Predicting Bitcoin Returns:
Comparing the Roles of Newspaper- and Internet Search-Based Measures of Uncertainty#

Elie Bouri[a,*] and Rangan Gupta[b]

[a]USEK Business School, Holy Spirit University of Kaslik, Jounieh, Lebanon
[b]Department of Economics, University of Pretoria, Pretoria, South Africa

* Corresponding author. eliebouri@usek.edu.lb

Highlights

• Study the predictability of Bitcoin returns using measures of economic uncertainty.
• Newspaper- and internet search-based measures of economic uncertainty are used.
• Based on monthly data, Bitcoin is a hedge against both measures.
• Predictive ability of the internet-based measure is statistically stronger.
• This result is confirmed by various additional analyses.

Abstract

We compare the ability of a newspaper-based measure and an internet search-based measure of uncertainty in predicting Bitcoin returns. Based on monthly data, we show that Bitcoin is a hedge against both measures. However, the predictive ability of the internet-based economic uncertainty related queries index is statistically stronger than the measure of uncertainty derived from newspapers in predicting Bitcoin returns, which is possibly due to the fact that the former measure of uncertainty is directly obtained by the individual investors, based on their search of the internet for terms related to uncertainty. This result is confirmed by various additional analyses.

Keywords: Bitcoin; Hedging; Predictability; Economic Uncertainty

JEL Codes: C32, G12

We would like to thank two anonymous referees for many helpful comments. However, any remaining errors are solely ours.

1. Introduction

Many recent studies consider the role of Bitcoin as a hedge directly against macroeconomic and financial uncertainties (see, Bouri et al., (2017a, 2018), Aysan et al., (2019), and Fang et al., (2019) for detailed reviews of this literature). This is based on the rationale that, during heightened uncertainty, returns in conventional asset markets are negatively impacted, and hence, instead of studying whether the correlation between the returns of conventional assets and Bitcoin is negative during these periods of turmoil (as discussed in detail in Bouri et al., (2017b)), the idea behind these studies is to check the direct impact of various metrics of uncertainty on Bitcoin returns. If indeed, Bitcoin serves as a hedge against uncertainties, then Bitcoin returns should increase, when the returns of other conventional assets are negatively impacted. In this regard, Demir et al., (2018) showed that increases in the newspaper-based measure of economic policy uncertainty (EPU) of the United States (US), as developed by Baker et al., (2016), tend to predict higher Bitcoin returns.[1] Note that the EPU index is based on search results from 10 large newspapers (USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the WSJ) for 210 terms related to economic and policy uncertainty. In particular, Baker et al., (2016) search for articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'congress', 'legislation', 'white house', 'regulation', 'federal reserve', or 'deficit'.

We aim to add to this literature, by hypothesizing that when we replace the frequency of newspaper articles that contain specific terms with the intensity of individual searches on the internet of similar words aiming to measure uncertainty, the latter approach is likely to have a relatively stronger predictive content (hedging impact) for Bitcoin returns. This is because, an index that measures the volume of internet searches of uncertainty-related topics, involves a shift in focus, from the channel through which the message is conveyed (i.e., newspapers) to the receivers of the message (i.e., individual investors) directly. If indeed our hypothesis is not rejected, then relying on the information from the EPU is likely to lead to future underprediction of Bitcoin returns, and hence, inaccurate hedging strategies. To aid us in our objective, we use the Economic Uncertainty Related Queries (EURQ) index developed by Bontempi et al., (2019), and compare its predictive impact with the EPU on Bitcoin returns. Bontempi et al. (2019) measures volumes

[1] Wang et al., (2018) analyse risk spillovers from EPU to Bitcoin, and find negligible impact to suggest that Bitcoin can act as a safe-haven or a diversifier under EPU shocks.

of "economic uncertainty related queries", and thus reflects the intensity of individual searches of the internet for specific terms related to economic and financial uncertainty. Note that these authors selected 184 queries closely related to 210 search terms Baker et al., (2016) used to create the EPU. Form an econometric modelling perspective, we make the comparison across the predictive abilities of EPU and EURQ based on a predictive regression model characterized with an Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH)-based error structure. The heteroskedastic model not only controls for the well-known volatility in the Bitcoin returns, but also controls for possible biases due to omitted variables, which in turn, are strictly related to heterskedasticity effects (Caporin, et al., 2018). To the best of our knowledge, this is the first paper to compare the predictive impact of EPU and EURQ of the US on Bitcoin returns.

The remainder of the paper is organized as follows: Section 2 discusses the data and methodology, Section 3 presents the results, while Section 4 concludes.

2. Data and Methodology

Our main variable of interest is Bitcoin return, defined as logarithmic-returns ($r_t = \ln(p_t)\text{-}\ln(p_{t-1})$), where p_t denotes Bitcoin price in US dollars. The corresponding data is obtained from CryptoCompare.[2] Figure A1 in the Appendix plots the Bitcoin return, while Table A1 provides summary statistics for the same. Bitcoin return is found to have positive skewness and excess kurtosis, resulting in a non-normal distribution as indicated by the overwhelming rejection of the null of normality under the Jarque-Bera test. Data for EPU and EURQ are based on the works of Baker et al., (2016) and Bontempi et al. (2019) respectively, and are freely available for download online.[3] The readers are referred to these two papers for further details. In sum, the basic difference is that the EURQ replaces the frequency of newspaper articles that contain specific terms as under the EPU with the intensity of individual searches of similar words, and hence involves a shift in focus, from the channel through which the message is conveyed (the press, the media) to the receivers of the message (individuals). Though EURQ is available from January of 2004 and the EPU from January of 1985, our data sample covers the monthly period from July 2010 to May 2019 (i.e. 107 observations), with the start date determined by the availability of Bitcoin price data, and the end date by the two measures of uncertainty. The natural logarithms of

[2] See: https://www.cryptocompare.com.

[3] The two measures of uncertainty are available at: http://policyuncertainty.com/us_monthly.html and http://policyuncertainty.com/EURQ_monthly.html.

EPU (*LEPU*) and EURQ (*LEURQ*) are plotted in Figure A1 and summarized in Table A1. EPU has a lower mean but higher volatility than EURQ. Neither of the uncertainty measures are non-normally distributed based on the Jarque-Bera test. Since we want to compare the relative strengths of EPU and EURQ, we standardize them to have a unit variance when estimating the EGARCH model.[4]

To relate Bitcoin returns to the EPU and EURQ of the US, we use an exponential GARCH (EGARCH) model (Nelson, 1991). Notably, the choice of the EGARCH model over the family of other GARCH models is based on the ability of the former to better fit the data, in terms of standard goodness-of-fit measures.[5] This, in turn, is possibly a reflection of the impact of negative price movements on future volatility being different from that of positive price movements.

Formally, the EGARCH model used in this paper is described by assuming that the return process of Bitcoin (r_t) is given by:

$$r_t = \mu + \theta_1 LEPU_{t-1}^{std} + \theta_2 LEURQ_{t-1}^{std} + \sigma_t \varepsilon_t \tag{1}$$

where, ε_t is a sequence of $N(0, 1)$ *i.i.d.* random variables, and

$$\ln(\sigma_t^2) = \alpha_0 + \frac{\alpha_1 a_{t-1} + \gamma \,|\, a_{t-1} \,|}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2) \tag{2}$$

where $a_t = \sigma_t \varepsilon_t$. Notice that equation (2) allows us to capture an asymmetric effect between positive and negative returns. Also, to avoid the possibility of a negative variance, the model is an *AR*(1) on $\ln(\sigma_t^2)$ rather than σ_t^2. If Bitcoin indeed does serve as a hedge to the two measures of uncertainty, we would expect both θ_1 and θ_2 to be positive in a statistically significant manner in equation (1). Our hypothesis that standardized *LEURQ* ($LEURQ^{std}$) provides a stronger predictive impact than standardized *LEPU* ($LEPU^{std}$), which would require us to have $\theta_2 > \theta_1$ in the statistical sense.

3. Empirical Results

To motivate the use of a model with heteroskedastic error structure, we first use ordinary least squares to estimate the linear predictive regression model, as is standard in the literature of

---

[4] We do not make any further transformations to the natural logarithms of EPU and EURQ, as both uncertainty measures are stationary based on standard unit root tests. The results of these tests are available from the authors upon request.

[5] Complete details of the estimations of various symmetric and asymmetric GARCH models are available upon request from the authors.

predicting asset returns at a low-frequency (Rapach and Zhou, 2013): $r_t = \mu + \theta_1 LEPU_{t-1}^{std} + \theta_2 LEURQ_{t-1}^{std} + u_t$, with $u_t \sim N(0, \sigma^2)$,[6] and perform diagnostic tests of serial correlation and heteroskedasticity on the residual, i.e., u.[7] As shown in Table A2 in the Appendix of the paper, while there is no evidence of serial correlation, the null of no-heteroskedasticity cannot be rejected (at least at the 10% level of significance). These results provide strong motivation for the usage of a GARCH-based predictive regression model.[8]

Hence, we now turn next to the results from the estimation of the EGARCH model, which in turn are reported in Table 1. As can be seen from the volatility equation, γ is negative and significant, which highlights the fact that negative innovations are more destabilizing than positive innovations, i.e., the leverage effect holds here, with negative shocks increasing volatility more than positive shocks to Bitcoin returns. Furthermore, the impact of both lagged EPU and EURQ are positive and strongly significant in the mean equation, suggesting that Bitcoin does serve as a hedge against uncertainty. More importantly, we find that the predictability of EURQ is stronger (0.0350) than that of EPU (0.0179), with the coefficient of the former being larger than the latter by 0.0171 (i.e. almost double).[9] In fact, the null of $\theta_2 = \theta_1$ is rejected at the highest level of significance, based on Wald-type test of coefficient restriction, which has a $F(1,99)$-statistic of 130.1980, with a corresponding p-value of 0.000.[10]

[6] Interestingly, neither of θ_1 and θ_2 were found to be significant even at the 10% level, though they were both positive (0.0174 and 0.0343, respectively). Understandably, the existence of strong heteroskedasticity, as shown in Table A2, resulted in the non-significance.

[7] Note that, based on the suggestion of an anonymous referee, we tested for the validity of a linear predictive regression based on the Brock et al., (1996, BDS) test applied to the residual u. The test could not detect any evidence of uncaptured nonlinearity, complete details of which are available upon request from the authors.

[8] The ARCH test on the residual of the EGARCH model however, showed no evidence of any further heteroskedasticity, given the F-statistic of 0.1004, with a p-value of 0.7520.

[9] Based on the suggestion of an anonymous referee, we estimated a VAR model with $LEPU^{std}$, $LEURQ^{std}$ and Bitcoin returns (r), and found that for a shock of equal size, the impulse response of Bitcoin returns is stronger under EURQ than EPU consistently over a one-year horizon. This is again in line with the result obtained under the EGARCH-augmented predictive regression model, and is available upon request from the authors.

[10] We estimate equation (1) with contemporaneous values of EPU and EURQ, and find $\theta_1 = 0.0470$ and $\theta_2 = 0.0734$, with both being statistically significant at the 1% level, and also with $\theta_1 < \theta_2$ in a statistical fashion, given the $F(1,100)$-statistic being 525.3594 and a p-value of 0.0000. Note the contemporaneous responses of Bitcoin returns to EPU and EURQ are stronger than the lagged responses. In addition, following Bouri et al. (2017) and Aysan et al. (2019), we include the lagged Chicago Board Options Exchange (CBOE) Volatility Index (VIX) and the geopolitical risks (GPR) index of Caldara and Iacoviello (2018) respectively in equation (1), along with the lagged EPU and EURQ. The VIX data comes from the FRED database, while the GPR data is downloaded from: https://www2.bc.edu/matteo-iacoviello/gpr.htm. Interestingly, our basic result of the stronger hedging ability of EURQ relative to EPU continues to hold, with $\theta_1 = 0.0201$ and $\theta_2 = 0.0308$, with both being statistically significant at the 1% level, and also with $\theta_1 < \theta_2$ in a statistical fashion, given the $F(1,97)$-statistic being 3.6940 and a p-value of 0.0575. Complete details of these results are available upon request from the authors.

Table 1. Estimation Results

Parameter	Coefficient	Standard Error	*z*-Statistic	*p*-value
		Mean Equation		
μ	-1.9889	0.0002	-8905.3980	0.0000
θ_1	0.0179	0.0013	13.6384	0.0000
θ_2	0.0350	1.70E-05	2058.7590	0.0000
		Volatility Equation		
α_0	0.0568	0.0914	0.6215	0.5343
γ	-0.3164	0.1015	-3.1187	0.0018
α_1	0.2151	0.0759	2.8343	0.0046
β	0.9297	0.0005	1868.9570	0.0000

Note: The mean and volatility equations of the model are respectively: $r_t = \mu + \theta_1 LEPU_{t-1}^{std} + \theta_2 LEURQ_{t-1}^{std} + \sigma_t \varepsilon_t$, and $\ln(\sigma_t^2) = \alpha_0 + \frac{\alpha_1 a_{t-1} + \gamma \mid a_{t-1} \mid}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2)$.

As an additional analysis, we conduct a forecasting exercise over the out-of-sample of January 2015 to May 2019, with an in-sample of July 2010 to December 2014 (a 50% split of the whole sample as suggested by Rapach et al. (2005)). Basically, we estimate the model given by equations (1) and (2), by first using only $LEPU^{std}$ in the model, and next only with $LEURQ^{std}$,[11] and then produce recursive one-step-ahead forecasts over the out-of-sample period.

We found that the Root Mean Square Errors (RMSEs) for Bitcoin returns produced under the first case, i.e., with information based only on EPU was slightly higher (at 0.2119) than under the second case (at 0.2116), i.e., when the model used information only from EURQ. As suggested by an anonymous referee, we also analysed the forecasts with profit- or utility-based metric, which provides a more direct measure of the value of forecasts to economic agents. A leading utility-based metric for analysing forecasts is the average utility gain for a mean-variance investor as developed by Campbell and Thompson (2008). Using this measure, we found that the annualized utility gain for an economic agent based on the forecasts generated from EURQ relative to EPU would be 5.4907%.

As correctly pointed to us by an anonymous referee, even though the focus of the paper is predictability, to put our results into the context of hedging, we must be able to show that Bitcoin performs well in states characterized by high uncertainty. Given this, we disaggregated the two

[11] It must be note that, when the model was estimated with either EPU or EURQ, the impact of the latter in increasing Bitcoin returns was found to be relatively stronger, with corresponding coefficients of 0.0209 and 0.0383 respectively, both of which were significant at the highest possible level of significance. Hence, even if there are concerns regarding multicollinearity (though the positive correlation of 0.0853 was not significant even at the 10% level of significance), our basic result of stronger predictability from EURQ relative to EPU continues to hold. Complete details of these versions of the EGARCH model is available upon request from the authors.

metrics of uncertainty into their high and low values. We do this by first defining dummy variables that take the value of 1 when EPU and EURQ are above or below their mean respectively, and zero otherwise, and then multiplying these dummy variables with the two measures of uncertainty. Based on this decomposition, as can be seen from Table 2, high or low values of EPU are insignificant, but the corresponding values of EURQ are indeed statistically significant at the 5% level. This result again corroborates the fact that EURQ has more predictive information than EPU for Bitcoin returns. Interestingly, high values of EURQ increases Bitcoin returns, while low values of EURQ the negatively impact the same. This result suggests that Bitcoin actually acts as a hedge against EURQ, when it tends to increase from an initial state of high-values.

Table 2. Estimation Results with High- and Low-Levels of Uncertainties

		Mean Equation (High-Uncertainty)		
Parameter	Coefficient	Standard Error	*z*-Statistic	*p*-value
μ	0.0249	0.0284	0.8773	0.3803
θ_1	0.0137	0.0108	1.2680	0.2048
θ_2	0.0206	0.0095	2.1810	0.0292
		Volatility Equation (High-Uncertainty)		
α_0	0.0440	0.0793	0.5555	0.5786
γ	-0.3097	0.0848	-3.6537	0.0003
α_1	0.2065	0.0727	2.8420	0.0045
β	0.9269	1.74E-05	53181.8400	0.0000
		Mean Equation (Low-Uncertainty)		
Parameter	Coefficient	Standard Error	*z*-Statistic	*p*-value
μ	0.1484	0.0425	3.4921	0.0005
θ_1	-0.0146	0.0118	-1.2395	0.2151
θ_2	-0.0227	0.0101	-2.2582	0.0239
		Volatility Equation (Low-Uncertainty)		
α_0	0.0494	0.0886	0.5580	0.5768
γ	-0.3068	0.0965	-3.1803	0.0015
α_1	0.2065	0.0807	2.5582	0.0105
β	0.9313	2.50E-05	37276.2100	0.0000

Note: See notes to Table 1. $LEPU^{std}$ and $LEURQ^{std}$ in Table 1 are replaced by their high and low values; High (Low)-Uncertainty correspond to the values of the measures above (below) mean.

In summary, EURQ is found to be a relatively more important (statistically and economically) predictor of Bitcoin returns than EPU (both in- and out-of-sample),[12] which in turn adds to the

[12] We also estimate EGARCH models for gold returns (with gold prices derived from the FRED database of the Federal Reserve Bank of St. Louis) with EPU and EURQ as predictors over the monthly period from January 2004 (which corresponds to the starting date of the EURQ index) to May 2019, given gold's well-known ability to act as a safe-haven (Baur and Lucey, 2010). Interestingly, the impact of the two measures of lagged uncertainties is positive but not significant, even at the 10% level, but the contemporaneous effect is positive and significant at the 5% level. The coefficient of EPU is found to be 0.0060 (*p*-value = 0.0350) and that of EURQ 0.0061 (*p*-value = 0.0250). In

prior findings of Demir et al., (2018) which limit their analyses to a news-based measure of uncertainty.

4. Conclusion

In this paper, we analyse the predictive ability of two alternative measure of uncertainties for predicting Bitcoin returns. While the first is a news-based measure, the second is obtained from internet searches of uncertainty related queries. We postulate that the latter index is likely to have a stronger positive impact on Bitcoin returns, as it involves a shift in focus from newspapers, i.e., the channel through which the message is conveyed to individual investors who receive the message. When we test this hypothesis using a predictive regression model accounting for heteroskedasticity, we find that our hypothesis is indeed validated by both in-sample and out-of-sample analyses. This finding can be explained by the fact most of investors in the Bitcoin market are individual and inexperienced investors (Bouri et al., 2019), who often make investment decisions based on the information-content of search engines (Kristoufek, 2013). Our results imply that, compared to a metric of uncertainty based on newspaper articles, the intensity of individual searches on the internet of words aiming to measure uncertainty, would allow investors to design better hedging strategies associated with Bitcoin in their portfolios.

As part of future research, it would be interesting to extend our analysis to other cryptocurrencies, and check if our results continue to hold. In this regard, one could also compare our results when using other assets, which are traditionally considered as hedges against uncertainty, if not safe-havens, like US Treasury bonds, the Swiss franc etc. Moreover, in the current paper, we rely on a low-frequency analysis based on monthly data, it would be interesting to extend our analysis to daily data by creating our own Google Trends-based measure of uncertainty, and also using a nonlinear approach, which is likely to exist in high-frequency data, as in Jahanshahi et al., (2019).

other words, unlike Bitcoin, the impact of the news-based measure of uncertainty and internet-based search queries on uncertainty are similar for gold's hedging ability. Complete details of these results are available upon request from the authors.

References

Aysan, A.F., Demir, B., Gozgor, G., Lau, C.K.M. (2019). Effects of the geopolitical risks on Bitcoin returns and volatility. Research in International Business and Finance, 47, 511-518.

Baker, S.R., Bloom, N., Davis, S.J. (2016). Measuring economic policy uncertainty. The Quarterly Journal of Economics, 131(4), 1593-1636.

Baur, D.G., and Lucey, B.M. (2010). Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold. The Financial Review, 45, 217–229.

Bontempi, M.E., Frigeri. M., Golinelli., R., Squadrani, M. (2019). Uncertainty, Perception and Internet. University of Bologna, Mimeo. Available for download from: https://www.dropbox.com/s/w4qhwk303hufueu/BGS_Interest.pdf?dl=0.

Bouri, E., Gupta, R., Lau, C.K.M., Roubaud, D., Wang, S. (2018). Bitcoin and global financial stress: A copula-based approach to dependence and causality in the quantiles. The Quarterly Review of Economics and Finance, 69, 297-307

Bouri, E., Gupta, R., Roubaud, D. (2019). Herding behaviour in cryptocurrencies. Finance Research Letters, 29, 216-221.

Bouri, E., Gupta, R., Tiwari, A.K., Roubaud, D. (2017a). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 23, 87-95.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L.I. (2017b). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters, 20, 192-198.

Brock, W., Dechert, D., Scheinkman, J., and LeBaron, B. (1996). A test for independence based on the correlation dimension. Econometric Reviews, 15, 197–235.

Caldara, D., Iacoviello, M. (2018). Measuring Geopolitical Risk. Board of Governors of the Federal Reserve System, International Finance Discussion Paper No. 1222.

Campbell, J.Y. and Thompson, S.B. (2008). Predicting the Equity Premium Out of Sample: Can Anything Beat the Historical Average? Review of Financial Studies, 21(4), 1509-1531.

Caporin, M., Pelizzon, L., Ravazzolo, F., Rigobon, R. (2018). Measuring sovereign contagion in Europe. Journal of Financial Stability, 34, 150–181.

Demir, E., Gozgor, G., Lau, C.K.M., Vigne, S.A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. Finance Research Letters, 26, 145-149.

Engle, R.F. (1982). Autoregressive conditional heteroskedasticity with estimates of U.K. inflation. Econometrica, 50, 987-1008.

Fang, L., Bouri, E., Gupta, R., Roubaud, D. (2018). Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? International Review of Financial Analysis, 61, 39-36.

Jahanshahi, H., Yousefpour, A., Zhouchao, W., Alcaraz, R., and Bekiros, S. (2019). A financial hyperchaotic system with coexisting attractors: Dynamic investigation, entropy analysis, control and synchronization. Chaos, Solitons & Fractals, 126, 66-77.

Kristoufek, L. (2013). BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. Scientific reports, 3, 3415.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: a new approach. Econometrica, 59, 347-370.

Rapach D.E., Wohar, M.E., Rangvid, J. (2005). Macro variables and international stock return predictability. International Journal of Forecasting, 21(1), 137–166.

Rapach, D. E., and Zhou, G. (2013). Forecasting stock returns. Handbook of Economic Forecasting, 2 (Part A), Graham Elliott and Allan Timmermann (Eds.), Amsterdam: Elsevier, 328−383.

Wang, G-J., Xie, C., Wen, D., and Zhao, L. (2018). When Bitcoin meets economic policy uncertainty (EPU): Measuring risk spillover effect from EPU to Bitcoin. Finance Research Letters. DOI: https://doi.org/10.1016/j.frl.2018.12.028.

APPENDIX:

Table A1. Summary Statistics

Statistic	Bitcoin Log-Returns (*r*)	LEPU	LEURQ
Mean	0.1122	4.8995	5.1834
Median	0.0721	4.9008	5.1762
Maximum	1.7421	5.6495	5.5373
Minimum	-0.4921	4.1570	4.9836
Std. Dev.	0.3616	0.3027	0.1014
Skewness	1.6295	0.2344	0.3985
Kurtosis	7.8901	2.5481	3.2731
Jarque-Bera	153.9635 (0.0000)	1.8904 (0.3886)	3.1640 (0.2056)
Observations	107		

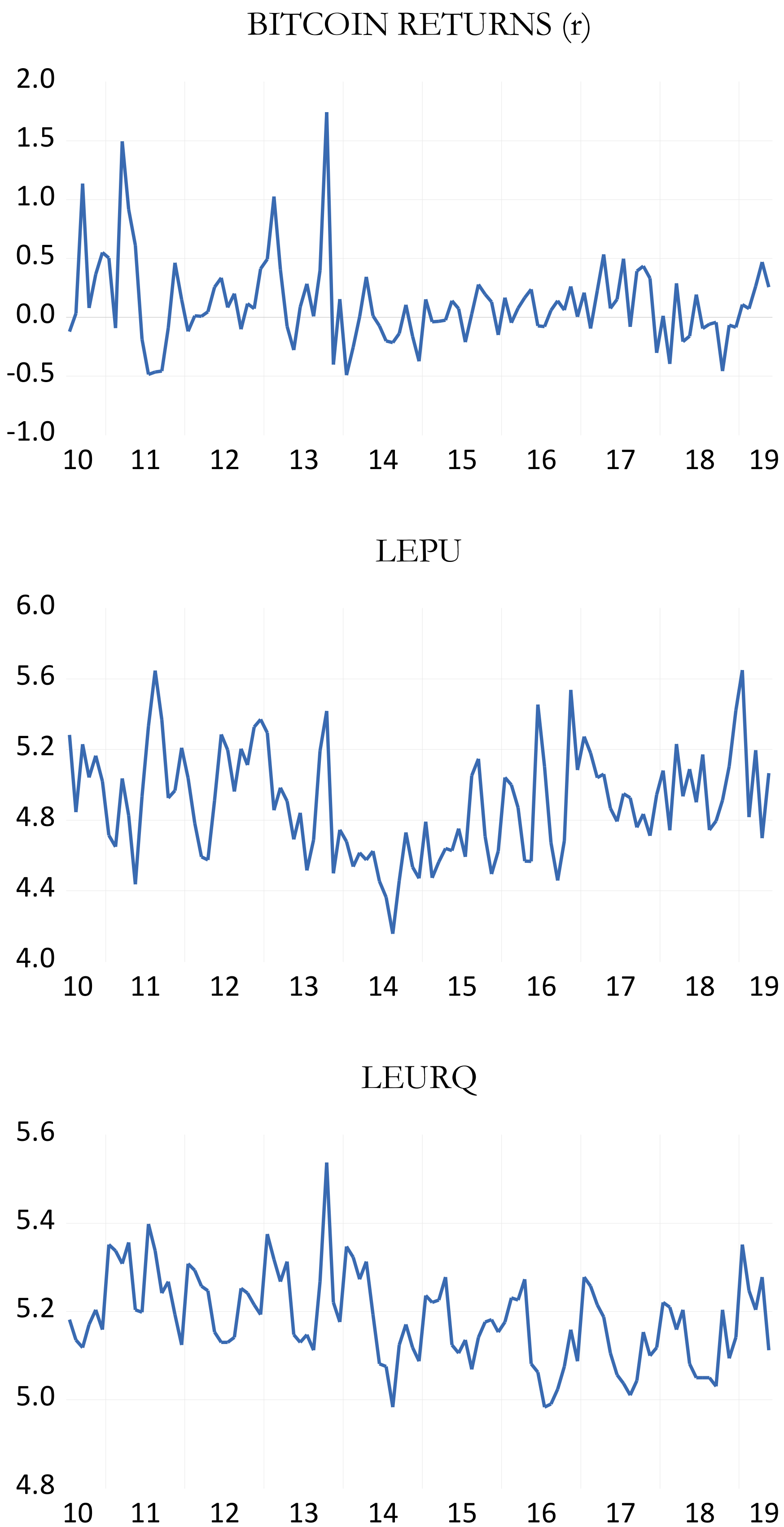
Note: LEPU and LEURQ are the natural logarithms of the uncertainty indices of Baker et al. (2016) and Bontempi et al. (2019) derived from newspapers and internet search queries, respectively; Jarque-Bera test statistic corresponds to a test of the null hypothesis of normality.

Table A2. Residual Diagnostic Tests of the Ordinary Least Squares Estimation of the Predictive Regression Model

Serial Correlation Test	F-statistic
Breusch-Godfrey	0.6121 (0.5442)
Heteroskedasticity Tests	F-statistic
Breusch-Pagan-Godfrey	4.1728 (0.0181)
Harvey	5.0155 (0.0083)
Glejser	6.6215 (0.0020)
ARCH	3.5178 (0.0635)
White	2.1446 (0.0662)

Note: Tests performed on the residual of: $r_t = \mu + \theta_1 LEPU_{t-1}^{std} + \theta_2 LEURQ_{t-1}^{std} + u_t, u_t \sim N(0, \sigma^2)$; Null hypothesis of the tests are no-serial correlation and no-heteroskedasticity; Entries in parentheses correspond to the *p*-values of the various test statistics.

Figure A1. Data Plots



Note: See Notes to Table A1.