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Dynamics of Return and Liquidity (Co)Jumps in Emerging Foreign Exchange Markets[☆]

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Abstract

We investigate the dynamics of return and liquidity (co)jumps for three of the most traded emerging market currencies vis-à-vis US dollar. We find that an increase in the average bid-ask spread significantly reduces the duration between consecutive return jumps, while liquidity and volatility only play a partial role on the duration between consecutive liquidity jumps and return-liquidity cojumps. There is also evidence of vicious return-liquidity spirals in views of the positive contemporaneous impact of liquidity jumps on volatility and return jumps on the bid-ask spread. Moreover, scheduled macroeconomic news and central bank announcements increase the likelihood of both return and liquidity (co)jumps. Finally, jump adjusted high frequency FX trading strategies are shown to have superior performance over the buy-and-hold strategy.

Keywords: Exchange rates, jumps, cojumps, emerging markets, market microstructure

JEL: C14, F31, G11, G14, G15

[☆] The views expressed in this paper are those of the authors and do not necessarily represent the official views of the Central Bank of the Republic of Turkey.

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1. Introduction

Decomposition of returns into jumps and time-varying diffusion components is increasingly being studied in the recent empirical finance literature. This identification has undisputed implications on modeling and forecasting asset prices as well as their volatility for the scope of investment, policy making and risk management. As far as foreign exchange (FX) markets are concerned, the characterization of the different types of price and liquidity discontinuities is particularly important. This is not only because they are the world's largest markets in terms of trading volume and relatively more volatile than stock and bond counterparts, but also because foreign portfolio investments in equities and bonds, or carry trade strategies require well elaboration of risk factors related to FX markets. Hence, the need for studying and gaining insight into the jump and co-jump dynamics of exchange rates is of utmost significance for investors, regulators and policymakers. In this paper, we address this issue by focusing on the dynamics of discontinuities in both the level and liquidity of exchange rates for three highly popular emerging market currencies, namely Mexican peso, Turkish lira and South African rand which are among the most traded emerging market currencies in the world.

To date, previous literature has recognized the importance of jumps in asset returns and liquidity on several grounds, which could certainly be the case of exchange rates. The first and maybe the most important reason is that sudden changes in liquidity levels may serve as a signal for upcoming return jumps. Boudt and Petitjean (2014) show that for the stocks that constitute the Dow Jones Industrial Average Index, liquidity shocks in the effective bid-ask spread significantly increases the probability of a jump occurrence in stock prices. Likewise, liquidity conditions surrounding the scheduled macroeconomic news announcements can predict the reaction of asset prices in the US Treasury market to the surprises in these announcements (Jiang et al., 2011). With regard to same bond market, Dungey et al. (2009) document that two-thirds of co-jumps across the maturity structure coincide with liquidity shocks around scheduled US news releases. Another substantial issue is that jumps may carry information on informed trading activity and changes in liquidity provision of monetary authorities (Piccotti, 2018), and they might as well trigger false rumours on central bank interventions (Gnabo et al., 2012). Moreover, from the portfolio's design and allocation, both return and liquidity jumps have important risk and return implications for investors since they directly influence return predictability, crash risk, risk premium determination, and hedging cost (Mancini et al., 2013; Novotny et al., 2015; Li et al., 2017; Barunik and Vacha, 2018; Oliva and Reno, 2018; Chorro et al., 2020). For example, Novotny et al. (2015) find that jumps in currency returns provide profitable trade opportunities, while Lee and Wang (2020) show that carry trade strategies achieve higher returns and lower standard deviations when jumps are robustly taken into account. There is finally evidence to suggest that the comovement of FX liquidities tends to be stronger in distressed markets, particularly during times of high volatility and funding constraints (Karnaukh et al., 2015).

Another strand of the literature has focused on the determinants of jumps through linking jumps and cojumps with scheduled macroeconomic news announcements (Lahaye et al., 2011; Dungey and Hvozdyk, 2012; Chatrath et al., 2014; Lahaye, 2016; Kapetanios et al., 2019; Lee and Wang, 2020), with central bank actions or communications (Beine et al., 2007; Andersen et al., 2007; Ahn and Melvin, 2007; Conrad and Lamla, 2010; Dewachter et al., 2014), and with the liquidity conditions of the FX market and the traded asset (Breedon and Ranaldo, 2013; Mancini et al., 2013). In most of these studies, jumps occur as a response to liquidity or information shocks, and the feedback from jumps to liquidity and liquidity to jumps are two-sided.

Our current study extends the above-mentioned literature by examining the dynamics of jumps (discontinuities) in the returns and liquidity of FX rates as well as their cojumps for three major emerging market currencies (Mexican peso, South African rand and Turkish lira) using high frequency intraday data.[1] The currencies under consideration respectively

[1]The use of intraday data is common in the literature and particularly important since algorithmic (especially high frequency) trading constitutes the major part of all trading activities in today's modern

rank, according to the BIS 2019 Triennial Survey of foreign exchange and OTC derivatives trading, 2nd, 5th and 6th in the category of the world's most traded emerging market currencies, with $113.7, $72.1, $71.2 billion average daily turnovers of both spot and derivative transactions.[2] Moreover, according to Oxford Economics, they belong to the group of top five risky currencies in the world together with Argentine peso and Ukrainian hryvnia as of early 2019[3] as well as suffered both systematic and idiosyncratic shocks in recent years.[4] All these stylized facts prove the necessity for an analysis on the jump and co-jump dynamics of these currencies, which would be beneficial not only for the sample markets but also for a wider range of emerging markets as well.

To conduct our empirical investigation, we first detect jumps in exchange rate returns and liquidity by employing the high frequency non-parametric jump test of Lee and Mykland (2008). Then, we split our analysis into two stages. The first stage examines jump and cojump activity for individual FX rates by successively looking at the intraday timing of return and liquidity jumps, the return-liquidity cojumps, the duration between consecutive jumps/cojumps, the impact of jumps on FX return and liquidity, and the determinants of jumps and return-liquidity cojumps using several global risk factors. In the second stage, we

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FX markets where computers react to information instantaneously. In such an environment, high frequency analysis is the only way to uncover the true dynamics of jump and cojump processes.

[2]In the same ranking, Chinese yuan, Indian rupee and Russian ruble take the 1st, 3rd and 4th place. However, due to (i) controlled exchange rate regime (Chinese yuan), (ii) different valuations and spreads via off-shore trading (Chinese yuan and Russian ruble), and (iii) lack of high-frequency data availability (Indian rupee), they are not included in our analysis. Moreover, we are technically limited at this stage due to our data source and can not expand the currency list further.

[3]https://www.lemoci.com/wp-content/uploads/2019/05/navigating-the-next-em-currency-crisis-130519.pdf

[4]While Fed's signal in 2013 to end the quantitative easing operations and late global trade wars fuelled growing fear of renewed volatility in all these markets, Mexico had to face several tariffs on its imports to the US and political tensions with its government. In the mean time, Turkey experienced its biggest financial crisis since 2001 after concerns about its overheating economy and spurred inflation, followed by political tensions with the US. South Africa, on the other hand, has unexpectedly entered into an economic recession in 2018 for the first time in nearly a decade and its currency has consistently been seen as a prime candidate for contagion for a brief period of time in recent years.

perform similar analysis for the cojumps across FX rates, but only focus on return cojumps because the number of liquidity cojumps is not high enough to make reliable statistical inference.

Our main findings can be summarized as follows. We first document that an increase in the average bid-ask spread between two consecutive return jumps significantly reduces the return jump duration of exchange rates. Liquidity and volatility between two consecutive liquidity jumps (return-liquidity cojumps) are found to play only a partial and mixed role on the duration between consecutive liquidity jumps (return-liquidity cojumps). We also find evidence of vicious return-liquidity spirals discussed by Brunnermeier and Pedersen (2009) since the contemporaneous impact of liquidity jumps on volatility and the one of return jumps on the bid-ask spread are both significantly positive. When global risk factors are used to explain FX return and liquidity jumps as well as their cojumps, only the economic policy uncertainty has a significant and positive impact on both type of jumps, whereas no common source of risk factors is found in the case of return-liquidity cojumps. Moreover, our analysis regarding the impact of local and global scheduled macroeconomic news and central bank announcements reveals that the US CPI, FOMC, and non-farm payroll announcements mostly coincide with not only return and liquidity jumps, but also their cojumps. The impact of domestic news and announcements is generally neglectable. Finally, as to the cojumps across FX rates, our results show that both global and local factors play a significant role on the duration of two consecutive cojumps, with a decrease in FX cojump duration following an increase in the US economic policy uncertainty and the US equities' implied volatility (VIX). The US CPI and non-farm payroll announcements are found to drive cojumps across FX returns.

Overall, our study sheds light on not only the dynamics of jumps in return and liquidity, but also the return-liquidity cojumps of the selected emerging market FX rates. An analysis of cojumps across FX rates is also conducted to detect the potential of jump spillovers. Moreover, our sample period typically coincides with a diminished investor confidence environment after 2013 following the Fed's signal to tighten its monetary policy, therefore findings are especially important for the global distress periods.[5]

The rest of the paper is organized as follows. Section 2 explains the data and its sources. Section 3 describes the jump detection methodology employed throughout the paper. Section 4 analyzes return and liquidity jumps, and return-liquidity cojumps for each exchange rate individually. Section 5 discusses the dynamics of cojumps across exchange rates. Section 6 concludes.

2. Data and Summary Statistics

We consider intraday data of the US dollar exchange rates for three emerging market currencies including the Mexican peso (USDMXN), Turkish lira (USDTRY) and South African rand (USDZAR). Data is obtained from Gain Capital, a New-York based dealer which was founded in 1999 and now provides service to 140,000+ retail and institutional investors with access to trade in over 12,500+ FX, shares, commodities markets and contracts-for-differences indices. The dataset refers to the sub-second level tick-by-tick bid and ask quotations with time stamps. The observations are available in global forex trading hours which is from Sunday 22:00 to Friday 22:00 in Greenwich Mean Time (GMT).[6] The sample covers a four-year period from 5 January 2015 to 14 December 2018, adding up to 1029 trading days in total. We aggregate the ultra-high frequency bid and ask rate data into 5-min intervals and obtain 296,352 (288x1029) intraday observations. We use the mid-quote, i.e., simple average of bid and ask quotes, as the exchange rate level. Our main liquidity measure is the proportional quoted spread which is defined as the ratio of bid-ask spread to the mid-quote.[7]

[5]Between 2008 and 2013, emerging markets borrowed heavily in dollar-denominated debt with almost zero rates, while many of them were still struggling with chronic current-account deficit problems. After Fed's tightening policy, high dollar debt combined with high current account deficit diminished investors' confidence in these markets' ability to repay their external debt.

[6]Throughout the paper, all timestamps in figures and tables are stated in GMT.

[7]In microstructure literature, other common measures of liquidity are realized spread and quoted volume. However, realized spread requires trade prices whereas quoted volume can be obtained only if order size data

—————————— **INSERT TABLE 1 HERE** ——————————

We obtain the actual times of scheduled macroeconomic news announcements and central bank actions from Bloomberg terminal. Table 1 shows the summary information for both local and US macroeconomic news releases. The daily local and global risk and liquidity proxies (TED spread, VIX, rate differential (RD) between US and local rates implied by 3 month forward rates, and risk reversal (RR)) are obtained from Bloomberg terminal with a daily frequency and the daily US economic policy uncertainty index (EPU) is obtained from the EPU website.[8] The descriptive statistics for 5-min FX rate returns and the corresponding liquidity measures are tabulated in Table 2.

—————————— **INSERT TABLE 2 HERE** ——————————

3. Jump Detection Methodology

We employ the intraday jump detection procedure developed by Lee and Mykland (2008) to identify both return and liquidity jumps. Among the variety of jump detection methodologies, this procedure is particularly useful since it determines the size, direction and exact timestamp of each jump (Neely, 2011; Boudt and Petitjean, 2014; Arouri et al., 2019). This identification further allows calculation of average and total jump sizes or jump intensities within lower frequencies to make daily or monthly analysis.

Since standard continuous diffusion models fail to account for sudden price changes in forms of spikes or jumps in asset prices, Lee and Mykland (2008) assume a model class called Brownian semi-martingale with finite activity jumps as the underlying stochastic process. This allows for decomposing exchange rate volatility into jumps and time-varying diffusion

is available. In our dataset, we only have the best bid and ask quotations for the exchange rate levels therefore we are limited to using proportional quoted spread as the liquidity measure.

[8] https://www.policyuncertainty.com/

components as follows:

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t) \tag{1}$$

where p_t is the log of mid-quote exchange rate in our setup, $\mu(t)$ is the continuous locally bounded variation process, $\sigma(t)$ is a stochastic volatility process, $W(t)$ is the standard Brownian motion, $q(t)$ is a counting process independent of $W(t)$ and taking binary values depending on whether there is a jump or not, and finally, $\kappa(t)$ is the jump size. Consequently, the authors introduce a test statistic for each return observation by comparing its absolute value with a rolling window local variation measure as follows:

$$J_{t,i} = \frac{\mid r_{t,i} \mid}{\eta_{t,i}} \tag{2}$$

In this framework, each trading day i consists of M equally spaced intraday returns, where $r_{t,i}$ is the 5-min log-return of the mid-quote spot exchange rate in the interval t of day i and $\eta_{t,i}$ is the local variation measure calculated by an integrated volatility measure. Standard realized volatility measures (e.g., sum of squared log-returns) fail to estimate integrated volatility consistently in the presence of jumps. Barndorff-Nielsen and Shephard (2004, 2006) show that under the price generation process defined in equation (1), realized bipower variation (RBPV) defined in equation (3) converges to integrated volatility and thus consistently estimates the integrated variance,

$$RBPV_t(M) = \mu^{-2} \frac{1}{M-2} \sum_{t=2}^{M} \mid r_{t,i} \mid\mid r_{t-1,i} \mid \tag{3}$$

where $\mu = \sqrt{2/\pi}$ and M is the number of observations in the local variation window. One free parameter to choose in this setup is the window length of the local variation measure. Accordingly, we follow Lee and Mykland (2008) and use a window length of 270 data points for 5 minutes returns.[9]

Another situation that needs to be taken into account is the intraday periodicity which might have a deteriorating effect on $J_{t,i}$. In order to correct this, Boudt et al. (2011) propose to re-scale the returns by an intraday periodicity adjustment factor. We perform this adjustment following the procedure suggested by Boudt and Petitjean (2014) and estimate the modified filtered jump statistic $\tilde{J}_{t,i}$ provided in equation (4),

$$\tilde{J}_{t,i} = \frac{\mid r_{t,i} \mid}{\eta_{t,i} f_{t,i}} \tag{4}$$

where $f_{t,i}$ is the intraday periodicity factor obtained by a flexible Fourier specification as in Andersen and Bollerslev (1998).

Final step of the jump detection procedure involves filtration of the unhealthy data. In times of many repeating quotations or missing values, we might face with the problem of underestimating $\eta_{t,i}$, and thus over-rejecting the null hypothesis of no jump in the local variation window. To avoid this situation, we eliminate the jump statistics for the returns whose local variation window contains 58 or more 5-minute intervals without the dealer quotation (that is more than 20% of 288, the number of 5-minute observations in a trading day).

Lee and Mykland (2008) show that the obtained jump statistic follows a standard Gumbell distribution. Thus we reject the null hypothesis of no jump if the filtered $\tilde{J}_{t,i}$ statistic is greater than the value suggested by the Gumbell distribution; i.e.,

$$\tilde{J}_{t,i} > G_{-1}(1-\alpha)S_n + C_n \tag{5}$$

[9]Interested readers might be concerned with the fact that all jump tests deem to be useless because they all pick up the discrete changes in asset prices as jumps due to market microstructure noise if ultra-high frequency data is used (Christensen et al., 2014). In our study, we do not face with this problem since we aggregate the data at 5-min frequency. For other studies that suggest to use 5-min sampling frequency for intraday analysis, see Andersen et al. (2001) and Hansen and Lunde (2006).

where $G_{-1}(1-\alpha)$ is the $(1-\alpha)$ quantile function of the standard Gumbell distribution,

$$C_n = (2\log n)^{0.5} - \frac{\log(\pi) + \log(\log n)}{2(2\log n)^{0.5}} \tag{6}$$

and

$$S_n = \frac{1}{(2\log n)^{0.5}} \tag{7}$$

with n denoting the number of total observations. The α term in equation (5) is the significance of discontinuity in the local variation window and we use an α level of 5% in the rest of the paper.

Regarding liquidity jumps, we apply the non-parametric setup above to our liquidity measure motivated by Adrian et al. (2015). In particular, as a proxy for high-frequency liquidity measure, we employ the widely used proportional bid-ask spread which is calculated as follows,

$$L_t = \frac{Q_t^{ask} - Q_t^{bid}}{(Q_t^{ask} + Q_t^{bid})/2} \tag{8}$$

where Q_t^{ask} and Q_t^{bid} refer to ask and bid quotations at time t respectively. Consequently, $p(t)$ is replaced by L_t in equation (1) and the whole procedure is repeated. In this way, we are able to identify sudden changes in liquidity such that the positive jumps indicate deteriorating liquidity conditions and the negative ones denote improving liquidity of the exchange rate.

——————————-**INSERT FIGURE 1 HERE** ——————————-

Figure 1 emphasizes the importance of appropriate handling of diurnal cycles in intraday volatility and liquidity respectively since both variables exhibit strong intraday periodicities. The upper subfigure displays the intraday volatility pattern that is obtained by averaging the absolute value of logarithmic returns in the cross-section of sample days.[10] Likewise,

[10] It is common to use the absolute value of returns as a proxy for volatility. For example, see Ding et al. (1993); Cont (2001); Ghysels et al. (2006); Forsberg and Ghysels (2007).

lower subfigure presents intraday liquidity pattern obtained by averaging the proportional quoted bid-ask spread for each 5-min interval across sample days. The liquidity pattern shows spikes around opening and closing sessions as well as around macro-economic news announcements, and it is highest during local trading hours.[11] In an earlier work, Bollerslev and Melvin (1994) state that magnitude of the bid-ask spread of an exchange rate increases with higher volatility, which is validated by our findings at the high-frequency level as well. According to Figure 1, the intraday periodicity of liquidity is almost like the mirror image of the daily volatility pattern.

4. Jump and cojump analysis for the individual exchange rates

In this section, we attempt to characterize the dynamics of jumps and cojumps in both return and liquidity by (i) modeling the duration between jumps and also between liquidity-return cojumps, (ii) analyzing the impact of liquidity jumps on volatility, (iii) investigating the effect of return jumps on liquidity, and finally (iv) examining the determinants of return jumps, liquidity jumps, and return-liquidity cojumps for the separate cases of USDMXN, USDTRY and USDZAR.

4.1. Preliminary analysis

Before describing the econometric framework, we start with providing the summary statistics for all (and also only news-related) FX return and liquidity jumps in Table 3.[12] This table provides information about the number of return jumps (RJ) and liquidity jumps (LJ), their probability of occurrence, and the maximum and average jump size for all (RJ, LJ) as well as positive (RJ^+, LJ^+) and negative (RJ^-, LJ^-) jumps. According to Table 3, the highest numbers of both return and liquidity jumps are observed for USDTRY with 4393 and 1937 jumps respectively, supporting the recent work by Lee and Wang (2019). On the

[11]Since the liquidity measure in the figure is the bid-ask spread, an increase (decrease) in this variable refers to a decrease (increase) in liquidity.

[12]In the rest of the paper, when we talk about jumps in general, we use the notation J, whereas if we want to specify whether it is a return or liquidity jump, we use RJ and LJ respectively.

other hand, the highest average jump size for return (liquidity) is obtained for USDZAR (USDMXN) with a magnitude of 0.2% (2.68%). For all FX rates, both the size and number of return jumps are larger for positive jumps compared to negative ones indicating the relatively higher downside risk in the value of the local currency in these emerging countries. In addition, the comparison of the number of return and liquidity jumps for all cases shows that experiencing a liquidity jump is almost as half likely as experiencing a return jump.

INSERT TABLE 3 HERE

The basic properties of jumps that are associated with scheduled-news announcements may differ in nature. For instance, Evans (2011) shows that news-related jumps have higher average size compared to non-news related jumps. In order to empirically differentiate between these two types, we define news-jumps as the jumps surrounding the scheduled macro-news announcements (Boudt and Petitjean, 2014; Piccotti, 2018). To do this, we identify the key domestic and US scheduled macroeconomic news announcements and if a jump occurs within three 5-min intervals that precede or follow the news announcement interval (that is 15 minutes before or after, denoted by [-3,+3]), we define those jumps as the jumps that occur in the interval surrounding the scheduled macro-news announcements that are described in Table 1. In the right-hand-side panel of Table 3, we provide the same statistics for only news-related jumps. The number of such jumps indicate that only a small portion of total jumps are occurring around scheduled news announcements. This is in line with the findings of Lahaye et al. (2011), and Boudt and Petitjean (2014) who argue that a large number of both FX return and liquidity jumps have no association with scheduled news announcements. Furthermore, it supports Li et al. (2017) who find that jumps can coincide with other announcements on political or financial events as well. For all FX rates and different jump variants, the news-related average jump size is significantly larger compared to the one of full-sample jumps. In addition, contrary to full-sample jump statistics, the negative return jumps are more frequent than positive ones suggesting that on average, the realizations of news releases are better than expectations for the selected emerging markets, thus have an appreciating impact on local currencies in the sample period. The higher number of positive liquidity jumps indicates the associated uncertainty surrounding news releases. While the jumps following news might be related to surprises, the preceding jumps can be associated with private information or position closing.

———————————**INSERT TABLE 4 HERE** ———————————

We now turn to the identification of cojumps in return and liquidity for each FX rate. As a first analysis of return-liquidity cojump relation, we report, in Table 4, the conditional probabilities of return jumps at various lags around liquidity jumps. Conditioned upon a liquidity jump, the probability of a return jump in the same interval is 3.5%, 21.1% and 10% for USDMXN, USDTRY and USDZAR respectively. For all FX rates, the highest probability of a return jump occurrence is in the same interval in which the liquidity jump occurs. For USDTRY and USDZAR, it is more likely that a return jump will follow a liquidity jump within 5 intervals (i.e., 25 minutes), whereas the reverse case is valid only for USDMXN. An interpretation for this finding is the probability of informed trading. In other words, traders might considerably extend bid-ask spread in the period following return jumps to avoid costs from informed trading. We observe that the return jump occurrence around [-5,+5] neighborhood is most prevalent for USDTRY with 80% probability. This probability is only 25% and 55% for USMXN and USDZAR respectively. Overall, this table supports the view that while liquidity jumps may lead return jumps, the reverse scenario is also very likely and can not be disregarded.

———————————**INSERT TABLE 5 HERE** ———————————

In Table 5, we provide intraday frequencies of return and liquidity jumps and also return-liquidity cojumps for each exchange rate. A cojump CJ technically refers to a simultaneous jump in both return and liquidity levels. However, to extend our analysis further, we introduce two variants of the cojump definition that are (i) return jumps followed by liquidity jumps ($LJ \rightarrow RJ$) and (ii) liquidity jumps followed by return jumps ($RJ \rightarrow LJ$) within three 5-min intervals.[13] Accordingly, for all FX rates, the return-liquidity cojump activity is the most intense around the off-shore trading hours when liquidity is lower. In addition, the cojump activity slightly intensifies during the period between 12:00 and 14:00 where a huge portion of US macroeconomic news announcements are made. Thus macroeconomic news announcements appear to have a significant positive impact on jump counts which will be further investigated in this paper later.

——————————-**INSERT FIGURE 2 HERE** ——————————-

While Tables 4 and 5 tabulate microdetails about the jump and cojump activities, Figure 2 provides a wider picture and displays the number of return jump, liquidity jump and return-liquidity cojump activities per month for the whole sample. Regarding return jumps, USDTRY and USDZAR display relatively more uniform patterns compared to USDMXN. The significant increase in the number of return jumps in USDMXN by the end of 2016 is most probably due to the US presidential election and the following escalated political tension between the United States and Mexico. Concerning liquidity jumps, USDTRY and USDZAR exhibit similar patterns through time, with a significant increase in 2017 and afterwards. A similar pattern is also observed in the number of return-liquidity cojumps for these two exchange rates, probably due to the similar characteristics in Turkey's and South Africa's economic and financial fundamentals.

4.2. Duration between consecutive jumps and cojumps

This section focuses on modeling the duration between consecutive return and liquidity jumps, and also return-liquidity cojumps for each exchange rate using logarithmic autoregressive conditional duration (LACD) model of Bauwens and Giot (2000). The latter is an

[13]Throughout the paper, when we mention about cojumps, we denote them by CJ and refer to simultaneous jumps in the same 5 minute interval. However, results regarding the other two definitions are always presented in the relevant tables under the corresponding notations (i.e., $LJ \rightarrow RJ$ or $RJ \rightarrow LJ$) whenever we perform an analysis on the actual cojumps.

extension of the ACD model presented in the seminal paper by Engle and Russell (1998). In calculation of consecutive jump and cojump durations, we exclude the non-trading weekend periods (i.e., from Friday 22:00 GMT to Sunday 22:00 GMT). Table 6 presents the summary statistics for the estimated durations. The units of presented numbers are in days. The average duration between two consecutive return (liquidity) jumps is 0.56 (1.56), 0.23 (0.53) and 0.32 (0.72) days for USDMXN, USDTRY and USDZAR respectively, which indicates that a liquidity jump is, on average, less likely to occur than a return jump for each exchange rate, supporting the earlier evidence. Moreover, standard deviations of the average durations between both consecutive return and liquidity jumps are much higher for USDMXN than the other two exchange rates, showing the relatively irregular jump occurrence patterns for the USDMXN compared to USDTRY and USDZAR. Interestingly, USDTRY experiences return-liquidity cojumps in every two and a half days on average, which is almost three times more often than USDZAR and 13 times more often than USDMXN, indicating the emphasized liquidity-return spirals for this specific exchange rate.

INSERT TABLE 6 HERE

Following the conventional notation, we define x_i as the adjusted duration Δt_i[14] between two consecutive return jumps, which is modelled as the following,

$$x_i = \mu_i \epsilon_i \tag{9}$$

where ϵ_i is a sequence of independent and identically distributed non-negative random variables following an exponential distribution such that $E(\epsilon_i) = 1$ and μ_i has the following LACD(1,1) form:

$$ln\mu_i = \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \varepsilon_i \tag{10}$$

[14] The detected jumps are already adjusted for intraday seasonality in our setup.

While modeling the duration between consecutive return jumps, we incorporate average liquidity $\overline{LIQ}_i = \sum_{j=1}^{N} L_j/N$ and average realized volatility of the exchange rate $\overline{RV}_i = \sum_{j=1}^{N} r_j^2/N$ between these consecutive jump occurrences to the model as exogenous variables to determine their impacts on the duration. The estimated parameters are reported in Table 7. Accordingly, the LACD model parameters are statistically significant at the 1% level, and an increase in the average bid-ask spread between two jumps significantly reduces the duration between two consecutive return jumps for the three currencies. Likewise, a higher realized volatility between consecutive jumps significantly reduces the duration except for USDMXN.

INSERT TABLE 7 HERE

In a similar fashion above, we model the adjusted duration $\tilde{x}_i$ between consecutive liquidity jumps as follows:

$$\begin{aligned} \tilde{x}_i &= \mu_i \epsilon_i \\ ln\mu_i &= \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \varepsilon_i \end{aligned} \tag{11}$$

We present the estimated coefficients in Table 8. The model parameters are statistically significant in almost all cases. While an increase in the average bid-ask spread between two consecutive liquidity jumps significantly reduces the duration between them for USDTRY and USDZAR, it has the opposite effect in the case of USDMXN where liquidity jumps are less frequent compared to other two exchange rates. Regarding the impact of realized volatility, the results are not alike across considered exchange rates, probably due to the specific (systematic and idiosyncratic) shocks affecting their dynamics over the study period. Indeed, the impact is insignificant for the case of USDTRY, whereas an increase in realized volatility reduces the duration between liquidity jumps for USDMXN and increases the duration between liquidity jumps for the case of USDZAR.

INSERT TABLE 8 HERE

We finally model the duration $\hat{x}_i$ between consecutive return-liquidity cojumps for each exchange rate. Like the earlier models, we adopt the following approach:

$$\begin{aligned} \hat{x}_i &= \mu_i \epsilon_i \\ ln\mu_i &= \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \varepsilon_i \end{aligned} \tag{12}$$

The results reported in Table 9 show that individual components of liquidity and volatility do not play a significant role on the duration between liquidity-return cojumps for the USDMXN, suggesting that other systematic components might be responsible for this phenomena. The volatility plays, however, a partial and both volatility and liquidity play a strong role on the return-liquidity cojumps in the cases of USDTRY and USDZAR respectively, indicating evidence of an idiosyncratic structure of cojumps for these exchange rates relative to the USDMXN.

——————————**INSERT TABLE 9 HERE** ——————————

Overall, our analysis reveals that jump and cojump duration dynamics are much alike for USDTRY and USDZAR, whereas USDMXN differs from these two exchange rates with respect to some important characteristics.

4.3. Impact of liquidity jumps on volatility

We now examine the high-frequency impact of liquidity jumps on exchange rate volatility. Figure 3 shows how absolute value of the exchange rate returns, a proxy for volatility, behave around liquidity jumps. There is an undeniable positive impact of liquidity jumps on the magnitude of realized returns, and motivated by this observation, we further investigate this relationship.

——————————-**INSERT FIGURE 3 HERE** ——————————-

For this analysis, we employ a two-stage weighted least squares (WLS) estimation procedure with a similar setting by Andersen et al. (2003). Since we look at the impact of liquidity jumps on conditional volatility, this model suits well for our analysis. In the first stage, we fit the following linear model for each exchange rate:

$$r_t = \beta_0 + \sum_{k=1}^{K} \beta_k r_{t-k} + \sum_{d \in \{+,-\}} \sum_{l=-3}^{L} \delta_{d,l} \times LJ^d_{t+l} + \sum_{d \in \{+,-\}} \eta_d \times D^d_t + \epsilon_t \tag{13}$$

where the left hand side variable r_t denotes the 5-minute logarithmic returns.[15] To capture the persistence in return series, we add its lagged values up to 5 unit lags, thus $K = 5$ with each unit lag refers to 5 minutes. LJ^d_t denotes the size of the liquidity jump with direction d at time t. L equals 3, thus we get coefficient estimates of jumps with -3 to +3 unit lags, that is, 15 minutes before and after the liquidity jump arrival. We include both lead and lag jump variables since the volatility may rise ahead of the liquidity jumps, or it might as well increase as a response to a liquidity shock. To discriminate the effects of negative and positive liquidity jumps, we use different variables for each type of jumps, thus d runs over $\{+, -\}$ separately where $+$ and $-$ denote positive and negative jumps respectively. D^d_t is a dummy variable which equals 1 if the liquidity jump with direction d within $[t-3, t+3]$ is associated with a scheduled macroeconomic news announcement, that is if there is a US or local news announcement in 15 minutes that precede or follow the liquidity jump. These dummies are added to the model to assess whether scheduled news-related jumps have differential impact on volatility.

In the second stage, we fit the absolute value of estimated residuals from equation (13) to the following specification similar to those of Andersen et al. (2003) and Dominguez et al. (2013):

$$\begin{aligned} |\epsilon_t| = c + \varphi \frac{\hat{\sigma}_{d,t}}{\sqrt{288}} + \sum_{d \in \{+,-\}} \sum_{l=-3}^{L} \delta_{d,l} \times LJ^d_{t+l} + \sum_{d \in \{+,-\}} \eta_d \times D^d_t \\ + \sum_{q=1}^{Q} (\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288}) + \sum_{p=1}^{P} \mu_p n^p + \vartheta_t \end{aligned} \tag{14}$$

[15]Readers should be aware that the notation used in this part is independent of the notation in Section 3.

where $\hat{\sigma}_{d,t}$ is the one day ahead volatility forecast estimated with a MA(1)-GARCH(1,1) model which captures expected volatility in day t. The sine and cosine terms capture the intraday circadian nature of volatility. The polynomial terms $\mu_p n^p$ capture the persistence in volatility with $P = 3$. We also include the period before the announcements because the pre-announcement activity is documented in the literature (Lucca and Moench, 2015) and the lead coefficients capture such effects (Neely and Dey, 2010).

The regression results are reported in Table 10. For all the exchange rates, the contemporaneous impact of liquidity jumps on volatility is significantly positive for both positive and negative jumps. Significant and positive lead coefficients for negative liquidity jumps suggest that the volatility is considerably higher before negative liquidity jumps. However, lagged effects have no significant impact for USDMXN and USDTRY, but it is significantly negative for USDZAR. Past literature on the volume-volatility nexus proposes a positive relationship between trading activity and liquidity. From this perspective, the sudden improvements in liquidity, which are likely to be observed around opening of local or global trading hours, may lead to increased volatility as well. We see such an impact contemporaneously and ahead of the liquidity jumps for all cases, but not with lags. Another explanation for these liquidity jumps following significantly higher volatility episodes can be found in the literature on asymmetric information which is often proxied by the bid-ask spread (Aldridge, 2010). As argued by Venkatesh and Chiang (1986), the increasing bid-ask spread reflects the suspicion of traders for the certain underlying information causing the jump. Likewise, as pointed out by Chordia et al. (2001), trading activity may slow down in the period following high volatility episodes and bid-ask spread may widen as a response to risk of engaging in short-term speculative activity. For the positive liquidity jumps, lead coefficients are significantly positive and negative for USDTRY and USDZAR respectively, whereas lagged coefficients are significantly positive for both exchange rates. The Wald statistic that tests the significance of cumulative impact of lead and lag effects indicates that the impact is significantly positive only for USDTRY, and the cumulative impact is not significant for USDMXN.

———————————**INSERT TABLE 10 HERE** ———————————

The news dummy for negative jumps is significantly positive for USDMXN and USDTRY, indicating that news-related negative liquidity jumps have a significant impact on volatility of these FX rates. On the other hand, dummy for news-related positive liquidity jumps is significant only for USDTRY with a negative sign and it has weaker significance compared to the positive jump case. This finding indicates that the conditional impact of news associated with negative liquidity jumps on volatility is limited relative to that of news associated with positive liquidity jumps.

4.4. Impact of return jumps on liquidity

We change the dependent and the explanatory variables of the previous model in equations (13) and (14) to examine the high-frequency impact of return jumps on the liquidity levels. The motivation behind this exploration is provided in Figure 4 whereby liquidity responds dramatically to the return jumps and we observe abnormal liquidity levels right before and after these jumps as well.

———————————-**INSERT FIGURE 4 HERE** ———————————-

For further examination, we revise our previous WLS setting with the following equations:

$$L_t = \beta_0 + \sum_{k=1}^{K} \beta_k L_{t-k} + \sum_{d \in \{+,-\}} \sum_{l=-3}^{L} \gamma_{d,l} \times RJ_{t+l}^{d} + \sum_{d \in \{+,-\}} \eta_d \times D_t^d + \epsilon_t \tag{15}$$

where L_t is the 5-minute proportional bid-ask spread described in equation (8), and RJ and D are the return counterparts of the liquidity related variables defined for the estimation of equation (13). In the second stage, we fit the absolute value of estimated residuals in equation (15) to the following specification in equation (16) where we find the expected daily liquidity $l\hat{i}q_{d,t}$ by estimating a MA(1)-GARCH(1,1) model in a similar spirit with the previous analysis.

$$
\begin{aligned}
|\epsilon_t| = c + \varphi \hat{liq}_{d,t} + \sum_{d \in \{+,-\}} \sum_{l=-3}^{L} \gamma_{d,l} \times RJ_{t+l}^{d} + \sum_{d \in \{+,-\}} \eta_d \times D_t^d \\
+ \sum_{q=1}^{Q} (\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288}) + \sum_{p=1}^{P} \mu_p n^p + \vartheta_t
\end{aligned}
\tag{16}
$$

The regression results in Table 11 show that the contemporaneous impact of both positive and negative return jumps is significantly positive on the liquidity of USDTRY and USDZAR, but not that of USDMXN. According to the Wald test results, lead coefficients of both negative and positive return jumps significantly increase the proportional bid-ask spread, which indicates that liquidity conditions become significantly worse for both positive and negative jumps for all currencies. Furthermore, significantly higher or lower bid-ask spread before the jumps may lead to asymmetries in buyer- and seller-initiated order flows and create those jumps. This finding is in line with that of Piccotti (2018) who shows that illiquidity increases before jumps. Our results suggest that worsening liquidity conditions in the period following return jumps is valid for only the negative return jumps in USDZAR. All the news dummies that identify return jumps that are related to US and local news releases are found to have a significant and negative impact on liquidity, which is not surprising as the majority of the news announcements are done in local trading hours for all currencies. In this period, liquidity conditions are far better compared to jumps that occur in off-shore trading hours.

INSERT TABLE 11 HERE

4.5. Determinants of jumps and cojumps

What are the determinants of return jumps, liquidity jumps and also return-liquidity cojumps for each exchange rate? To answer this question, we first count daily jump and cojump arrivals and for each count series, we run the following generalized linear model with

Poisson model family:

$$J_t\,(or\,CJ_t) = \beta_0 + \beta_1 \Delta TED_t + \beta_2 \Delta VIX_t + \beta_3 EPU + \beta_4 \Delta RD_t + \beta_5 \Delta CDS_t + \beta_6 \Delta RR_t + \epsilon_t \quad (17)$$

where TED denotes a popular market-wide funding liquidity measure (e.g., Brunnermeier et al. (2008), Mancini et al. (2013)) which is calculated as the spread between the three-month London Interbank Offered Rate (LIBOR) Eurodollar rate and the three-month T-bill rate. VIX is the implied volatility of options written on the SP500 index and captures the market stress level. EPU denotes the daily US policy uncertainty index and is added to the model to capture both monetary and fiscal policy related uncertainties. These variables are included to control for both the market stress and uncertainty. Abrupt increases (decreases) in these variables can cause dramatic decreases (increases) in foreign investment positions and might lead to capital flight to (from) safer currencies. Among the independent variables that control idiosyncratic factors for each currency, RD denotes the rate differential between US and the local rate. RR is the risk reversal which is a proxy for downside risk and provides a measure for downside risk pricing (Hutchison and Sushko, 2013). Since series are not stationary in levels except for the EPU, we use the first differences as the regressors.

The regression results of the equation (17) are tabulated in Table 12. They show that different risk and liquidity factors significantly affect jump counts of different exchange rates. For USDMXN, changes in CDS significantly affect both return and liquidity jumps. We also find that, while return jumps followed by liquidity jumps (i.e., $LJ \rightarrow RJ$) are not significantly related to any of the regressors, the number of liquidity jumps followed by return jumps ($RJ \rightarrow LJ$) significantly increases with the rise in both EPU and CDS. This asymmetry is not surprising because the reaction of liquidity to return jumps is more severe with increasing probability of private information in higher uncertainty conditions. On the other hand, for USDTRY, both return and liquidity jump frequencies show a significant and positive response to an increase in TED, EPU and rate differential RD. This finding supports the earlier evidence on positive relation between jump arrivals and interest rate differentials as shown by Li et al. (2017). The number of cojumps significantly increases with higher TED spread and risk reversal. TED spread being significant for both individual return and liquidity jumps as well as their cojumps confirms the findings by Karnaukh et al. (2015) who show a significantly negative relationship between the TED spread and the foreign exchange liquidity. These findings are also consistent with those of Banti and Phylaktis (2015) who show that the individual liquidity conditions of relatively less liquid currencies like Turkish lira is very sensitive to market-wide liquidity. For USDZAR, while return jumps increase with higher EPU, rate differential and CDS, the liquidity jumps are only positively related to EPU and risk reversal.

Overall, among different risk and liquidity factors, EPU is the only one that has a significant positive impact on both return and liquidity jumps. This finding is not so surprising since a higher EPU implies higher uncertainty and, as suggested by Beckmann and Czudaj (2017), the uncertainty in the future stance of economic policy significantly deteriorates foreign exchange expectations that causes forecast errors. This would, in turn, lead to speculative trading activity and increase both return and liquidity jump occurrences. Also, the risk reversal significantly increases liquidity jumps for all three exchange rates under consideration. While the literature that provides empirical examination between VIX and FX liquidity finds a significantly negative relationship between the two variables (Mancini et al., 2013), we do not observe such an occurrence in the case of liquidity jump arrivals for any of the sample exchange rates.

INSERT TABLE 12 HERE

4.5.1. Responses to local and global macro-news announcements

We further investigate the determinants of jumps and cojumps by examining their linkages with the dissemination of the US and local macroeconomic news announcements. For this purpose, we run the following probit regression model for each exchange rate:

$$P(J_t \, (or \, CJ_t) = 1|X) = \Phi(\alpha + \sum_{m=1}^{M} \phi_m News_t^{US} + \sum_{n=1}^{N} \theta_n News_t^{Local}) \tag{18}$$

In this setup, $News^{US}$ and $News^{Local}$ are dummy variables for US based and local macro-news announcements respectively, where the full list of announcement can be found in Table 1.[16] The estimated coefficients are in Table 13. Occurrences of return jumps are found to coincide with the dissemination of key macroeconomic variables like CPI and non-farm payroll, and also FOMC announcements which is consistent with the earlier works by Lahaye et al. (2011) and Lee (2012). In both studies, the authors show that among all US macroeconomic news announcements, non-farm payroll and FOMC announcements are the most important ones for jumps in bond and equity prices and also exchange rates. For the local news announcements, the dissemination of the central bank rate decisions is found to have a significantly positive impact on return jump probabilities. For the liquidity jumps, the CPI announcement is effective for Turkey, whereas the release of the central bank rate decision in Mexico has a significant impact on both return and liquidity jumps for USDMXN. However, monetary policy rate decision announcements by these central banks have no effect on the probability of return-liquidity cojump occurrence for any of the exchange rates.

INSERT TABLE 13 HERE

4.6. Jump based hedging strategies and their performance comparison

As we point out earlier, the findings of the paper can provide implications for different investment styles. We propose, in this subsection, a jump modified high frequency FX hedge strategy to demonstrate one of these implications. We thus assume a hypothetical

[16] As argued by Andersen et al. (2003), quantifying surprises in central bank decisions requires more advanced techniques since FOMC rate announcements, meeting minutes or local rate decisions are non-standard as they may contain information on unconventional policies like quantitative easing or forward guidance that may surpass the rate decision. Therefore, we use dummy variables instead of surprises for monetary policy decision announcements.

US-based investor who holds equity, bond or carry trade portfolios denominated in one of our emerging market currencies. While the investor gains returns from these portfolios, the invested amount is subject to exchange rate risk against US dollar at the same time. In our jump modified high frequency FX hedge strategy, the investor mitigates potential losses stemming from depreciated currencies by temporarily closing the emerging market currency FX position (against a trade for US dollar) when a jump occurs, then re-opening the position in the following hour.[17] The basic intuition behind this strategy is the serially correlated and clustered nature of the jumps. Furthermore, as shown in the empirical part earlier, the liquidity jumps may significantly increase the likelihood of return jump occurrences in the upcoming periods with the majority of them depreciating the emerging market currencies.

An important aspect in implementing jump-based strategies is to take the transaction costs into account because these strategies involve very frequent trading and ignoring these costs would result in an overestimation of the strategy performance. Furthermore, since the majority of both the return and liquidity jumps occur in the off-shore trading hours when the liquidity is significantly lower, the transaction costs might easily offset the gains from a jump modified strategy which further magnifies this overestimation. In our designed trading strategy, the investor sells the emerging market currency against the US dollar in the spot market at the ask price when a jump occurs and unwinds its foreign exchange position, and then sells the US dollar for the emerging market currency at the bid price one hour after the jump occurrence.

INSERT TABLE 14 HERE

In Table 14, we provide returns from a buy-and-hold strategy of each currency in the first column. In the remaining columns, excess returns of hedging strategies based on the corresponding jump type is calculated over the benchmark returns. For example, gains

[17] At this stage, every jump event is considered within its own category. For example, a trading strategy in our framework can only depend on either return jumps or liquidity jumps, not both.

for MXN from a hedging strategy considering return jumps is 11.66% compared to buying MXN and holding till the end of the analysis period, whereas the hedging strategy based on liquidity jumps produces an excess return of 6.55% for the same currency. Overall, the modified hedging strategy based on both return and liquidity jumps offers superior performance compared to a benchmark buy-and-hold strategy. However, the strategies based on positive return and liquidity jumps provide negative excess returns for TRY and ZAR. A potential explanation for this observation is the increasing bid-ask spread and thus higher transaction costs in the period following positive return and liquidity jumps.

INSERT FIGURE 5 HERE

Figure 5 displays the evolution of the US dollar values of benchmark buy-and-hold strategy, and return and liquidity jump based strategies during the analysis period where we index the initial US dollar value of the investment to 100. Figure 5 shows a higher performance of jump based strategies relative to benchmark, in particular right after mid-2016 where the jump activity intensified for the sample three emerging market currencies.

5. Cojumps across exchange rates

Cojumps across exchange rates are of paramount interest for investors and policymakers as they signal the potential of important comovements in the foreign exchange markets. Naturally, such cojumps might arise due to two reasons: (i) a shock to the US dollar which is the common denominator of all three currency exchange rates, or (ii) there are common factors among the three exchange rates. Table 15 shows the daily distribution of return cojumps and liquidity cojumps across our sample exchange rates.

INSERT TABLE 15 HERE

The number of return cojumps is highest for the USDTRY-USDZAR pair, given their higher similarities. While return cojumps are mostly accumulated in off-shore trading hours, they also intensify between 12:00 and 14:00, suggesting that the US macroeconomic news releases can be a major driver behind these cojumps. For the liquidity cojumps, the number of occurrences is very low. While the maximum number of liquidity cojumps is found for the USDTRY-USDZAR pair with 46 occurrences, the number of such cojumps that occur at the same time for all three exchange rates is only 2. Since the number of liquidity cojumps is very low, we limit our analysis to return cojumps. We proceed in a similar manner to the previous section, and focus on the analysis of the duration between consecutive return cojumps, and also examine the determinants of these cojumps through macroeconomic news announcement analysis.

5.1. Duration of cojumps across exchange rates

Tables 16 reports the summary statistics related to the duration between consecutive return cojumps across exchange rates. We see that the shortest average duration between return cojumps is observed for the USDTRY-USDZAR pair, with cojumps occurring on every 2.4 days, which is 50% more frequent than cojumps of the USDTRY-USDMXN pair. Return cojumps across all three exchange rates occur, on average, around every 10 days. Among all bilateral return cojumps, the ones between USDMXN-USDZAR pair have the most irregular pattern with a standard deviation of 5.1 days, whereas the most regular pattern arises in the case of USDTRY-USDZAR pair with the lowest standard deviation of 3.14 days for duration.

INSERT TABLE 16 HERE

Next, we model the duration x_i between consecutive return cojumps across exchange rates using a similar LACD(1,1) model that we have implemented earlier. The main difference is, in addition to the exchange rate specific factors, the introduction of the global factors (TED spread, VIX and EPU index) as explanatory variables since cojumps across borders are most likely driven by these widely influential factors. The model is presented in equation (19) and the estimation results are provided in Table 17.

$$
\begin{aligned}
x_i &= \mu_i \epsilon_i \\
ln\mu_i = \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} &+ \theta_1 TED + \theta_2 VIX + \theta_3 EPU \\
+\varphi_{FX1}\overline{LIQ}_{i1} + \psi_{FX1}\overline{RV}_{i1} + \varphi_{FX2}\overline{LIQ}_{i2} &+ \psi_{FX2}\overline{RV}_{i2} + \varepsilon_i
\end{aligned} \tag{19}
$$

INSERT TABLE 17 HERE

According to Table 17, the global and idiosyncratic factors play a significant role on the duration between consecutive cojumps. For all three combinations of bilateral cojumps, an increase in the EPU index has a strong negative impact on the duration, i.e., the rising uncertainty in US economic policy increases the intensity of return cojumps across exchange rates. Similar effect is found for VIX on the cojumps between USDMXN-USDZAR and USDTRY-USDZAR pairs. Idiosyncratic factors of liquidity and volatility mostly preserve their original impacts that they had on return and liquidity jumps respectively.

5.2. Cojumps and US macro-news announcements

Our framework also allows us to examine the impact of scheduled US monetary policy decisions and macroeconomic news releases on the cojumps across exchange rates via equation (20). Different from equation (18), we include only the US announcements since the cojumps across exchange rates are expected to be not idiosyncratic but systematic in general, potentially caused by a highly influential news source. Moreover, due to the very limited number of observations for liquidity cojumps, analysis is performed only for return cojumps across exchange rates.

$$
P(CJ_t = 1|X) = \Phi(\alpha + \sum_{m=1}^{M} \phi_m News_t^{US}) \tag{20}
$$

The regression results in Table 18 show that announcements of CPI and non-farm payrolls have a significant and positive impact on all pairwise exchange rate cojump combinations. For the triple exchange rate cojump probabilities, none of the announcements has a significant impact. By contrast, the FOMC announcements, FOMC meeting minutes and GDP-advance announcements significantly and positively affect return cojumps across USD-MXN and USDTRY. Taken together, the results that are found in this section and also those found in Section 4.5.1 suggest that investor sentiment in emerging markets is now dependent on the US economy and the policy actions of the US Fed more than ever, which points out to the potential challenges faced with policymakers around the world due to this increasing policy interdependence.

INSERT TABLE 18 HERE

6. Conclusion

Despite a growing attention on return jump and cojump events in the foreign exchange markets, little is know about the linkages between return and liquidity jumps. Our research has a unique focus regarding the effect of liquidity, in particular, large and unusual increases (jumps) in liquidity, and their impact on pricing in the FX markets. Likewise, the determinants of liquidity jumps have not, to the best of our knowledge, been examined along with their interaction and co-occurrence with return jumps. This paper takes a first step in this subject by investigating the dynamics of both return and liquidity (co)jumps as well as their intraday interaction for the case of three major emerging market exchange rates (Mexican Peso, Turkish Lira, and South African Rand vis-à-vis US dollar). Once the jumps and cojumps are identified, we particularly focus on the duration of the two consecutive jumps, the high-frequency shock transmission of liquidity jumps on volatility and return jumps on liquidity, and the determinants of return and liquidity (co)jumps. Similar analysis is also conducted on the cojumps across selected FX rates.

Our main findings reveal that the duration between consecutive return jumps is significantly reduced by the increased average spread of the same period. However, we are not able to make such strict inference for the effect of liquidity or realized volatility on neither liquidity jumps nor return-liquidity cojumps. We also find that contemporaneous effects of return and liquidity jumps of either sign (negative or positive) on liquidity and volatility respectively are significant and positive for all three exchange rates. Furthermore, daily arrivals of jump variants significantly increase with the rise in the US economic policy uncertainty, while news announcements concerning the US CPI, GDP, non-farm payroll, and the release of FOMC decisions and minutes significantly increase the likelihood of both return and liquidity (co)jumps.

Several policy implications can be suggested from the above-mentioned findings. First, the insights from characterization of different jumps and cojumps can be incorporated in decision making process. It can, for example, be used for establishing an efficient operational framework in managing foreign exchange liquidity because, as demonstrated by Ait-Sahalia et al. (2015), jump intensity can serve as a proxy for market stress with significant out-of-sample forecasting performance. Leading indicators providing early warning signals can thus be built based on detected jumps and their intensity to provide guidance to policymakers. From the investors' point of view, jump adjusted trading strategies can be developed. In fact, as a supporting evidence to this case, we introduce a jump modified high frequency FX hedging strategy that provides superior performance in excess of the buy-and-hold approach that can reach up to 11.66% return in US dollar terms after taking transaction costs into account. Second, for a country that needs important foreign financing sources, the presence of jumps in its exchange rate increases the volatility risk premium and, in turn, affects the cost of funding. In a lower frequency horizon where high pass-trough effects from exchange rate to prices exist, jumps also lead to deteriorated inflation forecasts and hence distort central bank decisions in inflation targeting regimes as in the case of the selected currencies. Conrad et al. (2015) propose designated market maker contracts to reduce the number of jumps in the case of equities. Even though the market structures are different, a framework similar to this suggested one could be designed in the FX markets to step in exclusively during liquidity dry-up periods in order to prevent such negative consequences of exchange rate jumps. Finally, the evidence of a vicious return-liquidity spirals would call for more attention from investors and fund managers to take FX return-liquidity (co)jump patterns into account when forming their portfolios.

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Table 1: Summary table for US and domestic macroeconomic news and central bank announcements

	Mexico			Turkey			South Africa		
Event	Frequency	Hour	Obs	Frequency	Hour	Obs	Frequency	Hour	Obs
Consumer Price Index (CPI)	Monthly	13:00	48	Monthly	07:00	48	Monthly	08:00	48
Gross Domestic Product (GDP)	Quarterly	13:00	16	Quarterly	07:00	16	Quarterly	09:30	16
Central Bank Rate Decision	Six-week	18:00	32	Monthly	11:00	41	8-weeks	13:25	24
Industrial Production [a]	Monthly	13:00	48	Monthly	07:00	47	Monthly	11:00	48
Current Account Balance	Quarterly	14:00	16	Monthly	07:00	48	Quarterly	08:00	16
Budget Balance	Monthly	19:30	47	Monthly	08:00	40	Monthly	12:00	47
Unemployment Rate	Monthly	13:00	47	Monthly	07:00	47	Quarterly	09:30	16

	US		
Event	Frequency	Hour	Obs
Budget Statement	Monthly	18:00	48
Business Inventories	Monthly	14:00	48
Consumer Confidence	Monthly	14:00	47
Consumer Credit	Monthly	19:00	48
CPI	Monthly	12:30	48
Durable Goods Orders	Monthly	12:30	47
Factory Orders	Monthly	14:00	48
FOMC Announcement	Six-week	18:00	31
FOMC Meeting Minutes	Six-week	18:00	32
GDP-Advance	Quarterly	12:30	16
GDP-Second	Quarterly	12:30	15
GDP-Final	Quarterly	12:30	16
Housing Starts	Monthly	12:30	47
Industrial Production	Monthly	13:15	48
Initial Jobless Claims	Bi-weekly	12:30	206
ISM Manufacturing	Monthly	14:00	47
Leading Index	Monthly	14:00	47
New Home Sales	Monthly	14:00	47
Non-farm Payrolls	Monthly	12:30	48
Personal Income	Monthly	12:30	47
Producer Price Index (PPI)	Monthly	12:30	48
Retail Sales	Monthly	12:30	48
Trade Balance	Monthly	12:30	48

This table presents the list of scheduled macroeconomic news and central bank announcements for Mexico, Turkey, South Africa and US. For each macroeconomic news announcement we provide the number of observations between January 5, 2014 and December 14, 2018. The presented time stamps are in GMT and 1 hour forward for the daylight saving time. The timing of some of the announcements may change due to delays in releases or unscheduled monetary policy meetings but we present their standard times in the table.

[a] For South Africa, we use manufacturing production announcements due to data unavailability.

Table 2: Summary statistics for exchange rate returns and liquidity

	Returns			Liquidity		
	USDMXN	USDTRY	USDZAR	USDMXN	USDTRY	USDZAR
Mean	$1.05\text{x}10^{-6}$	$2.80\text{x}10^{-6}$	$0.70\text{x}10^{-6}$	0.0003	0.0006	0.0007
Min	-0.0178	-0.0551	-0.0459	$5.32\text{x}10^{-7}$	$20.83\text{x}10^{-7}$	$6.37\text{x}10^{-7}$
Max	0.0313	0.1036	0.0395	0.0040	0.0093	0.0041
Std.	0.0005	0.0007	0.0007	0.0002	0.0007	0.0006
Skew.	0.6393	9.1241	0.4282	2.2078	4.0276	1.6610
Kurt.	106.41	1,784.10	161.80	6.05	28.17	2.42
Obs	296,352	296,352	296,352	296,352	296,352	296,352

This table shows the summary statistics for high frequency returns and liquidity measures for the sample foreign exchange rates. The sample covers the period from January 5, 2015 to December 14, 2018. The data is sampled at 5-min frequency. Returns are calculated with logarithmic foreign exchange rate changes and the liquidity measure is the proportional quoted spread; i.e., the ratio of bid-ask spread to the mid-quote.

Table 3: Summary statistics for the detected return and liquidity jumps

		All Jumps				News related Jumps			
		$\#J$	$P(J)$	$max(J)$	$mean(J)$	$\#J$	$P(J)$	$max(J)$	$mean(J)$
USDMXN	RJ	1827	0.62%	0.0313	0.0017	81	0.03%	0.0171	0.0042
	RJ^-	912	0.31%	0.0178	0.0017	53	0.02%	0.0171	0.0044
	RJ^+	915	0.31%	0.0313	0.0017	28	0.01%	0.0074	0.0039
	LJ	707	0.24%	6.8349	2.6794	22	0.01%	6.2660	2.6740
	LJ^-	399	0.13%	6.3951	2.6475	9	0.00%	6.2660	3.5016
	LJ^+	308	0.10%	6.8349	2.7208	13	0.00%	3.6554	2.1009
USDTRY	RJ	4393	1.48%	0.1036	0.0017	124	0.04%	0.0551	0.0046
	RJ^-	2040	0.69%	0.0551	0.0016	68	0.02%	0.0551	0.0047
	RJ^+	2353	0.79%	0.1036	0.0017	56	0.02%	0.0277	0.0045
	LJ	1937	0.65%	5.9194	1.4584	53	0.02%	4.8429	1.9540
	LJ^-	1020	0.34%	5.9194	1.4193	14	0.00%	4.8429	2.2143
	LJ^+	917	0.31%	5.5216	1.5018	39	0.01%	3.1201	1.8606
USDZAR	RJ	3205	1.08%	0.0459	0.0020	94	0.03%	0.0147	0.0050
	RJ^-	1596	0.54%	0.0459	0.0020	61	0.02%	0.0147	0.0047
	RJ^+	1609	0.54%	0.0395	0.0021	33	0.01%	0.0112	0.0056
	LJ	1422	0.48%	7.4223	1.9826	32	0.01%	6.5923	3.8024
	LJ^-	774	0.26%	6.9953	1.9137	14	0.00%	6.4730	4.1498
	LJ^+	648	0.22%	7.4223	2.0648	18	0.01%	6.5923	3.5322

This table provides descriptive statistics for detected jumps. The sample covers the period from January 5, 2015 to December 14, 2018. The jumps are detected by using the non-parametric jump test procedure of Lee and Mykland (2008). In this table, $\#J$, $P(J)$, $max(J)$ and $mean(J)$ denote the number of jumps, probability of jump occurrence, maximum jump size and the average jump size respectively. RJ and LJ refer to return and liquidity jumps respectively whereas $-$ and $+$ superscripts symbolize negative and positive jumps respectively,

Table 4: Conditional probabilities of return jump occurrences around liquidity jumps

	-5	-4	-3	-2	-1	0	1	2	3	4	5	before	after	no-cojump
USDMXN	2.12%	2.12%	2.12%	2.26%	3.11%	3.54%	1.84%	1.70%	2.55%	2.12%	1.27%	11.74%	9.48%	75.25%
USDTRY	4.80%	4.90%	5.01%	5.89%	8.05%	21.12%	7.95%	6.35%	5.83%	5.11%	5.06%	28.65%	30.30%	19.93%
USDZAR	2.88%	2.81%	2.74%	2.32%	4.64%	9.99%	5.06%	3.52%	3.94%	3.31%	3.87%	15.40%	19.69%	54.92%

This table presents the probability of observing a return jump within a specific period around a liquidity jump. In the columns, numbers ranging from -5 to 5 denote the number of 5-minute lagged and lead intervals respectively around a liquidity jump, while value under these columns are the empirical probabilities of return jumps withing the defined time intervals. Values under the columns titled 'before' and 'after' report the aggregate probability of observing a return jump before and after 25 minutes of a liquidity jump respectively. Finally, the values under the column 'no-cojump' indicates the probability of observing zero return jump before or after 25 minutes of a liquidity jump.

Table 5: Intraday jump and cojump distribution of exchange rate returns and their liquidity

	USDMXN					USDTRY					USDZAR				
	RJ	LJ	$CJ^{RJ,LJ}$	$LJ \rightarrow RJ$	$RJ \rightarrow LJ$	RJ	LJ	$CJ^{RJ,LJ}$	$LJ \rightarrow RJ$	$RJ \rightarrow LJ$	RJ	LJ	$CJ^{RJ,LJ}$	$LJ \rightarrow RJ$	$RJ \rightarrow LJ$
00:00-02:00	351	80	5	7	11	925	374	95	56	67	643	123	27	21	23
02:00-04:00	386	83	6	11	11	1007	298	100	64	61	630	90	16	11	12
04:00-06:00	342	88	8	5	5	616	149	31	18	27	468	71	10	14	9
06:00-08:00	63	37	0	0	0	71	38	1	2	0	55	23	0	0	0
08:00-10:00	14	37	0	0	0	28	15	0	1	0	19	52	0	0	1
10:00-12:00	17	33	0	0	0	46	30	0	2	2	24	46	0	2	0
12:00-14:00	51	34	0	3	2	71	42	3	7	0	57	44	1	3	1
14:00-16:00	17	57	0	0	0	34	22	0	0	0	14	62	0	0	0
16:00-18:00	37	59	0	0	1	65	28	0	0	1	42	44	1	0	1
18:00-20:00	79	73	0	4	1	274	56	4	6	6	172	28	1	3	0
20:00-22:00	102	34	1	0	1	291	133	14	8	10	239	229	14	20	15
22:00-00:00	368	92	5	6	9	965	752	161	144	132	842	610	72	73	60
Total	1827	707	25	36	41	4393	1937	409	308	306	3205	1422	142	147	122

In this table, we provide intraday distribution of return jumps, liquidity jumps, and return-liquidity cojumps for each exchange rate. RJ and LJ refer to return and liquidity jumps respectively. $CJ^{RJ,LJ}$ denote return-liquidity cojump that occurred in the same 5 minute interval. As extended definitions of cojumps, $LJ \rightarrow RJ$ and $RJ \rightarrow LJ$ refer to (i) return jumps followed by liquidity jumps and (ii) liquidity jumps followed by return jumps within 15-minutes respectively.

Table 6: Summary statistics of the duration between consecutive return jumps, liquidity jumps, and return-liquidity cojumps

	Return Jumps			Liquidity Jumps			Return-Liquidity Cojumps		
	USDMXN	USDTRY	USDZAR	USDMXN	USDTRY	USDZAR	USDMXN	USDTRY	USDZAR
Min	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
Max	6.292	4.045	4.156	16.976	11.545	14.024	120.122	41.757	65.007
Mean	0.563	0.234	0.321	1.456	0.530	0.723	31.292	2.490	7.079
Std.	0.788	0.402	0.514	2.085	0.916	1.127	33.936	3.981	9.985
Obs.	1826	4392	3204	706	1936	1421	24	408	141

Note: The values in the table (except the number of observations) are in days.

Table 7: LACD(1,1) model fit results for the duration between consecutive return jumps

	USDMXN	USDTRY	USDZAR
ω	-0.561***	-1.674***	-1.683***
α	0.097***	0.143***	0.120***
β	0.133***	-0.157***	-0.098***
φ	-0.819***	-0.532***	-1.237***
ψ	0.759***	-0.110***	-0.144***

This table presents the estimation results of the following LACD(1,1) model for x_i, the duration between consecutive return jumps,

$$x_i = \mu_i \epsilon_i$$
$$ln\mu_i = \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \varepsilon_i$$

with $\overline{LIQ}_i$ and $\overline{RV}_i$ are the average proportional spread and the average realized volatility of the exchange rate between consecutive return jump occurrences respectively. *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 8: LACD(1,1) model fit results for the duration between consecutive liquidity jumps

	USDMXN	USDTRY	USDZAR
ω	0.211***	0.027***	0.010***
α	-0.080***	0.017***	0.009***
β	-0.201***	0.997***	0.982***
φ	0.758***	-0.002***	-0.008***
ψ	-0.472***	0.003	0.029***

This table presents the estimation results of the following LACD(1,1) model for $\tilde{x}_i$, the duration between consecutive liquidity jumps,

$$\tilde{x}_i = \mu_i \epsilon_i$$
$$ln\mu_i = \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \varepsilon_i$$

with $\overline{LIQ}_i$ and $\overline{RV}_i$ are the average proportional spread and the average realized volatility of the exchange rate between consecutive liquidity jump occurrences respectively. *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 9: LACD(1,1) model fit results for the duration between consecutive return-liquidity cojumps

	USDMXN	USDTRY	USDZAR
ω	-0.8714	0.0143***	-0.0914***
α	-0.0845**	0.0104***	-0.0069***
β	1.2474***	1.001***	1.0423***
φ	0.0021	-0.0037	-0.0022***
ψ	0.0063	0.0287*	-0.0007***

This table presents the estimation results of the following LACD(1,1) model for $\hat{x}_i$, the duration between consecutive return-liquidity cojumps,

$$\hat{x}_i = \mu_i \epsilon_i$$
$$ln\mu_i = \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} + \varphi \overline{LIQ}_i + \psi \overline{RV}_i + \varepsilon_i$$

with $\overline{LIQ}_i$ and $\overline{RV}_i$ are the average proportional spread and the average realized volatility of the exchange rate between consecutive return-liquidity cojump occurrences respectively. *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 10: Impact of liquidity jumps on volatility

	USDMXN		USDTRY		USDZAR	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
LJ^-_{t+3}	0.0112*	0.0708	0.0154	0.1648	0.0177**	0.0275
LJ^-_{t+2}	0.0196**	0.0205	0.0262**	0.0300	-0.0029	0.7942
LJ^-_{t+1}	0.0373***	0.0000	0.0481***	0.0001	0.0251**	0.0223
LJ^-_{t}	0.0482***	0.0000	0.149***	0.0000	0.1035***	0.0000
LJ^-_{t-1}	0.0145*	0.0876	-0.008	0.5076	-0.0044	0.6881
LJ^-_{t-2}	0.0149*	0.0783	-0.0084	0.4864	0.0052	0.6346
LJ^-_{t-3}	-0.0038	0.6550	-0.0089	0.4634	-0.0558***	0.0000
LJ^+_{t+3}	-0.0135	0.1528	0.0194	0.1160	-0.0089	0.4261
LJ^+_{t+2}	-0.0101	0.2837	0.0323***	0.0090	-0.0211*	0.0585
LJ^+_{t+1}	-0.0088	0.3517	0.038***	0.0021	-0.0471***	0.0000
LJ^+	0.0312***	0.0011	0.2235***	0.0000	0.1201***	0.0000
LJ^+_{t-1}	0.0193***	0.0052	0.0314***	0.0056	0.0167**	0.0408
LJ^+_{t-2}	-0.007	0.4602	0.0439***	0.0004	0.0097	0.3842
LJ^+_{t-3}	0.0057	0.5477	0.1276***	0.0000	0.0142	0.2041
D^-_t	0.4108***	0.0015	0.5545***	0.0008	0.2156	0.1359
D^+_t	-0.0253	0.8127	-0.2292**	0.0226	0.0249	0.8450
ΣLJ^-_{lead}	0.0682***	0.0000	0.0897***	0.0000	0.0399**	0.0239
ΣLJ^-_{lag}	0.0256*	0.0863	-0.0253	0.2387	-0.055***	0.0048
ΣLJ^+_{lead}	-0.0324*	0.0504	0.0896***	0.0000	-0.0772***	0.0001
ΣLJ^+_{lag}	0.018	0.2322	0.2029***	0.0000	0.0406**	0.0236

This table presents the estimation results for the two-stage weighted least squares model defined by the following equations

$$r_t = \beta_0 + \sum_{k=1}^{K} \beta_k r_{t-k} + \sum_{d\in\{+,-\}} \sum_{l=-3}^{L} \delta_{d,l} \times LJ^d_{t+l} + \sum_{d\in\{+,-\}} \eta_d \times D^d_t + \epsilon_t$$

and

$$|\epsilon_t| = c + \varphi \frac{\hat{\sigma}_{d,t}}{\sqrt{288}} + \sum_{d\in\{+,-\}} \sum_{l=-3}^{L} \delta_{d,l} \times LJ^d_{t+l} + \sum_{d\in\{+,-\}} \eta_d \times D^d_t$$
$$+ \sum_{q=1}^{Q} (\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288}) + \sum_{p=1}^{P} \mu_p n^p + \vartheta_t$$

where r_t denotes the 5-minute logarithmic returns with $K = 5$ units, LJ^d_t is the size of the liquidity jump with direction d at time t with $L = 3$, D^d_t is a dummy variable which equals 1 if the liquidity jump with direction d within $[t-3, t+3]$ is associated with a scheduled macroeconomic news announcement. ΣLJ^d_{lead} and ΣLJ^d_{lag} denote the cumulative impact of lead and lagged liquidity jumps in direction d. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 11: Impact of return jumps on liquidity

	USDMXN		USDTRY		USDZAR	
	Coef.	p-value	Coef.	p-value	Coef.	p-value
RJ^{-}_{t+3}	3.4282***	0.0091	6.9956**	0.0399	6.1209**	0.0111
RJ^{-}_{t+2}	2.526*	0.0500	10.3494***	0.0047	12.8544***	0.0000
RJ^{-}_{t+1}	24.9407***	0.0000	28.9326***	0.0000	29.7468***	0.0000
RJ^{-}_{t}	3.705*	0.0737	41.0154***	0.0000	45.5505***	0.0000
RJ^{-}_{t-1}	2.3818	0.1166	-11.6889***	0.0012	-3.4852	0.2097
RJ^{-}_{t-2}	-1.4891	0.3179	3.2032	0.4359	9.3527***	0.0022
RJ^{-}_{t-3}	0.476	0.7593	7.3047*	0.0955	14.6245***	0.0000
RJ^{+}_{t+3}	-0.1698	0.9160	-2.905	0.2784	8.0561***	0.0007
RJ^{+}_{t+2}	3.8372**	0.0151	-0.5047	0.8498	-0.7944	0.7198
RJ^{+}_{t+1}	23.3074***	0.0000	17.5283***	0.0000	22.8608***	0.0000
RJ^{+}_{t}	3.8289	0.1008	44.6823***	0.0000	27.1048***	0.0000
RJ^{+}_{t-1}	-1.4251	0.4294	-9.5513***	0.0024	-2.2549	0.3685
RJ^{+}_{t-2}	0.1083	0.9472	2.3077	0.4224	-1.2735	0.5772
RJ^{+}_{t-3}	-5.1358***	0.0095	11.6259***	0.0007	7.0076**	0.0170
D^{-}_{t}	-0.1781***	0.0000	-0.3337***	0.0000	-0.4609***	0.0000
D^{+}_{t}	-0.1962***	0.0000	-0.3288***	0.0000	-0.3675***	0.0000
ΣRJ^{-}_{lead}	30.8949***	0.0000	46.2776***	0.0000	48.7221***	0.0000
ΣRJ^{-}_{lag}	1.3687	0.5914	-1.181	0.8624	20.492***	0.0001
ΣRJ^{+}_{lead}	26.9748***	0.0000	14.1186***	0.0033	30.1224***	0.0000
ΣRJ^{+}_{lag}	-6.4526**	0.0283	4.3823	0.4005	3.4792	0.4142

This table presents the estimation results for the two-stage weighted least squares model defined by the following equations

$$L_t = \beta_0 + \sum_{k=1}^{K} \beta_k L_{t-k} + \sum_{d\in\{+,-\}} \sum_{l=-3}^{L} \gamma_{d,l} \times RJ^d_{t+l} + \sum_{d\in\{+,-\}} \eta_d \times D^d_t + \epsilon_t$$

and

$$|\epsilon_t| = c + \varphi \hat{liq}_{d,t} + \sum_{d\in\{+,-\}} \sum_{l=-3}^{L} \gamma_{d,l} \times RJ^d_{t+l} + \sum_{d\in\{+,-\}} \eta_d \times D^d_t$$
$$+ \sum_{q=1}^{Q} (\phi_q \sin \frac{q2\pi t}{288} + \psi_q \cos \frac{q2\pi t}{288}) + \sum_{p=1}^{P} \mu_p n^p + \vartheta_t$$

where L_t denotes the proportional bid-ask spread at time t with $K = 5$ units, RJ^d_t is the size of the return jump with direction d at time t with $L = 3$, D^d_t is a dummy variable which equals 1 if the return jump with direction d within $[t-3, t+3]$ is associated with a scheduled macroeconomic news announcement. ΣRJ^d_{lead} and ΣRJ^d_{lag} denote the cumulative impact of lead and lagged return jumps in direction d. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 12: Determinants of return jumps, liquidity jumps and return-liquidity cojumps for each exchange rate

USDMXN

	RJ	LJ	$CJ^{RJ,LJ}$	$LJ \rightarrow RJ$	$RJ \rightarrow LJ$
ΔTED	1.0033	0.5988	2.4686	7.6576	5.5565
ΔVIX	3.4122	-0.609	-0.6713	-1.9529	-4.5912
EPU	0.0032*	0.0038***	0.0004	0.0019	0.0096***
ΔRD	-0.6673	0.6028**	-1.0868**	-1.1382	0.3902
ΔCDS	16.5556**	10.6222***	6.9134*	17.7987	27.3372**
ΔRR	-7.9201*	2.718***	2.2994	-17.2989*	5.6485

USDTRY

	RJ	LJ	$CJ^{RJ,LJ}$	$LJ \rightarrow RJ$	$RJ \rightarrow LJ$
ΔTED	0.0012***	2.3151***	2.8723***	2.4087	-0.623
ΔVIX	0.013***	0.7495*	0.0827	0.9497	0.7872
EPU	0.0001***	0.0017***	0.0002	0.0003	0.0019
ΔRD	0.0028***	0.1086**	0.0278	-0.1649	0.0899
ΔCDS	-0.0056***	2.8817*	-0.4951	6.0736	10.5918*
ΔRR	-0.0214***	2.3933**	3.1865**	6.1647*	2.9211

USDZAR

	RJ	LJ	$CJ^{RJ,LJ}$	$LJ \rightarrow RJ$	$RJ \rightarrow LJ$
ΔTED	0.9366	1.2049	1.9485*	-1.377	4.3053
ΔVIX	-1.9829	0.7491	0.0112	3.0096	3.7374*
EPU	0.0032***	0.0026***	0	0.0022	0.0028*
ΔRD	2.9417**	-0.1164	-0.2291	-1.2332	-2.2772
ΔCDS	16.1051***	0.5198	0.9645	9.2576	14.9434*
ΔRR	-7.9153**	5.1241***	-1.9345	-8.0127	0.6287

This table present the estimation results of the Poisson regression $X_t = \beta_0 + \beta_1 \Delta TED_t + \beta_2 \Delta VIX_t + \beta_3 EPU + \beta_4 \Delta RD_t + \beta_5 \Delta CDS_t + \beta_6 \Delta RR_t + \epsilon_t$ where X can be RJ, LJ, $CJ^{RJ,LJ}$, $LJ \rightarrow J$ or $J \rightarrow LJ$. RJ and LJ refer to return and liquidity jumps respectively. $CJ^{RJ,LJ}$ denotes return-liquidity cojump. As extended definitions of cojumps, $LJ \rightarrow RJ$ and $RJ \rightarrow LJ$ refer to (i) return jumps followed by liquidity jumps and (ii) liquidity jumps followed by return jumps within 15-minutes respectively. TED is the spread between the three-month London Interbank Offered Rate (LIBOR) Eurodollar rate and the three-month T-bill rate. VIX is the implied volatility of options written on the SP500 contracts and captures market stress level. EPU denotes the daily US policy uncertainty index. RD denotes the rate differential between US and the local rate for the selected currency. RR is the risk reversal. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 13: Impact of US based and local macroeconomic news announcements on return jumps, liquidity jumps and return-liquidity cojumps for each exchange rate

	USDMXN			USDTRY			USDZAR		
	RJ	LJ	$CJ^{RJ,LJ}$	RJ	LJ	$CJ^{RJ,LJ}$	RJ	LJ	$CJ^{RJ,LJ}$
US News Announcements									
Budget Statement	-3.617	-2.995	-2.313	-3.589	-2.909	-2.751	-3.474	-2.801	-2.609
Business Inventories	-2.696	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	-2.806	-2.614
Consumer Confidence	-2.64	-2.7	-2.276	-2.986	-2.873	-2.718	-2.864	-2.765	-2.577
Consumer Credit	-2.696	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	-2.806	-2.614
CPI	1.392***	-2.633	-2.137	1.18***	0.854**	1.349***	0.911***	0.43	1.66***
Durable Goods Orders	0.426	-3.455	-2.168	0.18	0.592	-2.564	-3.488	-2.936	-2.411
Factory Orders	0.478	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	0.553	-2.614
FOMC Announcement	2.474***	-2.753	-2.323	2.222***	-2.914	-2.756	2.425***	0.742*	1.457***
FOMC Meeting Minutes	1.762***	-2.745	-2.316	1.428***	-2.906	-2.748	1.439***	-2.798	-2.606
GDP-Advance	0.962*	-2.715	-2.242	1.087***	-3.124	-2.665	1.313***	-2.847	-2.526
GDP-Final	-2.648	1.409**	-2.156	-2.87	-2.941	-2.566	-2.742	-2.908	-2.429
GDP-Second	-2.757	-2.735	-2.294	-3.032	-3.049	-2.723	-2.875	-2.816	-2.582
Housing Starts	0.15	-2.704	-2.24	-3.692	-3.326	-3.602	0.124	-2.989	-3.768
Industrial Production	-2.696	-2.753	-2.323	-3.03	-2.914	-2.756	-2.907	-2.806	-2.614
Initial Jobless Claims	-0.298	-0.022	-2.208	-0.649*	-0.279	-3.479	-0.512	0.235	-3.612
ISM Manufacturing	0.793**	0.795*	-2.323	0.459	0.454	-2.756	-2.907	0.562	-2.614
Leading Index	-2.72	-2.731	-2.303	-3.021	-2.891	-2.735	-2.911	-2.783	-2.593
New Home Sales	-2.61	-2.673	-2.251	-2.966	-2.853	-2.699	-2.844	-2.745	-2.559
Non-farm Payrolls	2.489***	0.512	-2.222	2.196***	1.189***	1.493***	2.368***	-3.267	-2.506
Personal Income	0.51	-2.726	-2.252	0.23	-3.004	-2.676	0.378	-2.857	-2.536
PPI	0.589*	-2.649	-2.148	0.003	0.515	-2.551	0.515	-3.113	-2.414
Retail Sales	0.955***	-2.572	-2.092	0.981***	0.003	-3.758	0.946***	0.483	-3.932
Trade Balance	-0.526	0.518	-2.157	-0.147	-3.846	-3.997	-0.62	0.676	-2.437
Local News Announcements									
Budget Balance	0.486	-2.753	-2.323	-3.03	-2.914	-2.756	-2.903	-2.815	-2.608
CPI	-2.696	-2.753	-2.323	0.81***	0.761**	-2.756	0.284	-2.795	-2.604
Current Account Balance	-2.619	-2.681	-2.258	-2.968	-2.855	-2.701	-2.97	-2.772	-2.583
GDP NSA YoY	-2.696	-2.753	-2.323	-2.848	-2.741	-2.595	1.629***	-2.806	-2.614
Industrial Production	-2.696	-2.753	-2.323	-3.012	-2.897	-2.74	0.572*	-2.806	-2.614
Central Bank Decision	1.525***	0.974**	-2.316	2.089***	0.512	-2.756	0.979***	-2.823	-2.603
Unemployment Rate	-2.685	-2.742	-2.313	-3.012	-2.897	-2.74	-2.907	-2.806	-2.614

This table presents the estimation results of the following probit regression: $P(J_t\,(or\,CJ_t) = 1|X) = \Phi(\alpha + \sum_{m=1}^{M} \phi_m News_t^{US} + \sum_{n=1}^{N} \theta_n News_t^{Local})$. In the model, $News^{US}$ and $News^{Local}$ are dummy variables for US based and local macro-news announcements respectively. J and LJ refer to return and liquidity jumps respectively. $CJ^{RJ,LJ}$ denotes return-liquidity cojump. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 14: Excess returns of jump modified strategies on benchmark buy-and-hold strategy

	Benchmark returns	Excess returns of jump modified hedge strategies					
	Buy-and-hold FX	RJ	RJ^-	RJ^+	LJ	LJ^-	LJ^+
MXN	-26.81%	11.66%	10.95%	11.58%	6.55%	4.54%	3.01%
TRY	-56.58%	2.61%	13.04%	-11.54%	7.38%	12.67%	-3.51%
ZAR	-18.84%	10.24%	20.80%	-11.69%	8.33%	23.17%	-10.96%

Note: The benchmark returns are the returns for holding the emerging market currencies during the entire sample period. Jump modified hedge strategies refer to selling the currency for USD at the ask price after observing the corresponding jump type, and then buying it back 1-hour later at the bid price.

Table 15: Intraday cojump distribution across exchange rates

	$RCJ^{MXN,TRY}$	$RCJ^{MXN,ZAR}$	$RCJ^{TRY,ZAR}$	$RCJ^{MXN,TRY,ZAR}$	$LCJ^{MXN,TRY}$	$LCJ^{MXN,ZAR}$	$LCJ^{TRY,ZAR}$	$LCJ^{MXN,TRY,ZAR}$
00:00-02:00	51	62	85	20	1	1	1	0
02:00-04:00	55	67	82	24	3	1	4	0
04:00-06:00	40	29	44	9	0	0	0	0
06:00-08:00	2	4	5	1	0	0	0	0
08:00-10:00	2	1	1	1	0	0	0	0
10:00-12:00	2	2	2	1	1	0	0	0
12:00-14:00	28	28	31	23	3	1	4	1
14:00-16:00	3	1	3	1	0	0	0	0
16:00-18:00	6	6	7	3	0	2	0	0
18:00-20:00	32	38	53	25	0	0	1	0
20:00-22:00	14	14	29	7	0	2	1	0
22:00-00:00	40	35	74	13	7	6	35	1
Total	275	287	416	128	15	13	46	2

This table provides the intraday distribution of cojumps in FX return and liquidity. $RCJ^{i,j}$ and $LCJ^{i,j}$ refer to return cojump and liquidity cojump between exchange rates i and j respectively. $RCJ^{i,j,k}$ and $LCJ^{i,j,k}$ refer to cojump occurrences at the same time for all three exchange rates.

Table 16: Summary statistics for the duration between consecutive return cojumps across exchange rates

	$CJ^{MXN,TRY}$	$CJ^{MXN,ZAR}$	$CJ^{TRY,ZAR}$	$CJ^{MXN,TRY,ZAR}$
Min	0.003	0.003	0.003	0.003
Max	27.358	46.656	16.750	55.840
Average	3.633	3.510	2.400	7.806
Std.	4.400	5.096	3.136	9.499
Obs.	274	286	415	1271

Note: The values in the table (except the number of observations) are in days.

Table 17: LACD(1,1) model fit results for duration between consecutive return cojumps across exchange rates

	$CJ^{MXN,TRY}$	$CJ^{MXN,ZAR}$	$CJ^{TRY,ZAR}$	$CJ^{MXN,TRY,ZAR}$
ω	0.6985***	0.4034***	0.2314***	-0.1029
α	0.0695**	0.0116	0.1117***	-0.0551
β	-0.0539	0.0641	0.0582**	1.016
TED	-0.0969	-0.0479	0.1309**	-0.0152
VIX	-0.0591	-0.1884***	-0.2906***	-0.0015
EPU	-0.4165***	-0.0985*	-0.2148***	-0.0108
φ_{MXN}	-0.6241***	-0.149**		-0.0029
ψ_{MXN}	0.0078	-0.2271***		-0.0021
φ_{TRY}	-1.0633***		-0.1901***	-0.0168
ψ_{TRY}	-1.9046***		-0.147***	0.0007
φ_{ZAR}		-1.0466***	-1.3625***	-0.0169
ψ_{ZAR}		-1.0533***	-1.4053***	-0.0098

This table presents the estimated parameters of the following LACD(1,1) model that investigates the determinants of the duration x_i between consecutive return cojumps.

$$
\begin{aligned}
x_i &= \mu_i \epsilon_i \\
ln\mu_i = \omega + \alpha ln\epsilon_{i-1} + \beta ln\mu_{i-1} &+ \theta_1 TED + \theta_2 VIX + \theta_3 EPU \\
+\varphi_{FX1}\overline{LIQ}_{i1} + \psi_{FX1}\overline{RV}_{i1} &+ \varphi_{FX2}\overline{LIQ}_{i2} + \psi_{FX2}\overline{RV}_{i2} + \varepsilon_i
\end{aligned}
$$

TED is the spread between the three-month London Interbank Offered Rate (LIBOR) Eurodollar rate and the three-month T-bill rate. VIX is the implied volatility of options written on the SP500 contracts and captures market stress level. EPU denotes the daily US policy uncertainty index. $\overline{LIQ}$ and $\overline{RV}$ denote the average liquidity and realized volatility variables of the corresponding exchange rate between consecutive return cojumps. In case that three exchange rates are considered simultaneously, model is extended to cover $\overline{LIQ}_{i3}$ and $\overline{RV}_{i3}$ as well. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Table 18: Impact of US based macroeconomic news announcements on return cojumps across exchange rates

	$CJ^{MXN,TRY}$	$CJ^{MXN,ZAR}$	$CJ^{TRY,ZAR}$	$CJ^{MXN,TRY,ZAR}$
US News Announcements				
Budget Statement	-3.589	-2.7231	-2.5762	-2.6671
Business Inventories	-3.0315	-2.7287	-2.5814	-2.6721
Consumer Confidence	-2.9882	-2.686	-2.5421	-2.6341
Consumer Credit	-3.0315	-2.7287	-2.5814	-2.6721
CPI	1.1784***	0.8537**	1.3496***	-2.4725
Durable Goods Orders	0.1791	0.5917	-2.3832	-2.5057
Factory Orders	-3.0315	-2.7287	-2.5814	-2.6721
FOMC Announcement	2.2198***	-2.7287	-2.5814	-2.6721
FOMC Meeting Minutes	1.4267***	-2.7202	-2.5736	-2.6646
GDP-Advance	1.0858***	-2.9292	-2.4878	-2.5855
GDP-Final	-2.8719	-2.7518	-2.3854	-2.4937
GDP-Second	-3.034	-2.8558	-2.548	-2.641
Housing Starts	-3.6929	-3.1278	-3.4113	-2.5831
Industrial Production	-3.0315	-2.7287	-2.5814	-2.6721
Initial Jobless Claims	-0.6503*	-0.2792	-3.2832	-2.5492
ISM Manufacturing	0.4576	0.4541	-2.5814	-2.6721
Leading Index	-3.0225	-2.705	-2.5596	-2.6511
New Home Sales	-2.9673	-2.6654	-2.5231	-2.6158
Non-farm Payrolls	2.1941***	1.1886***	1.4934***	-2.5642
Personal Income	0.2283	-2.811	-2.4988	-2.5964
PPI	0.0017	0.5147	-2.3699	-2.4845
Retail Sales	0.9801***	0.0033	-3.5731	-2.4244
Trade Balance	-0.1473	-3.6516	-3.8149	-2.494

This tables present the estimation results of the following probit regression: $P(CJ_t = 1|X) = \Phi(\alpha + \sum_{m=1}^{M} \phi_m News_t^{US})$. $News^{US}$ is a dummy variable for US based macro-news announcements. $CJ^{i,j}$ refers to return cojump between exchange rates i and j. $CJ^{i,j,k}$ refers to return cojump occurrences at the same time for all three exchange rates i, j, k. In this table, *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

Figure 1: Intraday volatility and liquidity patterns

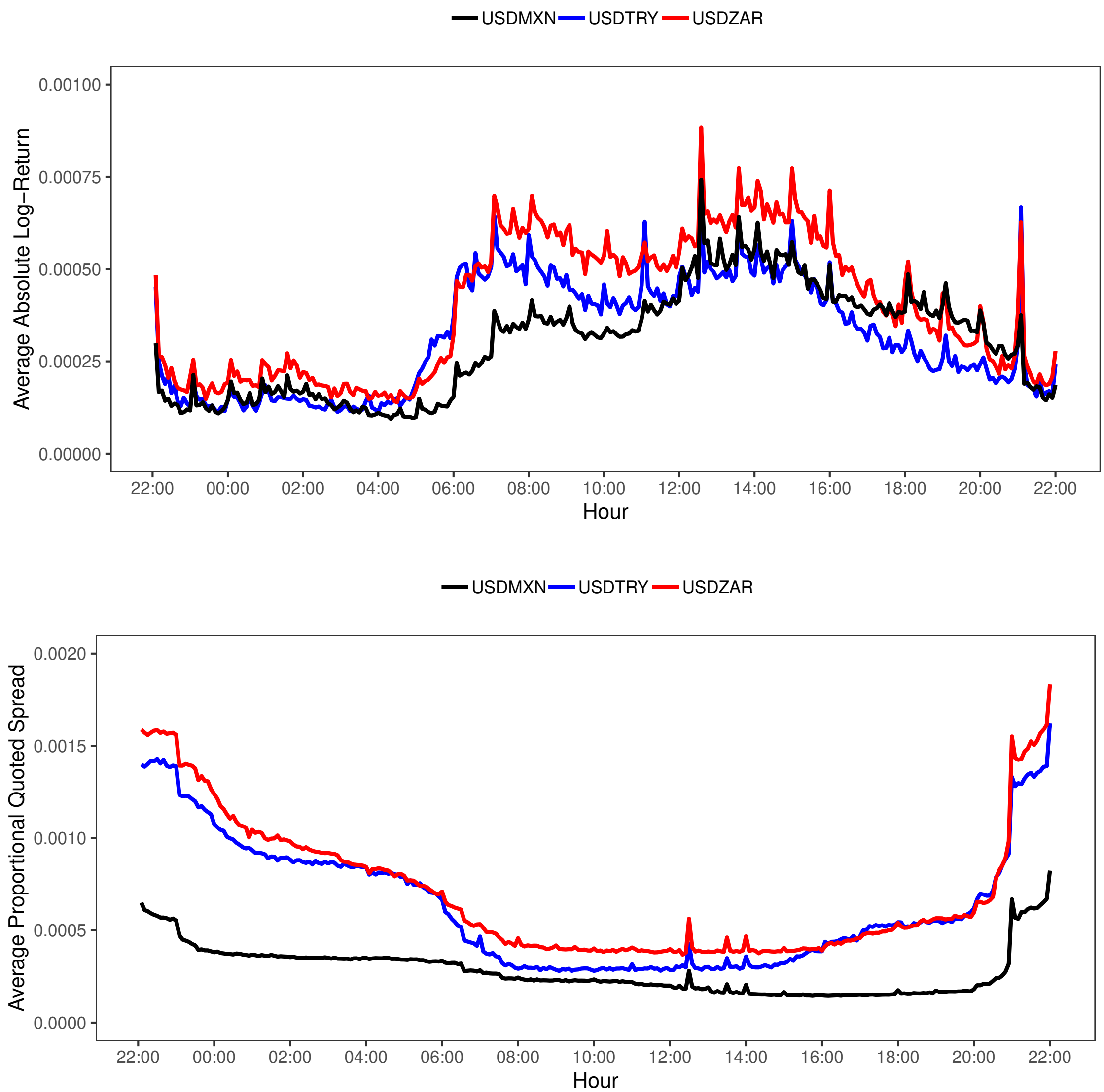

Figure 2: Monthly time series of return jumps, liquidity jumps, and return-liquidity cojumps for each exchange rate

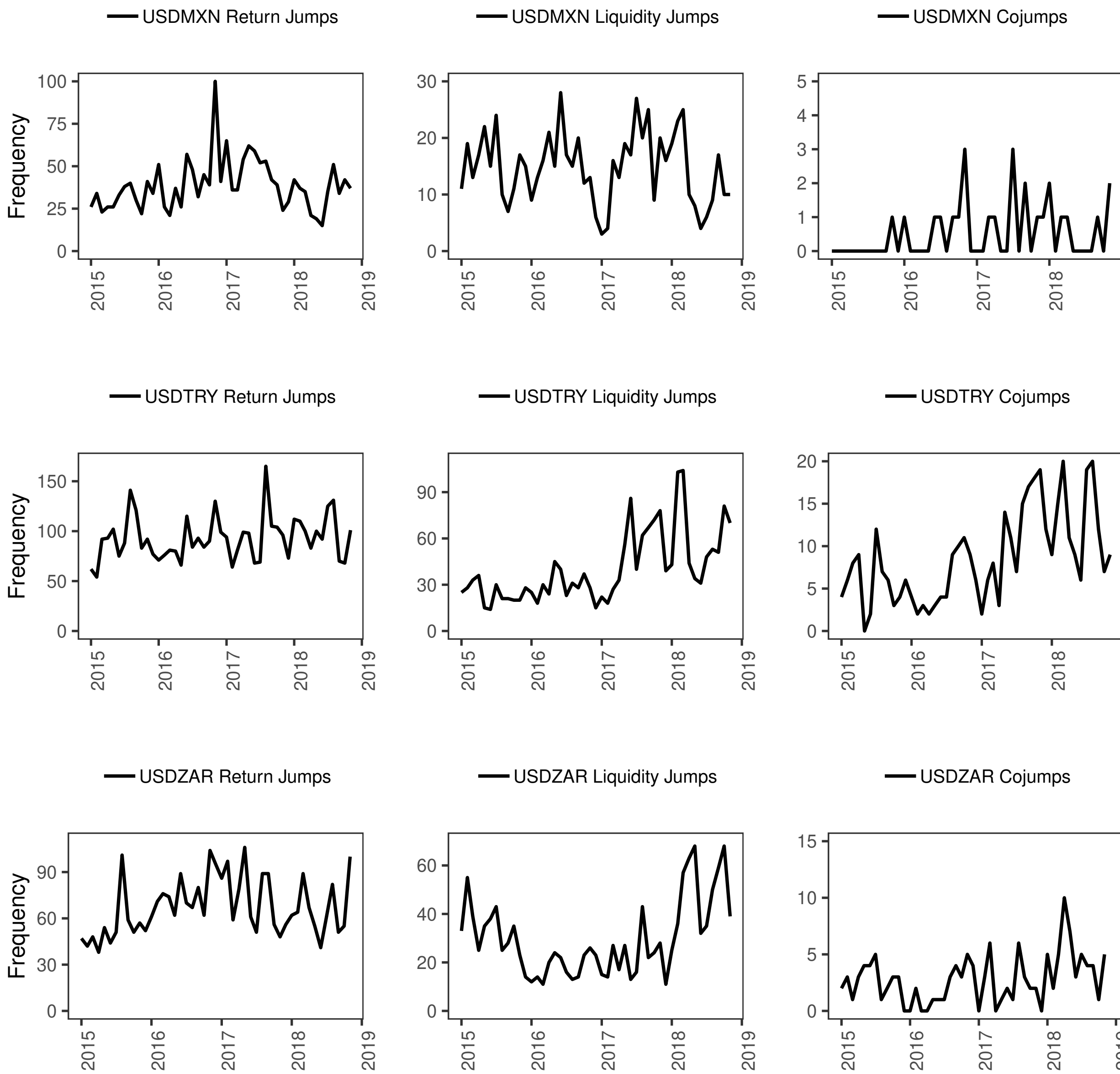

Figure 3: Average absolute log-returns around liquidity jumps ($t = 0$)

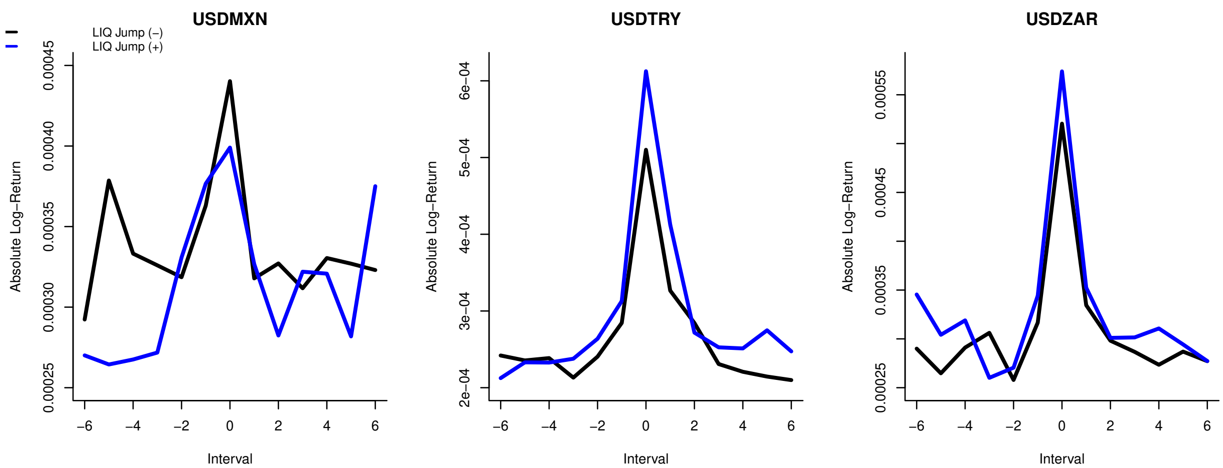

Figure 4: Average proportional quoted spread around return jumps ($t = 0$)

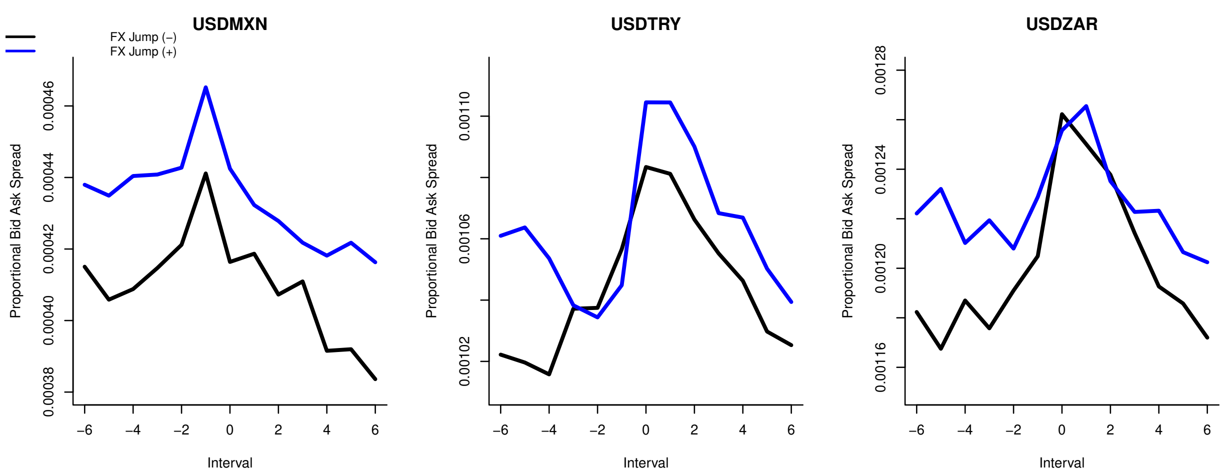

Figure 5: Performance comparison of buy-and-hold strategy against return jump (RJ) and liquidity jump (LJ) based FX trade strategies (Initial investment value in US dollar terms is taken as 100)