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Tales of tails: Jumps in currency markets[☆]

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ABSTRACT

We investigate the predictability of jumps in currency markets and show the implications for carry trades. Formulating new currency jump analyses, we propose a general method to estimate the determinants of jump sizes and intensities at various frequencies. We employ a large panel of high-frequency data and identify significant predictive relationships between currency jumps and national characteristics. In addition, we find the patterns of intraday jumps (i.e., multiple currency jump clustering and time-of-day effects). Macroeconomic information releases in the United States, particularly FOMC announcements, lead to currency jumps. Using these jump predictors, investors can construct jump-robust carry trades to mitigate left-tail risks.

1. Introduction

A carry trade is a popular currency trading strategy in which investors invest in higher interest rate currencies and sell lower interest rate currencies. The popularity of carry trades is related to the well-known puzzle, the violation of uncovered interest rate parity (UIP).[1] Despite its popularity, a carry trade occasionally suffers from dramatic losses during unusually volatile markets (Brunnermeier et al., 2008; Daniel et al., 2017; Menkhoff et al., 2012). One good example is the financial crisis from 2007 to 2009. In this paper, we are interested in refining our understanding about such highly volatile currency markets to improve risk management.

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[1] UIP implies that the interest rate differential between two countries is canceled out by changes in the foreign exchange rate. However, empirically, the changes in the exchange rate tend to be insufficient to offset the interest rate differential. See, for example, (Hansen and Hodrick, 1980; Bilson, 1981; Fama, 1984).

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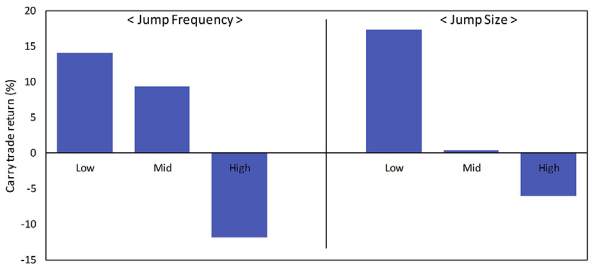


Fig. 1. Carry trade returns and jumps. This figure presents the annualized daily carry trade returns depending on jumps. For this figure, the carry trades are defined as an investment in which investors, reviewing the interest rates of the 18 countries every day, lend the five highest interest rate currencies and borrow the five lowest interest rate currencies. The investment horizon is from 1999 to 2015. We sort days on jump frequencies (sizes) and then construct three groups using the 33rd and 67th percentiles. "High" represents high (large) jump frequencies (sizes), and "Low" represents low (small) jump frequencies (sizes).

Volatile markets are well represented by pricing models with jumps.[2] Because jumps can generate excessive volatility, one can expect carry trade returns to be lower when larger sized jumps occur more frequently. We confirm this simple intuition in Fig. 1, where we present carry trade returns depending on jump sizes and frequencies. Specifically, we group the whole sample period into High, Mid, and Low periods of days, using the 33rd and 67th percentiles of jump size and frequency distributions, and compute carry trade returns for each period. The carry trade returns during periods of high jump frequencies (sizes) are approximately 26% (23%) lower than those during periods of low jump frequencies (sizes). The differences in returns are economically and statistically significant. Given this significant negative relationship between jumps and carry trade returns, we aim to identify determinants that affect jump sizes and frequencies to hedge extreme risks involved in carry trades.

Because the currency markets operate for 24 h in real-time during weekdays, we identify currency jumps at intraday frequencies for better jump identification. However, variables that represent the potential determinants of intraday jumps have various sampling frequencies from intraday to lower frequencies such as quarterly levels. We resolve this frequency mismatch with our flexible approach called a generalized jump regression (GJR), which allows us to link the intraday jumps with information variables observable at different frequencies. To consider information variables at lower frequencies, the GJR approach enables us to aggregate intraday jumps over a certain period of time and across currencies and to link the aggregated jump measures to information variables. A jump analysis has been limited to an intraday level and an event-oriented study. However, such time aggregations of jump sizes and frequencies allow us to investigate the relationship between jump measures and economic fundamentals with a lower frequency. With the identified determinants of jump sizes and intensities, we can filter out currencies with greater jump risks or rebalance currency portfolios to enhance risk management.

To apply our approach to currency markets, we employ a large panel dataset covering 18 foreign exchange rates collected every 15 min from 1999 to 2015. At the intraday level, we find strong deterministic time-of-day effects, which indicate that jumps are more likely to arrive when global currency markets open and close. We formally test jump-clustering effects in currency markets and find that currency jumps are more likely to occur in subsequent periods after jumps arrive in previous periods. This jump clustering effect is prolonged for approximately one day with decaying strength. These deterministic intraday jump patterns and clustering effects hold not only for individual currency jumps but also for common jumps that simultaneously arrive for multiple currencies.

Macroeconomic variables can be used to predict jumps in currency markets because economic news triggers jumps in asset prices. At intraday and daily frequencies, we investigate whether the times of prescheduled macroeconomic news releases can predict exchange rate jumps. After controlling for the deterministic intraday patterns and jump clustering effects, we find that Federal Open Market Committee (FOMC) announcements and nonfarm payroll employment are important information releases that are associated with greater jump sizes and frequencies. Using national characteristics available at quarterly frequencies, we find a significant contemporaneous relationship between currency jumps and economic fundamentals. We also identify the predictive power of these economic fundamentals for future jump arrivals and sizes over the subsequent quarters. Among many macroeconomic variables (e.g., GDP, interest rates, M1, foreign direct investments, exports, and imports), GDP is significantly and negatively related to jumps aggregated over a quarter.

Finally, we demonstrate that our findings on jump predictors can substantially improve risk management for carry trades. In particular, we show that if carry trade investors unwind their original positions when jumps are more likely to occur, they earn approximately 80% higher cumulative returns from January 1999 to December 2015 (i.e., 4.3% per annum). The Sharpe ratio increases from 0.5 to 1.2. If we include transaction costs, the difference decreases to 71% (i.e., 3.9% per annum). Investors, using only the currencies that are less exposed to jumps, enhance the cumulative carry trade returns by an additional 4%. We refer to carry trades that reduce the exposure to jump risks as *jump-robust carry trades*. These carry trades have a higher skewness and

[2] See (Bakshi et al., 2008; Jurek, 2014; Farhi and Gabaix, 2016; Chernov et al., 2018; Lee and Wang, 2019) for the impact of jumps on pricing in currency markets. See (Andersen et al., 2003a; Huang and Tauchen, 2005; Bollerslev et al., 2008), who indicate that the squared jumps are a substantial portion of realized variance.

certainty equivalent and a less dispersed return distribution than the regular carry trade. We conclude that the left-tail risk in carry trade returns can be partially predicted via information available beforehand (e.g., market opening times, jump clustering effects, or macroeconomic variables).

This paper is related to the following streams of the literature. First, it is related to recent studies about how to explain and predict currency investment returns. (Brunnermeier et al., 2008) show the negative skewness (crash) of currency returns, while we stress that low carry trade returns tend to coincide with large and frequent jumps. Because we focus on the effects of jumps on carry trade returns, this paper differs from the works of (Lustig et al., 2011; Menkhoff et al., 2012), who identify common factors related to interest rate differentials and volatility in currency markets. We use return predictors (i.e., jumps) that are different from those in (Bakshi and Panayotov, 2013), who use commodity returns, liquidity, and volatility in currency returns. In addition, our paper extends the literature that relates currency returns to national characteristics by showing the significant relationship between currency jumps and GDP. For example (Lustig and Verdelhan, 2007; Hassan, 2013), demonstrate that consumption growth and GDP can explain currency returns.

Second, we provide various approaches to adjust the regular carry trade to avoid jump risks, called jump-robust carry trades. Because our approaches are intended to enhance risk management, our paper differs from a recent study by (Lee and Wang, 2019), who propose the jump-modified carry trade. The jump-modified carry trade requires investors to select currencies with high negative jump betas as investment currencies and is designed to achieve high carry trade returns. Although (Lee and Wang, 2019) also introduce a jump-robust carry trade to compare the performances of different carry trades, their jump-robust carry trade is based on the jump clustering effect, while our jump-robust carry trades are based on the empirical results on jump predictions.[3] In fact, we construct jump-robust carry trades based on market opening times, jump clustering effects, and national characteristics and allow investors to use multiple approaches to avoid jumps (Lee and Wang, 2019) focus on the jump-modified carry trade, while we contribute to this literature by focusing on jump-robust carry trades, further developing the idea, and presenting new results with detailed performance measures. For example, we show that jumps are not sufficiently compensated, and thus, investors can enhance their carry trade performance by avoiding predictable jumps based on our new empirical finding. In addition, unlike the jump-modified carry trade that focuses on negative market jumps, our jump-robust carry trades do not distinguish systematic and idiosyncratic jumps.

Our jump-robust carry trades differ from the volatility-managed portfolios of (Moreira and Muir, 2017) because they avoid extreme left-tail risks, while the volatility-managed portfolios reduce the exposure to volatility risks that are not sufficiently compensated by returns and are not always related to extreme jump risk. In addition, the jump-robust carry trades use various information variables to predict the size and intensity of jumps, while the volatility-managed portfolios depend on the fact that volatility does not change much over a short time. The jump-robust carry trades are different from the crash-neutral carry trades proposed in (Jurek, 2014), whose hedging strategy depends on how option market participants anticipate extreme depreciation in currency markets. Our jump-robust carry trade is similar to the good carry of (Bekaert and Panayotov, 2017) in that it can supplement the existing risk-based explanations of carry trade returns. However, the good carry uses currencies with high Sharpe ratios, while our jump-robust carry trade uses currencies with low jump frequencies and sizes.

Third, we suggest the GJR approach to connect intraday jumps with market information. It is an important methodological contribution, as this approach allows jumps to be used for an application in various markets. Our approach differs from the jump regressions in (Li et al., 2017) in that they study the relationship between jumps in asset prices and aggregate risk factors, while we study potentially nonlinear relationships between jump sizes and intensities and various information variables that can include aggregate risk factors. Our study of jump predictors based on information releases appears similar to studies that investigate the effect of macro announcements on jumps and relate jumps to economic events.[4] However, we provide new theoretical support for jump analyses. Researchers have examined the coincidence of jumps with an event and the conditional probability of jumps. For example, the inference method of (Lahaye et al., 2011), which is based on a Tobit-probit framework, can be considered the special case of our GJR approach. In addition, the existing studies use the same frequencies of jumps as the data frequencies of information variables and announcements, while our GJR method allows us to relate intraday jumps to information variables with low frequencies by aggregating jump sizes and frequencies. Moreover, our extensive high-frequency exchange rate dataset is larger than in any published study.

Finally, this paper contributes to the literature on intraday patterns of currency returns (Baillie and Bollerslev, 1991; Andersen and Bollerslev, 1998b) investigate the calendar day effects on exchange rate volatilities.[5] In this paper, we newly identify that exchange rate jumps have deterministic patterns, even at the intraday level. We show how the patterns of jumps differ from those of volatility (e.g., the peak of the jump intensity comes before the peak of the volatility). Our intraday evidence is related

[3] (Lee and Wang, 2019) show that the jump-robust carry trade has smaller volatility than the regular carry trades, while the jump-modified carry trade has volatility similar to that of the regular carry trades.

[4] (Lahaye et al., 2011) characterize jump dynamics in four exchange rates, stock market indexes, and bond futures and relate these jump arrivals to news releases. Using one currency (Evans, 2011), shows that approximately one-third of jumps occur because of macroeconomic news announcements in the U.S. Separating jumps into news-related jumps and non-news-related jumps (Evans, 2011), reports that news-related jumps show more persistence and greater effects on microstructure variables (e.g., trading volume, tick frequency). Analyzing four currencies (Chatrath et al., 2014), report that announcements in the U.S. can explain 9%–15% of jumps and 22%–56% of jump returns and that news-related jumps are not persistent (Chernov et al., 2018) indicate that many jumps are associated with macroeconomic and political news (Piccotti, 2018) uses 14 exchange rates for four years and investigates the relationship between intraday jumps and macroeconomic news in the context of market efficiency and microstructures.

[5] (Baillie and Bollerslev, 1991) report that the hourly patterns are similar across currencies and are related to opening and closing hours (Andersen and Bollerslev, 1998b) show that foreign exchange volatility increases at the opening times of the Tokyo and London markets and has a U-shaped pattern for a day.

to (Breedon and Ranaldo, 2013), who find order flow patterns in currency markets.[6] Regarding the announcement effects (Engle et al., 1990; Andersen et al., 2003b), examine market efficiency and the speed of currency returns' reactions, while we focus on extreme market predictions and consider the prediction of jump sizes and frequencies around prescheduled information release days (rather than realized information release days).

The remainder of this paper is organized as follows. In Section 2, we present the testing procedure that we use to identify the determinants of jump sizes and intensities. In Section 3, we introduce the sample exchange rates and jump predictors. In Section 4, we characterize the intraday patterns of foreign exchange rate jumps and the effects of scheduled U.S. information releases on jumps. In Section 5, we show the relationship between jumps and macroeconomic fundamentals. We propose jump-robust carry trades in Section 6 and conclude in Section 7.

2. Inference for currency jumps

In this section, we provide a model for foreign exchange rate processes and justify the use of aggregated jumps in the various regression analyses. We first describe a multiple currency market model that incorporates intraday volatility patterns and jump risks. A process for the k-th foreign exchange rate is represented by the following stochastic differential equation:

$$ds_{k,t} = \mu_{k,t}dt + \sigma_{k,t}f_{k,t}dW_{k,t} + Y_{k,t}dJ_{k,t}, \tag{1}$$

where $s_{k,t}$ is a log spot foreign exchange rate k at time t. The drift $\mu_{k,t}$ and volatility $\sigma_{k,t}f_{k,t}$ are $\mathcal{F}_t$-adapted and bounded processes, where $\{\mathcal{F}_t : t \in [0, T]\}$ is information filtration and $W_{k,t}$ is a standard Brownian motion. $Y_{k,t}$ is the jump size at time t, and $dJ_{k,t}$ is the jump arrival process at time t.

$f_{k,t}$ is an adjustment factor for the k-th exchange rate's intraday volatility pattern around time t. As indicated by (Andersen and Bollerslev, 1998b), the intraday patterns of foreign exchange volatility exist and are closely related to the trading cycles of currency markets. If the volatility at time t is substantially higher than that in the previous period, the return around time t is more likely to be detected as a jump even if no jump occurs around time t. To avoid such spurious detection of jumps driven by trading mechanisms, we control for this pattern by incorporating it into the jump filtering procedure.[7] To confirm the performance of our approach, we perform a Monte Carlo simulation study, which shows that this jump detection method is effective in distinguishing jumps from the intraday volatility patterns. The details and results of the simulation are explained in Appendix B.

2.1. General jump regression models

To characterize the patterns of jump sizes and arrivals in relation to information variables, we impose a regression framework that can link the jump sizes or arrivals to the information variables available at frequencies chosen by analysts. We consider a general regression model for a jump size $Y_{k,t}$ on which we impose no distributional assumption, except for the existence of its mean μ_Y and standard deviation σ_Y. The jump size $Y_{k,t}$ for the k-th currency is specified by a general regression model with a parameter θ, as shown in the following equation:

$$\int_{s\in[t,t+\delta]} E[h(Y_{k,s})]ds = \gamma_{\text{size}}(t, X_{k,t}; \theta), \tag{2}$$

where $X_{k,t}$ denotes the information variable that affects the jump sizes over time interval $[t, t + \delta]$ in the k-th exchange rate with δ chosen to reflect the frequency of analysis. The time interval can be an intraday time interval for an intraday analysis, a one-day interval for a daily analysis, a one-month interval for a monthly analysis, or a one-quarter interval for a quarterly analysis. $h(\cdot)$ is a continuous function of jump sizes that allows for the transformation of jump sizes. γ_{size} is a general function of the time and information variables and can be currency specific or related to broader market conditions. Accordingly, with this jump size model, we can investigate how risks related to jump sizes are linked to various economic variables.

For the jump intensity regression, we consider a model similar to that in (Lee, 2012).[8] Each currency jump follows a doubly stochastic Poisson process $J_{k,t}$ with an integrated stochastic intensity $\Lambda_{k,t|\theta} = \int_t^{t+\delta} d\Lambda_{k,s|\theta}$. Its integrated intensity process $\Lambda_{k,t|\theta}$ is specified as:

$$\Lambda_{k,t|\theta} = \int_{s\in[t,t+\delta]} E[dJ_{k,s}] = \gamma_{\text{intensity}}(t, X_{k,t}; \theta), \tag{3}$$

[6] (Breedon and Ranaldo, 2013) find that local currencies tend to depreciate during their own market opening hours. Using intraday quotes, trade intensity, and order flow data on DM/USD (Evans, 2002), argues that the transactions driven by non-common knowledge can give rise to an equilibrium distribution of transaction prices rather than a single price level. When trade intensity is high, non-common knowledge yields significant variances and price movements.

[7] This consideration is motivated by (Boudt et al., 2011). We include $f_{k,t}$ to reduce jumps that are spuriously detected because of only the higher volatility associated with trading mechanisms. We estimate this quantity as $f_{k,t_i} = Max(1, RIV_{k,t_i})$ with $i \in \{0, 1, 2, \ldots, n\}$, where t_i is the $(i + 1)$-th observation and RIV_{k,t_i} is an average intraday volatility at time t_i. Practically, when 15-min intraday data for D days are used, $RIV_{k,t_i} = \sum_{d=1}^{D} |r_{k,d,m}|/(\frac{1}{96}) \sum_{m=1}^{96} \sum_{d=1}^{D} |r_{k,d,m}|$, where $r_{k,d,m}$ is the m-th 15-min log changes in the k-th foreign exchange rate on day d and $m = i - [i/96] \times 96 + 1$.

[8] (Lee, 2012) proposes an inference technique called the jump predictor test, which is based on a likelihood inference for stochastic jump intensity models within a jump diffusion framework.

where $X_{k,t}$ denotes the information variable that affects the likelihood of aggregated jump arrivals over the time interval $[t, t + \delta]$ and $\gamma_{\text{intensity}}$ is a general function of time and information covariates.

We assume a time horizon of $[0, T]$ and n observations within the horizon. The total number of days is D, and the total number of quarters is Q, such that $[0, T] = \cup_{d=1}^{D} D_d = \cup_{q=1}^{Q} Q_q$ with the daily interval D_d for day d and the quarterly interval Q_q for quarter q. The observation of the k-th exchange rate $s_{k,t}$ and the informational variables $X_{k,t}$ occurs only at discrete times $0 = t_0 < t_1 < \cdots < t_n = T$. For the sake of simplicity, we set equally spaced observation times: $\Delta t = t_i - t_{i-1} = T/n$. The assumptions imposed on each component of this model are presented in Appendix A. The assumptions allow for stochastic drift, volatility, and jumps, which accommodate most of the general models in the literature.

2.2. Inference for the general jump regression model

To identify latent jump sizes and times in continuous time models, as established in the previous subsection, we first employ multiple jump detection tests on the time series of exchange rate data. Using these filtered jumps, we estimate jump size and intensity regression models by linking jumps with information variables via chosen estimating functions.[9] We can choose estimation functions in accordance with intended jump regression models and make likelihood inferences and other least squared error approaches. The limiting distribution of parameter estimates allows us to perform significance tests to determine important information variables for jump size and intensity predictions. In addition, we make proper time aggregation of jumps, depending on the frequency of information data, because jumps are detected at intraday levels, while information variables can be observable at longer frequencies (e.g., daily and quarterly). The time aggregation allows us to link intraday jumps to information variables with lower frequencies.

We make the simple but important generalization of the inference method proposed in (Lee, 2012) in multiple dimensions. First, we estimate jump size regressions, which are not considered in the aforementioned study. Separate analyses on jump size determinants are important because the outcomes can offer additional insights into the severity of jump events, which may not be adequately captured by the jump intensity studies alone. Second, our approach accommodates the use of information data available at various frequencies – from intraday to quarterly levels. Accordingly, researchers can perform more flexible research that uses jumps and investigate how intraday jumps are related to economic variables with a lower frequency. This generalization is new to the literature and accommodates many generalized linear models, such as logistic regressions, Poisson regressions, and regular panel regressions, for jumps embedded in the jump diffusion model framework that we employ.

3. Data

In this section, we introduce our extensive intraday exchange rate data and explain our choice of jump predictors. We also report the summary statistics of detected jumps in currency markets.

3.1. Intraday exchange rates

To investigate the predictability of foreign exchange rate jumps, we use 18 bilateral spot rates from January 1999 to December 2015. The sample includes exchange rates between USD and the following currencies: the Australian dollar (AUD), Brazilian real (BRL), Canadian dollar (CAD), euro (EUR), Hungarian forint (HUF), Indian rupee (INR), Japanese yen (JPY), Korean won (KRW), Norwegian krone (NOK), New Zealand dollar (NZD), Polish zloty (PLN), Russian ruble (RUB), Singapore dollar (SGD), South African rand (ZAR), Swedish krona (SEK), Swiss franc (CHF), Turkish lira (TRY), and British pound (GBP). We select these currencies by considering the trading volumes and data availability and believe that our data are very comprehensive intraday exchange rate data. These data are obtained from Olsen Financial Technologies, which collects and provides credible high-frequency data by using different consolidation services such as Reuters, Knight Ridder, GTIS, and Tenfore. In addition, intraday exchange rate data from Olsen Financial Technologies are widely used in the literature (e.g., [3, 6, 41). In our main analyses, we use the mid quotes obtained every 15 min, but the results are robust to different data frequencies (e.g., five minutes to one hour) and the consideration of bid-ask spreads. All the exchange rates are expressed in USD per unit of foreign currency. The specified time is based on Greenwich Mean Time (GMT).

Although currency markets operate 24 h a day during weekdays, trading intensity tends to decrease on weekends and holidays. To avoid such a clear calendar day effect, we eliminate weekends and holidays including Christmas, Independence Day, Thanksgiving, and New Year's Eve/Day. To obtain the undistorted distributional characteristics of returns and to delete uncaptured (e.g., irregular or foreign) holidays, we omit days with fewer than 50 observations. In addition, following (Lustig et al., 2011), we remove observations that clearly violate the covered interest rate parity (CIP).[10] Finally, we analyze 1,100–4,400 days (6,209 days in total) or 71,000–410,000 observations (596,064 observations in total) per exchange rate.

[9] Appendix A provides all the related technical details, including the formal definition of the estimating functions and the justification for why optimizing the partial estimating function is sufficient to make an inference regarding the generalized jump regression that we assume.

[10] For example, we delete the observations from October 2000 to November 2001 for TRY. In addition, we investigate the absolute differentials between forward rates and CIP implied exchange rates and then remove the observations whose deviations are more than five times the standard deviation. For example, we remove the observations in December 2008 for KRW and March 1999 for NZD.

Table 1
Summary statistics. This table provides summaries of the changes in foreign exchange rates and national characteristics. The exchange rate data cover 18 spot rates from 1999 to 2015. Panel A reports the distributions of realized daily returns and normalized daily returns. The daily return is defined as the daily sum of changes in the log exchange rate at 15-min intervals. The normalized daily return is defined as the daily return divided by the realized daily standard deviation, which is calculated by the square root of the daily realized variance. Panel B provides the maximum, mean, and minimum of averages across the 18 countries for quarterly GDP, net FDI inflow, M1 growth rate, forward premium, and monthly exports to and imports from the U.S.

Panel A. Daily realized return of foreign exchange rates.

Country (Currency code)	Daily realized return				Normalized daily realized return			
	Mean	Stdev	Skew	Kurt	Mean	Stdev	Skew	Kurt
Australia (AUD)	0.000100	0.0076	−0.35	6.14	0.0482	0.92	−0.04	2.60
Brazil (BRL)	−0.000860	0.0166	0.05	6.48	−0.0440	1.00	0.06	3.18
Canada (CAD)	−0.000019	0.0054	−0.44	6.12	0.0105	0.90	−0.06	2.61
Euro (EUR)	−0.000023	0.0062	−0.05	3.97	0.0038	0.97	−0.01	2.60
Hungary (HUF)	−0.000060	0.0090	−0.18	5.41	0.0045	0.89	−0.04	2.86
India (INR)	0.000447	0.0121	0.23	10.12	0.0044	0.61	−0.16	5.56
Japan (JPY)	−0.000013	0.0061	0.05	4.23	−0.0284	0.93	−0.10	2.54
Korea (KRW)	0.000240	0.0061	0.19	6.82	0.0360	0.72	0.04	3.37
Norway (NOK)	−0.000103	0.0076	−0.14	4.34	0.0014	0.92	−0.03	2.82
New Zealand (NZD)	0.000137	0.0081	−0.36	5.11	0.0402	0.87	−0.07	2.73
Poland (PLN)	0.000002	0.0093	−0.24	6.52	0.0350	0.96	−0.08	2.68
Russia (RUB)	−0.000425	0.0087	−1.18	16.01	−0.0281	0.92	−0.10	3.14
Singapore (SGD)	0.000002	0.0033	−0.26	5.55	0.0210	0.89	−0.06	2.84
South Africa (ZAR)	−0.000399	0.0120	−0.54	6.20	−0.0187	0.97	−0.11	2.87
Sweden (SEK)	−0.000066	0.0078	−0.12	4.43	−0.0008	0.96	−0.01	2.77
Switzerland (CHF)	−0.000018	0.0066	0.04	3.79	−0.0091	0.95	0.01	2.62
Turkey (TRY)	−0.000721	0.0098	−0.64	10.59	−0.0950	0.98	−0.09	2.72
United Kingdom (GBP)	0.000021	0.0054	−0.21	5.00	0.0079	0.94	−0.02	2.70
Avg. of 18 FX	−0.000098	0.0082	−0.23	6.49	−0.0006	0.91	−0.05	2.96

Panel B. National characteristics

	Q. GDP ($B)	Q. FDI ($M)	Q. M1 (%)
Max	3,068 (eurozone)	8,335 (Brazil)	6.98 (Turkey)
Mean	440	−1,934	2.82
Min	32 (Hungary)	−27,452 (eurozone)	1.39 (Japan)
U.S.	3,621	−17,458	1.54
	M. Export ($M)	M. Import ($M)	Forward premium (%)
Max	26,304 (eurozone)	19,136 (Canada)	8.98 (Turkey)
Mean	4,478	3,302	2.89
Min	224 (Poland)	100 (Hungary)	−2.07 (Japan)

In Table 1, we report the distributions of the daily realized returns and normalized returns for the 18 foreign exchange rates as summary statistics. We calculate realized moments by following earlier studies.[11] Panel A shows the distribution of the returns. For overall currency returns, the absolute values of the means are much smaller than the standard deviations. The returns of 13 foreign exchange rates are negatively skewed. The distributions of daily realized returns for all exchange rates have fatter tails than a normal distribution because the kurtosis for each one is greater than three. However, the distributions of the normalized returns are closer to a normal distribution than those of the realized returns because the average skewness decreases in absolute value and because the kurtosis for each currency ranges from 2.6 to 3.4 after normalization.[12]

3.2. Jump predictor

To predict jump arrivals and sizes at various frequencies, we use jump predictors with intraday to quarterly frequencies. We include such a high-frequency pattern because investors can have specific rebalancing hours and this intraday analysis

[11] See, for example, (Andersen et al., 2001a, 2001b; Bollerslev et al., 2008; Amaya et al., 2015). Without a confusion, "return" $r_{\cdot,t}$ means changes in exchange rates, and "excess return" or "carry trade return" $rx_{\cdot,t}$ includes the interest rate differential. If the price process is assumed to follow Eq. (1), the daily realized return (DR) of foreign exchange rate k on day d is

$$DR_{k,d} = \sum_{t_i \in D_d} r_{k,t_i}, \quad \{t_i \mid d = [i/96] + 1, \quad 0 \le t_i \le T\} \in D_d, \quad d \in [1, 2, .., D-1, D],$$

where $r_{k,t_i} = s_{k,t_i} - s_{k,t_{i-1}}$ is the (15-min) log return (i.e., changes in the exchange rate). D_d is the time interval for day d, D is the total number of days over $[0, T]$, and t_i is the i-th observation. The normalized return (NR) is defined as the daily return divided by the daily realized standard deviation (DRSD) as follows:

$$NR_{k,d} = DR_{k,d}/DRSD_{k,d} \quad \text{with} DRSD_{k,d} = DRV_{k,d}^{1/2}, \quad \text{where} DRV_{k,d} = \sum_{t_i \in D_d} r_{k,t}^2.$$

[12] These results are consistent with the previous results for the U.S. stock market (Andersen et al., 2001a), as well as the results in a previous paper for currency markets (Andersen et al., 2001b).

can capture jump arrivals that are incurred by routine trading flows. In addition, we are motivated by the intraday volatility patterns in currency markets (Andersen and Bollerslev, 1998b) and the higher jump likelihood in the U.S. stock markets during the market opening times (Lee, 2012). Specifically, if jumps have an intraday pattern, times can be used to predict jumps. Therefore, we hypothesize that the likelihood of exchange rate jump arrivals is related to market hours. Another possible jump predictor at intraday frequencies is based on jump clustering effects. If jumps tend to be clustered, an observed (or realized) jump implies the higher likelihood of jumps in a subsequent period.

We examine whether prescheduled information releases predict jumps. As argued in the literature on jumps, news flows are the important drivers of jumps in financial markets. Therefore, the releases of economic policies and information related to exchange rates can trigger exchange rate jumps. Because our goal is to predict jumps, we need to know the times of information releases in advance. Therefore, we focus on the U.S. information where releases are prescheduled. The U.S.-oriented news is likely to be systematic because of the creation of USD exchange rates, and its release timings are usually prespecified.[13] Specifically, considering the literature, we use the prescheduled times of FOMC announcements, GDP, international trade, nonfarm payroll employment, personal income, producer price index (PPI), and consumer price index (CPI) to identify important news releases in the U.S.[14] We do not use the surprise measures of the above announcements. Because the surprise is the difference between realization and expectation, it cannot be obtained before the announcements and are not appropriate for jump predictions.

We use various sources to collect the information release times. Following the scheduled meetings of the FOMC, which occur eight times a year, FOMC announcements have been released at 14:15 Eastern Standard Time (EST) since 1994 (Lucca and Moench, 2015). To find the scheduled times of FOMC announcements, we use (Lucca and Moench, 2015) and the Federal Reserve website. The BEA releases GDP, trade, and personal income information at 8:30 EST every month. The Bureau of Labor Statistics provides nonfarm payroll employment, PPI, and CPI information at 8:30 EST every month. To make the time zones consistent, we convert these times to the GMT-based times, considering daylight saving time in the U.S. Over the entire sample period, we consider 136 FOMC, 204 GDP, 203 trade, 204 personal income, 204 nonfarm payroll employment, 204 PPI, and 204 CPI information releases.[15]

For longer-term (i.e., quarterly) analysis, we choose the national characteristics of countries that use our sample currencies. Considering the theories on exchange rate determination, we employ the following macroeconomic variables as proxies for national characteristics. GDP is adopted as a proxy for country sizes, which can affect currency returns as indicated by (Hassan, 2013). Interest rates are also important in currency returns according to (Ready et al., 2017) and are directly included in computing excess returns. In addition, interest rates can affect foreign exchange rates via covered and uncovered interest rate parities. The interest rate parity became widely known due to Keynes [see, for example (Keynes, 1923),]. Exports and imports are included because of the classical argument that an increase in the net exports of a country induces the country's currency to appreciate toward the equilibrium [see (Frenkel and Razin, 1987) for Mundell-Fleming model] and because of the possible relationships between trade and foreign exchange volatility (Baron, 1976) and currency misalignment (Dornbusch, 1996). The use of M1 is motivated by the equation of exchange (Fisher, 1911) and purchasing power parity (PPP). The amount of foreign direct investment (FDI) serves as a proxy for foreign currency demand with an investment motivation. The data for export to and import from the U.S. are obtained from the U.S. Department of Commerce. The other variables are collected from Datastream. In Panel B of Table 1, we summarize the macroeconomic variables by showing the cross-sectional maximums, means, and minimums.

3.3. Summary statistics of detected currency jumps

We apply the jump test statistics, as described in Definition 1 of Appendix A, for each foreign exchange rate. For the main analyses, we use jumps that are filtered under the 5% significance level. Considering (Huang and Tauchen, 2005; Andersen et al., 2007), we also use the 0.1% significance level and find the robust results. In Table 2, we provide summaries of the numbers of detected jumps and the realized jump sizes. To examine whether any asymmetric feature exists, we classify jumps as positive or negative.

We report the total number of jump tests applied, the number of jumps detected, and the relative frequency. For example, jumps for AUD occur 564 times (column 3), and the percentage of intraday jumps (column 4) is 0.14%. Overall, jumps arrive for 0.1%–1.4% of the time points, and the average jump frequency is approximately 0.35%. Intuitively, this frequency indicates that a jump is likely to arrive every four to five days. The currency with the most infrequent (frequent) jumps is SEK (INR). Because the number of positive jumps is similar to that of negative jumps, there is symmetry in the number of jump arrivals. In the "#J Day" and "% J Day" columns in Table 2, we report the number of days with at least one jump and the percentage of days with jumps relative to the total number of days. The percentage of jump days ranges from 7.9% for SEK to 38% for KRW, and the

[13] Information in other countries is likely to be idiosyncratic. Central banks and government agencies in our sample countries tend to announce release schedules on a daily basis without a specific time. However, we also include the realized announcements of monetary policies and (un)employment information in the eurozone and Japan. We find that this additional inclusion does not qualitatively change our results and that the effect of these additional releases is weak for the other sample countries.

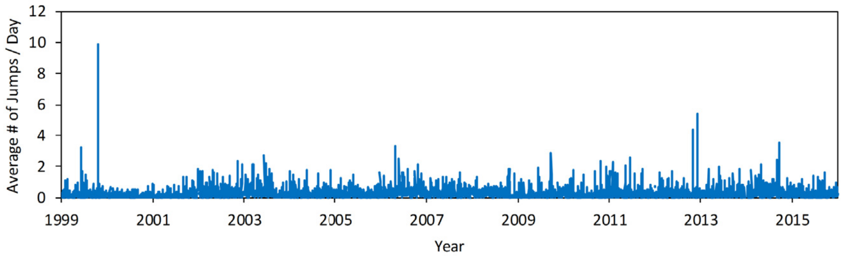
[14] See (Andersen et al., 2003b; Lahaye et al., 2011) for the list of macroeconomic news releases.

[15] Although quarterly GDP is announced as an advance (first) estimate in the first month, as a preliminary (second) estimate in the next month, and as a final (third) estimate in two months, our main analysis does not distinguish between these releases.

Table 2
Summary statistics for detected currency jumps. This table provides descriptive statistics for currency jumps detected by the test in Definition 1.c in Appendix A, which considers the intraday volatility patterns in respective currency markets. A significance level of 5% is applied for jump detection. This table reports the number of detected jumps and their size distribution for the 18 foreign exchange rates. The country names and currency codes in parentheses are listed in alphabetical order. "# Test" is the number of times that we apply jump detection tests. "# Jp" is the number of detected jumps. "% Jp" is the percentage of detected intraday jumps out of the total number of test times (# Test). "# Jup" is the number of positive jumps. "# Jdn" is the number of negative jumps. "#J Day" is the number of days when at least one jump occurs. "% J Day" is the percentage of jump days relative to the total number of tested days. This table reports jump size distributions for positive and negative jumps, separately. The last six columns list the first, second, and third quartiles of their distributions.

Country (Currency code)	# Test	# Jp	% Jp	# Jup	# Jdn	#J Day	% J Day	Positive jump			Negative jump		
								25p	50p	75p	25p	50p	75p
Australia (AUD)	404,721	564	0.14	255	309	466	10.72	0.0030	0.0038	0.0049	−0.0048	−0.0039	−0.0031
Brazil (BRL)	71,013	488	0.69	252	236	161	14.29	0.0024	0.0045	0.0068	−0.0069	−0.0047	−0.0028
Canada (CAD)	402,079	519	0.13	267	252	396	9.11	0.0015	0.0024	0.0030	−0.0030	−0.0022	−0.0015
Euro (EUR)	409,738	617	0.15	328	289	502	11.53	0.0023	0.0030	0.0038	−0.0036	−0.0030	−0.0023
Hungary (HUF)	407,309	759	0.19	365	394	462	10.58	0.0024	0.0038	0.0049	−0.0052	−0.0039	−0.0027
India (INR)	190,005	2,672	1.41	1,339	1,333	591	23.69	0.0016	0.0030	0.0057	−0.0061	−0.0033	−0.0016
Japan (JPY)	409,679	753	0.18	425	328	561	12.90	0.0023	0.0029	0.0036	−0.0036	−0.0030	−0.0022
Korea (KRW)	289,574	3,436	1.19	1,764	1,672	1,267	38.34	0.0029	0.0038	0.0049	−0.0049	−0.0038	−0.0029
Norway (NOK)	403,662	450	0.11	217	233	367	8.45	0.0027	0.0037	0.0046	−0.0043	−0.0036	−0.0026
New Zealand (NZD)	402,351	703	0.17	299	404	561	12.91	0.0036	0.0045	0.0053	−0.0053	−0.0045	−0.0034
Poland (PLN)	328,185	927	0.28	467	460	416	11.70	0.0013	0.0025	0.0039	−0.0043	−0.0026	−0.0014
Russia (RUB)	214,006	1,081	0.51	542	539	457	18.39	0.0019	0.0030	0.0047	−0.0048	−0.0029	−0.0016
Singapore (SGD)	378,539	712	0.19	334	378	484	11.35	0.0015	0.0019	0.0023	−0.0023	−0.0019	−0.0015
South Africa (ZAR)	316,214	754	0.24	374	380	444	11.64	0.0023	0.0042	0.0061	−0.0065	−0.0045	−0.0024
Sweden (SEK)	402,930	417	0.10	208	209	342	7.87	0.0030	0.0037	0.0046	−0.0044	−0.0035	−0.0026
Switzerland (CHF)	406,233	628	0.15	336	292	504	11.58	0.0025	0.0033	0.0042	−0.0043	−0.0034	−0.0024
Turkey (TRY)	242,040	694	0.29	288	406	391	13.15	0.0019	0.0035	0.0054	−0.0047	−0.0031	−0.0020
United Kingdom (GBP)	407,759	487	0.12	246	241	400	9.18	0.0020	0.0027	0.0034	−0.0034	−0.0026	−0.0020
Avg. of 18 FX	338,113	926	0.35	461	464	487	13.74	0.0023	0.0033	0.0046	−0.0046	−0.0034	−0.0023

Panel A. Number of jumps per day



Panel B. Daily sum of absolute jump size

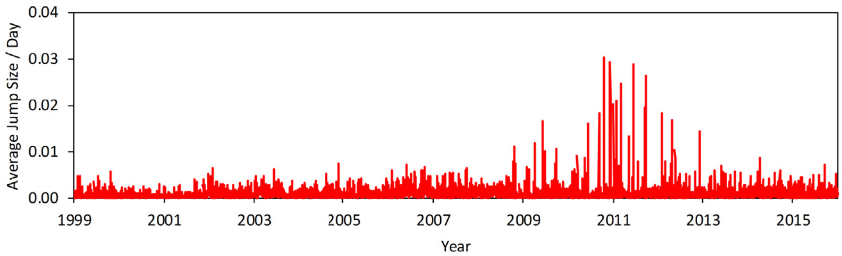


Fig. 2. Time series behavior of number & size of currency jumps. This figure illustrates the time series of the number and absolute magnitude of currency jumps per day. The figure uses the 18 foreign exchange rates sampled every 15 min over the sample period from 1999 to 2015. The currency jumps are detected by the test stated in Definition 1.c in Appendix A. Panel A shows the daily number of jumps averaged across the 18 foreign exchange rates. Panel B shows the daily sum of the absolute jump sizes.

average is 13.7%. This frequency is higher than that in the U.S. stock market.[16] The higher jump frequencies for exchange rates are consistent with (Evans, 2011; Lahaye et al., 2011; Chatrath et al., 2014). The last six columns in Table 2 provide the 25th, 50th, and 75th percentiles of positive and negative jump size distributions. Asymmetry between negative and positive jump sizes is not identified.

The time series for the jump frequencies and sizes are provided in Fig. 2. Panel A presents the time series of the daily number of jumps averaged across the 18 exchange rates; the averages appear to indicate jump clustering. Panel B demonstrates the daily sum of the absolute values of jump sizes averaged across the 18 currencies. The number and size of jumps during the U.S. recession appear to be greater than those during the expansion. According to the National Bureau of Economic Research (NBER), the recession periods are from March 2001 to November 2001 and from December 2007 to June 2009 during the whole sample period.

4. Determinants of intraday jumps

Currency markets are the most active financial markets up to intraday levels. It is important to characterize the predictable patterns and dynamics of jumps at intraday levels, in that investors can use the results for risk management by setting their rebalancing times to avoid predictable jumps. Therefore, in this section, we formally test the intraday seasonality of jump arrivals and potential currency jump clustering effects over time at intraday levels. Another way to improve currency jump prediction is to take advantage of the times of prescheduled information releases. Our analyses do not distinguish positive and negative jumps, but the separation of jump signs does not change the main idea.

4.1. Global jump arrivals

Before formally testing the existence of intraday jump patterns, we report the percentage of jumps that occur over an hour to understand the overall patterns for all currency jumps in the sample. In Table 3, the 18 foreign exchange rates are listed according to time zones. Five arrows indicate the operating hours of the major currency markets. For example, in the column denoted NZD, 3.4% of the jumps occur between 0:00 and 1:00 GMT. The other results can be interpreted similarly.

[16] According to (Bollerslev et al., 2008), there are 137 jump days from 2001 to 2005 when jumps are detected at the 5% significance level (on average, a jump arrives every 10–15 days) (Lee, 2012) reports 1.82 jumps per month.

Table 3
Deterministic intraday jump patterns in currency markets. Panel A shows the percentage of jumps that occur over one hour (e.g., 3.4% of the New Zealand Dollar's jumps arrive between 0:00 and 1:00 GMT). The currencies in the Asia-Pacific region, Europe and Africa, and America are presented in the left, middle, and right columns, respectively. The five arrow lines are added to indicate the opening hours of currency markets. The London and New York markets have two lines; the line on the right is for summer time (daylight saving) periods in London and New York, and the line on the left is for the other periods. In addition, the opening hours (based on GMT) of other global and local markets are provided in Panel B. Panel A. Intraday jump frequency and market hour Panel B. Other market hours.

Panel A. Intraday jump frequency and market hour

Hour	NZD	AUD	JPY	KRW	SGD	INR	TRY	RUB	HUF	PLN	CHF	SEK	NOK	EUR	GBP	ZAR	BRL	CAD	Avg.	Market hour
0:00	3.4	7.6	0.7	1.8	2.7	4.6	1.4	3.2	2.2	1.6	2.2	2.2	3.8	2.9	1.4	2.0	3.5	1.5	2.7	
1:00	3.7	13.3	4.4	2.4	1.8	2.4	2.7	2.0	2.8	1.0	2.5	1.7	1.3	2.8	1.6	1.6	3.1	0.6	2.9	T
2:00	4.6	3.2	3.7	2.9	3.4	2.1	2.2	3.6	1.3	0.8	1.6	1.0	1.1	1.3	1.2	2.1	1.4	1.7	2.2	O
3:00	2.1	3.9	2.9	5.3	4.5	4.2	1.7	2.1	1.6	1.0	1.8	1.0	1.3	1.3	0.8	2.8	2.9	0.6	2.3	K
4:00	3.1	5.0	3.9	3.8	4.6	4.7	6.5	5.8	2.8	1.9	1.9	3.4	2.0	2.9	2.7	3.3	2.0	0.8	3.4	Y
5:00	1.7	2.0	5.3	3.8	5.1	7.6	9.9	15.8	6.9	6.7	1.9	5.0	4.7	2.3	3.3	10.5	1.4	4.2	5.4	O
6:00	4.7	3.4	4.4	8.1	3.4	6.6	8.5	9.8	15.2	15.1	8.0	12.2	13.6	6.5	13.1	13.1	2.9	8.3	8.7	
7:00	2.1	2.7	6.2	2.7	1.8	5.4	6.9	5.5	8.7	11.5	6.2	11.8	8.7	5.8	6.6	7.2	2.3	11.0	6.3	
8:00	3.7	2.1	5.7	1.7	2.4	4.9	8.1	4.4	6.6	9.8	6.4	9.4	7.3	6.3	12.3	5.8	0.6	9.1	5.9	
9:00	3.8	4.1	5.2	1.4	3.2	4.8	4.0	3.4	5.1	6.6	4.9	2.6	8.9	5.2	7.8	4.5	1.6	5.6	4.6	L
10:00	3.6	4.8	5.6	2.1	2.5	5.0	3.7	3.4	4.6	5.7	7.6	5.5	4.7	6.6	4.5	4.6	2.5	9.1	4.8	O
11:00	3.3	4.4	4.4	2.6	4.4	5.2	3.7	3.0	5.1	4.3	6.8	4.1	3.8	6.3	4.5	4.2	11.1	9.8	5.1	N
12:00	6.0	7.3	11.0	6.5	7.7	6.0	8.8	4.3	5.7	5.1	9.2	9.4	8.0	9.1	7.0	5.7	14.8	8.5	7.8	D
13:00	3.8	3.5	5.3	5.5	4.9	6.4	4.8	2.0	3.4	2.5	7.2	3.6	4.7	7.3	5.1	1.7	11.5	4.4	4.9	O N
14:00	2.8	2.5	3.9	5.6	4.4	5.1	1.2	2.2	1.3	2.4	2.9	2.4	1.6	3.2	2.9	1.2	8.0	0.8	3.0	N E
15:00	2.8	2.5	3.5	6.3	3.1	4.2	1.0	2.3	1.6	1.5	2.7	2.2	1.3	2.3	2.3	0.5	6.6	1.0	2.6	W
16:00	3.7	3.7	4.1	5.4	4.6	3.1	1.2	2.5	2.8	2.0	2.2	2.9	2.2	2.9	6.0	1.7	4.5	2.5	3.2	
17:00	1.7	2.7	2.7	5.0	3.8	2.4	1.9	2.3	3.6	3.0	4.9	3.4	3.8	6.5	3.1	3.7	2.0	2.1	3.3	Y
18:00	7.4	9.0	7.7	5.0	6.9	2.8	4.8	4.7	5.3	5.8	8.0	8.6	6.7	9.2	7.6	7.7	2.3	8.1	6.5	O
19:00	3.6	4.4	3.6	5.6	3.9	3.2	2.7	2.7	4.0	3.1	4.1	2.9	3.1	3.9	3.5	3.7	2.5	4.4	3.6	R
20:00	6.5	1.2	1.5	6.1	3.8	2.9	3.2	4.7	3.4	1.5	1.4	1.2	0.4	0.8	0.4	2.3	2.3	1.2	2.5	K
21:00	10.1	0.9	1.6	4.6	5.6	3.4	3.3	3.7	3.0	2.9	1.4	0.7	1.1	1.1	0.4	5.0	3.7	2.3	3.1	
22:00	8.4	3.2	0.7	3.1	6.2	2.0	4.3	3.4	2.0	2.5	1.6	1.0	3.3	2.1	0.8	3.8	2.5	1.2	2.9	
23:00	3.3	2.7	2.3	2.7	5.3	1.3	3.5	2.9	1.2	1.6	2.4	2.2	2.7	1.3	1.0	1.1	4.3	1.3	2.4	

Panel B. Other market hours

Market	Hour	Market	Hour	Market	Hour
Sydney	22:00–07:00	Singapore	02:00–11:00	Istanbul	06:30–14:30
Hong Kong	01:00–10:00	Franfurt	07:00–16:00		

Overall, Table 3 demonstrates that foreign exchange jumps are more likely to occur around the times the major currency markets open and close. The jumps of a particular currency are more likely to arrive around the opening hours of the corresponding regional or closer global markets. For AUD, more than 20% of the jumps occur from 0:00 to 2:00, when the Tokyo market opens. In the case of all European and African currencies, more than 20% of the jumps arrive between 6:00 and 9:00 (the London market opens at 7:00 during the U.K. summer time periods or 8:00 during the other periods). Furthermore, when the New York market opens (i.e., 11:00 to 13:00), the currency with the highest percentage of jumps is BRL, and CAD also has relatively high jump frequency. Admittedly, there are exceptions, such as JPY and TRY. For instance, the hourly percentages of the jump arrivals for JPY are distributed in a relatively even manner compared with the others. For TRY, jumps most frequently occur from 5:00 to 7:00 when the local market in Istanbul opens (Panel B). Such a tendency can arise because of the high dependence on the local and U.S. markets.

4.2. Time-of-day effect

The strong time dependence of jump arrivals in the previous subsection indicates the potential for time-of-day effects. In this subsection, we examine whether jump arrivals are driven by market hours. Because currency markets could show jump clustering effects, similar to the U.S. stock markets, we control for the potential jump clustering effects.

We run the following jump intensity regression model for each foreign exchange rate k:

$$d\Lambda_{k,t} = \frac{1}{1+\exp(-\theta_{k,0} - \sum_{j=1}^{7}\theta_{k,j}X_{j,t} - \sum_{h=0}^{22}\delta_{k,h}T_{h,t} - \gamma_k CL_{k,t})}, \quad (4)$$

where $d\Lambda_{k,t}$ is the instantaneous jump intensity for the k-th foreign exchange rate (i.e., $k = 1, 2, \cdots, 18$) at time t. $X_{j,t}$ is an indicator that takes the value of unity when a type of information release is scheduled or zero otherwise. $T_{t,h}$ is a time indicator for time t that belongs to each trading hour between h and $h+1$, and $CL_{k,t}$ is a dummy variable for the jump clustering effects. To investigate the time-of-day effect, we set $\theta_{k,j} = 0$ and use 30 min for the clustering periods (i.e., $CL_{k,t} = I_{[\int_{t-30\ \min}^{t} dJ_{k,s}>0]}$).

This model can be applied to cojumps, which are simultaneous jumps of multiple exchange rates. For risk management and investment purposes, such application is important in that common currency jumps can influence systematic jump arrivals. We

Table 4
Time-of-day effect of currency jump arrivals. This table provides parameter estimates for the following jump intensity model for the k-th foreign exchange rate at time t: $d\Lambda_{k,t} = \frac{1}{1+\exp\left(-\theta_{k,0}-\sum_{h=0}^{22}\theta_{k,h+1}T_{t,h}-\theta_{k,24}CL_{k,t}\right)}$. The definitions and explanations of variables are provided in Subsection 4.2. This model is also applied to the same analysis for the time-of-day effect of simultaneous jump (cojump) arrivals. Odd-numbered hours are omitted for the sake of simplicity. The last row, "Avg 18", is the cross-sectional average of the coefficients across the 18 individual currencies. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cons.	0:00	2:00	4:00	6:00	8:00	10:00	12:00	14:00	16:00	18:00	20:00	22:00	Cluster
Coj2	−6.709***	−0.102	−0.087	0.419	1.500***	1.109***	0.917***	1.669***	0.694***	0.601**	1.295***	−0.338	−0.233	3.138***
z-stat	−32.96	−0.34	−0.29	1.58	6.69	4.73	3.80	7.50	2.78	2.36	5.72	−1.10	−0.77	35.47
Coj5	−9.861***	0.051	1.672	0.000	2.294**	1.649	1.437	3.121***	1.111	1.843*	3.490***	0.999	−0.041	4.179***
z-stat	−9.86	0.04	1.53		2.19	1.51	1.29	3.05	0.96	1.71	3.44	0.86	−0.03	14.28
AUD	−7.459***	1.015***	0.080	0.615*	0.229	−0.214	0.549*	0.966***	−0.083	0.329	1.162***	−0.744	0.192	3.746***
z-stat	−28.80	3.37	0.23	1.92	0.66	−0.55	1.70	3.19	−0.22	0.97	3.96	−1.63	0.55	23.25
BRL	−7.619***	−0.143	−0.991**	−0.560	−0.237	−1.680***	−0.328	0.696**	0.263	0.083	−0.421	−0.514	−0.604	6.655***
z-stat	−31.00	−0.41	−2.11	−1.38	−0.65	−2.68	−0.84	2.47	0.90	0.26	−1.09	−1.31	−1.53	64.04
CAD	−8.192***	0.123	0.251	−0.556	1.725***	1.770***	1.790***	1.723***	−0.583	0.603	1.705***	−0.171	−0.169	3.868***
z-stat	−21.81	0.24	0.50	−0.89	4.23	4.35	4.40	4.22	−0.93	1.29	4.18	−0.31	−0.31	25.33
EUR	−8.065***	0.800*	0.002	0.810*	1.555***	1.521***	1.569***	1.861***	0.858**	0.800*	1.857***	−0.471	0.490	3.479***
z-stat	−22.84	1.88	0.00	1.91	4.01	3.91	4.05	4.91	2.05	1.88	4.91	−0.83	1.09	21.92
HUF	−8.023***	0.627	0.106	0.825**	2.106***	1.460***	1.245***	1.355***	0.085	0.805**	1.315***	0.952**	0.497	4.780***
z-stat	−24.27	1.54	0.23	2.08	6.01	4.04	3.35	3.68	0.19	2.03	3.55	2.48	1.19	48.70
INR	−6.832***	0.896***	0.364*	0.868***	0.969***	0.915***	0.941***	1.015***	0.898***	0.608***	0.606***	0.521**	0.182	5.113***
z-stat	−40.67	4.47	1.68	4.49	5.12	4.78	4.94	5.32	4.66	2.98	2.93	2.48	0.82	118.05
JPY	−7.313***	−1.237**	0.440	0.490	0.580*	0.835***	0.823***	1.445***	0.461	0.537*	1.120***	−0.444	−1.223**	3.796***
z-stat	−30.16	−2.43	1.43	1.61	1.94	2.91	2.86	5.39	1.51	1.78	4.06	−1.15	−2.41	30.77
KRW	−5.819***	−0.399**	0.061	0.160	0.803***	−0.430**	−0.232	0.703***	0.516***	0.426***	0.459***	0.588***	0.011	4.054***
z-stat	−57.26	−2.43	0.42	1.17	6.53	−2.59	−1.49	5.63	4.05	3.33	3.58	4.73	0.08	100.48
NOK	−7.683***	0.342	−0.831	−0.266	1.511***	0.932***	0.545	1.052***	−0.545	−0.160	0.856**	−1.761**	0.225	3.908***
z-stat	−26.70	0.91	−1.56	−0.60	4.76	2.76	1.50	3.15	−1.15	−0.37	2.51	−2.31	0.58	22.67
NZD	−7.173***	0.157	0.412	0.084	0.473*	0.234	0.198	0.669**	−0.037	0.234	0.862***	0.737***	0.938***	3.918***
z-stat	−33.94	0.54	1.50	0.28	1.73	0.81	0.68	2.56	−0.12	0.81	3.42	2.87	3.78	30.23
PLN	−7.609***	0.042	−0.649	0.245	1.692***	1.405***	1.002***	0.933***	0.286	0.235	1.006***	−0.082	0.380	5.262***
z-stat	−30.07	0.12	−1.43	0.71	6.14	5.08	3.45	3.12	0.85	0.69	3.41	−0.22	1.15	65.27
RUB	−7.051***	0.117	0.261	0.689***	0.656***	0.334	0.148	0.291	−0.227	−0.122	0.457**	0.452**	0.171	5.470***
z-stat	−40.33	0.48	1.11	3.16	3.10	1.46	0.61	1.23	−0.84	−0.46	2.01	1.99	0.71	74.51
SGD	−6.725***	−0.658**	−0.375	−0.088	−0.446*	−0.668**	−0.667**	0.327	−0.195	−0.110	0.185	−0.289	0.111	4.805***
z-stat	−41.53	−2.32	−1.43	−0.37	−1.70	−2.29	−2.31	1.52	−0.80	−0.46	0.85	−1.15	0.50	48.40
ZAR	−8.135***	0.623	0.706	1.065***	2.053***	1.481***	1.306***	1.497***	0.118	0.512	1.761***	0.744*	1.131***	4.918***
z-stat	−23.25	1.43	1.64	2.63	5.55	3.86	3.33	3.87	0.24	1.15	4.67	1.75	2.86	52.42
SEK	−7.950***	−0.019	−0.798	0.451	1.602***	1.337***	0.889**	1.379***	0.072	0.273	1.292***	−0.584	−0.792	4.029***
z-stat	−23.82	−0.04	−1.33	1.06	4.41	3.59	2.26	3.71	0.16	0.62	3.46	−1.05	−1.32	22.51
CHF	−7.448***	−0.068	−0.399	−0.209	1.136***	0.922***	1.085***	1.281***	0.129	−0.059	1.104***	−0.510	−0.386	3.622***
z-stat	−28.85	−0.18	−0.98	−0.54	3.85	3.04	3.66	4.41	0.37	−0.16	3.74	−1.21	−0.95	24.16
TRY	−7.177***	−0.809**	−0.411	0.591**	0.670***	0.596**	0.018	0.649**	−0.989**	−0.976**	0.271	−0.015	0.177	5.274***
z-stat	−36.00	−2.19	−1.28	2.36	2.75	2.42	0.06	2.59	−2.42	−2.40	1.02	−0.05	0.65	54.84
GBP	−8.525***	0.332	0.174	0.945*	2.415***	2.361***	1.409***	1.861***	0.984*	1.703***	1.911***	−0.918	−0.218	3.751***
z-stat	−19.06	0.57	0.29	1.80	5.19	5.06	2.84	3.88	1.89	3.51	4.01	−1.10	−0.33	22.37
Avg 18	−7.489	0.097	−0.089	0.342	1.083	0.728	0.683	1.095	0.112	0.318	0.973	−0.139	0.062	4.469

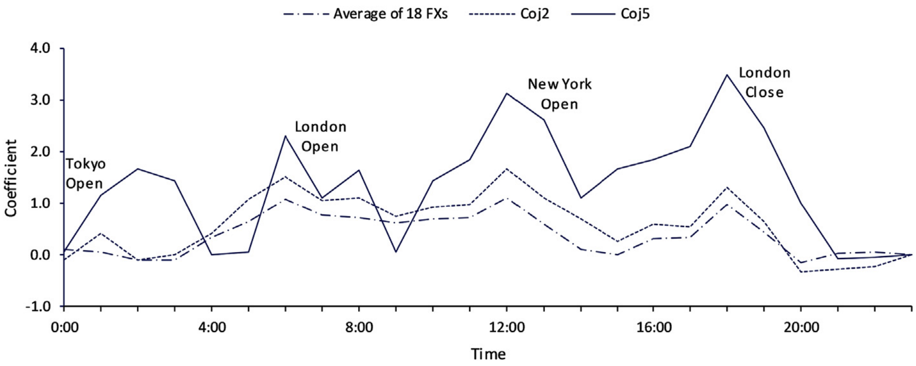


Fig. 3. Time-of-day effect: Coefficients on time indicators. This figure shows the magnitudes of the parameter estimates that are obtained from the jump intensity models reported in Table 4. The estimation is performed after controlling for jump clustering effects. The long and short dash line represents the average coefficients of the time indicators $T_{t,l}$ of the 18 foreign exchange rates. The dotted line represents the coefficient magnitudes for cojump 2, and the solid line represents the coefficient magnitudes for cojump 5. The figure includes the opening and closing hours of the global currency markets.

define "*cojump m*" as the case in which jumps simultaneously occur for at least m exchange rates during the same period. We identify 1,283 cojumps 2, 163 cojumps 5, and 29 cojumps 9. Considering the total number of jumps, we use cojumps 2 and 5 in our analysis.

The results in Table 4 indicate that jumps in all currency markets are more likely to occur from 6:00 to 12:00 GMT than at other times. This time period coincides with Tokyo market closing hours and London market opening hours. The magnitude and significance of the coefficients of the time indicators decrease at 4:00 for currencies in the Asian-Pacific region. After 6:00 GMT, jumps are more likely to occur with the exception of Asian-Pacific currencies, such as the AUD and SGD and American currencies such as the BRL. Then, the likelihood of jumps is significantly higher near the opening time of the New York market and the closing time of the London market, after which the level of significance drops rapidly. Along with the findings in the previous subsection, these results can arise because of the local market dependency of currency investments. The average coefficients of the time indicators for the 18 foreign exchange rates and the coefficients for cojumps 2 and 5 are graphically presented in Fig. 3, which also confirms that a change in the jump likelihood substantially depends on the operating hours of the major global markets.

4.3. *Jump clustering effect*

Motivated by the volatility clustering effect, we hypothesize that there is a jump clustering effect in currency markets, which suggests that a current exchange rate jump tends to increase the likelihood of subsequent jumps. This jump clustering effect can enhance jump predictions. Therefore, we investigate the existence of the jump clustering effect and examine how long this effect remains by varying the clustering periods.

We apply the same jump intensity model as in the previous subsection (i.e., Eq. (4)) to individual exchange rate jumps and cojumps. However, we use various jump clustering indicators with different clustering periods (i.e., 30 min, 1 h, 2 h, 4 h, 8 h, 16 h, and 1 day) and consider time indicators as control variables.

In Table 5, the positive coefficients on the cluster dummies indicate the existence of jump clustering for every foreign exchange rate at the 1% significance level. Accordingly, if we observe a jump for an exchange rate, we can expect that another jump for that exchange rate is more likely to occur within the clustering periods. For all the exchange rates, the clustering effect does not disappear for one day, but the strength decreases over time. The 30-min jump cluster has the strongest effect in terms of the magnitudes and z-statistics of coefficient estimates. In addition, cojumps provide results similar to those of the individual exchange rates. Because the jump clustering effect is the strongest for the 30-min period, we use the 30-min cluster when we need to control this clustering effect for our analyses.

4.4. *Informational effect on jump intensity and size*

Because macroeconomic news is often periodically released at prespecified times and such announcements can result in jumps, we investigate whether jump intensities and sizes at scheduled information release times are greater than usual ones. To examine potential increases in the likelihood of jumps that result from U.S. news announcements, we use Eq. (4) and remove the restriction of $\theta_{k,j} = 0$. For information releases (i.e., $X_{j,t}$), we use FOMC announcement, GDP, trade, personal income, nonfarm payroll employment, PPI, and CPI.[17]

[17] Although there are other scheduled information releases, we include these seven variables. First, in (Lahaye et al., 2011), the conditional probability of jump arrivals at the other information release times are negligible. Second, specifying the narrow time spans for information releases in other countries is difficult. Because of these features, other information releases are not appropriate for our research purpose.

Table 5
Jump clustering. This table includes the parameter estimates of the jump intensity model for the individual currency markets. For each foreign exchange rate k, the model estimates $d\Lambda_{k,t} = \frac{1}{1+\exp(-\theta_{k,0}-\theta_{k,l}CL_{k,l,t})}$, where $CL_{k,l,t} = I_{\left[\int_{t-l}^{t} dJ_{k,s}>0\right]}$ is a cluster dummy for the period of time l, and l = 30 min, 1 h, 2 h, 4 h, 8 h, 16 h, and 1 day. The dependent variable in this jump intensity regression model is the time series indicator of the k-th currency jump arrival $dJ_{k,t}$ within a 15-min interval. This table also reports the results for cojumps 2 and 5, which are defined as jumps that simultaneously occur with at least two and five exchange rates, respectively. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cons.	30min	Cons.	1hr	Cons.	2hr	Cons.	4hr	Cons.	8hr	Cons.	16hr	Cons.	1 day
Coj2	−6.709	3.138***	−6.726	2.817***	−6.731	2.371***	−6.753	1.934***	−6.814	1.467***	−6.884	1.083***	−6.883	0.873***
z-stat	−32.96	35.47	−33.00	35.74	−33.02	31.95	−33.10	27.39	−33.35	22.11	−33.65	17.59	−33.62	14.84
Coj5	−9.861	4.179***	−9.863	3.729***	−9.861	3.299***	−9.896	3.014***	−9.997	2.539***	−9.994	2.128***	−9.974	1.828***
z-stat	−9.86	14.28	−9.86	13.32	−9.86	11.93	−9.89	11.63	−9.98	10.68	−9.97	9.31	−9.96	8.39
AUD	−7.459	3.746***	−7.473	3.293***	−7.471	2.830***	−7.473	2.346***	−7.524	1.918***	−7.560	1.526***	−7.612	1.376***
z-stat	−28.80	23.25	−28.84	22.15	−28.86	20.68	−28.91	18.13	−29.03	16.44	−29.09	14.41	−29.16	14.00
BRL	−7.619	6.655***	−7.753	6.385***	−7.971	6.044***	−8.073	5.743***	−8.152	5.359***	−8.332	4.885***	−8.344	4.652***
z-stat	−31.00	64.04	−31.31	64.56	−32.34	63.09	−32.89	60.22	−33.40	55.67	−34.10	49.16	−34.55	45.44
CAD	−8.192	3.868***	−8.195	3.490***	−8.213	3.188***	−8.251	2.876***	−8.322	2.496***	−8.491	2.124***	−8.439	1.751***
z-stat	−21.81	25.33	−21.78	24.90	−21.81	24.78	−21.90	23.95	−22.13	22.17	−22.52	20.89	−22.39	17.92
EUR	−8.065	3.479***	−8.082	3.294***	−8.080	2.818***	−8.093	2.358***	−8.153	1.821***	−8.243	1.518***	−8.243	1.330***
z-stat	−22.84	21.92	−22.87	24.95	−22.87	22.74	−22.90	20.20	−23.04	16.40	−23.27	15.23	−23.26	14.31
HUF	−8.023	4.780***	−8.054	4.458***	−8.104	4.060***	−8.181	3.616***	−8.291	3.141***	−8.412	2.631***	−8.428	2.284***
z-stat	−24.27	48.70	−24.37	49.24	−24.43	46.92	−24.59	43.94	−24.91	39.67	−25.32	35.12	−25.41	31.15
INR	−6.832	5.113***	−7.051	4.985***	−7.497	4.834***	−7.841	4.580***	−7.968	4.327***	−8.202	4.093***	−8.410	4.023***
z-stat	−40.67	118.05	−40.81	119.53	−42.62	114.16	−44.23	103.99	−45.00	92.29	−46.13	80.21	−46.94	73.01
JPY	−7.313	3.796***	−7.315	3.397***	−7.324	2.937***	−7.357	2.536***	−7.448	2.170***	−7.568	1.781***	−7.577	1.552***
z-stat	−30.16	30.77	−30.16	30.43	−30.19	28.36	−30.36	26.54	−30.68	24.67	−31.10	21.87	−31.16	19.85
KRW	−5.819	4.054***	−5.919	3.787***	−6.093	3.505***	−6.293	3.152***	−6.397	2.768***	−6.510	2.462***	−6.712	2.417***
z-stat	−57.26	100.48	−57.64	100.03	−58.37	96.41	−59.86	88.80	−60.72	79.07	−61.33	67.05	−62.61	61.46
NOK	−7.683	3.908***	−7.699	3.578***	−7.709	3.220***	−7.707	2.752***	−7.758	2.317***	−7.841	1.861***	−7.837	1.573***
z-stat	−26.70	22.67	−26.72	23.35	−26.74	22.61	−26.72	19.97	−26.85	18.00	−27.07	15.60	−27.05	14.09
NZD	−7.173	3.918***	−7.219	3.458***	−7.277	3.019***	−7.238	2.439***	−7.215	1.968***	−7.206	1.515***	−7.205	1.319***
z-stat	−33.94	30.23	−34.15	29.11	−34.25	27.79	−34.25	23.46	−34.32	20.32	−34.34	16.85	−34.38	15.51
PLN	−7.609	5.262***	−7.708	5.036***	−7.796	4.680***	−7.865	4.276***	−8.094	3.862***	−8.225	3.349***	−8.259	3.047***
z-stat	−30.07	65.27	−30.22	66.77	−30.28	64.63	−30.42	62.18	−31.10	56.82	−31.57	49.96	−31.74	45.24
RUB	−7.051	5.470***	−7.116	5.176***	−7.207	4.819***	−7.338	4.387***	−7.391	3.917***	−7.511	3.398***	−7.617	3.091***
z-stat	−40.33	74.51	−40.20	73.65	−40.44	71.45	−41.02	67.00	−41.24	61.12	−41.56	53.70	−42.22	48.73
SGD	−6.725	4.805***	−6.776	4.397***	−6.820	3.871***	−6.792	3.300***	−6.815	2.710***	−6.855	2.203***	−6.855	1.914***
z-stat	−41.53	48.40	−41.77	48.02	−41.90	44.17	−41.85	38.77	−41.95	33.08	−42.14	27.85	−42.05	24.57
ZAR	−8.135	4.918***	−8.233	4.637***	−8.369	4.249***	−8.434	3.802***	−8.505	3.259***	−8.552	2.659***	−8.573	2.384***
z-stat	−23.25	52.42	−23.48	54.43	−23.72	52.51	−23.85	48.35	−24.01	42.24	−24.17	35.62	−24.22	32.53
SEK	−7.950	4.029***	−7.954	3.612***	−7.952	3.255***	−7.974	2.859***	−8.047	2.382***	−8.128	1.891***	−8.100	1.514***
z-stat	−23.82	22.51	−23.83	22.01	−23.84	21.72	−23.89	20.25	−24.09	17.52	−24.21	14.87	−24.23	12.59
CHF	−7.448	3.622***	−7.463	3.373***	−7.456	2.905***	−7.475	2.437***	−7.538	1.987***	−7.627	1.564***	−7.585	1.201***
z-stat	−28.85	24.16	−28.99	26.38	−28.98	24.14	−29.03	21.39	−29.28	18.74	−29.57	15.90	−29.42	12.62
TRY	−7.177	5.274***	−7.256	4.866***	−7.363	4.533***	−7.389	4.110***	−7.384	3.570***	−7.560	2.983***	−7.537	2.635***
z-stat	−36.00	54.84	−35.74	53.47	−36.10	52.11	−36.39	48.91	−36.32	43.47	−36.82	38.02	−36.75	34.59
GBP	−8.525	3.751***	−8.532	3.363***	−8.530	2.902***	−8.540	2.403***	−8.613	2.071***	−8.701	1.687***	−8.701	1.449***
z-stat	−19.06	22.37	−19.07	22.10	−19.09	20.34	−19.11	17.41	−19.26	16.39	−19.48	14.51	−19.47	13.38
Avg. 18 FX	−7.489	4.469	−7.544	4.144	−7.624	3.759	−7.684	3.332	−7.756	2.891	−7.862	2.452	−7.891	2.195

Table 6
Intraday effect of information releases on currency jump arrival. This table shows how scheduled U.S. macroeconomic news releases affect the likelihood of currency jump arrivals at the intraday level. The table reports the parameter estimates for the following jump intensity model: $d\Lambda_{k,t} = \frac{1}{1+\exp\left(-\theta_{k,0}-\sum_{j=1}^{7}\theta_{k,j}X_{j,t}-\sum_{h=0}^{22}\delta_{k,h}T_{h,t}-\gamma_k CL_{k,t}\right)}$. This table shows the results for each individual currency jump indicator for foreign exchange rate k and cojumps 2 and 5. $X_{j,t}$'s are dummy variables that take the value of one if FOMC announcements and information releases regarding GDP, trade, personal income, nonfarm payroll employment, PPI, and CPI (listed in the first row) are scheduled at time t. The other variables are explained in Subsection 4.2. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cons.	FOMC	GDP	Trade	Income	Employ	PPI	CPI
Coj2	−6.709***	4.454***	1.889***	1.199***	−0.294	3.807***	0.904*	1.980***
z-stat	−32.96	21.16	5.42	3.55	−0.45	21.75	1.77	6.07
Coj5	−9.856***	4.706***	2.426***	1.871***	0.000	4.494***	0.000	2.626***
z-stat	−9.86	13.86	3.20	3.72		12.41		4.06
AUD	−7.458***	4.076***	2.265***	1.718***	0.000	4.192***	0.000	3.230***
z-stat	−28.79	12.84	3.62	3.43		13.55		7.65
BRL	−7.621***	1.677	1.895**	0.000	0.318	1.049	1.104	0.000
z-stat	−30.97	1.00	2.56		0.48	1.32	1.10	
CAD	−8.191***	4.261***	0.000	0.695	0.377	2.618***	1.759***	1.454**
z-stat	−21.80	13.86		0.89	0.36	5.75	2.78	2.00
EUR	−8.062***	4.572***	2.207***	1.763***	0.507	3.555***	0.000	2.056***
z-stat	−22.83	16.51	4.65	4.17	0.66	12.71		4.21
HUF	−8.023***	4.044***	1.680**	0.453	0.000	4.076***	1.120	2.875***
z-stat	−24.27	9.23	2.13	0.63		13.88	1.10	6.01
INR	−6.832***	1.416**	0.750	0.000	0.486	1.717***	0.120	−0.042
z-stat	−40.67	2.03	1.34		0.98	4.06	0.19	−0.06
JPY	−7.311***	4.112***	1.876***	0.446	0.380	3.446***	1.747***	1.963***
z-stat	−30.15	13.23	3.79	0.72	0.49	12.08	3.32	4.19
KRW	−5.820***	1.913***	−0.195	0.822**	0.408	1.220***	0.220	1.121***
z-stat	−57.26	5.60	−0.36	2.30	0.94	3.29	0.43	3.08
NOK	−7.680***	4.607***	1.772**	1.622***	0.000	3.933***	2.116***	1.482*
z-stat	−26.69	12.10	2.31	3.10		11.78	3.47	1.94
NZD	−7.168***	3.950***	0.896	1.465***	0.072	3.854***	0.000	2.783***
z-stat	−33.91	12.15	0.87	2.74	0.07	12.14		6.10
PLN	−7.611***	3.538***	2.124***	0.899	0.000	4.030***	1.123	2.562***
z-stat	−30.08	6.07	3.04	1.53		13.42	1.10	4.84
RUB	−7.053***	2.609***	−0.386	0.019	1.423*	2.626***	1.074	1.786**
z-stat	−40.33	3.72	−0.33	0.02	1.84	4.99	1.06	2.43
SGD	−6.737***	3.286***	2.152***	1.600***	0.000	4.346***	0.795	1.157
z-stat	−41.49	6.96	3.63	3.52		17.17	0.82	1.44
ZAR	−8.135***	3.813***	0.768	0.870	0.000	4.084***	1.186	1.702**
z-stat	−23.25	9.18	0.67	1.24		13.23	1.15	2.08
SEK	−7.947***	4.855***	2.418***	2.566***	0.000	3.669***	0.687	1.556**
z-stat	−23.82	13.21	3.98	5.54		9.87	0.69	2.01
CHF	−7.445***	4.764***	1.901***	1.704***	−0.317	3.474***	0.000	1.466**
z-stat	−28.84	16.33	3.62	3.78	−0.30	12.30		2.41
TRY	−7.177***	4.104***	1.092	1.234*	−1.246	2.596***	0.000	0.000
z-stat	−35.99	9.43	1.41	1.75	−1.15	5.25		
GBP	−8.523***	4.647***	2.368***	1.070	0.000	4.218***	0.000	1.138
z-stat	−19.05	13.32	3.92	1.80		14.36		1.12
Avg. 18 FX	−7.489	3.680	1.421	1.053	0.134	3.261	0.725	1.572

Table 6 presents estimation results for the jump intensity model. The results show that the impact of FOMC announcements and nonfarm payroll employment is significant for 17 of the 18 currencies and for cojumps. Similarly, the coefficients of GDP news for 11 exchange rates, trade news for 8 exchange rates, and CPI news for 12 exchange rates are significant at the 5% level. Notably, FOMC announcements are the most important in terms of the magnitude of the impact and the precision of the results. In contrast, for personal income and PPI news releases, the small numbers of currencies provide positively significant coefficients. The coefficients in this table can be interpreted as changes in jump likelihood relative to times when there is no corresponding information release. For example, for AUD, the coefficient on the indicator for FOMC announcement times is 4.1, which means that the odds ratio increases $e^{4.1}(\approx 60.34)$ times when FOMC announcements are scheduled.

Separate analyses for jump size prediction can offer additional insights into the impact of jump events. Hence, we test how these information events contribute to unusual uncertainty and generate extreme volatility through jumps by running the following jump size models:

$$E(|Y_{k,t}|) = \theta_{k,0} + \sum_{j=1}^{7}\theta_{k,j}X_{j,t} + \sum_{h=0}^{22}\delta_{k,h}T_{h,t} + \gamma_{k,in}SC_{k,t}^{inner} + \gamma_{k,out}SC_{k,t}^{outer}, \tag{5}$$

where $|Y_{k,t}|$ is the absolute value of the jump size for the k-th foreign exchange rate and cojumps 2 and 5 (i.e., $k = 1, 2, \cdots, 18$, coj(2), and coj(5)) at time t. In this jump volatility model, we control for jump size clustering because we examine the impact

Table 7
Intraday effect of information releases on currency jump size. This table presents how the absolute size of currency jumps at the intraday level differs from the average when macroeconomic news releases are scheduled. We report the parameter estimates for the following jump size model that controls for the time-of-day effect and the jump size clustering effect: $E(|Y_{k,t}|) = \theta_{k,0} + \sum_{j=1}^{7} \theta_{k,j} X_{j,t} + \sum_{h=0}^{22} \delta_{k,h} T_{h,t} + \gamma_{k,in} SC_{k,t}^{inner} + \gamma_{k,out} SC_{k,t}^{outer}$. We report the results for each individual currency jump size for foreign exchange rate k, cojump 2, and cojump 5. $X_{j,t}$'s are dummy variables that take the value of one if FOMC announcements and information releases regarding GDP, trade, personal income, nonfarm payroll employment, PPI, and CPI (listed in the first row) are scheduled at time t. The other variables are explained in Subsection 4.4. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cons.	FOMC	GDP	Trade	Income	Employ	PPI	CPI
Coj2	0.040***	8.128***	0.871**	0.765**	−0.101	6.227***	0.190	0.951***
t-stat	4.18	7.99	2.59	2.23	−0.57	7.87	1.03	2.82
Coj5	0.001	3.739***	0.149	0.377*	−0.078***	1.791***	−0.040***	0.330
t-stat	0.82	5.23	1.18	1.77	−3.50	4.12	−2.85	1.58
AUD	0.024***	2.971***	0.240	0.466*	−0.095***	2.006***	−0.061***	0.694**
t-stat	3.54	4.46	1.45	1.85	−3.87	4.19	−3.32	2.57
BRL	0.040***	0.388	0.309	−0.085***	0.178	0.514	0.068	−0.127***
t-stat	3.16	0.86	1.39	−3.85	0.57	1.38	0.53	−2.71
CAD	0.004**	2.200***	−0.033***	0.054	0.014	0.552**	0.197	0.159
t-stat	2.24	4.57	−6.41	0.54	0.21	2.44	1.41	1.15
EUR	0.007**	3.569***	0.325*	0.526**	0.079	1.925***	−0.077***	0.309*
t-stat	2.47	5.63	1.82	2.18	0.57	4.57	−4.20	1.80
HUF	0.011**	3.254***	0.283	0.113	−0.107***	2.138***	0.058	0.714**
t-stat	2.31	4.24	1.23	0.58	−3.93	3.99	0.57	2.19
INR	0.039***	0.525	0.059	−0.174***	−0.114	0.440*	0.008	−0.061
t-stat	2.77	1.02	0.37	−6.97	−0.74	1.95	0.04	−0.76
JPY	0.022***	2.883***	0.283*	0.010	0.049	1.991***	0.272	0.425**
t-stat	3.90	4.99	1.78	0.08	0.39	4.73	1.60	1.97
KRW	0.109***	1.073**	0.018	0.383	0.288	0.854**	0.026	0.468*
t-stat	7.15	2.35	0.09	1.50	1.03	2.32	0.17	1.92
NZD	0.016***	2.448***	0.194	0.349	−0.097***	1.748***	0.262	0.139
t-stat	3.11	4.26	1.21	1.61	−4.17	3.82	1.47	0.94
NOK	0.029***	3.098***	0.010	0.357	−0.031	2.171***	−0.070***	0.647**
t-stat	3.30	4.29	0.15	1.55	−0.39	4.24	−3.67	2.20
PLN	0.015***	2.698***	0.396	0.212	−0.091***	1.885***	0.119	0.523*
t-stat	2.96	4.00	1.57	1.01	−3.68	3.81	0.73	1.86
RUB	0.037***	0.824*	−0.070	0.031	0.042	0.571**	0.028	0.073
t-stat	3.79	1.91	−0.92	0.25	0.69	2.11	0.52	1.05
SGD	0.027***	0.663***	0.115	0.240*	−0.071***	1.548***	0.008	0.064
t-stat	5.08	3.19	1.40	1.86	−4.05	5.33	0.22	0.89
ZAR	0.011*	4.471***	0.113	0.158	−0.191***	2.625***	0.047	0.212
t-stat	1.87	4.36	0.61	0.70	−4.07	3.80	0.48	1.08
SEK	0.012***	3.270***	0.331	0.819**	−0.096***	1.445***	0.046	0.176
t-stat	2.76	4.82	1.60	2.54	−4.41	3.60	0.38	1.01
CHF	0.015***	4.350***	0.266	0.532**	−0.052	2.290***	−0.090***	0.214
t-stat	3.33	5.73	1.55	1.98	−0.56	4.49	−4.35	1.21
TRY	0.032***	2.324***	0.325	0.278	−0.070	1.151***	−0.191***	−0.079***
t-stat	3.56	3.40	1.35	1.27	−0.39	2.85	−4.35	−4.30
GBP	0.006**	2.532***	0.210	0.164	−0.087***	1.751***	−0.030***	0.060
t-stat	1.97	4.83	1.50	1.13	−4.13	4.48	−3.14	0.68
Avg. 18 FX	0.025	2.419	0.188	0.246	−0.025	1.534	0.034	0.256

on jump sizes.[18] $SC_{k,t}^{size}$ with $size = inner, outer$ is an indicator for the 30-min jump size cluster, which takes the value of unity when at least a jump with an inner (or outer) quartile size arrives within 30 min prior to time t.

Table 7 shows the results for the jump size model. The impacts of U.S. GDP and trade information releases are positively significant for only two and five exchange rates, respectively, whereas those of FOMC announcements and nonfarm payroll employment are positively significant for 16 and 17 individual currencies and cojumps, respectively. Personal income, PPI, and CPI also provide positive and significant coefficients for only a few currencies. The larger coefficients on FOMC announcements indicate that FOMC announcements amplify instantaneous volatility through jumps. For example, the size of the AUD jump coinciding with FOMC announcements tends to be, on average, 3.0 bps larger than usual ones.

In both jump intensity and size analyses, the effects of FOMC announcements are more distinct in both magnitude and significance, whereas those of the other information releases are weaker or nearly negligible for some currencies.[19] The strong results for FOMC announcements reflect the direct effect of monetary policies on currency markets. First, FOMC decisions, including

[18] The jump size clustering issue can be studied at intraday levels, as shown in Appendix C.

[19] Although we emphasize the important contribution of FOMC announcements to exchange rate jumps, it differs from (Mueller et al., 2017; Karnaukh, 2018). Our results suggest higher likelihood of jumps on FOMC announcement days, while (Mueller et al., 2017) explain higher returns on FOMC announcement days. In addition, we use FOMC announcements as jump predictors, while (Karnaukh, 2018) uses other variables as the predictors of returns on FOMC announcement days.

decisions related to government intervention, interest rates, and money supply, are directly related to the value of the USD. Second, FOMC decisions are related to future discrete changes in the economy, while the releases of macroeconomic information are the periodic announcements of flow variables about the past.

The results in Tables 6 and 7 are robust to the additional inclusion of other information releases in other countries. We add the most influential information and economies (i.e., monetary policy announcements and (un)employment information releases in the eurozone and Japan) as independent variables. This analysis provides similar results, and the added information releases show a weak or insignificant influence on other countries' currencies. To consider whether there is a difference in response times for information releases, we aggregate intraday jumps over a longer time horizon and link the aggregated jumps to information variables, as indicated in Appendix D.

5. The effect of national characteristics

Because carry trades involve taking positions on multiple currencies, it would be useful to know whether national characteristics are significantly associated with currency jump sizes and frequencies. According to cross-sectional differences in jump sizes and frequencies across currencies, we can choose carry trade currencies with intended risk profiles and manage jump risks. For this analysis, we extend our analysis horizon to longer periods because much of the data on national characteristics are available on a quarterly basis and economic fundamentals are unlikely to change dramatically over a short period of time. Therefore, we make the time aggregations of jump arrivals and sizes over a quarter to link them to the corresponding information. Although the results in this section are based on the full sample, subsample analyses that use only the currencies of relatively large countries and/or periods beyond those associated with the U.S. recessions provide robust results.

5.1. Quarterly effect on expected number of jumps

In this subsection, we use a jump intensity regression to identify national characteristics that are more likely to influence jump arrivals. Specifically, we aggregate the number of intraday currency jumps detected in the k-th foreign exchange rates over quarter q. The aggregated jump frequency is denoted by $\int_{s\in Q_q} \mathrm{d}J_{k,s}$ with $Q_q = \{s \mid s \mathrm{belongstoquarter} q\}$. Then, we set the integrated currency jump intensity model for quarter q using the following Poisson linking function:

$$E\left(\int_{s\in Q_q} \mathrm{d}J_{k,s}\right) = \exp\left(\alpha + \sum_{l=1}^{7}\theta_l X_{k,q,l} + \sum_{i=1}^{17}\delta_i C_i + \delta_{18} REC_q\right), \tag{6}$$

where $X_{k,q,l}$ is the l-th macroeconomic variable of the country with exchange rate k during quarter q. C_i is a dummy variable to control for the fixed effects of country i, and $REC_q = I_{[\text{quarter } q \text{ belongs the recession in the U.S.}]}$ is an indicator variable to control for the time fixed effect because of business cycles. The regressors X's, national characteristics, are defined as follows:

$X_{k,q,1} = \log(GDP_{k,q}) - \log(GDP_{US,q})$ is the GDP difference between country with currency k and the U.S.[20];
$X_{k,q,2} = Export_{k,q} - Import_{k,q}$ is the trade balances (net exports) between a country with currency k and the U.S.;
$X_{k,q,3} = interest_{k,q} - interest_{US,q}$ is the quarterly average of the interest rate differential between a country with currency k and the U.S.;
$X_{k,q,4} = (\Delta M1/M1)_{k,q} - (\Delta M1/M1)_{US,q}$ is the difference in the M1 growth rates between a country with currency k and the U.S.[21];
$X_{k,q,5} = Export_{k,q} + Import_{k,q}$ is the trade volume in relation to the U.S.;
$X_{k,q,6} = FDI_{k,q} - FDI_{US,q}$ is the net FDI inflows of a country with currency k minus those of the U.S.;
and $X_{k,q,7} = X_{k,q,5}/GDP_{k,q}$ is the U.S. related trade propensity. Because every foreign exchange rate in this paper is the relative price of a currency denoted in USD, the regressors are expressed against the corresponding values in the U.S.

Columns (I) and (III) in Table 8 show the expected number of jumps that is estimated from the jump intensity models integrated over a quarter. The first column includes the results based on the contemporaneous regressors, and the third column includes those based on the one-quarter lagged regressors (i.e., $E\left(\int_{s\in Q_{q+1}} \mathrm{d}J_{k,s}\right) = \exp\left(\alpha + \sum_{l=1}^{7}\theta_l X_{k,q,l} + \sum_{i=1}^{17}\delta_i C_i + \delta_{18} REC_q\right)$). Both columns provide similar results.

The coefficients of the GDP difference are significantly negative at the 1% level, implying that the number of individual currency jumps for a quarter is expected to be lower for countries with greater GDP. This finding arises because economies with greater GDP tend to be better at diversifying shocks and, in turn, experience less extreme excess volatility in the form of individual currency jumps. Other national characteristics are not significant in both contemporaneous and predictive regressions.

5.2. Quarterly effect on expected jump sizes

In this subsection, we study the relationship between national characteristics and jump sizes. We aggregate intraday jump sizes by taking the sum of the absolute values of jump sizes in the k-th exchange rate in quarter q (i.e., $\int_{s\in Q_q} |Y_{k,s}| \mathrm{d}s$). We then set the jump size regression model over a quarter, as shown in the following panel regression model:

Table 8
Quarterly effect of national characteristics on jump frequency and size. This table reports the coefficients resulting from two types of panel regressions. The jump frequency model is $E(\int_{s\in Q_q} dJ_{k,s}) = \exp\left(\alpha + \sum_{l=1}^{7}\theta_l X_{k,q,l} + \sum_{i=1}^{17}\delta_i C_i + \delta_{18} REC_q\right)$. The jump size model estimates $E(\int_{s\in Q_q}|Y_{k,s}|ds) = \alpha + \sum_{l=1}^{7}\theta_l X_{k,q,l} + \sum_{i=1}^{17}\delta_i C_i + \delta_{18} REC_q$. The definitions and explanations of variables are provided in Section 5. The left part of this table shows a contemporaneous relationship between national characteristics and jumps, whereas the right part illustrates a predictive relationship. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Contemporaneous		Predictive	
	Frequency (I)	Size (II)	Frequency (III)	Size (IV)
GDP Diff.	−3.194 ***	−0.467 ***	−2.960***	−0.440***
t/z-stat	−9.59	−4.65	−8.87	−4.55
Interest Diff.	0.0057	0.0015	0.0037	−0.0006
t/z-stat	0.23	0.28	0.26	−0.18
M1 Diff.	−1.480	−0.194	0.849	0.083
t/z-stat	−1.32	−1.16	1.16	0.79
FDI Diff.	−0.468	−0.058	−0.356	0.010
t/z-stat	−0.42	−0.35	−0.51	0.09
Trade volume	0.005	0.001	0.007**	0.001***
t/z-stat	1.52	1.63	2.15	2.61
Trade balance	0.001	−0.004 *	−0.010	−0.004***
t/z-stat	0.05	−1.91	−0.91	−2.62
Trade propensity	−5.223 **	−0.596 **	−3.702	−0.590**
t/z-stat	−2.17	−2.07	−1.49	−2.25
Fixed effect:				
Country	O	O	O	O
Recession	O	O	O	O
Adj. R^2 (%)	57.67	44.10	56.64	43.46

$$E\left(\int_{s\in Q_q}|Y_{k,s}|ds\right) = \alpha + \sum_{l=1}^{7}\theta_l X_{k,q,l} + \sum_{i=1}^{17}\delta_i C_i + \delta_{18} REC_q, \tag{7}$$

where $X_{k,q,l}$, C_i, and REC_q are all defined as in the previous subsection.

The regression results are presented in Columns (II) and (IV) of Table 8. As in the previous subsection, the second column reports the results found with the contemporaneous regressors, whereas the fourth column presents those found with the one-quarter lagged regressors. The contemporaneous and predictive analyses provide qualitatively similar results. Jump sizes are negatively related to GDP and trade propensity, and the coefficients are significant at the 5% level.

In the regressions of this section, the macrovariables do not dramatically change on a quarter-to-quarter basis. The results mainly show the cross-sectional relationship between currency jumps and national characteristics. Moreover, our results in this section indicate that GDP can be used to predict jump frequencies and jump sizes in the subsequent quarter. These findings are valuable for longer-term investors and currency risk managers. Considering that jumps are more frequent and larger for the currencies of countries with lower GDPs, investors who are concerned about extreme losses during volatile periods can exclude the currencies of small economies in their carry trades.

6. Implications for carry trades

This section shows how investors use the results in the previous sections (i.e., jump predictability) to avoid unusual risks during extremely volatile periods and how effective the suggested approach is.

6.1. Introduction of jump-robust carry trades

One simple way to reduce exposure to a risk is to avoid taking any investment position during periods with greater expected risks. Carry trade returns are lower when jumps occur frequently and/or larger-sized jumps arrive. If investors take a zero position when jumps are expected to occur, they can enhance their investment performance. Using this intuition, we consider carry trade strategies that temporarily reduce the exposure to currency jump risks and call the strategies *jump-robust carry trades*.[22] We demonstrate how investors who take advantage of our findings can construct jump-robust carry trades.

[20] We use the log of GDP because the eurozone and the U.S. have much greater GDP than other countries.

[21] We use quarter-to-quarter money base changes for unit consistency. Money base data are provided in local currencies.

[22] The jump-robust carry trade described in this section differs from the trading strategy in (Novotný et al., 2015); the former is designed to avoid jumps, while the latter is designed to speculate on jump size clustering.

Specifically, considering the time-of-day effect, jump-robust investors hold no carry trade position around the Tokyo market closing time and the London market opening time because approximately 30% of jumps arrive from 6:00 to 10:00 GMT (Subsection 4.2). Another way of constructing jump-robust carry trades is that investors unwind their carry trade position if they observe jumps in exchange rates. Because of jump and jump size clustering effects (Subsection 4.3), a jump in the current period can predict another jump in the subsequent period. Moreover, investors can avoid times when important information (e.g., FOMC announcements and nonfarm payroll employment) is scheduled to be released (Subsection 4.4). Finally, motivated by evidence from the quarterly analysis (Section 5), investors can use only the currencies of larger countries for their carry trades (instead of all 18 currencies). By using a smaller number of currencies and holding no position at prespecified times, these investors are less likely to have a carry trade position when large jumps arrive. If unusually severe losses occur during periods of higher volatility and if the jump prediction is, on average, correct, jump-robust carry trades are expected to circumvent losses and achieve higher returns.[23] Although we suggest four approaches for the jump-robust carry trades, investors can combine some of the above approaches by considering their investment purposes and frequencies.

The jump-robust carry trades are different from the crash-neutral carry trades in (Jurek, 2014). For the crash-neutral carry trades, investors use a put option to hedge the extreme depreciation of a foreign currency, while for the jump-robust carry trades, they take a zero position if frequent and/or large jumps are predicted. The strategy in (Jurek, 2014) differs from our jump-robust strategy because its hedge depends on the market expectations of extreme depreciation implied in put options. Moreover, the jump-robust carry trade differs from the jump-modified carry trade in (Lee and Wang, 2019) in terms of the purposes and approaches. The jump-robust carry trade cuts the left tail of carry trade returns by reducing the investments during a certain period of time, while the jump-modified carry trade achieves high returns by selecting currencies with high expected returns as investment currencies. Because of such differences, the jump-robust carry trade shows lower volatility, while the jump-modified carry trade gives higher returns.[24]

6.2. *Performance of jump-robust carry trades*

In this subsection, we show the effectiveness of the jump-robust carry trades by comparing their performance with that of the regular carry trades. To be specific, we define regular carry traders as investors who invest in the five highest interest rate currencies and sell the five lowest interest rate currencies among the 18 currencies in the sample. These investors review the interest rates at 10:00 GMT every day and rebalance their carry trade portfolios. We assume daily investors to use our findings up to intraday levels. Unlike regular investors, jump-robust carry traders do not take a carry trade position if jumps are highly likely to arrive; instead, they take the same position as regular investors during other periods.

We consider jump-robust carry traders who use all approaches that are explained in the previous subsection. First, they clear their position at 6:00 GMT and initiate the next day carry trades at 10:00 GMT to avoid the frequent jumps during the market opening hours. Second, using the jump and jump size clustering, if investors observe a cojump 2, they take a zero position until the next rebalancing time (i.e., 10:00 GMT). Third, as the analysis of the information release times indicates, jump-robust investors can have a zero carry trade position for 12 h around FOMC announcements. Fourth, investors are assumed to drop the currencies of the two smallest countries from their carry trade candidates.

Fig. 4 shows the differences in the cumulative carry trade returns between regular and jump-robust carry trades. The investment horizon for Panel A is the same as the whole sample period (January 1999 to December 2015). At the end of the investment horizon, the cumulative returns of jump-robust carry trades that avoid the market opening/closing hours from 6:00 to 10:00 GMT are approximately 80% higher than those of the regular carry trade. The difference implies that this jump-robust carry trade provides approximately 4.3% higher returns per annum than the regular carry trade. Such a high return contributes to the enhancement of the Sharpe ratio from 0.5 to 1.2. Such a high Sharpe ratio implies that the jump-robust carry trade is effective in avoiding high volatility and crash periods.

The cumulative returns of jump-robust carry trades that use jump clustering effects are 24.5% higher than those of the regular strategy. However, if investors do not hold a carry trade position around FOMC announcements, the cumulative carry trade returns are lower than those of regular carry trades. This outcome results from the uniqueness of FOMC announcements.[25] Together with the strategy of avoiding the first two time periods, which are implied by the market opening/closing hours and the jump clustering effects, if investors remove the two smallest GDP currencies from their carry trade currencies, the cumulative returns increase by approximately 84% (compared with those of regular carry trades). In the jump-robust carry trades, investors earn higher cumulative returns by using more jump predictors (except for FOMC announcements). The higher cumulative returns of the jump-robust carry trades are consistent with the argument that (regular) carry trade returns are lower during more volatile and crash-like periods. The higher returns of jump-robust carry trades are statistically and economically significant.

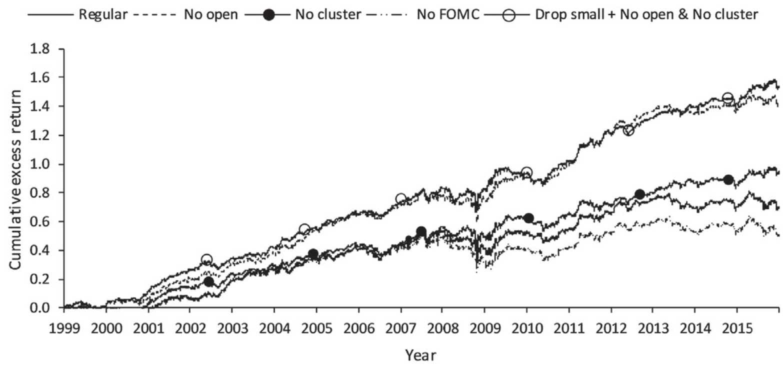
The jump-robust carry trades provide a better hedge against extreme losses than the regular carry trade. As Panel A of Table 9 shows, the skewness of the jump-robust carry trade (in the last column) is higher than that of the regular carry trade. The maximum drawdown is lower for the jump-robust carry trades. The certainty equivalent, which is computed by the approach of

[23] The losses during high-volatility periods can result from the appreciation of funding currencies. If we consider volatility to be a proxy for uncertainty, increased uncertainty motivates investors to move to safe haven currencies, such as JPY and CHF, which are usually lower interest rate currencies.

[24] See (Lee and Wang, 2019) for a numerical performance comparison of these two carry trades.

[25] Similar to the stock market, currency markets experience pre-FOMC drift (Lucca and Moench, 2015). More detailed research is left for future studies.

Panel A. Full sample analysis



Panel B. Out-of-sample analysis

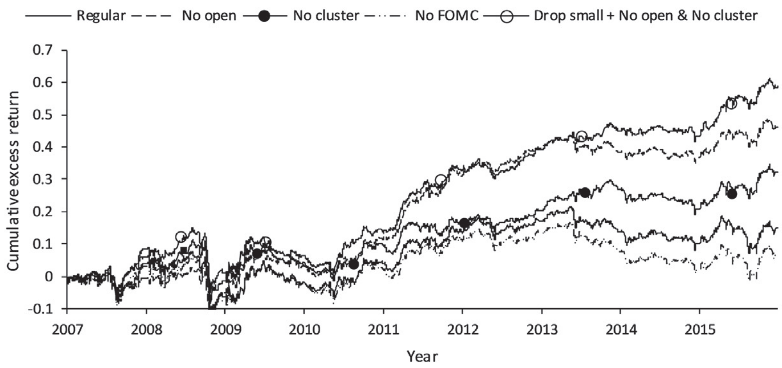


Fig. 4. Comparison of carry trade returns. This figure presents the cumulative carry trade returns of various strategies. The solid line ("Regular") is for a regular carry trade in which investors, reviewing the interest rates of the 18 countries every day, lend the five highest interest rate currencies and borrow the five lowest interest rate currencies. The investment horizon is from 1999 to 2015 for Panel A and from 2007 to 2015 for Panel B. The other lines represent the cumulative carry trade returns of the carry trades in which investors temporarily stop the (regular) carry trades during prespecified time periods. The dotted line ("No open") represents the cumulative carry trade returns for investors who do not have a carry trade position around the London market opening time or Tokyo market closing time (6:00–10:00 GMT). The solid line with solid circles ("No cluster") reflects the cumulative carry trade returns for investors who do not have a carry trade position after a cojump 2 arrives (until the next rebalancing time). The double-dotted line ("No FOMC") refers to the cumulative carry trade returns for investors who do not have a carry trade position around FOMC announcements (for 12 h). The solid line with empty circles ("Drop small + No open & No cluster") represents the cumulative carry trade returns for investors who use a smaller number of currencies for carry trades by eliminating the currencies of the two smallest GDP countries in the carry trade currencies and implement the same strategies as represented by the dotted line and the solid line with circles. The horizontal line denotes the time, and the vertical line indicates the cumulative excess returns in raw numbers.

(Janecek, 2004), shows that the jump-robust carry trades achieve higher performance than the regular carry trade. In addition, as Panel A of Fig. 5 shows, the returns of the jump-robust carry trade returns have a less dispersed distribution than those of the regular carry trade. This result implies that the jump-robust carry trade is effective in cutting the left tail in carry trade returns.

If we consider transaction costs, the differences decrease but remain significant. For the carry trade to reflect on transaction costs, we assume that investors take long positions at ask quotes and short positions at bid quotes. As Panel B of Table 9 shows, these bid-ask spreads of exchange rates decrease the returns of all carry trades in our sample. However, in terms of the relative performance, the jump-robust carry trades provide significantly higher returns and lower standard deviations than the regular carry trade. As shown in Panel B of Fig. 5, the probability density function of the jump-robust carry trades continues to have a less dispersed distribution than that of the regular carry trade. We do not consider the different lending and borrowing rates because our current comparison provides a conservative result. Inclusion of the different interest rates reduces the interest rate differentials that carry trade investors obtain as gains. The jump-robust carry trades require a shorter time for investors to hold a certain carry trade position than the regular carry trade. If we allow the different lending and borrowing legs, the return differences between the jump-robust and regular carry trades are expected to be greater than those for the current comparison. As another robustness check, when we use jumps that are detected at the 0.1% significance level, the relative performance of the carry trades does not change.

Table 9

Performance comparison of carry trades. This table reports the performances of carry trades. The full sample ranges from 1999 to 2015 for Panels A and B, and the out-of-sample covers from 2007 to 2015 for Panels C and D. “Regular” is for a regular carry trade in which investors, reviewing the interest rates of the 18 countries every day, lend the five highest interest rate currencies and borrow the five lowest interest rate currencies. “No open” is for a jump-robust carry trade in which investors do not have a carry trade position from 6:00 to 10:00 GMT. “No cluster” is for a jump-robust carry trade in which investors do not have a carry trade position after a cojump 2 arrives (until the next rebalancing time). “No FOMC” is for a jump-robust carry trade in which investors do not have a carry trade position around FOMC announcements (for 12 h). “No open + No cluster” refers to a jump-robust carry trade that combines “No open” and “No cluster” strategies. “Drop small + No open & No cluster” is a jump-robust carry trade in which investors use a smaller number of currencies for carry trades by eliminating the currencies of the two smallest GDP countries in the carry trade currencies and use “No open + No cluster” strategy. This table shows the first four central moments of returns, Sharpe ratios, maximum drawdown, and certainty equivalent (denoted in “CE”). We compute the CEs by using the approach of (Janecek, 2004), which assumes the constant relative risk aversion (CRRA). “p” is the risk aversion parameter. For Panels B and D, we assume that investors take long positions at ask quotes and short positions at bid quotes.

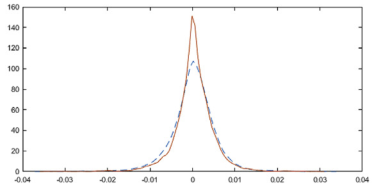
	Regular	No open	No cluster	No FOMC	Drop small + No open & No cluster
Panel A. Full sample analysis without a bid-ask spread					
Mean	4.167	8.405	5.587	3.063	9.069
Std. deviation	8.113	7.199	7.382	8.037	7.257
Skewness	−0.288	−0.254	−0.217	−0.312	−0.146
Kurtosis	6.941	7.425	8.423	7.086	8.435
Sharpe ratio	0.514	1.167	0.757	0.381	1.250
Max drawdown	7.032	1.204	5.878	6.190	1.232
CE (CRRA, p = 1)	1.141	1.977	1.332	1.075	2.184
CE (CRRA, p = 30)	1.004	1.023	1.010	1.002	1.026
CE (CRRA, p = 100)	1.001	1.007	1.003	1.001	1.008

	Regular	No open	No open + No cluster	Drop small + No open & No cluster
Panel B. Full sample analysis with a bid-ask spread				
Mean	1.236	5.102	5.422	5.498
Std. deviation	8.115	7.201	6.601	7.261
Skewness	−0.298	−0.267	−0.237	−0.157
Kurtosis	6.943	7.442	8.874	8.445
Sharpe ratio	0.152	0.708	0.821	0.757
Max drawdown	13.747	1.673	1.771	2.027
CE (CRRA, p = 1)	1.012	1.285	1.401	1.332
CE (CRRA, p = 30)	1.000	1.008	1.011	1.010
CE (CRRA, p = 100)	1.000	1.003	1.003	1.003

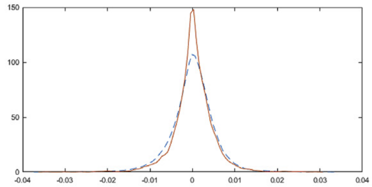
	Regular	No open	No cluster	Drop small + No open & No cluster
Panel C. Out-of-sample analysis without a bid-ask spread				
Mean	3.507	9.490	6.790	11.793
Std. deviation	10.294	9.024	9.447	9.402
Skewness	−0.340	−0.308	−0.335	−0.269
Kurtosis	5.338	5.868	6.325	6.775
Sharpe ratio	0.341	1.052	0.719	1.254
Max drawdown	5.396	7.130	4.411	6.682
CE (CRRA, p = 1)	1.060	1.739	1.295	2.196
CE (CRRA, p = 30)	1.002	1.019	1.009	1.027
CE (CRRA, p = 100)	1.001	1.006	1.003	1.008
Panel D. Out-of-sample analysis with a bid-ask spread				
Mean	0.580	5.040	2.339	5.900
Std. deviation	9.596	8.525	8.740	8.818
Skewness	−0.248	−0.227	−0.157	−0.127
Kurtosis	5.991	6.530	7.428	6.913
Sharpe ratio	0.060	0.591	0.268	0.669
Max drawdown	7.854	4.647	2.489	2.708
CE (CRRA, p = 1)	1.002	1.191	1.036	1.251
CE (CRRA, p = 30)	1.000	1.006	1.001	1.007
CE (CRRA, p = 100)	1.000	1.002	1.000	1.002

For the carry trades in our sample, we use daily interest rates that we obtain from Datastream and assume that interest rates do not change dramatically within a day because it is difficult and costly to obtain intraday interest rate or short-term government bond data for the 18 currencies over our full sample period. Because of this data limitation, our analysis of carry trade returns might show unrealistic results if extreme changes in interest rates frequently occur during periods when jump-robust carry traders take a zero position. For example, if interest rates for investment currencies substantially increase (or jump) around macroeconomic and monetary policy announcement times, our comparison may underestimate the performance of the regular carry trade. In addition, we admit that the use of daily interest rate data prevents us from distinguishing various ways of implementing carry trades (e.g., using forward and spot rates, carrying government bonds, and depositing investment currencies). For example, without firm intraday quotes, it is difficult to address the transaction costs associated with short-term trading.

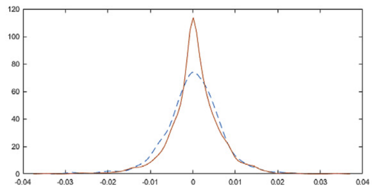
Panel A. Full sample analysis without a bid-ask spread



Panel B. Full sample analysis with a bid-ask spread



Panel C. Out-of- sample analysis without a bid-ask spread



Panel D. Out-of- sample analysis with a bid-ask spread

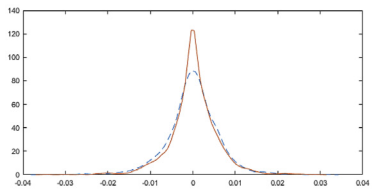


Fig. 5. Probability density function of regular and jump-robust carry trades. This figure presents the probability density functions of carry trade returns to fully show the characteristics of return distributions. For comparison, this figure uses "Regular" and "Drop small + No open & No cluster" strategies. The dashed curve is for the distribution of the regular carry trade, and the solid curve is for that of the jump-robust carry trade. The investment horizons are from 1999 to 2015 for Panels A and B and from 2007 to 2015 for Panels C and D. To consider bid-ask spread in Panels B and D, we assume that investors take long positions at ask quotes and short positions at bid quotes.

Despite the issues resulting from the limitations of the daily interest rate data, we believe that our analysis still provides meaningful implications. The assumption of stable interest rates is not extremely strong because the volatilities of interest rates and short-term bond prices are lower than those of exchange rates.[26] In addition, jumps in interest rates would not often occur during specific times or favor investment currencies. Although government bond markets can have a liquidity problem, investors can take or unwind their carry trade positions in the rebalancing times (i.e., 6:00 and 10:00 GMT) because major global financial markets such as London and Tokyo are operating; currency trading intensity is fair enough, according to the U.S. Federal Reserve; and large banks can deposit currencies by using their corresponding banking relationships. To address the liquidity concern for the feasibility of our proposed carry trades, we also construct the subsample by excluding BRL, HUF, INR, KRW, PLN, RUB, and TRY. Although investors use only relatively liquid currencies, we can still find that the jump-robust carry trades exhibit superior performance.

[26] For example (Abbassi et al., 2017), implies that changes in interest rate are at most 15 bps from 2006 to 2012, which is much smaller than the average standard deviation of changes in exchange rates (i.e., 85 bps) during the same period.

6.3. Comparison with volatility-managed portfolios

Volatility tends to be higher when jumps occur frequently and/or when jump sizes are large. Despite our formal control for intraday volatility in jump identification,[27] there can be doubt about the marginal benefit of considering the jump-robust carry trades because we already have other carry trades with reduced exposure to volatility risks. To clearly demonstrate the different benefit of using jump information, we perform comparative analyses.

Specifically, we consider two different carry trades with reduced exposure to volatility risks. First, we consider the volatility-managed portfolio proposed by (Moreira and Muir, 2017). The volatility-managed portfolios are rebalanced monthly with the current month's investment weight depending on the previous month's realized volatility level. To make the volatility-managed portfolios comparable to our jump-modified carry trades that are rebalanced daily, we modify their original definition for the volatility-managed portfolios by adjusting the investment weights over time depending on the previous day's realized volatility level. During our sample period, we find the cumulative return of volatility-managed portfolios is 44% higher than that of the regular carry trades and is 40% lower than that of the jump-robust carry trades with the highest cumulative returns.

The second strategy we consider for comparison involves taking into account the intraday volatility pattern in currency markets. In particular, we consider investors who take a zero position during periods when volatility is expected to be higher. Previous studies on intraday volatility patterns, such as (Andersen and Bollerslev, 1998b) and others, indicate that volatility in currency markets is the highest from 12:00 to 16:00 GMT. Investors can avoid taking any positions during the highly volatile periods by rebalancing their carry trade portfolios at 16:00 and unwinding their positions the next day at 12:00. This volatility-based strategy provides lower returns than the jump-robust carry trade strategy.

The difference between the performances of the jump-robust and volatility-based carry trades indicates that jumps and volatility can capture different information. However, these two strategies are not exclusive to one another. For example, investors can determine their investment weights over time by considering the current realized volatility (as indicated by the volatility-managed portfolios) and set their rebalance times and carry trade currencies by avoiding predictable jumps (as indicated by the jump-robust carry trades).

6.4. Out-of-sample performance

The jump-robust carry trades can be implemented on an ex ante basis. Investors can specify in advance the rules to circumvent jump risks in carry trades because the information relevant for the prediction of jump sizes and frequencies is available before investors make trades. As the previous sections show, market opening/closing hours are fixed and deterministic. Most economic news releases are prescheduled, and the release times are known in advance. To take advantage of the jump clustering effect, carry traders can rebalance their portfolios after observing previous jumps. If they aim to include the currencies of larger countries, GDP information from the previous quarter can be used. Therefore, with the prespecified rules, investors can control their exposure to the left tail risk and hedge against extreme losses to some extent with the large jump-triggering information found in our analyses.

Despite the aforementioned advantage in the implementation with the prespecified rules, there can be concerns regarding the out-of-sample performance of our proposed trading strategy. To demonstrate that our results continue to hold, we split the whole sample period into the first and second half period samples (i.e., the first period from 1999 to 2006 and the second period from 2007 to 2015). We perform the same analyses as those in the previous sections to confirm the results on jump predictability for the first half period sample and analyze the performance of the jump-robust carry trades using the second half period sample.

Using the first half period sample, we find that the results are qualitatively similar to those using the full sample. We also check whether the second half period sample provides similar implications for the jump-robust carry trades. Panel B of Fig. 4 shows the cumulative returns of the same carry trades as in the previous subsection. The only difference is that the carry trades in this subsection adopt the second half period sample (instead of the whole sample). As indicated in Panel B of Fig. 4, we confirm that the out-of-sample performance is consistent with our main results, which show that the jump-robust carry trades provide higher returns than regular carry trades. Specifically, during the latter sample period, the cumulative returns of the jump-robust carry trades that exclude small countries' currencies, take a zero position during the market opening hours, and avoid the jump clustering effects are 44% higher than those of the regular carry trades. Other jump-robust carry trades also have significantly higher returns (one exception is the jump-robust carry trades that take a zero position around FOMC announcements as in the previous subsection).

For a numerical performance comparison, we report the first four central moments, Sharpe ratios, maximum drawdown, and certainty equivalents of the regular and jump-robust carry trades in Panel C of Table 9. During the latter sample period, the jump-robust carry trades provide approximately 8.3% higher returns and a 0.8% lower standard deviation (per annum) than the regular carry trades. The certainty equivalent of the jump-robust carry trade is higher than that of the regular carry trade. Because of the exceptional period, the fourth quarter of 2007, the maximum drawdown of the jump-robust carry trade is marginally higher than that of the regular carry trade. However, as Panel C of Fig. 5 shows, the return distribution of the jump-robust carry trade is clearly less dispersed than that of the regular carry trade. As in Panel D of Table 9 and Panel D of Fig. 5, we also find consistent

[27] The jump test that we employ essentially scales down realized returns with instantaneous volatility to control for their magnitudes.

results when we consider the bid-ask spreads of exchange rates. As acknowledged for the in-sample tests in Subsection 6.2, because of our intraday quote data limitation, we use daily interest rate data from Datastream, which can underestimate the effect of transaction costs in the out-of-sample tests as well.

7. Conclusion

We study currency jumps and their relationship with information from the real economy to provide implications for currency risk management. We first provide a general jump regression method to estimate the important determinants of jump sizes and intensities. We then exploit rich information from data sampled up to intraday levels to identify relevant jump determinants over an arbitrary horizon through various regression models. Specifically, we use 18 intraday exchange rate data from 1999 to 2015 and jump predictors such as market hours, prescheduled information releases, and macrovariables.

Using the generalized approach and comprehensive data, we provide a variety of novel evidence about jump predictions. We first characterize the distinct intraday pattern of currency jump arrivals in relation to deterministic trading mechanisms. Notably, jumps are more likely to occur around the opening hours of the major global markets. We also find a jump clustering effect in currency jumps. Furthermore, we present similar time-of-day and clustering effects for cojumps.

We examine the effects of U.S. information releases on currency jumps after controlling for the deterministic intraday patterns. The effects of FOMC announcements are the most significant for all exchange rates examined. Nonfarm payroll employment information releases are also associated with greater jump frequencies and sizes. Aggregating currency jumps over a quarter, we also discover that jump risks are significantly related to contemporaneous and lagged national economic fundamentals. The expected frequencies and absolute sizes of exchange rate jumps over a quarter are negatively related to the GDP of the country with the corresponding currency.

Using these findings, carry trade investors who intend to mitigate the extreme losses of carry trades during extremely volatile periods can construct jump-robust carry trades. The jump-robust carry trades show higher returns and lower standard deviations than the regular carry trade, and their certainty equivalents and skewness are also larger. Therefore, investors and risk managers can better predict the unusually high volatility of exchange rates by elucidating the fundamental patterns of foreign exchange jumps and their relationships with macroeconomic variables and use predictable jumps for their currency investments.

Appendix A. Theory of inference for jump regression

In this appendix, we define and justify our inference method. Currency market dynamics are specified by continuous-time models. To better approximate their true dynamics, it is ideal to take advantage of high-frequency data. The general intuition behind the jump regression is that as long as true jumps in continuous time are correctly identified using high-frequency data, one can discover the true relationship between jumps (arrivals and sizes) and information variables.

Assuming instantaneous changes in exchange rates are described by the continuous-time process in Eq. (1), we identify jumps by applying the jump test statistics as stated in Definition 1.c below. This approach allows us to incorporate intraday volatility patterns into the test of (Lee and Mykland, 2008) for jump detection and to make the results robust to a potential distortion due to the intraday volatility patterns in currency markets. For our jump regression method to be valid, it is important to correctly identify jump arrival times and their sizes. Our estimated jumps show necessary properties. In essence, for every discrete time interval during which we do (or do not) have a jump, we do (or do not) detect the jump by conducting our jump tests [see (Lee, 2012) for more details]. Jump sizes can be estimated with the returns from those discrete time intervals with jumps because the absolute magnitudes of those returns are dominated mainly by the jump part in the limit.

These asymptotic properties hold even after taking into account the intraday volatility pattern and its associated estimation errors. Theoretically, in the presence of jumps, the jump magnitude dominates the volatility component including the estimation error for the intraday volatility adjustment factor in the limit, and thus, the jump test statistics will fall into our rejection region, which is based on the extreme value distribution (i.e., Gumbel distribution). On the other hand, in the absence of jumps, this jump test statistic is bounded in the limit. Hence, as $\Delta t \to 0$ and $T \to \infty$, the probability that this test correctly classifies times with jumps (and no jump) approaches 1. We also confirm the finite sample performance of this theory in Appendix B. Therefore, as long as we use high-frequency data over a sufficiently long sample period, it is fine to approximate the unobserved true jumps with the estimated jumps for both arrival times and sizes.

Using the estimated jumps, econometricians can establish a jump regression model and estimate parameters by minimizing the estimating function. To provide a more concrete description of our approach, we define the following three estimating functions.

Definition 1. Three estimating functions

1.a. True Estimating Function

$$\widetilde{G(\theta \mid \mathcal{F}_T)} = \widetilde{g}(\theta \mid dJ_{k,s}, Y_{k,s}, X_{k,s}, s \in [0, T]). \tag{A1}$$

1.b. Full Estimating Function

$$G_n(\theta \mid \mathcal{F}_T) = g_n(\theta \mid dJ_{k,s_i}, Y_{k,s_i}, X_{k,s_i}, s_i \in [t_0 = 0, t_1, \dots, t_n = T]). \tag{A2}$$

1.c. Partial Estimating Function

$$G_n\widehat{(\theta \mid \boldsymbol{\mathcal{F}}_T)} = g_n(\theta \mid \widehat{dJ}_{k,s_i}, \widehat{Y}_{k,s_i}, \widehat{X}_{k,s_i}, s_i \in [t_0 = 0, t_1, \ldots, t_n = T]), \tag{A3}$$

where $\widehat{Y}_{k,t_i} = (s_{k,t_i} - s_{k,t_{i-1}}) I_{[\boldsymbol{\mathcal{L}}(k,i) \in \boldsymbol{\mathcal{R}}_n(\alpha_n)]}$, $\widehat{dJ}_{k,t_i} = I_{[\boldsymbol{\mathcal{L}}(k,i) \in \boldsymbol{\mathcal{R}}_n(\alpha_n)]}$, with the foreign currency jump detection test statistic $\boldsymbol{\mathcal{L}}(k,i) \equiv \frac{s_{k,t_i} - s_{k,t_{i-1}}}{\widehat{\sigma_{k,t_i}} \widehat{f_{k,t_i}} \sqrt{\Delta t}}$, rejection region for the jump detection test $\boldsymbol{\mathcal{R}}_n(\alpha_n)$, and overall error rate α_n. $\widehat{X}_{k,s_i}$ is the information variable observed at available discrete times. The instantaneous volatility estimator $\widehat{\sigma_{k,t_i}}$ can be scaled to jump-robust volatility estimators.[28] $\widehat{f}_{k,t_i}$ is an intraday volatility adjustment factor, which can be estimated using data from the same time across different trading days.

The true estimating function defined in Definition 1.a describes the true relationship in continuous time between jumps and information. In practice, it is not available for real applications but is usually approximated by its discrete time version such as the full estimating function defined in Definition 1.b. Because we cannot directly observe the jump arrivals or sizes at discrete times (only with return data), we estimate them with our jump tests and use the estimated jumps in setting up the partial estimating function as defined in Definition 1.c, which one can make inference with. Essentially, we approximate the true relationship in continuous time with the partial estimating function based on discrete observations. This approximation is valid because the probability that the partial estimating function and the true estimating function are different from each other becomes negligible in the limit. In other words, those two estimating functions are asymptotically equivalent. Given this asymptotic equivalence, we can estimate the relationship between estimated jumps and information variables and expect this estimated relationship to be consistent with the true relationship in continuous time.

We now present the main theoretical results to support our inference using the jump regressions as follows.

Theorem 1. Inference for Jump Regressions in Continuous Time

Suppose that Assumption H stated below holds. Let X_t be the vector of the information variables that could affect jump size or jump intensity in currency markets. Furthermore, let $\widehat{\theta}_n$ be the optimal estimate based on the partial estimating function, such that $G_n\widehat{(\theta \mid \boldsymbol{\mathcal{F}}_T)} = 0$, as outlined in Definition 1. In addition, let θ_0 be the true parameter, such that $G\widetilde{(\theta \mid \boldsymbol{\mathcal{F}}_T)} = 0$. Then, the following results hold as $\Delta t \to 0$ and $T \to \infty$.

A. $\widehat{\theta}_n$ is a θ_0-consistent estimator, which means that the estimate $\widehat{\theta}_n$ converges to the true value θ_0.

B. $\widehat{\theta}_n$ exhibits asymptotic normality, such that:

$$\sqrt{n}(\widehat{\theta}_n - \theta_0) \xrightarrow{\mathcal{D}} -W_0(\theta_0)^{-1} Z, \tag{A4}$$

where $W_0(\theta)$ is the limit of the matrix of the first-order partial derivatives of the estimating function $G_n\widehat{(\theta \mid \boldsymbol{\mathcal{F}}_T)}$, evaluated at θ_0. Z is a normal random variable with mean zero and covariance matrix V.

C. $X_{k,t,p'}$ is selected as an important information variable for the jump size or intensity in the k-th currency markets if $Prob\left(z > \frac{\widehat{\theta}_{k,p',n}}{SE(\widehat{\theta}_{k,p',n})}\right) < \beta$, where β is the chosen significance level and z is a standard normal random variable. The standard error $SE(\widehat{\theta}_{k,p',n})$ can be found from B stated above.

Theorem 1 justifies our significance tests on the parameters that relate jump sizes (or arrivals) and information variables in various functional forms. For example, if we aim to study the relation between jump arrivals and some information variables available only at low frequencies, our estimated intraday jumps can be transformed in the estimating function through $g_n(\cdot)$ in Definition 1.c. Specifically, we can aggregate estimated jumps by summing jump arrivals over the longer period of time to have the same lower frequency as that for information variables. With aggregated jumps, usual regression analyses can be performed to identify the relationship. This solution is new and general to accommodate the applications of generalized linear models or nonlinear regression models for panel data, among others. Importantly, this approach allows the linking of intraday jumps to information variables available at lower sampling frequencies. Because the estimation error for the adjustment factor f_{k,t_i} does not affect the asymptotic behavior of jump test statistics in the jump detection stage, it does not matter for the limiting distribution of the regression coefficient estimates, as stated in Theorem 1.

For Theorem 1, we impose the following assumptions, which are general enough to include most of the pricing models in the literature.

Assumption H for Theorem 1.

H.1. For each currency k, we assume that drift $\mu_{k,t}$, volatility $\sigma_{k,t}$, and intraday adjustment factor $f_{k,t}$ are all bounded and can be time-varying and stochastic.

H.2. Let θ_0 be the true parameter value under the true probability measure in continuous time. There is a connected neighborhood Θ_0 of θ_0 in which the linking functions γ_{size} (or $\gamma_{intensity}$) for the regression models are continuous and differentiable to ensure that $G_n(\theta)$ is continuously differentiable for all n, and there is a function W, such that:

[28] It can be based on a bipower variation or truncated power variation, among others.

$$\sup_{\theta\in\Theta_0} \|\partial_{\theta^T} G_n(\theta) - W(\theta)\| \xrightarrow{P} 0,$$

where $\partial_{\theta^T} G_n(\theta)$ the $p \times p$-matrix, with the ij-th entry is $\partial_{\theta_j} G_n(\theta)_i$.

H.3. $G_n(\theta_0) \xrightarrow{P} 0$ and $\sqrt{n}G_n(\theta_0) \xrightarrow{\mathcal{D}} Z$ with Z being a nondegenerate random variable.

H.4. The matrix $W(\theta_0)$ is invertible with probability 1.

Proof of Theorem 1. We impose Assumption H, which is a modified version of the conditions for Theorems 1.58 and 1.60 of (Sørensen, 2012) for the asymptotic properties of parameter estimates for our purpose. To prove the results stated in our theorem, it is sufficient to verify that our Assumption H is satisfied not only for $G_n(\theta)$ but also for $\widehat{G_n(\theta)}$. It is straightforward to observe that $G_n(\theta \mid \boldsymbol{\mathcal{F}}_T)$ and $G_n\widehat{(\theta \mid \boldsymbol{\mathcal{F}}_T)}$ are asymptotically equivalent. Therefore, $G_n(\theta \mid \boldsymbol{\mathcal{F}}_T) \xrightarrow{P} 0$ implies $G_n\widehat{(\theta \mid \boldsymbol{\mathcal{F}}_T)} \xrightarrow{P} 0 = G\widehat{(\theta \mid \boldsymbol{\mathcal{F}}_T)}$. Moreover, by combining the Slutsky Theorem in (Ferguson, 1996), we can also state that $\sqrt{n}\widehat{G_n(\theta)} \xrightarrow{\mathcal{D}} Z$, which causes H.3 to be satisfied. For H.2, notice that:

$$\sup_{\theta\in M} \|\partial_{\theta^T}\widehat{G_n(\theta)} - W(\theta)\| \le \sup_{\theta\in M}\|\partial_{\theta^T}\widehat{G_n(\theta)} - \partial_{\theta^T} G_n(\theta)\| + \sup_{\theta\in M}\|\partial_{\theta^T} G_n(\theta) - W(\theta)\| \xrightarrow{P} 0.$$

The second term is simply due to the condition imposed, and the first term is due to a similar argument used in Proposition 1 in (Lee, 2012). For H.4, note that the determinants of $\widehat{W}(\theta)$ are positive and, in turn, invertible because the determinant of $W(\theta)$ is positive and $\widehat{W}(\theta)$ takes each component that is asymptotically equivalent to the corresponding component of $\partial_{\theta^T} G_n(\theta)$, making the differences negligible, as n goes to ∞.

Appendix B. Intraday patterns of volatility and jumps

Motivated by (Theodosiou and Zikes, 2011), we show that our jump detection approach with the adjustment factor of intraday volatilities can distinguish jumps from high volatility patterns. To this end, we perform the following Monte Carlo simulation study.

We simulate returns based on Eq. (1). Following (Andersen and Bollerslev, 1998a; Boudt et al., 2011), we simulate daily variance with the generalized autoregressive conditional heteroscedasticity (GARCH) model, $\mathrm{d}\sigma^2_{k,t} = -\psi_{k,1}(\sigma^2_{k,t} - \overline{\sigma_k}^2)\mathrm{d}t + \psi_{k,2}\sigma^2_{k,t}\mathrm{d}B_{k,t}$, where $\mathrm{d}\sigma^2_{k,t}$ is the instantaneous variance, and $\mathrm{d}B_{k,t}$ is the Brownian motion. For the parameter estimates (i.e., $\psi_{k,\cdot}$) for volatility simulation, we use six representative exchange rates among our intraday exchange rate data (i.e., the Australian dollar (AUD), Canadian dollar (CAD), euro (EUR), Japanese yen (JPY), Swiss franc (CHF), and British pound (GBP)). With the 15-min interval data, we impose intraday volatility patterns for each currency by using the volatility levels during a 15-min interval relative to the unconditional volatility. We apply the same method to the six currencies and the 96 15-min intervals (per day). To simulate jumps with an intraday pattern, we use Tables 2 and 3. Using the overall probability of jumps for each currency (% Jp in Table 2), we generate indicators for random jumps. Taking advantage of the relative frequencies in Table 3, we set the different jump probabilities for every hour (i.e., $Pr(Jump)_{k,m} = 24/100 \cdot (\mathrm{Averagejumpprobability})_k \cdot (\mathrm{Percentageofhourlyjumpprobability})_{k,m}$, where m denotes the m-th 15-min interval a day.).

By combining the stochastic volatilities and jumps, we simulate 15-min returns for 3,005 days (i.e., 96 returns per day × 3,005 days). In this simulation, we use the latter 3,000 days for one run of the simulation, considering that our sample is composed of 1,000–4,400 days. We simulate additional five-day returns because we set a burn-in period and need lagged observations (about two days) to apply our jump detection approach. Using these 3,000-day returns, we compare the realized intraday volatilities and jumps and perform statistical tests. We iterate the above simulation 2,000 times, then summarize the results in Table B.1.

First, we investigate whether the diurnal patterns of volatilities that are estimated from the simulated data are consistent with the imposed patterns in the model. For each run of the simulation (composed of 3,000 days), we perform the test at the 1% significance level. As the first row of Table B.1 shows, we find that 99.2%–100% of simulation runs indicate that the estimated volatility patterns are not different from the imposed volatility patterns. Then, we examine whether the intraday jump patterns that are estimated from the simulated data are in line with the imposed patterns. As the second row of Table B.1 shows, 95.6%–100% of simulation runs result in patterns that do not differ from the imposed patterns. These outcomes indicate that our jump detection method can distinguish intraday jump patterns from intraday volatility patterns with fairly low error rates.

We also investigate how many jumps are spuriously detected. The spurious detection is defined as the case in which a jump is detected by our filtering approach even though a jump is not imposed. Such a spurious detection might be driven by a high volatility. However, as the last row of Table B.1 indicates, we find that more than 99% of detected jumps are imposed jumps (i.e., the percentage of spurious detection is lower than 1%).

Table B.1
Simulation result for intraday patterns of volatilities and jumps.

	AUD	CAD	EUR	JPY	CHF	GBP
%correctly matching volatility pattern among 2,000 simulations	99.800	99.200	100.000	100.000	99.600	99.600
% correctly matching jump arrival pattern among 2,000 simulations	100.000	99.800	99.200	99.800	97.400	95.600
Overall performance of jump detection % of correctly detected jumps	99.946	99.909	99.943	99.970	99.925	99.921

Appendix C. Jump size clustering in foreign currency markets

In this Appendix, we present evidence that similar-sized jumps are clustered over time (i.e., jump size clustering effect). To consider different jump sizes, jumps are categorized into two groups according to their jump magnitudes. Larger jumps are called outer quartile jumps (OQJs) and smaller jumps are called inner quartile jumps (IQJs). Specifically, OQJs are jumps with sizes exceeding the upper and lower quartiles of the jump size distribution. IQJs are jumps within the upper and lower quartiles.

To estimate the jump size clustering effect, we use the following jump intensity models: $d\Lambda^{size}_{k,t} = \frac{1}{1+\exp(-\theta_{k,0}-\sum_{l=1}^{5}\theta_{k,l}SC^{size}_{k,l,t}-\sum_{h=0}^{22}\theta_{k,h+6}T_{k,h})}$, where $d\Lambda^{size}_{k,t}$ with $size = outer$, $inner$ is the jump intensity for each group, $SC^{size}_{k,1,t} = I_{[\int_{t-30\,\mathrm{min}}^{t} dJ^{size}_{k,s}>0]}$ with $dJ^{outer}_{k,s} = I_{[Y_{k,s}\in OQJ]}$ and $dJ^{inner}_{k,s} = I_{[Y_{k,s}\in IQJ]}$ is a jump size cluster indicator for 30 min, $SC^{size}_{k,2,t} = I_{[\int_{t-2\mathrm{hours}}^{t-30\,\mathrm{min}} dJ^{size}_{k,s}>0]}$ is a jump size cluster indicator for two hours, $SC^{size}_{k,3,t} = I_{[\int_{t-8\mathrm{hours}}^{t-2\mathrm{hours}} dJ^{size}_{k,s}>0]}$ is a jump size cluster indicator for eight hours, $SC^{size}_{k,4,t} = I_{[\int_{t-16\mathrm{hours}}^{t-8\mathrm{hours}} dJ^{size}_{k,s}>0]}$ is a jump size cluster indicator for 16 h, $SC^{size}_{k,5,t} = I_{[\int_{t-1\mathrm{day}}^{t-16\mathrm{hours}} dJ^{size}_{k,s}>0]}$ is a jump size cluster indicator for one day, and $T_{k,h}$ is a time dummy to control for the time-of-day effect. Table C.1 reports the estimation results for selected exchange rates. To save space, we provide the results for cojumps and selected currencies. For each currency (and cojump), this table shows the information about jump size distributions in the columns on the left and the estimation results in the columns on the right.

The overall results indicate that IQJ size clustering tends to last longer than OQJ size clustering. For example, both IQJs and OQJs cluster for at least 30 min in all the currency markets. IQJs continue to cluster for 8 h for 18 currencies, whereas OQJ clustering lasts for 11 currencies.

Table C.1
Jump size clustering in foreign currency markets. This table shows the distributions of jump sizes and jump size clustering effects. *z*-stats appear beneath the coefficients. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Min	25p	75p	Max	Inner Quartile Jump					Outer Quartile Jump				
					30 min	2 h	8 h	16 h	1 day	30 min	2 h	8 h	16 h	1 day
Coj 2	−0.0111	−0.0031	0.0032	0.0084	2.812***	1.780***	0.501***	0.416**	0.129	3.062***	1.359***	0.313	−0.220	0.409**
					15.74	10.09	2.77	2.18	0.65	19.67	7.01	1.64	−0.81	2.31
Coj 5	−0.0055	−0.0036	0.0039	0.0058	4.221***	1.463	1.677**	0.790	0.820	3.937***	0.000***	2.172***	0.000***	0.810
					7.44	1.25	2.11	0.77	0.81	7.31		3.70		0.81
AUD	−0.0061	−0.0040	0.0036	0.0061	4.042***	1.360***	1.442***	0.815***	1.002***	3.527***	1.770***	0.012	0.653*	1.049***
					14.33	2.95	5.19	2.60	3.42	11.75	4.36	0.02	1.90	3.60
CAD	−0.0042	−0.0021	0.0024	0.0043	3.919***	2.245***	2.135***	0.462	0.859**	3.219***	2.073***	0.511	0.796*	0.290
					15.25	7.57	8.02	0.90	2.24	9.82	5.73	1.11	1.91	0.69
EUR	−0.0046	−0.0029	0.0030	0.0046	3.292***	2.516***	0.697*	1.156***	0.451	3.259***	2.007***	−0.297	0.666*	0.648**
					10.64	8.70	1.91	4.05	1.22	11.02	6.22	−0.51	1.74	2.10
JPY	−0.0048	−0.0027	0.0030	0.0048	4.106***	1.398***	1.596***	0.872***	0.785***	3.263***	1.476***	1.329***	0.215	0.402
					19.08	4.22	7.54	3.48	3.16	12.43	4.59	6.09	0.62	1.36
NZD	−0.0060	−0.0036	0.0036	0.0060	3.483***	2.911***	0.798*	0.433	0.641	3.638***	1.831***	0.616	0.699	0.952***
					8.87	7.72	1.72	0.71	1.25	10.92	3.86	1.22	1.55	2.61
SGD	−0.0030	−0.0019	0.0018	0.0030	4.245***	1.954***	1.129***	0.560*	0.800***	4.691***	1.792***	0.954***	0.559*	0.634**
					15.98	5.74	4.31	1.74	3.02	21.55	5.71	3.48	1.69	2.01
ZAR	−0.0095	−0.0045	0.0042	0.0093	3.564***	2.728***	1.553***	1.141***	0.794**	4.658***	0.978***	0.966***	0.972***	0.976***
					11.99	9.21	6.22	3.51	2.49	22.72	2.77	3.70	4.29	4.03
SEK	−0.0058	−0.0035	0.0035	0.0057	3.970***	2.217***	1.328***	0.678	0.713	3.307***	1.038	0.936**	0.046	−0.321
					9.26	4.54	3.23	1.15	1.39	8.09	1.43	2.03	0.07	−0.45
CHF	−0.0054	−0.0032	0.0034	0.0054	3.262***	2.639***	1.251***	0.959***	−0.249	3.276***	1.782***	−0.052	0.115	0.119
					12.20	10.46	4.80	3.05	−0.49	11.45	5.20	−0.10	0.23	0.31
GBP	−0.0042	−0.0025	0.0026	0.0042	3.714***	1.874***	1.781***	0.842*	0.688*	3.586***	1.312**	0.120	0.291	0.729**
					12.40	4.91	5.74	1.94	1.73	11.44	2.46	0.21	0.50	2.01

Appendix D. Daily effect of information releases on expected number and size of jumps

The macroeconomic news releases that we study are prescheduled, and the timing of the news announcements is known to investors in advance. Depending on market expectations about the announcements, transactions can occur before the actual release times. Conversely, interpretations of the news can be delayed, and the market may not react immediately (Evans and Lyons, 2005, 2008). In addition, because of the jump clustering effects, a news release can incur a series of jumps. To address these issues, we analyze jumps that are aggregated over a day (i.e., 24 h).

We aggregate the intraday currency jump arrivals over day d with daily interval D_d and denote the aggregated jump frequencies by $\int_{s\in D_d} \mathrm{d}J_{k,s}$ ($D_d = \{s \mid s \text{belongstoday} d\}$). We set the integrated currency jump intensity model at the daily level using the following Poisson linking function:

$$\int_{s\in D_d} E(\mathrm{d}J_{k,s}) = \int_{s\in D_d} \mathrm{d}\Lambda_{k,s} = \exp\left(\alpha + \sum_{l=-6}^{6} \theta_l B_{l,d} + \sum_{i=1}^{17} \delta_i C_i + \gamma REC_d\right), \tag{D1}$$

where $B_{l,d} = I_{[d=v-l]}$ is a day indicator that takes the value of unity if the observation belongs to day $v - l$, where v is the information release day. C_i is a dummy variable that indicates country i to control for country fixed effects, and REC_d is a dummy variable to control for the fixed effect of the U.S. recession periods. The intraday patterns are not controlled for because intraday effects are averaged and are reflected in the constant term α. We examine 12 days around information release days to measure the currency market jump reaction around the news. This model and the graphical representation are motivated by (Patton and Verardo, 2012). We estimate these models using the panel data on all currency jumps and the two separate time series datasets on common currency jumps (cojumps 2 and 5), such that $\int_{s\in D_d} \mathrm{d}J_{coj(m),s} = \int_{s\in D_d} I_{[\sum_{k=1}^{18} \mathrm{d}J_{k,s} \geq m]}$ with $m = 2$ and 5.

To examine the impact of information releases on jump sizes around scheduled event days, we aggregate intraday jump sizes by taking the sum of the absolute values of the jump sizes on day d. We then set our jump size regression model over one day as follows:

$$E\left(\int_{s\in D_d} |Y_{k,s}| \mathrm{d}s\right) = \alpha + \sum_{l=-6}^{6} \theta_l B_{l,d} + \sum_{i=1}^{17} \delta_i C_i + \gamma REC_d. \tag{D2}$$

In Fig. D.1, the left panels show the results for the jump intensity model. The coefficients for the days of the FOMC announcements are all positive, indicating that the expected number of intraday currency jumps is greater on the FOMC announcement day than on other days. The expected number of jumps for individual currencies on an FOMC announcement day is, on average, greater by $e^{0.68}$ ($\approx .1.97$) than those on other days. For cojumps, we also find that jumps are more likely to occur on FOMC announcement days than on other days. These results demonstrate that the impact of FOMC announcements on simultaneous currency jump arrivals is statistically and economically significant. The daily patterns for the expected number of intraday jumps on the nonfarm payroll release days are similar to, though not as distinct as, the case for the FOMC announcement days. The effects of GDP and trade information releases are negative in the regressions for individual exchange rates. Moreover, the coefficients of the GDP or trade information release days in the regression for cojumps do not show a clear pattern for understanding changes in the jump frequencies, which conflicts with those on an FOMC announcement day.

The right panels of Fig. D.1 show the results for the jump size model. Similar to the jump intensity, we note that the coefficients on FOMC announcement days are significantly positive. In addition, on nonfarm payroll employment release days, the expected jump sizes are significantly larger than on usual days. Unlike these two cases, we find only insignificant results for the other information releases.

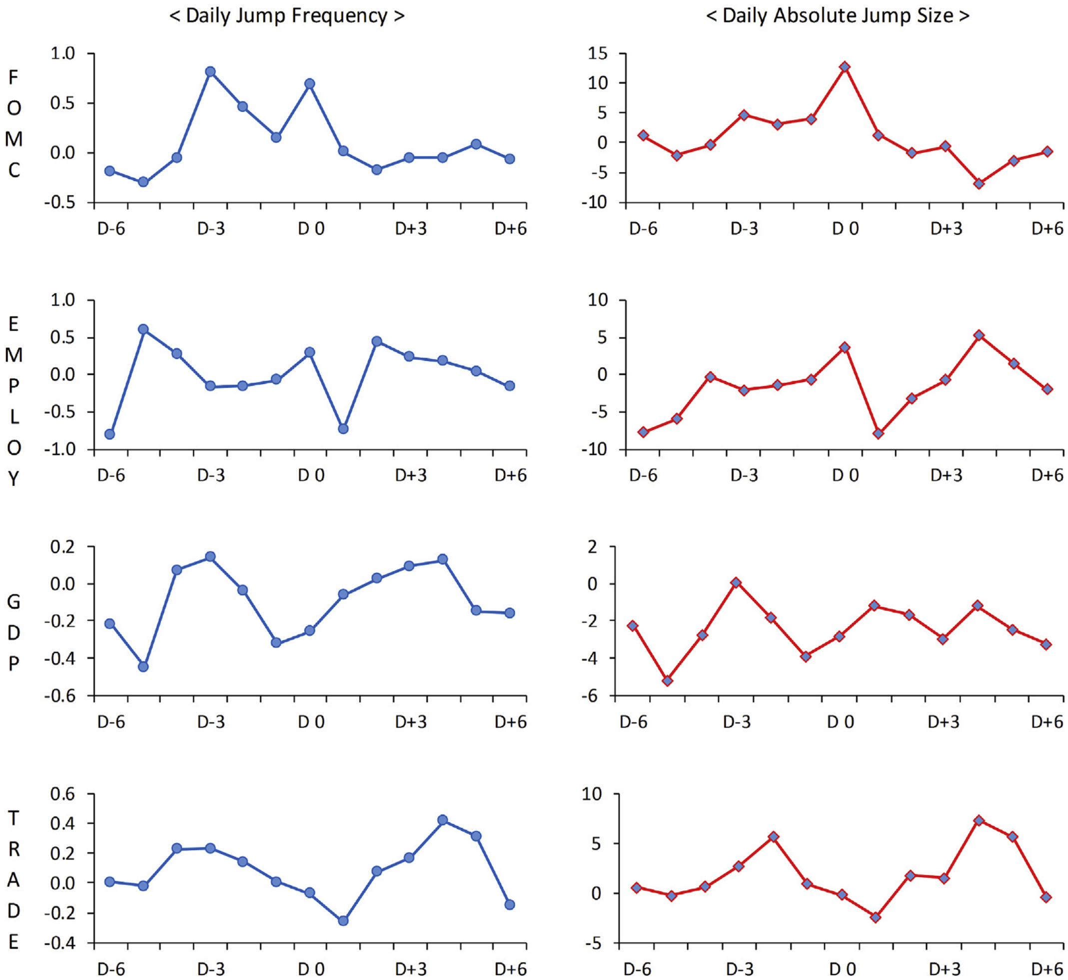


Fig. D.1 Expected jump frequency and size of individual currencies around information release days. This figure graphically presents how individual currency jumps respond to scheduled information releases regarding FOMC announcements, nonfarm payroll employment, GDP, and trade. In particular, it shows the regression coefficients estimated by the jump frequency and size models considered in Eqs. (D1) and (D2). The horizontal axis indicates the days around information release days, and the vertical axis shows the level of the coefficients. "D 0" indicates the scheduled release day.

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