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Konstantinos Gkillas
University of Patras
Rangan Gupta
University of Pretoria
Dimitrios Vortelinos
University of Lincoln
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Department of Economics
University of Pretoria
0002, Pretoria
South Africa
Tel: +27 12 420 2413

Uncertainty and Volatility Jumps in the Pound-Dollar Exchange Rate: Evidence from Over One Century of Data

Konstantinos Gkillas[*], Rangan Gupta[**] and Dimitrios Vortelinos[***]

Abstract

In this paper, we analyse the role of economic uncertainty, in predicting volatility jumps in the pound-dollar exchange rate over the monthly period of 1900:02 to 2018:05, with the jumps computed using daily data over the same period. Standard linear Granger causality test fail to detect any evidence of uncertainty causing volatility jumps. But given strong evidence of nonlinearity and structural breaks between jumps and economic uncertainty, we next use a nonparametric causality-in-quantiles test, given the misspecification of the linear model. Using this data-driven robust approach, we detect overwhelming evidence of uncertainty causing volatility jumps of the dollar-pound exchange rate over its entire conditional distribution, with the strongest effect observed at the lowest considered conditional quantile. In addition, our results are, in general, found to be robust to alternative measures of uncertainty, jumps generated at daily frequency based on shorter-samples of intraday data, and across three other dollar-based exchange rates.

Keywords: Exchange Rates, Volatility Jumps, Uncertainty.
JEL Codes: C22, F31.

1. Introduction

The foreign exchange market is the largest and most liquid financial market in the world. As reported in the Triennial Survey of global foreign exchange market volumes of the Bank for International Settlement (BIS), the average daily turnover was 5.1 trillion of U.S. dollars in April of 2016. Currency markets tend to be volatile and, with traders reacting to new information, exhibit periods of volatility clustering. Accurate prediction of exchange rate volatility is important to multinational firms, financial institutions and traders aiming to hedge currency risks. Traders of foreign currency options look to make profits by buying (selling) options if they expect volatility to rise above (fall below) of what is implied in currency option premiums. In addition, a large body of theoretical research has linked exchange rate volatility to trade and welfare (Clark et al., 2004). In sum, prediction of volatility is a key element in terms of portfolio selection, option pricing, risk management, and policy decisions. Hence, it is not surprising that a vast methodological and empirical literature exists around the development, assessment and application of exchange rate volatility predictions (see for example, Rapach and Strauss (2008), Babikir et al. (2012) and Pilbeam and Langeland (2015) for detailed reviews).

[*] Corresponding author. Department of Business Administration , University of Patras, University Campus, Rio, P.O. Box 1391, 26500 Patras, Greece. Email: gillask@upatras.gr or gillask@gmail.com.
[**] Department of Economics, University of Pretoria, Pretoria, 0002, South Africa. Email: rangan.gupta@up.ac.za.
[***] Lincoln Business School, University of Lincoln, Lincoln, UK. E-mail: dvortelinos@lincoln.ac.uk.

In this regard, it is also important to point out that, currency market participants care not only about the nature of volatility, but also about its level, with all traders making the distinction between good and bad volatilities (Giot et al., 2010). Good volatility is directional, persistent and relatively easy to predict, while, bad volatility is jumpy and comparatively difficult to foresee. Therefore, good volatility is generally associated with the continuous and persistent part, while bad volatility captures the discontinuous and jump component of volatility. Given this, it has been stressed that modeling jumps can improve the overall fit of volatility models (Caporin et al., 2016; Gkillas et al., 2018). Understandably, a large literature has been developed trying to not only model exchange rate jumps, but also explain the causes behind such jumps based on macroeconomic and financial variables (see for example, Li et al., (2013), Chan et al., (2014), Chatrath et al., (2014), Frömmel et al., (2015), and Lee and Wang (2016)).

Against this backdrop, our paper aims to add to the literature on the drivers of exchange rate volatility jumps by analysing for the first time, the predictive ability of a (news-based measure) of (relative) economic uncertainty. In this regard, recent studies by Colombo (2013), Krol (2014), Sin (2015), Balcilar et al., (2016), Kido (2016), Kurasawa (2016), Dai et al., (2017), Simo-Kengne et al., (2018) and Christou et al., (forthcoming) for example, have related exchange rate returns and volatility to economic uncertainty, realizing the fact that financial assets are functions of the state of the economy, which in turn are subject to fluctuations caused by uncertainty, as indicated by Martin and Urrea (2007) and Benigno et al., (2012) based on new Keynesian general equilibrium frameworks. Note that, with uncertainty affecting macroeconomic and financial variables, as widely empirically verified (see for example, Kang and Ratti (2013), Uribe et al., (2017), Chuliá et al., (2017), Castelnuovo et al., (2017), Phan et al., (2018) and Gupta et al., (forthcoming a, b)), one could associate uncertainty to be the underlying reason behind the movements of these variables, which in turn, have been so far related with volatility jumps of the currency market, as pointed out above. In other words, movements in economic uncertainty encompass the information content in the variability of macroeconomic and financial variables associated with volatility jumps in the exchange rate markets.

For our predictability analysis, we rely on the nonparametric causality-in-quantiles test of Jeong et al., (2012), and hence, in the process capturing various phases (sizes) of volatility jumps of the UK pound to US dollar exchange rate covering over a century of (longest possible available) monthly data (1900:02-2018:05). 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 volatility jumps series is generated) and uncertainty data, to help us track historical volatility jumps. In the process of using the longest possible data on volatility jumps, we avoid our results from being sample-specific, like the above-mentioned studies, which in general, covers a decade or slightly more of data. It must be noted however, that these studies compute volatility jumps at daily frequency based on intraday data, something which we also do as part of our robustness analyses.

Understandably, the causality-in-quantiles test used here is inherently a time-varying approach as various parts of the conditional distribution of volatility jumps would relate to various points in time associated with the evolution of jumps. The causality-in-quantile approach has the following two main novelties: First, it is robust to misspecification errors as it detects the underlying dependence structure between the examined time series in a nonparametric fashion, which in turn, is particularly important as we show that volatility jumps are nonlinearly associated with the uncertainty. And second, using this methodology, we are able to test not only for nonlinear causality-in-mean (1st moment) (see for example, Heimstra and Jones, 1994; Diks and Panchenko, 2005, 2006), but also for causality that may exist in the tails of the joint distribution of the variables. This is again of tremendous importance since our dependent variable, i.e., volatility jumps is shown to have fat-tails.

The remainder of the paper is organized as follows: Section 2 provides some initial information regarding realized volatility and jumps. Section 3 lays out the basics of the econometric methodologies involving volatility jumps and the causality-in-quantiles approach; Section 4 presents the data and results, with Section 5 concluding the paper.

2. Theoretical backround

Volatility is the second moment of the price process of a financial time series and quantifies the dispersion risk. Its evolution is time-varying and latent. Implied volatility is considered as an efficient forecast of the latent volatility. It requires a rational expectations assumption that the market option price reveals the market's true volatility estimate, however (Latane and Rendleman, 1976). In real options valuation, Schwartz (1997) emphasizes in the importance of pricing uncertainties/risks. The most common ways of volatility estimation are either parametric or non-parametric. 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 depend on similar assumptions, imposing similar restrictions and conditions on the price process.

The concept of non-parametric volatility estimates was introduced in Merton (1980). Andersen and Bollerslev (1998) were the first to suggest that the realized volatility estimation is consistent estimate of the actual volatility, using the theory of quadratic variation. Monthly realized variance is highly predictable and useful for risk management and asset allocation purposes (Barosso and Santa-Clara, 2015). French et al. (1987), Schwert (1989, 1990a, b) and Schwert and Seguin (1991) introduced the construction of realized volatility estimates, based on 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 estimated with the use of daily returns as in Christensen and Hansen (2002) and Barroso and Santa-Clara (2015), among others. Degiannakis et al. (2014) and Kang et al. (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, hereafter ABD), among others. This form, and not the realized volatility in levels, passes all tests for structural stability. The logarithmic standard deviation of realized volatility follow a close-to Gaussian distribution, as the Jarque-Bera test and sample-quantiles based Cramer-Von Mises test indicate. These results are consistent to the monthly realized volatility literature (see Thomakos and Koubouros, 2011, among others). The asymptotics is reliable for the logarithmic transform of realized volatility, when twelve or more observations are employed to produce one-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) in 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 modelling and forecasting, as they can be approximated by Inverse Gaussian distributions, under temporal aggregation (Barndorff-Nielsen and Shephard (2002)).

Furthermore, literature provides evidence that the assumption of a continuous diffusion is violated. Volatility asymmetries indicated the need for a more detailed description of the volatility process (Black, 1976). ABD introduced a jump detection non-parametric scheme for realized volatility, building on the theoretical results in 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). In their turn, they proved that the conception of realized bipower variation and jumps applies to finite number of observations and a fixed interval of time; whether it is a trading day or a calendar month (see equation 1, Barndorff-Nielsen and Shephard (2004b)). The explanatory power of the monthly jump components of realized volatility is compatible to implied volatility, in encompassing regressions (Giot and Laurent (2007)). Jump diffusion parameters can also be important in pricing and analyzing 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 et al. (2010), Duong and Swanson (2015), and Degiannakis and Filis (2017) researched such importance. They all employed the HAR-RV base model with incorporation of jumps series. Most of the studies reveal the importance of monthly jumps series in modeling and/or forecasting daily realized volatility. Others (e.g. Liu et al. (2018)) provide evidence of their significance in monthly realized volatility forecasting as well.

3. Econometric Methodologies

3.1. Volatility Jumps

French et al. (1987), Schwert (1989, 1990a, b) and Schwert and Seguin (1991) introduced the construction of realized volatility estimates, based on daily returns.[1] Campbell et al. (2001) were the first to employ various 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.

We employ daily log returns of the pound-dollar exchange rate to estimate the monthly realized volatility RV_t. In each month t, we retrieve a monthly point estimate of the RV_t by employing all daily returns. We calculate monthly volatility by the realized volatility, RV_t, which is the benchmark realized volatility measure:

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

where $r_{i,t}$ is the daily return for day i within month t and $i = 1, \dots T$, where T is the total number of daily observations within a month.

The asymptotic results of Barndorff-Nielsen and Shephard (2004b) allow for the non-parametric distinction between the two components (continuous and jump) of the quadratic

[1] As the sampling frequency of financial data available to researchers has been increasing, the notion of realized volatility moved from monthly to daily estimates, however.

variation process. The standardized realized bipower variation has been considered as a jump-robust measure of realized volatility:

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

where $\mu_1 \equiv \sqrt{2/\pi} = E\left(| Z |\right)$ denotes the mean of the absolute value of standard normally distributed random variable $\left(Z\right)$. The integrated quarticity can be consistently estimated by the standardized realized tri-power quarticity measure:

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

where $\mu_{4/3} \equiv 2^{2/3} \cdot \Gamma\left(7/6\right) \cdot \Gamma\left(1/2\right)^{-1} = E\left(| Z |^{4/3}\right)$. The log-version of the jump statistic, as employed here, is:

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

We use the logarithmic transformation of the ABD jumps statistic. ABD in an earlier version of their paper found no difference between the plain jumps statistic and its logarithmic transformation. Significant jumps (***JUMPS***) are identified under the following condition:

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

where denotes the indicator function. The continuous component is:

$$C_{t,a} \equiv I\left[U_t \leq \Phi_a\right] \cdot \log\left(RV_t\right) \tag{6}$$

where $\log\left(RV_t\right) \equiv J_{t,a} + C_{t,a}$. The non-negativity of both components corresponds directly to a significance level of $a = 0.5$ (ABD).The explanatory power of the monthly jump components of realized volatility is compatible to implied volatility, in encompassing regressions (Giot and Laurent (2007)).

3.2. Causality-in-Quantiles

This sub-section provides a brief description of the quantile based methodology based on the framework of Jeong et al. (2012). As mentioned earlier, this approach is robust to extreme values in the data and captures general nonlinear dynamic dependencies. Let y_t denote volatility jumps and x_t denote the predictor variable, in our case the relative uncertainty, i.e., economic uncertainty of the UK relative to that of the US (discussed in detail in the Data segment of the paper). Since exchange rate is a relative variable, it makes perfect sense to also use the uncertainty in its relative form (Balcilar et al., 2016).

Formally, let $Y_{t-1} \equiv (y_{t-1},...,y_{t-p})$, $X_{t-1} \equiv (x_{t-1},..., x_{t-p})$, $Z_t = (X_t, Y_t)$ and $F_{y_t|Z_{t-1}}(y_t, Z_{t-1})$ and $F_{y_t|Y_{t-1}}(y_t, Y_{t-1})$ denote the conditional distribution functions of y_t given Z_{t-1} and Y_{t-1}, respectively. If we denote $Q_\theta(Z_{t-1}) \equiv Q_\theta(y_t \mid Z_{t-1})$ and $Q_\theta(Y_{t-1}) \equiv Q_\theta(y_t \mid Y_{t-1})$, we have $F_{y_t|Z_{t-1}}\{Q_\theta(Z_{t-1}) \mid Z_{t-1}\} = \theta$ with probability one. Consequently, the (non)causality in the θ-th quantile hypotheses to be tested can be specified as:

$$H_0: \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} = 1, \tag{7}$$

$$H_1: \quad P\{F_{y_t|Z_{t-1}}\{Q_\theta(Y_{t-1}) \mid Z_{t-1}\} = \theta\} < 1. \tag{8}$$

Jeong et al. (2012) employ the distance measure $J = \{\varepsilon_t E(\varepsilon_t \mid Z_{t-1}) f_z(Z_{t-1})\}$, where ε_t is the regression error term and $f_z(Z_{t-1})$ is the marginal density function of Z_{t-1}. The regression error ε_t emerges based on the null hypothesis in (1), which can only be true if and only if $E[1\{y_t \le Q_\theta(Y_{t-1}) \mid Z_{t-1}\}] = \theta$ or, equivalently, $1\{y_t \le Q_\theta(Y_{t-1})\} = \theta + \varepsilon_t$, where $\mathbf{1}\{\cdot\}$ is an indicator function. Jeong et al. (2012) show that the feasible kernel-based sample analogue of J has the following form:

$$\hat{J}_T = \frac{1}{T(T-1)h^{2p}} \sum_{t=p+1}^{T} \sum_{s=p+1, s\neq t}^{T} K\left(\frac{Z_{t-1} - Z_{s-1}}{h}\right) \hat{\varepsilon}_t \hat{\varepsilon}_s. \tag{9}$$

where $K(\cdot)$ is the kernel function with bandwidth h, T is the sample size, p is the lag order, and $\hat{\varepsilon}_t$ is the estimate of the unknown regression error, which is estimated as follows:

$$\hat{\varepsilon}_t = 1\{y_t \le Q_\theta(Y_{t-1})\} - \theta. \tag{10}$$

$\hat{Q}_\theta(Y_{t-1})$ is an estimate of the θ^{th} conditional quantile of y_t given Y_{t-1}, and we estimate $\hat{Q}_\theta(Y_{t-1})$ using the nonparametric kernel method as

$$\hat{Q}_\theta(Y_{t-1}) = \hat{F}^{-1}_{y_t|Y_{t-1}}(\theta \mid Y_{t-1}), \tag{11}$$

where $\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1})$ is the *Nadarya-Watson* kernel estimator given by

$$\hat{F}_{y_t|Y_{t-1}}(y_t \mid Y_{t-1}) = \frac{\sum_{s=p+1, s\neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right) 1(y_s \le y_t)}{\sum_{s=p+1, s\neq t}^{T} L\left((Y_{t-1} - Y_{s-1})/h\right)}, \tag{12}$$

with $L(\cdot)$ denoting the kernel function and h the bandwidth.

The empirical implementation of causality testing via quantiles entails specifying three important choices: the bandwidth h, the lag order p, and the kernel type for $K(\cdot)$ and $L(\cdot)$ respectively. In this study, we use p=12 based on the Akaike Information Criterion (AIC). The bandwidth value is chosen by employing the least squares cross-validation techniques.[2] Finally, for $K(\cdot)$ and $L(\cdot)$ Gaussian-type kernels was employed.

4. Data and Results

4.1. Data

Daily data on the UK pound relative to the US dollar exchange rate is obtained from the Global Financial Database, covering the period of 2nd January, 1900 to 31st May, 2018 with exchange rate returns are defined as the first-differences of the natural logarithmic values. As shown in the summary statistics of Table A1, the monthly exchange rate volatility jump variable (*JUMPS*) over the period of 1900:02 to 2018:05, derived from daily data, is non-normal due to positive skewness and excess kurtosis and hence, provides an initial motivation to use a quantiles-based method. French et al. (1987) found that the logarithmic monthly standard deviations from daily returns (i.e. monthly realized volatility) is close to Gaussian. 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 short-memory and stationary process.Also, the monthly jumps exhibit less serial dependence than other volatility measures (Andersen et al. (2007), and Busch, Christensen and Nielsen (2011)).

Uncertainty is a latent variable, but, in order to quantify the impact of uncertainty on volatility jumps, one requires ways to measure uncertainty. In this regard, besides the various alternative measures of uncertainty associated with financial markets, such as the implied-volatility indices (popularly called the VIX), realized volatility, idiosyncratic volatility of equity returns, corporate spread associated, primarily three broad approaches to quantify the effect of uncertainty on the economy exists (see Gupta et al., (forthcoming) for a detailed discussion in this regard): (1) A news-based approach, where the main idea is to perform searches of newspapers for terms related to economic and policy uncertainty (EPU) and to use the results of this search to construct measures of uncertainty; (2) Uncertainty measures have also been recovered from estimates of various types of small and large-scale structural models related to macroeconomics and finance. Specifically speaking, the uncertainty measure is the average time-

[2] For each quantile, we determine the bandwidth h using the leave-one-out least-squares cross validation method of Racine and Li (2004) and Li and Racine (2004).

varying variance in the unpredictable component of a large set of real and financial time-series, i.e., it attempts to capture the average volatility in the shocks to the factors that summarize real and financial conditions, and; (3) Finally, estimates of uncertainty has been constructed using information on dispersion of professional forecaster disagreement.

While there exists no clear-cut consensus in terms of which approach to use in constructing measures of uncertainty, the news-based measures of uncertainty, as developed by Baker et al., (2016), seems to have gained tremendous popularity in various applications in macroeconomics and finance. This is most likely due to the fact that creating a measure of uncertainty does not require any complicated estimation of a model to generate it in the first place, and also because the news-based measure of uncertainty for a large number of developed and emerging economies are freely available for download on a regularly updated basis from: www.policyuncertainty.com. In our case, we use the EPU data for the UK and the US, since it is the only available data on uncertainty stretching back to 1900 at monthly frequency.[3] Given that exchange rate is a relative price, we create a relative measure of uncertainty (relative EPU) by subtracting the natural log of US EPU from the natural log of the UK EPU. As observed from Table A1, relative EPU is also non-normal due to positive skeweness and excess kurtosis. A positive average value of the EPU, suggests that on average over our sample period uncertainty in the UK has been higher than that of the US. Figure A1 in the Appendix plots the two variables of our interest: *JUMPS* and relative EPU.[4]

4.2. Empirical Results

Before we discuss the findings from the causality-in-quantiles test, for the sake of completeness and comparability, we first conducted the standard linear Granger causality test, with a lag-length of four, as determined by the AIC. The resulting $\chi^2(12)$ statistic, is found to be 16.6368 with a p-value of 0.1638, suggesting that the null that relative EPU does not Granger cause volatility jumps, cannot be rejected even at the 10 percent level of significance.

Given this evidence of lack of predictability, and realizing the possibility that financial market variables are likely to be nonlinearly related with its predictors, we next statistically examine the presence of nonlinearity and structural breaks in the relationship between *JUMPS* and relative EPU. Nonlinearity and regime changes, if present, would motivate the use of the

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[3] Further details can be found under the following links: 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.

[4] Standard unit root tests reveal that both *JUMPS* and relative EPU are stationary, and hence can be used directly without further transformation in the causality-in-quantiles approach, which in turn requires the variables used in the model to be mean-reverting. Complete details of the unit root tests are available upon request from the authors.

nonparametric quantiles-in-causality approach, as the quantiles-based test would formally address nonlinearity and structural breaks in the relationship between the two variables under investigation. For this purpose, we apply the Brock *et al.,* (1996, BDS) test on the residuals from the jump equation involving twelve lags of *JUMPS* and relative EPU. Table A2 in the Appendix presents the results of the BDS test of nonlinearity. As shown in this table, we find strong evidence, at highest level of significance, for the rejection of the null of *i.i.d.* residuals at various embedded dimensions (*m*), which in turn, is indicative of nonlinearity in the relationship between *JUMPS* and relative EPU. To further motivate the causality-in-quantiles approach, we next used the powerful *UDmax* and *WDmax* tests of Bai and Perron (2003), to detect 1 to *M* structural breaks in the relationship between *JUMPS* and relative EPU, allowing for heterogenous error distributions across the breaks. When we applied these tests again to the jump equation involving twelve lags of *JUMPS* and relative EPU, we detected five breaks at: 1919:12, 1937:07, 1965:04, 1982:11, and 2000:09. These findings indicate that, the result of no-predictability based on the linear Granger causality test, cannot be deemed robust and reliable.

Given the strong evidence of nonlinearity and structural break(s) in the relationship between volatility jumps and relative EPU, we now turn our attention to the causality-in-quantiles test, which is robust to misspecification due to its nonparametric (i.e., data-driven) approach. As can be seen from Column 2 of Table 1, which reports this test for the quantile range of 0.05 to 0.95, the null that relative EPU does not Granger causes *JUMPS* is overwhelmingly rejected at the 1 percent level of significance (given the critical value of 2.575), with the strongest evidence of predictability observed at the lowest quantile of the conditional distribution of *JUMPS*. But more importantly, our results highlight that when we account for nonlinearity and structural breaks using a nonparametric approach, we are able to find strong evidence of predictability emanating from relative EPU onto volatility jumps of the pound-dollar exchange rate, unlike what was observed under the linear framework. To put it alternatively, we observe that relative uncertainty can predict volatility jumps of the pound-dollar exchange rate, irrespective of the (conditional) magnitude of the jumps as captured by the various quantiles of the conditional distribution of *JUMPS*.

To check for the robustness of our results, and to be in line with the existing exchange rate literature (Busch, et al., 2011), we compute daily values of volatility jumps using 5-minutes intraday returns data (obtained from 1-minute price data) on the pound-dollar exchange rate sourced from π-Trading.com,[5] covering the period of 1st of July 2003 to 28th of August, 2015. The sample size is purely driven by the availability of the intraday data. The corresponding news-

[5] The official website being: https://pitrading.com/historical-market-data.html.

based daily relative EPU is again based on the work of Baker et al., (2016).[6] As can be seen again from Table 1 (Column 3), predictability is observed over the conditional distribution ranging between the quantiles of 0.05 to 0.65 at the 1 percent level of significance, and also for the quantile of 0.70 at the 10 percent level (given critical value of 1.645). In other words, unlike the long-span monthly data, causality of relative EPU to volatility jumps is not observed at upper end of the conditional distribution, though the strongest effect is again observed at the lowest quantile.

As a further robustness check, we use an alternative measure of daily relative uncertainty based on dispersion of professional forecaster disagreement as created by Scotti (2016),[7] and repeat the above volatility jumps analysis derived from intraday data over the same period. We again compute a relative measure of uncertainty by subtracting the natural log of US uncertainty from that of the UK. As can be seen from Column 4 of Table 1, the earlier daily results reported in Column 3, carries over under this alternative metric of uncertainty. In this case, predictability is observed over the extended quantile range of 0.05 to 0.70 at the 1 percent level of significance, with quantiles 0.75 and 0.80 also 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 volatility jumps of the Canadian dollar, the euro and the Japanese yen relative to the US dollar. 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. The volatility jumps for these currencies are also obtained based on 5-minute intraday returns data, and again sourced from π-Trading.com. These results have been reported in Columns 5 through 7 of Table 1. As with the case of the UK, we again observe predictability of volatility jumps due to relative uncertainty barring the upper end of the conditional distributions of *JUMPS* of these three additional currencies. In sum, we can say that relative uncertainty does predict volatility jumps, with predictability being strongest at the lower end of the conditional distribution.

[INSERT TABLE 1]

Finally, to get additional insights into the results obtained, we repeat our analysis using the cross-quantilogram approach of Han et al., (2016) for the long-span data set of ours. The cross-quantilogram measures quantile dependence and tests for directional predictability between two time series. Using this approach, as reported in Figures A2(i)-A2(vi), we re-confirm our

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6 The data is downloaded from: http://www.policyuncertainty.com/uk_daily.html and http://www.policyuncertainty.com/us_daily.html for the UK and the US respectively.

7 The data is available for download from: https://sites.google.com/site/chiarascottifrb/data-and-other-materials.

findings. More specifically, there is a statistically significant relationship between relative EPU and *JUMPS*. We also observe that there is positive and statistically significant relation between large *JUMPS* (higher quantiles) and relative EPU. On the other hand, we observe a statistically significant negative relationship between *JUMPS* and relative EPU, at the lower quantiles of the former. The first result means that it is more likely to have large *JUMPS* during periods of high relative EPU. The latter result highlights the importance of relative EPU in prediction of *JUMPS* in period close to normal times (i.e., with *JUMPS* lower quantiles), as the variables are are negatively related even at low levels of relative EPU.

5. Conclusions

In the recent volatility-related literature related to currency markets, it has been stressed that jumps in volatility can improve the overall fit of volatility models. Therefore, a large literature has developed trying to not only model volatility jumps, but also attempting to explain the causes behind such jumps based on macroeconomic and financial variables. Given this, in this paper we analyse the role of economic uncertainty, in predicting volatility jumps of the pound-dollar exchange rate over the monthly period covering over a century of data (1900:02 to 2018:05), with the jumps having been computed based on daily data over the same period. For our predictability analysis, we rely on a nonparametric causality-in-quantiles test, which in turn, is robust to misspecication due to nonlinearity and structural breaks being a data-driven procedure.

Starting off with the standard linear causality test, we were unable to detect any evidence of uncertainty causing volatility jumps. But, we indicate that linear Granger causality test results cannot be relied upon because formal tests reveal strong evidence of nonlinearity and structural breaks between volatility jumps and the measure of economic uncertainty. Hence, linear Granger causality tests are misspecified. When we use the nonparametric causality-in-quantiles test instead, we were able to detect overwhelming evidence rejecting the null hypothesis that uncertainty does not Granger cause jumps over the entire conditional distribution of the latter, with the strongest effect observed at the lowest considered conditional quantile. Thus, our results indicated that when we control for misspecification due to nonlinearity and regime changes, it is indeed true that economic uncertainty can predict movements in volatility jumps of the pound-dollar exchange rate, irrespective of the (conditional) size of such jumps. Our results are, in general, (barring the upper quantiles of the conditional distribution of volatility jumps) robust to alternative measures of uncertainty, jumps generated at daily frequency using shorter-samples of intraday data, and across the dollar-based exchange rates of Canada, the Euro area and Japan. In sum, recalling the dominance of jumps in the volatility process, our results tend to suggest that the channel through which uncertainty affects currency market variance is primarily jumps, i.e., bad volatilities. With jumps being source of non-diversifiable risks, heightened uncertainty in the domestic economy relative to the foreign country would cause investors to demand large premia to carry these risks. Furthermore, 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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Table 1. Results from the Causality-in-Quantiles Test

	Exchange Rate Volatility Jumps					
Quantile	**Monthly UK Pound-US Dollar JUMPS**	**Daily UK Pound-US Dollar JUMPS_1**	**Daily UK Pound- US Dollar JUMPS_2**	**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

Note: ***, ** and * indicate the rejection of the null hypothesis of no-Granger causality from relative uncertainty to various volatility jumps for various quantiles at 1 percent, 5 percent and 10 percent levels of significance respectively, with the critical values being 2.575, 1.96 and 1.645 respectively. The second (third) column corresponds to results for monthly (daily) volatility jumps based on relative EPU, while results in columns 4 through 7 is that of daily volatility jumps based on the relative uncertainty, with uncertainty being measured by dispersion of professional forecaster disagreement.

APPENDIX:

Table A1. Summary Statistics

	Variable	
Statistic	*JUMPS*[a]	Relative EPU
Mean	5.79e-05	0.2324
Median	2.16e-06	0.1695
Maximum	0.0033	5.3959
Minimum	5.77e-10	-1.3102
Std. Dev.	0.0002	0.7559
Skewness	11.1206	1.8923
Kurtosis	157.9517	10.0713
Jarque-Bera	777003.4001	3805.9530
p-value	0.0000	0.0000
Observations	1420	

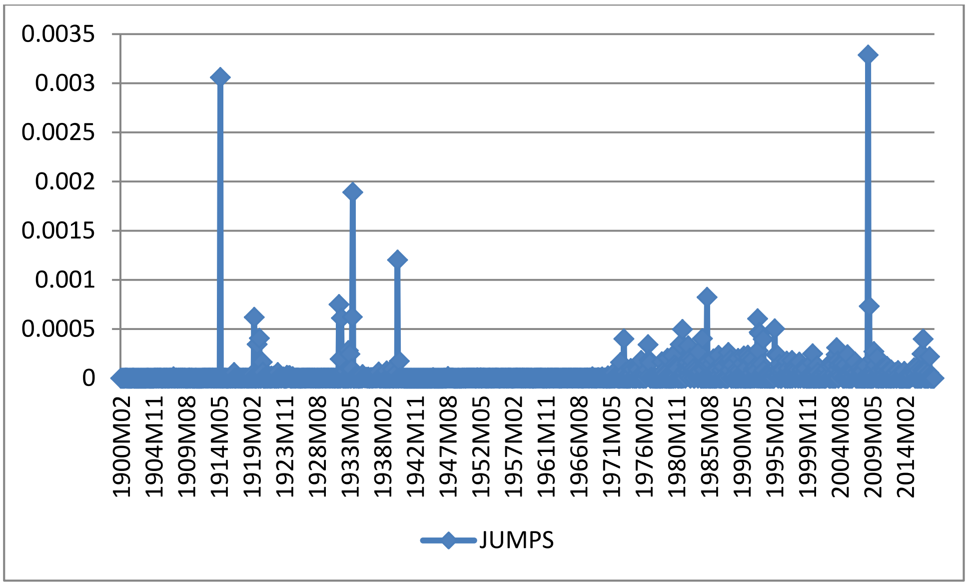
Note: Std. Dev: stands for standard deviation; *p*-value corresponds to the Jarque-Bera test with the null of normality. [a] We provide descriptive statistics only for the significant *JUMPS*.

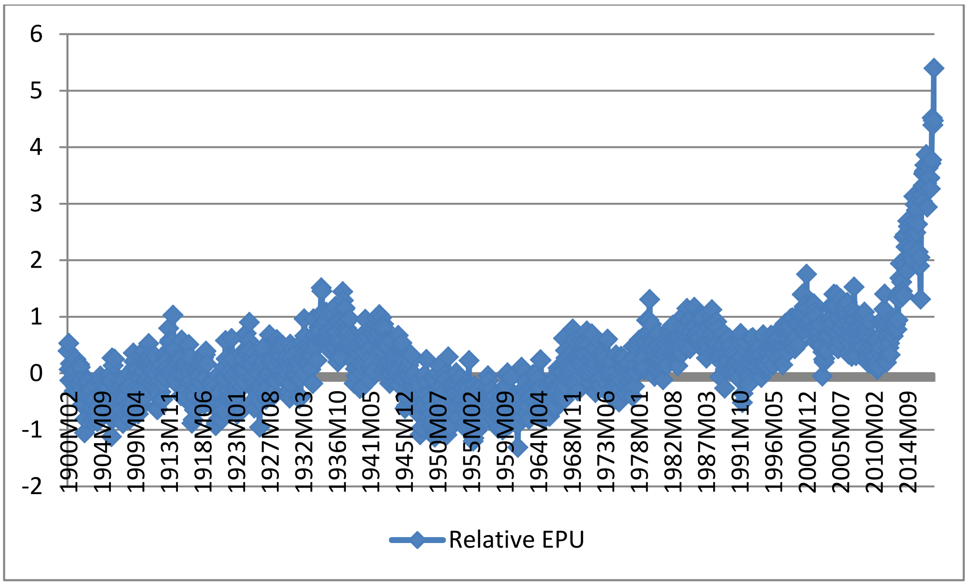
Table A2. Brock et al., (1996, BDS) Test of Nonlinearity

Independent Variable	*m*				
	2	3	4	5	6
Relative EPU	13.0029***	16.4635***	19.1773***	21.8845***	25.1611***

Note: Entries correspond to the *z*-statistic of the BDS test with the null of *i.i.d.* residuals, with the test applied to the residuals recovered from the jump equation with twelve lags each of *JUMPS* and the relative EPU; *** indicates rejection of the null hypothesis at 1 percent level of significance.

Figure A1. Data Plots





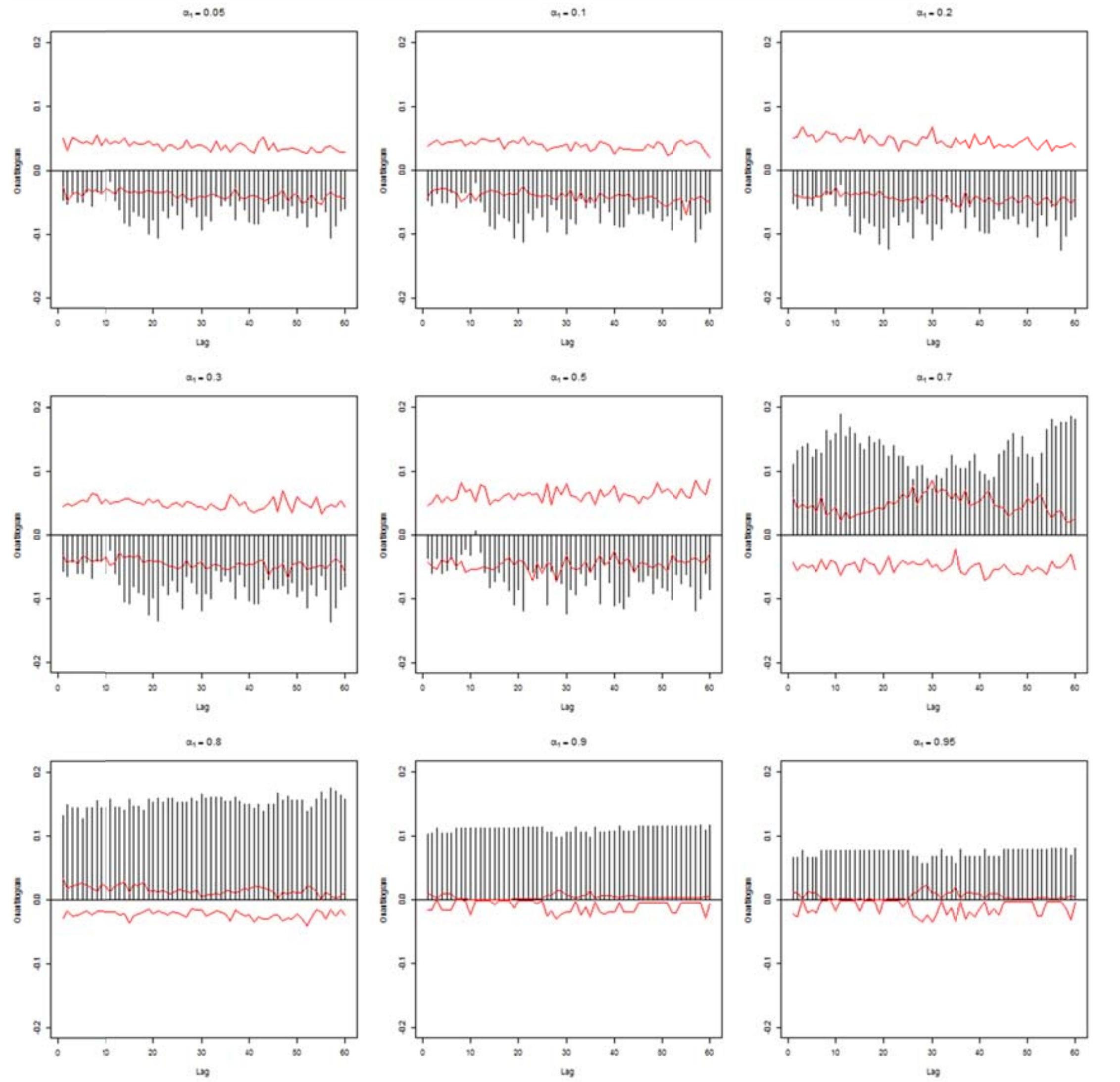


Figure A2(i). Sample cross-quantilograms for $a_2 = 0.10$ to detect directional predictability from relative EPU to *JUMPS*. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations.

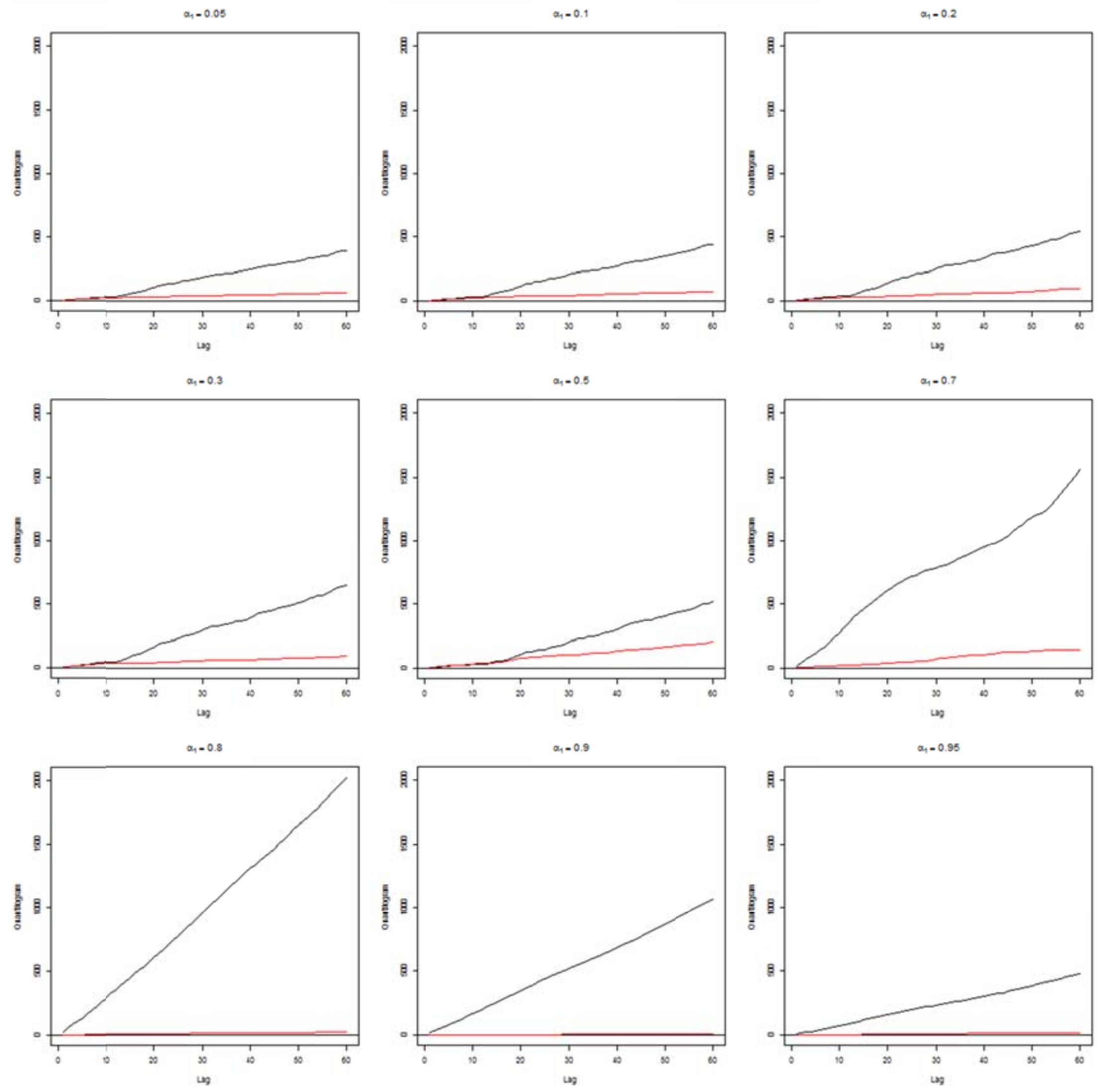


Figure A2(ii). Sample cross-quantilograms for $a_2 = 0.10$ to detect directional predictability from relative EPU to *JUMPS*. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations.

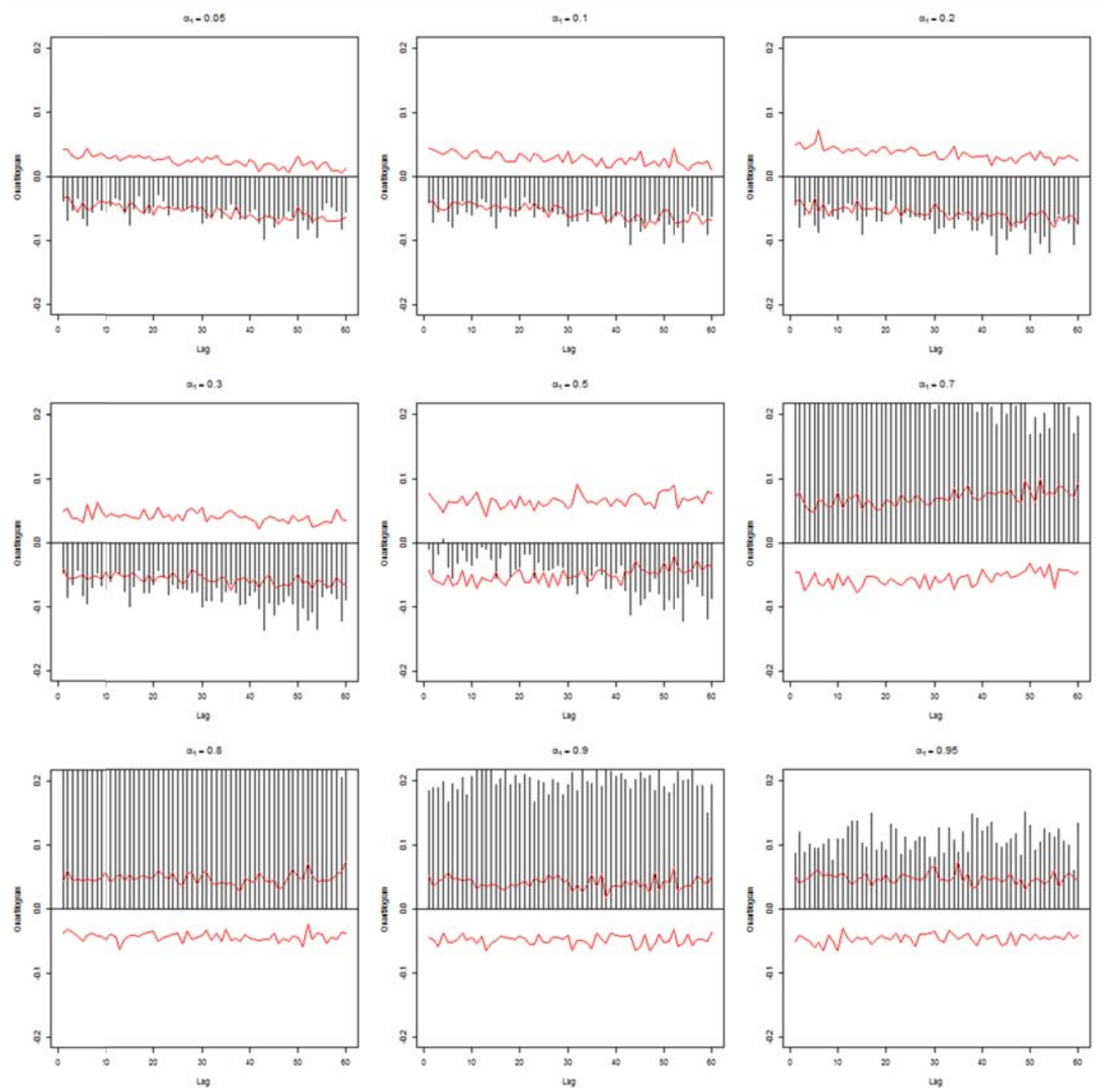


Figure A2(iii). Sample cross-quantilograms for $a_2 = 0.50$ to detect directional predictability from relative EPU to *JUMPS*. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations.

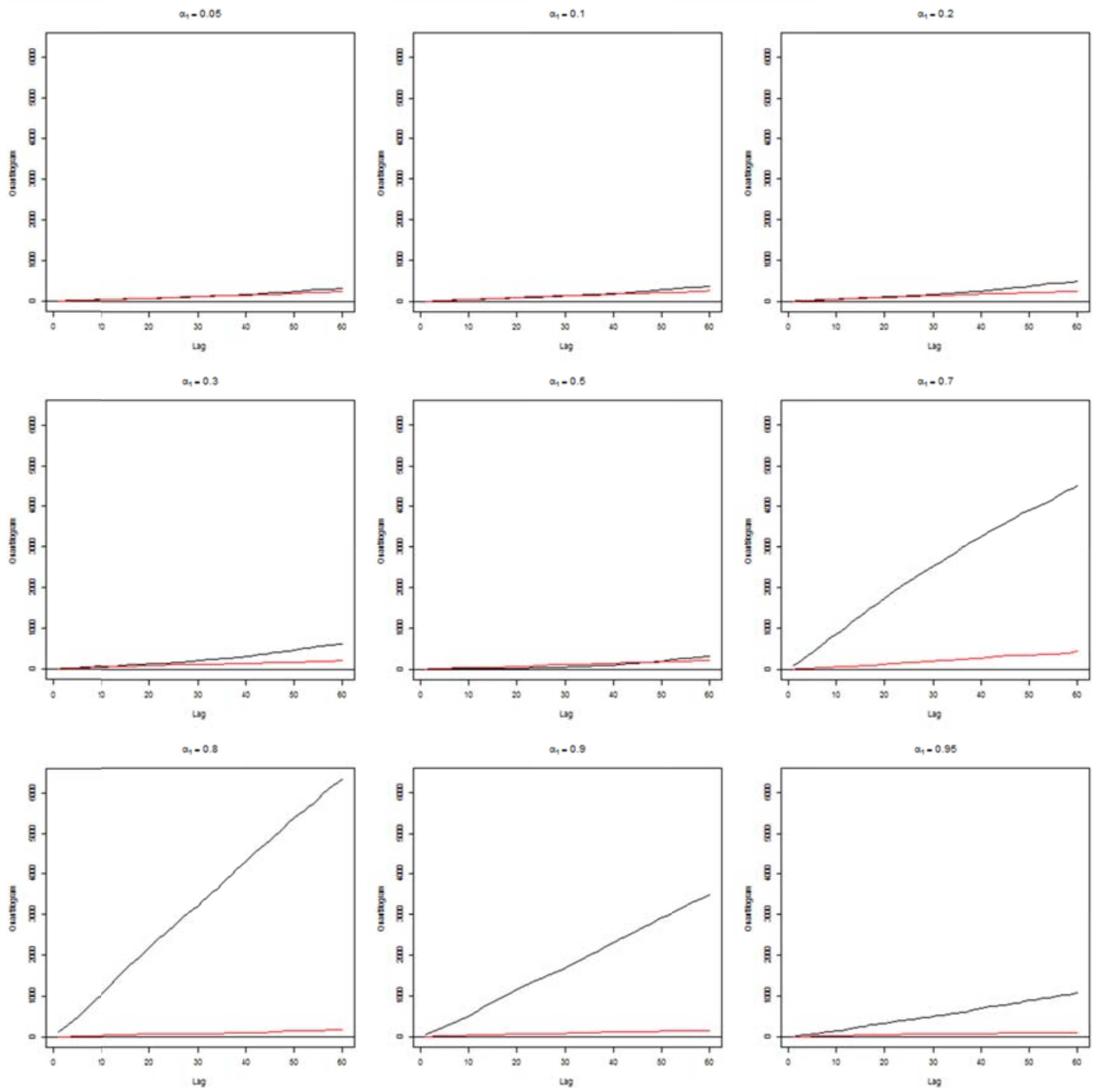


Figure A2(iv). Sample cross-quantilograms for $a_2 = 0.50$ to detect directional predictability from relative EPU to *JUMPS*. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations.

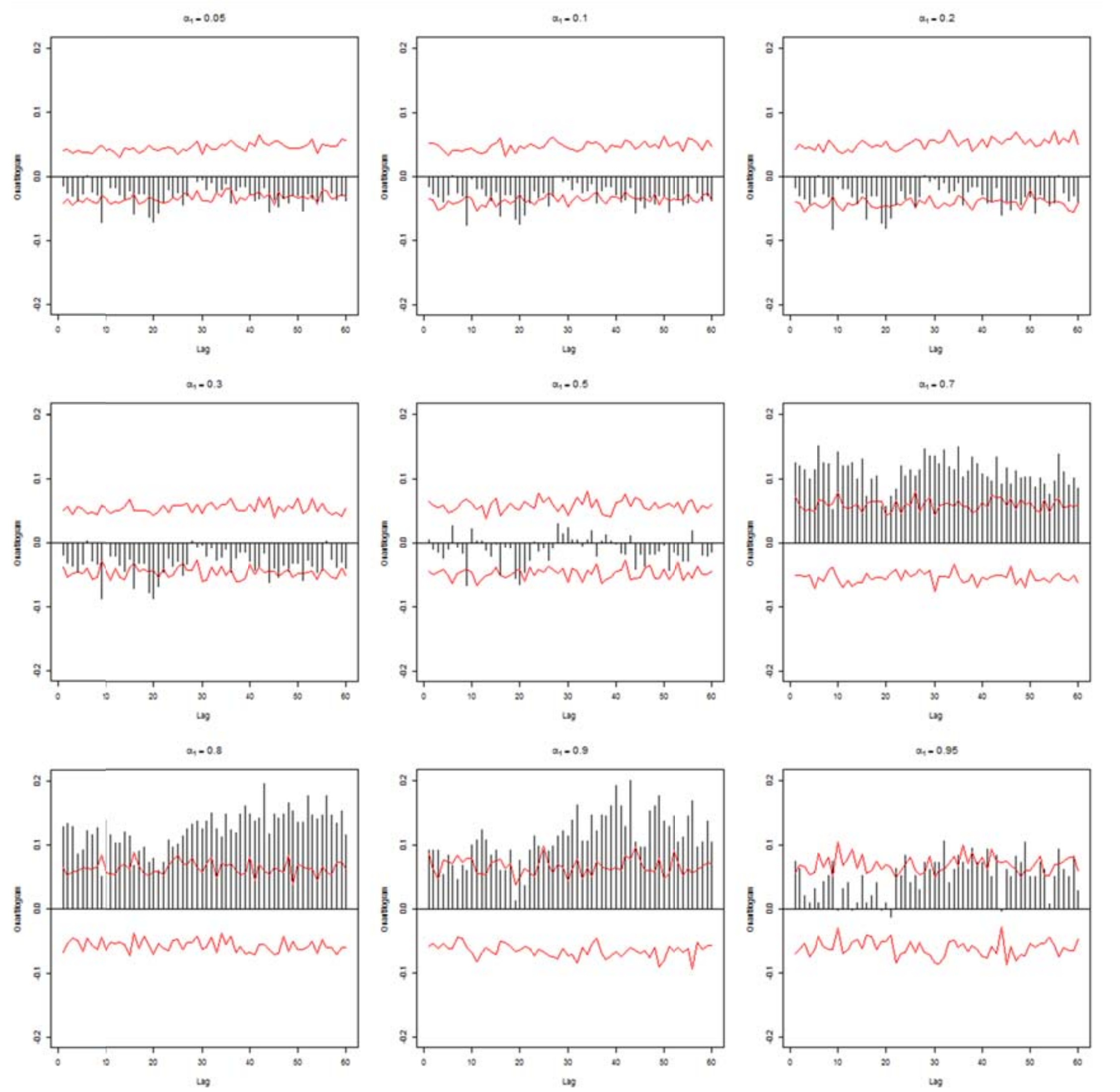


Figure A2(v). Sample cross-quantilograms for $a_2 = 0.90$ to detect directional predictability from relative EPU to *JUMPS*. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations.

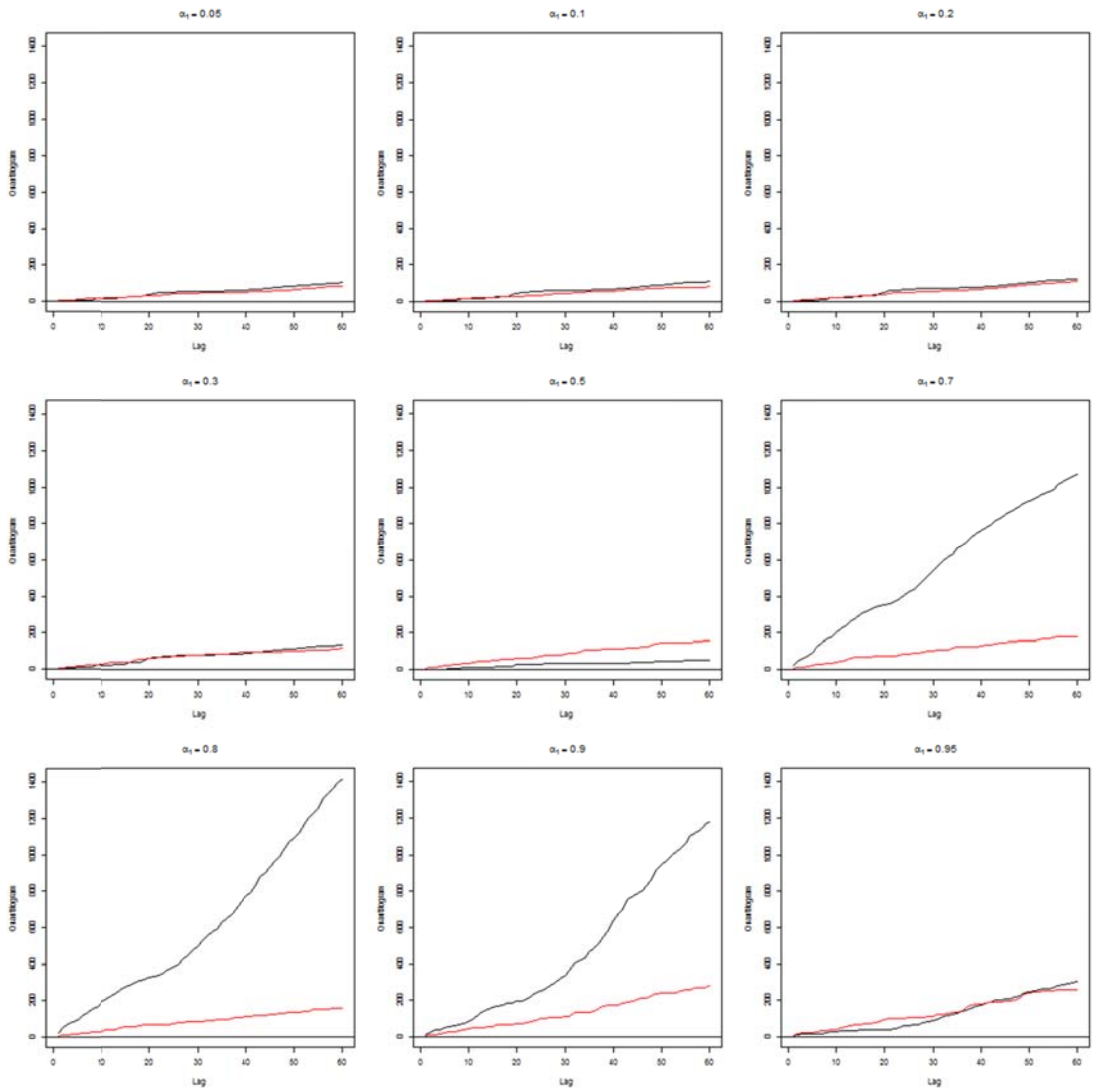


Figure A2(vi). Sample cross-quantilograms for $a_2 = 0.90$ to detect directional predictability from relative EPU to *JUMPS*. Bar graphs describe sample cross-quantilograms and red lines are the 95% bootstrap confidence intervals for 2,000 bootstrap iterations.