The Impact of Jumps on Carry Trade Returns

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Abstract

This paper investigates how jump risks are priced in currency markets. We find that currencies whose changes are more sensitive to negative market jumps provide significantly higher expected returns. The positive risk premium constitutes compensation for the extreme losses during periods of market turmoil. Using the empirical findings, we propose a jump modified carry trade strategy, which has approximately two-percentage-point (per annum) higher returns than the regular carry trade strategy. These findings result from the fact that negative jump betas are significantly related to the riskiness of currencies and business conditions.

JEL classification: G15
Key words: jump beta, jump modified carry trade, foreign exchange rate, carry trade

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1. Introduction

Recent empirical studies suggest that extreme discontinuous changes (i.e., jumps) in foreign exchange rates are undiversifiable and hence priced in currency markets (e.g., Chernov, Graveline, and Zviadadze, 2015; Jurek, 2014). In this article, we aim to examine the impact of such jumps on returns to carry trades. The carry trade is an investment strategy in which an investor borrows lower interest rate currencies and lends higher interest rate currencies, and it is recognized as one of the most profitable currency investment strategies. Because the carry trade uses a pool of currencies, it is important to refine our understanding of how individual exchange rates respond to the market jump risks and how differences in individual responses are related to carry trade returns. Therefore, we investigate how jumps are cross-sectionally priced in currency markets.

Given this background, we provide a simple graphical illustration of how jumps affect different currencies. After categorizing currencies into funding and investing currencies and separating the whole sample period into the subperiods when jumps are more likely to occur (called the Jump Period for brevity) and other subperiods (called the No Jump Period), we compare the excess returns of the two types of currencies in the two subperiods.[1] Panel A of Fig. 1 shows that the funding currencies of carry trades achieve higher excess returns than investing currencies during the Jump Period. In contrast, during the No Jump Period, the excess returns of investing currencies are higher than those of funding currencies. Considering this variation in the excess returns, we hypothesize that differences in the sensitivity of exchange rate changes to jumps significantly affect carry trade returns.

To confirm this hypothesis, we explicitly include jumps in our model for foreign exchange rate processes. Specifically, we carve out signed market jump components in the model

[1]In currency markets, jumps are more likely to occur around economic information releases and foreign exchange market opening times (Lahaye, Laurent, and Neely, 2011; Lee and Wang, 2016), and there is a jump clustering effect, where a jump arrival implies a higher likelihood of another jump arrival in the near future [Lee and Wang (2016)].

and decompose the market jump components into positive and negative components because investors' reactions and attentiveness differ with respect to continuous and discontinuous price changes and with respect to negative and positive changes.[2] In addition, because there could be non-market systematic and diversifiable components, the model of this paper includes individual components. Therefore, our model includes market continuous, market positive and market negative jump, individual continuous, and individual jump components.[3] In this paper, we focus on the market component because Lustig, Roussanov, and Verdelhan (2011) shows that the first principal component explains approximately 70% of the variance and that the dollar risk factor (market) corresponds to the principal component. Because of this decomposition, the model in this paper is sufficiently general to accommodate the research purpose of revealing how different factors are priced. Another feature of the model is that it explicitly allows individual exchange rates to respond to the separated market components with different magnitudes. Accordingly, we can estimate the various exposures of an exchange rate to different risk factors and the associated risk premiums and specifically identify the most important systematic risk components that explain currency returns.

We refer to the sensitivity of exchange rate changes to market components as betas and estimate the betas for the decomposed market components. Employing the above model, we estimate monthly continuous, positive jump, and negative jump betas, which represent the sensitivities of exchange rate changes to market continuous, positive jump, and negative jump risks and can be considered the decomposition of the standard beta. The beta decomposition in this paper is different from that in Bollerslev, Li, and Todorov (2016), which decomposes the standard beta into continuous, jump, and overnight betas to reflect the features of stock markets. To estimate the betas, we use intraday data sampled every 15 minutes for 17

[2]See, e.g., Dobrynskaya (2014), Patton and Sheppard (2015), Bollerslev, Li, and Todorov (2016), Guo, Wang, and Zhou (2015).

[3]If we define market returns as the average returns of individual foreign exchange rates, the (aggregated) market component is equivalent to the dollar risk factor in Lustig, Roussanov, and Verdelhan (2011) and Verdelhan (2015).

foreign exchange rates, which are expressed in the U.S. Dollars (USD) per unit of a currency. We run the Fama-MacBeth (FMB, 1973) regressions to test whether the risk premiums associated with decomposed market risks are significant. The results of the FMB regressions indicate that only negative jump betas have significantly positive coefficients; in contrast, the coefficients on continuous and positive jump betas are insignificant. These results are robust to the inclusion of controls for the exposures of exchange rates to common factors studied in Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012). Moreover, we use daily exchange rates and perform the same analysis as above and obtain qualitatively similar results.[4]

This finding reveals that currencies that are more sensitive to negative market jumps have higher expected returns. Such a positive risk premium for the negative market jump component implies that a significant portion of carry trade returns constitutes a compensation for the extreme depreciation in individual currencies that coincides with the discontinuous depreciation in the overall market. Because high negative jump beta currencies provide higher expected returns, carry trade investors can improve their (expected) returns by lending higher negative jump beta currencies and borrowing lower negative jump beta currencies.

Incorporating the results of the cross-sectional analysis, we propose a jump modified carry trade strategy in which an investor considers not only interest rate differentials but also negative jump betas. Because higher negative jump beta currencies have higher expected returns, the investor takes a long position in higher negative jump beta currencies among higher interest rate currencies and a short position in lower negative jump beta currencies among lower interest rate currencies. However, returns to high negative jump beta currencies would decrease severely when overall currencies suddenly depreciate (i.e., negative market jumps occur). To mitigate such adverse returns, the investor can temporarily unwind positions that bet on negative jump betas if he/she expects a negative jump in the market. Using the

[4] A description of the analysis with daily exchange rates is provided in Appendix A. The specific results are available upon request.

17 currencies in the sample, we find that the implemented jump modified strategy provides approximately two-percentage-point higher returns (per annum) than regular carry trades and that its standard deviation is comparable to that of the regular carry trade.

To understand the sources of the positive risk premium on negative market jumps, we investigate the cross-sectional and time series properties of negative jump betas. From the cross-sectional analyses, we find that negative jump betas are negatively related to the gross domestic product (GDP) and positively related to the interest rate of a country. Considering that the GDP and interest rate can represent the riskiness of a country (and the corresponding currency), negative jump betas appear to properly capture currency risks (i.e., a higher negative jump beta represents higher currency risk).[5] By comparing the time series of negative jump betas with those of the other betas, we find that the standard and continuous betas are stable over time, whereas negative jump betas fluctuate in accordance with business conditions. In addition, the variation of negative jump betas is more dynamic than that of the standard and continuous betas.

This paper is related to the literature on the profitability of carry trades with a risk premium.[6] However, this study differs from previous studies in the following ways. First, Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012) investigate common factors in currency markets. The former paper uses dollar and carry risk factors, whereas the latter one depends on dollar and global volatility factors. However, unlike Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012), this paper explicitly examines jump components and decomposes the dollar risk factor into continuous and discontinuous components, and the finding indicates that negative market jumps are cross-sectionally priced. Second, unlike Chernov, Graveline, and Zviadadze (2015) and Jurek (2014), this paper explicitly fo-

[5]See Hassan (2013) and Ready, Roussanov, and Ward (2016).

[6]The risk premium based explanation is related to the violation of uncovered interest rate parity (Hansen and Hodrick, 1980; Bilson, 1981; Fama, 1984). In this paper, we omit detailed discussion on this strand of papers for brevity. See, e.g., Lustig and Verdelhan (2007), Brunnermeier, Nagel, and Pedersen (2008), Lustig, Roussanov, and Verdelhan (2011, 2014), Menkhoff et al. (2012), and Sarno, Schneider, and Wagner (2012).

cuses on the cross-sectional asset pricing of market jumps and directly uses realized jump risks from spot rate data (not option data). Chernov, Graveline, and Zviadadze (2015) and Jurek (2014) use option implied jumps and indicate that jump risks are priced. Finally, unlike Brunnermeier, Nagel, and Pedersen (2008) and Dobrynskaya (2014), this paper formally detects jumps with a non-parametric approach. Specifically, we detects jumps by applying the approach of Lee and Mykland (2008) and use the jump sizes as risk measures. Brunnermeier, Nagel, and Pedersen (2008) investigates carry trade returns by focusing on crash risks and (negative) skewness. Dobrynskaya (2014) also focuses on negative (co-) skewness.

In terms of methodology, this paper is supported by the following studies. The cross-sectional asset pricing analysis using negative jump betas in this paper is related to that of Bollerslev, Li, and Todorov (2016), which uses the continuous, jump, and overnight betas in the U.S. stock markets. However, the model of this paper includes signed jumps and does not adopt overnight jumps for currency markets. The beta estimation approach in this paper modifies and incorporates that of Ang, Chen, and Xing (2006) and Bollerslev, Li, and Todorov (2016), and we apply this approach to currency markets. Li, Todorov, and Tauchen (2017) studies jump betas that can depend on the sign and size of a market jump and develops tests for constant beta on a given interval. We employ the approach of the aforementioned paper to formally confirm the assumptions imposed in our regression analysis. The method of constructing a jump modified carry trade strategy is related to that of Bekaert and Panayotov (2016), which suggests that investors can improve the performance of carry trades by removing currencies with a lower historical Sharpe ratio from the carry trade currencies; likewise, the approach in this paper involves deleting currencies with higher negative jump betas when negative market jumps are highly likely to occur.

The remainder of this paper is organized as follows. Section 2 illustrates the motivation of this study by providing an example in which we compare the carry trade returns for investors who use jump information with those for investors who do not. Section 3 explains empirical approaches to the decomposition of market components and the estimation of discontinuous betas in currency markets. Section 4 describes the data for exchange rates and estimated betas. Section 5 presents a cross-sectional asset pricing analysis that uses negative jump betas. Section 6 links negative jump betas to economic fundamentals. Section 7 proposes a jump modified carry trade strategy and reports the results that show the improved performance of this strategy. Section 8 concludes the paper.

2. Jumps and carry trade returns

This section explains the importance of jumps in carry trades. One way to show whether a factor has pricing related information is to separate the whole period into the period related to the factor and other periods and to investigate the returns during each period.

First, we separate our sample period from January 1999 to December 2015 into two subperiods, namely, the "Jump Period" and the "No Jump Period", where we define the Jump Period as times when jumps are highly likely to occur and the No Jump Period as the other times. To separate the sample period into the two subperiods, we rely on Lahaye, Laurent, and Neely (2011) and Lee and Wang (2016). According to these previous studies, jump intensity is higher when markets open and close and when economic information arrives. Because the market operation times are predetermined, we can anticipate that jumps are more likely to occur during these times. In addition, the aforementioned studies show that there are jump clustering and jump size clustering effects, where the arrival of a jump increases the likelihood that another subsequent jump occurs within a day. Therefore, for the illustration in this section, we set the Jump Period as the period around the Tokyo market closing and London market opening times [i.e., 06:00-10:00 Greenwich Mean Time (GMT)] and the jump clustering window, which is the six hours immediately after two simultaneous jumps occur. Our Jump Period includes these two periods because jumps are clearly more likely to arrive in currency markets during these times. Then, for the Jump and No Jump Periods, we compute the average excess returns of holding funding or investing currencies, which are the five lowest or highest interest rate currencies, respectively, among the 17 sample currencies.[7]

Panel A of Fig. 1 shows that during the No Jump Period, the excess returns of investing currencies are 11% (per annum), whereas those of funding currencies are -6%. The higher returns of investing currencies during most of the periods are related to the profitability of carry trades. In contrast, during the Jump Period, the excess returns of funding currencies are 16 percentage points higher than those of investing currencies. This finding implies that investing currencies react more negatively to jumps than funding currencies. Consequently, carry trade returns decrease, which is consistent with the findings of Menkhoff et al. (2012) and Daniel, Hodrick, and Lu (2016). This variation in the excess returns according to currency types and jumps highlights the cross-sectional differences in the sensitivity of individual exchange rates to jumps. If the sensitivity were equal across all currencies, the average return of investing currencies would not be lower than that of funding currencies even during the Jump Period.

The adverse effects of jumps on carry trade returns are shown as in Panel B of Fig. 1. Here, two different types of investors are considered: the first type of investors are typical regular carry traders, who use funding and investing currencies as discussed above, whereas the second type of investors take the same position as the first type of investors but temporarily suspend their carry trades (i.e., take a zero position) during the Jump Period. The blue line (labeled "Regular") represents returns for the first type of investors, and the red line (labeled "No Jump") represents returns for the second type of investors. The gray line (labeled "Jump") represents the investors who take carry trade positions only when jumps are highly likely. The last case is the opposite strategy to that of the second type of investors and is provided for reference.

[7]Because we have daily interest rates, currency separation is assumed to be conducted on a daily basis. The list of the 17 currencies is presented in the data section.

The cumulative carry trade returns are higher for the second type of investors, who avoid taking a position during the Jump Period. Although both types of investors take the same positions during most of the periods, there is an approximately 20-percentage-point difference in the returns for the two types of investors at the end of the sample period. The only difference between the two types of investors is that the second type of investors circumvent negative returns during the Jump Period. Considering this observation, we hypothesize that the substantial difference in the carry trade returns between the two types of investors is related to the cross-sectional difference in the sensitivity of exchange rates to jump risks.

3. Model and beta estimation

To investigate how jump risks in currency markets are priced, we set up a model for foreign exchange rate processes that explicitly incorporates jump components. We then propose approaches to measure the exposures of foreign exchange rates to jump risks.

3.1. Foreign exchange rate process

The literature suggests that the expected return variations that result from discontinuous price changes are more significantly priced than those associated with continuous price movements. Chernov, Graveline, and Zviadadze (2015) and Farhi and Gabaix (2016) indicate that jumps are not diversifiable and therefore should be priced risks. Importantly, Bakshi, Carr, and Wu (2008) proposes a theoretical framework in which only downside (negative) jumps are priced because investors are more attentive to losses. Therefore, we separate jump components into positive and negative components in our models. Moreover, we decompose the process into market and individual (i.e., non-market systematic and idiosyncratic) components. First, the market risks (i.e., dollar risks in the literature) are noticeable, in that the principal component that is related to the market risks explains approximately 70% of the variation in currency returns [Lustig, Roussanov, and Verdelhan (2011)]. Second, idiosyncratic (jump) risks can be diversified — or (at least) their effects on currency pricing can be different from those of market risks.[8]

For the above reasons, we define a process for the i-th foreign exchange rate as the stochastic differential equation:

$$ds_{i,t} = \mu_{i,t}dt + \beta_{i,t}^{(c)}\sigma_{0,t}dW_{0,t} + \delta_{i,t}dW_{i,t} + \beta_{i,t}^{(j+)}Y_{0,t}dJ_{0,t}^{(+)} + \beta_{i,t}^{(j-)}Y_{0,t}dJ_{0,t}^{(-)} + Y_{i,t}dJ_{i,t}, \tag{1}$$

where $ds_{i,t} = \Delta lnS_{i,t}$ is the instantaneous change in the logarithmic spot foreign exchange rate for currency i at time t. The first three terms represent continuous components. Specifically, $\mu_{i,t}$ is the instantaneous drift. $\beta_{i,t}^{(c)}\sigma_{0,t}dW_{0,t}$ is a market continuous diffusion term, where $\beta_{i,t}^{(c)}$ is the continuous beta, $\sigma_{0,t}$ is the instantaneous market volatility, and $W_{0,t}$ is a Brownian motion describing market continuous shocks. Subscript "0" denotes the market or the market component in this paper. $\delta_{i,t}dW_{i,t}$ is an individual continuous diffusion term, where $\delta_{i,t}$ is the individual volatility and $W_{i,t}$ is a Brownian motion capturing individual continuous shocks. $W_{0,t}$ and $W_{i,t}$ are orthogonal to each other, and $W_{i,t}$ and $W_{j,t}$ for $i \neq j$ can be correlated.

The last three terms reflect discontinuous changes (or jumps) in a foreign exchange rate. $\beta_{i,t}^{(j+)}Y_{0,t}dJ_{0,t}^{(+)}$ and $\beta_{i,t}^{(j-)}Y_{0,t}dJ_{0,t}^{(-)}$ are market jump terms, which are separated into positive and negative jump components, respectively. $\beta_{i,t}^{(j+)}$ ($\beta_{i,t}^{(j-)}$) is the positive (negative) market jump beta, $Y_{0,t}$ is the size of the market jump, and $dJ_{0,t}^{(+)}$ ($dJ_{0,t}^{(-)}$) indicates the positive (negative) market jump arrival. $Y_{i,t}dJ_{i,t}$ is an individual jump term, where $Y_{i,t}$ is the size of the individual jump and $dJ_{i,t}$ indicates the individual jump arrival. The jump arrival $J_{i,t} = \int_0^t dJ_{i,s}ds$ is a nonhomogeneous Poisson process with an integrated stochastic intensity $\Lambda_{i,t} = \int_0^t d\Lambda_{i,s}ds$. The individual jumps do not arrive together with the market jumps, but $dJ_{i,t}$ and $dJ_{j,t}$ for $i \neq j$ can be correlated.

[8]Merton (1976) assumes that idiosyncratic jumps are diversifiable. Bates (1996) incorporates systematic jumps to develop a method of pricing Deutsche Mark (American) options.

By separating the market components into continuous, positive jump, and negative jump components and including the betas for the market components, we can explicitly decompose the market risks and consider the sensitivities of individual exchange rates to the different market risks. This model, represented by Eq. (1), allows us to consider the cross-sectional differences of individual exchange rates because the betas in Eq. (1) can vary across foreign exchange rates. In addition, because the three betas (i.e., $\beta_{i,t}^{(c)}$, $\beta_{i,t}^{(j+)}$, and $\beta_{i,t}^{(j-)}$) can be different within a foreign exchange rate, this model can be used to capture the cross-sectional differences in the pricing of the three types of market risk components. Using these decomposed betas, we can separately estimate the risk premiums on market risk components. Therefore, with this model, we can identify which component is the most important in explaining changes in individual exchange rates.

We can define the process for the market in a manner consistent with Eq. (1). Because the sensitivity of the market to changes in the market is one and because the market does not include an individual component, we can set the process of the currency market as

$$ds_{0,t} = \mu_{0,t}dt + \sigma_{0,t}dW_{0,t} + Y_{0,t}dJ_{0,t}^{(+)} + Y_{0,t}dJ_{0,t}^{(-)}. \tag{2}$$

Because individual exchange rates have different jump betas (i.e., $\beta_{i,t}^{(j+)}$ and $\beta_{i,t}^{(j-)}$), the sizes of the market jumps can be different from those of exchange rate jumps that occur simultaneously.[9]

Although we focus only on the impact of market jump risks in our study, the model described in this section is general enough to support pricing kernels that allow for other pricing factors in addition to the market factors (e.g., carry and global volatility factors). This

[9]Even if a jump test does not detect a market jump, it can identify an individual exchange rate jump. In this case, the size of a market jump would be much smaller than that of the coinciding individual exchange rate jump. In addition, if the jump betas of individual exchange rates are small, an individual exchange rate jump could be undetected when a corresponding market jump occurs. See Lee and Hannig (2010) for details on small-sized jumps.

is because we can assume the existence of a pricing kernel following the standard approach in the asset pricing literature. The individual diffusive and jump risks driven by $W_{i,t}$ and $J_{i,t}$ can be priced in the cross-section, as they can be correlated with other risks that appear in the part of the pricing kernel capturing the pricing of other systematic (non-market) factors [see Bollerslev, Li, and Todorov (2016) for a related discussion].

3.2. Beta estimation approach

Because the continuous, positive jump, and negative jump betas are not directly observable, we propose an approach to estimate them in this subsection.

Todorov and Bollerslev (2010) and Bollerslev, Li, and Todorov (2016) provide an estimation approach for discontinuous betas in stock markets, which inspires the approach introduced in this paper. However, because the approach in these two papers does not separate positive and negative jumps and because currency markets operate without an overnight break, it is less relevant to the context of our analysis. Motivated by Ang, Chen, and Xing (2006), Dobrynskaya (2014) provides an approach to estimate the signed (standard) betas of currency markets. Although these betas are separated by the signs of the market returns, they are not related to the discontinuities of foreign exchange rates. Li, Todorov, and Tauchen (2017) studies jump betas that can depend on the sign and size of a market jump. Here, we describe our beta estimation approach that is in line with the purpose of this paper and the model defined in the previous subsection.

We use finely spaced high frequency data and assume that the betas remain constant over a short period of time. When the above conditions are satisfied, we can separately estimate the betas in the following manner.[10] Intuitively, the estimation of the continuous beta employs only the observations that do not contain any discontinuous term for individual foreign

[10]To confirm the stability of the betas, we apply the approach of Li, Todorov, and Tauchen (2017). The detailed discussion and evidence are provided in Section 5.

exchange rates and the market because this method guarantees that any jump component is not included in the estimation process. Similarly, the positive jump beta is estimated by using only the observations with a positive market jump, whereas the negative jump beta is estimated by using only the observations with a negative market jump. The approach of using part of the observations is motivated by Ang, Chen, and Xing (2006) and Dobrynskaya (2014), which use observations with negative returns to estimate a (standard) negative beta.

In this context, we can define the estimators of the continuous, positive jump, and negative jump betas as

$$\hat{\beta}_{i,p}^{(q)} = \frac{\Sigma_{l\in P_p}\ r_{i,t(l)}r_{0,t(l)} \cdot I(q)_{i,t(l)}I(q)_{0,t(l)}}{\Sigma_{l\in P_p}\ r_{0,t(l)}^2 \cdot I(q)_{0,t(l)}}, \tag{3}$$

where $q = \{c,\ j+,\ j-\}$ is a notation to distinguish the three kinds of betas. "c", "$j+$", and "$j-$" indicate "continuous", "positive jump", and "negative jump", respectively. Subscript "p" indicates the p-th period for the estimation, and $P_p = \{l|t(l)$ belongs to the p-th estimation period.$\}$ denotes a set of indices for the observations during the p-th period. $t(l)$ is the l-th discrete observation if we define the whole time horizon $0 = t(0) < t(1) < \cdots < t(n) = T$. Estimation periods can be partitioned in accordance with the purpose of the analysis. Assuming that N is the number of time-partitions, $P_1 \cup \cdots \cup P_N = \{0,\ 1,\ \cdots,\ n\}$. $r_{i,t(l)} = lnS_{i,t(l)} - lnS_{i,t(l-1)}$ is a change in log spot rate from time $t(l-1)$ to $t(l)$, and $r_{0,t(l)}$ is the market return. $I(q)_{i,t(l)}$ and $I(q)_{0,t(l)}$ are indicators for jump arrivals. $I(c)_{0,t(l)}$ ($I(c)_{i,t(l)}$) takes the value of unity if a market jump (an individual jump for exchange rate i) does not occur from time $t(l-1)$ to $t(l)$ and zero otherwise. $I(j+)_{0,t(l)}$ ($I(j-)_{0,t(l)}$) takes the value of unity if a positive (negative) market jump does occur and zero otherwise. $I(j+)_{i,t(l)}$ and $I(j-)_{i,t(l)}$ take the value of unity for all l. The drift term [i.e., μ in Eq. (1)] has no impact on the asymptotic behavior of the beta estimates. In practice, for the frequencies used in this paper, the drift is negligible and very small to be of importance. Finally, this approach in Eq. (3) is consistent with the model defined in Eq. (1) and Eq. (2).

As shown in Eq. (3), these decomposed betas use only a portion of the observations that are mutually exclusive. We can also consider the aggregated beta of these decomposed betas to be the standard beta, which represents the overall sensitivity of an individual currency to the market. The estimator of the standard beta employs all available observations. Accordingly, the estimator is defined by setting $I(s)_{i,t(l)} = I(s)_{0,t(l)} = 1$ for all l in Eq. (3), where "s" represents "standard".

4. Data and estimated betas

This section describes the exchange rate data and reports the estimated betas.[11] We use the intraday spot exchange rates sampled every 15-minute interval. The sampling frequency of 15 minutes is used to maintain power for the jump test and to mitigate problems that result from microstructure noise. As argued in Patton and Verardo (2012) and Bollerslev, Li, and Todorov (2016), a higher sampling frequency can engender problems that result from nonsynchronous trading and make the beta estimators biased toward zero. Therefore, we adopt a 15-minute interval, which is longer than that of the papers studying realized moments in exchange rate changes [e.g., Andersen et al. (2001b)] for the main analyses. As indicated in the introduction, we also performed similar analyses with daily exchange rate data. An explanation of the daily exchange rates is provided in Appendix A. The results based on the daily exchange rates are available upon request.

4.1. Intraday foreign exchange rates

The data on foreign exchange rates cover 17 bilateral spot rates, which are expressed in USD per unit of foreign currency. The sample period is from January 1999 to December 2015, and the sample includes the following currencies: the Australian Dollar (AUD), Canadian

[11] The data in this paper are similar to those of Lee and Wang (2016). The following data description is similar to that of Lee and Wang (2016). However, considering the different purpose and context, this data section presents the data from a different viewpoint and provides more information.

Dollar (CAD), Euro (EUR), Hungarian Forint (HUF), Indian Rupiah (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). The data are obtained from Olsen Financial Technologies. To select the above exchange rates, we consider the popularity of trading and the data availability. We do not include pegged currencies (e.g., the Danish Krone, Hong Kong Dollar, and currencies of Middle Eastern countries). This paper uses the mid points of spot bid and ask quotes as exchange rates.

The data filtering process adopted in this paper follows the steps used in papers that study intraday exchange rates (e.g., Andersen et al., 2001b; Lahaye, Laurent, and Neely, 2011). Weekends and holidays, including Christmas, Independence Day, Thanksgiving, and New Year's Eve/Day, are removed because the trading intensity of currency markets tends to substantially decrease on these days. Furthermore, quotes that are the same as the previous two consecutive quotes are dropped because they are likely to be inactive quotes. Moreover, some extreme quotes whose returns are greater than seven standard deviations are deleted. Days with fewer than 50 observations are eliminated not only because the data on these days could distort the smooth characteristics of return distributions, but also because such days might be holidays that are not captured in the previous step (e.g., irregular or non-U.S. holidays). Overall, this paper analyzes approximately 2,480-4,350 days (of 6,209 days in total) or 190,000-410,000 observations (of 596,064 observations in total) per exchange rate.

4.2. Summary statistics

This subsection reports the summary statistics for the 17 foreign exchange rates. Following Andersen et al. (2001a), we choose to present the first four central moments of daily returns that are obtained from 15-minute interval. The daily realized return (DR) of foreign exchange rate i on day d is $DR_{i,d} = \sum_{l \in D_d} r_{i,t(l)}$, where $r_{i,t(l)} = s_{i,t(l)} - s_{i,t(l-1)}$ is the

(15-minute) log return. $D_d = \{l | t(l) \text{ belongs to day } d\}$ is a set of indices for observations in day d. In addition, the national characteristics of the corresponding countries are provided because we relate our analysis results to them in Sections 6 and 7. We use GDP, money base, foreign direct investment (FDI), interest rate, exports to the U.S., and imports from the U.S. These data are obtained from Datastream and the U.S. Census Bureau.

In Table 1, the four left columns show the first four central moments of the daily realized returns. The last row (denoted by "Market (USD)") presents those of the market returns, which are constructed by taking the average of the 17 foreign exchange returns [i.e., $r_{0,t(l)} = (1/17)\sum_{i=1}^{17} r_{i,t(l)}$]. Most of the currencies have depreciated (i.e., 10 among 17 currencies). The standard deviations range from 5% to 19%, in which the lower standard deviations tend to correspond to lower interest rate currencies (e.g., JPY and SGD). The skewness is negative overall, with a range from -0.64 to 0.23. The exchange rates of the two highest interest rate countries (i.e., ZAR and TRY) have the most negative skewness. The kurtosis ranges from 4 to 16, indicating the fat-tailed distribution of returns. The asymmetric and fat-tailed features motivate us to distinguish negative and positive returns and to focus on extreme changes in exchange rates.

The right columns of Table 1 provide the average values of the national characteristics, and the last row shows those of the U.S. for reference. The national characteristics of a country are related to those of the U.S. for the analysis because the pricing kernel for a foreign exchange rate comprises both foreign and U.S. components.

4.3. Jump detection results

Using the intraday data described in the previous subsection and the jump detection approaches explained in Appendix B, we detect jumps for individual exchange rates and the market. A 5% significance level is used for the jump detection. These detected intraday jumps are then employed for the empirical analysis and the carry trade modification.

Table 2 reports the jump detection results. The fourth column (denoted by "% Jp") shows that the percentage of detected jumps ranges from 0.7% (SEK) to 5.2% (INR) with an average of 1.5%. Intuitively, the figure of 1.5% implies that approximately ten intraday jumps occur for a week. In the row denoted by "Market (USD)", the ratio of detected market jumps to total tests is 0.6%, which is lower than that for each individual foreign exchange rate because small-sized market jumps are less likely to be detected and because the step of averaging individual returns might smoothen extreme values. The fifth and sixth columns show that the frequencies of positive jumps and of negative jumps are not substantially different. As shown in the last row, the average number of intraday positive jumps is 2,309, and that of intraday negative jumps is 2,376. The next two columns (denoted by "# Jday" and "% Jday") report the number of and the relative frequency of jump days, which are defined as days when at least one intraday jump occurs. The percentage of jump days ranges from 39% to 76% of days for individual foreign exchange rates and is 34% for the market. The last six columns provide the distribution of jump sizes and show that the positive and negative jumps are symmetric. The median ranges from 0.0013 (SGD) to 0.0033 (ZAR) for the positive jumps and from -0.0013 (SGD) to -0.0033 (ZAR) for the negative jumps.

4.4. Beta estimation results

This subsection presents the results of the beta estimation that follows the approach defined in Eq. (3). We estimate a beta in month m by using the observations from month $m - 11$ to month m (i.e., we update the estimation monthly by using the previous one-year observations).

Table 3 provides the estimated standard, continuous, positive jump, and negative jump betas and their statistical properties. Panel A reports the (time series) mean and standard deviation of each beta for all of the individual exchange rates in the sample. The standard and continuous betas are very similar to each other, and their correlation is 98.3%. This similarity arises because the observations used in the estimation are almost the same, in that a jump is a rare event (e.g., only 1.5% of the observations contain jump components). For the standard and continuous betas, while HUF has the highest values (i.e., 1.45 for the standard beta and 1.43 for the continuous beta), JPY has the lowest (i.e., 0.23 for the standard beta and 0.19 for the continuous beta). For the positive jump beta, while HUF has the highest value (i.e., 1.72), SGD has the lowest (i.e., 0.38). The range of the positive jump beta is 1.34, which is wider than the ranges of the standard and continuous beta (i.e., 1.22 and 1.24, respectively). Similarly, for the negative jump beta, while HUF has the highest value (i.e., 1.79), JPY has the lowest (i.e., 0.36). The range of the negative jump beta is 1.43, which is greater than those of the other betas. This wide variation in jump betas suggests that the market jump risks, unlike the market continuous risk, can be priced cross-sectionally.[12] Eq. (1) in Section 3 implies that the cross-sectional average of each estimated beta across the 17 currencies is close to one because we construct market returns by taking the averages across the 17 individual exchange rate returns. Our results indicate that the cross-sectional averages of the four types of estimated betas are not statistically different from one at the 5% significance level.

Panel B presents the correlations among these four betas. The correlations are computed for each individual exchange rate, and the averages of 17 correlations are then reported. As mentioned above, the correlation between the standard and continuous betas is close to one. However, the other correlations are relatively low. The correlation between the continuous and negative (positive) jump betas is 74% (72%), indicating that jump betas can represent different information. For example, changes in the exchange rates of AUD and CHF are similarly sensitive to market jump risks, but these exchange rates are differentially sensitive to market diffusive risks. Moreover, the correlation between the positive and negative jump betas is also lower than one (i.e., 77%). Despite such a lower correlation, we formally confirm

[12] We relate the magnitudes of the betas to national characteristics in Section 6.

that these decomposed betas are statistically different from each other. As Panel C reports, for each individual exchange rate, we find the significant differences between positive and negative jump betas as well as significant differences between jump betas and continuous betas (with few exceptions).

5. Cross-sectional asset pricing

This section examines the pricing of the decomposed market risks, including the continuous, positive jump, and negative jump risks of the market. For this purpose, we investigate whether the different types of risk components require different risk premiums. The findings from this analysis could have practical financial implications. For example, if the jump risks are cross-sectionally priced, carry trade investors can improve their performance by selecting currencies with higher expected returns as investing currencies and currencies with lower expected returns as funding currencies. Although the analysis and results presented in this section are based on intraday exchange rate data, the analysis of daily data yields qualitatively the same results.

5.1. Cross-sectional asset pricing test

In this subsection, to investigate how these estimated betas are related to currency returns and to measure the risk premium for each market risk, we run standard predictive FMB regressions. The following analysis is based on one month of holding periods, and the analyses using different holding periods (e.g., one week and one quarter) provide consistent results.

Assuming that the betas do not change over 13 months, we establish the following cross-sectional regression model:

$$mrx_{i,m+1} = \lambda_{0,m} + \lambda_{1,m}\beta^{(c)}_{i,m} + \lambda^{(j+)}_{2,m}\beta^{(j+)}_{i,m} + \lambda^{(j-)}_{3,m}\beta^{(j-)}_{i,m} + \gamma'_m X_{i,m} + \varepsilon_{i,m+1}, \tag{4}$$

where subscript m denotes the m-th month. $mrx_{i,m} = \int_{t \in m} drx_{i,t}$ is the monthly realized excess return related to currency i from the end of month $m-1$ to the end of month m ($drx_{i,t} = ds_{i,t} + int_{i,t} - int_{US,t}$ is the instantaneous excess return at time t). $\beta_{i,m}^{(q)}$ represents the four types of betas ($q = \{s,\ c,\ j+,\ j-\}$, where "s", "c", "$j+$", and "$j-$" denote "standard", "continuous", "positive jump", and "negative jump", respectively). The betas are estimated as explained in the previous subsection (i.e., we use the observations from month $m-11$ to month m to estimate $\beta_{i,m}^{(q)}$). $X_{i,m}$ is a vector of control variables for country i and month m. As control variables, we use the sensitivities of an individual exchange rate to the carry risk factor of Lustig, Roussanov, and Verdelhan (2011) and to innovations in the global foreign exchange volatility factor of Menkhoff et al. (2012).

In this FMB regression analysis, jump betas are assumed to be constant over 13 months because we estimate our betas using observations over the past 12 months and because the predictive regression model assumes the same constant beta for the subsequent month. We first confirm whether the assumption is valid. For negative and positive jump betas in the estimation window of 13 months, we perform a formal test by applying the approach introduced by Li, Todorov, and Tauchen (2017).[13] We use the algorithm that is based on a large number of *Monte Carlo* simulations to compute the critical value. In this analysis, we set the number of simulations at 30,000 and apply multiple tests for each currency over the whole sample period to be consistent with our empirical analysis. We find that the null hypothesis of constant betas is not rejected at the 1% significance level for the majority of cases. For example, we cannot reject the constant negative jump betas for more than 94% of the testing times and the constant positive jump betas for more than 95% of testing times. In addition, we support the constant beta in Fig. 2 by depicting the scatter plots between the positive (negative) market jump sizes and corresponding individual returns. As representative examples, we use the most recent 13-month observations of the EUR and JPY.

[13] We thank the referee for suggesting this test.

From these scatter plots, we find the existence of significant fitted lines, and this finding can be seen for other periods and currencies.

In Eq. (4), the time series means of the estimated coefficients ($\lambda_{\cdot,m}$) represent the average risk premium estimates for the corresponding market components. This FMB regression model is in line with Eq. (1) because the expected excess returns over a period are the sum of the risk premiums multiplied by the sensitivity measures (or betas) and because the expected returns and risk premiums are the conditional expectation of changes in exchange rates and systematic components that are aggregated over the period.[14]

Table 4 provides the coefficient estimates (risk premiums) and the robust t-statistics [Newey and West (1987)] of the regressions. Columns (I) and (II) present the results of the univariate regressions that include a standard beta or a continuous beta. Columns (III) and (IV) provide the estimates for regressions that include the continuous and positive jump (or negative jump) betas. Column (V) presents the results of the regression that includes the continuous and two jump betas as regressors; and Column (VI) reports the results of the regression that includes the betas and the two control variables as regressors.

In Columns (I)-(III), the coefficients on standard, continuous, and positive jump betas are insignificant. As indicated in the other columns, the coefficients of the negative jump betas are positive and statistically and economically significant, indicating that an increase in negative jump beta by one increases the expected excess return by 18- to 30-percentage-points per annum. The coefficients of the other betas are insignificant.

In Table 4, we focus on the specifications in Columns (V) and (VI) because they use all mutually exclusive observations (unlike the specifications in Columns (II)-(IV)) and show the

[14] Our model allows us to separately capture risk premiums that are not explained by our decomposed market risk components. Such premiums can appear as in the following pricing formula,

$$\begin{aligned} E_m\big(\textstyle\int_m^{m+1} dr x_{i,t}\big) &= \beta_{i,m}^{(c)} E_m\big(\textstyle\int_m^{m+1} \lambda_{1,t} dt\big) + \beta_{i,m}^{(j+)} E_m\big(\textstyle\int_m^{m+1} \lambda_{2,t} dt\big) \\ &\quad + \beta_{i,m}^{(j-)} E_m\big(\textstyle\int_m^{m+1} \lambda_{3,t} dt\big) + E_m\big(\textstyle\int_m^{m+1} \chi_{i,t} dt\big) + o_{i,m}, \end{aligned}$$

where $\chi_{i,t}$ is the instantaneous risk premium for currency i arising from the pricing of the individual diffusive and jump risks (i.e., $W_{i,t}$ and $J_{i,t}$), and $o_{i,m}$ is a negligible term. See Bollerslev, Li, and Todorov (2016).

effects of separated market risks (unlike the specification in Column (I)). In Column (V), the significantly positive coefficient on the negative jump beta indicates that currencies whose returns are more sensitive to negative market jumps (with the same direction as the market) require higher returns. In addition, as shown in Column (VI), such a positive risk premium is maintained when the regression model includes the control variables that are closely related to common risk factors.

The positive risk premium for the negative market jump risk constitutes compensation for the extreme negative returns during times when the market is in negative turmoil (i.e., when a negative market jump occurs). High negative jump beta currencies do not provide good hedges because changes in their exchange rates are in the same direction as those of the market and because the magnitudes of these changes in the exchange rates tend to be greater than those of the market. Because of this adverse property, the expected returns of high negative jump beta currencies should be higher. To confirm this explanation, we separate the sample period into the "Good Time" and the "Bad Time" and construct the tercile currency portfolios sorted on the negative jump betas. During the "Good Time" ("Bad Time"), the market returns are higher (lower) (i.e., they belong to the upper (lower) quartile of the market return distribution). The average excess returns of the portfolios are reported in Table 5. As shown in the second and forth columns, during the "Good Time", the high negative jump beta currencies provide higher returns than the low negative jump beta currencies. However, this pattern changes as the market returns decline. Indeed, during the "Bad Time", the excess returns of high negative jump beta currencies are approximately 30 percentage points lower than those of low negative jump beta currencies.

In sum, this analysis shows that negative market jump risks, unlike the other market risks, are cross-sectionally priced and that the expected returns of higher negative jump beta currencies are higher. Therefore, carry traders can enhance expected returns by lending currencies with relatively higher negative jump betas among their carry trade currencies.

5.2. *Robustness: sorting and subsample analyses*

We confirm the results of the previous subsection by analyzing single- and double-sorted contemporaneous portfolios.

Following Bollerslev, Li, and Todorov (2016), we estimate the four types of betas at the beginning of each month, using the next 12-month observations. For single sorting analysis, we sort the 17 exchange rates on each beta into tercile portfolios (on a monthly basis) and then compute the excess returns and changes in log spot rates of the sorted portfolios during the month. In addition, we perform the double sorting analysis to control for the effects of the carry risk factors. Every month, we first sort the 17 currencies on the sensitivities of the carry risk factors (denoted HML beta, hereafter) into tercile portfolios and then sort the currencies that belong to each portfolio on the two jump betas into tercile portfolios.

Panel A of Table 6 reports the results for the single sorting analysis. The excess returns of higher jump beta currencies (presented in Column (III)) are significantly higher than those of lower jump beta currencies (presented in Column (I)). In contrast, continuous beta or standard beta sorted portfolios do not show significant patterns in their excess returns or changes in log spot rates. In addition, the results for negative jump beta sorted portfolios are consistent with the FMB regression results, while those for positive jump beta sorted portfolios are not. As Panel B of Table 6 indicates, this significant relationship is still found in the double-sorted portfolios. For the low HML beta sorted portfolio, the higher negative jump beta currencies have higher excess returns. The mid and high HML beta sorted portfolios provide insignificant spreads because of relatively small return spreads. However, the mid and high HML beta portfolios show the positive relationship between the negative jump betas and excess returns. As Panel C of Table 6 indicates, the significant relationship for the low HML beta sorted portfolios arises because these portfolios have the widest jump beta spread. Although the higher positive jump beta currencies show a similar positive relationship to the excess returns, this result is inconsistent with the FMB regression results. Therefore, the unique positive relationship between the negative jump betas and excess returns, which is investigated in the previous subsection, is also confirmed by these sorting analyses.

There could be a concern that this result is driven by a specific sample. To address this issue, we perform robustness checks by using subsample analyses in which we run the regression of Eq. (4) for different subsamples; the results are provided in Table 7.

First, to mitigate the effect of small countries, we remove HUF, PLN, and TRY from the sample, considering the size of the corresponding economies and the stability of the currency systems. We refer to the remained currencies as “G14”; the estimation results of the FMB regression are presented in the left two columns. We find a significant and positive risk premium on negative market jumps as in the previous subsection.

Second, to address the possibility that business cycles (especially recession periods) drive the coefficients in the regressions, we separate our sample into recession and expansion periods. For this separation, We use the business cycle of the National Bureau of Economic Research (NBER). As indicated in the middle columns of Table 7, for recession periods, we still find positive coefficients on the negative jump betas. Admittedly, the sample size and period of this paper are relatively small, and the significance of the coefficients is weak. For expansion periods, we find a significant and positive risk premium on negative market jumps in both regressions with and regressions without control variables.

All the coefficients on the negative jump betas in these robustness checks are not much different from each other in terms of their magnitudes. Therefore, the positive risk premium on negative market jumps that we find in this paper can be considered a general result. The results of the robustness check with daily exchange rates are also qualitatively consistent with those of the analysis with intraday data.

6. Negative jumps & economic fundamentals

The results of the previous section show that only negative market jumps bear positive risk premiums. In this section, we elucidate the underlying reasons behind the significant risk premium of negative jumps. Specifically, we aim to identify how the sensitivities of returns to negative market jumps are related to economic fundamentals and business conditions.

6.1. Cross-section of negative jump betas

If a risk factor is cross-sectionally priced, the sensitivities of returns to the risk factor would have wide cross-sectional variation and be related to the risk factor in a consistent manner. Considering that the GDP and interest rate of a country are significantly related to the riskiness of the currency (Hassan, 2013; Ready, Roussanov, and Ward, 2016), we link negative jump betas to economic fundamentals that represent currency risks. If we find a significant relationship between negative jump betas and national characteristics, negative jump betas might also capture currency risks.

To confirm whether such a relationship exists, we establish the following regression model;

$$\beta_{i,m}^{(j-)} = a + b_1 GDPD_{i.m} + b_2 INTD_{i,m} + c' Z_{i,m} + \eta_{i,m}, \tag{5}$$

where $\beta_{i,m}^{(j-)}$ is the negative jump beta for foreign exchange rate i in month m, as defined in the previous section. In this regression model, the main independent variables are the GDP difference ($GDPD$) and interest rate differential ($INTD$) between country i and the U.S. We use continuous beta and other national characteristics (i.e., the net FDI inflow difference, difference in quarter-to-quarter percentage changes in the money base, trade propensity and trade balance between country i and the U.S.) as control variables (represented in $Z_{i,m}$). Among these economic variables, we focus our discussion on GDP and interest rate differentials because these two economic variables can represent the overall risk of a country and because the literature indicates that they are strongly related to currency values. Because the original data of national characteristics have different frequencies, we normalize the frequencies to a monthly basis.[15]

Using Eq. (5), we estimate the coefficients via regular panel and FMB regressions. We use these two different regressions for robustness, in that FMB regressions show the cross-sectional relationship but do not incorporate time series variations. In Table 8, the left part of the table is based on panel regressions, and the right part is based on FMB regressions. These two different approaches provide qualitatively similar results. As Table 8 shows, negative jump betas are negatively related to the GDP and positively related to the interest rate of a country, indicating that currencies of large economies with low interest rates tend to be less sensitive to negative market jumps. Therefore, the values of such currencies are relatively stable when a negative market jump occurs. These significant relationships do not change when we add other national characteristics and (international) trading variables.

These findings are consistent with those of Hassan (2013) and Ready, Roussanov, and Ward (2016). According to these papers, the currencies of larger economies provide better hedges to consumption risks than the currencies of smaller countries. In addition, compensation for the risks of economies can be embedded into the interest rates (i.e., the interest rates of riskier countries tend to be higher). Therefore, because currencies that are more sensitive to negative market jumps are related to higher risk in the economies that use the currencies, investors require higher expected returns to invest in these currencies. The significant relationships between negative jump betas and national characteristics indicate that negative jump betas properly capture the fundamentals of economies and currencies.

[15]GDP, FDI, and M1 data are on a quarterly basis and are assumed to be distributed evenly within the quarter. Interest rate data are on a daily basis, and the monthly average is taken for each country. We use differences for national characteristics because foreign exchange rates are the relative prices of two currencies. Because the data for exports and imports are based on transactions between a foreign country and the U.S., it is not necessary to use differences. Regarding the money base, because the original data provide local currency denoted numbers, we use the rates of increases in money bases for consistency in units.

6.2. *Time series of negative jump betas*

Economic risks change with business cycles, and investors' attentiveness to risks varies with time. Accordingly, although betas do not change dramatically over a short period of time, they can be time-varying over a long horizon. If negative jump betas reflect such risks well, they would change over time in accordance with the risks. Therefore, in this section, we investigate how negative jump betas vary in a descriptive way. We illustrate the time series of negative jump betas along with other three betas to examine whether the change in negative jump betas over time differs from that of the other betas.

Fig. 3 shows the time series plots of the four betas estimated in Section 4. We select low beta and high beta currencies (i.e., JPY and NZD) among typical carry trade currencies to examine the patterns of specific currencies and the variations in each beta. As Panels A and B show, the standard and continuous betas change in an indistinguishable way. In addition, the differences between the standard (and continuous) betas of the two currencies are more stable over time than those between the jump betas of the two currencies. The stable trend and variation in the standard betas might engender the insignificant premium on aggregated market risks. Unlike the standard and continuous betas, the jump betas dynamically change over time, as indicated in Panels C and D. In particular, the differentials between the jump betas of the two selected currencies are greater during recession periods.

As these time series plots indicate, negative jump betas vary more dynamically, and a greater number of them coincide with recessions. Therefore, negative jump betas incorporate information about the overall economic conditions well, and this property can be related to the significant premium associated with negative market jumps.

6.3. *Relationship between negative jump betas and liquidity*

As Section 5 shows, negative jump betas appear to deliver important fundamental pricing information. However, there could be a concern that the information embedded in negative jump betas is associated with liquidity because liquidity constraints are negatively related to business conditions and positively related to risks. In addition, as Brunnermeier, Nagel, and Pedersen (2008) and Mancini, Ranaldo, and Wrampelmeyer (2013) indicate, liquidity in foreign exchange markets can play an important role in currency pricing.

To confirm that the results in this paper are not driven by liquidity effects, we investigate the correlations between the monthly negative jump betas and the proxies for liquidity. Considering the literature, we use the monthly average of the bid-ask spread ratio (i.e., $(bid - ask)/mid$), the monthly realized variance, and the monthly average of interest rate differentials as liquidity proxies.[16] Table 9 reports the correlations between negative jump betas and each liquidity proxy. Overall, the correlations between negative jump betas and liquidity proxies are less than 23%. In addition, the correlations are less than 26% during recessions and expansions, respectively.

Although a simple correlation would not provide a decisive result, we believe that such low correlations are sufficient to support the conclusion that negative jump betas contain fundamental information that is different from that of liquidity. Considering these findings, we argue that negative jump betas are significantly related to economic fundamentals and that the dynamic variations in the cross-section of negative jump betas are sufficiently wide to clearly distinguish the characteristics of individual currencies.

7. Jump modified carry trade strategy

We demonstrate the financial implications of the results in the previous sections by proposing a jump modified carry trade strategy that incorporates the evidence obtained from the cross-sectional analyses. First, we explain the essence of constructing the jump modified

[16] See Mancini, Ranaldo, and Wrampelmeyer (2013) and Karnaukh, Ranaldo, and Sönderlind (2015) for details on liquidity in currency markets.

carry trade and compare it with regular carry trade. Then, we show the performance of the jump modified carry trade. For our demonstration, we assume high frequency traders whose strategies are based on the intraday analysis.[17]

7.1. Construction and adjustment of jump modified carry trade strategy

Our cross-sectional analysis suggests that carry traders achieve higher expected returns by lending higher negative jump beta currencies and borrowing lower negative jump beta currencies. Motivated by this result, we suggest that investors can modify their approach to selecting carry trade currencies. As described in the upper part of Fig. 4, when carry traders implement regular carry trades, they consider only the interest rates of the countries in which their carry trade currencies are used. However, if carry traders intend to enhance the expected returns of their carry trades, they can also consider the negative jump betas of carry trade currencies. Specifically, these investors lend currencies whose negative jump betas are higher among higher interest rate currencies and borrow currencies whose negative jump betas are lower among lower interest rate currencies, as described in the lower left part of Fig. 4. Using these two aspects of currencies, carry trade investors can take advantage of both interest rate differentials between investing and funding currencies and the higher appreciation of higher negative jump beta currencies. Therefore, the core idea of this modified approach is to consider "both" negative jump betas and interest rates. Because this modification of carry trades is based on jumps (i.e., negative jump betas), we call this currency trading strategy the *jump modified carry trade strategy.*

Although the jump modified carry trade strategy would provide higher expected returns than the regular carry trade strategy, it is more exposed to negative jump risks. As indicated

[17] For investors who have longer investment horizons (e.g., a month) and/or use daily analyses, we also provide a jump modified carry trade strategy that is based on the daily analysis in Appendix A. The performance of the jump modified strategy that is based on daily exchange rates is also consistent with that explained in this section. The quantitative results are available upon request.

in Section 5, the currency portfolios constructed by the jump modified carry trade strategy could experience severe losses when a negative market jump occurs. To mitigate such an adverse effect, investors can adopt adjustment schemes for their jump modified carry trades, as described in the lower right part of Fig. 4. First, investors can reduce the pool of their carry trade currencies by removing currencies that tend to have high negative jump betas from the pool. Because the currencies of countries with smaller GDPs and higher interest rates tend to have higher negative jump betas (recall Section 6), they are fair candidates for elimination from the carry trades. This approach is motivated by Bekaert and Panayotov (2016), which suggests that investors can improve the performance of carry trades by removing currencies with a lower historical Sharpe ratio from the pool of carry trade currencies.

The second approach is to identify the periods when negative market jumps are more likely to occur and adjust the carry trade portfolio during periods of market turmoil. Considering that negative market jumps coincide with severe depreciation of high negative jump beta currencies, investors could take a conservative position by lending currencies with lower negative jump betas among higher interest rate currencies and borrowing currencies with higher negative jump betas among lower interest rate currencies during periods when a negative market jump is likely to occur.[18] By conservatively changing the currency selection scheme, investors reduce the exposure of their carry trades to negative market jumps and consequently mitigate the adverse returns of carry trades during periods of market turmoil.

One concern of implementing the second approach of taking a conservative position is that investors need to identify periods when negative market jumps are likely to occur. To identify such periods, we use the empirical evidence in Lee and Wang (2016), which indicates that jumps in exchange rates tend to cluster. Specifically, if a negative jump arrives to the market, another negative market jump is likely to occur within a day. Therefore, if

[18] A negative jump can be detected in individual exchange rates or the market. In this section, we use the cases in which an individual negative jump coincides with a negative market jump because the prediction by these cases provides the highest likelihood of a negative market jump in the future.

investors who implement jump modified carry trades observe a negative market jump, they can temporarily take the above conservative positions. Because the jump clustering effects in currency markets weaken after a day, the time span of taking the conservative positions should be shorter than a day. Admittedly, this jump prediction is based on the increased likelihood of jumps and is not perfect. However, the rebalancing of carry trade portfolios that results from the jump prediction reduces (at least) some portion of the exposure to negative jump risks.

This jump modified carry trade strategy involves more frequent trading. If liquidity is low when investors desire to change their carry trade positions, the investors may not be able to implement the modified strategy. However, because the correlation between negative jump betas and illiquidity is relatively low, most transactions can be fulfilled without substantial costs. In addition, if funding liquidity is low, investors are required to unwind their positions. Low funding liquidity is less problematic for jump modified carry traders because these investors must remove their existing positions, as requested by their financial intermediaries. Nevertheless, a potential concern regarding limited funding liquidity is that the investors who use the jump modified carry trade strategy would find it difficult to take the conservative position after clearing their original positions, and the trading volumes that these investors incur to take the conservative positions could be smaller than those of their original positions. However, because this rebalancing aims to avoid the substantial depreciation of high negative jump beta currencies (i.e., to avoid negative jump risks), the investors implementing the jump modified carry trade strategy can still achieve this purpose (at least partially) if they take a zero position for the amounts for which they cannot change their position. Therefore, we believe that a liquidity problem is not a critical hurdle for jump modified carry trades.

In sum, investors who employ the jump modified carry trade strategy bear higher risks for higher expected returns by selecting high (low) negative jump beta currencies among high (low) interest rate currencies as investing (funding) currencies in general. However, these investors can also adopt the two suggested adjustments to cut the left tails of the return distribution of their carry trades if they observe a negative market jump. The first adjustment involves reducing the number of carry trade currencies by including only currencies whose negative jump betas are not extremely high, and the second adjustment involves rebalancing their carry trade portfolios temporarily by selecting low (high) negative jump beta currencies among high (low) interest rate currencies as investing (funding) currencies. Therefore, the jump modified carry trade strategy, unlike the regular one, involves a currency selection scheme that requires investors to consider not only interest rates but also negative jump betas. In addition, while the regular carry trade strategy does not include an adjustment scheme, the jump modified carry trade strategy allows investors to reduce their currency pool and to rebalance their carry trade portfolios conservatively.

7.2. Performance comparison

In this subsection, we demonstrate the performance of the jump modified carry trade strategy and compare it with that of the regular carry trade strategy. For complete comparison, we also analyze two additional carry trade strategies, which are introduced below. We define the specific portfolio construction and rebalancing approaches of the compared strategies.

As a benchmark, we first introduce the regular carry trade strategy and call investors who implement the regular strategy "Regular" investors. Regular investors take a long (short) position in the five highest (lowest) interest rate currencies among the 17 sample currencies and rebalance their positions every day. The next strategy is the jump modified carry trade strategy that we explain in the previous subsections. Investors who employ this strategy are called "Modified" investors. Modified investors consider both interest rates and negative jump betas, and they take a long position in the currencies with the five highest negative jump betas among the eight higher interest rate currencies and take a short position in the currencies with the five lowest negative jump betas among the eight lower interest rate currencies. In addition, taking advantage of jump information, they then temporarily rebalance their carry trade portfolios if they observe a negative jump. Immediately after a negative jump that coincides with a market jump occurs, they drop the currencies of the two lowest GDP and the two highest interest rate countries from the candidate currencies for 12 hours. We set 12 hours as the period for taking conservative positions because the jump clustering effect is strong during this time span. Subsequently, they pick the currencies with lower (higher) negative jump betas among the remaining higher (lower) interest rate currencies as investing (funding) currencies.

The two additional carry trade strategies for comparison are as follows. In Section 2, we introduced investors who implement regular carry trades in general but who take a zero position during the periods when jumps are highly likely. The period in which they take a zero position is the same as the Jump Period (defined in Section 2). Because such investors avoid jump risks, we call their carry trade strategy the "jump robust carry trade strategy" and label them "Robust" investors. Finally, because investors can use both jump modified and robust carry trades, we also include such investors in our consideration. In particular, these investors implement the jump modified strategy in general but take a zero position when a jump is highly likely to occur. Considering that such investors combine two carry trade strategies, we call their carry trade strategy the "hybrid carry trade strategy" and label them "Hybrid" investors.

For the above four types of investors, we analyze their investment performance for the period from September 2000 to December 2015. This time span is shorter than the whole sample period because we can maintain the sufficient numbers of currencies in the cross-section and because we use previous one-year observations to estimate betas. The available currencies are the 17 currencies in the sample. For market returns, we use the equally weighted average of the returns of these currencies. To clearly show the difference between the various strategies, we assume that the transaction costs are negligible.[19]

The performance comparison of the four types of investors is provided in Fig. 5 and Table 10. Fig. 5 depicts the cumulative carry trade returns. The blue (denoted by "Regular"), red (denoted by "Robust"), gray (denoted by "Modified"), and yellow (denoted by "Hybrid") lines represent returns for Regular, Robust, Modified, and Hybrid investors, respectively. The cumulative carry trade returns for Modified investors are approximately 31 percentage points higher than those for Regular investors at the end of the investment horizon. Further, the returns of the jump modified carry trades tend to increase more rapidly during bull market periods than those of the regular carry trades, while they tend to decrease more slowly during bear market periods. For example, regular carry trades provide substantially lower returns in 2011, and jump modified carry trades capture upward returns at the end of 2009. Fig. 5 also shows that Robust investors achieve almost the same level of cumulative returns as Modified investors. However, if Robust investors implement the jump modified strategy instead of regular carry trades, they (i.e., Hybrid investors) would achieve even higher cumulative returns, approximately 42% higher than those of Regular investors.

Table 10 summarizes the means and standard deviations of the returns to the above four strategies. Among the regular, jump robust, and jump modified carry trade strategies, the jump modified strategy provides the highest annualized mean returns [i.e., 3.74% (Modified)> 3.48% (Robust)> 2.19% (Regular)]. In addition, the standard deviation of the jump modified strategy (5.55%) is comparable to that of the regular strategy (5.40%). Therefore, because it has approximately two-percentage-point higher returns than and the standard deviation similar to the regular carry trade strategy, the jump modified carry trade strategy has a higher Sharpe ratio than the regular carry trade strategy [i.e., 0.67 (Modified)>0.41 (Regular)]. Finally, as implied in the above explanation regarding cumulative returns, the strategy that combines the jump modified and robust strategies provides much higher returns and a lower

[19] Even if we include the transaction costs, we can still find the superior performance of jump modified carry trades.

standard deviation. Therefore, the Sharpe ratio of the Hybrid strategy is 0.99.

The better performance of jump modified carry trades is consistent with our findings of the cross-sectional asset pricing tests in Section 5. Modified investors can exploit the higher expected returns of higher negative jump beta currencies; simultaneously, because these investors use lower negative jump beta currencies as funding currencies, they owe less in their leverage positions. Furthermore, because Modified investors mitigate the risks of extreme losses that coincide with negative jumps by taking conservative positions, they can achieve such higher returns with comparable volatility (than Regular investors).[20]

8. Conclusion

This paper examines how jump risks are priced in currency markets and shows the financial implications by proposing a jump modified carry trade strategy. We establish a model that decomposes the process of a foreign exchange rate into market and individual (or non-market) components. In addition, the market components are separated into continuous, positive jump, and negative jump components. We then suggest approaches for estimating the sensitivities of exchange rate changes to the decomposed market components (i.e., betas). By explicitly separating these components and the estimated beta for each component, we test how various types of risks are differently priced.

The cross-sectional analysis provides unique evidence showing that only negative jump risks are priced and bear the positive risk premium in currency markets. This finding suggests that investors can enhance their carry trade returns by considering negative jump betas. In particular, high negative jump beta currencies, which provide higher expected returns, increase the carry trade returns if they are chosen as investing currencies. However, the results

[20] We check whether idiosyncratic jumps affect this result. After excluding realized idiosyncratic jumps, we continue to find that the jump modified strategy outperforms the regular strategy. Our conclusion on relative performance of the jump modified strategy is robust to the presence of idiosyncratic jump risks.

also suggest that when the market experiences negative jumps, these currencies depreciate sharply. To mitigate this concern, the jump modified carry trade strategy involves temporarily reversing carry trade positions. If carry trade investors lend the currencies with higher negative jump betas during normal periods and lend the currencies with lower negative jump betas during periods when negative (market) jumps are likely to occur, the resulting carry trade returns are higher than regular carry trade returns, and the standard deviation is comparable. These results are obtained because negative jump betas are significantly related to economic fundamentals and contain information that is different from liquidity.

The empirical results of this paper contribute to the literature on the profitability of carry trades with a risk premium by revealing that investors require greater compensation for currencies that are more sensitive to negative market jumps. This paper also suggests a practical approach to enhance the performance of carry trades.

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Table 1. Summary statistics

This table reports the distributions of the daily realized returns of the 17 foreign exchange rates and the national characteristics of the 17 countries during the sample period of January 1999 to December 2015. The last row, denoted by "Market (USD)", provides the moments of the market returns, which are the average of the 17 currency returns and the national characteristics of the U.S. for reference. The first column lists the country names and currency codes (the exception is the last row for the U.S.). The next four columns provide the first four central moments of the daily return tht are obtained from the 15-minute log returns of each currency. The log return is defined as $r_{i,t(l)} = lnS_{i,t(l)} - lnS_{i,t(l-1)}$, where $S_{i,t(l)}$ is the l-th discrete observation of spot exchange rate i and expressed in USD per unit of the currency. The numbers reported as means and standard deviations are denoted in percentage per annum. The remaining part shows the average quarterly GDP denoted in 2010 USD, the average (risk-free) interest rate denoted in percentage per annum, the average of the quarter-to-quarter percent change in the money base, the average quarterly net FDI inflow, a country's average monthly exports to the U.S., and a country's average monthly imports from the U.S.

Country	Daily Return				National Characteristic					
(Currency Code)	Mean (%)	Stdev (%)	Skew	Kurt	GDP ($B)	Int (%)	M1 (%)	FDI ($M)	Exp ($M)	Imp ($M)
Australia (AUD)	2.53	12.04	-0.35	6.14	288	4.68	1.58	5,535	689	1,607
Canada (CAD)	-0.47	8.55	-0.44	6.12	389	2.53	2.08	-753	23,045	19,136
Euro area (EUR)	-0.57	9.87	-0.05	3.97	3,068	2.08	1.97	-27,452	26,304	18,022
Hungary (HUF)	-1.50	14.28	-0.18	5.41	32	7.47	2.90	-506	256	100
India (INR)	11.26	19.21	0.23	10.12	333	8.81	3.26	3,186	2,056	1,083
Japan (JPY)	-0.33	9.63	0.05	4.23	1,349	0.18	1.39	-17,093	10,978	4,991
Korea (KRW)	6.05	9.69	0.19	6.82	243	2.86	2.73	-1,733	4,011	2,733
Norway (NOK)	-2.60	12.08	-0.14	4.34	104	3.60	3.09	-1,433	511	224
New Zealand (NZD)	3.45	12.92	-0.36	5.11	34	4.98	1.89	238	245	222
Poland (PLN)	0.04	14.76	-0.24	6.52	107	6.62	3.13	2,695	224	187
Russia (RUB)	-10.71	13.86	-1.18	16.01	340	7.78	5.62	-906	1,488	487
Singapore (SGD)	0.06	5.29	-0.26	5.55	50	1.21	2.69	3,929	1,421	1,982
South Africa (ZAR)	-10.05	19.05	-0.54	6.20	86	8.66	2.84	639	565	400
Sweden (SEK)	-1.66	12.31	-0.12	4.43	116	2.31	1.81	-1,829	895	351
Switzerland (CHF)	-0.46	10.43	0.04	3.79	137	0.87	1.65	-7,739	1,455	1,363
Turkey (TRY)	-17.47	15.56	-0.64	10.58	168	10.33	6.98	2,002	402	605
United Kingdom (GBP)	0.53	8.64	-0.21	5.00	589	3.11	2.09	-1,934	4,129	3,793
Market (USD)	-1.20	7.95	-0.10	4.83	3,621	2.24	1.54	-17,458	-	-

Table 2. Realized jumps in the currency market

This table presents the descriptive summary statistics of the jump detection results. To detect jumps in currency markets, we employ the approach by Lee and Mykland (2008) and adjust the intraday volatility patterns of individual exchange rates. We apply the significance level of 5% and use data sampled every 15 minutes from January 1999 to December 2015. In the first column, the country names and currency codes are listed. The last two rows report the statistics for the market composed of the 17 foreign exchange rates and for the averages across the sample foreign exchange rates. "#Test" is the number of times we apply jump detection tests. "#Jp" is the number of intraday jumps. "%Jp" is the percentage of the number of detected jumps relative to the number of jump tests. "(+)Jp" and "(−)Jp" are the numbers of jumps with positive and negative jump sizes. "#Jday" is the number of days with at least one intraday jump. "%Jday" is the percentage of the number of jump days relative to the total number of days in the sample. The last six columns show the 25th, 50th, and 75th percentiles of positive and negative jump size distributions.

Country								Positive Jump Size			Negative Jump Size		
(Currency Code)	#Test	#Jp	% Jp	#(+)Jp	#(−)Jp	#Jday	%Jday	25p	50p	75p	25p	50p	75p
Australia (AUD)	404,721	3,437	0.85	1,581	1,856	1,984	45.66	0.0021	0.0027	0.0035	-0.0035	-0.0028	-0.0021
Canada (CAD)	402,079	3,548	0.88	1,784	1,764	1,829	42.07	0.0012	0.0017	0.0024	-0.0024	-0.0017	-0.0011
Euro area (EUR)	409,738	3,471	0.85	1,691	1,780	2,023	46.47	0.0017	0.0022	0.0030	-0.0030	-0.0023	-0.0017
Hungary (HUF)	407,309	4,337	1.06	2,073	2,264	1,951	44.70	0.0022	0.0031	0.0041	-0.0042	-0.0031	-0.0022
India (INR)	190,005	9,875	5.20	4,955	4,920	1,365	54.71	0.0010	0.0020	0.0047	-0.0048	-0.0021	-0.0010
Japan (JPY)	409,679	4,020	0.98	2,195	1,825	2,074	47.69	0.0017	0.0022	0.0029	-0.0029	-0.0022	-0.0016
Korea (KRW)	289,574	11,090	3.83	5,598	5,492	2,501	75.67	0.0020	0.0027	0.0038	-0.0038	-0.0027	-0.0020
Norway (NOK)	403,662	3,134	0.78	1,518	1,616	1,785	41.10	0.0021	0.0028	0.0037	-0.0037	-0.0028	-0.0021
New Zealand (NZD)	402,351	4,666	1.16	2,190	2,476	2,288	52.66	0.0025	0.0032	0.0041	-0.0041	-0.0032	-0.0025
Poland (PLN)	328,185	4,918	1.50	2,437	2,481	1,562	43.94	0.0011	0.0019	0.0031	-0.0033	-0.0021	-0.0011
Russia (RUB)	214,006	5,501	2.57	2,753	2,748	1,409	56.70	0.0012	0.0020	0.0031	-0.0031	-0.0020	-0.0012
Singapore (SGD)	378,539	4,132	1.09	2,025	2,107	2,013	47.19	0.0010	0.0013	0.0017	-0.0017	-0.0013	-0.0010
South Africa (ZAR)	316,214	4,721	1.49	2,264	2,457	1,801	47.21	0.0020	0.0033	0.0047	-0.0047	-0.0033	-0.0019
Sweden (SEK)	402,930	2,864	0.71	1,403	1,461	1,689	38.85	0.0020	0.0027	0.0036	-0.0035	-0.0026	-0.0020
Switzerland (CHF)	406,233	3,632	0.89	1,859	1,773	2,034	46.74	0.0018	0.0025	0.0032	-0.0033	-0.0024	-0.0018
Turkey (TRY)	239,242	3,184	1.33	1,433	1,751	1,266	43.31	0.0015	0.0025	0.0039	-0.0038	-0.0024	-0.0014
United Kingdom (GBP)	407,759	3,110	0.76	1,488	1,622	1,887	43.32	0.0015	0.0019	0.0026	-0.0026	-0.0020	-0.0015
Market (USD)	396,168	2,353	0.59	1,121	1,232	1,471	33.88	0.0013	0.0017	0.0022	-0.0021	-0.0016	-0.0012
Average of 17 FX	353,660	4,685	1.53	2,309	2,376	1,851	48.12	0.0017	0.0024	0.0034	-0.0034	-0.0024	-0.0017

Table 3. Beta estimation results

This table reports the estimation results of the standard, continuous, positive jump, and negative jump betas. The estimators of the four betas are defined as $\hat{\beta}^{(q)}_{i,m} = \frac{\Sigma_{l \in P_m} r_{i,t(l)} r_{0,t(l)} \cdot I(q)_{i,t(l)} I(q)_{0,t(l)}}{\Sigma_{l \in P_m} r^2_{0,t(l)} \cdot I(q)_{0,t(l)}}$, where $r_{i,t(l)} = \ln S_{i,t(l)} - \ln S_{i,t(l-1)}$ and $S_{i,t(l)}$ is the spot rate of currency i at time $t(l)$. Subscript "0" denotes the market, for which the returns are the average of the 17 currency returns. Subscript m denotes month m. $q = \{s,\ c,\ j+,\ j-\}$ is a notation to distinguish the four kinds of betas (i.e., standard, continuous, positive jump, and negative jump betas). $P_m = \{l|t(l)$ belongs to month $m\}$ is a set of indices of time points from month $m-11$ to month m. $\hat{\beta}_{i,m}$ in this table is based on the one-month rolling estimation over one year, and this estimation uses the observations from the end of month $m-12$ to the end of month m. $I(q)_{i,t(l)}$ and $I(q)_{0,t(l)}$ are dummy variables that are related to individual and market jump arrivals. If $q = s$, $I(q)_{i,t(l)}$ and $I(q)_{0,t(l)}$ take the value of one for all l. If $q = c$, $I(q)_{i,t(l)}$ ($I(q)_{0,t(l)}$) is one when an individual (the market) jump does not arrive for foreign exchange rate i (the market) from time $t(l-1)$ to $t(l)$ and zero otherwise. If $q = j+(j-)$, $I(q)_{0,t(l)}$ is one when a market jump with a positive (negative) jump size occurs and zero otherwise. In this case, $I(q)_{i,t(l)}$ is one for all l. Panel A summarizes the (time series) means and standard deviations of the four monthly estimated betas for the 17 foreign exchange rates. In each column labeled Mean, the maximum and minimum are in boldface. Panel B shows the average correlations among the betas. For each beta, we compute the correlations within an individual exchange rate and then report the average of the correlations of the 17 exchange rates. Panel C reports the differences between continuous, positive jump, and negative jump betas along with the significance. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Means and standard deviations of the betas

Country	Std. Beta		Con. Beta		(+) Jp Beta		(−) Jp Beta	
(Currency Code)	Mean	Stdev	Mean	Stdev	Mean	Stdev	Mean	Stdev
Australia (AUD)	1.01	0.20	1.03	0.22	1.01	0.14	1.05	0.16
Canada (CAD)	0.64	0.14	0.64	0.16	0.67	0.16	0.68	0.15
Euro area (EUR)	0.99	0.14	0.98	0.15	1.22	0.13	1.19	0.18
Hungary (HUF)	**1.45**	0.17	**1.43**	0.18	**1.72**	0.17	**1.79**	0.23
India (INR)	0.27	0.18	0.23	0.15	0.78	0.61	0.95	0.89
Japan (JPY)	**0.23**	0.32	**0.19**	0.31	0.47	0.28	**0.36**	0.36
Korea (KRW)	0.32	0.26	0.28	0.26	0.48	0.32	0.45	0.32
Norway (NOK)	1.11	0.14	1.09	0.15	1.28	0.13	1.34	0.16
New Zealand (NZD)	1.01	0.20	1.01	0.24	1.07	0.16	1.00	0.19
Poland (PLN)	1.38	0.19	1.38	0.21	1.65	0.21	1.60	0.21
Russia (RUB)	0.49	0.10	0.46	0.09	0.71	0.22	0.62	0.17
Singapore (SGD)	0.34	0.08	0.32	0.09	**0.38**	0.10	0.40	0.08
South Africa (ZAR)	1.03	0.17	1.01	0.18	1.26	0.20	1.22	0.21
Sweden (SEK)	1.12	0.14	1.10	0.16	1.33	0.15	1.36	0.15
Switzerland (CHF)	0.87	0.21	0.84	0.21	1.17	0.18	1.04	0.29
Turkey (TRY)	0.70	0.16	0.68	0.17	0.76	0.18	0.90	0.19
United Kingdom (GBP)	0.68	0.16	0.68	0.16	0.75	0.13	0.73	0.15

Panel B. Correlations of the betas

	Std. Beta	Con. Beta	(+) Jp Beta	(−) Jp Beta
Std. Beta	1			
Con. Beta	0.983	1		
(+) Jp Beta	0.789	0.743	1	
(−) Jp Beta	0.766	0.721	0.769	1

Table 3. Beta estimation results (continued)

Panel C. Difference between the betas

	Con. vs. (+)Jp beta	Con. vs. (−)Jp beta	(+)Jp vs. (−)Jp beta
AUD	0.000	0.028***	0.037***
CAD	0.038***	0.046***	0.014
EUR	0.262***	0.220***	0.045***
HUF	0.308***	0.373***	0.062***
INR	0.524***	0.705***	0.196***
JPY	0.299***	0.186***	0.117***
KRW	0.203***	0.178***	0.021*
NOK	0.200***	0.261***	0.056***
NZD	0.069***	0.009	0.065***
PLN	0.293***	0.240***	0.055***
RUB	0.244***	0.155***	0.090***
SGD	0.054***	0.075***	0.019***
ZAR	0.246***	0.204***	0.039***
SEK	0.241***	0.265***	0.023***
CHF	0.350***	0.211***	0.144***
TRY	0.076***	0.219***	0.139***
GBP	0.101***	0.067***	0.030***

Table 4. Cross-sectional regression with jump betas

This table provides the results of the cross-sectional asset pricing analysis with jump risks in currency markets. We run the traditional Fama-MacBeth regression: $mrx_{i,m+1} = \lambda_{0,m} + \lambda_{1,m}\beta_{i,m}^{(c)} + \lambda_{2,m}^{(j+)}\beta_{i,m}^{(j+)} + \lambda_{3,m}^{(j-)}\beta_{i,m}^{(j-)} + \gamma_m' X_{i,m} + \varepsilon_{i,m+1}$, where subscript m denotes the m-th month. $mrx_{i,m} = \int_{t\in m} drx_{i,t}$ is the monthly realized excess return related to currency i from the end of month $m-1$ to the end of month m. $\beta_{i,m}^{(q)}$ represents the sensitivity of the log return of currency i to the average return of the 17 exchange rates. The betas are estimated by $\hat{\beta}_{i,m}^{(q)} = \frac{\Sigma_{l\in P_m}\ r_{i,t(l)} r_{0,t(l)} \cdot I(q)_{i,t(l)} I(q)_{0,t(l)}}{\Sigma_{l\in P_m}\ r_{0,t(l)}^2 \cdot I(q)_{0,t(l)}}$. $\hat{\beta}_{i,m}^{(q)}$ is based on the one-month rolling estimation over one year (i.e., the estimation uses the observations from the end of month $m-12$ to the end of month m). $r_{i,t(l)} = \ln S_{i,t(l)} - \ln S_{i,t(l-1)}$ is a change in log spot rate i from time $t(l-1)$ to $t(l)$. $S_{i,t(l)}$ is the spot rate of currency i at time $t(l)$. Subscript "0" denotes the market, for which the returns are the average of the 17 currency returns. $q = \{s,\ c,\ j+,\ j-\}$ is a notation to distinguish the four kinds of betas (i.e., standard, continuous, positive jump, and negative jump betas). $P_m = \{l | t(l)$ belongs to month $m\}$ is a set of indices of time points from month $m-11$ to month m. $I(q)_{i,t(l)}$ and $I(q)_{0,t(l)}$ are dummy variables that are related to individual and market jump arrivals. If $q = s$, $I(q)_{i,t(l)}$ and $I(q)_{0,t(l)}$ take the value of one for all l. If $q = c$, $I(q)_{i,t(l)}$ ($I(q)_{0,t(l)}$) is one when an individual (the market) jump does not arrive for foreign exchange rate i (the market) from time $t(l-1)$ to $t(l)$ and zero otherwise. If $q = j+(j-)$, $I(q)_{0,t(l)}$ is one when a market jump with a positive (negative) jump size occurs and zero otherwise. In this case, $I(q)_{i,t(l)}$ is one for all l. $X_{i,m}$ is a vector of control variables for country i and month m. The two control variables are VOL and HML. VOL is the exposure to the innovations in the global volatility factor ($= (1/NP)\Sigma_{l\in P_m}(1/17)\Sigma_{i=1}^{17}|r_{i,t(l)}|$, where NP is the number of available time points during month m). HML is the exposure to the carry risk factor (the difference between the excess returns of high interest rate currencies and low interest rate currencies). Columns (I) and (II) report the coefficients and robust t-statistics of the univariate regressions of standard and continuous betas. Columns (III) and (IV) present the estimation results of the regressions of the two jump betas with the control of continuous beta. Columns (V)-(VI) show those of multivariate regressions employing both positive and negative jump betas as regressors. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(I)	(II)	(III)	(IV)	(V)	(VI)
Cons.	1.274	1.553	-4.514	-4.695	-5.508	-5.198
t-stat	0.30	0.37	-1.12	-1.15	-1.33	-1.38
S. beta	-2.247					
t-stat	-0.47					
C. beta		-2.508	-6.654	-20.548*	-15.888	-11.305
t-stat		-0.52	-0.47	-1.75	-1.17	-0.81
(+)Jp beta			6.062		-15.235	-14.790
t-stat			0.51		-1.12	-1.04
(−)Jp beta				18.691*	30.171**	25.709**
t-stat				1.86	2.55	2.01
Control:						
VOL						0.042
HML						-5.197
Adj. R^2 (%)	15.01	15.21	31.37	31.61	39.72	54.54

Table 5. Average excess returns by market conditions
This table shows that currencies with higher negative jump betas depreciate substantially during periods of market turmoil. It presents the excess returns depending on the levels of market returns, which are the averages of the 17 currency returns. The "Good Time" denotes months when the market returns are above the fourth quartile, while the "Bad Time" denotes months when the market returns are below the first quartile. For each month, the 17 currencies are sorted on the negative jump betas, and tercile portfolios are constructed (i.e., the currencies in the first tercile portfolio (denoted by "Low $\beta^{(-j)}$" in the table) have the lowest negative jump betas). For each portfolio, the time series averages of the excess returns are reported by the two types of periods. The return differences between the Good and Bad Times are shown in the last row, and those between high and low negative jump beta portfolios are reported in the right column. The numbers are denoted in percentage per annum.

	Low $\beta^{(-j)}$	Mid $\beta^{(-j)}$	High $\beta^{(-j)}$	High-Low
Good Time	36.45	48.61	64.22	27.78
Bad Time	-43.06	-72.34	-72.70	-29.64
Good-Bad	79.50	120.95	136.92	57.42

Table 6. Returns of sorted portfolios
This table confirms the positive relationship between negative jump betas and excess returns. Panel A reports the excess returns and log returns of portfolios that are sorted on negative jump, positive jump, continuous, and standard betas. The results for portfolios sorted on the sensitivity to carry risk factors (denoted HML beta) are provided in the last row. Following Bollerslev, Li, and Todorov (2016), at the beginning of a month, we sort the 17 exchange rates on each beta on a monthly basis and construct tercile portfolios. The excess returns (log returns) of portfolios with the lowest beta are reported in Column (I) of the left (right) part. The excess returns (log returns) of portfolios with the highest beta are reported in Column (III) of the left (right) part. The differences between the excess returns (log returns) of portfolios with the highest and lowest betas are shown in Column (III)-(I) of the left (right) part. Panel B reports the excess returns and log returns of portfolios that are first sorted on HML beta and then sorted on negative and positive jump betas. Specifically, we construct tercile portfolios depending on HML betas. Within each HML beta sorted portfolio, we separate exchange rates into tercile portfolios depending on jump betas. The results for negative (positive) jump betas are reported in the upper (lower) part. The excess returns and log returns of sorted portfolios are reported in the same way as Panel A. Panel C shows the values of jump betas of the double sorted portfolios. The left (right) part is for negative (positive) jump betas, and Columns (III)-(I) reports their spreads. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Single sort

	Excess returns				Changes in log spot exchange rates			
	(I)	(II)	(III)	(III)-(I)	(I)	(II)	(III)	(III)-(I)
Sort on (−)Jp beta	-0.758	0.453	4.944	5.702*	-1.509	-2.598	2.747	4.256
Sort on (+)Jp beta	-2.188	2.576	3.906	6.094*	-3.258	-0.259	1.920	5.178
Sort on C. beta	0.692	1.653	-1.420	-2.112	-0.802	-0.230	-3.731	-2.929
Sort on S. beta	0.739	1.925	-1.513	-2.252	-0.805	-0.049	-3.815	-3.010
Sort on HML beta	1.564	9.070	-1.066	-2.630	1.127	6.708	-4.195	-5.322

Panel B. Double sort

	Excess returns				Changes in log exchange rates			
(−)Jp beta	(I)	(II)	(III)	(III)-(I)	(I)	(II)	(III)	(III)-(I)
Low HML beta	1.653	0.097	12.279	10.625**	1.664	-0.025	10.659	8.995*
Mid HML beta	4.941	-	5.846	0.905	2.757	-	3.667	0.910
High HML beta	-2.904	-6.097	0.302	3.206	-6.043	-12.863	-0.788	5.254
	Excess returns				Changes in log exchange rates			
(+)Jp beta	(I)	(II)	(III)	(III)-(I)	(I)	(II)	(III)	(III)-(I)
Low HML beta	1.399	0.262	10.870	9.471**	1.363	0.043	9.343	7.980*
Mid HML beta	4.226	-	5.012	0.786	2.616	-	2.867	0.251
High HML beta	-8.082	0.502	-2.750	5.332	-11.445	-6.618	-3.133	8.311

Panel C. Jump betas of double sorted portfolios

	Negative jump beta				Positive jump beta			
	(I)	(II)	(III)	(III)-(I)	(I)	(II)	(III)	(III)-(I)
Low HML beta	0.480	0.999	1.531	1.051***	0.531	1.066	1.499	0.968***
Mid HML beta	0.600	-	1.258	0.658***	0.613	-	1.233	0.621***
High HML beta	0.575	1.006	1.456	0.881***	0.565	0.961	1.425	0.860***

Table 7. Robustness check: cross-sectional regression of subsamples

This table demonstrates the robustness of the positive risk premium on negative jump risks. We run the traditional Fama-MacBeth regression: $mrx_{i,m+1} = \lambda_{0,m} + \lambda_{1,m}\beta_{i,m}^{(c)} + \lambda_{2,m}^{(j+)}\beta_{i,m}^{(j+)} + \lambda_{3,m}^{(j-)}\beta_{i,m}^{(j-)} + \gamma_m' X_{i,m} + \varepsilon_{i,m+1}$, where subscript m denotes the m-th month. $mrx_{i,m} = \int_{t\in m} drx_{i,t}$ is the monthly realized excess return related to currency i from the end of month $m-1$ to the end of month m. $\beta_{i,m}^{(q)}$ represents the sensitivity of the log return of currency i to the average return of the 17 foreign exchange rates. The betas are estimated by $\hat{\beta}_{i,m}^{(q)} = \frac{\Sigma_{l\in P_m}\ r_{i,t(l)}r_{0,t(l)}\cdot I(q)_{i,t(l)}I(q)_{0,t(l)}}{\Sigma_{l\in P_m}\ r_{0,t(l)}^2\cdot I(q)_{0,t(l)}}$. $\hat{\beta}_{i,m}^{(q)}$ is based on the one-month rolling estimation over one year, and this estimation uses the observations from the end of month $m-12$ to the end of month m. $r_{i,t(l)}$ =ln$S_{i,t(l)}$−ln$S_{i,t(l-1)}$ is a change in log spot rate i from time $t(l-1)$ to $t(l)$. $S_{i,t(l)}$ is the spot rate of currency i at time $t(l)$. Subscript "0" denotes the market, for which the returns are the average of the 17 currency returns. $q = \{s,\ c,\ j+,\ j-\}$ is a notation to distinguish the four kinds of betas (i.e., standard, continuous, positive jump, and negative jump betas). $P_m = \{l|t(l)$ belongs to month $m\}$ is a set of indices of time points from month $m-11$ to month m. $I(q)_{i,t(l)}$ and $I(q)_{0,t(l)}$ are dummy variables that are related to individual and market jump arrivals. If $q = s$, $I(q)_{i,t(l)}$ and $I(q)_{0,t(l)}$ take the value of one for all l. If $q = c$, $I(q)_{i,t(l)}$ ($I(q)_{0,t(l)}$) is one when an individual (the market) jump does not arrive for foreign exchange rate i (the market) from time $t(l-1)$ to $t(l)$ and zero otherwise. If $q = j+(j-)$, $I(q)_{0,t(l)}$ is one when a market jump with a positive (negative) jump size occurs and zero otherwise. In this case, $I(q)_{i,t(l)}$ is one for all l. $X_{i,m}$ is a vector of control variables for country i and month m. The two control variables are VOL and HML. VOL is the exposure to the innovations in the global volatility factor ($= (1/NP)\Sigma_{l\in P_m}(1/17)\Sigma_{i=1}^{17}|r_{i,t(l)}|$, where NP is the number of available time points during month m). HML is the exposure to the carry risk factor (the difference between the excess returns of high interest rate currencies and low interest rate currencies). Under "G14", we report the results based on the subsample without HUF, PLN, and TRY. Under "Recession" ("Expansion"), we show the results of the subperiods that include the observations during U.S. recessions (expansions). We choose the subperiods and business cycles that are based on the National Bureau of Economic Research (NBER). Column (I) reports the regression results without a control variable, while Column (II) shows those with control variables. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	G14		Recession		Expansion	
	(I)	(II)	(I)	(II)	(I)	(II)
Cons.	-4.936	-2.237	-36.708**	-30.875*	-0.250	-0.870
t-stat	-1.10	-0.53	-2.66	-2.05	-0.06	-0.25
C. Beta	-13.486	-5.352	-48.500	-21.975	-10.391	-9.507
t-stat	-0.94	-0.36	-1.62	-0.70	-0.69	-0.62
(+)Jp Beta	-25.477	-25.667	46.403	2.536	-25.623*	-17.709
t-stat	-1.62	-1.61	1.70	0.10	-1.72	-1.10
(−)Jp Beta	39.798***	30.535**	-4.416	12.061	36.000**	28.010*
t-stat	2.75	2.08	-0.25	0.59	2.68	1.93
Control:						
VOL		0.386		-1.634		0.324
HML		-1.863		-26.440*		-2.344
Adj. R^2 (%)	44.68	61.56	35.52	53.11	40.43	54.78

Table 8. Relationship among negative jump betas and national characteristics

This table investigates the cross-sectional relationship among negative jump betas and national characteristics. We run a regression, $\beta^{(j-)}_{i,m} = a + b_1 GDPD_{i.m} + b_2 INTD_{i,m} + c' Z_{i,m} + \eta_{i,m}$, where $\beta^{(j-)}_{i,m}$ is the exposure of an individual exchange rate i to negative market jumps. The negative jump beta for foreign exchange rate i in month m is estimated by $\hat{\beta}^{(j-)}_{i,m} = \frac{\Sigma_{l \in P_m}\ r_{i,t(l)} r_{0,t(l)} \cdot I(j-)_{i,t(l)} I(j-)_{0,t(l)}}{\Sigma_{l \in P_m}\ r^2_{0,t(l)} \cdot I(j-)_{0,t(l)}}$. The β's in this table are based on the one-month rolling estimation over one year, and month m indicates the end of month $m-12$ to the end of month m. $I(j-)_{0,t(l)}$ takes the value of one when a negative market jump occurs and zero otherwise, and $I(j-)_{i,t(l)}$ always takes the value of one. In this regression model, the main independent variables are the GDP difference (GDPD) and interest rate differential (INTD). We use continuous beta and other national characteristics (i.e., the net FDI inflow difference, difference of quarter-to-quarter percentage changes in the money base, trade propensity and trade balance between country i and the U.S.) as control variables (represented in $Z_{i,m}$). GDP, FDI, and M1 data are on a quarterly basis and are assumed to be distributed evenly within the quarter. Interest rate data are on a daily basis, and the monthly average is taken for each country. This table is composed of the two parts; the left three columns are based on a regular panel regression, while the right three columns use Fama-MacBeth (1973) regression. For each part, Column (I) uses the main independent variables (i.e., GDP and interest rate differential); Column (II) additionally includes M1 growth, net FDI differences, trade propensity, and trade balance as regressors; and Column (III) additionally includes continuous beta as a control. ***, **, and * denote statistical significance at the 1%, 5%, and 10%, respectively.

	Panel Regression			FMB Regression		
	(I)	(II)	(III)	(I)	(II)	(III)
Cons.	0.820***	0.877***	-0.030	0.808***	0.056	-0.377***
t-stat	17.74	10.09	-0.71	40.47	0.40	-4.81
GDP difference	-0.100**	-0.196***	-0.206***	-0.036**	-0.894***	-0.339***
t-stat	-2.44	-2.66	-6.34	-2.12	-7.48	-5.28
Interest rate differential	0.021***	0.006*	0.015***	0.048***	0.027***	0.030***
t-stat	5.50	1.68	6.02	8.24	4.42	6.21
M1 growth difference		-0.003	-0.011***		-0.052***	-0.012
t-stat		-0.42	-2.67		-2.70	-0.93
net FDI difference		-0.363	0.605		6.201	5.095**
t-stat		-0.48	1.30		1.19	2.17
Trade propensity		-1.927***	-0.635***		-1.902***	-0.465***
t-stat		-16.82	-10.80		-15.34	-5.33
Trade balance		1.204	26.689***		35.095***	46.207***
t-stat		0.17	7.92		3.35	8.40
Continuous beta			0.95***			0.97***
t-stat			54.54			48.00
Adj. R^2 (%)	2.92	11.97	69.76	12.87	39.28	88.08

Table 9. Relationship between negative jump betas and liquidity
This table reports correlations between negative jump betas and liquidity. We investigate whether information embedded in negative jump betas is different from that in a liquidity proxy. As proxies for liquidity, we use the monthly average of bid-ask spreads ($=(ask-bid)/mid\ quotes$), monthly realized variances, and interest rate differentials [following Mancini, Ranaldo, and Wrampelmeyer (2013) and Karnaukh, Ranaldo, and Sönderlind (2015)]. The column denoted by "Overall" provides the correlations during the beta estimation period, the column "Recession" shows those during the recession period, and the column "Expansion" reports those during the expansion period. We choose the business cycles that are based on the National Bureau of Economic Research (NBER).

Liquidity	Overall	Recession	Expansion
BAS	0.147	0.106	0.172
Variance	0.222	0.188	0.257
Int. Differential	0.175	0.259	0.111

Table 10. Performance comparison of various carry trade strategies
This table compares the performance of four different carry trade strategies. Carry trade investors in this table use the 17 currencies in our sample as candidate currencies. For “regular carry trades”, investors borrow the five lowest interest rate currencies and lend the five highest interest rate currencies, and they are assumed to consider rebalancing every day. For “jump robust carry trades”, investors implement the same carry trade strategies as regular carry trades. However, they temporarily suspend their carry trades when jumps are highly likely (i.e., around Tokyo market closing and London market opening times (i.e., 06:00-10:00 GMT) and during the cojump window, which is defined as the six-hour window immediately after two simultaneous jumps arrive). For “jump modified carry trades”, investors take a long position in the currencies with the five highest negative jump betas among the eight higher interest rate currencies and take a short position in the currencies with the five lowest negative jump betas among the eight lower interest rate currencies. These investors also rebalance their portfolio every day. In addition, taking advantage of jump information, they temporarily change the portfolio construction scheme if they observe a negative jump that coincides with a market jump. Specifically, immediately after a negative jump arrives across the sample foreign exchange rates, these investors drop the two lowest GDP and the two highest interest rate currencies from the carry trade candidates for 12 hours. Using the remaining currencies, the investors select the currencies whose negative jump betas are lower (higher) among higher (lower) interest rate currencies as investing (funding) currencies. With these three carry trades, we also consider the carry trade strategy in which investors implement the jump modified carry trade strategy in general and take a zero position during the periods when jumps are highly likely (denoted as the “hybrid carry trade strategy”). This table provides the mean returns, standard deviations, and Sharpe ratios of these four types of carry trade strategies; the numbers are annualized. Columns “Regular”, “Robust”, “Modified”, and “Hybrid” are for the regular, jump robust, jump modified, and hybrid carry trade strategies, respectively.

	Regular	Robust	Modified	Hybrid
Mean Return (%)	2.19	3.48	3.74	4.46
Standard Deviation (%)	5.40	4.05	5.55	4.52
Sharpe Ratio	0.41	0.86	0.67	0.99

Fig. 1. Change in carry trade returns with and without jumps

This figure illustrates changes in carry trade returns around times with and without jumps. Panel A shows how the excess returns of holding investing (or funding) currencies differ depending on jump arrivals (in the view of the U.S. investor). Investing (funding) currencies are defined as the five highest (lowest) interest rate currencies among the 17 currencies in our sample. In Panel A, the "Jump Period" represents times when jumps are highly likely to arrive (e.g., four hours around Japanese market closing time and six hours just after simultaneous jumps arrive in at least two foreign exchange rates). The "No Jump Period" is for the times not belonging to the "Jump Period". In both left and right parts, the red inequality signs show which types of currencies provide higher excess returns, on average.

Panel A. Change in excess return with and without jumps

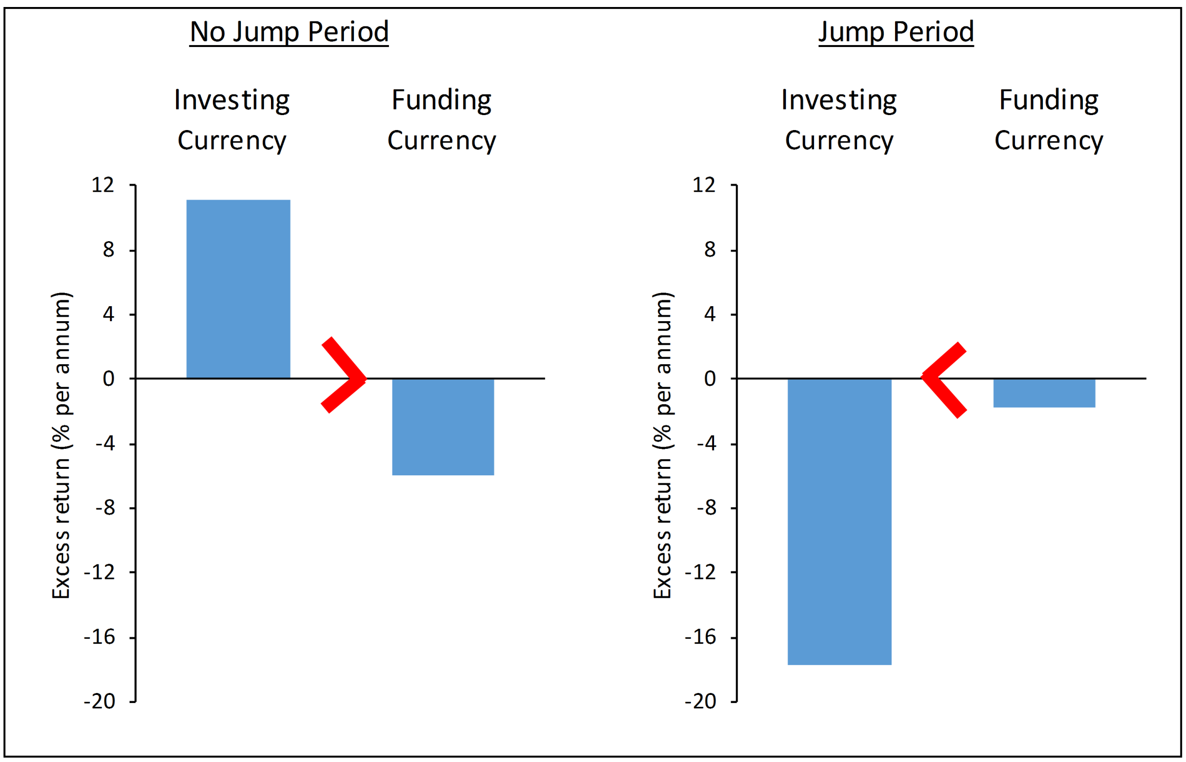


Fig. 1. Change in carry trade returns with and without jumps (continued)
Panel B compares the cumulative excess returns of two carry trade schemes. The currencies that are used for carry trades are adjusted on a daily basis, as defined for Panel A. "Regular" represents the cumulative return of taking a regular carry trade position. "Jump" denotes the cumulative returns of taking a carry trade position only when jumps are highly likely to occur (e.g., the four hours around the Japanese market closing time and the six hours just after simultaneous jumps occur in at least two foreign exchange rates). "NoJump" represents the cumulative returns of taking a carry trade position except during times when jumps are highly likely to occur.

Panel B. Cumulative excess returns of currency carry trades

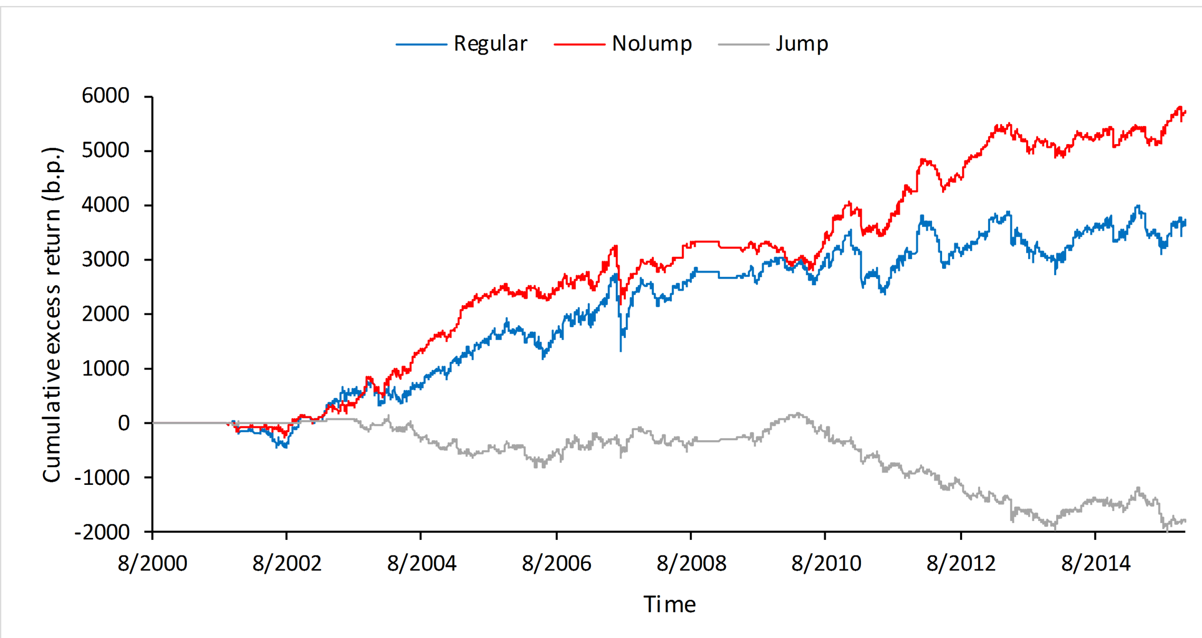
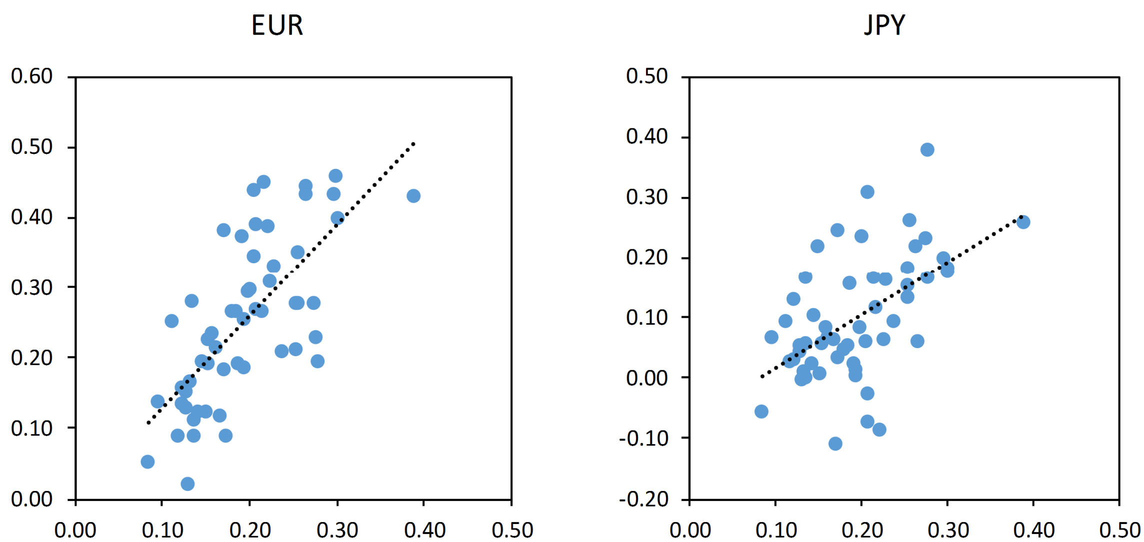


Fig. 2. Stability of the sensitivity of individual returns to market jumps
This figure shows the stability of the sensitivity of individual exchange returns to market jumps. We provide the relationship between individual returns and market returns that are used for jump beta estimation. Panel A is for positive market jumps, and Panel B is for negative market jumps. In each panel, we report the results that employ the observations during the most recent 13-month sample period. In each plot, the vertical axis is for changes in the log spot rates of individual exchange rates, and the horizontal axis is for market jumps. The dotted lines are the fitted lines.

Panel A. Positive market jump



Panel B. Negative market jump

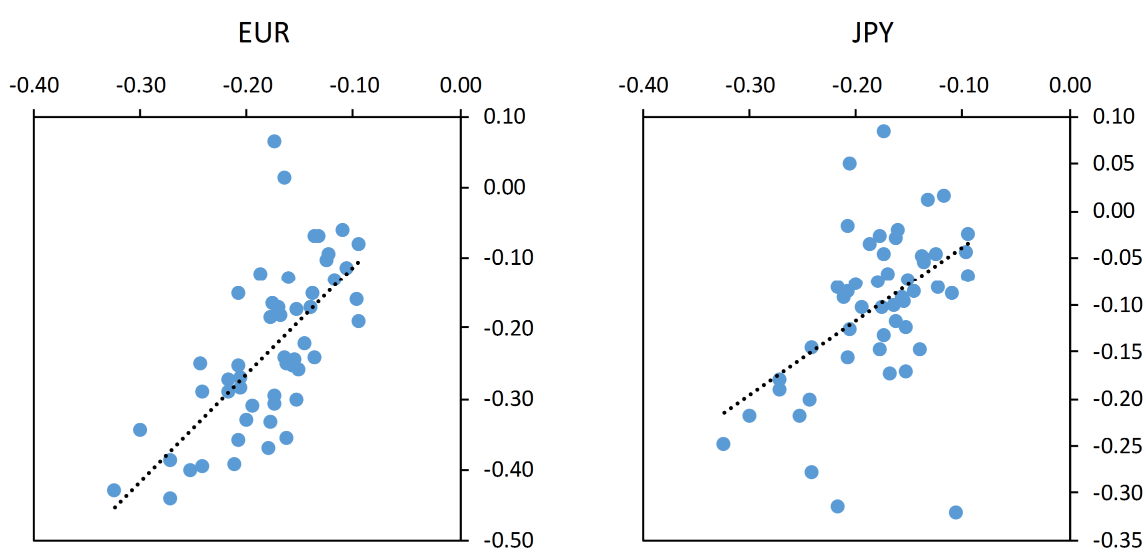
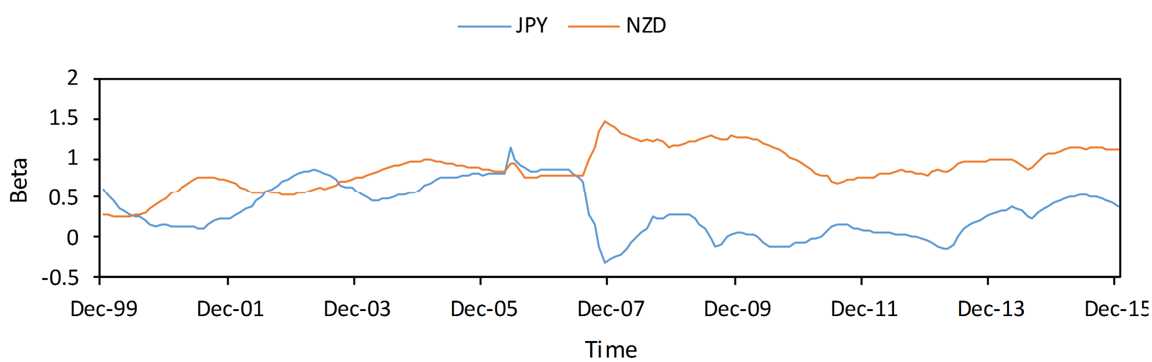


Fig. 3. Time series of betas

This figure indicates that the (time series) properties of jump betas are different from those of standard and continuous betas. We depict the time series plots of (monthly) estimated standard, continuous, positive jump, and negative jump betas. Panels A, B, C, and D present the time trends of the four betas for selected exchange rates (i.e., NZD and JPY). In these panels, the red lines are for NZD, while the blue lines are for JPY.

Panel A. Trend of standard betas for selected foreign exchange rates (NZD vs. JPY)



Panel B. Trend of continuous betas for selected foreign exchange rates (NZD vs. JPY)

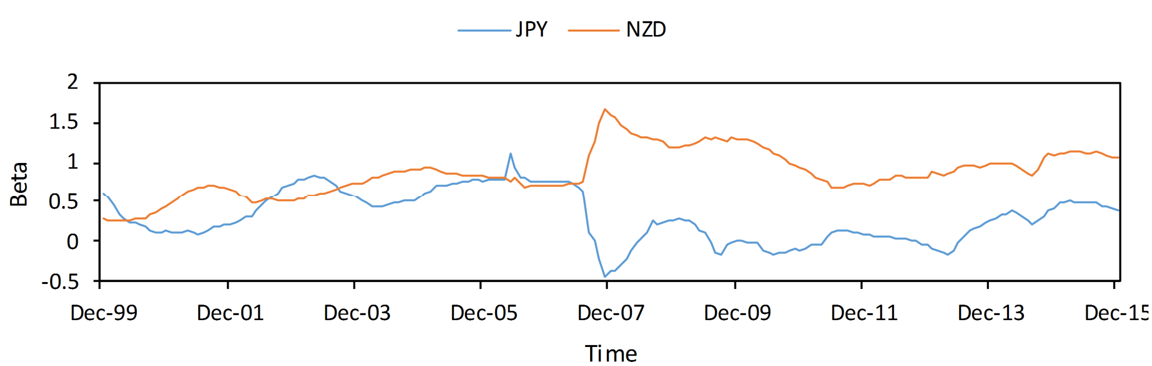
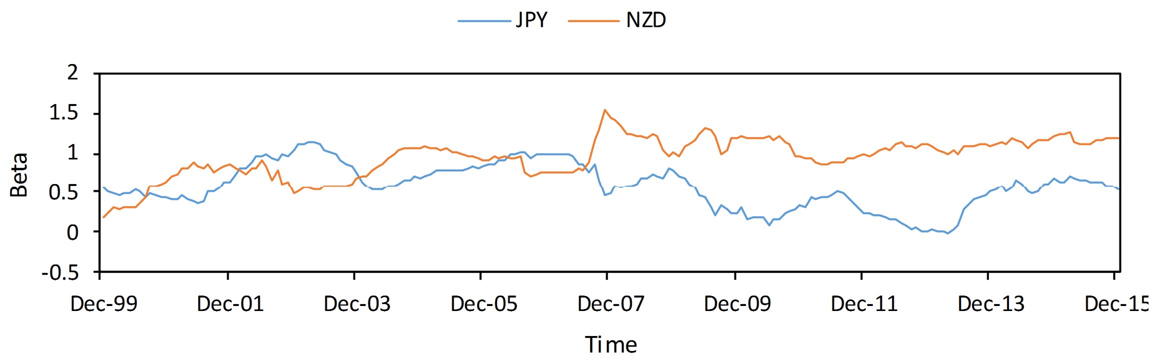


Fig. 3. Time series of betas (continued)

Panel C. Trend of positive jump betas for selected foreign exchange rates (NZD vs. JPY)



Panel D. Trend of negative jump betas for selected foreign exchange rates (NZD vs. JPY)

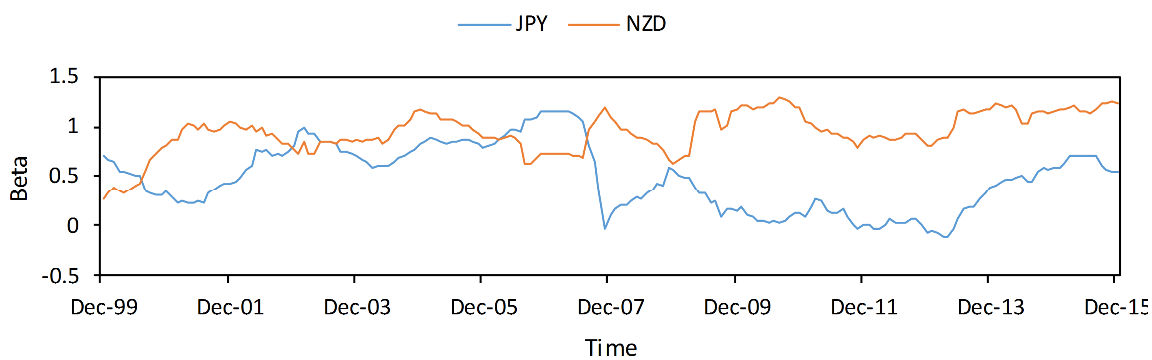


Fig. 4. Regular vs. jump modified carry trade strategies

This figure illustrates the regular carry trade strategy in the upper part and the jump modified carry trade strategy in the lower part. The blue circles represent the currencies selected as investing or funding currencies. The currencies are categorized into four groups depending on the negative jump betas (denoted by "Beta") and the interest rates. For regular carry trades, investors consider only interest rates by choosing higher (lower) interest rate currencies as investing (funding) currencies. For jump modified carry trades, investors consider interest rates and negative jump betas. In general (i.e., "Normal Period" in the lower part), investors lend currencies whose negative jump betas are higher among higher interest rate currencies and borrow currencies whose negative jump betas are lower among lower interest rate currencies. If a negative market jump occurs, these investors perform "Temporary Adjustment". After observing a negative market jump, these investors drop low GDP and high interest rate currencies, the negative jump betas of which are likely to be higher than those of the other currencies. In addition, the currencies whose negative jump betas are lower among higher interest rate currencies are selected as investing currencies, while the currencies whose negative jump betas are higher among lower interest rate currencies are chosen as funding currencies.

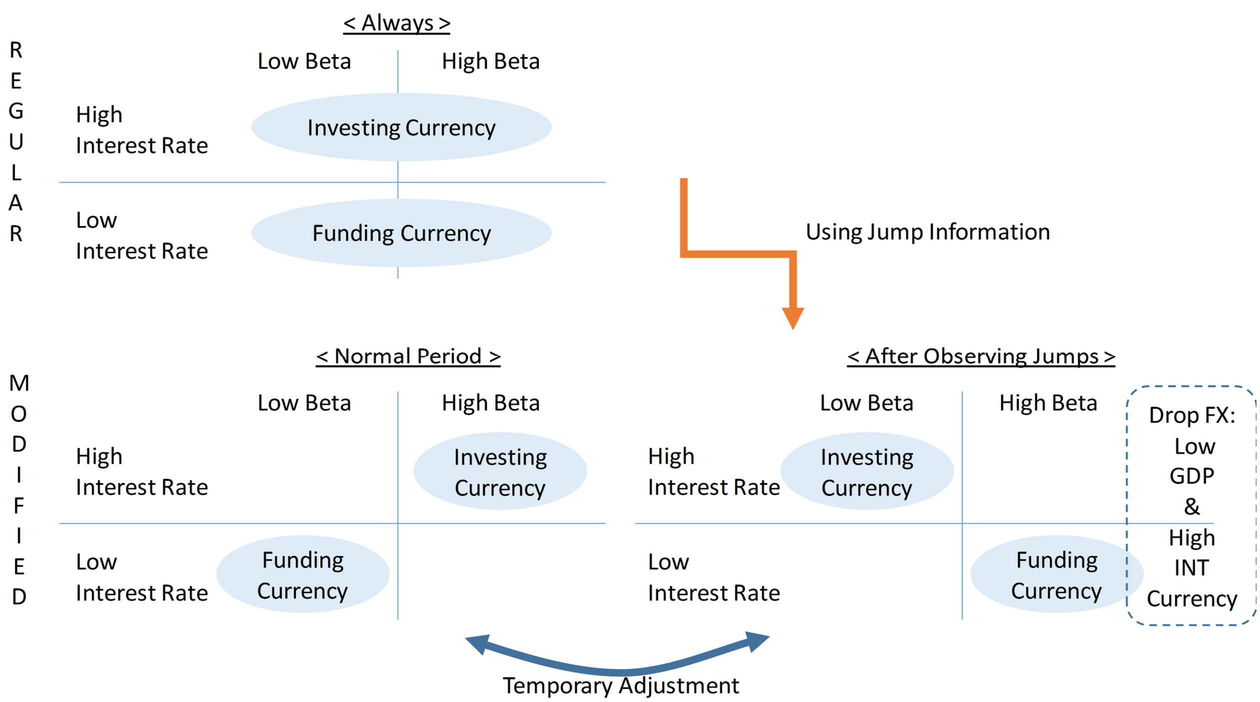
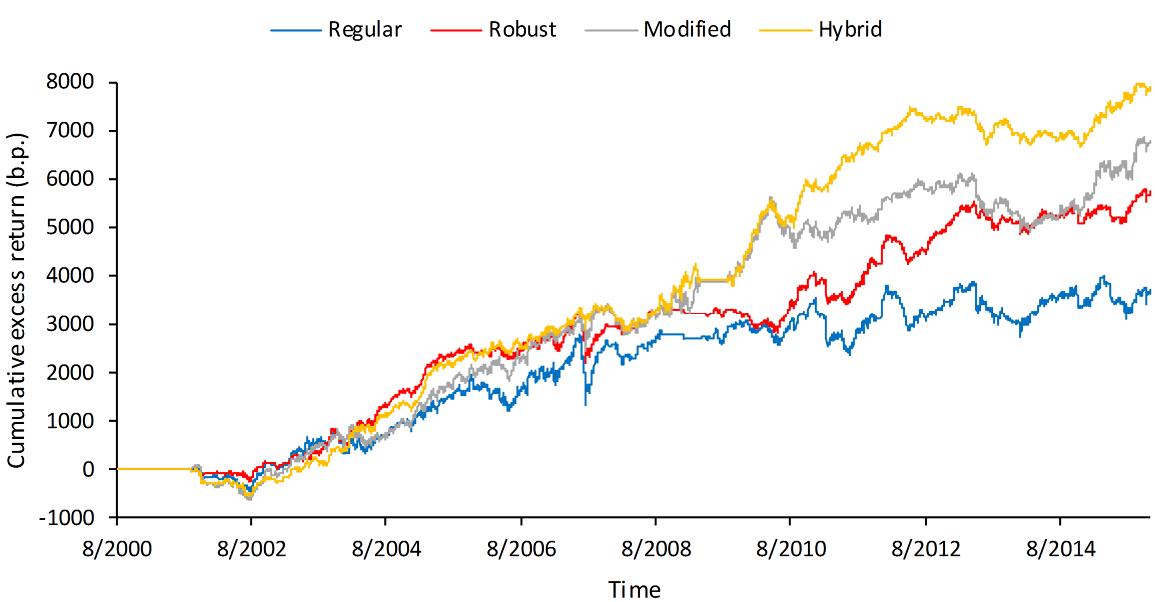


Fig. 5. Performance comparison of jump modified vs. regular carry trade strategies

This figure illustrates the cumulative excess returns of four carry trade schemes. Negative jump betas are estimated as $\hat{\beta}_{i,m}^{(j-)} = \frac{\Sigma_{l \in P_m} \; r_{i,t(l)} r_{0,t(l)} \cdot I(j-)_{i,t(l)} I(j-)_{0,t(l)}}{\Sigma_{l \in P_m} \; r_{0,t(l)}^2 \cdot I(j-)_{0,t(l)}}$ for foreign exchange rate i in month m. The estimators of β's are based on a one-month rolling estimation over one year (i.e., the estimation uses the observations from the end of month $m-12$ to the end of month m). $I(j-)_{0,t(l)}$ takes the value of one when a negative market jump occurs and zero otherwise, and $I(j-)_{i,t(l)}$ always takes the value of one. For "regular carry trades" [presented by the blue line (Regular)], investors consider only interest rates and rebalance their portfolio every day. They take a long (short) position in the five highest (lowest) interest rate currencies. For "jump robust carry trades" [presented by the red line (Robust)], investors take the same positions as investors who use the regular strategy in general. However, they take a zero position if a jump is highly likely to occur (e.g., the four hours around the Japanese market opening time and the six hours just after simultaneous jumps occur in at least two foreign exchange rates). For "jump modified carry trades" [presented by the gray line (Modified)], investors consider both interest rates and negative jump betas. They take a long position in the currencies with the five highest negative jump betas among the eight higher interest rate currencies and take a short position in the currencies with the five lowest negative jump beta among the eight lower interest rate currencies. In addition, they temporarily rebalance their carry trade portfolios if they observe a negative jump. Immediately after a negative jump that coincides with a market jump arrives across the sample exchange rates, they drop the currencies of the two lowest GDP and the two highest interest rate countries from the candidate currencies for 12 hours. Using the remaining currencies, they select the currencies whose negative jump betas are lower (higher) among higher (lower) interest rate currencies as investing (funding) currencies. The "hybrid carry trade" strategy [presented by the yellow line (Hybrid)] is a combination of the jump modified and robust carry trade strategies. In particular, investors implement the jump modified strategy in general but take a zero position when a jump is highly likely to arrive (as defined above). The cumulative excess returns are expressed in basis points.



Appendix A. Analysis with daily exchange rates

We analyze daily foreign exchange rates to show the robustness of the findings in the main text and to provide a practical application for investors who use longer frequency data. This appendix introduces daily foreign exchange rate data and explains the differences between the daily and intraday data analyses. All the results related to the discussion in this appendix are available upon request.

A.1. Daily foreign exchange rates

We consider 55 foreign exchange rates, which are denoted in USD per unit of foreign currency. We collect the daily spot and forward rates for the 55 exchange rates from Barclays and Reuters via Datastream. The sample period is from 1997 to 2015 because most observations before 1996 are missing. To be included in the sample, USD-denoted exchange rates should have spot and forward bid/ask quotes. The specific countries (entities) in the sample are Argentina, Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, Colombia, Croatia, Cyprus, Czech, Denmark, Egypt, European Union, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Japan, Kuwait, Malaysia, Mexico, the Netherlands, New Zealand, Norway, Peru, Poland, Portugal, Russia, Saudi Arabia, Singapore, Slovakia, Slovenia, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Turkey, the United Arab Emirates, the United Kingdom, and Vietnam. All currencies do not have a floating exchange rate (e.g., the exchange rates of Middle Eastern countries and Hong Kong are pegged to the USD, and the Danish Krone is pegged to EUR). We include these pegged currencies for the general analysis, but we also perform a subsample analysis in which we exclude such currencies.

To filter the data, we investigate the forward premium of each exchange rate and remove the observations that clearly violate covered interest rate parity. In addition, we remove the periods that are filtered in Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012).

A.2. Jump detection

To detect jumps in the daily exchange rate data, we modify the approach in Appendix B because the number of jumps detected by the original approach in Appendix B is not sufficiently large to consistently estimate jump betas. Other jump detection methods [e.g., Barndorff-Nielsen and Shephard (2006)] identify observations (or returns) whose jump test statistics are outside the critical values based on the standard normal distribution as jumps. Following such approaches, we use critical values from the standard normal distribution, instead of the Gumbel distribution. Because critical values from the standard normal distribution are smaller than those from the Gumbel distribution, we detect a greater number of jumps by using this modification.

A.3. Jump modified carry trade strategy

When investors choose carry trade currencies for jump modified carry trades, they consider not only interest rates but also negative jump betas. In addition, jump modified carry trades allow investors to adopt measures to temporarily reduce the exposures of their carry trade portfolios to negative jump risks when a negative market jump is highly likely to occur.

When investors use daily foreign exchange rates, they still select carry trade currencies as explained in the main text. However, it would be difficult to employ the approach of taking conservative positions to avoid negative jump risks. In the intraday data analysis, we use jump and jump size clustering effects to predict a future negative market jump. As we decrease the frequency of observations to the daily level, the jump clustering effects become weaker. Indeed, these jump clustering effects are not strong for periods longer than one day. Because of the weak power of the jump prediction, investors with longer investment horizons (e.g., month or quarter) can simply implement the jump modified carry trade strategy without making temporary adjustments for conservative positions. Nonetheless, our analysis of daily exchange rates indicates that jump modified carry trades without the temporary adjustment achieve better performance than regular carry trades.

Appendix B. Jump detection method

This appendix shows how we apply the jump detection method of Lee and Mykland (2008) to currency markets.

Under the process of a foreign exchange rate defined in Eq. (1), a jump is detected between time $t(l-1)$ to $t(l)$ if the (absolute) instantaneous return over the interval is significantly larger than the magnitude that can be expected by the diffusion terms. This approach is reflected in the test statistics for a jump:

$$L_{i,t(l)} = \frac{r_{i,t(l)}}{\hat{\sigma}_{i,t(l)}\sqrt{\Delta t}}, \tag{6}$$

where $L_{i,t(l)}$ is the test statistics for the l-th discrete observation of foreign exchange rate i. $r_{i,t(l)} = s_{i,t(l)} - s_{i,t(l-1)}$ is a change in the log foreign exchange rate over a short period between $t(l-1)$ and $t(l)$. $\hat{\sigma}_{i,t(l)}$ is the jump robust volatility, which can be based on bipower variation as $\hat{\sigma}^2_{i,t(l)} = \frac{1}{(K-2)c^2}\Sigma_{k=j-K+2}^{l-1}|s_{i,t(k)} - s_{i,t(k-1)}||s_{i,t(k-1)} - s_{i,t(k-2)}|$ ($K = b\Delta t^a$ with $-1 < a < -0.5$ for some constant b and $c = E|u| \approx 0.7979$ with a standard normal random variable u, and $\Delta t = |t(l+1) - t(l)|$ is a discrete time period between two consecutive observations).

If the drift and diffusion coefficients do not dramatically change over a short time interval, we use the rejection region for the jump test, $R_n(\alpha) = (-\infty, -q_\alpha H_n - C_n) \cup (q_\alpha H_n + C_n, \infty)$, where q_α is the $(1-\alpha)$th percentile of a standard Gumbel distribution, α is the overall error rate, $C_n = (2\ln n)^{1/2} - (\ln\pi + \ln(\ln n))/(2(2\ln n)^{1/2})$, and $H_n = 1/(2\ln n)^{1/2}$ (n is the number of observations). Therefore, if the computed test statistics belongs to the rejection region, the corresponding observation is detected as a jump.

For the window size K over which the volatility is computed, we follow the recommendation made by Lee and Mykland (2008). Specifically, we use $K = 156$ for our 15-minute data. We also perform sensitivity analyses, using the window sizes within the theoretical range for K. Although the window size affects the number of detected jumps, our ultimate conclusion is robust with respect to the choice of window sizes.