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Bitcoin and Global Political Uncertainty – Evidence from the U.S. Election Cycle

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Abstract

In this study, we investigate the impact of political uncertainty on Bitcoin. Introducing the U.S. federal election cycle as a proxy for political uncertainty, we find that (i) an increase in political uncertainty leads to a decrease in Bitcoin return, (ii) political uncertainty has the strongest impact on Bitcoin six and three months prior the election and decreases as the election date approaches, and (iii) the effect is more pronounced in the left and right tail of the distribution. The results shed a new light on the property of Bitcoin being a safe haven asset and provide important information for investors and policymakers.

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1 Introduction

The US-China trade war, Brexit, impeachment proceedings in the U.S. – political developments move financial markets and have become a major concern for investors. For example, on September 24, 2019, the S&P 500 dropped 0.8% on Trump impeachment concerns (Imbert, 2019). On December 2, 2019, the S&P 500 fell another 0.9% as President Donald Trump stoked U.S.-China trade fears with the announcement to impose metal tariffs on Brazil and Argentina (Swanson, 2019).

The extreme levels of uncertainty led to a growing body of empirical literature on the analysis of political uncertainty.[1][2] Building upon the theoretical work of Pástor & Veronesi (2013) and Pastor & Veronesi (2012), several studies find that political uncertainty yields a risk premium. For example, Brogaard & Detzel (2015) find that news-based measures of economic policy uncertainty positively forecast log excess market returns. Erb et al. (1996) measure political risk based on the International Country Risk Guide and show that change in political rating has explanatory power in emerging equity markets. Belo et al. (2013) use a measure of industry exposure to government spending to show predictable variation in cash flows and stock returns over political cycles. Hassan et al. (2019) use textual analysis of quarterly earnings conference-calls to construct firm-level measures of political risk, validating that it correlates with the firm's actions and stock market volatility. Finally, Bittlingmayer (1998) and Voth (2002) find evidence from interwar data for a positive relation between political uncertainty and stock volatility.

The empirical literature on the effects of government-induced uncertainty on Bitcoin is fairly small, and mostly focused on the news-based economic policy uncertainty (EPU) measure introduced by Baker et al. (2016).[3] Bouri et al. (2017) and Demir et al. (2018) were among the first to investigate the impact of EPU on Bitcoin using ordinary least squares (OLS) and wavelet-based quantile-on-quantile regression. Wang et al. (2018) examine whether EPU affects the behavior of Bitcoin from a risk spillover perspective. In a related study, Plakandaras et al. (2019) show that US–China trade-war related information have weak predictive power for Bitcoin return. A more recent study by Fang et al. (2019) assesses whether the long-run volatility of Bitcoin is affected by global EPU. They find evidence supporting this hypothesis, showing that investors can exploit these

[1] A simple Scopus search for "political uncertainty" generates about 8,883 results, as of December 04, 2019.

[2] In the original model of Pástor & Veronesi (2013), political uncertainty is defined as uncertainty about future governmental policy choice. Later, Kelly et al. (2016) reinterpret political uncertainty as uncertainty about the election outcome. In this study, we follow the latter definition.

[3] The index is a weighted average of three measures of EPU – the frequency of major news discussing economic policy-related uncertainty, expiring tax provisions, and forecaster disagreement about government purchases and inflation.

information to maker better predictions about Bitcoin volatility. Finally, Bouri & Gupta (2019) compare newspaper-based and internet search-based measures, showing that the predictive power of internet-based economic uncertainty related queries indices is statistically stronger.

From the discussion above one main observations emerges, namely that news-based EPU has received much attention while alternative measures remain somewhat unexplored. This is suprising given the broad consensus among researchers that no single best measure for political uncertainty exists. We aim to fill this research gap by introducing the U.S. federal elections borrowed from the existing literature (see, for example, Baker et al., 2016; Brogaard et al., 2019; Jens, 2017; Julio & Yook, 2012; Kelly et al., 2016) as a source of government policy uncertainty. We believe that U.S. elections are better suited to capture political uncertainty for several reasons. First, and most importantly, a major obstacle in assessing the impact of political uncertainty is the difficulty of isolating exogenous uncertainty, such as macroeconomic uncertainty, from government-related uncertainty. Elections can result in major political shifts and therefore provide the most direct measure of political uncertainty. Second, the logic of using elections to study political uncertainty is most closely related to the theoretical model of Pástor & Veronesi (2013) and the later reinterpretation of Kelly et al. (2016), defining political uncertainty as uncertainty about who will be elected. Lastly, the dates of elections are determined sufficiently far in advance, so that they are publicly known on the dates we perform our analysis. Moreover, we use elections in the United States as a proxy of global political uncertainty for three reasons. First, U.S. elections are watched and tracked by almost all non-U.S. countries. Second, the U.S. economy is the largest economy worldwide. Third, U.S. election results do not only impact future government policy, but also have significant influence on global policy direction (Brogaard et al., 2019).

This study contributes to two strands of literature. First, it contributes to the growing literature on political uncertainty. While previous studies examine the impact on various asset classes such as equities (Brogaard et al., 2019; Liu et al., 2017), fixed income (Gao et al., 2019), precious metals (Baur & Smales, 2018) or options (Kelly et al., 2016), our paper is the first to investigate the impact of political uncertainty on Bitcoin measured by the U.S. election cycle. Second, we contribute to the debate whether Bitcoin serves as a safe haven during periods of market turmoil.[4] In contrast to other studies (Bouri et al., 2017; Dyhrberg, 2016a,b; Stensås et al., 2019; Urquhart & Zhang, 2019), we do not find evidence for Bitcoin being a safe haven. In fact, our results indicate that an increase in political uncertainty leads to a decrease in Bitcoin price. These findings provide im-

[4] A safe haven asset is uncorrelated or negatively correlated with another asset or portfolio in time of market distress (Baur & Lucey, 2010).

portant information to a variety of stakeholders, including investors and policymakers.

The remainder is structured as follows. Section 2 describes the data and introduces the quantile regression model. Section 3 provides empirical results and section 4 concludes.

2 Data and Methodology

Daily Bitcoin closing prices for the period April 28, 2013 to October 31, 2019 are sourced from coinmarketcap[5], resulting in a total of 2,378 observations. U.S. election data for the same period are collected from the Federal Election Commission (FEC)[6] including election dates, results for Congressional races, and election results for the office of the President. In addition, we gather data for Bitcoin volatility[7] and trading volume, S&P 500, MSCI World, MSCI China, EUROSTOXX, Nikkei, VIX and EPU from various sources. We aggregate daily data to monthly data to reduce noise and produce less residual variance.

To examine the impact of global political uncertainty on Bitcoin, we employ quantile regression as our baseline model. Instead of being interested in the conditional mean, quantile regression aims at estimating the conditional median or quantile. This comes with the advantage of being more robust to outliers than least squares regression and providing complete characterization of the conditional distribution. Following Kroenker (2005), we define the $\tau-$th conditional quantile function as

$$Q_{Y|X}(\tau) = X\beta_\tau. \tag{1}$$

Given the distribution function of Y, β_τ can be optained by solving the following linear programming problem[8]

$$\underset{\beta,\mu^+,\mu^-\in\mathbb{R}^k\times\mathbb{R}_+^{2n}}{\arg\min}\left\{\tau 1_n'\mu^+ + (1-\tau)1_n'\mu^- | X\beta + \mu^+ - \mu^- = Y\right\} \tag{2}$$

where $\mu_j^+ = \max(\mu_j, 0), \mu_j^- = -\min(\mu_j, 0)$.

In this study, we want to investigate the relationship between global political uncertainty and Bitcoin. Therefore, we specify quantile regressions of the following form:

[5] https://coinmarketcap.com/.
[6] https://www.fec.gov/.
[7] We use one-month rolling window volatility to smooth out short-term fluctuations and highlight longer-term trends. In addition, the approach better accounts for the time invariance of the volatility.
[8] Simplex methods or interior point methods can be applied to solve the linear programming problem (Koenker, 2005).

$$Q_{Return_t|GPU_t}(\tau) = \beta_0 + GPU_t\beta_{1,\tau} + Z_t\beta_{2,\tau} + \epsilon_t \tag{3}$$

where $Return_t$ is Bitcoin return. The main explanatory variable is GPU_t, which is a dummy variable measuring global political uncertainty. It is assigned a value of 1 if it falls within a window of six, three, or one month prior to a federal election, and zero otherwise. Dummy variables are denoted GPU_{6M}, GPU_{3M} and GPU_{1M}, respectively. Finally, Z_t is a vector of lagged control variables and ϵ_t is the error term. We run quantile regressions for the 5-, 10-, 25-, 50-, 75-, 90- and 95-th quantile.

3 Empirical Results

Table 1 reports summary statistics of our key variables. Average daily Bitcoin return is 0.002, standard deviation is 0.007. The Jarque-Bera test of normality is rejected for all variables but Bitcoin. Applying quantile regression which better accounts for outliers and skewed distributions is therefore reasonable. Figure A.1 in the Appendix plots Bitcoin return and volatility over the sample period.

Table 1: Descriptive statistics

	Mean	SD	Min	Max	Skew	Kurt	JB
Bitcoin	0.002	0.007	-0.015	0.017	0.068	2.821	0.060
GPU_{6M}	0.318	0.469	0.000	1.000	0.781	1.610	34.820***
GPU_{3M}	0.182	0.389	0.000	1.000	1.650	3.722	17.500***
GPU_{1M}	0.091	0.290	0.000	1.000	2.846	9.100	40.000***

Note: JB is the Jarque-Bera test of normality and reports adjusted chi-squared test statistics. The augmented Dickey-Fuller and Phillips-Perron test for non-stationarity are rejected at the 1% level. Test results are avaialbe upon request. Bitcoin is in logarithmic first differences. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

The correlation between Bitcoin and political uncertainty is negative for all three variables GPU_{6M}, GPU_{3M}, and GPU_{1M} (-0.220, -0.276, and -0.152, respectively), which gives us a first indication of the directional relationship. When political uncertainty goes up, Bitcoin return goes down. To test whether Bitcoin return is different for low and high political uncertainty, we run a one-sample t-test for difference of means. Bitcoin return is positive during low political uncertainty, and negative during high political uncertainty. The difference between low political uncertainty and high political uncertainty for GPU_{6M} is positiv ($0.003 - (-0.001) = 0.003$) and significant at the 10% level. The difference for GPU_{3M} is also positiv ($0.002 - (-0.003) = 0.005$) and significant at the

Table 2: Quantile regression results

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
GPU_{6M}	-0.007**	-0.004**	-0.005*	-0.010***	-0.007**	-0.010***	-0.010***
	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Constant	0.021	0.012	0.007	0.036	0.080***	0.033*	0.035
	(0.026)	(0.013)	(0.019)	(0.023)	(0.023)	(0.018)	(0.034)
R-squared	0.393	0.31	0.172	0.148	0.184	0.263	0.333
GPU_{3M}	-0.012***	-0.010***	-0.005*	-0.005	-0.006**	-0.009***	-0.010***
	(0.004)	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.004)
Constant	0.019	0.060**	0.018	0.037*	0.051***	0.046***	0.060***
	(0.026)	(0.021)	(0.017)	(0.021)	(0.019)	(0.016)	(0.021)
R-squared	0.392	0.367	0.136	0.105	0.199	0.303	0.367
GPU_{1M}	-0.010	-0.011***	-0.001	-0.002	-0.004	-0.008**	-0.005
	(0.008)	(0.002)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
Constant	0.003	0.007	0.011	0.026	0.047	0.044**	0.027
	(0.013)	(0.012)	(0.021)	(0.026)	(0.022)	(0.021)	(0.040)
R-squared	0.391	0.25	0.068	0.057	0.148	0.242	0.308

Note: The table presents quantile regression results. Control variables include global market controls (S&P 500, MSCI World, VIX), country-level controls (MSCI China, EUROSTOXX, Nikkei), news-based economic policy controls (EPU), and asset-level controls (Bitcoin volatility, trading volume). We use variance inflation factors (VIFs) to check for multicollinearity. Because all values are well below the threshold value, we do not find evidence for multicollinearity. Furthermore, we perform the Breusch-Pagan Cook-Weisberg test and do not reject the null hypothesis of homoskedasticity. In addition, we run ordinary least squares regression with robust standard errors. Coefficients for GPU_{6M}, GPU_{3M}, and GPU_{1M} are negative and significant at the 1% level, except for the latter coefficient. Details are provided in Table A.3 in the Appendix.
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

5% level. We do not find a significant effect for GPU_{1M}.[9] Figure 1 provides graphical illustration of the t-tests. The correlation matrix and detailed t-test results are provided in Table A.1 and A.2 in the Appendix.

Table 2 reports estimated coefficients based on our quantile regression model. We make three main observations. First, we observe that all coefficients are negative. This implies that an increase in global political uncertainty has negative impact on Bitcoin return. Second, coefficients are highly significant for GPU_{6M} and GPU_{3M} and become insignificant for GPU_{1M}.[10] This is in line with survey and public opinion research, showing

[9] Given the non-normal distribution of Bitcoin return and to ensure robustness of our results, we perform two additional, non-parametric tests, namely bootstrapped one-sampe t-test and Mann-Whitney two-sample test. Both tests yield the same p-values as our base case t-test. Results are available upon request.

[10] All coefficients are at least significant at the 5% or 1% level, except for GPU_{3M} at the 25- and 50-th quantile.

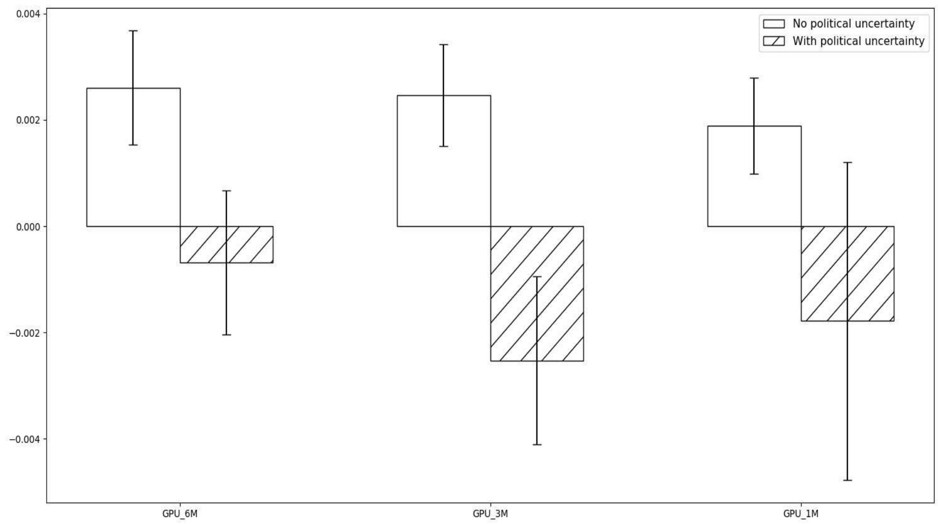


Figure 1: Average Bitcoin return with and without political uncertainty.
The solid lines show standard errors of the mean.

that as election day approaches, voter certainty becomes greater, thereby reducing the effect of political uncertainty.[11] Third, the impact of political uncertainty tends to be more pronounced in the left and right tail of the distribution. For instance, while the impact of GPU_{3M} is strong (-0.012) and significant at the 1% level for the 5-th quantile, it becomes relatively weak (-0.005) and insignificant at the median. The impact then increases (-0.010) and becomes significant again at the 1% level for the 95-th quantile. GPU_{6M} and GPU_{1M} exhibit similar patterns, although with lower magnitude.
We complement our analysis by conducting two sets of tests to assess the robustness of our results. First, we repeat our regressions by applying nonparametric, simultaneous-quantile regression via bootstrapping to test the robustness and account for the relative short time series of our data.[12] We obtain very similar coefficients, and the same p-values. Second, we conduct a placebo test to alleviate potential concerns that our results might be caused by other events than political uncertainty. Therefore, we construct random pseudoevents that match the lengths of GPU_{6M}, GPU_{3M}, and GPU_{1M}, respectively, but do not fall within the same period. Running the same quantile regressions as before, we obtain insignificant p-values across all quantiles. Hence, we do not find evidence that placebo political uncertainty influences Bitcoin return. The results are provided in Tables A.4 and A.5 in the Appendix.

The findings provide helpful information to better understand the role of Bitcoin and contribute to the debate whether Bitcoin can serve as a safe haven asset during times of political uncertainty. During such periods, investors tend to sell their risky assets

[11] The increase in voter certainty is reflected by the convergence of polls right before the election, and is often referred to as the "convergence mystery" (see, for example, Moore, 2008).
[12] We perform 1,000 bootstrap replications.

and reallocate their holdings towards safer ones, such as cash, government bonds, or gold (Kindleberger & Aliber, 2011). The rationale is low or negative correlation with another asset or portfolio, thereby acting as a hedge against uncertainty. However, and unlike previous studies (see, for example, Bouri et al., 2017; Dyhrberg, 2016a,b; Stensås et al., 2019; Urquhart & Zhang, 2019), we observe that Bitcoin reacts negatively to political uncertainty across all quantiles. Therefore, we do not find evidence that Bitcoin is immune against uncertain political situations or can serve as a safe haven and advise investors to not use Bitcoin as a hedging or diversification tool for their portfolios. Furthermore, our results provide valuable information to policymakers trying to better understand the role Bitcoin might play during future political crises. In addition to more difficult price discovery, higher volatility and transaction costs, as well as lower liquidity relative to traditional assets (Smales, 2019), our empirical evidence adds another dimension to the debate of Bitcoin's safe haven properties by showing that it is not immune against market downturns at times of political uncertainty. Taken together, the results do not provide evidence that Bitcoin can serve as a save haven, but should rather be considered what it is – an investment that provides high reward at the cost of high risk.

4 Conclusion

In this study, we investigate the impact of political uncertainty on Bitcoin. We introduce the U.S. federal election cycle as a proxy for political uncertainty, which tends to better isolate exogenous variation in uncertainty than EPU. Our results shed a new light on the property of Bitcoin being a safe haven asset and can be summarized as follows. First, using quantile regression, which is most appropriate to detect left and right tail dependence structures, we find that an increase in global political uncertainty has negative impact on Bitcoin return. Second, political uncertainty has the strongest impact on Bitcoin six and three months prior the election and decreases as the election date approaches. Third, the effect of political uncertainty is more pronounced in the left and right tail of the distribution. Lastly, the results are robust using alternative model specifications, such as OLS and bootstrapped quantile regression.

The results provide important information for investors, policymakers and regulators. While Bitcoin is often referred to as a hedging tool that can help investors during difficult times, our empirical results suggest that Bitcoin itself cannot live up to those expectations. Nevertheless, investors can use the proposed framework to predict future Bitcoin return and to make better informed investment decisions. For example, our model can be implemented in the context of portfolio risk management, where signals from the model trigger the purchase of Bitcoin futures or a reallocation of the portfolio from Bitcoin to other asset classes. As popularity grew, policymakers and regulators became increasingly concerned about the role of Bitcoin in the global financial system and the underlying forces that determine its price. We show that global political uncertainty measured by the U.S. election cycle is an important variable to take into account and that Bitcoin may not mitigate the effects of the next crisis. This finding is especially alarming given the mounting evidence of significant spillover effects from Bitcoin to conventional asset classes during market downturns (Bouri et al., 2018; Gillaizeau et al., 2019).

Future research could investigate and validate the results by expanding the sample to other cryptocurrencies. In addition, it would be interesting to see the impact of political uncertainty on traditional safe haven assets such as gold, U.S. Treasury bonds, or the Swiss franc. Lastly, future research could use higher frequency data or non-linear models.

References

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., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? an analysis of stocks, bonds and gold. *Financial Review*, *45*(2), 217–229.

Baur, D. G., & Smales, L. A. (2018). Gold and geopolitical risk. *Working paper*.

Belo, F., Gala, V. D., & Li, J. (2013). Government spending, political cycles, and the cross section of stock returns. *Journal of Financial Economics*, *107*(2), 305–324.

Bittlingmayer, G. (1998). Output, stock volatility, and political uncertainty in a natural experiment: Germany, 1880–1940. *The Journal of Finance*, *53*(6), 2243–2257.

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between bitcoin and other assets during bear and bull markets. *Applied Economics*, *50*(55), 5935–5949.

Bouri, E., & Gupta, R. (2019). Predicting bitcoin returns: Comparing the roles of newspaper-and internet search-based measures of uncertainty. *Finance Research Letters*, 101398.

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

Brogaard, J., Dai, L., Ngo, P. T. H., & Zhang, B. (2019, 08). Global Political Uncertainty and Asset Prices. *The Review of Financial Studies*.

Brogaard, J., & Detzel, A. (2015). The asset-pricing implications of government economic policy uncertainty. *Management Science*, *61*(1), 3–18.

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.

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar–a garch volatility analysis. *Finance Research Letters*, *16*, 85–92.

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. is it the virtual gold? *Finance Research Letters*, *16*, 139–144.

Erb, C. B., Harvey, C. R., & Viskanta, T. E. (1996). Political risk, economic risk, and financial risk. *Financial Analysts Journal*, *52*(6), 29–46.

Fang, L., Bouri, E., Gupta, R., & Roubaud, D. (2019). Does global economic uncertainty matter for the volatility and hedging effectiveness of bitcoin? *International Review of Financial Analysis*, *61*, 29–36.

Gao, P., Murphy, D., & Qi, Y. (2019). Political uncertainty and public financing costs: Evidence from us gubernatorial elections and municipal bond markets. *Working paper*.

Gillaizeau, M., Jayasekera, R., Maaitah, A., Mishra, T., Parhi, M., & Volokitina, E. (2019). Giver and the receiver: Understanding spillover effects and predictive power in cross-market bitcoin prices. *International Review of Financial Analysis*, *63*, 86–104.

Hassan, T. A., Hollander, S., van Lent, L., & Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, *134*(4), 2135–2202.

Imbert, F. (2019). S&p 500 drop the most in a month on trump impeachment concerns. *CNBC*, Retrieved from: https://www.cnbc.com/2019/09/24/stock-market-us-china-trade-talks-in-focus-on-wall-street.html.

Jens, C. E. (2017). Political uncertainty and investment: Causal evidence from us gubernatorial elections. *Journal of Financial Economics*, *124*(3), 563–579.

Julio, B., & Yook, Y. (2012). Political uncertainty and corporate investment cycles. *The Journal of Finance*, *67*(1), 45–83.

Kelly, B., Pástor, L., & Veronesi, P. (2016). The price of political uncertainty: Theory and evidence from the option market. *The Journal of Finance*, *71*(5), 2417–2480.

Kindleberger, C. P., & Aliber, R. Z. (2011). *Manias, panics and crashes: a history of financial crises.* Palgrave Macmillan.

Koenker, R. (2005). Frontmatter. In *Quantile regression* (p. i-vi). Cambridge University Press.

Liu, L. X., Shu, H., & Wei, K. J. (2017). The impacts of political uncertainty on asset prices: Evidence from the bo scandal in china. *Journal of financial economics*, *125*(2), 286–310.

Moore, D. (2008). Explaining the convergence mystery: A tautology problem? *Survey Practice*, *1*(5), 2898.

Pastor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The journal of Finance*, *67*(4), 1219–1264.

Pástor, L., & Veronesi, P. (2013). Political uncertainty and risk premia. *Journal of Financial Economics*, *110*(3), 520–545.

Plakandaras, V., Bouri, E., Gupta, R., et al. (2019). *Forecasting bitcoin returns: Is there a role for the us–china trade war?* (Tech. Rep.).

Smales, L. A. (2019). Bitcoin as a safe haven: Is it even worth considering? *Finance Research Letters*, *30*, 385–393.

Stensås, A., Nygaard, M. F., Kyaw, K., & Treepongkaruna, S. (2019). Can bitcoin be a diversifier, hedge or safe haven tool? *Cogent Economics & Finance*, *7*(1), 1593072.

Swanson, A. (2019). Trump says u.s. will impose metal tariffs on brazil and argentina. *The New York Times*, Retrieved from: https://www.nytimes.com/2019/12/02/business/economy/trump-tariffs-brazil-argentina-metal.html.

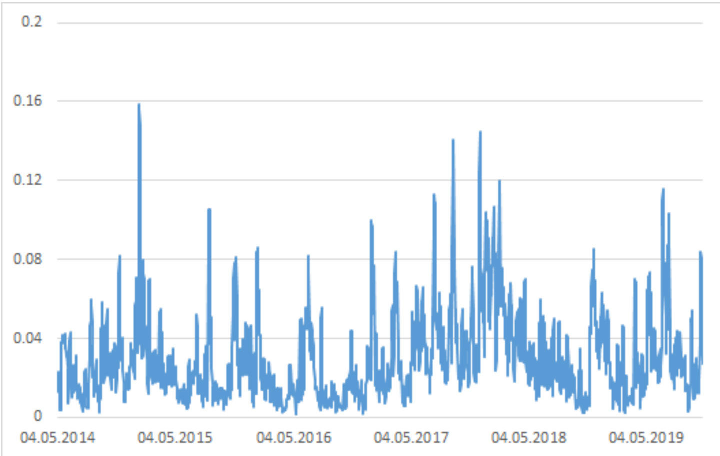
Urquhart, A., & Zhang, H. (2019). Is bitcoin a hedge or safe haven for currencies? an intraday analysis. *International Review of Financial Analysis*, *63*, 49–57.

Voth, H.-J. (2002). Stock price volatility and political uncertainty: Evidence from the interwar period.

Wang, G.-J., Xie, C., Wen, D., & Zhao, L. (2018). When bitcoin meets economic policy uncertainty (epu): Measuring risk spillover effect from epu to bitcoin. *Finance Research Letters*.

Appendix

(a) Bitcoin return



(b) Bitcoin volatility

Figure A.1: Bitcoin return, volatility and global political uncertainty for the period April 28, 2013 to October 31, 2019. The shaded area displays six month GPU.

Table A.1: Correlation matrix

	Return	GPU_{6M}	GPU_{3M}	GPU_{1M}
Return	1			
GPU_{6M}	-0.220*	1		
GPU_{3M}	-0.276**	0.690***	1	
GPU_{1M}	-0.152	0.463***	0.671***	1

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table A.2: Bitcoin return during low and high political uncertainty

	Mean	Std. Err.	Std. Dev.	95% Conf. Interval	
GPU_{6M}					
low	0.003	0.001	0.007	0.000	0.005
high	-0.001	0.001	0.006	-0.004	0.002
low − high	0.003*	0.000	0.001	0.004	0.003
GPU_{3M}					
low	0.002	0.001	0.007	0.001	0.004
high	-0.003	0.002	0.005	-0.006	0.001
low − high	0.005**	-0.001	0.002	0.007	0.003
GPU_{1M}					
low	0.002	0.001	0.007	0.000	0.004
high	-0.002	0.003	0.007	-0.009	0.006
low − high	0.004	-0.002	0.000	0.010	-0.002

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table A.3: OLS regression results

	(1)	(2)	(3)
GPU_{6M}	-0.006***		
	(0.002)		
GPU_{3M}		-0.007***	
		(0.002)	
GPU_{1M}			-0.005
			(0.003)
Volatility	-0.071	-0.067	-0.031
	(0.068)	(0.068)	(0.070)
Volume	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
S&P 500	-0.028	-0.041	-0.029
	(0.050)	(0.050)	(0.052)
MSCI World	0.0007***	0.0006**	0.0007
	(0.000)	(0.000)	(0.000)
MSCI China	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Nikkei	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
EUROSTOXX	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
VIX	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)
EPU	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
R-squared	0.252	0.242	0.160

Note: Robust standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table A.4: Bootstrapped quantile regression results

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
GPU_{6M}	-0.007**	-0.004	-0.005**	-0.010***	-0.007**	-0.010***	-0.009***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Constant	0.021	0.012	0.007	0.036*	0.080*	0.033	0.035
	(0.021)	(0.023)	(0.018)	(0.021)	(0.041)	(0.026)	(0.027)
R-squared	0.393	0.310	0.172	0.148	0.184	0.263	0.333
GPU_{3M}	-0.012***	-0.009**	-0.005	-0.005*	-0.006*	-0.009***	-0.010***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Constant	0.019	0.027	0.018	0.037	0.051**	0.046*	0.060**
	(0.017)	(0.036)	(0.021)	(0.038)	(0.024)	(0.025)	(0.026)
R-squared	0.392	0.271	0.136	0.105	0.199	0.303	0.367
GPU_{1M}	-0.010	-0.011	-0.001	0.002	-0.004	-0.008	-0.005
	(0.008)	(0.008)	(0.006)	(0.006)	(0.003)	(0.006)	(0.005)
Constant	0.003	0.007	0.010	0.026	0.047	0.044	0.027
	(0.020)	(0.015)	(0.026)	(0.039)	(0.029)	(0.042)	(0.044)
R-squared	0.391	0.250	0.068	0.057	0.148	0.242	0.308

Note: The table presents bootstrapped quantile regression results. R-squareds are pseudo R-squareds. Bootstrapped standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table A.5: Placebo quantile regression results

	Q5	Q10	Q25	Q50	Q75	Q90	Q95
GPU_{6M}	-0.004	-0.001	0.000	-0.003	-0.005	-0.006	-0.001
	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.005)
Constant	-0.001	0.009	0.011	0.037	0.042*	0.026	0.029
	(0.046)	(0.041)	(0.036)	(0.031)	(0.022)	(0.025)	(0.029)
R-squared	0.293	0.199	0.065	0.058	0.146	0.224	0.278
GPU_{3M}	0.004	0.003	0.005	0.002	-0.002	-0.007	-0.007
	(0.004)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)	(0.005)
Constant	-0.018	-0.002	0.006	0.025	0.047	0.082**	0.067*
	(0.037)	(0.025)	(0.027)	(0.032)	(0.034)	(0.036)	(0.035)
R-squared	0.321	0.236	0.114	0.058	0.121	0.248	0.323
GPU_{1M}	0.003	0.003	0.008	0.005	0.001	0.002	0.001
	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)	(0.004)	(0.005)
Constant	-0.010	-0.002	-0.012	0.028	0.037	0.029	0.019
	(0.041)	(0.034)	(0.042)	(0.046)	(0.039)	(0.043)	(0.052)
R-squared	0.304	0.221	0.082	0.078	0.125	0.212	0.278

Note: The table presents placebo quantile regression results. R-squareds are pseudo R-squareds. Bootstrapped standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.