Konstantinos Gkillas*, Rangan Gupta and Dimitrios I. Vortelinos

Uncertainty and realized jumps in the pound-dollar exchange rate: evidence from over one century of data

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Abstract: We study the importance of economic uncertainty so as to predict realized jumps (hereafter jumps) in the pound-dollar exchange rate. The empirical analysis covers the time period from February 1900 to May 2018 on a monthly basis, incorporating several market states, including various booms and crashes. First, we apply a standard linear Granger causality test in order to identify causal effects from economic uncertainty to jumps. We show that the standard linear Granger causality test fails to capture such casual effects. Providing the misspecification of the linear model, we next make use of a nonparametric causality-in-quantiles test. This test allows us to take into account the substantial evidence of nonlinearity along with the structural breaks between economic uncertainty and jumps. In applying this data-driven robust procedure, we find strong evidence of uncertainty causing jumps of the dollar-pound exchange rate. These results are robust over the entire conditional distribution of jumps, exhibiting the strongest impact at the lowest conditional quantiles considered. In addition, our results are generally found to be robust to alternative measures of uncertainty, jumps generated at a daily frequency based on shorter samples of intraday data, and across three other dollar-based exchange rates.

Keywords: exchange rates; realized jumps; uncertainty.

JEL Classification: C22; F31.

1 Introduction

The foreign exchange market (hereafter exchange market) is by far one of the most sizeable and liquid financial markets in the globe. According to the Triennial Survey regarding the global foreign exchange market volumes of the Bank for International Settlement (BIS), in April 2016, the average turnover on a daily basis stood at 5.1 trillion US dollars. Exchange markets have the tendency to be volatile and, considering the reaction of traders to new information, they present periods of volatility clustering. Improvements in the prediction of exchange rate volatility are crucial for currency risk hedging for multinational firms and traders. A major pursuit of traders of foreign currency options is profit-making by means of selling or buying options in case volatility is expected to decrease below or increase above the currency option premiums implied. Several theoretical studies have connected exchange rate volatility to trade and welfare (see e.g. Clark et al. 2004). Overall, the

***Corresponding author: Konstantinos Gkillas**, Department of Accounting and Finance, Hellenic Mediterranean University, Crete, Greece, E-mail: gillask@hmu.gr. https://orcid.org/0000-0001-8790-080X
Rangan Gupta, Department of Economics, University of Pretoria, Pretoria 0002, South Africa, E-mail: rangan.gupta@up.ac.za
Dimitrios I. Vortelinos, Department of Accounting and Finance, Hellenic Mediterranean University, Crete, Greece; and Lincoln Business School, University of Lincoln, Lincoln, UK, E-mail: dvortelinos@lincoln.ac.uk

prediction of volatility is a key factor with regard to portfolio choices and portfolio risk management, option pricing, and policy actions. In light of this, several theoretical and empirical studies have been conducted on the application, modeling, and assessment of the prediction of the exchange rate volatility (see e.g. Rapach and Strauss 2008).

The nature of the exchange rate volatility as a measure of risk, along with its levels, is crucial for currency market participants, with all traders making the distinction between good and bad volatility (Giot, Laurent, and Petitjean 2010). On the one hand, good volatility is considered to be directional, persistent, and comparatively easier to predict. Therefore, good volatility is generally related to the continuous and persistent part of the price process. On the other hand, bad volatility is associated with discontinuous movements (jumps) in the market and thus is comparatively hard to predict (Huang et al. 2019). Jumps add an extra locally source of non-diversifiable risk in volatility, making the prediction much more difficult. Considering the different features of the price process, it is important to mention that modeling the jump component can provide a better fitting of the models used (see Andersen, Bollerslev, and Diebold 2007; Caporin, Rossi, and Santucci de Magistris 2016; Duffie, Pan, and Singleton 2000; Eraker, Johannes, and Polson 2003; Gkillas, Gupta, and Wohar 2018; among others). Jumps help in forecasting returns and volatility (Andersen, Fusari, and Todorov 2015), equity risk premium (Santa-Clara and Yan 2010), as well as variance risk premium. Jumps are also a quite important tool for pricing options and account for price fluctuations and market risks. In light of this, incorporating jumps is required for portfolio risk management and asset allocation. Thus, a large body of the exchange rate literature cannot only focus on modeling and detecting jumps but also try to explain the causes behind such jumps relating to the state of the economy using macroeconomic and financial variables (see Chan, Powell, and Treepongkaruna 2014; Chatrath et al. 2014; Lee and Wang 2019; Li, Zhou, and Wu 2013; among others).

Against this backdrop, we provide a better understanding of the driving forces of exchange rate jumps by studying the predictive power of economic uncertainty based on a news-based measure of (relative) uncertainty. To our knowledge, this is the first such study. Recent studies by Colombo (2013), Sin (2015), Balcilar et al. (2016), Kido (2016), and Christou et al. (2018) have connected exchange rate returns and volatility to economic uncertainty. As suggested by Benigno, Benigno, and Nisticò (2012), building on new Keynesian general equilibrium frameworks, financial assets are closely linked to the state of the economy undergoing fluctuations induced by uncertainty. Note that with uncertainty affecting macroeconomic and financial variables, as it is widely verified empirically (see Chuliá et al. 2017; Gupta et al. 2019; Kang and Ratti 2013; Mousavi and Gigerenzer 2014; Phan, Sharma, and Tran 2018; Uribe, Chuliá, and Guillén 2017; among others), one could consider uncertainty to be the underlying reason behind the movements of these variables, which in turn have been related to exchange rate jumps so far. In other words, movements in economic uncertainty encompass the information content in the variability of macroeconomic and financial variables associated with jumps in the exchange rate markets.

For our study, we make use of the nonparametric causality-in-quantiles test proposed by Jeong, Härdle, and Song (2012). This procedure allows us to capture various market phases (sizes), such as booms and crashes, associated with the jumpy behavior of the UK pound to US dollar exchange rate. Furthermore, it can be considered to be an inherently time-varying procedure, since various parts of the conditional distribution can be related to different time points throughout the evolution of the jumpy part. The procedure used in this paper presents the following two major advantages. Firstly, as it is based on a nonparametric framework, it is robust to misspecification errors, capturing nonlinearities that are most relevant to the dependence structure between the time series analyzed. This is crucial, as we provide clear evidence about jumps are nonlinearly connected with uncertainty. Secondly, by applying this procedure, we are able to capture casual effects across the whole conditional distribution of jumps and more importantly in the tails of the joint distribution of variables (see Diks and Panchenko 2005, 2006; Hiemstra and Jones 1994; among others), especially in case jumps exhibit heavy-tailed behavior. But more importantly and closely associated with the research question of this study, the framework of the nonparametric quantile-based analysis is based on another stream of literature. This stream suggests that exchange rate movements may be explained by a set of macroeconomic and financial variables (Christiansen, Schmeling, and Schrimpf 2012; Paye 2012; among others). A recent paper that connects exchange rate volatility, news, and trading volume, under the mixture-of-distribution hypothesis theory, is Ranaldo and Magistris (2019). Our work tries to mitigate this study, in terms of theory. We employ the economic and policy uncertainty (EPU) index as an uncertainty measurement that tries to inherit the informational content to explain jumps in the exchange rate market.

Our analysis covers over a century of (the longest possible available) monthly data (from February 1900 to May 2018). The choice of the pound-dollar exchange rate is purely driven by the importance of these two currencies and also the corresponding availability of long-span daily exchange rate (based on which the monthly jumps series is generated) and uncertainty data to help us track historical jumps. In using the longest possible sample available, we are able to avoid sample-specific results, as in the above-mentioned studies, which are generally restricted to a decade of data or slightly more than that. It must be noted, however, that these studies compute jumps at a daily frequency based on intraday data, something which we also do as part of our robustness analyses.

In applying the nonparametric causality-in-quantiles approach, we find strong evidence of uncertainty causing jumps of the dollar-pound exchange rate. These results are robust over the entire conditional distribution of jumps. So, there is strong evidence that uncertainty triggers jumps. In other words, exchange rate movements as they are driven primarily by the EPU are affected by the state of the economy providing further consequences for currency risk management. Such evidence has profound implications for multinational managers and business practitioners who weigh operational decisions under exchange variability and uncertainty. According to Kim and Park (2014), the profitability of multinational firms is subject to exchange rate variability, which in turn affects the internal transactions of these firms. Finally, following Todorov and Tauchen (2011), in periods of high uncertainty, an econometric understanding of casual inferences of jumps is important for policymaking. During such periods, policymakers' decisions are likely to create additional turbulence or chaotic conditions in currency markets. Thus, policymakers must aim to reduce policy-related uncertainty by being transparent in their communication about their decisions.

The remainder of the paper is organized as follows: Section 2 presents the theoretical background regarding some initial information of realized volatility and jumps. Section 3 presents the methodology used. Section 4 describes the data and discusses summary statistics. Section 5 presents the empirical results along with several robustness checks conducted in this study. Finally, Section 6 concludes the paper by providing further implications.

2 Theoretical background

Volatility is the second moment of the price process of a financial time series quantifying the dispersion risk. It presents time-varying behavior, while it is latent. Implied volatility is considered to be an effective (widely used) predictor of latent volatility. It requires rational expectation assumptions that the prices of the options market reveal, that is the market's true volatility estimate (Latane and Rendleman 1976). In real options valuation, emphasized the importance of pricing uncertainties/risks. The most common ways in order to estimate volatility are either parametric or nonparametric. Parametric volatility models are complicated and difficult to estimate, as they impose restrictions and conditions. They may be beneficial for prediction and forecasting purposes; they are less important for describing historical volatility movements, however. Moreover, the parametric models' estimates move closely together, as their estimates are based on similar assumptions, imposing similar restrictions and conditions on the price process.

The concept of nonparametric volatility estimates was introduced in Merton (1980). Using the theory of quadratic variation, Andersen and Bollerslev (1998) were among the first to suggest that the realized volatility estimation stands for a consistent estimate of the actual volatility. Monthly realized variance is considered to be quite predictable and thus helpful for optimal asset allocation and portfolio risk management (Barroso and Santa-Clara 2015). French, Schwert, and Stambaugh (1987), Schwert (1989, 1990a, 1990b), and Schwert and Seguin (1991) introduced the construction of realized volatility estimates, incorporating daily returns. Campbell et al. (2001) were the first to estimate the dispersion of returns in a monthly frequency, based on the conception of the nonparametric realized volatility estimation. In this paper, monthly realized volatility has been constructed by the use of daily returns as in Christensen and Hansen (2002) and Barroso and Santa-Clara (2015), among others. Degiannakis, Filis, and Kizys (2014) and Kang, Ratti, and Yoon (2015), among others, researched monthly realized volatility in its standard deviation form. However, due to small values of realized variance (volatility) estimates, we employ a double-stabilizing transformation of logarithm and square root (standard deviation); i.e. the logarithmic standard deviation of the realized variance estimates. Such transformation is suggested in Andersen, Bollerslev, and Diebold (2007). This form, and not the realized volatility in levels, passes all tests for structural stability. The logarithmic version of the standard deviation of realized volatility follows a close-to-Gaussian distribution, as the Jarque–Bera test and sample-quantiles based Cramer–Von Mises test indicates. These results are consistent with the monthly realized volatility literature (see Thomakos and Koubouros 2011, among others). The asymptotics of the logarithmic version of realized volatility is reliable, in case twelve or more daily observations are employed to construct one monthly point estimate of realized volatility (Barndorff-Nielsen and Shephard 2004a). This condition is fulfilled in the present paper, as twenty-two observations (trading days per month) on average are used for a monthly realized volatility point estimate. As the monthly realized volatility in its logarithmic standard deviation form, is log-normally distributed; realized volatility in lower frequencies will not be. The distributions of realized volatility in lower frequencies are useful for volatility modeling and forecasting, as they can be approximated by Inverse Gaussian distributions, under temporal aggregation (Barndorff-Nielsen and Shephard 2002).

Furthermore, the literature provides evidence that the assumption of continuous diffusion is violated. Volatility asymmetries indicated the need for a more detailed description of the volatility process (Black 1976). Andersen, Bollerslev, and Diebold (2007) introduced a jump detection nonparametric scheme for realized volatility, building on the theoretical findings proposed by Barndorff-Nielsen and Shephard (2004b). This scheme is applicable to monthly realized volatility estimates, similarly to daily, as it does not rely on direct estimates of the transition density function and directly builds on the theoretical results of Barndorff-Nielsen and Shephard (2004b).[1] In their turn, they proved that the conception of realized bipower variation and jumps applies to a finite number of observations and a fixed interval of time; whether it is a trading day or a calendar month (see Barndorff-Nielsen and Shephard 2004b). The explanatory power of the monthly jumps is compatible with implied volatility, in encompassing regressions (Giot and Laurent 2007). Jump diffusion parameters can also be important in pricing and analyzing the properties of futures contracts (Murphy and Ronn 2015). Moreover, several studies found monthly jumps are significant in realized volatility modeling and forecasting. Indicatively, Corsi (2009), Corsi, Pirino, and Reno (2010), Duong and Swanson (2015), and Degiannakis and Filis (2017) researched such importance. They all employed the HAR-RV base model with the incorporation of jumps series. Most of the studies reveal the importance of monthly jumps series in modeling and/or forecasting daily realized volatility. Others (see e.g. Liu et al. 2018) provided evidence of their significance in monthly realized volatility forecasting, as well.

3 Methodology

3.1 Jumps

This subsection provides a detailed overview of the jump detection scheme used in this study. French, Schwert, and Stambaugh (1987), Schwert (1989, 1990a, 1990b) and Schwert and Seguin (1991) put forward the construction of realized volatility using daily returns. Campbell et al. (2001) were the first to employ various

1 In order to determine the finite sample performance of the jump detection scheme described in Sub-section 3.1. When using daily data, we proceed to a simulation analysis. To this end, we conducted a small-scale Monte Carlo study that simulates a jump-diffusion process as described in Meucci (2005) in a daily frequency of prices; as the literature suggests (Bollerslev, Gibson, and Zhou 2011, among others). We report the simulation in Appendix B.

alternative measures to estimate the dispersion of returns in a monthly frequency, based on the conception of the nonparametric realized volatility estimation.

In this paper, we estimate monthly realized volatility with the use of daily returns, as in Christensen and Hansen (2002), and Barroso and Santa-Clara (2015), among others. More specifically, we employ daily log-returns of the pound-dollar exchange rate to construct monthly point estimates of realized variance RV_t. We make use of the realized variance which is the benchmark realized volatility measure. For each month t, we construct a monthly point estimate by using all daily returns, as follows:

$$RV_t \equiv \sum_{i=1}^{T} X_{t,i}^2 \tag{1}$$

where $X_{t,i}$ stands for the daily return for day i within month t for $i = 1, \ldots, \mathrm{T}$, and T stands for the total number of daily returns within a month.

The asymptotic results of Barndorff-Nielsen and Shephard (2004b) enable the nonparametric distinction between continuous and jump variation of returns. More precisely, although the realized variance RV_t defined in Eq. (1) measures both the continuous and jump variation, the standardized realized bipower variation given below captures only the amount of continuous variation, thus it has been considered to be a jump-robust estimator of realized volatility. The latter estimator is given as follows:

$$BV_t \equiv \mu_1^{-2} \sum_{i=2}^{T} |X_{t,i}| \cdot |X_{t,i-1}| \tag{2}$$

where $\mu_1 \equiv \sqrt{2/\pi} = E(|Z|)$ is the mean of the absolute value of a random variable (Z) which is normally distributed. The integrated quarticity can be estimated using the standardized realized tri-power quarticity measure, as follows:

$$TQ_t \equiv T \cdot \mu_{4/3}^{-3} \sum_{i=3}^{T} |X_{t,i}|^{4/3} |X_{t,i-1}|^{4/3} |X_{t,i-2}|^{4/3} \tag{3}$$

where $\mu_{4/3} \equiv 2^{2/3} \cdot \Gamma(7/6) \cdot \Gamma(1/2)^{-1} = E\left(|Z|^{4/3}\right)$.

We use the logarithmic transformation of Andersen et al. (2007) jump statistic to detect realized jump intensity. In an earlier version of their study, Andersen, Bollerslev, and Diebold (2007) found no difference between the plain jump statistic and its logarithmic transformation. The log-version of the jump statistic, as employed here, is given as follows:

$$U_t \equiv T \cdot \frac{(\log(RV_t) - \log(BV_t))}{\left[\left(\mu_1^{-4} + 2\mu_1^{-2} - 5\right) \cdot TQ_t \cdot (BV_t)^{-2}\right]^{1/2}} \tag{4}$$

where significant jumps are identified by an indicator function, $1\{U_t > \Phi_a\}$, under the following condition:

$$J_{t,a} \equiv 1\{U_t > \Phi_a\} \cdot [\log(RV_t) - \log(BV_t)] \tag{5}$$

Analogically, the continuous component denoted by $C_{t,a}$ is equal to $1\{U_t \le \Phi_a\} \cdot \log(RV_t)$, where $\log(RV_t) \equiv J_{t,a} + C_{t,a}$. The non-negativity of both components corresponds directly to a significance level of $a = 0.05$ (Andersen, Bollerslev, and Diebold 2007). The explanatory power of monthly jumps is compatible with implied volatility in encompassing regressions (Giot and Laurent 2007).

3.2 Causality-in-quantiles

This subsection offers a sketchy overview of the nonparametric quantile-based approach proposed by Jeong, Härdle, and Song (2012). As already mentioned, this method constitutes a robust approach far away from the center of the distribution. Furthermore, it enables us to capture nonlinear dynamic causal effects between two-time series. In our study, let y_t be the dependent variable which stands for jumps, while x_t stands for the predictor variable, that is, the relative uncertainty corresponding to the economic uncertainty of the UK related to that of the US (see Section 4). Considering that the exchange rate constitutes a relative variable, it is plausible to use uncertainty in its relative form.

In particular, let the variables $Y_{t-1} \equiv (y_{t-1}, \dots, y_{t-p})$, $X_{t-1} \equiv (x_{t-1}, \dots, x_{t-p})$, $Z_t = (X_t, Y_t)$, while let $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ be the functions of the conditional distribution of the dependent variable y_t, given Z_{t-1} and Y_{t-1}, respectively. By denoting $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t|Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t|Y_{t-1})$, we obtain the function $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1})|Z_{t-1}\} = \theta$ with probability being equal to one. Thus, the existence of (non)causality in the θth quantile hypotheses to be tested is formed as follows:

$$\begin{aligned} H_0&: P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} = 1 \\ H_1&: P\left\{F_{y_t|Z_{t-1}}\left\{Q_\theta\left(Y_{t-1}\right)|Z_{t-1}\right\} = \theta\right\} < 1 \end{aligned} \tag{6}$$

we make use of distance measure $J = \{\varepsilon_t E(\varepsilon_t|Z_{t-1}) f_z(Z_{t-1})\}$ proposed Jeong, Härdle, and Song (2012) for the marginal density function of Z_{t-1}, denoted by $f_z(Z_{t-1})$. ε_t represents the regression error term that arises from the above null hypothesis. This hypothesis can only be true if and only if $E[1\{y_t \le Q_\theta(Y_{t-1})|Z_{t-1}\}] = \theta$ or, equivalently, when the indicator function $1\left\{y_t \le Q_\theta\left(Y_{t-1}\right)\right\}$ is equal to $(\theta + \varepsilon_t)$. According to Jeong, Härdle, and Song (2012), the feasible kernel-based sample analogue of J is given by:

$$\hat{J}_{\mathrm{T}} = \frac{1}{T\left(T-1\right)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s \tag{7}$$

where $K(\cdot)$ represents the kernel function with bandwidth h, T corresponds to the sample size, p stands for the lag order, while $\hat{\varepsilon}_t$ is estimated from $1\{y_t \le Q_\theta(Y_{t-1})\} - \theta$.

Furthermore, an estimate of the θth conditional quantile of y_t, given Y_{t-1}, is denoted by $\hat{Q}_\theta(Y_{t-1})$ and can be estimated by using a nonparametric kernel technique, based on the Nadarya–Watson kernel estimator by the following:

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{(y_t|Y_{t-1})}(\theta|Y_{t-1}) \tag{8}$$

where $\hat{F}_{y_{t|Y_{t-1}}}(y_t|Y_{t-1})$ is given by $\frac{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{(Y_{t-1}-Y_{s-1})}{h}\right) 1(y_s \le y_t)}{\sum_{s=p+1,s\neq t}^{T} L\left(\frac{(Y_{t-1}-Y_{s-1})}{h}\right)}$, with h standing for the bandwidth and $L(\cdot)$ for the kernel. For each quantile, we define bandwidth h by employing the leave-one-out least-squares cross-validation approach, based on the studies of Li and Racine (2004), and Racine and Li (2004). Lag order p is selected using the Akaike Information Criterion (AIC) and is equal to 12. Finally, following Jeong, Härdle, and Song (2012), for $K(\cdot)$ and $L(\cdot)$ we use Gaussian-type kernels.

4 Data and summary statistics

We employ daily data on the UK pound relative to the US dollar exchange rate obtained from the Global Financial Database spanning from 2nd January 1900 to 31st May 2018. This period covers over a century of data (the longest possible available) incorporating various markets phases, such as booms and crashes. Such a period of time allows us to avoid sample-specific results, as in the existing literature, which is generally restricted to a decade of data or slightly more than that. We construct daily returns as the first logarithmic difference between two consecutive daily prices within a day. Then, we extract jumps nonparametrically by employing the jump detection scheme presented in Eq. (5). We report the summary statistics of the jump series in Table 1 over the time period considered. Although French, Schwert, and Stambaugh (1987) found that the logarithmic monthly standard deviations from daily returns (i.e. monthly realized volatility) are close to Gaussian, as shown by this table, the jump series is non-normal due to positive skewness and excess kurtosis. Such evidence provides an initial motivation to use a quantiles-based method. What is more, the most important feature of our realized volatility estimates is temporal persistence. Volatility clustering is evident with strong serial correlation estimates. This allows us to treat realized volatility estimates as a

Table 1: Summary statistics for monthly UK Pound–US Dollar realized jumps and the (relative) EPU.

Statistic	Variables	
	Monthly UK Pound–US Dollar jumps	**Relative EPU**
Mean	5.79×10^{-5}	0.2324
Median	2.16×10^{-6}	0.1695
Maximum	0.0033	5.3959
Minimum	5.77×10^{-10}	−1.3102
Standard deviation	0.0002	0.7559
Skewness	11.1206	1.8923
Kurtosis	157.9517	10.0713
Jarque–Bera	777,003.4001	3805.9530
p-value	[0.0000]	[0.0000]
Observations	1420	1420

Table 1 reports summary statistics for monthly UK Pound–US Dollar realized jumps and the (relative) EPU. Nine statistics are reported. The null hypothesis that the data is normally distributed is also tested using the Jarque–Bera test. The *p*-value of the test is provided below in brackets. We provide descriptive statistics only for the significant jumps.

short-memory and stationary process. Monthly jumps also exhibit less serial dependence than other volatility measures (Andersen, Bollerslev, and Diebold 2007; Busch, Christensen, and Nielsen 2011).

Uncertainty is definitely a latent variable, and thus, in order to be able to quantify its effect on jumps, one needs ways to define and measure uncertainty as accurately as possible. In the existing literature, there are various alternative measures of uncertainty associated with financial markets. Examples include the implied volatility indices (the so-called VIX), idiosyncratic volatility of equity returns, or corporate spreads. There are three main broad procedures for quantifying the impact of uncertainty on the economy. First, there are news-based approaches that create measures of uncertainty by searching terms associated with economic and policy uncertainty (EPU) in newspapers. Second, uncertainty measures can also be constructed by using estimates obtained from small and large-scale structural models associated with finance or macroeconomics. In particular, such measures are associated with average time-varying variances in unpredictable parts of financial variables. In other words, they aim to model the average volatility during periods of shocks which in turn summarize real and financial conditions. Third, estimates of uncertainty have been constructed using the information on the dispersion of professional forecaster disagreements.

Although there is not any clear evidence on which approach is superior to be adopted for the construction of a measure of uncertainty, Baker et al. (2016) news-based measure of uncertainty is widely used in several studies in the field of macroeconomics and finance. One possible reason why it is preferred is that this measure can be used much more easily, as it does not need to estimate any complicated model for generating it at first. What is more, this measure is freely available to download from: http://www.policyuncertainty.com, while it is updated on a regular basis for various developed and emerging economies. In our case, we use EPU data for the UK and the US, since they are the only available data on uncertainty dating back to 1900 at monthly frequency.[2] Taking into account that exchange rate prices are a relative variable, we create a relative measure of uncertainty (that is, a relative EPU measure, hereafter EPU), by subtracting the natural log of the EPU for the US from the natural log of the EPU for the UK. We also report the summary statistics of the EPU series in Table 1 over the time period considered. As shown by Table 1, the EPU is also non-normal due to positive skewness and excess kurtosis.

In Figures 1A and 1B, we present the plots of the two variables of our interest, i.e. the jumps and the EPU. In particular, Figure 1A refers to the monthly UK Pound–US Dollar jumps series, while Figure 2B refers to

2 We refer to the following links for further details: http://www.policyuncertainty.com/uk_historical.html, http://www.policyuncertainty.com/us_historical.html, http://www.policyuncertainty.com/europe_monthly.html, and http://www.policyuncertainty.com/us_monthly.html.

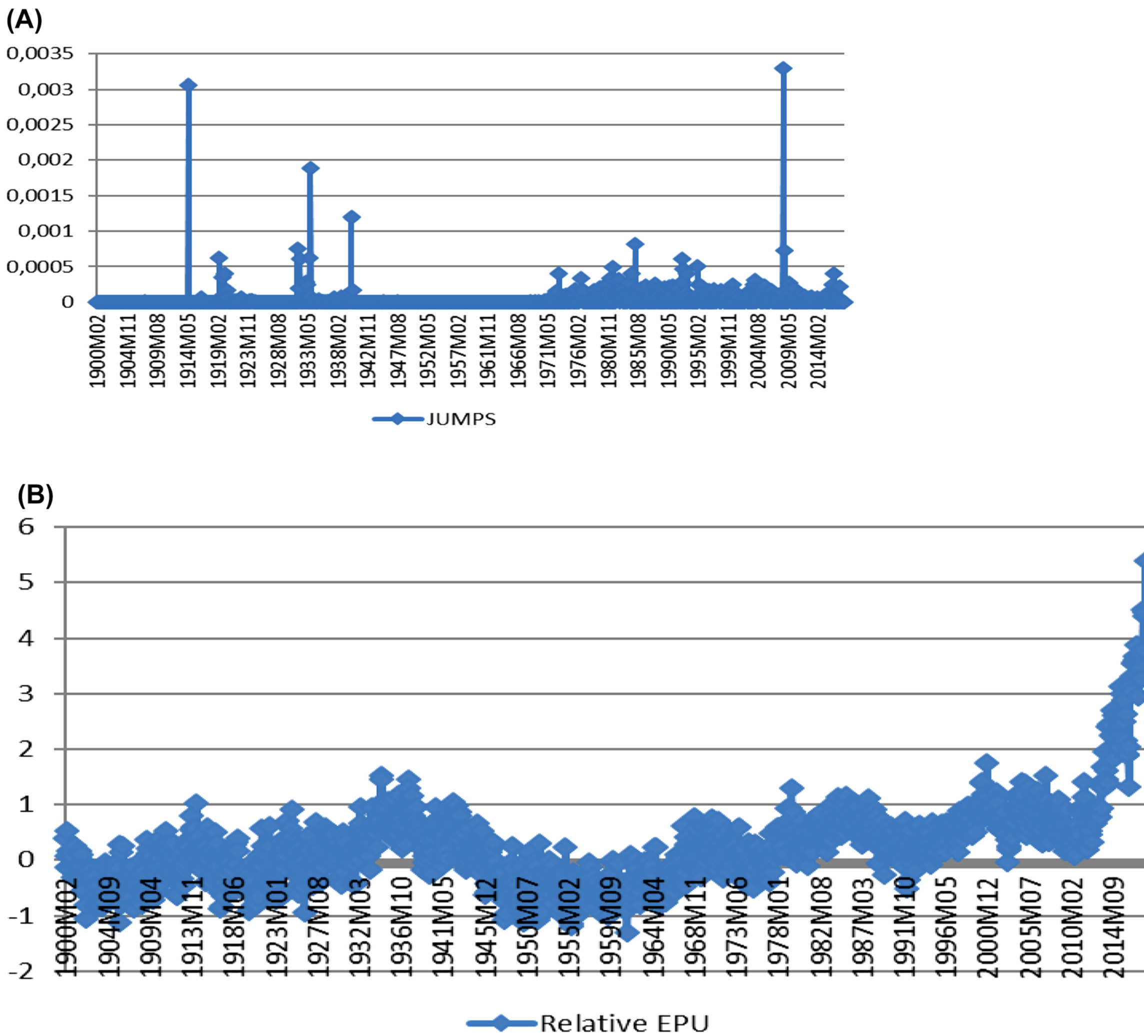

Figure 1: A) Data plots for monthly UK Pound-US Dollar realized jumps. B) Data plots for the monthly (relative) EPU. Figure 1 represents data plots for monthly UK Pound-US Dollar realized jumps and the (relative) EPU series spanning from the 2nd of January 1900 to the 31st of May 2018. Figure 1A refers to the monthly UK Pound–US Dollar realized jumps series. Figure 2B refers to the monthly (relative) EPU series.

the monthly (relative) EPU series. We also apply standard unit root tests to reveal whether both jumps and the EPU are stationary. These results are available upon request and suggest that both variables can be used directly without further transformation in the causality-in-quantiles procedure, which in turn requires the variables used in the model to be mean-reverting.

5 Empirical results

5.1 Preliminary analysis

We now present our empirical results in order to detect casual patterns between jumps and the EPU. As in the preliminary analysis, we first employ the standard linear Granger causality method for the sake of completeness and comparability. Then, we statistically examine the presence of nonlinearity and structural breaks in the relationship between jumps and the EPU to further motivate the use of the causality-in-quantile method.

As for the linear Granger causality test, we determine the lag length of the test using the Akaike information criterion (AIC). The resulting $\chi^2(12)$ statistic is equal to 16.6368, while the corresponding p-value is equal to 0.1638. This evidence suggests that we cannot reject the null hypothesis - that is, the relative EPU does not Granger cause jumps – even at the 10 percent level of significance. Such evidence indicating a significant lack of predictability arising from the linear model suggests that maybe the variables under consideration are nonlinearly associated.

The presence of nonlinearity and regime changes in the joint dependence structure between the variables used in this study further support making use of the nonparametric quantiles-in-causality procedure. Such a quantiles-based test is more appropriate to capture nonlinearities and breakpoints which are more relevant to crisis situations. To this end, we employ Brock et al. (1996) test for nonlinearity, also known as BDS, on the residuals arising from a regression between jumps (including twelve lags) and the EPU. We report the results for the BDS test in Table 2. According to this table, we reject the null hypothesis of independent and identically distributed residuals (i.i.d.) at various embedded dimensions (m) at least at a 1% perfect level of significance. This provides strong evidence of nonlinearity in the relation concerning jumps and the EPU. In this vein, we also use the powerful *UD*max and *WD*max tests proposed by Bai and Perron (2003) in order to detect $1, \dots, M$ structural breaks in the relation between jumps and the EPU. In turn, this allows us to take into account heterogenous error distributions throughout the breakpoints. By applying these tests again on the residuals arising from a regression between jumps (including twelve lags) and the EPU, we find the following breakpoints in (i) December 1919, (ii) July 1937, (iii) April 1965, (iv) November 1982 (v) and September 2000. These results further support the lack of predictability using the linear Granger causality procedure, and consequently, they cannot be reliable and robust.

5.2 Causality-in-quantiles

In the previous subsection, we find clear evidence of the non-linear association between jumps and the EPU, while we detect five structural breaks in their relation. We now apply a robust to misspecification method which is data-driven (nonparametric), namely the causality-in-quantiles. We report the estimates for the causality-in-quantiles test between exchange rate jumps and uncertainty measures in Table 3. The first column of this table corresponds to the quantile considered, while quantiles range from 0.05 to 0.95. The second column corresponds to results for (monthly) jumps and the EPU. As we can see from Column 2 of Table 3, the null hypothesis that the EPU does not Granger cause the dependent variable, i.e. jumps, is overwhelmingly rejected at the 1 percent level of significance over the whole conditional distribution of jumps. The corresponding critical value of the test is equal to 2.575 for a 1 percent level of significance. Furthermore,

Table 2: Estimates for Brock et al. (1996) test of nonlinearity between monthly UK Pound–US Dollar realized jumps and the (relative) EPU.

	Embedded dimensions (m)				
Independent variable	2	3	4	5	6
Relative EPU	13.0029***	16.4635***	19.1773***	21.8845***	25.1611***

Table 2 reports the estimates for Brock et al. (1996) test (BDS) of nonlinearity between monthly UK Pound-US Dollar realized jumps and the (relative) EPU. The test is applied on the residuals arising from the regression between monthly UK Pound–US Dollar realized jumps as the dependent variable and the (relative) EPU as the independent variable (including twelve lags). The number of lags is defined from the Akaike Information Criterion (AIC). The null hypothesis of independent and identically distributed residuals (i.i.d.) at various embedded dimensions (m) is tested by a z-statistic of the BDS test. ***, **, and * indicate the rejection of the null hypothesis of the BDS test at 1 percent, 5 percent, and 10 percent levels of significance, respectively.

Table 3: Estimates for the causality-in-quantiles test between exchange rate realized jumps and uncertainty measures.

Quantile	Exchange rate volatility jumps					
	(Relative) EPU		(Professional forecaster disagreement) Uncertainty			
	Monthly UK Pound–US Dollar jumps	Daily UK Pound–US Dollar jumps	Daily UK Pound–US Dollar jumps	Daily Canadian Dollar–US Dollar jumps	Daily Euro–US Dollar jumps	Daily Japanese Yen–US Dollar jumps
0.05	51.7338***	1945.5717***	1970.0296***	2069.1864***	3287.8160***	2422.0161***
0.10	34.0740***	1150.7966***	1166.7697***	1182.5275***	1957.0250***	1381.1866***
0.15	26.0609***	794.5105***	806.7095***	781.8652***	1340.5421***	895.4213***
0.20	21.3100***	578.7529***	588.6404***	539.8889***	961.2258***	598.4213***
0.25	18.1910***	430.0097***	438.2639***	375.0730***	698.0424***	396.4249***
0.30	16.0699***	320.1232***	327.1238***	256.0422***	503.8397***	252.7374***
0.35	14.6458***	235.6847***	241.6689***	167.8628***	355.9248***	149.7406***
0.40	13.7603***	169.4217***	174.5479***	102.5122***	241.9411***	77.9906***
0.45	13.3283***	117.0558***	121.4345***	55.3998***	155.6535***	32.2020***
0.50	13.3089***	75.9561***	79.6657***	23.8890***	90.8030***	9.5477***
0.55	13.2103***	44.5026***	47.5978***	6.6852***	45.8389***	6.2777***
0.60	13.0120***	21.7763***	24.2929***	2.6676***	17.7481***	8.3372***
0.65	12.6571***	7.4329***	9.3894***	3.0242***	4.5066***	8.2735***
0.70	12.1605***	1.7185*	3.1146***	2.2004**	3.0205***	7.8325***
0.75	11.4806***	1.4552	1.8064*	1.5279	2.6563***	6.7726***
0.80	10.6714***	1.6087	1.8004*	1.9256*	2.2163**	6.5031***
0.85	9.4710***	1.5767	1.2939	1.7373*	2.3976**	4.7080***
0.90	7.9245***	1.1764	1.2196	1.3461	1.1465	2.7078***
0.95	5.7110***	0.8291	0.4844	0.4645	0.4748	0.9561

Table 3 reports the estimates for the causality-in-quantiles test between exchange rate realized jumps and uncertainty measures. The first column corresponds to the quantile considered. The second (third) column corresponds to results for monthly (daily) realized jumps based on the (relative) EPU. The results in columns 4 through 7 are for daily realized jumps based on relative uncertainty. Uncertainty is measured by the dispersion of professional forecaster disagreement. ***, ** and * indicate the rejection of the null hypothesis of no-causality from uncertainty to various realized jumps for various quantiles at 1 percent, 5 percent, and 10 percent levels of significance, respectively. The corresponding critical values are 2.575, 1.96, and 1.645.

we find the strongest evidence of predictability at lower quantiles of the jumps' conditional distribution.[3] More importantly, such evidence highlights the importance of making use of a nonparametric (data-driven) procedure when dealing with nonlinear relations exhibiting various structural breaks. Hence, we are in the position to find clear evidence of predictability originating from the EPU onto jumps of the pound-dollar exchange rate, contrary to what we found by using the linear Granger causality test. In other words, we do find that the EPU can be an important predictor of jumps occurring in the UK Pound-US Dollar exchange market regardless of the (conditional) size of jumps, as captured by different quantiles of its conditional distribution.[4]

5.3 Robustness analysis

5.3.1 Daily jumps

To check the validity of our results among data frequencies, we compute daily values of jumps on the pound-dollar exchange rate. Daily data allow us – among others – to be in line with the existing exchange rate literature (see Busch, Christensen, and Nielsen 2011). We now use 5-min intraday returns data (obtained from 1-min price data) sourced from the *p*-trading database. This data frequency is consistent with the study conducted by Liu, Patton, and Sheppard (2015). They suggested a 5-min frequency for liquid assets. On the one hand, 5-min frequency is not as high so as to lead to spurious jumps because of market frictions. On the other hand, this frequency is not too low to cause poor data analysis. Data has been cleaned following the suggestions of Barndorff-Nielsen et al. (2009). To this end, we removed weekends and a set of fixed and irregular holidays as well as days when the number of 1-min prices is less than 40% of the number of observations on a normal trading day. The new sample covers the period of the 1st of July 2003 to the 28th of August 2015 and is solely driven by the availability of high-frequency data. The corresponding news-based daily (relative) EPU proposed by Baker, Bloom, and Davis (2016) is used again. This measure for the UK is also freely available to download from: http://www.policyuncertainty.com/uk_daily.html, while that for the US is available at: http://www.policyuncertainty.com/us_daily.html.

We also report the estimates for the causality-in-quantiles test between jumps and the EPU in Table 3. As we can see from Table 3 (see Column 3), predictability is detected over the conditional distribution of jumps ranging between the quantiles of 0.05 and 0.65 at the 1 percent level of significance. What is more, as for the quantile of 0.70 predictability, it is detected at the 10 percent level (since the critical value is equal to 1.645). In other words, unlike the long-span monthly data, the causality of the EPU to jumps is not observed at the upper endpoint of the conditional distribution, though the greatest effect is detected again at lower quantiles.[5]

5.3.2 Alternative measures uncertainty

As a further robustness check, we use an alternative measure of daily (relative) uncertainty on the basis of dispersion of professional forecaster disagreement, as created by Scotti (2016). This measure of uncertainty

3 Based on the suggestion of an anonymous referee, we re-conducted our analysis by dropping the months from our data set that has zero value for the jumps series. We found that the EPU differential continued to predict the jumps series over its entire conditional distribution at 1% level of significance, though in this case, the strongest effect was observed around the conditional median. Complete results are available upon request from the authors.

4 We re-estimated our model using the sum and real-GDP weighted sum of the UK and the US EPUs, and obtained qualitatively similar results, complete details are reported in an Online appendix.

5 We re-estimated our model using the real-GDP weighted sum of the UK and the US EPUs, and obtained qualitatively similar results, though now predictability was observed over the entire conditional distribution of the jump variable. Complete results are reported in an Online appendix.

can be downloaded from: https://sites.google.com/site/chiarascottifrb/data-and-other-materials. We repeat the above analysis deriving from intraday data over the same period. We compute again a relative measure of uncertainty by subtracting the natural log of US uncertainty from that of the UK. We report the estimates for the causality-in-quantiles test between jumps and EPU in Table 3 (see Column 4). As we can see from Column 4 of Table 3, the earlier daily results, reported in the subsection above, carry over under this alternative metric of uncertainty. In this case, predictability is observed over the extended quantile range of 0.05–0.70 at the 1 percent level of significance, with quantiles 0.75 and 0.80 also being included at the 10 percent level of significance.

Since Scotti (2016) also provides daily uncertainty indexes for Canada, the Euro area, and Japan, we are also able to check for the impact of daily relative uncertainty on the jumps of the Canadian dollar, the Euro, and the Japanese yen relative to the US dollar. These major currencies used in this subsection are globally traded. From a broad economic viewpoint, the Euro and the Japanese yen are dominant currencies of the two main developed markets. In particular, the Japanese yen is considered a global funding currency to carry trades (Novotný, Petrov, and Urga 2015). We also use 5-min intraday returns data (obtained from 1-min price data) sourced from the p-trading database. For comparison purposes, we also apply the data adjustment procedure described in the above subsection. The new sample covers the same period (i.e. from the 1st of July 2003 to the 28th of August 2015). We compute relative measures of uncertainty by subtracting the natural log of US uncertainty from the natural log of the uncertainty of the specific country under consideration. These results have been reported in Columns 5 through 7 of Table 3. As in the case of the UK, again we observe predictability of jumps due to relative uncertainty restricting the upper end of jumps' conditional distributions of the currencies considered. In sum, we can say that relative uncertainty does predict jumps, with predictability being strongest at the lower end of the conditional distribution.[6]

5.3.3 Cross-quantilograms

As a final robustness check, in order to obtain additional views into the tail dependence between jumps and the EPU, we repeat our analysis presented in Subsection 5.2 by employing the cross-quantilogram procedure proposed by Han et al. (2016). In particular, cross-quantilograms allow us to model the quantile dependence structure between two-time series by testing for directional predictability between them. We describe this approach in Appendix A in detail.

Turning now our attention to the estimation results obtained by using this procedure, we report in Figure 2A–2C the quantile dependencies between jumps and the EPU at various lags and quantiles. As for the jumps, we consider nine quantiles in which $\alpha_1 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95\}$ corresponding to periods in which jumps are at their low ($\alpha_1 \in \{0.05, 0.1, 0.2\}$), median $\alpha_1 \in \{0.3, 0.5, 0.7\}$) and high levels $\alpha_1 \in \{0.8, 0.9, 0.95\}$). As for the EPU, we consider three quantiles where $\alpha_2 \in \{0.1, 05, 0.90\}$ corresponding to periods in which the EPU is at its low (Figure 2A), median (Figure 2B), and high levels (Figure 2C), respectively. In each figure, bar graphs depict the sample cross-quantilograms for 60 lags, while red lines depict the 95 percent bootstrap confidence intervals obtained by using 2000 bootstrap iterations. For negative (positive) values of a sample cross-quantilogram, a bar below (above) the red line leads to a rejection of the null hypothesis of no dependency at a 5 percent level of significance. More specifically, as reported in Figures 2A–2C, we re-confirm our findings obtained in Subsection 5.2. There is a statistically significant (different from zero) relation between jumps and the EPU. We observe that there is a positive and statistically significant relation between large jumps (higher quantiles) and the EPU. In other words, this means that it is more likely to have large jumps during periods of high EPU. We also observe a statistically significant negative relation between jumps and the EPU when jumps are at their lower quantiles. Such evidence highlights the importance

6 We re-estimated our model using the real-GDP weighted sum of the UK or Canada or the Euro Area or Japan, and the US forecaster-disagreements-based metrics of uncertainties and obtained qualitatively similar results. Complete results are reported in an Online appendix.

(A)

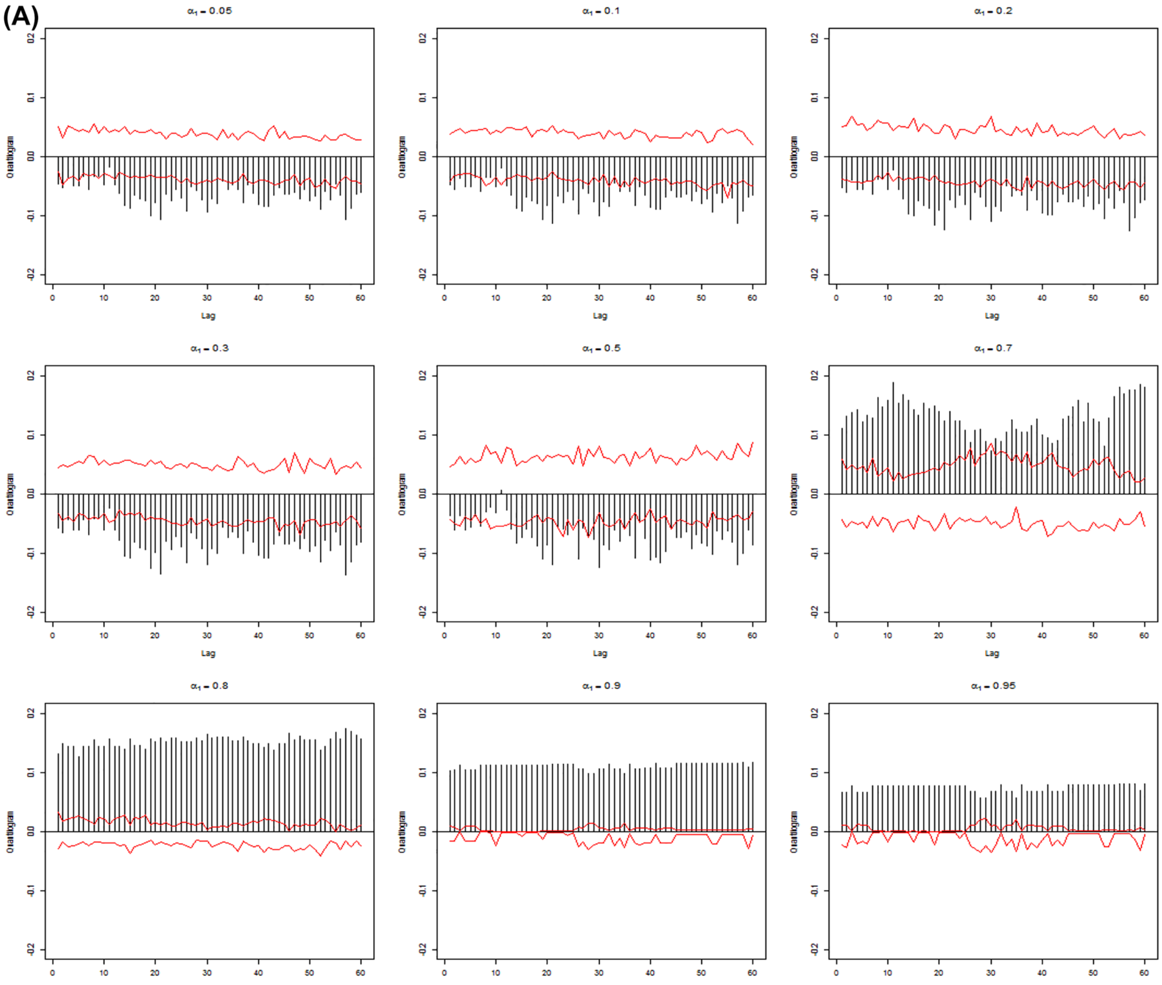

Figure 2: A) Quantile dependencies between monthly UK Pound–US Dollar realized jumps and the (relative) EPU when the (relative) EPU is at its low levels. B) Quantile dependencies between monthly UK Pound–US Dollar realized jumps and the (relative) EPU when the (relative) EPU is at its median levels. C) Quantile dependencies between monthly UK Pound–US Dollar realized jumps and the (relative) EPU when the (relative) EPU is at its high levels.
Figure 2A represents sample cross-quantilograms at various lags and quantiles between monthly UK Pound–US Dollar realized jumps and the (relative) EPU. As for monthly UK Pound–US Dollar volatility jumps, nine quantiles are considered, in which $\alpha_1 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95\}$ corresponding to periods when UK Pound–US Dollar realized jumps are at their low ($\alpha_1 \in \{0.05, 0.1, 0.2\}$), median $\alpha_1 \in \{0.3, 0.5, 0.7\}$) and high levels $\alpha_1 \in \{0.8, 0.9, 0.95\}$). As for the (relative) EPU, one quantile is considered where $\alpha_2 \in \{0.1\}$ corresponding to periods when the (relative) EPU is at its low levels. Bar graphs depict the sample cross-quantilograms for 60 lags. Red lines depict the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. For negative (positive) values of a sample cross-quantilogram, a bar below (above) the red line leads to a rejection of the null hypothesis of no dependency at a 5 percent level of significance.
Figure 2B represents sample cross-quantilograms at various lags and quantiles between monthly UK Pound–US Dollar realized jumps and the (relative) EPU. As for monthly UK Pound–US Dollar volatility jumps, nine quantiles are considered, in which $\alpha_1 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95\}$ corresponding to periods in which UK Pound–US Dollar realized jumps are at their low ($\alpha_1 \in \{0.05, 0.1, 0.2\}$), median $\alpha_1 \in \{0.3, 0.5, 0.7\}$) and high levels $\alpha_1 \in \{0.8, 0.9, 0.95\}$). As for the (relative) EPU, one quantile is considered, where $\alpha_2 \in \{0.5\}$ corresponding to periods in which the (relative) EPU is at its low levels. Bar graphs depict the sample cross-quantilograms for 60 lags. Red lines depict the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. For negative (positive) values of a sample cross-quantilogram, a bar below (above) the red line leads to a rejection of the null hypothesis of no dependency at a 5 percent level of significance.

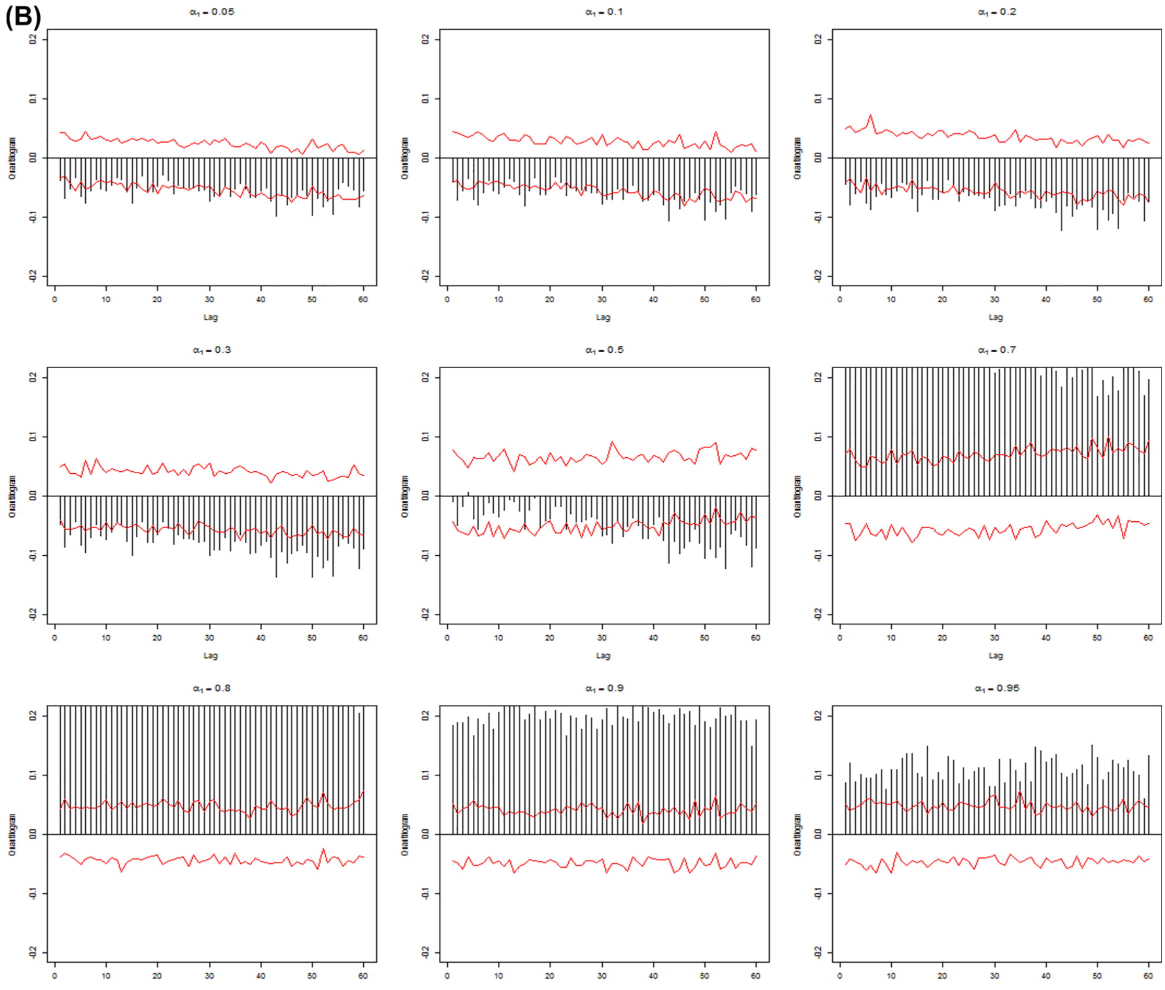

Figure 2: (continued) Figure 2C represents sample cross-quantilograms at various lags and quantiles between monthly UK Pound–US Dollar realized jumps and the (relative) EPU. As for monthly UK Pound-US Dollar volatility jumps, nine quantiles are considered, in which $\alpha_1 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95\}$ corresponding to periods when UK Pound–US Dollar realized jumps are at their low ($\alpha_1 \in \{0.05, 0.1, 0.2\}$), median $\alpha_1 \in \{0.3, 0.5, 0.7\}$) and high levels $\alpha_1 \in \{0.8, 0.9, 0.95\}$). As for the (relative) EPU, one quantile is considered where $\alpha_2 \in \{0.9\}$, corresponding to periods in which the (relative) EPU is at its high levels. Bar graphs depict the sample cross-quantilograms for 60 lags. Red lines depict the 95% bootstrap confidence intervals for 2,000 bootstrap iterations. For negative (positive) values of a sample cross-quantilogram, a bar below (above) the red line leads to a rejection of the null hypothesis of no dependency at a 5 percent level of significance.

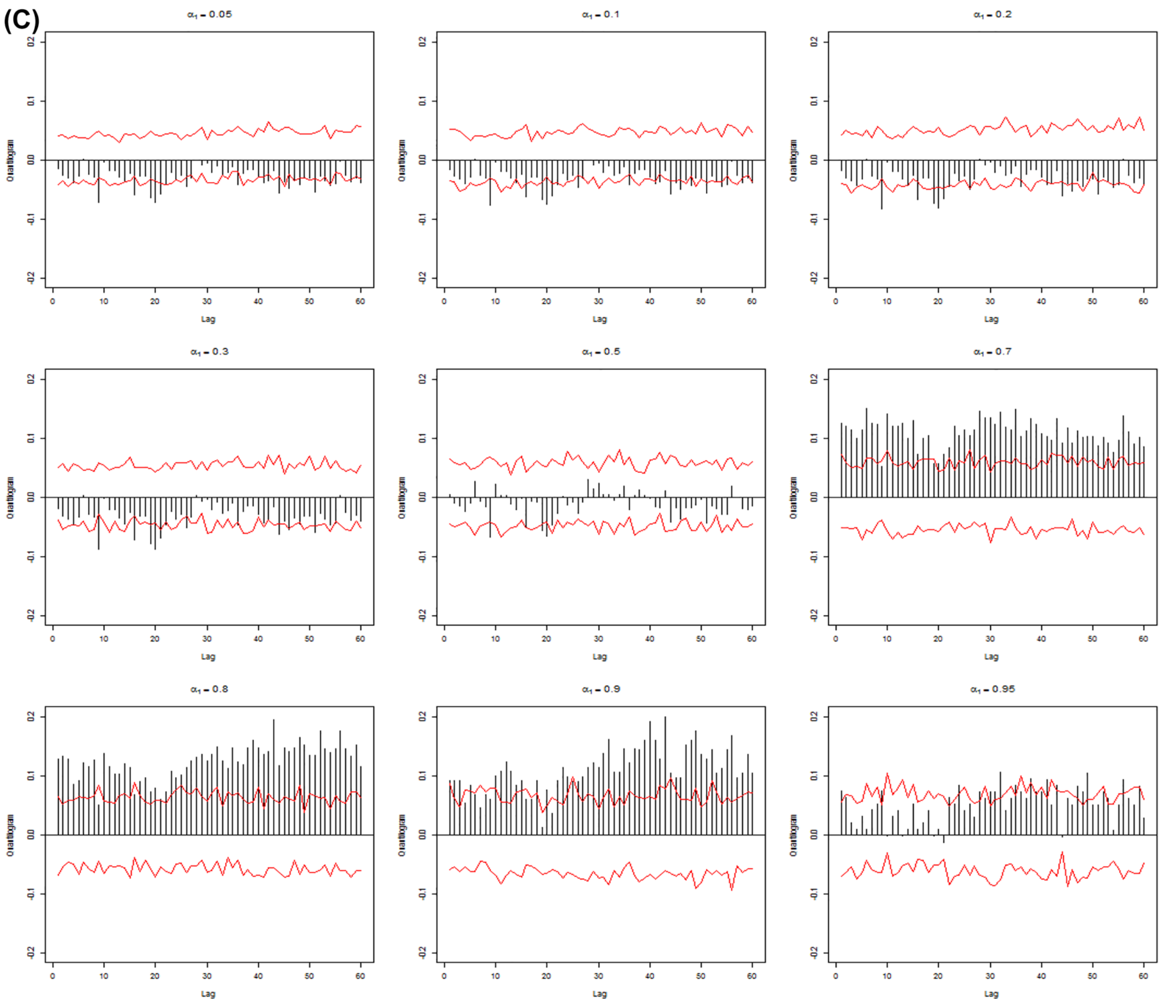

Figure 2: (continued)

of the EPU in the prediction of jumps not only in periods of high uncertainty but also close to ordinary market conditions (i.e. with jumps being at their lower quantiles).

Following Han et al. (2016), we investigate the finite-sample performance of the Box–Ljung test statistics based on a stationary bootstrap procedure. We report these results in Figures 3A–3C. Figures 3A–3C represents the Box–Ljung test statistics between jumps and the EPU again at various lags and quantiles arising from the sample cross-quantilograms in Figures 2A–2C. As for jumps, we also consider nine quantiles, while as regards the EPU, we consider three quantiles. Red lines stand for the 95 percent bootstrap confidence intervals centered at zero for 2000 bootstrap iterations. Figures 3A–3C clearly indicates that there is predictability from the EPU to jumps.[7]

7 We also re-estimated our cross-quantilogram model using the real-GDP weighted sum of the UK and the US EPUs and obtained qualitatively similar results for both the quantile dependencies and the Box–Ljung test statistics. Complete results are reported in an Online appendix.

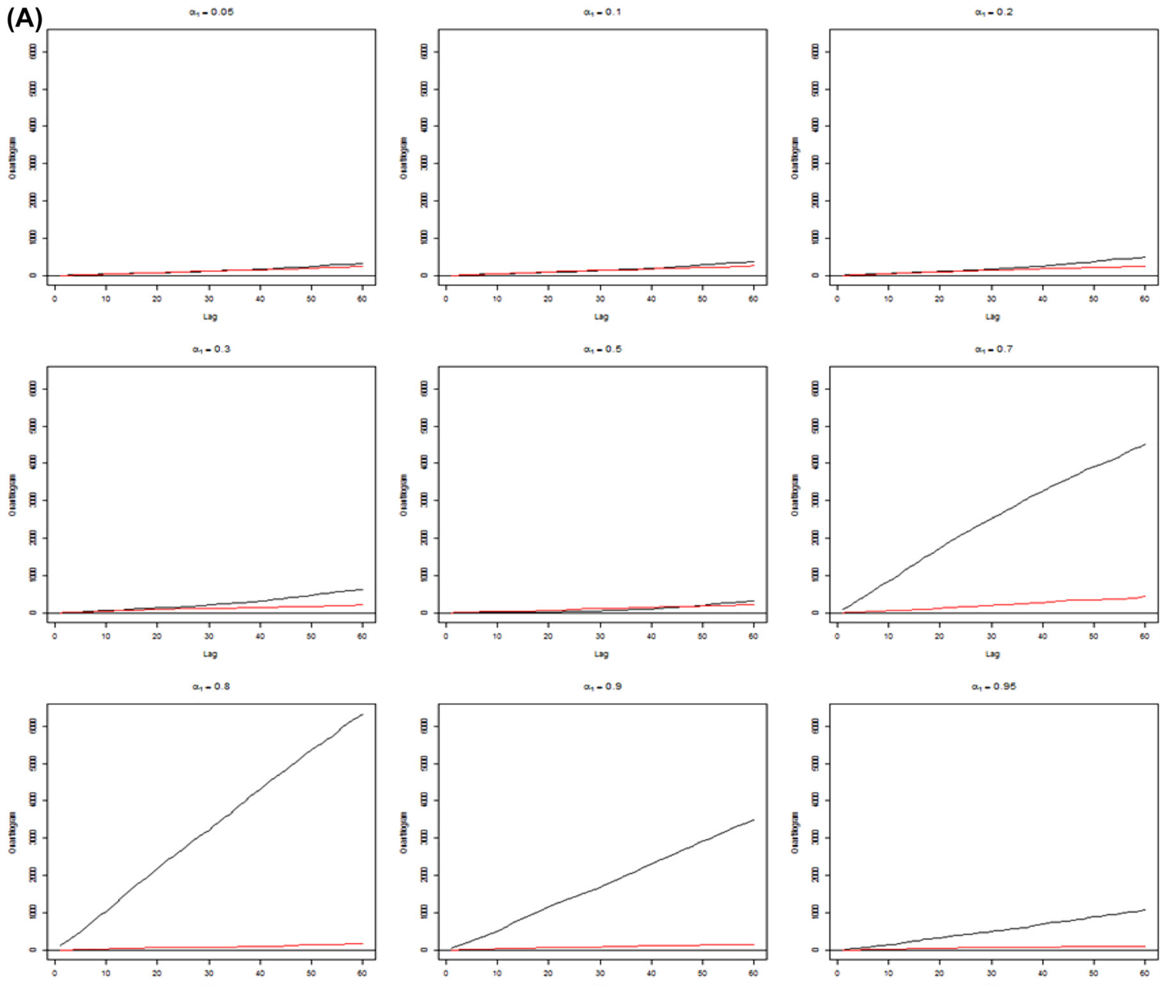

Figure 3: A) Estimation results for the Box–Ljung test statistic between monthly UK Pound–US Dollar realized jumps and the (relative) EPU when the (relative) EPU is at its low levels. B) Estimation results for the Box-Ljung test statistic between monthly UK Pound–US Dollar realized jumps and the (relative) EPU when the (relative) EPU is at its median levels. C) Estimation results for the Box-Ljung test statistic between monthly UK Pound–US Dollar realized jumps and the (relative) EPU when the (relative) EPU is at its high levels.

Figure 3A represents the Box–Ljung test statistics between monthly UK Pound–US Dollar realized jumps and the (relative) EPU at various lags. Quantiles arise from the sample cross-quantilograms in Figure 2A. As for monthly UK Pound–US Dollar jumps, nine quantiles are considered, in which $\alpha_1 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95\}$ corresponding to periods when UK Pound–US Dollar realized jumps are at their low ($\alpha_1 \in \{0.05, 0.1, 0.2\}$), median $\alpha_1 \in \{0.3, 0.5, 0.7\}$) and high levels $\alpha_1 \in \{0.8, 0.9, 0.95\}$). As for the (relative) EPU, one quantile is considered where $\alpha_2 \in \{0.1\}$ corresponding to periods in which the (relative) EPU is at its low levels. Red lines stand for the 95% bootstrap confidence intervals centered at zero for 2, 000 bootstrap iterations.

Figure 3B represents the Box–Ljung test statistics between monthly UK Pound–US Dollar realized jumps and the (relative) EPU at various lags. Quantiles arise from the sample cross-quantilograms in Figure 2B. As for monthly UK Pound–US Dollar jumps, nine quantiles are considered, in which $\alpha_1 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95\}$ corresponding to periods when UK Pound–US Dollar realized jumps are at their low ($\alpha_1 \in \{0.05, 0.1, 0.2\}$), median $\alpha_1 \in \{0.3, 0.5, 0.7\}$) and high levels $\alpha_1 \in \{0.8, 0.9, 0.95\}$). As for the (relative) EPU, one quantile is considered where $\alpha_2 \in \{0.5\}$ corresponding to periods in which the (relative) EPU is at its median levels. Red lines stand for the 95% bootstrap confidence intervals centered at zero for 2, 000 bootstrap iterations.

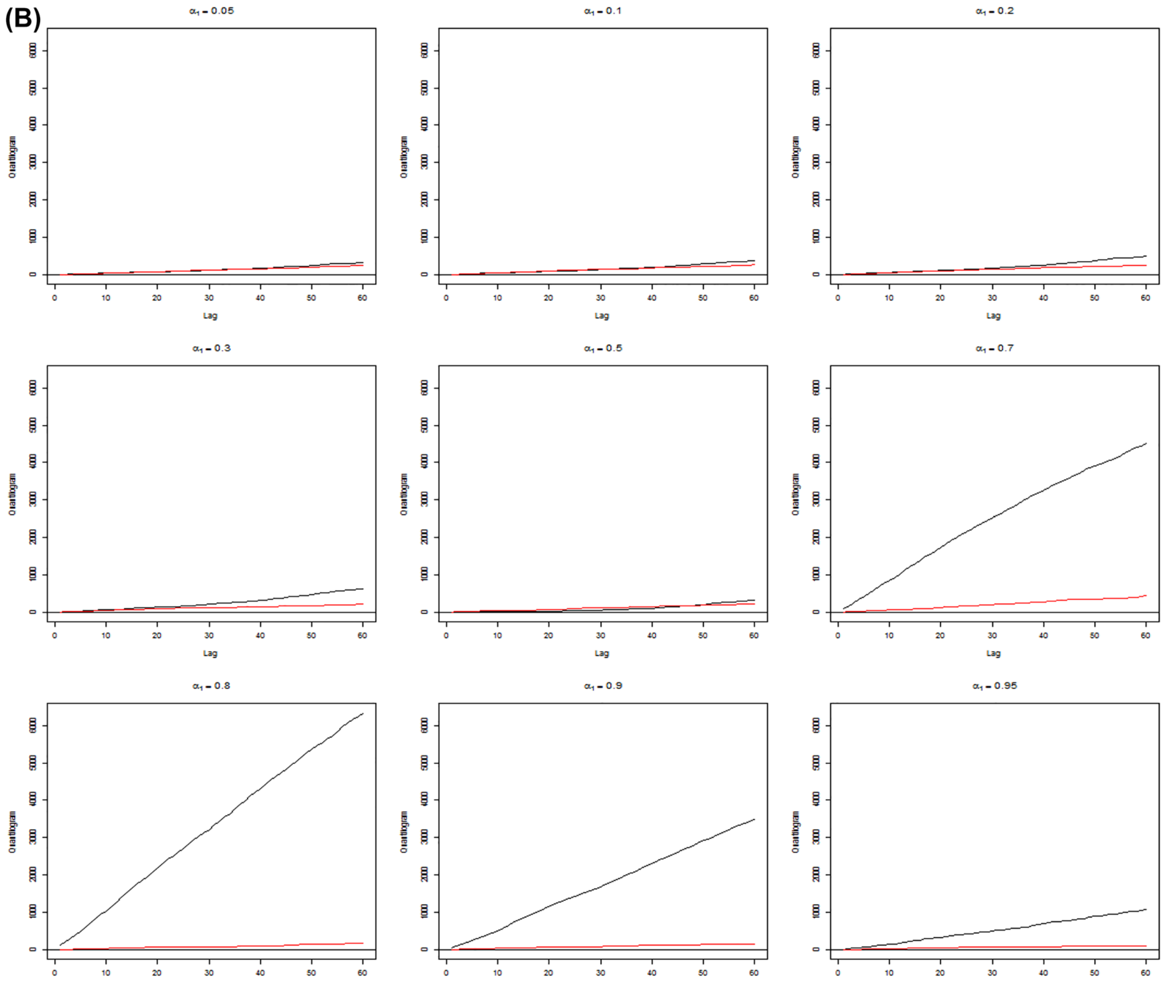

Figure 3: (continued) Figure 3C represents the Box–Ljung test statistics between monthly UK Pound–US Dollar realized jumps and the (relative) EPU at various lags. Quantiles arise from the sample cross-quantilograms in Figure 2C. As for monthly UK Pound–US Dollar jumps, nine quantiles are considered, in which $\alpha_1 \in \{0.05, 0.1, 0.2, 0.3, 0.5, 0.7, 0.8, 0.9, 0.95\}$ corresponding to periods when UK Pound–US Dollar realized jumps are at their low ($\alpha_1 \in \{0.05, 0.1, 0.2\}$), median $\alpha_1 \in \{0.3, 0.5, 0.7\}$) and high levels ($\alpha_1 \in \{0.8, 0.9, 0.95\}$). As for the (relative) EPU, one quantile is considered where $\alpha_2 \in \{0.9\}$ corresponding to periods in which the (relative) EPU is in its high levels. Red lines stand for the 95% bootstrap confidence intervals centered at zero for 2, 000 bootstrap iterations.

(C)

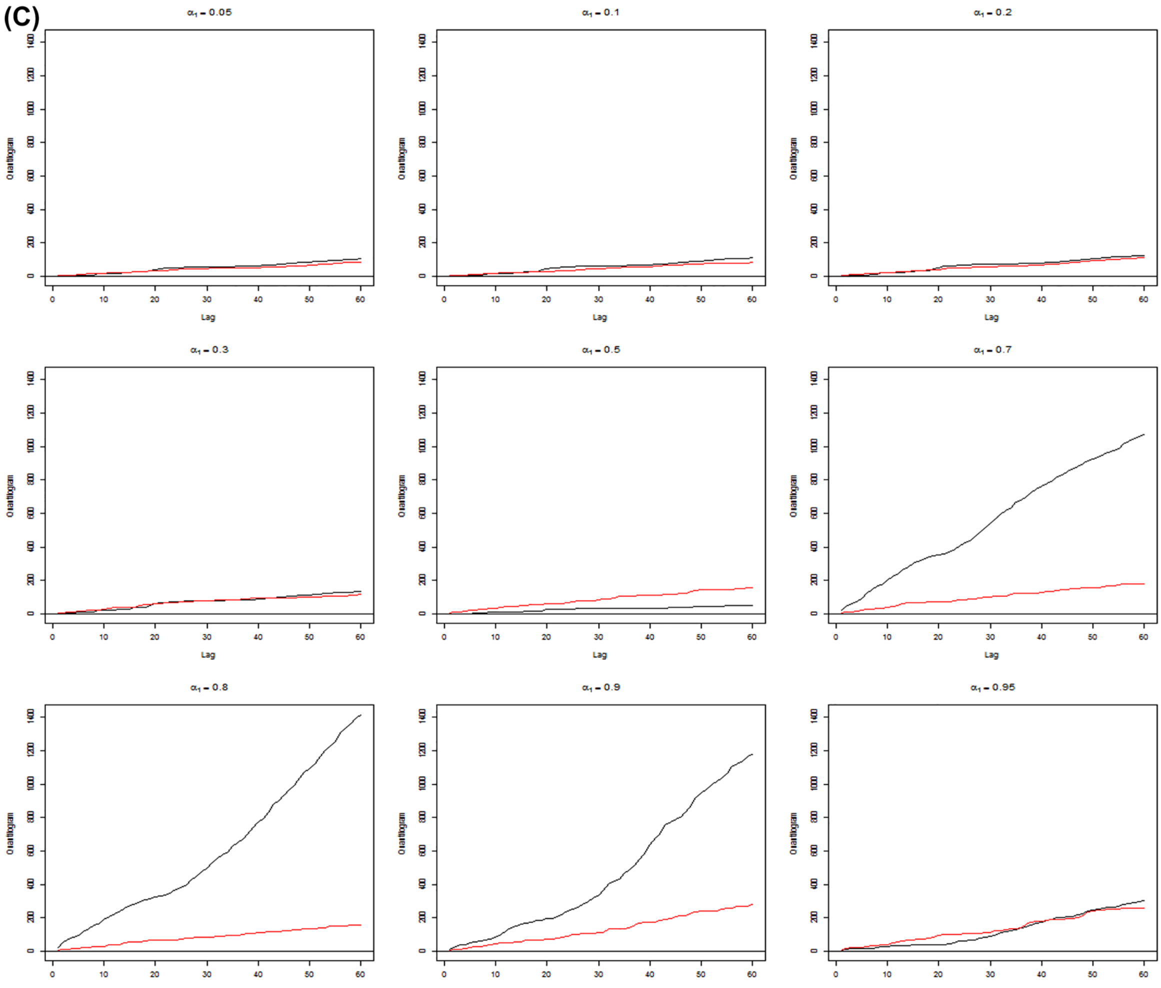

Figure 3: (continued)

6 Conclusions

In this paper, our objective is to provide a rigorous answer to the question of whether the amplification of economic uncertainty can cause an increase in discontinuous movements in the market, also known as jumps. Apparently, these consequences ensue various implications for policymaking. Therefore, many studies have been conducted trying to model and provide a better econometric understanding of the causes behind such discontinuity, based on national macro-economic or financial variables. We contribute to this issue by analyzing the role of economic uncertainty by predicting jumps in the pound-dollar exchange rate. Our dataset covers over a century of data (the longest possible available), spanning from the 2nd of January 1900 to the 31st of May 2018, incorporating various markets phases, such as booms and crashes. Such a dataset enables us to avoid sample-specific results, as observed in the existing literature, which is generally restricted to a decade of data or slightly more than that.

Our analysis unfolds following methodological steps. First, we apply the standard linear causality test which failed to detect any evidence of uncertainty causing jumps. To better evaluate this result, we further investigate the data structures used in our study. To this end, we employ Brock et al. (1996) test for nonlinearity (BDS test), on the residuals arising from a regression between jumps and the EPU. Our findings reveal strong evidence of nonlinearity in the relation of the series used. We also use the powerful *UD*max and *WD*max tests proposed by Bai and Perron (2003) to capture structural breaks in the relation between jumps and the EPU. By applying these tests, we find there are several breakpoints. These results further support the lack of predictability using the linear Granger causality. We indicate that the linear Granger causality test results cannot be reliable as several formal tests show strong evidence of nonlinearity and structural breaks in the relation between jumps and uncertainty. Second, we apply a robust to misspecification method, namely causality-in-quantiles, proposed by Jeong, Härdle, and Song (2012). Being a (nonparametric) data-driven method, causality-in-quantiles enables us to capture nonlinear dynamic causal effects between two-time series far away from the center of the distribution. We detect overwhelming evidence rejecting the null hypothesis that economic uncertainty does not cause jumps over the entire conditional distribution of jumps. Consequently, by controlling misspecification due to nonlinearity and regime changes, indeed economic uncertainty can trigger discontinuous movements in the market, irrespective of the (conditional) size of such jumps. These results are robust, by performing several robustness checks i.e. (i) we incorporate alternative measures of uncertainty, (ii) we estimate jumps at daily frequency using shorter-samples of intraday data, and (iii) we consider other exchange rates of international interest, such as the dollar-based exchange rates of Canada, the Euro area and Japan.

In sum, recalling the dominance of jumps in the currency market, our results suggest that the transmission channel through uncertainty affects jump variation which in turn can be associated with bad volatility. In other words, discontinuous exchange rate movements – which are much more difficult to predict – as they are driven primarily by the economic uncertainty are affected by the state of the economy providing further consequences for currency risk management. Such evidence has profound implications for multinational managers and business practitioners who weigh operational decisions under periods of high exchange variability. With jumps being the source of non-diversifiable risk, heightened uncertainty in the domestic economy relative to the foreign country would cause investors to demand large jump risk premia to carry such types of risks. Finally, as deduced by our analysis, policymakers who must make decisions in real-time during times of jump-inducing chaotic conditions in currency markets must aim to reduce policy-related uncertainty by being transparent in their communication about their policy decisions.

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Conflict of interest statement: The authors declare no conflicts of interest regarding this article.

Appendix A: Cross-quantilograms

This appendix provides an overview of the nonparametric quantile-based approach proposed by Han et al. (2016). As already mentioned, this procedure enables us to detect directional predictability between two-time series contemporarily (e.g. from the EPU to jumps) at different quantiles and lags. In this appendix, let y_t be the dependent variable which stands for jumps, while x_t stands for the predictor variable, that is, the EPU. Both series are strictly stationary.

In particular, the sample cross-quantilogram for positive values of $k = 0, \pm1, \pm2, \ldots$, which corresponds to the number of lags considered, is given by:

$$\hat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{N} \Psi_{\alpha_1}\left(y_t - \hat{q}_{1,t}(\alpha_1)\right) \Psi_{\alpha_2}\left(x_{t-k} - \hat{q}_{2,t-k}(\alpha_2)\right)}{\sqrt{\sum_{t=k+1}^{N} \Psi^2_{\alpha_1}\left(y_t - \hat{q}_{1,t}(\alpha_1)\right)}\sqrt{\sum_{t=k+1}^{N} \Psi^2_{\alpha_2}\left(x_{,t-k} - \hat{q}_{2,t-k}(\alpha_2)\right)}} \tag{A.1}$$

where $\hat{q}_{1,t}(\alpha_1)$ stands for the unconditional sample of the y_t time-series (i.e. jumps), while $\hat{q}_{2,t}(\alpha_2)$ stands for the unconditional sample of x_t time-series (i.e. the EPU). By construction, $\hat{\rho}_\alpha(k) \in [-1, 1]$. The case that $\hat{\rho}_\alpha(k)$ is equal to 0 refers to the case of no directional predictability from the EPU to jumps. The case that $\hat{\rho}_\alpha(k)$ is either equal to +1 or−1 refers to the case of total positive or negative predictability, respectively.

We also make use of the quantile version of the Ljung-Box-Pierce test statistic to construct the null hypothesis H_0: $\rho_\alpha(k) = 0$ against the alternative hypothesis H_1: $\rho_\alpha(k) \neq 0$, for all $k \in 1, \ldots, p$. The quantile version of the Ljung–Box–Pierce test statistic is given by:

$$\hat{Q}_\alpha^{(p)} = \frac{\mathrm{N}(\mathrm{N}+2)\sum_{k=1}^{p} \hat{\rho}_\alpha^2(k)}{(\mathrm{N}-k)} \tag{A.2}$$

where $\hat{Q}_\alpha^{(p)}$ is a portmanteau test of the directional predictability from the EPU to jumps. We carry out this test by taking into account lags up to p order for each pair of quantiles denoted by $\alpha = (\alpha_1, \alpha_2)$. Han et al. (2016) showed that in the case of the null hypothesis which presupposes a lack of directional predictability, the asymptotic null distribution of cross-quantilograms is subject to nuisance parameters. In order to surmount this obstacle, they used the stationary bootstrap method of Politis and Romano (1994) to approximate the null distribution and thus conduct statistical inferences constructing critical values. Contrary to the usual bootstrap resampling, this method helps to address serial dependence in the data series, as it allows random block lengths to be stationary.

Appendix B: Simulation analysis

This appendix provides a simulation analysis to determine the finite sample performance of the jump detection scheme described in Subsection 3.1. In particular, we conducted a small-scale Monte Carlo study that simulates a jump-diffusion process as described in Meucci (2005) in a daily frequency of prices; as the literature suggests (Bollerslev, Gibson, and Zhou 2011, among others).

The accuracy of the asymptotic approximations is illustrated by contrasting the results for sample sizes of 25, 50, 100, and 200 observations. The total number of Monte Carlo replications is 500. In the simulation exercise, in line with Li and Xiu (2016), we retrieve simulated monthly realized volatilities from daily returns as Bollerslev, Gibson, and Zhou (2011) did, and we detect jumps using the method presented in Section 3. These authors found that the use of realized volatilities from daily returns generally results in a larger bias and noticeable lower efficiency. Indeed, we find similar patterns in our simulation analysis. Specifically, in our case, the bias was equal to 8.3640% considering 25 observations, 6.4340% for 50 observations, 5.8140% for 100 observations, and 5.5660% for 200 observations. Such evidence makes jumps series acceptable for the purposes of the analysis of our paper as suggests that the estimated monthly realized volatility series inherit informational content.

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