The jump dynamics of foreign exchange rates: how reliable and consistent are the results of widely utilized jump detection procedures

Serkan Yesilyurt*, Umit Erol

University of Bahçeşehir, Istanbul, Turkey

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ABSTRACT

This paper investigates the jump dynamics of foreign exchange rates utilizing Barnsdorff-Nielsen and Shepherd (BNS) and Ait-Sahalia Jacob (AJ) jump detection procedures. The sample includes the nine major exchange rates of the world as well as two exchange rates from an emerging market (Turkey). The observation period is from January 1, 2010 to December 31, 2016. The number of jumps, number of jump days, average jump sizes and the ratio of negative (positive) jumps to total jumps of that observation period are estimated by BNS and AJ methods and the results are reported separately for five different sampled frequencies. The empirical results strongly suggest that jump dynamics of each exchange rate is quite unique and different from the others rather than displaying common patterns. A major result is the extreme sensitivity of the results to the chosen sampled frequencies which raises serious questions about the practical value of these tests for the investors. The paper by utilizing Event Study Analysis also shows that the foreign exchange rate jumps are related to scheduled macroeconomic news announcements.

1. Introduction

The increasing availability of high frequency data in the recent two decades popularized the testing for presence of jumps in financial time series. The dynamics of the financial time series is usually assumed to be a jump-diffusion process which can be represented by the following stochastic differential equation;

\[ dp_t = \mu_t dt + \sigma_t dW_t + dJ_t \]  

(Aith-Sahalia et al., 2011)

where \( p_t \) is logarithmic asset price, \( \mu_t \) is drift, \( \sigma_t \) is a strictly positive stochastic volatility process and \( W_t \) is Brownian motion at time \( t \). \( J_t \) represents the jump process at time \( t \) defined as \( J_t = \sum \kappa_j \) with \( \Sigma \) running from \( j = 1 \) to \( N_t \) and \( \kappa_j \) representing the size of jump at time \( t \) while \( N_t \) is a counting process that represents the number of jumps up to time \( t \).

The quadratic variation of this price process during a certain interval (e.g. one day) is the sum of a diffusion component and a jump component which can be expressed as

\[ QV_t = \int \sigma^2_s ds + \sum \kappa_j^2 \]  

(2)

(Andersen et al., 2012)

\( QV_t \) is the integrated volatility of the continuous sample path. Several alternative estimators have been developed for both the quadratic variance and the integrated volatility. Provided that the \( j \)th intraday return \( r_j \) on day \( t \) is defined as \( r_j = p_{t-j} + \delta - p_{t-j-1} + (j - 1)\delta; \)

\( QV_t \) can be estimated by the realized variance (RV) as;

\[ RV_t = \sum r_j^2 \]  

(3)

(Andersen et al., 2012)

A wide range of estimators which are robust to jumps in the limit are suggested to measure \( IV_t \) in the literature. The majority of the jump detection procedures commonly in use today are based on a comparison between \( RV_t \) and \( IV_t \).

Some of the well known tests include Barndorff-Nielsen and Shephard (2004), Huang and Tauchen (2005), Andersen et al. (2007), Jiang and

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* Corresponding author.
E-mail address: serkan.yesilyurt@eas.bau.edu.tr (S. Yesilyurt).

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Oomen (2008); Lee and Mykland (2007) and Ait-Sahalia and Jacod (2011). These tests have been applied extensively to financial data series (e.g. Bollerslev et al., 2008; Corsi et al., 2010; Andersen et al., 2012; Lee and Mykland, 2012; El Quadghiri and Uctum, 2016). Though there is by now a voluminous empirical literature in this area; it is also a fact that the existing jump detection procedures are beset with some serious difficulties. The reported empirical results seem to be highly sensitive to specific data series, how prices are measured (quotes vs. transactions), the chosen observation periods and the way the data is treated including filtering procedures (Ait-Sahalia et al., 2012). Of a major source of the problems encountered in the empirical work is related to the fact that none the procedures can directly test the absence or presence of jumps in the data generating process (Dumitru and Urga, 2012). They merely provide information on whether the realization of the process in a certain interval is continuous or not with the alternative hypothesis being the discontinuity of the sample path (e.g occurrence of at least one jump). So they require a decision to be made regarding the mechanism used to distinguish the continuous increments from the discontinuous ones. These decisions, however, have impact on the outcome of the tests and the measured jump values.

A specific problem is the selection of the appropriate significance level which determines the value beyond which the null of “no jump” is rejected. Unfortunately; there is not yet a consensus in the literature regarding this choice. Higher significance levels lead to identification of more jumps including the small ones but also increase the probability of spurious jump detection. A more serious problem is the one posed by residual microstructural noise (due to order arrival latency, block trades, bid-ask spreads, asymmetric information, discreetness of prices, bounce backs). The presence of zero intraday returns and microstructure noise is a potential major source of bias. They lead to biased and inconsistent realized volatility estimates introducing an upward bias to estimated integrated variance (Andersen et al., 2007). Those possible biases and non-existence of noise robust statistics fully immune to presence of noise is a matter of serious consideration given the profound implications on risk management, portfolio allocation and derivative pricing of the correct identification of the timing and size of the jumps (Ait-Sahalia; 2011).

The presence of microstructure noise poses a specifically important problem for jump detection procedures. This problem is the extreme sensitivity of the detected jumps to the chosen intraday sampling frequency. Theoretically; the ideal estimator of the integrated variance is achieved when δ in Eq. (3) approaches zero implying the utilization of all available high-frequency observations. This, in practice, is not possible due to severe contamination of observed prices by noise at higher frequencies. The noise term starts to dominate the contribution to realized volatility as δ → 0 as a result of which the realized variance (RV) becomes an inconsistent estimator of the quadratic variation (Andersen et al., 2007). There is not yet a clear guideline in the literature regarding which optimal frequency to use in applying jump tests (Dumitru and Urga, 2012). Though the choice of 5-min sampling frequency is suggested in the literature based on the premises that this interval represents best bias-variance tradeoff leading to minimum bias in realized variation measures; we also observe a lack of consensus in the reported empirical studies regarding this issue. In fact, quite a variety of different frequencies were used in the recent literature (e.g. 1 min in Jiang and Oomen (2008); 2 min in Christensen et al. (2014); 5 min in Laakonen and Lamme (2008) and Lahaye et al. (2011); 17.5 min in Bollerslev et al. (2008). When jump detection tests are performed using prices the sampled at different frequencies; one normally expects similar results since all of these samples are based on the same original data set. Unfortunately; this is not the case. As we commonly see in recent literature; the number of jumps detected and the timing of jumps varies significantly depending on which test is employed and which sampling frequency is used. The potential for a high degree of inconsistency in the results as a function of chosen frequencies is also documented by a variety of different simulation studies (Theododosiou and Zikes, 2011; Dumitru and Urga, 2012; Manessoonthorn at al., 2020). It is possible to find radically different results if a sample with a different frequency is chosen.

The remarks mentioned above shapes the primary purpose of this article. The majority of the published work in the jump literature is about the application of the jump detection procedures to the common stock data (particularly U.S. stocks). The jump dynamics of foreign exchange (FX) series is a relatively less investigated issue. Also; most of the empirical work investigating the jump dynamics of FX data is limited to utilizing only two or three different exchange rates. We used a much more extensive high-frequency data set in this study including world’s nine major foreign exchange (FX) cross rates and also two exchange rates from an emerging market (Turkey) covering the period from January 1; 2010 to December 31; 2016. Two alternative jump detection tests which are widely used in the literature are then implemented to analyze the jump dynamics of these eleven cross rates. We applied Barndorff-Nielsen and Shephard test (BNS) and the Ait-Sahalia and Jacod test (AJ) to our extensive data set using alternative sampling frequencies of 1-min, 5-min, 15 min, 30 min and 60 min intervals. We couldn’t find enough published articles on FX jump dynamics at this extent.

Our purpose in that article is two-fold. The first one is to empirically assess and compare the jump dynamics of different exchange rates which obviously is an important information for market practitioners and academicians. The second and more important goal of this article is to highlight the sensitivity of the test results to the chosen sampling frequencies when these tests are empirically applied to actual FX data series. More specifically; we explored if the jump tests lead to serious inconsistencies depending on the frequency at which the price data is sampled. Unfortunately; this is an area which is largely ignored in the previous literature with the possible exception of Schwert (2011). We examined how a change in the sampling frequency affects the number of detected jumps, the number of jump days, average jump size and ratio of negative (positive) jumps by applying BNS and AJ tests to eleven different exchange rates. Additionally; we also explored the role of scheduled macroeconomic announcements in the generation of detected jumps. The impact of announcements on jumps in FX markets is an issue which was extensively analyzed in the recent literature (e.g. Andersen et al., 2003; Lahaye et al., 2011; Dewachter et al., 2014). The type and presence of a relationship between the announcements and jumps may also be sensitive to the chosen sampling frequencies. We investigated this possibility for the case of Euro/Dollar exchange rate by using Dewachter et al. (2014) event study approach and Bloomberg ECO page.

Due to brevity considerations and the extensive scope of the data set; we used only two jump detection procedures in this article. The specific choice of BNS and AJ as the test procedures rather than others is due to the following reason. These two procedures are widely different in their approach to testing. BNS infers whether jumps occur during a time interval (e.g. a day) by comparing realized variance (RV) with the integrated variance (IV) at a specifically chosen frequency. The AJ test, on the other hand, is based on comparing variations of power greater than 2 at two different frequencies and taking their ratio. Its distinguishing feature is the evaluation of quadratic variation at two different frequencies in order to capture the volatility of prices at lower frequencies and variation of noise process at very high frequencies. It then allows us to extract as much information as possible on jumps from different time

1 For example; only one exchange rate (DM/$) is covered in Andersen et al. (2007); two exchange rates ($/DM and $/Yen) in Barndorff-Nielsen and Sheph- herd; one exchange rate (EUR/$) in Laakonen and Lamme (2008), four exchange rates ($/EUR,$/GBP,$/JPY,$/CHF/$) in Lahaye et al. (2011).
2 It uses rMinVar (Minimum Realized Variance) for integrated variance and rMediQuatr (Median Realized Variance) for Integrated Quadratic estimator. Realized tri-power quarticity (TPQ) is default. Confidence level is set as 95 %.
scales by making use of more data (Wang, 2015). In the context of our study, an interesting question is if the use of two different time scales (as in AJ) and power variations alleviate the problem of frequency specific sensitivity or not. A comparison of BNS results with the AJ results may provide an answer to this question.

The questions and remarks above determined the empirical setup of this paper. The results which are discussed later in detail do indeed show that the jump dynamics of exchange rates display a significant difference from one exchange rate to another. More volatile exchange rates such as Euro/Dollar exchange rate tend to generate more jumps. The test results of BNS and AJ at the same sampling frequencies do differ from each other in most cases. The most important result, however, is the extreme sensitivity of the results to the chosen frequencies. The outcome of widely used 1-min, 5 min and 15 min frequencies display drastic changes in regard to the number of jumps detected, estimated average jump sizes and ratio of negative (positive) jumps. The results also indicate the possibility of inconsistent ordering and the absence of a discernible pattern across frequencies. It is also apparent that the utilization of AJ test procedure based on two scales instead of BNS do not lead to any improvement in dealing with these problems. Overall; the results indicate that the question of if the information gleaned from jump detection procedures can effectively be used for practical purposes remains as a big if.

The empirical results of this paper also raise questions about the validity of the two arguments mentioned in the recent literature. Christensen et al. (2014) argued that the bursts of volatility emanating from the continuous sample path are easily mistaken for jumps leading to an overestimation of jumps when 5-minute sampling frequency is used. They further argue that the distinction between true discrete jumps and continuous diffusion variation progressively diminishes at the lower frequencies and consequently the number of jumps detected by the commonly used tests tends to increase consistently at lower frequencies. Our results based on actual data do not confirm such a pattern implying that the change in the number of detected jumps as a function of sampled frequencies cannot be explained only by bursts of volatility.

A second issue concerns the fact that several simulations reported in the literature (whose references are given above) unanimously find that the AJ test has extremely low power leading to detection of significantly less jumps compared to other test alternatives. Our results based on an actual extensive dataset do not lend support to this argument as well since the number of jumps detected by AJ exceed the ones detected by BNS in a number of non-negligible cases and do not imply a particularly low power for the AJ test.

The rest of the paper follows with the explanation of data and methodology in section two, presentation of empirical results in section three and conclusion in section four.

2. Data and methodology

2.1. Data

The currency pairs included in the data set are U.S Dollar/Swiss Franc (USD/CHF), U.S Dollar/Japanese Yen (USD/JPY), Euro/Dollar (EUR/USD), Euro/Swiss Franc (EUR/CHF), Euro/British Pound (EUR/GBP); Euro/Japanese Yen (EUR/JPY); British Pound/Swiss Franc (GBP/CHF), British Pound/Japanese Yen (GBP/JPY) Swiss Franc/Japanese Yen (CHF/JPY); U.S. Dollar/Turkish Lira (USD/TRY) and Euro/Turkish Lira (EUR/TRY). The observation period is from January 1,2010 to December 31, 2016 covering nearly seven years. That period is a particularly volatile period characterized by two major crises which are the Global Financial Crisis (GFC) and the European Debt Crisis (EDC).

The high frequency exchange rate data of the eleven currency pairs is extracted from www.histdata.com and Bloomberg. It includes tick by tick tradable quotes of the best bid and the best ask spot exchange rates and size. Each quote is time stamped to seconds with two decimals in Greenwich Mean Time (GMT) to Eastern Standard Time (EST) starting from 00:00:00 EST to 23:59:59 GMT. The test statistics of jumps derived from BNS and AJ tests are calculated at different sampling frequencies of 1-min, 5-min, 15-min, 30-min and 60-min intervals for each day. We used the immediately preceding and following quote at the end of each relevant interval (e.g. 5-min interval) to construct the bid and ask prices. The log-prices used in estimations are the midpoints of the logarithmic bid and ask prices. FX markets operate on a 24-hour basis; so there are 1440 1-min, 288 5-min, 96 5-min, 48 30-min and 24 60-min intervals. Consequently; the number of available observations are 2,587,655 for 1-min interval, 735,264 for 5-min interval, 245,088 for 15-min interval, 122,544 for 30 min interval and 61,272 for 60 min interval.

We used Andersen and Bollerslev (1998) and Bauwens et al. (2005) methods to delete the returns from the first interval of each day. The weekend data is not excluded. We only used scheduled macroeconomic news for testing the impact of the news on detected jumps. The scheduled macroeconomic news are extracted from the Bloomberg ECO service. These news are then ranked according to their relevance level. The relevance ranking system of Bloomberg runs from 0 to 100. We only used the news whose relevance level is over 50. Though we collected 46,880 news announcements in the relevant observation period with exact date and timing; we finally used 10,850 of them after applying the relevance criteria of Bloomberg.

2.2. Barndorff- Nielsen and Shephard test (BNS)

As mentioned in the Introduction; the inference of whether jumps occur during a certain interval (e.g. day) in BNS test depends on the comparison of quadratic variance estimator \( \text{RV}_t \) (defined in Equation 3) with the realized bipower variation \( \text{BV}_t \) which is an estimator of the integrated variance. The realized bipower variation \( \text{BV}_t \) is defined as

\[
\text{BV}_t = 1.57 \sum_{j=1}^{n} |r_j| |r_j - 1|
\]

(Andersen et al., 2012)

where \( \Sigma \) runs from 1 to \( n \), \( r_j \) and \( r_{j-1} \) denote respectively the \( j \)th and \( (j-1) \)th intraday returns and \( n \) is number of observations. The null hypothesis of no jumps is tested by the following ratio test following Huang and Tauchen (2005).

\[
1 - \frac{\text{BV}_t}{\text{RV}_t} = \sqrt{0.61} \delta \max(1, A \text{TQ}_t, \text{BV}_t^2) \rightarrow N(0, 1)
\]

(Andersen et al., 2012)

where \( \text{TQ}_t \) is realized tripower quarticity which is used to estimate the integrated quarticity \( \delta_2^3 \) and is defined as

\[
\text{TQ}_t = n 1.74 \left( \frac{n}{n-2} \sum_{j=1}^{n} |r_j - 2| |r_j - 1| |r_j - 4| / 3 \right)
\]

(Andersen et al., 2012)

2.3. Ait-Sahalia and Jacod test (AJ)

The AJ Test is based on comparing variations of power greater than 2 at two different frequencies and taking their ratio (Ait-Sahalia; 2011). The ratio of power variations calculated under two different time scales \( 1/N \) and \( k/N \) can be expressed as

\[
S(p, k, \frac{1}{N}) = \frac{B(p, k, \frac{1}{N})}{B(p, \frac{1}{N})},
\]

(Ait-Sahalia and Jacod, 2011)

where

\[
3 \text{ Relevance level of the news are defined based on the Bloomberg Data Vendor.}
\]
\( B\left( \frac{1}{N} \right) = \sum |n|/p \) for \( p > 2 \)

(\text{Ait-Sahalia and Jacod, 2011})

denotes the power variation. Under the null hypothesis of no jumps S \( (p, k, 1/N) \) converges to \( k^{p-2} - 1 \) (to 2 if \( p = 4 \) and \( k = 2 \)) while it converges to 1 in presence of jumps. The test statistic for the null hypothesis of no jumps is

\[
S\left( p, k, \frac{1}{N} \right) \sim k^{p-2} - 1 / \sqrt{N}, M^i
\]

(\text{Ait-Sahalia and Jacod, 2011})

where \( V^i \) denotes the asymptotic variance of \( S(p, k, 1/N) \), and is given by

\[
V^i = \left[ \frac{1}{N} \right. N(p, k) A\left( \frac{2p}{N} \right)^2 / A\left( \frac{1}{N} \right)^2 \right. \]

(\text{Ait-Sahalia and Jacod, 2011})

with the following definitions;

\[
A\left( \frac{p}{N} \right) = \left[ \frac{1}{N} \right. \left. N(p) \right] \sum r_{0}^{\beta} t \left\{ \epsilon_{0} < \alpha \left( \frac{r}{N} \right) \right. \]

(\text{Ait-Sahalia and Jacod, 2011})

\[
N(p, k) = 1/\left( \frac{1}{N} \right. \left. \left( k^{p-2} + k^{p-2} (k-1) \mu_p^2 + k^{p-2} (k-1) \mu_p^2 + 2k^{p-2} - 1 \right) \right. \]

(\text{Ait-Sahalia and Jacod, 2011})

\[
\mu_p = E\left( |U| \right) U + \sqrt{k} - 1 \right. \]

(\text{Ait-Sahalia and Jacod, 2011})

for \( U, V \) are independent standard random variables.

The implementation of AJ test requires the choice of four parameters \( p, k, \alpha, \) and \( w \). We used \( p = 4, k = 2 \) and \( w = 0.48 \) following author’s (\text{Aith-Sahalia et al., 2011}) suggestions and we also experimented with different values for threshold parameters.

The use of volatility signature plots developed by \text{Andersen et al. (2007)} is suggested to deal with frequent event problems. This method tracks the effect of sampling frequency on realized intra-day volatility by plotting sampling intervals on the horizontal axis and volatility on the vertical axis. The logic behind the plots is the fact that the variance of a price process is independent of the frequency. Consequently; a distortion of realized variance at a certain frequency implies that microstructure noise causes a distortion at this frequency. We implemented this tool prior to tests finding that these plots suggest five and 15 min intervals as more optimal ones.\(^5\) The use of volatility signature plots, however, was far from solving the problem of extreme sensitivity of the results to the chosen frequencies as will be discussed later in detail.

Choosing test procedures that reduces the percentage of spurious jumps is essential for the cases in which a large number of zero returns is observed which is common in practice. In these cases; integrated volatility is underestimated especially by those based on bipower variation (\text{Andersen et al., 2007a}). To deal with this problem; we removed the zero intraday returns following \text{Roghnie (2010)} approach. We also used the Holm-Bonferroni correction method to control FWER (family wise error rate) in order to avoid spurious detections due to multiple testing.

\(^5\) The volatility plots are available upon request.

2.4. Event Study Analysis

We investigated the effects of scheduled macroeconomic news announcements on jumps detected by BNS using \text{Dewachter et al. (2013)} event study approach. For that purpose; we compiled the macroeconomic news of U.S, U.K, Switzerland, Japan, Germany, Italy, France, Aggregate Eurozone and Turkey using the Bloomberg ECO pages. We then ranked them according to Bloomberg relevance index. We utilized the 10,850 scheduled macro news announcements which have a ranking over 50. The post-announcement effect of these macroeconomic news on jumps is searched by using the jumps detected during the 30-minute interval following the announcement. The probability of observing a jump conditional on a communication event (a specific macroeconomic announcement) is calculated by

\[
p\left( \text{jump}_{\text{event}} \right) = \frac{N_{j}}{N_{all}}
\]

(\text{Dewachter et al., 2013},) where \( N_j \) is the number of events matching with jumps and \( N_{all} \) is the total number of events. We then created a subsample of intraday return observations that excludes the communication event days and their intra-day periods. This is then used to calculate the unconditional probability

\[
p\left( \text{jump}_{\text{control}} \right) = \frac{J_{\text{control}}}{J_{\text{all}}}
\]

(\text{Dewachter et al., 2013})

where \( J_{\text{control}} \) is the number of jumps in the subsample and \( J_{\text{all}} \) is the number of observations in the subsample. Then \( p(\text{jump/ event}) \) is compared with \( p(\text{jump/ control}) \) to check if there is a significant difference between the probability of observing jumps in normal non-event days and the probability of observing jumps conditional on the events. The null and alternative hypotheses are set as

\[ H_0 : p(\text{jump}_{\text{event}}) = p(\text{jump}_{\text{control}}) \]

\[ H_1 : p(\text{jump}_{\text{event}}) \neq p(\text{jump}_{\text{control}}) \]

Under the null hypothesis; conditional and unconditional jump likelihoods are identical implying that the communication event do not affect the probability of jump occurrences. The rejection of null hypothesis indicates that the communication events trigger the detected jumps.

3. Empirical results

3.1. The BNS and AJ test results

The total number of jumps detected by BNS and AJ methods during the whole observation period is reported in Table 1. The reported results which are based on 95% statistical significance level are separately displayed for 1-min, 5-min, 15-min, 30 min and 60-min sampling frequencies. Table 2 reports the number of jump days identified by BNS and AJ methods.

Our sample covers 1822 days. The number of days in which jumps are detected varies between 900 and 1200 but the ratio of intra-day realized returns involving jumps is very small. For example; BNS detects 997 jump days (detecting a jump in 54.72% of days) for EURUSD using 5 min sampling frequency. However; the number of EURUSD 5-min intervals displyaling jumps is 1216 out of a total of 735 264 meaning that jumps are detected only in 0.1653% of the total cases.
Based on both AJ and BNS.

We observe a moderate amount of variation among the exchange rates regarding both the total number of identified jumps and the number of jump days. The total number of jumps identified by BNS (based on the widely utilized 5 min sampling frequency) varies between 1216 (EURUSD) and 1466 (USDTRY) with an average value (for all 11 exchange rates) of 1351.54. The number of jump days detected by BNS (for 5-min) varies between 997 days (EURUSD) and 1256 days (USDJPY).

Both BNS and AJ tests identifies the pound/yen (GBPJPY) as the exchange rate with the highest number of jumps (1569 BNS and 1565 AJ jumps). This result, however, is valid only for the 1-min sampling frequency. On the other hand; euro/dollar (EURUSD) which appears to be the exchange rate with the least number of jumps when 5-min sampling frequency is used, turns out to be one of the exchange rates with the highest number of detected jumps when other frequencies are used. The number of detected jumps varies significantly depending on which sampling frequency is used. This is an important issue that will be discussed further in part 3.2. The overall evidence in Table 1 indicates that the exchange rates of Turkey (USDTRY) and EURUSD generated more jumps than the others during the relevant observation period. Table 2 shows that the dollar/Turkish Lira (USDTRY), Euro/Turkish Lira(EURUSD), Euro/Dollar (EURUSD) and Euro/Yen (EURJPY) are also the exchange rates displaying more jump days than the others.

We present the average jump sizes estimated by BNS and AJ in Table 3. The average jump sizes estimated by BNS are around 3%–4%. The AJ yields higher average jump sizes than BNS (around 4%) in 1-min sampling frequency but jump sizes estimated by AJ are significantly less than those estimated by BNS in the other frequencies and vary between 1% and 2%. In case of AJ; the estimated average jump sizes decline significantly from 1-min to 5 min sampling frequency and for further frequencies. This declining trend is not observed in BNS estimations.

The ratio of negative jumps to total jumps (based on both BNS and AJ) is displayed in Table 4. This is an important information since negative jumps constitute a particularly serious risk for investors. The EURJPY generated more negative jumps (over 50%) than positive jumps while USDTRY and EURGBP generated more positive jumps than negative jumps.7 AJ also identifies CHFJPY, GBPCHF, GBPJPY and EURJPY as having more negative jumps than positive jumps. One noteworthy fact is

6 The total number of jumps detected by AJ (for 5 min) varies between 1143 (EURGBP) and 1383 (USDTRY) with an average value of 1284.18. The total number of jump days detected by AJ (for 5-min) varies between 951 (CHFJPY) and 1172 (EURTRY).

7 Based on both AJ and BNS.
the disagreement between the two tests (AJ and BNS) regarding the ratio of negative (positive) jumps to total jumps. According to BNS, majority of exchange rates display a higher ratio of positive jumps in 5, 15 and 30 min sampling frequencies but 1-min sampling frequency stands as an exception with most of the exchange rates displaying a higher ratio of negative jumps. The disagreement between the two tests is especially more pronounced at the 5-min sampling frequency. They only agree in case of EURUSD with both tests finding more positive jumps than negative jumps. In the remaining ten cases; when one method finds a higher number of positive jumps for a specific exchange rate, the other method identifies a higher number of negative jumps.\textsuperscript{9}

3.2. The sensitivity issue

The empirical results of the four tables presented in this article points out to a problem which deserves special attention. This problem is the extreme sensitivity of the test results to the chosen sampling frequencies. As an example; BNS detects 1168 jumps in dollar/yen exchange rate (USDJPY) using 1-min sampling frequency which contrasts sharply with the 1413 detected jumps when 5-min sampling frequency is used. That means a 20.97% increase in the number of detected jumps even though the same method and same observation period is used in the estimations. The number of detected jumps then falls to 1057 (a decline of 25.1%) when BNS is implemented with a 15-min sampling frequency but then rising again 1332 (an increase of 26.01%) with the 30-min sampling frequency. Such drastic changes are also observed in the other exchange rates. For example; the number of jumps detected by BNS in EURCHF increases 21.3% (from 1117 to 1355) if we use 5-min sampling frequency instead of 1-min sampling frequency. When we consider the number of jumps detected by BNS in the more relevant 1-min,5-min,15-min and 30-min sampling frequencies; we observe that there is more than 10% change between the results of adjacent sampling frequencies (e.g 1-min vs. 5-min; 5-min vs. 15 min) in 14 cases and more than 20% change in 6 cases.

The variation of detected jumps between the adjacent sampling frequencies is less pronounced in case of AJ compared to BNS but it is far from being negligible. We observe a decline of 14.89% decrease in the number of detected jumps (from 1565 to 1332) when AJ uses the 5-min sampling frequency instead of the 1 min sampling frequency for GBPJPY estimations while the number of detected jumps increases 17.58% (from 1155 to 1358) as we move from 1-min to a 5 min sampling frequency in the case of USDCHF. There are still 6 cases with a more than 10% change in the number of detected jumps between the adjacent sampling frequencies when AJ is the preferred test methodology. This implies that the utilization of a two-scale approach and powered variations do not completely alleviate the problem of extreme sensitivity of the test results to the chosen sampling frequencies.\textsuperscript{10}

The sensitivity problem may be a more serious problem than what the mere numbers suggest since there is also a severe order inconsistency problem. The EURUSD is the exchange rate with the least number of BNS detected jumps among all eleven exchange rates if we use the highly

\textsuperscript{9} According to AJ; the ratio of negative jumps is over 50% for seven exchange rates (as in BNS) if 1-min sampling frequency is used. The results of the two tests differ from each other regarding the ratio of negative jumps in the other sampling frequencies. AJ identifies six exchange rates with more negative jumps than positive jumps in case of five – minute sampling frequency and seven exchange rates with a higher number of negative jumps in both fifteen and 30 min sampling frequencies.

\textsuperscript{10} For example; the ratio of negative jumps in case of USDCHF with a 5 min sampling frequency is only 47.28% according to BNS which implies a higher number of positive jumps than negative ones. AJ, however, finds a ratio of 54.37% at the same sampling frequency implying that USDCHF generated more negative jumps than positive ones in the same period. This type of inconsistency between the results of the two tests is also observed for nine other exchange rates.
popular 5-min sampling frequency but it is also the exchange rate with the highest number of BNS detected jumps if we use the 30-minute sampling frequency and one of the highest if we use the 1-min sampling frequency. GBPJPY turns out to be the exchange rate with the highest number of BNS detected jumps when 1-min sampling frequency is used but it is also the exchange rate with the least number of BNS detected jumps if a 5-min sampling frequency is used.

The estimated average jump sizes also display inconsistencies across the test methods and sampling frequencies. Similar inconsistencies are also observed in Table 4 regarding the ratio of negative jumps to total jumps. Ratio of negative jumps to total jumps for GBPCHF measured by BNS is 60% utilizing 1-min sampling frequency, 56.8% with the 5-min sampling frequency but only 41.53% with the 15-min sampling frequency. The ratio of negative jumps (using BNS) for EURTRY increases from 44% to 71.21% when 30-minute sampling frequency is used instead of the 15-min sampling frequency. AJ is not immune to such inconsistencies as illustrated by the fact that the negative jump ratio of USDJPY drops from 52.25% to 35.96% when 15-minute sampling frequency is used instead of the 5-min sampling frequency.

These results indicate that the possible value of tests for practical purposes such as hedging and risk control is quite doubtful. It is a well-known fact that large instantaneous drops in asset prices result in large instantaneous losses. Investors can perfectly hedge their positions by derivative contracts when asset prices are continuous but this is not possible in case of jumps. One can envisage the simple case of a FX investor who wants to avoid the negative jump risk as much as possible. Let us assume that this investor uses the results of BNS jump test derived from the 5-min frequency given the fact that this frequency is widely regarded as the one with the best bias-variance tradeoff. Using our dataset; this investor may decide that the exchange rate with the minimum risk is EURUSD since this exchange rate leads to less jumps (1216 jumps) than the others and also it is the exchange rate with more positive jumps than negative jumps where the ratio of negative jumps to total jumps (41.22%) is minimum among all 11 exchange rates. This may however lead to disastrous results if his/her trades are usually realized within a 1-min interval in case of a FX portfolio characterized by a high proportion of EURUSD. This result is inevitable since EURUSD is the exchange rate with one of the highest jumps (1433) and also having a high negative jump ratio (54.01%) in the 1-min interval.

3.3. Announcements

Table 5 reveals the impact of announcements on jumps detected by BNS. We observe that the probability of an unconditional announcement is 0.92% implying that 0.92% of the intraday intervals have at least one significant macroeconomic announcement. P (jumps/news) in Table 5 shows the probability of a jump conditional on a macroeconomic news announcement. The range of this probability changes from 2.17% (USDJPY) to 3.29% (EURUSD)13. EURUSD, EURTRY and USDTRY have more jumps corresponding to the macroeconomic news announcements while USDJPY has the least number of jumps associated with announcements. The jumps generated by cross rates of Japanese Yen (EURJPY, GBPJPY, CHFJPY, GBPJPY, USDJPY) display less sensitivity to macro announcements.

The row P (matched news/jumps) in Table 5 shows the percentage of jumps associated with announcements with respect to total detected jumps for the 11 exchange rates. The ratio varies between 17.44% (GBPJPY) and 27.66% (EURTRY) indicating that nearly one fourth of detected jumps are associated with a specific macro announcement.

Table 6 provides a more detailed picture of the announcement effects by emphasizing what type of specific announcements lead to BNS detected jumps. Due to brevity considerations; the analysis covers only the jump related specific announcements effects of Euro/Dollar (EURUSD) exchange rate and presents the results for five different frequencies. We have chosen 10 largest jumps of EURUSD and matched them with the major macroeconomic news announcements. The empirical results of Table 6 display a high degree of sensitivity and variation with respect to sampled frequencies. The Consumer Price Index (excluding food and energy) of U.S is the major factor leading to Euro/Dollar jumps. This effect is particularly observed in the 5-minute and 15-minute frequencies. The other leading factors leading to Euro/Dollar jumps are the U.S. Trade Balance (especially observed in 5-minute sampled frequency) and the U.S. Consumer Confidence Index (especially observed in 15-minute sampled frequency). The ECB (European Central Bank) interest rate is another important factor contributing to Euro/Dollar exchange rate jumps but this effect shows itself only in lower frequencies and particularly in the 60-minute sampled frequency.

3.4. Other issues

The empirical results of this paper also raise questions about the validity of some arguments that are reported in the recent literature. Christensen et al. (2014) argue that jumps are substantially smaller than currently thought since bursts of volatility are spuriously identified as jumps at lower frequencies and that mistake becomes more likely as sampling frequency is lowered. They also mention that detected jumps has a U-shape as the frequency changes from 5 to 60 min with a minimum at 1 min frequency.14 Our results do not confirm such a smooth U shape mentioned by Christensen et al. (2014) but rather show that the changes across frequencies are far from displaying a certain pattern. For example; the number of jump days detected by BNS increases in the case 5 exchange rates but declines in the other 5 cases as we move from the 1-min frequency to the 5-min frequency. There is an increase in the number of detected jump days only in 4 cases but a decrease in 6 cases as the frequency changes from 5-min to 15 min. The lack of a clear and consistent pattern is also valid between the 15-minute and 30-minute frequencies where an increase is detected in 6 cases with a decrease in 5 cases as we move to lower frequencies.

The deviation of the detected jump days from a U-shape is even more pronounced when AJ is used for jump detection since our results show that the jump days detected decreases in 8 cases when frequency changes from 5-minutes to 15-minutes. The AJ detected jump days increase in 4 cases but decline in 7 cases as we move from 15-minute to 30-minute frequency clearly emphasizing the fact that the detected jump days do not display either a U-shape or any other definite pattern which is valid for all currencies.15 The overall results strongly imply that the variation of jumps or jump days across frequencies cannot easily be explained by spurious identification of volatility bursts in the case of foreign exchange rates but rather is due to other factors.

12 For example; the average jump size of GBPJPY is 2.63% using BNS approach and 1-min sampling frequency. The estimated average jump size of the same exchange rate is 4.03% when 5-min sampling frequency is used in the BNS approach. The AJ, however, estimates an average jump size of only 0.94 % for GBPJPY using 5-min sampling frequency and an average jump size pf 3.42 % using 1-min sampling frequency. The average jump size of EURUSD estimated by AJ is 4.53% using 1-min sampling frequency but drops drastically to 0.95% if 5-min sampling is used.

13 For example; there are 357 jumps matching with news (announcements) in case of EURUSD out of a total of 10850 scheduled news announcements leading then to a ratio of 357/10850 = 0.0329.

14 The authors, however, also note that this U-shape is particularly valid for the common stock jumps and that pattern is less pronounced in case of foreign exchange jumps.

15 For example; the number of jump days detected by BNS show a decline of 18.1% (from 1296 days to 1028 days) in case of USDJPY and a decline of 16.37% (from 1282 days to 1047 days) in case of USDTRY as we move from 5-minute frequency to 15-minute frequency. On the other hand, the jump days detected rather increases by 19.53% (from 1014 days to 1212 days) in case of EURTRY and increases by 16.45% (from 997 days to 1161 days) in case of EURUSD for the same movement from 5-minute to 15-minutes.
A second question is if the empirical results presented in Tables 1 and 2 display conformity with the results of several simulation based studies. Theodosiou and Zikes (2011) reports that AJ test has high power only at 1 s frequency plummeting very rapidly in lower frequencies also finding that BNS having considerably higher power than AJ in 1-minute, 5-minute, 15-minute and 30 min sampled frequencies. Maneesoonthorn (2020) reports that AJ is severely undersized at all frequencies (including 1 min and 5-minute frequencies) detecting less jumps and being the least powerful test compared to other models. Theodosiou and Zikes (2011) reports almost zero power at 5-minute frequency for AJ test adding that AJ test loses power very quickly as sampling frequency is decreased.

### Table 5. Descriptive statistics of jumps and news (BNS method).

|          | CHFJPY | GBPCHF | GBPJPY | USDCHF | USDJPY | USDTRY | EURCHF | EURGBP | EURJPY | EURTRY | EURUSD |
|----------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|--------|
| # of observation | 735.264 | 735.264 | 735.264 | 735.264 | 735.264 | 735.264 | 735.264 | 735.264 | 735.264 | 735.264 | 735.264 |
| # of days | 2555 | 2555 | 2555 | 2555 | 2555 | 2555 | 2555 | 2555 | 2555 | 2555 | 2555 |
| # of news | 10850 | 10850 | 10850 | 10850 | 10850 | 10850 | 10850 | 10850 | 10850 | 10850 | 10850 |
| # of news days | 2355 | 2355 | 2355 | 2355 | 2355 | 2355 | 2355 | 2355 | 2355 | 2355 | 2355 |
| P(news) % | 0.922 | 0.922 | 0.922 | 0.922 | 0.922 | 0.922 | 0.922 | 0.922 | 0.922 | 0.922 | 0.922 |
| # of Jumps | 1136 | 1198 | 1565 | 1155 | 1168 | 1450 | 1117 | 1381 | 1229 | 1258 | 1433 |
| # of Jumps-matched news | 258 | 254 | 273 | 277 | 273 | 342 | 309 | 315 | 267 | 348 | 357 |
| P (jump/news) % | 2.38 | 2.34 | 2.52 | 2.55 | 2.17 | 3.15 | 2.85 | 2.90 | 2.46 | 3.21 | 3.29 |
| P (matched news/jump) % | 22.71 | 21.20 | 17.44 | 23.98 | 20.12 | 23.59 | 27.66 | 22.81 | 21.72 | 27.66 | 24.91 |

### Table 6. Largest EURUSD jumps matched with macroeconomic news.

| Time       | Country | News                                      | 1 Minute Frequency | 5 Minutes Frequency | 15 Minutes Frequency | 30 Minutes Frequency | 60 Minutes Frequency |
|------------|---------|-------------------------------------------|--------------------|--------------------|---------------------|----------------------|----------------------|
| 01/06/10 10:00 | United States | ABD Consumer Confidence | 0.534603 | 0.5300978 | 2.218841 | 0.8575945 | 0.854854 |
| 02/10/10 14:00 | United States | Bloomberg Global Confidence | 0.482391 | 0.8733484 | 0.1381038 | 0.0331457 | 0.2327889 |
| 01/04/11 14:20 | United States | ABD Employment Change | 1.267094 | 0.228312 | 0.26268 | 0.3487291 | 1.429528 |
| 01/07/11 04:00 | China | Business Climate Index | 1.363586 | 0.9343289 | 1.052548 | 1.10969 | 0.3957099 |
| 02/08/11 10:00 | United States | New Home Sales | 0.315577 | 1.140027 | 0.6688684 | 0.6887274 | 0.1378783 |
| 01/12/11 11:00 | Eurozone | ECB Announcement Interest Rate | 0.964051 | 0.7619185 | 0.8878731 | 0.8513959 | 2.419744 |
| 04/04/13 08:35 | United States | CPI Ex Food and Energy | 0.232815 | 3.366511 | 3.385785 | 0.969689 | 1.786926 |
| 12/07/16 09:45 | France | Current Account Balance | 1.02768 | 0.8020738 | 1.21229 | 0.8465937 | 0.5529328 |
| 12/09/16 09:00 | Germany | Labor Costs SA QoQ | 2.01471 | 0.3159773 | 0.8802566 | 0.3338352 | 1.588172 |
| 05/12/16 14:30 | United States | Trade Balance | 1.094689 | 3.141009 | 0.3551635 | 0.133704 | 1.094689 |
| 01/17/11 14:25 | United States | FOMC Rate Decision | 0.531507 | 0.9104603 | 0.3176433 | 0.806296 | 0.0327121 |
| 01/29/16 07:38 | Japan | BOJ Basic Balance Rate | 1.963759 | 0.4420359 | 1.69314 | 3.67733 | 0.2846371 |
| 05/25/11 08:35 | United States | Initial Job Claims | 0.132368 | 0.7366009 | 1.361477 | 0.3367218 | 1.308521 |
| 07/27/10 16:00 | Italy | Chamber Votes Confidence on Deficit Cuts | 0.964835 | 0.2660378 | 0.6627792 | 0.2255138 | 0.3668787 |
| 12/13/16 11:30 | United Kingdom | House Price Index YoY | 0.116775 | 0.5893646 | 0.5316566 | 1.719844 | 0.3653225 |
| 12/15/16 11:30 | Italy | General Government Debt | 1.606214 | 1.655951 | 1.606214 | 0.3488216 | 0.6064087 |
| 20/01/15 10:00 | China | Bloomberg GDP Monthly Estimate YoY | 0.91323 | 1.0433784 | 1.0772075 | 0.8009661 | 0.84122 |
jump days detected by AJ is far from being close to zero. In fact; AJ detects more jump days than BNS for four exchange rates (CHFJPY, USDTRY, EURCHF, EURTRY) when sampling is 1-min; also detecting more jump days for three exchange rates (EURJPY, EURTRY,EURUSD) when sampling is 5-min and detecting more jump days for two exchange rates (EURJPY, EURUSD) in the case of 15-min.

The discordance between our results and the simulation results may be due to the discordance between the stochastic volatility models used in simulations and the actual stochastic volatility dynamics of the empirically observed exchange rates. Overall results presented in this paper strongly suggest that the jump characteristics of the exchange rates and the variation of detected jumps over different frequencies do not display a common pattern but rather each exchange rate has its unique jump characteristics with a considerable difference from the others.

4. Conclusions

This study employed a quiet extensive data set with eleven different exchange rates and utilizing up to 2 587 655 observations based on a seven year observation period from January 1, 2010 to December 31, 2016. We explored the jump characteristics of the exchange rates during that period on the basis of BNS and AJ jump detection procedures. Both procedures are non-parametric without any specific model assumption about the observed series. The BNS method uses realized bipower variation defined as the sum of the products of consecutive absolute returns as an estimator of integrated volatility and takes the difference between the realized quadratic variation and the bipower variation to detect the jumps in a given interval. The AJ test uses two different scales and consider cases of quadratic variation with p > 2 while the realized quadratic variation used in BNS test assumes that p = 2.

The overall empirical results inferred from these two tests with distinctly different structural properties agree on the point that the exchange rate dynamics are characterized by a jump diffusion process which is a well known fact since Merton (1976). The number of jump days detected vary between 900 and 1200 out of a total of 1822 available days in the sample. It shows that jump components are critical ingredients of the data generating mechanism in case of FX rates.

The stochastic volatility diffusions without jumps fail to explain the return characteristics of the exchange rates. The presence of a negligible number of jumps detected by both methods may well explain the commonly observed phenomena of skewness and leptokurtosis in these series which is an issue also mentioned in the earlier literature (Andersen et al., 2002). A positive association between the jump intensity and the overall volatility of the series is another empirical result of the paper. The more volatile exchange rates (e.g. Euro/Dollar and Turkish exchange rates) tend to generate more jumps.

These results may have important practical consequences since presence of jumps pose specific problems for hedging, risk management and option pricing. Jumps are related to macroeconomic news announcements (Andersen et al., 2003) which is a fact also confirmed by the empirical results of this paper. We have found that nearly one-fourth of detected jumps are associated with a specific macro-announcement. For example; announcements of U.S Consumer Price Index, U.S. Trade Balance and ECB interest rate contribute significantly to the generation of jumps in Euro/Dollar exchange rates.

The sudden release of news induces a jump in the FX prices and discrete arrival of this information leads to an instantaneous revision in prices. The fact that jump dynamics display such stochastic features and irregularity is important since this character of jumps lead to incomplete markets (Lee and Mykland; 2008). As a result; jumps cannot be hedged by portfolios of underlying assets and derivatives. The impact of jumps on derivatives pricing is also important since jumps may add an upward tilt to implied volatility patterns.

The considerations above point out to the importance of correctly identifying the jump component of financial asset returns. The empirical results presented in this paper, however, raises important questions regarding the issue of correct identification.

Our evidence shows that the jump characteristics of the exchange rates detected by BNS and AJ differ from each other significantly. The average jump sizes vary between 3% and 4% if jumps are detected by BNS and but vary between 1% and 2% when AJ procedure is used. Also the ratio of negative jumps with respect to total jumps varies significantly depending on which jump detection procedure (BNS or AJ) is used. Unfortunately; we do not have a clear theoretical or empirical criteria to tell us which one to choose to resolve the discordance between these two different descriptions of the jump dynamics.

There is, in fact, an extensive literature that dealt with the problems of identifying jumps from the available discrete data. The problems such as the impact of market microstructure noise on detection procedures and the possibility of spurious detections are addressed in recent literature. Our contribution to this literature is to highlight a rather neglected aspect of the jump identification procedures. This aspect is the extreme sensitivity of the estimated jumps and jump days to the sampling of frequencies.

The results of 1-min, 5-min and 15-min frequencies all of which are widely utilized in the empirical literature vary drastically in regard to the number of detected jumps, estimated average jump sizes and the ratio of negative (positive) jumps. The detected jumps are characterized by the lack of a discernible pattern across frequencies. We also observe an inconsistent ordering in the sense that an exchange rate with the highest number of jumps among all exchange rates in the sample may turn out to be the one with the least number of jumps when an adjacent frequency is used for the estimation process.

This sensitivity may seriously constraint the possible use of jump detection procedures in practical applications such as hedging and risk control. Moreover; it may have other important theoretical implications. A significant part of asset and derivative pricing theory is based on pure diffusion models where the analytical formulas assume continuous representations of asset returns (Andersen et al., 2002). Black-Scholes option pricing formula is a well known example. The jumps, however, generate random and sporadic discontinuities in the actually observed series. A suggestion to deal with this problem is to remove the jumps from the observed series so that the resulting jump-adjusted returns can be seen as approximately generated by a pure diffusion process allowing the use of suitable techniques for that case (Andersen et al., 2007b).

The extraction of jumps from the actually observed series and the use of resulting jump-adjusted series may also lead to significant improvement in volatility forecasting (Andersen et al., 2007a). The empirical applicability of both approaches, however, is possible only if the jump detection procedures yield a satisfactory account of jumps. The empirical implementation compels us to choose a certain procedure and a certain frequency for the estimation process. This implies that the characteristics of the jump-adjusted series depend heavily on which frequency and which procedure is used. Given the absence of a convincing theoretical criteria to choose one particular frequency as the optimal one; the empirical validity of the approaches mentioned above remains questionable even though the idea is attractive theoretically. Apparently; this is more of a problem if the detected jumps vary significantly across different frequencies. A more detailed analysis of these problems may be an interesting avenue for future research.

The results of this paper also raise questions about the validity of some arguments mentioned in the recent literature. The observed random pattern of variation (of jumps) deviates considerably from what

\[\text{17 When we consider all 11 exchange rates; the minimum number of jump days detected by AJ is 892 (EURJPY) in 1-min frequency, 951 (CHFJPY) in 5-minute frequency, 953 (GBPJPY) in 15-minute frequency and 910 (CHFJPY) in 30-minute frequency.}\]

\[\text{18 Also note that AJ detects 142 more jump days than BNS for USDTRY in 1-min window (a difference of 13.27%) and detects 158 more jump days for EURTRY in 5 min window (detecting 15.58% more days).}\]
would be expected from the Christensen et al.; (2014) argument who attributes most of the detected jumps in lower frequencies to bursts of volatility. The lack of a discernible pattern may rather suggest an increasing but randomly behaving stochastic volatility in response to announcements and leading to rather irregular bursts of volatility.

Our results also show a marked disagreement with the results of several simulation studies reported in the recent literature. This literature finds extremely low power especially in the widely utilized 5 min and 15 min frequencies. Our results, however, show that the detection power of AJ do not seem to be low when applied to actual data and is even better than BNS in case of several exchange rates. This raises questions about the adequacy of the mathematical representations of stochastic volatility used in such simulations and their ability to reflect the actual behaviour of stochastic volatility.

Declarations

Author contribution statement

Serkan Yesilyurt: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Wrote the paper.

Umit Erol: Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data.

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References

Ait-Sahalia, Y., Mykland, P.A., Zhang, L., 2011. Ultra high frequency volatility estimation with dependent microstructure noise. J. Econom. 160 (1), 160–175.

Andersen, T.G., Bollerslev, T., 1998. Deutsche mark–dollar volatility: intraday activity patterns, macroeconomic announcements, and longer run dependencies. J. Finance 53 (1), 219–265.

Andersen, T.G., Benzoni, L., Lund, J., 2002. An empirical investigation of continuous time equity return models. J. Finance LVII (3), 1239–1284.

Andersen, T.G., Bollerslev, T., Diebold, F.X., Vega, C., 2003. Micro effects of macro announcements: real-time price discovery in foreign exchange. Am. Econ. Rev. 93 (1), 38–62.

Andersen, T.G., Bollerslev, T., Diebold, F.X., 2007a. Roughing it up: including jump components in the measurement, modeling, and forecasting of return volatility. Rev. Econ. Stat. 89 (4), 701–720.

Andersen, T.G., Bollerslev, T., Dobrev, D., 2007b. No-arbitrage semi-martingale restrictions for continuous-time volatility models subject to leverage effects, jumps and iid noise: theory and testable distributional implications. J. Econom. 138 (1), 125–180.

Andersen, T.G., Dobrev, D., Schaumburg, E., 2012. Jump-robust volatility estimation using nearest neighbor truncation. J. Econom. 169 (1), 75–93.

Barndorff-Nielsen, O.E., Shephard, N., 2004. Power and bipower variation with stochastic volatility and jumps. J. Financ. Econom. 2 (1), 1–37.

Bauwens, L., Omrane, W.B., Giot, P., 2005. News announcements, market activity and volatility in the euro/dollar foreign exchange market. J. Int. Money Finance 24 (7), 1108–1125.

Bollerslev, T., Law, T.H., Tauchen, G., 2008. Risk, jumps, and diversification. J. Econom. 144 (1), 234–256.

Christensen, K., Oomen, R.C.A., Podolskij, M., 2014. Fact of friction: jumps at ultra high frequency. J. Financ. Econ. 114 (3), 576–599.

Corsi, F., Pirillo, D., Reno, R., 2010. Threshold bipower variation and the impact of jumps on volatility forecasting. J. Econom. 159 (2), 276–288.

Devachter, H., Eeckhoutglo, D., Gnabo, J.Y., 2014. The intra-day impact of communication on Euro-Dollar volatility. J. Int. Money Finance 43.

Dumitru, A.M.H., Urga, G., 2016. Jumps in equilibrium prices and asymmetric news in financial markets: a new nonparametric test and finanical markets. J. Fun. Econom. 3, 125–180.

El Ouadghiri, I., Uctum, R., 2016. Jumps in equilibrium prices and asymmetric news in foreign exchange markets. Econ. Modell. 54, 218–234.

Huang, X., Tauschen, G., 2005. The relative contribution of jumps to total price variance. J. Financ. Econom. 3 (4), 456–499.

Jiang, G., Oomen, R.C.A., 2008. Testing for jumps when asset prices are observed with noise - a swap variance approach. J. Econom. 144 (2), 352–370.

Laakkonen, H., Lanne, M., 2008. Asymmetric News Effects on Volatility: Good vs. Bad news - a swap variance approach. J. Econom. 144 (2), 352–370.

Lee, S., Mykland, P.A., 2008. Jumps in financial markets: a new nonparametric test and jump dynamics. Rev. Financ. Stud. 21 (6), 2535–2563.

Lee, S., Mykland, P.A., 2012. Jumps in equilibrium prices and market microstructure noise. J. Econom. 168, 396–406.

Maneesoonthorn, W., Martin, G.M., Forbes, C.S., 2020. High-Frequency Jump Tests: Which Test Should We Use. Econometric and Business Statistics. Working Paper. 3/ 20, Monash University, Department of Economic and Business Statistics.

Merton, R.M., 1976. Option pricing when underlying stock returns are discontinuous. J. Econom. 1, 125–144.

Rogulje, M., 2010. Spurious Jump Detection and Intraday Changes in Volatility. Duke University Economics Honors Thesis.

Schwert, G.W., 2011. Stock volatility during the recent financial crisis. Eur. Financ. Manag. 17 (5), 789–805.

Theodosiou, Marina G., Zikes, Filip A., 2011. Comprehensive Comparison of Nonparametric Tests for Jumps in Asset Prices.

Wang, J., 2015. Macroeconomic news effects and foreign exchange jumps. Master of Science in Management (Finance, Goodman School of Business, Brock University, Master Thesis, 13–31.