0.0369	0.0840	0.0515	0.0712
−8	0.0001	−0.1365	−0.1105	−0.1369	0.0680	0.0137	0.0002	0.0236	0.0700	0.1029	0.0367	0.0506
−7	0.0001	−0.1146	−0.1321	−0.1374	0.0365	0.0201	0.0003	−0.0026	0.0899	0.0909	0.0370	0.0783
−6	0.0001	−0.0492	−0.0988	−0.0684	0.0244	0.1043	0.0003	−0.0138	0.1120	0.0773	0.0350	0.0585
−5	0.0001	−0.1307	−0.0546	−0.0876	0.0352	−0.0049	0.0004	−0.0026	0.1485	0.1477	0.0312	0.0855
−4	0.0001	−0.0873	−0.0317	−0.0686	0.0335	−0.0374	0.0004	0.0092	0.2052	0.1834	0.0380	0.0722
−3	0.0002	−0.0701	−0.0481	−0.0620	0.0173	**0.0197**	0.0005	0.0227	0.2771	0.2285	0.0209	0.0967
−2	0.0002	−0.0943	**0.0552**	−0.0521	0.0069	−0.0476	0.0006	0.0268	0.3560	0.3286	0.0086	0.1585
−1	**0.0001**	−0.1437	0.4861	**0.1694**	0.0136	−0.1108	0.0008	0.0551	0.5020	0.5083	−0.0102	0.2085
0	0.0042	1.6329	**2.5033**	6.1044	−0.3052	**2.5097**	0.0032	1.6281	1.9319	6.3191	−0.0821	3.3142
1	**0.0042**	−0.2723	**1.9724**	**0.6136**	−0.3653	−0.0998	0.0030	−0.1192	1.6125	0.8133	−0.1645	−0.4771
2	**0.0044**	−0.2155	**1.4489**	0.4176	−0.3733	**0.0105**	0.0030	−0.0946	1.0394	0.5131	−0.1803	−0.0975
3	**0.0045**	−0.1640	**1.1601**	0.4197	−0.3280	**0.1215**	0.0030	−0.0717	0.8193	0.4566	−0.1762	−0.1193
4	**0.0047**	−0.1703	**1.0325**	0.3285	−0.2910	**0.1824**	0.0030	−0.0701	0.6539	0.3526	−0.1659	−0.0381
5	**0.0047**	−0.1303	**0.8530**	0.3076	−0.2660	**0.1041**	0.0030	−0.0429	0.5325	0.2988	−0.1528	−0.0330
6	**0.0048**	−0.2125	**0.7329**	0.1382	−0.2448	**0.0537**	0.0029	−0.0471	0.4360	0.2084	−0.1377	−0.0589
7	**0.0048**	−0.1642	**0.6167**	0.1953	−0.2250	0.0269	0.0029	−0.0314	0.3679	0.2012	−0.1259	−0.0203
8	**0.0048**	−0.1533	**0.5671**	**0.1243**	−0.1892	0.0332	0.0030	−0.0233	0.3106	0.2025	−0.1182	−0.0215
9	**0.0048**	−0.1003	**0.4485**	**0.0638**	−0.1731	−0.0216	0.0029	−0.0178	0.2759	0.1757	−0.1008	−0.0716
10	**0.0048**	−0.1311	**0.4115**	0.0856	−0.1776	−0.0705	0.0029	−0.0236	0.2323	0.1041	−0.0918	−0.0281
11	**0.0048**	−0.1030	**0.3139**	−0.0027	−0.1664	−0.0340	0.0029	0.0071	0.1972	0.1349	−0.0828	−0.0173
12	**0.0047**	−0.1308	0.2242	**0.0113**	−0.1386	−0.0376	0.0029	−0.0026	0.1616	0.1036	−0.0782	−0.0603

informed trade contribution than no-news jumps. Whereas *S2XW* is −0.3052 at the intraday news jump time, it is −0.0821 at the intraday no-news jump time, which is consistent with the release of pre-scheduled macroeconomic news providing a greater resolution of information asymmetries.

Following a news jump, *PI* and *S2XW* are significantly lower than in the no-news jump case. *PI* increases from −0.2723 to −0.1308 in the post news jump event window and *S2XW* increases from −0.3653 to −0.1386 in the post news jump event window. The changes in *PI* and *S2XW* in the post no-news jump event window are, respectively, −0.1192 to −0.0026 and −0.1645 to −0.0782. That the information content of trades is lower following news jumps than it is following no-news jumps is in contrast to the findings by Green (2004), which shows that the information content of trades in government bonds is greater following the release of macroeconomic news announcements, but is in agreement with the findings of Tetlock (2010). *QV* and $OF^{\pm}$ are significantly larger following news jumps than no-news jumps, which shows that the effects of news jumps on volumes and order flows are longer lasting than the effects of no-news jumps.

3.2. Cojump events

In this section, I test how market conditions vary for cojumps in the spot foreign exchange market. Cojumps have been shown to have important implications for optimal portfolio allocation (Jin and Zhang, 2012) as well as for the optimal use of leverage (Das and Uppal, 2004). I define a cojump event as two or more exchange rates simultaneously experiencing jump events:

$$CJ_{t+j\triangle}(n) = \mathbf{1}\left(\sum_{q=1}^{14} \mathbf{1}\left(\kappa_{q,t+j\triangle} \neq 0\right) = n\right), \tag{3.4}$$

where $\mathbf{1}(x)$ is the indicator function which is equal to one if x is true and is equal to zero otherwise. $\kappa_{q,t+j\triangle}$ is the identified jump return whose precise definition is given in Appendix B. The unconditional probability of n exchange rates experiencing jumps simultaneously is given by:

$$\mathbf{P}\{CJ(n)\} = \left(T\triangle^{-1}\right)^{-1} \sum_{i=1}^{T\triangle^{-1}} \mathbf{1}\left(\sum_{q=1}^{14} \mathbf{1}\left(\kappa_{q,i} \neq 0\right) = n\right), \tag{3.5}$$

which is the fraction of the total number of 5-min return observations with which a cojump of order n is identified.[15]

3.2.1. Cojump events and news

The intraday distribution of CJ(≥ 2) events is plotted in Fig. 3. Intraweek volatility patterns are not controlled for in the left panel and the WSD estimator is used in the right panel to control for these patterns. Failing to control for volatility patterns results in an excess of cojump events being identified as coinciding with pre-scheduled news releases. Once the volatility patterns are controlled for, the distribution of cojump events is fairly uniformly distributed over the trading day.

Cojump statistics are presented in Table 6 with the cojump order indicated in the first column. The highest cojump order identified during the sample period is a CJ(11). Unconditionally, the probability of a cojump order occurring decreases from 0.28% for a CJ(2) to less than 0.01% for a CJ(11). The number of cojump days for a given cojump order decreases from 487 days for a CJ(2) to 1 day for a CJ(11) with associated probabilities of 42.76% and 0.09%. The expected number of cojumps, conditioned on a cojump day occurring, range from 1 for a CJ(11) to 1.48 for a CJ(2).

[15] In Eq. (3.5), i sweeps over all the $t + j\triangle$ dates.

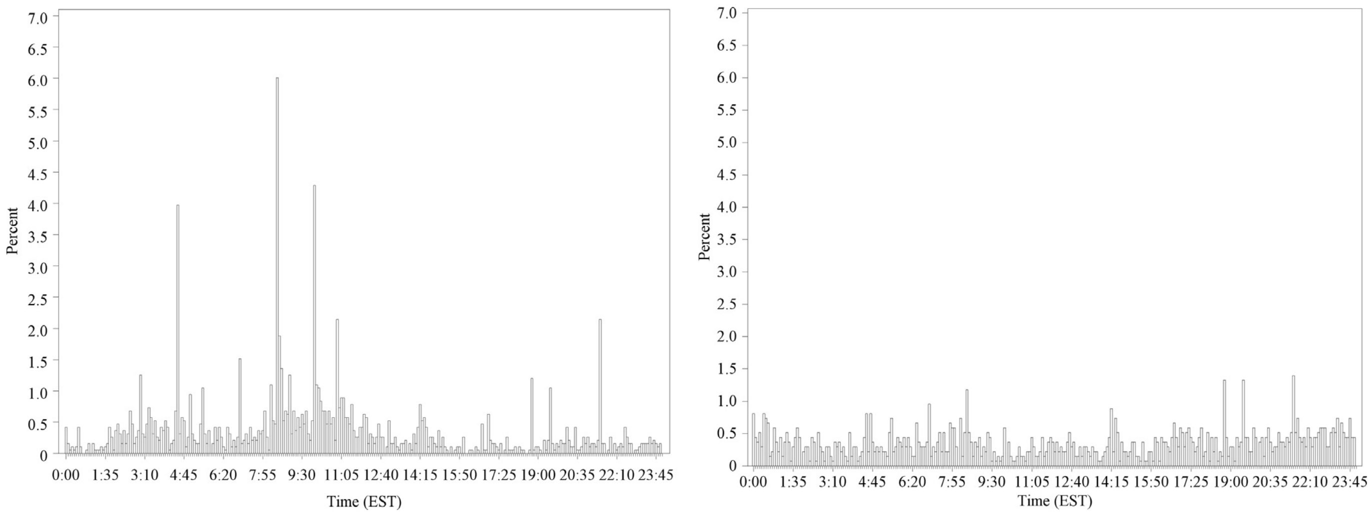

Fig. 3. Distribution of cojump times. This figure plots the intraday distribution of cojump events of order (≥ 2) without controlling for intraweek volatility patterns in the left panel and controlling for intraweek volatility patterns using the WSD estimator of Boudt et al. (2011) in the right panel. Cojump events of order (≥ 2) are defined as: $CJ_{t+j\triangle}(\geq 2) = \mathbf{1}\left(\sum_{q=1}^{14} \mathbf{1}\left(\kappa_{q,t+j\triangle} \neq 0\right) \geq 2\right)$, where $\mathbf{1}(x)$ is the indicator function, which is equal to one if x is true and equal to zero otherwise. $\kappa_{q,t+j\triangle}$ is defined as in Table 1 and Appendix B. Times are in Eastern Standard Time. The sample period is January 1, 2007–December 31, 2010.

Table 6
Cojump statistics. This table presents cojump statistics. Cojump events of order n are defined as: $CJ_{t+j\triangle}(n) = \mathbf{1}\left(\sum_{q=1}^{14} \mathbf{1}\left(\kappa_{q,t+j\triangle} \neq 0\right) = n\right)$, where $\mathbf{1}(x)$ is the indicator function which is equal to one if x is true and equal to zero otherwise. $\kappa_{q,t+j\triangle}$ is defined as in Table 1 and Appendix B. N, and # DAYS denote the number of 5-min periods in the sample period and the number of trading days in the sample period, respectively. CJ and CJ DAYS denote the total number of cojumps that are identified and the number of days that have at least one cojump occur, respectively. $\mathbf{P}\{CJ\}$ is the unconditional probability that a cojump occurs during a 5-min period, $\mathbf{P}\{CJD\}$ is the unconditional probability that at least one cojump will occur during a trading day, and $\mathbf{E}[\#CJ|JD]$ is the expected number of intraday cojumps that will occur, conditional on at least one cojump occurring during a trading day. $\mathbf{P}\{CJ|NEWS\}$ is the conditional probability of a cojump occurring, given that a pre-scheduled macroeconomic news event occurred. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. The sample period is January 1, 2007–December 31, 2010.

$CJ(n)$	N	# DAYS	CJ	CJ DAYS	$P\{CJ\}$	$P\{CJD\}$	$E[\#CJ\|CJD]$	$P\{CJ\|NEWS\}$	$P\{NEWS\|CJ\}$
2	258,852	1,139	723	487	0.0028	0.4276	1.4846	0.0113	0.1024
3	258,852	1,139	344	272	0.0013	0.2388	1.2647	0.0087	0.1657
4	258,852	1,139	125	113	0.0005	0.0992	1.1062	0.0024	0.1280
5	258,852	1,139	88	84	0.0003	0.0737	1.0476	0.0020	0.1477
6	258,852	1,139	37	36	0.0001	0.0316	1.0278	0.0011	0.1892
7	258,852	1,139	17	17	0.0001	0.0149	1.0000	0.0003	0.1176
8	258,852	1,139	14	13	0.0001	0.0114	1.0769	0.0008	0.3571
9	258,852	1,139	8	8	0.0000	0.0070	1.0000	0.0002	0.1250
10	258,852	1,139	3	3	0.0000	0.0026	1.0000	0.0002	0.3333
11	258,852	1,139	1	1	0.0000	0.0009	1.0000	0.0000	0.0000
12	258,852	1,139	0	0	0.0000	0.0000		0.0000	
13	258,852	1,139	0	0	0.0000	0.0000		0.0000	
14	258,852	1,139	0	0	0.0000	0.0000		0.0000	

News cojump probabilities are presented in the final two columns. The ex-ante probability of pre-scheduled news generating a cojump of order n, presented in the second to last column, decreases from 1.13% for a CJ(2) to less than 0.01% for a CJ(11). These low probabilities suggest that pre-scheduled macroeconomic news announcements have little explanatory power for the arrival of systematic jump events. The ex-post likelihoods of a news event having occurred, conditioned on a jump having occurred, which are presented in the final column, range from a low of zero percent for a CJ(11) to a high of 35.71% for a CJ(8). Generally, however, the ex-post likelihood of a pre-scheduled macroeconomic news event having occurred conditioned on a jump event having occurred is increasing in cojump order. These likelihoods are still low and warrant further investigation into the nature of cojumps.

3.2.2. Cojump event studies

Event studies of CJ(≥ 2) events are presented in Table 7, where bold-faced print denotes statistical significance at the 10% level or better using a difference-in-means (between CJ(≥ 2) values and single jump values) t-test assuming unequal sample variances. Prior to a cojump occurring, market conditions are insignificantly different from the case of single jumps. The mean cojump magnitude is significantly greater than in the single jump sample and, following a cojump event, mean $CAR^{\pm}$s remain significantly higher than in the single jumps sample. At the intraday cojump time, the mean values for PI, QV, and VAR are significantly greater in the cojump sample than in the single jump sample at 1.6756, 2.1234, and 6.4626, respectively, indicating that cojump events are the result of large systematic shocks to the market. Following a cojump, QV and VAR remain at higher levels than in the single jump case, which shows that market activity remains relatively heightened in the hour following a cojump event.

Table 7
Cojump event studies. This table presents the event study results of cojump events (two or more simultaneous jumps). Cojump events are defined in this table to be: $CJ_{t+j\triangle}(\geq 2) = \mathbf{1}\left(\sum_{q=1}^{14} \mathbf{1}\left(\kappa_{q,t+j\triangle} \neq 0\right) \geq 2\right)$. DATE is the intraday event time, $CAR^{\pm}$ is the cumulative abnormal return in the direction of jump sign, *PI* is standardized (Amihud, 2002) price impact per quote revision, *QV* is standardized quote volume, *VAR* is standardized return variance, *S2XW* is standardized (Hasbrouck, 1991) informed trade contribution, and $OF^{\pm}$ is standardized order flow in the direction of jump sign. Precise definitions for *PI, S2XW*, and *OF* are given in Appendix D. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. Bold-faced print denotes statistical significance at the 10% level or better using a difference-in-means (between CJ(≥ 2) values and single jump values) *t*-test assuming unequal sample variances. The sample period is January 1, 2007–December 31, 2010.

DATE	PI	QV	VAR	S2XW	OF$^{\pm}$	CAR$^{\pm}$
−12	0.0131	−0.0399	0.0253	0.0752	0.0729	0.0000
−11	0.0040	−0.0329	−0.0042	0.0714	0.0757	0.0001
−10	−0.0100	−0.0097	0.0065	0.0788	0.0508	0.0001
−9	−0.0158	0.0137	0.0498	0.0658	0.0536	0.0001
−8	−0.0033	0.0340	0.0573	0.0416	0.0582	0.0002
−7	−0.0468	0.0625	0.0660	0.0271	0.0817	0.0003
−6	−0.0207	0.0728	0.0522	0.0285	0.0767	0.0003
−5	−0.0471	0.1185	0.0830	0.0202	0.0724	0.0004
−4	−0.0421	0.1830	0.1109	0.0334	0.0544	0.0004
−3	−0.0033	0.2552	0.1834	0.0289	0.1062	0.0005
−2	−0.0125	0.3303	0.2666	0.0169	0.1579	0.0006
−1	0.0287	0.5022	0.4469	−0.0059	0.2150	0.0007
0	**1.6755**	**2.1234**	**6.4626**	−0.1148	**3.2957**	**0.0036**
1	−0.1570	**1.7757**	0.7568	−0.2017	−0.4007	**0.0034**
2	−0.1117	**1.1785**	**0.5475**	−0.2236	−0.0858	**0.0034**
3	−0.0911	**0.9316**	**0.4847**	−0.2195	−0.1284	**0.0034**
4	−0.1004	**0.7611**	**0.3782**	−0.2009	0.0251	**0.0034**
5	−0.0796	**0.6118**	0.3138	−0.1835	0.0220	**0.0034**
6	−0.0905	**0.5229**	**0.2194**	−0.1745	−0.0756	**0.0034**
7	−0.0760	**0.4363**	0.2170	−0.1543	−0.0325	**0.0034**
8	−0.0371	**0.3715**	**0.2335**	−0.1460	−0.0135	**0.0034**
9	−0.0308	**0.3145**	0.1910	−0.1233	−0.0693	**0.0034**
10	−0.0354	**0.2793**	0.1282	−0.1187	−0.0280	**0.0034**
11	−0.0150	**0.2272**	0.1293	−0.1081	−0.0229	**0.0034**
12	−0.0165	**0.1906**	0.1097	−0.0951	−0.0405	**0.0034**

In order to study the heterogeneity in the market state for varying cojump orders, event studies of market state by cojump order (note the reversed intraday time axis) are plotted in Fig. 4. *PI, QV, S2XW*, and $OF^{\pm}$ are presented in the top-left panel, top-right panel, bottom-left panel, and bottom-right panel, respectively. None of the cojump orders display a pre-cojump drift in *PI*; however, *PI* is positively related to the order of exchange rate cojump. *PI* during a cojump event increases from 1.5920 for a CJ(2) to 2.3685 for a CJ(8). This pattern could arise from common illiquidity shocks as in Mancini et al. (2013) or from illiquidity contagion as in Cespa and Foucault (2014). All cojump orders experience significant improvements in liquidity in the 5-min period immediately following a cojump, which is consistent with increased uninformed order flow following cojumps. *PI* in the 5-min period immediately following a cojump ranges from a low of −0.2200 for a CJ(4) to a high of 0.0819 for a CJ(7).

The cojump order is also increasing in *QV. QV* increases from 1.8535 for a CJ(2) to 3.2574 for a CJ(8). The pre-cojump drift in *QV* is observed in all cojump orders. Following a cojump event, *QV* gradually decreases and decreases more slowly for cojumps of higher order than for those cojumps of lower order, which shows that the effects of more systematic jump events are longer lasting. One hour following a cojump event, *QV* for a CJ(8) is 0.9292, whereas it is 0.0842 for a CJ(2).

The information content of trades and cojump order are negatively related. *S2XW* is −0.0868 for a CJ(2) and decreases to −0.3356 for a CJ(8). The bottom-right panel shows that cojump order is positively related to jump-signed order flow with $OF^{\pm}$ increasing from 3.1127 for a CJ(2) to 3.6674 for a CJ(8). $OF^{\pm}$ reaches a high of 4.6729 for a CJ(7). In the 5-min period following a cojump event, order flow is contrarian and the level of contrarianism is increasing in cojump order. This result supports the implications of the *PI* and *S2XW* results that, following more systematic cojumps, order flow has a greater propensity to be uninformed liquidity provision. In the 5-min period following a cojump, $OF^{\pm}$ decreases from −0.3728 for a CJ(2) to −0.8056 for a CJ(8).

4. Jump and cojump determinants

In this section, I test for the impact that market conditions have on the probabilities of jump and cojump events occurring by using a probit model, where the estimated probit model is:

$$\begin{aligned}\mathbf{1}\left(\kappa_{i,t+j\triangle} \neq 0\right) = {} & \beta_0 + \beta_1 CAR^{(12)}_{i,t+(j-1)\triangle} + \beta_2 NEWS_{t+j\triangle} \\ & + \beta_3 PI_{i,t+(j-1)\triangle} + \beta_4 BV_{i,t+(j-1)\triangle} + \beta_5 QV_{i,t+(j-1)\triangle} \\ & + \beta_6 S2XW_{i,t+(j-1)\triangle} + \beta_7 OF_{i,t+(j-1)\triangle} \\ & + \sum_{q=1}^{4} \beta_{7+q} CAR^{(12)}_{i,t+(j-1)\triangle} \times x_{q,i,t+(j-1)\triangle} \\ & + \sum_{q=1}^{h} \beta_{11+q} \mathbf{1}\left(\kappa_{i,t+(j-q)\triangle} \neq 0\right) \\ & + \sum_{z=1}^{g} \beta_{11+h+z} \mathbf{1}\left(CJ_{t+(j-z)\triangle}(n) > \mathbf{1}\left(\kappa_{i,t+(j-z)\triangle} \neq 0\right)\right) \\ & + \varepsilon_{i,t+j\triangle}, \end{aligned} \quad (4.1)$$

where $x \in \{PI, OF, S2XW, NEWS\}$. I include one-period lagged state variables so that they are contained in traders' information sets. $CAR^{(12)}_{i,t+(j-1)\triangle}$ is the one-hour cumulative abnormal return from time $t+(j-12)\triangle$ to time $t+(j-1)\triangle$, $NEWS_{t+j\triangle}$ is a dummy variable equal to one if a pre-scheduled macroeconomic news event occurs at time $t+j\triangle$ and is equal to zero otherwise, and $BV_{i,t+j\triangle}$ is the trading day's realized bipower variation for exchange rate i ($BV_{i,t+j\triangle}$ is formally defined in Appendix B). The contemporaneous news dummy variable is included in Eq. (4.1), since in efficient markets, information innovations should be incorporated into prices instantaneously. In Section IA.A of the Internet Appendix, I additionally include pre-scheduled news event dummy variable lags and the state variable coefficient results are relatively unchanged, which indicates that an omitted news variable is not driving the state variable results. *PI, QV, S2XW*, and *OF* are defined as before. *CAR* and *OF* are not signed in the direction of the jump return for these tests. Interaction terms with *CAR* are included to test if the observed pre-jump drift in *CAR*s is information-related or information-unrelated.

The last two terms in Eq. (4.1) are lagged own jump dummy variables and lagged cojump dummy variables. These are included to capture the explanatory power of jump clustering and cojump clustering for predicting exchange rate jumps. The lag lengths are chosen optimally using the Campbell and Perron (1991) methodology. First, the own jump lag length is set at 12 and iterated down until the largest lag length is significant at the one percent level and then, keeping the optimally found own jump lag length fixed, the cojump lag length is set at 12 and iterated down until the largest lag length is significant at the one percent level. Coefficient estimates from Eq. (4.1) can be interpreted as the increase in the z-score of the jump probability, given a one unit increase in the respective explanatory variable.

The results from estimating Eq. (4.1) are presented in Table 8. Column headers denote the subsamples of positive and negative jumps. Columns two and three use the full jump sample. *NEWS* enters significantly increasing the probability of a jump occurring.

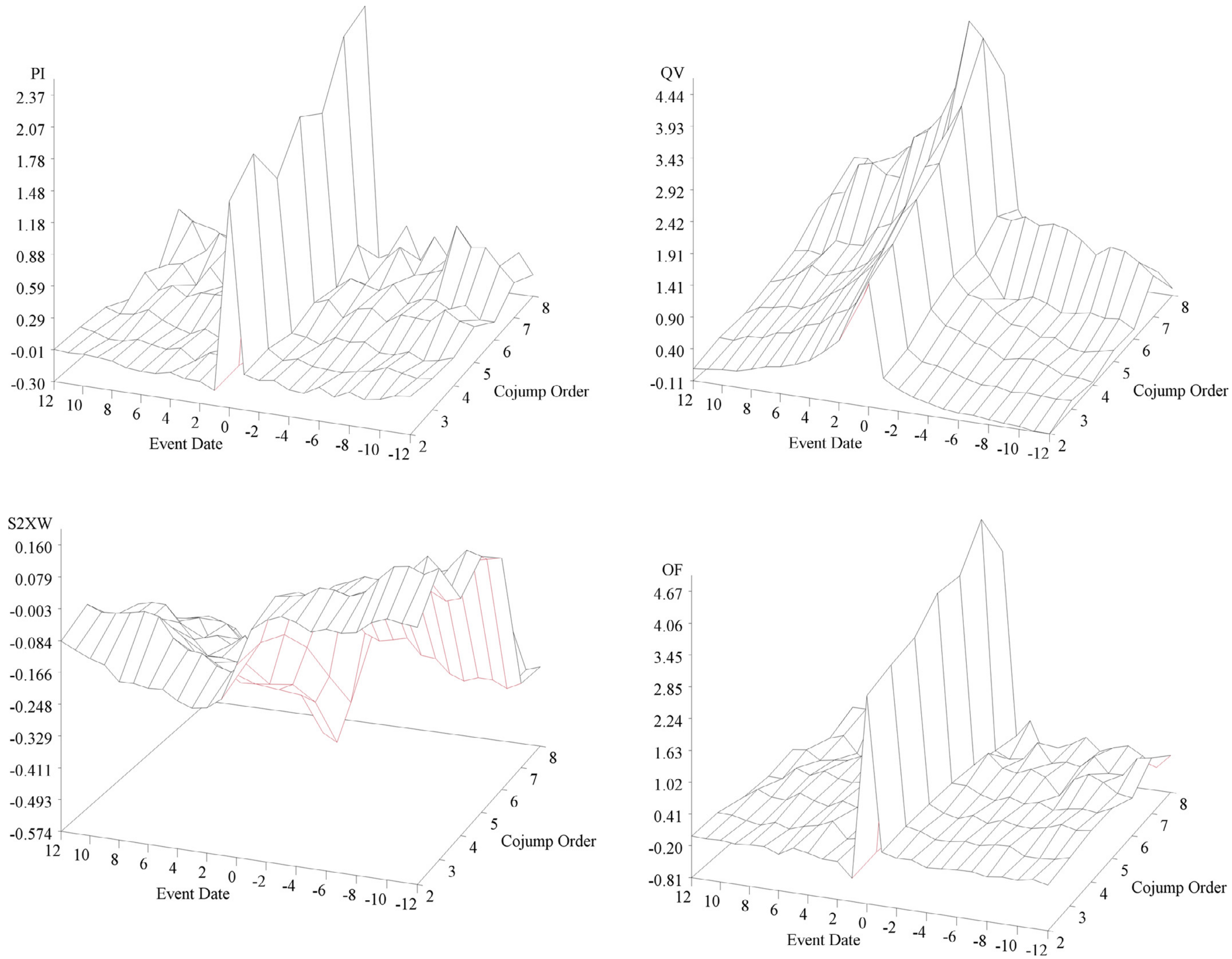

Fig. 4. Marketstates and cojump events. This figure plots event study results of cojump events. Exchange rate standardized (Amihud, 2002) illiquidity (*PI*) is in the top-left panel, standardized quote volume (*QV*) is in the top-right panel, standardized (Hasbrouck, 1991) informed trade contribution (*S2XW*) is in the bottom-left panel, and directional standardized order flow (*OF*) is in the bottom-right panel. Precise definitions for *PI*, *S2XW*, and *OF* are given in Appendix D. Note the reversed intraday event time axis. Cojump events of order n are defined as: $CJ_{t+j\triangle}(n) = \mathbf{1}\left(\sum_{q=1}^{14} \mathbf{1}\left(\kappa_{q,t+j\triangle} \neq 0\right) = n\right)$, where $\mathbf{1}(x)$ is the indicator function, which is equal to one if x is true and is equal to zero otherwise. $\kappa_{q,t+j\triangle}$ is defined as in Table 1 and Appendix B. The sample period is January 1, 2007–December 31, 2010.

Pre-scheduled macroeconomic news events increase the z-score of jump probability by 0.466 for negative jumps and by 0.550 for positive jumps. *PI*, *QV*, *S2XW*, and *OF* also significantly increase the probability of a jump event with the respective increases in z-scores being 0.032, 0.080, 0.011, and 0.014. The effects of market conditions on negative jump probabilities are qualitatively similar.

CAR significantly increases the probability of a jump occurring, and in the same direction, as the *CAR*. A 0.001 unit increase in *CAR* increases the jump probability z-score by 0.031 for positive jumps. The significant coefficients on *CAR* can arise for information-related and information-unrelated reasons. An information-related hypothesis is that a subset of traders posses privately leaked information regarding a news event that occurs. An information-unrelated hypothesis is that the market becomes increasingly one-sided until a liquidity shock causes a jump or cojump event (Mancini et al., 2013; Cespa and Foucault, 2014). The *CAR* interaction terms attempt to distinguish between these two hypotheses. Looking at positive jump events, the *CAR* interaction terms with *OF* and *S2XW* significantly increase the probability of a positive jump. Conversely, *CAR* interaction terms with *PI* and *NEWS* decrease the probability of a positive jump event. These results indicate that exchange rates partially adjust to incoming pre-scheduled macroeconomic news prior to the release time and that jumps occur with greater probability when the market becomes more one-sided with greater informed order flow. The results are qualitatively similar for negative jumps.

There is significant evidence of autocorrelation in jump intensity as well as cross-exchange rate jump dependence. The estimated *JLAGS* and *CJLAGS* coefficients are not presented to conserve space. In the case of positive jumps, exchange rate *i*'s jump history up to 25 min in the past (5 lags) continues to have explanatory power for a jump in exchange rate *i* in the current period. Jumps anywhere in the exchange rate space have a more long-lived dependence structure. A jump event in any of the exchange rates (excluding a jump in exchange rate *i* if one occurred) for up to 45 min in the past (9 lags) continues to have explanatory power for predicting a jump event in the current period for exchange rate *i*. The dependence structure for negative jumps is slightly longer-lived with optimal *JLAGS* and *CJLAGS* being 8 and 11, respectively.

Table 8

Jump determinants. This table presents results from estimating the following probit model: $\mathbf{1}(\kappa_{i,t+j\triangle} \neq 0) = f(CAR, NEWS, PI, BV, QV, S2XW, OF, JLAGS, CJLAGS)$, where the exact probit specification is Eq. (4.1). J+ and J- denote positive and negative jumps, respectively. *CAR* is the cumulative abnormal return from a constant expected return model from one hour prior to a jump occurring to five minutes prior to a jump occurring. *NEWS* is a dummy variable, which is equal to one if a pre-scheduled macroeconomic news event occurs and is equal to zero otherwise, *PI* is standardized Amihud (2002) price impact per quote revision, *BV* is realized bipower variation for the day, *QV* is standardized quote volume, *S2XW* is standardized (Hasbrouck, 1991) informed trade contribution, and *OF* is standardized order flow. Precise definitions for *PI, S2XW*, and *OF* are given in Appendix D. *JLAGS* and *CJLAGS* are lagged own jump dummy variables and lagged cojump dummy variables, respectively. Lag lengths are chosen using the Campbell and Perron (1991) methodology. Columns two and three use the full jump sample, columns four and five only consider news jumps, and columns six and seven only consider cojump jump events. T-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. The sample period is January 1, 2007–December 31, 2010.

	All jumps		News jumps		Cojumps	
	J−	J+	J−	J+	J−	J+
INT	−3.190***	−3.141***	−3.700***	−3.714***	−2.685***	−3.346***
	(−474.027)	−368.183)	(−190.711)	(−200.730)	(−739.587)	(−328.039)
CAR	−40.724***	31.366***	−3.364	13.085*	−16.386***	29.304***
	(−17.126)	(9.961)	(−0.431)	(1.884)	(−11.898)	(8.053)
NEWS	0.466***	0.550***			0.670***	0.639***
	(23.903)	(28.932)			(70.252)	(30.712)
PI	0.022***	0.032***	−0.006	−0.026	0.004	0.028***
	(3.993)	(5.403)	(−0.366)	(−1.445)	(1.403)	(3.791)
BV	0.000***	−0.001***	−0.001***	0.000***	0.000***	−0.001***
	(−7.143)	(−16.351)	(−4.257)	(−3.445)	(−14.706)	(−9.857)
QV	0.088***	0.080***	0.100***	0.103***	0.060***	0.081***
	(19.342)	(15.161)	(8.412)	(9.297)	(23.192)	(12.917)
S2XW	0.017***	0.011*	0.021	0.021	0.026***	0.008
	(3.074)	(1.826)	(1.458)	(1.511)	(9.449)	(1.055)
OF	−0.024***	0.014***	0.003	−0.038***	−0.016***	0.015**
	(−5.305)	(2.744)	(0.252)	(−3.307)	(−6.667)	(2.483)
CAR × PI	6.771***	−4.346***	−0.744	1.682	1.810***	−2.981**
	(9.699)	(−3.073)	(−0.108)	(0.334)	(3.451)	(−2.003)
CAR × OF	3.830***	4.166***	0.441	−5.268	6.129***	3.309***
	(5.391)	(3.589)	(0.112)	(−1.636)	(11.953)	(2.665)
CAR × S2XW	−5.185**	12.192***	1.060	12.000	−0.821	11.292***
	(−2.001)	(3.543)	(0.115)	(1.536)	(−0.533)	(2.827)
CAR × NEWS	39.792***	−16.191*			27.070***	−16.029*
	(4.969)	(−1.783)			(6.352)	(−1.723)
JLAGS	8	5	0	1	6	4
CJLAGS	11	9	0	1	12	12
N	3,623,808	3,623,853	3,623,913	3,623,913	3,623,838	3,623,868

Columns four and five of Table 8 restrict jump events to only news jumps. *CAR* enters weakly significantly for positive news jumps only and *PI* and *S2XW* are no longer significant. *QV* continues to enter significantly and with coefficient values that are relatively unchanged from the full jump sample. *OF* is not significant for negative news jumps, but enters with a negative sign for positive news jumps. None of the *CAR* interaction terms enter significantly, which suggests that news jumps are largely related to the news release and not the market conditions. The dependence structure between current jumps and lagged jumps and cojumps is weaker for news jumps. The optimal *JLAGS* and *CJLAGS* for positive jumps is 1 and 1, whereas none of the lag lengths are significant in the case of negative news jumps. These news jump results indicate that the occurrences of news jumps tend to be largely unconditional on the history of jump events.

Probit results for jumps that are part of a cojump event are presented in the final two columns of Table 8. *NEWS, PI, QV, S2XW, CAR*, and *OF* continue to attain coefficients with signs and magnitudes that are similar to those in the full jump sample, with the exception of *NEWS*. *NEWS* has a larger effect on cojump probability than it has in the full jump sample. A pre-scheduled news event increases the z-score of cojump probability by 0.670 for negative jumps that are part of a cojump event and by 0.639 for positive jumps that are part of a cojump event. These stronger coefficients are expected, since pre-scheduled news releases affect a wide range of exchange rates as well as the discount factor. Finally, the dependence structure with lagged cojumps for jumps that are part of a cojump event are longer-lived than those of the full jump sample with *CJLAGS* being optimally chosen to be 12 for positive and negative jumps.

I partition exchange rates into a USD exchange rate sample and a cross exchange rate sample in Table 9. Eq. (4.1) is estimated on each sample to test how jump determinants differ for USD rates versus cross-rates. Interactions of jump-signed *CAR* with *S2XW* and jump-signed *OF* are more likely to generate a jump in USD exchange rates than they are in cross rates, which reveals that USD exchange rate order flow is perceived to be more informative than order flow in cross rates. *NEWS* interacted with signed *CAR* decreases the probability of a jump event by a larger amount in the USD sample indicating that USD exchange rates partially adjust to future pre-scheduled macroeconomic news by a larger amount than cross rates do. The optimally chosen lag lengths for *JLAGS* and *CJLAGS* show that the dependence structure of jump arrivals on past jump arrivals differs for USD rates and cross rates as well with the dependence structure being longer-lived for cross rates than for USD exchange rates. Overall, the results in Table 9 reveal that USD exchange rates have greater informed order flow and adjust to new information more quickly than cross rates and this increased information asymmetry has a larger effect on the jump probability.

Table 9
USD and cross rate jump determinants. This table presents results from estimating the following probit model: $\mathbf{1}(\kappa_{i,t+j\triangle} \neq 0) = f(CAR, NEWS, PI, BV, QV, S2XW, OF, JLAGS, CJLAGS)$, where the exact probit specification is Eq. (4.1). J+ and J− denote positive and negative jumps, respectively. *CAR* is the cumulative abnormal return from a constant expected return model from one hour prior to a jump occurring to five minutes prior to a jump occurring. *NEWS* is a dummy variable, which is equal to one if a pre-scheduled macroeconomic news event occurs and is equal to zero otherwise, *PI* is standardized (Amihud, 2002) price impact per quote revision, *BV* is realized bipower variation for the day, *QV* is standardized quote volume, *S2XW* is standardized (Hasbrouck, 1991) informed trade contribution, and *OF* is standardized order flow. Precise definitions for *PI*, *S2XW*, and *OF* are given in Appendix D. *JLAGS* and *CJLAGS* are lagged own jump dummy variables and lagged cojump dummy variables, respectively. Lag lengths are chosen using Campbell and Perron (1991) methodology. Columns two and three use the sample of USD exchange rates and columns four and five use the sample of cross exchange rates. T-statistics are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. The sample period is January 1, 2007–December 31, 2010.

	USD		CROSS	
	J−	J+	J−	J+
INT	−3.161***	−3.093***	−3.227***	−3.175***
	(−332.017)	(−243.504)	(−325.939)	(−266.807)
CAR	−51.521***	35.399***	−32.561***	27.603***
	(−14.448)	(7.648)	(−10.222)	(6.313)
NEWS	0.453***	0.518***	0.483***	0.583***
	(16.708)	(19.033)	(17.257)	(21.917)
PI	0.016**	0.021***	0.026***	0.041***
	(2.096)	(2.582)	(3.246)	(4.958)
BV	0.000***	−0.002***	0.000***	−0.001***
	(−4.340)	(−12.206)	(−5.152)	(−11.512)
QV	0.077***	0.075***	0.101***	0.090***
	(12.120)	(9.987)	(14.978)	(11.952)
S2XW	0.022***	0.015*	0.010	0.005
	(2.969)	(1.869)	(1.228)	(0.535)
OF	−0.031***	0.029***	−0.014**	−0.003
	(−5.016)	(4.048)	(−2.261)	(−0.378)
CAR × PI	7.833***	−6.797**	5.808***	−3.100*
	(4.741)	(−2.410)	(7.422)	(−1.794)
CAR × OF	3.173***	6.903***	4.291***	2.000
	(2.618)	(4.018)	(4.890)	(1.389)
CAR × S2XW	−7.824**	12.791**	−3.000	10.769**
	(−2.031)	(2.564)	(−0.904)	(2.224)
CAR × NEWS	51.249***	−22.000	31.855***	−12.000
	(4.122)	(−1.496)	(3.111)	(−1.036)
JLAGS	5	2	9	3
CJLAGS	11	7	11	9
N	1,811,929	1,811,950	1,811,892	1,811,940

5. Jump events and market efficiency

5.1. Maximum quote revisions and quote discontinuity

Discontinuous jumps form a market incompleteness that cannot be hedged. Christensen et al. (2014), however, uses high frequency data to show that identified jumps are largely erroneously identified and represent volatility bursts rather than price discontinuities. Panel A of Table 10 presents the mean maximum quote revisions for jump events, where I define (similar to as in Christensen et al., 2014) the maximum quote revision as $g_{i,t+j\triangle} = max\{|ln(p_{i,\tau}/p_{i,\tau-1})|\}$ for $\tau \in [t+(j-1)\triangle, t+j\triangle)$, where τ indicates quote time. If a jump is truly discontinuous, then the maximum quote revision should be approximately equal to the absolute jump size $g_{i,t+j\triangle}/|\kappa_{i,t+j\triangle}| \approx 1$.

Bold-faced print in Table 10 in the DIF columns indicates that the difference in maximum quote revisions is significant at the 1% level using the Wilcoxon Rank-Sum test. The mean maximum quote revision across exchange rates is 2.03 pips (1 pip equals 0.0001) for normal times versus 5.95 pips for jump events, which indicates that identified jumps appear to have an increased level of quote discontinuity. For all exchange rates, the difference in the maximum quote revisions is significant.

Columns five to ten restrict the sample to only jump event observations and tests how maximum quote revisions differ for news jump events and for cojump events. News jumps have significantly larger maximum quote revisions than no-news jumps. Whereas the mean maximum quote revision is 4.83 pips for no-news jumps, it is 13.82 pips for news jumps. Maximum quote revision differences between cojump events and jump events are smaller. The mean maximum quote revision is 6.58 pips for cojumps, which is 1.90 pips greater than it is for jumps that are not part of a cojump. Further, cojump maximum quote revisions are only statistically significantly greater than jump maximum quote revisions in nine out of the fourteen exchange rates.

Columns 11–13 present the fractions of jump returns that maximum quote revisions make up for each of the exchange rates. If the fraction is approximately 1 then the entire jump is approximately discontinuous and if the fraction is approximately 0 then the identified jump is largely a continuous price move (a volatility burst). Jumps are considered in column 11, the sample is restricted to no-news jumps only in column 12, and the sample is restricted to news jumps only in column 13. The mean maximum quote revision ranges from 16.31% to 27.09% of the total jump return. News jumps generally have a maximum quote revision fraction which is more than twice as large as no-news jumps. Whereas no-news jump maximum quote revisions as a fraction of jump size range from a low of 14.14% for the AUD/JPY rate to a high of 27.15% for the EUR/CHF rate, news jump maximum quote revision fractions range from a low of 18.89% for the CHF/JPY rate to a high of 38.95% for the EUR/AUD rate. Overall, Table 10 shows that the identified jumps contain a significant discontinuous component and do not appear to simply be identifying shocks to volatility from increased trade. Section IA.D of the Internet Appendix provides further evidence of the discontinuous nature of the identified jumps using a gap measure which is similar to the one defined in Christensen et al. (2014).

As an additional robustness test to show that quote discontinuities are present in the data, Panel B of Table 10 presents the Aït-Sahalia and Jacod (2009) jump test statistic $S(p, k, \triangle)$. The test statistic is defined as:

$$\widehat{S}(p,k,\triangle) = \frac{\widehat{B}(p,k\triangle)}{\widehat{B}(p,\triangle)}, \tag{5.1}$$

where:

$$\widehat{B}(p,k\triangle) = \sum_{m=1}^{T\triangle^{-1}} |r_{mk\triangle}^{(k)}|^p, \tag{5.2}$$

where $T\triangle^{-1}$ is the number of $\triangle$-period returns in the sample, $r_{mk\triangle}^{(k)}$ is equal to the $k\triangle$-period currency return, and only non-overlapping returns are used. Under the null hypothesis of price continuity, $\lim_{\triangle\to 0}\widehat{S}(p,k,\triangle) = k^{p/2-1}$ and if discontinuous jumps are present, then $\lim_{\triangle\to 0}\widehat{S}(p,k,\triangle) = 1$. I use $p = 4$ and $k = 2$ so that the test statistic under the null hypothesis of no jump is that $\widehat{S}(4,2,\triangle) = 2$.

The jump identification test described in Eq. (5.1) is valid for high-frequency data and for jumps of any activity level (jumps arriving with any frequency). Therefore, if there is any price discontinuity at any $\triangle$-frequency then the estimate $\widehat{S}(p,k,\triangle)$ will be significantly less than $k^{p/2-1}$. There are two caveats to this approach, however. First, this jump identification test only identifies the presence of price discontinuity in the time series, but not when that price discontinuity occurs. Second, with microstructure noise, $\lim_{\triangle\to 0}\widehat{S}(p,k,\triangle) = \frac{1}{k}$. Since I use the exchange rate mid-quotes

Table 10

Maximum quote revisions and quote discontinuity. This table presents the mean maximum quote revisions, in Panel A, and the Aït-Sahalia and Jacod (2009) jump detection test statistics, in Panel B. The maximum quote revision is defined as the maximum log midquote return during a 5-min return period. Numbers are presented in pips (one pip equals 0.0001) in columns 2–10. The Wilcoxon Rank-Sum test is used to test for significantly different distribution locations. Jump events are identified using Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. S denotes the Aït-Sahalia and Jacod (2009) test statistic with $p=4$ and $k=2$, which makes the null hypothesis such that $S=2$. P01 and P99 denote the 99% boostrapped confidence interval for S from 1,000 random samples under the null hypothesis that returns have no jumps and are normally distributed with a mean equal to the exchange rate's sample mean return (removing jumps from the sample first) and with a variance equal to the exchange rate's sample return variance (removing jumps from the sample first). Bold-faced print denotes statistical significance at the 10% level or better, in Panel A, and in Panel B, ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. The sample period is January 1, 2007–December 31, 2010.

Panel A: Maximum quote revisions

FX rate	Full return sample		DIF	Restricted jump sample		DIF	Restricted jump sample		DIF	Discontinuous fraction		
	No J	J		No news	News		No CJ	CJ		All J	No-news J	News J
AUD/JPY	2.59	7.96	**5.37**	5.16	23.52	**18.36**	4.35	8.43	**4.08**	0.1774	0.1414	0.3773
AUD/USD	2.34	7.46	**5.12**	5.50	18.99	**13.49**	6.48	7.76	**1.28**	0.2078	0.1810	0.3652
EUR/GBP	1.68	4.87	**3.19**	4.10	10.67	**6.57**	4.50	5.20	**0.70**	0.2488	0.2418	0.3012
EUR/USD	1.32	3.34	**2.02**	2.99	8.11	**5.12**	2.42	3.80	**1.38**	0.1661	0.1622	0.2186
GBP/JPY	1.71	6.77	**5.06**	5.53	15.84	**10.31**	2.72	7.62	**4.90**	0.1647	0.1449	0.3101
GBP/USD	1.35	3.57	**2.22**	3.21	6.46	**3.25**	2.26	4.52	**2.26**	0.1711	0.1647	0.2222
USD/CHF	1.53	4.21	**2.69**	3.50	12.10	**8.59**	3.26	4.51	1.24	0.1697	0.1642	0.2311
USD/JPY	1.69	4.23	**2.54**	3.68	11.25	**7.57**	3.27	4.89	1.63	0.1562	0.1479	0.2614
USD/CAD	2.03	4.95	**2.92**	4.13	13.76	**9.64**	4.75	5.83	1.08	0.2553	0.2509	0.3017
NZD/USD	3.29	8.71	**5.41**	7.09	18.17	**11.08**	6.37	10.37	**4.01**	0.2664	0.2465	0.3826
CHF/JPY	1.90	5.09	**3.19**	4.77	8.85	**4.08**	4.32	5.22	**0.90**	0.1631	0.1609	0.1889
EUR/AUD	2.21	7.35	**5.14**	5.34	17.25	**11.91**	6.62	7.61	1.00	0.2270	0.1940	0.3895
EUR/CHF	1.22	3.70	**2.48**	3.43	7.84	**4.40**	2.71	5.30	**2.60**	0.2709	0.2715	0.2614
NZD/JPY	3.53	11.14	**7.61**	9.16	20.72	**11.56**	11.52	11.07	-0.45	0.2416	0.2183	0.3543

Panel B: Quote discontinuity test

FX Rate	S	P01	P99
AUD/JPY	2.855	1.965	2.034
AUD/USD	2.370	1.965	2.036
EUR/GBP	1.292***	1.967	2.035
EUR/USD	1.696***	1.967	2.033
GBP/JPY	1.399***	1.966	2.034
GBP/USD	1.634***	1.968	2.036
USD/CHF	1.439***	1.964	2.033
USD/JPY	1.383***	1.968	2.035
USD/CAD	1.749***	1.964	2.035
NZD/USD	1.885***	1.967	2.032
CHF/JPY	1.740***	1.969	2.035
EUR/AUD	1.921***	1.964	2.037
EUR/CHF	1.236***	1.967	2.033
NZD/JPY	1.914***	1.966	2.033

rather than transaction prices, the microstructure noise (such as bid-ask spreads) is expected to be largely filtered out so that price discontinuity can be clearly estimated. Therefore, I use the Aït-Sahalia and Jacod (2009) test for robustness to show that discontinuous jumps are present in the data.

To test if $\widehat{S}(4,2,\triangle)$ is significantly below the null of 2, I generate 1,000 random samples of $\triangle$-period exchange rate returns that are normally distributed with a mean that is equal to the exchange rate's sample mean (removing jump returns from the sample first) 5-min return and with a variance that is equal to the exchange rate's sample 5-min return variance (removing jump returns from the sample first). The bootstrapped 99% confidence interval for the $\widehat{S}(4,2,\triangle)$ statistic is presented next to the data-estimated jump test statistic. Generally, the estimated jump test statistic is significantly less than 2, which shows that discontinuous jumps are present in the exchange rates. The only exceptions are the AUD/JPY and AUD/USD currency pairs, which have jump statistics that are not significantly less than 2 (they have statistics that are greater than 2 in value). Additionally, since $\widehat{S}(4,2,\triangle)$ does not converge to $\frac{1}{2}$, microstructure noise does not appear to be confounding the Aït-Sahalia and Jacod (2009) jump test.

5.2. Triangular arbitrage and jump events

Since identified jumps have a large discontinuous component, this discontinuity may serve as an illiquidity cost that limits arbitrage as in the model of Liu et al. (2003). The triangular arbitrage errors using exchange rate bid-ask mid-quotes are defined as:

$$\eta_{t+j\triangle} = |1 - S^{i/j}_{t+j\triangle} S^{k/i}_{t+j\triangle} S^{j/k}_{t+j\triangle}|, \tag{5.3}$$

where $S^{a/b}$ denotes the cost of one unit of currency a in units of b. In Eq. (5.3), I assume that 1 unit of the domestic currency j buys $S^{i/j}$ units of currency i which is then used to buy $S^{i/j}S^{k/i}$ units of currency k which is then converted back into $S^{i/j}_{t+j\triangle} S^{k/i}_{t+j\triangle} S^{j/k}_{t+j\triangle}$ units of the domestic currency j. Therefore, the magnitude of 1 minus this resulting value is an estimate of the exchange rate triangle mis-pricing. If exchange rate processes do not contain jumps, then triangular arbitrage ensures that the triangle mis-pricing is small. However, if the entire triangle of exchange rates does not experience a jump event simultaneously and proportionately, then arbitrage pricing errors increase at a much quicker rate than arbitrage trades can correct the mis-pricing.

In order to test how jump events create a relative exchange rate mis-pricing, I estimate the following panel regression model:

$$\eta_{t+j\triangle} = \beta_0 + \beta_1 CJN_{t+j\triangle} + \beta_2 MQR_{t+j\triangle} + \beta_3 NEWS_{t+j\triangle} \tag{5.4}$$

Table 11
Jump events and triangulararbitrage. This table presents the results of regressing triangular arbitrage errors on jump events and controls. The within-estimator is used to estimate the following panel regression model: $\eta_{t+j\triangle} = f(CJN, MQR, NEWS, QV, PI, |OF|, S2XW, VAR)$, where the exact model specification is Eq. (5.4) and $\eta_{t+j\triangle} = |1 - S^{i/j}_{t+j\triangle} S^{k/i}_{t+j\triangle} S^{j/k}_{t+j\triangle}|$. *CJN* is the number of exchange rates in a triangle simultaneously experiencing a jump event. *MQR* is the maximum log quote revision in a 5-min period given by $max(\ln(^{p_\tau}/_{p_{\tau-1}}))$ for $\tau \in (t+(j-1)\triangle, t+j\triangle)$. *NEWS* is a dummy variable, which is equal to one if a pre-scheduled macroeconomic news event occurs and is equal to zero otherwise, *QV* is standardized quote volume, *PI* is standardized (Amihud, 2002) price impact per quote revision, |*OF*| is absolute standardized order flow, *S2XW* is standardized (Hasbrouck, 1991) informed trade contribution, and *VAR* is realized variance over the period $(t+(j-1)\triangle, t+j\triangle)$. Precise definitions for *PI*, *S2XW*, and *OF* are given in Appendix D. Coefficients and standard errors are multiplied by 1×10^3 for ease of presentation. White's heteroskedasticity standard errors are presented in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Jump events are identified using the Andersen et al. (2007) methodology controlling for volatility patterns with the WSD estimator of Boudt et al. (2011), which are described in Appendix B and in Appendix C, respectively. The sample period is January 1, 2007–December 31, 2010.

	(1)	(2)	(3)
CJN	0.025***	0.017***	−0.014**
	(0.0029)	(0.0028)	(0.0055)
MQR		45.020***	20.820*
		(10.9100)	(10.8300)
NEWS		0.002	0.002
		(0.0024)	(0.0024)
QV		−0.007***	−0.006***
		(0.0005)	(0.0006)
PI		0.007***	0.007***
		(0.0004)	(0.0004)
|*OF*|		0.001*	0.000*
		(0.0003)	(0.0003)
S2XW		0.001***	0.001***
		(0.0002)	(0.0002)
VAR		0.002***	0.003***
		(0.0006)	(0.0006)
CJN × MQR			115.830***
			(14.2700)
CJN × QV			−0.008***
			(0.0015)
CJN × PI			−0.005
			(0.0033)
CJN × |*OF*|			0.000
			(0.0007)
CJN × S2XW			0.003
			(0.0026)
F.E.	Yes	Yes	Yes
N	1,812,053	1,810,653	1,810,653
R^2	0.047	0.048	0.048

$$+\sum_{k=1}^{4}\beta_{3+k}x_{k,t+j\triangle} + \beta_8 VAR_{t+j\triangle}$$
$$+\sum_{k=1}^{4}\beta_{8+k}CJN_{t+j\triangle} \times x_{k,t+j\triangle} + \varepsilon_{t+j\triangle},$$

where *CJN* is the number of exchange rates in the triangle simultaneously experiencing a jump event, *MQR* is the maximum quote revision in a 5-min period, *NEWS* is a dummy variable equal to one if a pre-scheduled macroeconomic news event occurs at time $t + j\triangle$ and zero otherwise, and $x_k \in \{MQR, QV, PI, |OF|, S2XW\}$ where |*OF*| denotes the absolute value of order flow. Eq. (5.4) is estimated with exchange rate triangle fixed effects, using the within estimator.

CJN, *MQR*, and *PI* are expected to increase triangular arbitrage errors since each of these variables are increasing in illiquidity, which increases the cost of trade. Since a jump or cojump event may be the result of a rapid increase in volatility rather than a true price discontinuity, I include *MQR* to explicitly measure the effect that the increased level of discontinuity during jumps has on triangle pricing errors. *QV* and |*OF*| have ex-ante ambiguous expectations. Greater *QV* and |*OF*| increase liquidity in the market which makes the cost of trading cheaper and triangular arbitrage errors smaller. Alternatively, with a Kyle (1985) market maker, greater *QV* and |*OF*| increase the variance of quoted prices which results in a greater likelihood of discontinuous quote revisions. This resulting discontinuity would lead to greater triangular arbitrage pricing errors. The *CJN* interaction terms are included to estimate the economic impact of cojump events as a limit to arbitrage. Coefficients on the *CJN* interaction terms are expected to be of the same sign as the coefficients on the respective non-interacted variables.

Table 11 presents the results from estimating Eq. (5.4). Coefficients are multiplied by 1,000 for ease of presentation. Arbitrage errors are regressed on only the number of exchange rates jumping within a triangle in column (1). *CJN* enters significantly positively. An additional triangle exchange rate jump leads to an arbitrage error that is 0.25 pips greater in magnitude. Column (2) includes maximum quote revisions to test if it is the jump event or the increased level of quote discontinuity that is responsible for limiting arbitrage. Market condition variables are also included in column (2) as controls. *MQR* enters significantly with a positive sign. A 0.10% increase in *MQR* leads to an increase in arbitrage error of 4.502 pips in magnitude. *PI* and *VAR* also attain positive coefficients suggesting that illiquidity and variance are further limits to triangular arbitrage. *CJN* continues to enter significantly with a positive sign.

Column (3) includes jump interaction terms to test if the market conditions during jump events, rather than the jump event itself, explains the limit to arbitrage. Now, *CJN* enters significantly and with a negative sign. *MQR* continues to enter positively and the jump-*MQR* as well as the jump-quote volume interaction terms enter significantly. The jump-*MQR* interaction term attains a large positive coefficient and the jump-quote volume interaction term obtains a negative coefficient. These results suggest that it is the increased illiquidity cost that jump discontinuity results in that forms a limit to arbitrage and not the jump event itself per se, in agreement with the model of Liu et al. (2003). In fact, triangular arbitrage errors are smaller during jump events that are largely driven by a greater demand to trade.

6. Conclusion

I identify exchange rate jumps and cojumps (simultaneous jump events in two or more exchange rates) at the 5-min frequency using the Andersen et al. (2007) methodology, in conjunction with the weighted standard deviation (WSD) methodology of Boudt et al. (2011) which accounts for intraweek volatility patterns for jump identification. After controlling for intraweek volatility patterns, jump and cojump events largely occur in the absence of pre-scheduled macroeconomic news and occur fairly uniformly over the trading day. Event studies show that market conditions preceding jumps and cojumps are associated with greater quote volume, greater (Amihud, 2002) illiquidity, greater jump-signed order flow, and greater (Hasbrouck, 1991) information content of trade suggesting that jump events are consistent with rational Glosten and Milgrom (1985) and Kyle (1985) dealer quoting behavior. Following jump and cojump events, quote volume, and return variance remain heightened, while illiquidity, the information content of trade, and jump-signed order flow are lower, which shows that jumps are permanent innovations to investors' information sets and that order flow following jumps is largely uninformed liquidity provision.

The economic nature of jumps has important implications for market efficiency. Since identified jumps need to be discontinuous in nature to represent a limit to arbitrage, I examine the maximum quote revisions of identified jumps. Maximum quote revisions for jump events range from 16.31% to 27.09% of identified jump magnitudes showing that the identified jumps appear to have an increased level of discontinuity and are not simply volatility bursts (Christensen et al., 2014). No-news jump maximum quote revisions range from 14.14% to 27.15% of jump magnitude and maximum quote revisions range from 18.89% to 38.95% of jump magnitude for news jumps.

Triangular arbitrage errors are significantly larger during jump events. It is the economic nature of jumps that affects arbitrage errors, however, rather than the jump event itself. Jump events that are more discontinuous and illiquid in nature significantly increase the size of arbitrage errors whereas jump events that are largely driven by an increased demand to trade in fact lead to smaller arbitrage errors.

Appendix A

Table A1
News summary statistics. This table presents summary statistics for the sample of pre-scheduled macroeconomic news releases. Panel A presents the total number of news releases by country, Panel B presents the total number of unique news release times, and Panel C presents the frequencies of all economic indicators included in the news sample. FREQ denotes the number of economic news releases by a particular economic region in Panels A and B. FREQ denotes the number of occurrences of news releases on a particular economic indicator in Panel C.

Panel A: Frequencies of news releases by economic region					
COUNTRY	FREQ	%	COUNTRY	FREQ	%
United States	3,763	25.49	Canada	1,057	7.16
United Kingdom	2,603	17.63	Switzerland	612	4.15
Japan	2,127	14.41	New Zealand	506	3.43
European Monetary Union	1,634	11.07	Sweden	28	0.19
Australia	1,230	8.33	France	6	0.04
Germany	1,198	8.11			
Panel B: Frequencies of unique news events by economic region					
COUNTRY	FREQ	%	COUNTRY	FREQ	%
United States	2,073	24.24	Canada	657	7.68
United Kingdom	1,197	14.00	Switzerland	494	5.78
Japan	1,160	13.57	New Zealand	422	4.94
European Monetary Union	960	11.23	Sweden	28	0.33
Australia	833	9.74	France	6	0.07
Germany	721	8.43			
Panel C: Economic indicators					
EVENT	FREQ	%	EVENT	FREQ	%
Consumer Price Index (YoY)	377	2.55	Leading Indicators (MoM)	89	0.60
Consumer Price Index (MoM)	325	2.20	Unemployment Rate s.a.	89	0.60
Retail Sales (MoM)	229	1.55	Reuters/Michigan Consumer Sentiment Index	88	0.60
Purchasing Manager Index Manufacturing	213	1.44	M4 Money Supply (MoM)	87	0.59
Purchasing Manager Index Services	213	1.44	M4 Money Supply (YoY)	86	0.58
Initial Jobless Claims	196	1.33	Gross Domestic Product (YoY)	85	0.58
Unemployment Rate	196	1.33	Leading Economic Index	85	0.58
Industrial Production (MoM)	183	1.24	ZEW Survey - Economic Sentiment	83	0.56
Trade Balance	179	1.21	Gross Domestic Product Annualized	77	0.52
MBA Mortgage Applications	166	1.12	Fed’s Bernanke Speech	75	0.51
Continuing Jobless Claims	165	1.12	M3 Money Supply (YoY)	73	0.49
EIA Crude Oil Stocks change	165	1.12	New Motor Vehicle Sales (MoM)	71	0.48
ECB Trichet’s Speech	153	1.04	Coincident Index	68	0.46
Producer Price Index (YoY)	153	1.04	Gross Domestic Product s.a. (QoQ)	65	0.44
Industrial Production (YoY)	151	1.02	Machine Tool Orders (YoY)	60	0.41
Producer Price Index (MoM)	141	0.96	BoJ Interest Rate Decision	54	0.37
Retail Sales (YoY)	138	0.93	Current Account n.s.a.	51	0.35
Building Permits (MoM)	129	0.87	Mortgage Approvals	50	0.34
Gross Domestic Product (QoQ)	111	0.75	Treasury’s Geithner Speech	50	0.34
Capacity Utilization	101	0.68	Canadian Investment in Foreign Securities	48	0.33
Consumer Confidence	101	0.68	Bank of Canada Consumer Price Index Core (MoM)	47	0.32
Industrial Production s.a. (MoM)	93	0.63	Bank of Canada Consumer Price Index Core (YoY)	47	0.32
Retail Sales ex Autos (MoM)	91	0.62	Bank of England Minutes	47	0.32
Trade Balance s.a.	91	0.62	Business Inventories	47	0.32

Appendix B. Jump identification methodology

This appendix describes the Andersen et al. (2007) jump identification methodology. Log exchange rate processes are each assumed to follow the discrete jump-diffusion process:

$$ds_{t+j\triangle} = \mu_{t+j\triangle}\triangle + \sigma_{t+j\triangle} dB_{t+j\triangle} + \kappa_{t+j\triangle} dq_{t+j\triangle}, \tag{B.1}$$

where $s_{t+j\triangle}$ denotes the log exchange rate (the domestic price of one unit of foreign currency), $\mu_{t+j\triangle}$ is the instantaneous conditional expected return, $\sigma_{t+j\triangle}$ is the instantaneous conditional standard deviation of returns, and $B_{t+j\triangle}$ is a standard Brownian motion. $dq_{t+j\triangle}$ is a counting process that may have a time-varying intensity parameter, $\lambda_{t+j\triangle}$, and $\kappa_{t+j\triangle}$ determines the jump size. $dq_{t+j\triangle} = 1$ in the case that a jump occurs and $dq_{t+j\triangle} = 0$ when there is no jump. Therefore, the probability of a jump event occurring is $\mathbf{P}\{dq_{t+j\triangle} = 1\} = \lambda_{t+j\triangle}$. The quadratic variation of the cumulative return process associated with Eq. (B.1) is given by:

$$[r, r]_{t+j\triangle} = \int_0^{t+j\triangle} \sigma_s^2 ds + \sum_{0<s\le t+j\triangle} \kappa_s^2. \tag{B.2}$$

Denote the discretely sampled $\triangle$-period log returns by $r_{t+j\triangle} = s_{t+j\triangle} - s_{t+(j-1)\triangle}$. Barndorff-Nielsen and Shephard (2006) show that the jump component of return variance can be identified by relating their (Barndorff-Nielsen and Shephard, 2004) realized bipower variation to the realized variance of Andersen et al. (2003). Bipower variation, as $\triangle \to 0$, is defined as:

$$BV_{t+j\triangle} = \mu_1^{-2} \sum_{j\in\mathcal{N}_j} |r_{t+j\triangle}| \cdot |r_{t+(j-1)\triangle}| \to \int_{j\in\mathcal{N}_j} \sigma_s^2 ds, \tag{B.3}$$

where $\mathcal{N}_j$ is a local window (the trading day of 5-min intervals that time $t + j\triangle$ falls within), $\mu_1 = \sqrt{2/\pi}$ is a scaling constant, and $|\cdot|$ denotes the absolute value.

Andersen et al. (2007) extend the work of Barndorff-Nielsen and Shephard (2006) and develop a model which allows for the identification of multiple intraday jumps and their timing. The Andersen et al. (2007) intraday jump-detection test is given by:

$$\kappa_{t+j\triangle} = r_{t+j\triangle} \cdot \mathbf{1}\left(\frac{|r_{t+j\triangle}|}{card\left(\mathcal{N}_j\right)^{-1} \cdot BV_{t+j\triangle}} > \Phi_{1-\beta/2} \right), \quad j = 1, 2, \ldots, \triangle^{-1}. \tag{B.4}$$

$card\left(\mathcal{N}_j\right)$ is the cardinality of the set $\mathcal{N}_j$ (generally 288 for the 288 5-min periods in one 24-hour trading day), $\mathbf{1}(x)$ is the indicator function, which is equal to one if x is true and is equal to zero otherwise, $\Phi_{1-\beta/2}$ is the critical value from the standard normal distribution at the $1 - \beta/2$ confidence interval, and $\beta = 1 - (1 - \alpha)^{\triangle}$. α is the size of the jump test at the daily level and $\alpha = 0.1\%$ is used in Eq. (B.4). This corresponds to the 4.64143 critical value of the standard normal distribution.

An important property of Eq. (B.4) is that it assumes that the intraday diffusion component is constant over a trading day. Therefore, the test will over-reject the null hypothesis of no jump event if the financial time series displays considerable time-variation in intraday volatility. Contrary to constant volatility, volatility in the foreign exchange market has been shown to follow intraday volatility patterns (Andersen and Bollerslev, 1998; Baillie and Bollerslev, 1991; Harvey and Huang, 1991). Using unadjusted absolute log returns in Eq. (B.4) leads to a non-trivial number of false rejections of the null hypothesis of a diffusive process. To correct for this, I use the weighed standard deviation (WSD) methodology of Boudt et al. (2011), which is described in Appendix C, to estimate intraweek periodicities and adjust absolute returns. They show through simulations that the WSD estimator is a robust periodicity estimation methodology in the presence of jumps.

In the absence of jumps, the discrete form of Eq. (B.1) is given by:

$$r_{t+j\triangle} = \alpha_{t+j\triangle}\triangle + \sigma_{t+j\triangle} u_{t+j\triangle} \triangle^{1/2}. \tag{B.5}$$

$\alpha_{t+j\triangle}$ is the conditional expected return per unit of time defined as $\alpha_{t+j\triangle} \equiv \mathbf{E}_{t+(j-1)\triangle}\left[r_{t+j\triangle}\right]/\triangle$, $\epsilon_{t+j\triangle}$ is the unexpected return, $\sigma^2_{t+j\triangle}$ is the conditional return variance per unit of time defined as $\sigma^2_{t+j\triangle} \equiv \mathbf{E}_{t+(j-1)\triangle}\left[\epsilon^2_{t+j\triangle}\right]/\triangle$, and $u_{t+j\triangle} \equiv \epsilon_{t+j\triangle}/\left(\sigma_{t+j\triangle} \cdot \triangle^{1/2}\right)$. $u_{t+j\triangle}$ has an expected value of zero and a variance equal to one by design. Due to the high-frequency nature of the data, it is possible to make the simplifying assumption that $\alpha_{t+j\triangle} = 0$ without loss of generality. In order to capture intraweek periodicity in volatility, $\sigma_{t+j\triangle}$ is modeled as a function of a periodic component, $f_{t+j\triangle}$, where $\sum_{j=1}^{\triangle^{-1}} f^2_{t+j\triangle} = 1$, and a $v_{t+j\triangle}$ diffusive component that is constant during the twenty-four hour trading day that $t + j\triangle$ falls within:

$$\epsilon_{t+j\triangle} = f_{t+j\triangle} v_{t+j\triangle} z_{t+j\triangle}. \tag{B.6}$$

$z_{t+j\triangle} \sim N(0, 1)$ is a standard normal random variable included to maintain an expected value of zero for $\epsilon_{t+j\triangle}$. By substituting Eq. (B.6) into Eq. (B.5), assuming that $\alpha_{t+j\triangle} = 0$, and dividing both sides of Eq. (B.5) by the diffusive component, $v_{t+j\triangle}$, results in standardized returns with mean zero and variance entirely explained by the variance of the periodic factor:

$$\bar{r}_{t+j\triangle} \equiv \frac{r_{t+j\triangle}}{v_{t+j\triangle}} = f_{t+j\triangle} z_{t+j\triangle}, \tag{B.7}$$

$$\mathbf{E}\left[\bar{r}_{t+j\triangle}\right] = 0, \tag{B.8}$$

$$\mathbf{E}\left[\bar{r}^2_{t+j\triangle}\right] = f^2_{t+j\triangle}. \tag{B.9}$$

Both $f_{t+j\triangle}$ and $v_{t+j\triangle}$ are unobservable and need to be estimated. As an estimate of the daily diffusive component, $v_{t+j\triangle}$, the standard deviation of estimated realized bipower variation per time unit, given in Eq. (B.3) is used:

$$\widehat{v}_{t+j\triangle} = \sqrt{\frac{\mu_1^{-2}}{card\left(\mathcal{N}_j\right) - 1} \sum_{j\in\mathcal{N}_j} |r_{t+j\triangle}| \cdot |r_{t+(j-1)\triangle}|}. \tag{B.10}$$

The WSD estimator of Boudt et al. (2011) is used to estimate $f_{t+j\triangle}$, denoted by $\widehat{f}^{WSD}_{t+j\triangle}$.

Eq. (B.6) now becomes:

$$\kappa_{t+j\triangle} = r_{t+j\triangle} \cdot \mathbf{1}\left(\frac{|r_{t+j\triangle}|}{\widehat{f}^{WSD}_{t+j\triangle} \widehat{v}^{WSD}_{t+j\triangle}} > \Phi_{1-\beta/2} \right), \qquad j = 1, 2, \ldots, \triangle^{-1}, \tag{B.11}$$

where $\widehat{f}^{WSD}_{t+j\triangle}$ is given in Appendix C and $\widehat{v}^{WSD}_{t+j\triangle}$ is Eq. (B.10) computed on the $r_{t+j\triangle}/\widehat{f}^{ShortH}_{t+j\triangle}$ return series where $\widehat{f}^{ShortH}_{t+j\triangle}$ is defined in Appendix C. The term $|r_{t+j\triangle}|/\left(\widehat{f}^{WSD}_{t+j\triangle}\widehat{v}^{WSD}_{t+j\triangle}\right)$ in Eq. (B.11) is a standard normally distributed random variable under the null hypothesis of no jumps. Therefore, Eq. (B.11) identifies a jump as occurring if the magnitude of an observed return is significantly greater than what is implied by the periodicity-robust estimate of integrated volatility. This excess return is attributable to a jump having occurred. Once a jump has been identified in a 5-min return, the value of the jump is taken to be the observed return over that five minute period, $r_{t+j\triangle}$.

Appendix C. Weighted standard deviation (WSD) estimator

I use the weighted standard deviation (WSD) estimator of Boudt et al. (2011) to estimate $f_{t+j\triangle}$, the intraweek exchange rate volatility periodicity, which Boudt et al. show is a robust volatility estimator in the presence of discrete jumps. They suggest using the shortest half (ShortH) scale estimator of Rousseeuw and Leroy (1988), to first adjust the observed return series by filtering out the effects of jumps, since it is in the class of estimators that have the smallest maximum bias in the presence of jumps (Martin and Zamar, 1993). The ShortH estimator calculation is:

$$ShortH \equiv 0.7413 \cdot min\{\bar{r}_{h_j:j\triangle} - \bar{r}_{1:j\triangle}, \bar{r}_{h_j+1:j\triangle} - \bar{r}_{2:j\triangle}, \dots, \bar{r}_{n_j:j\triangle} - \bar{r}_{n_j-h_j+1:j\triangle}\}, \tag{C.1}$$

where $\bar{r}_{1:j\triangle}, \bar{r}_{2:j\triangle}, \dots, \bar{r}_{n_j:j\triangle}$ are order statistics such that $\bar{r}_{1:j\triangle} \leq \bar{r}_{2:j\triangle} \leq, \cdots, \leq \bar{r}_{n_j:j\triangle}$, n_j is the total number of observations of the $j\triangle$'th intraweek segment in the sample, $h_j = \lfloor n_j/2 \rfloor + 1$, and $min\{\cdot\}$ identifies the minimum of $\{\cdot\}$. The WSD estimator is given by:

$$\hat{f}^{WSD}_{t+j\triangle} = \frac{WSD_{t+j\triangle}}{\sqrt{\triangle \sum_{j=1}^{\triangle^{-1}} WSD^2_{t+j\triangle}}}, \tag{C.2}$$

$$WSD_{t+j\triangle} = \sqrt{1.081 \cdot \frac{\sum_{l=1}^{n_j} w_{l,j} \bar{r}^2_{l,j\triangle}}{\sum_{l=1}^{n_j} w_{l,j}}}, \tag{C.3}$$

$$\hat{f}^{ShortH}_{t+j\triangle} = \frac{ShortH_{t+j\triangle}}{\sqrt{\triangle \sum_{j=1}^{\triangle^{-1}} ShortH^2_{t+j\triangle}}}. \tag{C.4}$$

$w_{l,j} = w\left(\bar{r}_{l,j\triangle}/\hat{f}^{ShortH}_{t+j\triangle}\right)$ is a weight function where $w(z) = 1$ if $z^2 \leq 6.635$ and $w(z) = 0$ otherwise. 6.635 is the 99% level of the χ^2 distribution with one degree of freedom. Therefore, the weight function effectively filters out the contribution of jump returns.

Appendix D. State variable definitions

This appendix gives the formal definitions used for the *PI*, *S2XW*, and *OF* state variables. *PI* is defined as in Amihud (2002) as:

$$PI_{i,t+j\triangle} = \frac{|r_{i,t+j\triangle}|}{QV_{i,t+j\triangle} \cdot \bar{s}_{i,t+j\triangle}}, \tag{D.1}$$

where *QV* is the total number of quotes between the times $t + (j-1)\triangle$ and $t + j\triangle$, $\bar{s}_{i,t+j\triangle}$ is the mean midquote from time $t + (j-1)\triangle$ to $t + j\triangle$, and $|\cdot|$ denotes the absolute value. As a consequence of only having quote data and not the associated trade volume data, Eq. (D.1) implicitly assumes that all trades are for the same notional amount of a given currency. This assumption is not expected to be restrictive, since Menkhoff and Schmeling (2010) show that trade sizes in the foreign exchange market tend to cluster around a "normal" notional amount.

S2XW is the contribution of informed trade to the return variance, as defined in Hasbrouck (1991). Intuitively, Hasbrouck shows that the information revealed through trade can be identified through a variance decomposition of the return process. When past orders continue to lead to a revision in quotes today, as in Kyle (1985) and Glosten and Milgrom (1985), then the impulse-response function is non-zero, which shows that (private) information is revealed through the trading process. Let τ denote the integer quote time (the τ'th quote since the start of the sample.), r_τ denote the quote revision from time $(\tau - 1)$ to τ, and $x_\tau = sign(r_\tau)$ denote the signed trade direction. I use the tick test to sign trades since, the dataset does not have transaction prices, which makes it impossible to sign trades using the Lee and Ready (1991) algorithm. Assume that quote revisions and signed trades are modeled as the vector autoregressive (VAR) process:

$$\begin{pmatrix} 1-a(L) & -b(L)-1 \\ -c(L) & 1-d(L) \end{pmatrix} \begin{pmatrix} r_\tau \\ x_\tau \end{pmatrix} = \begin{pmatrix} \upsilon_{1,\tau} \\ \upsilon_{2,\tau} \end{pmatrix}, \tag{D.2}$$

where $a(L)$, $b(L)$, $c(L)$, and $d(L)$ are polynomials in the lag operator such that $L^p y_\tau = y_{\tau-p}$, and $g(L) = g_1 L + g_2 L^2 + g_3 L^3 + \cdots + g_p L^p$ for $g \in \{a, b, c, d\}$. $\upsilon_{1,\tau}$ and $\upsilon_{2,\tau}$ are independent error terms. Following the methodology of Hasbrouck (1991), note that x_0 is included in the equation for r_τ in Eq. (D.2). The vector moving average (VMA) processes associated with Eq. (D.2) is:

$$\begin{pmatrix} r_\tau \\ x_\tau \end{pmatrix} = \begin{pmatrix} 1+a^*(L) & b^*(L) \\ c^*(L) & 1+d^*(L) \end{pmatrix} \begin{pmatrix} \upsilon_{1,\tau} \\ \upsilon_{2,\tau} \end{pmatrix}, \tag{D.3}$$

where the lag polynomials are defined similarly to as in the VAR. VMA coefficients in Eq. (D.3) are related to the VAR coefficients in Eq. (D.2) by:

$$\begin{pmatrix} a_j^* & b_j^* \\ c_j^* & d_j^* \end{pmatrix} = \mathbf{F}^j_{11}, \mathbf{F} = \begin{pmatrix} \mathbf{A}_1 & \mathbf{A}_2 & \cdots & \mathbf{A}_p - 1 & \mathbf{A}_p \\ \mathbf{I}_2 & \mathbf{0} & \cdots & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_2 & \cdots & \mathbf{0} & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{I}_2 & \mathbf{0} \end{pmatrix},$$
$$\mathbf{A}_j = \begin{pmatrix} a_j & b_j \\ c_j & d_j \end{pmatrix}, \tag{D.4}$$

where $\mathbf{I}$ is the (2×2) identity matrix, $\mathbf{0}$ is a (2×2) matrix of zeros, $\mathbf{F}$ is a $(2p \times 2p)$ matrix, $\mathbf{F}^j_{11}$ denotes the upper left block of $\mathbf{F}^j$, and $\mathbf{F}^j$ is the $\mathbf{F}$ matrix raised to the j'th power. Hasbrouck (1991) shows that the variance decomposition of the VMA results in the random-walk variance and the contribution of trades to the random-walk variance, *S2XW*, given by:

$$S2W = \left(\sum_{j=1}^{p} b_j^*\right) \mathbf{V}[\upsilon_2] \left(\sum_{j=1}^{p} b_j^*\right) + \left(1 + \sum_{j=1}^{p} a_j^*\right)^2 \mathbf{V}[\upsilon_1], \tag{D.5}$$

$$S2XW = \frac{\left(\sum_{j=1}^{p} b_j^*\right) \mathbf{V}[\upsilon_2] \left(\sum_{j=1}^{p} b_j^*\right)}{S2W}, \tag{D.6}$$

where $\mathbf{V}[\upsilon_1]$ and $\mathbf{V}[\upsilon_2]$ are the variances of υ_1 and υ_2, respectively. *S2W* is the random walk variance for the exchange rate and *S2XW* is the fraction of the random walk variance that is attributable to informed trade.

In the empirical estimation of Eqs. (D.2)–(D.6), a lag length of five is used for p for the VAR as well as for the VMA. Since I require *S2XW* to be a time varying measure, I estimate Eqs. (D.2)–(D.6) over the sample period using a rolling window of 500 observations.[16] Since quote time is quicker than clock time when markets are more active, using a fixed 500 observation window results in regressions over varying clock time durations. This is not a problem, however, since aggregating quote revisions in order to essentially slow down the quote time to more closely align with clock time would corrupt the identification of information that is revealed through the trading process. The idea of business time and clock time varying from one another is discussed in Kyle and Obizhaeva (2016). To reduce the computational burden of the estimation methodology, I use a step size of three ticks for the rolling regression to move through the sample. For example, the first estimation would use observations (ignoring considerations for the lag length included in the model) 1–500, the second estimation would use observations 4–503, the third estimation

[16] Since quote observations are recorded in strict order of when they are offered, even multiple quotes that are recorded with the same time stamp appear chronologically in the dataset.

would use observations 7–506, and so on. A similar step methodology is used in Payne (2003). Letting τ continue to denote quote time, $S2XW_{t+j\triangle}$ is then defined to be the average $S2XW_{\tau}$ estimate in the 5-min interval:

$$S2XW_{t+j\triangle} = N_{t+j\triangle}^{-1} \sum_{\tau \in [t+(j-1)\triangle, t+j\triangle)} S2XW_{\tau}, \tag{D.7}$$

where $N_{t+j\triangle}$ is the number of $S2XW_{\tau}$ observations in the interval $[t+(j-1)\triangle, t+j\triangle)$.

Order flow (OF) is defined as:

$$OF_{t+j\triangle} = \sum_{\tau \in [t+(j-1)\triangle, t+j\triangle)} x_{\tau}, \tag{D.8}$$

where $x_{\tau} = sign(r_{\tau})$ is the signed trade direction.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.jbankfin.2017.09.007.

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