

Behavioural antecedents of Bitcoin trading volume: A panel Granger causality test

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Abstract. This paper aims to examine the behavioural determinants of Bitcoin trading volume within a cross-country framework of 14 world economies plus the Eurozone. We introduce a basic taxonomy of behavioural indicators, distinguishing between consumer confidence, economic policy uncertainty (EPU), and indicators of financial volatility. Our estimations reveal that the Bitcoin trading volume can be predicted more accurately by EPU than by any other class of indicators. Finally, we identify the COVID-19 shock as a catalyst for a psychologically-driven Bitcoin market and find evidence that Bitcoin was a macro hedging instrument in the pandemic. To obtain our results, we conducted a panel Granger-causality test, employing the Least Squares Dummy Variables (LSDV) estimator. Contrary to previous research, we found that market fundamentals (industrial production and equity market volume) became significant drivers of Bitcoin trading during the pandemic. This conclusion was preserved when we used the LSDV corrected estimator, which is more suitable for panels with a smaller time dimension. Apart from the practical implications for traders, this paper provides researchers with detailed steps for applying Granger causality testing in panel data settings.

Keywords: Bitcoin, economic policy uncertainty, LSDV estimator, LSDV-corrected estimator, panel Granger causality test

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1. Introduction

Fourteen years after the introduction of Bitcoin, this decentralized cryptocurrency is still attracting attention from both investors and researchers. Like other cryptocurrencies, Bitcoin is mainly traded by retail investors, and the general public is divided into two distinct camps: the sceptical camp, which considers the crypto revolution a mere bubble, and the enthusiastic one, which sees this market as an investment opportunity not to be missed. This emotionally charged nature of the Bitcoin market makes it hard to explain by market fundamentals [10, 32], but highly susceptible to sentiment shocks [13]. Previous studies have mostly indicated that macroeconomic variables do not have a significant impact on cryptocurrencies [35]. However, in light of the pandemic and the resulting disruptions to financial markets, it might be necessary to re-evaluate this view.

We add to the literature in three different aspects. The existing Bitcoin literature mostly relies on US data [21] or a smaller number of large world economies [14]. On the other hand,

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we still do not know much about Bitcoin trading determinants from a wider international perspective. To provide an initial impetus to this strand of literature, we introduce a multi-country framework, in which we examine 14 world economies plus the Eurozone, and shift the focus from Bitcoin price dynamics and returns to trading volume, which have insofar been rather neglected in the literature.

Next, we take a broader perspective on the behavioural determinants of crypto trading, and distinguish between three distinctive classes of indicators related to i) the expected future financial situation, ii) economic policy uncertainty, and iii) VIX uncertainty and risk aversion as proxies of global financial market volatility. Finally, we identify COVID-19 as an exogenous shock that disrupted financial markets and investigate if the pandemic has modified crypto-market specifics. We pay particular attention to the choice of the panel estimator used for the Granger causality test. We briefly discuss the theoretical properties of each estimator and formally test whether our empirical results are affected by the choice of the underlying estimator. We also distinguish between the short-run and long-run analysis.

Our results show that the EPU outperforms all other behavioural indicators in terms of predictive properties, and this result is robust to several specifications of panel Granger causality. The pandemic is found to have significantly altered the influence of trading determinants, showing that Bitcoin was significantly influenced by macro variables in the period following the initial COVID shock.

2. Literature review

A lion's share of crypto research focuses on the interrelationship between crypto market prices and macroeconomic fundamentals or other asset classes. The majority of these studies focuses on Bitcoin as the world's largest cryptocurrency by market capitalization.

Empirical studies dealing with forecasting Bitcoin returns have mostly focused not on finding the optimal predictor of the Bitcoin market, but on finding a methodological framework that is sophisticated enough to adequately capture Bitcoin dynamics and anticipate its future tendencies. In this regard, wavelet decomposition [31], random forest models [20], mixed frequency models and asymmetric GARCH estimations [38] are some of the forecasting techniques considered. Depending on the context and model specifications, all of these methods provide useful inputs for predicting Bitcoin returns or volatility.

Regarding potential leading indicators of the Bitcoin market, Choi and Shin [15] find that Bitcoin prices are related to inflation shocks (both actual and expected), but have no particular relationship with gold prices. Virk [37] also concludes that Bitcoin price patterns are decoupled from main fiat currencies. Basher and Sadorsky [5] perform Bitcoin price forecasting and find that Bitcoin reacts less intensively to inflation shocks than gold, giving gold the edge as an inflation hedge. Very similar conclusions are also drawn by Bouri et al. [10] and Shen et al. [32], who postulate that Bitcoin prices mostly move independently of market fundamentals. However, the COVID-19 pandemic seems to have altered this relationship to some extent. Huang et al. [23] identify the pandemic as a tipping point that accentuates Bitcoin's sheltering role vis-à-vis traditional financial assets (stocks and bonds). In a similar vein, Nguyen [29] detects an increased correlation between Bitcoin and stock prices during the pandemic.

Another strand of literature focuses on the role of sentiment in driving Bitcoin prices. In that sense, the literature on the impact of various behavioural variables on Bitcoin trading has literally proliferated. These include assessments of Twitter sentiment [16], Google-based indicators of investor sentiment [13], sentiment derived from news headlines [22], the Economic Policy Uncertainty (EPU) index [14, 25] and the Chicago Board Options Exchange Volatility (VIX) index [1]. The aforementioned papers almost uniformly find that sentiment variables contain relevant information for predicting Bitcoin prices.

It should be noted that the studies evaluated here focus exclusively on forecasting Bitcoin returns or Bitcoin volatility. However, the literature has mostly ignored trading volume as the dependent variable in the model, and it precisely is this niche that we aim to fill in this paper. As the crypto market has grown to billions of dollars, it has become essential to be able to predict its transaction volume, not only to enable better trading strategies, but also to improve the management of blockchain platforms [28]. Finally, it has been found that Bitcoin trading volume is an important determinant of tail events such as extremely positive or extremely negative Bitcoin returns [11]. In light of this, we contribute to the literature by providing a panel data framework for predicting Bitcoin trading volume.

3. Data and methodology

To investigate the impact of behavioural variables on Bitcoin trading volume, weekly observations of the Bitcoin trading volume variable (VOL) are collected for the period from April 2013 to February 2022. This data was obtained from the website https://coin.dance/ for a total of 14 economies (Australia, Brazil, Canada, Chile, China, Colombia, Denmark, Japan, Korea, Mexico, Russia, Sweden, the United Kingdom, and the United States) plus the Eurozone. The choice of countries and the specific period of analysis were dictated by the data availability, as it was necessary to ensure that sufficient data was available to generate reliable conclusions. To make the data comparable across countries, the data are first converted from local currencies to USD using the corresponding historical exchange rates for each observed week, and then converted from weekly to monthly by summing the corresponding proportions of weekly volumes that fall within each month. There are two specific reasons why we chose VOL as the dependent variable in the model. The first reason is that the ability to predict the volume of Bitcoin transactions allows for better trading strategies and better management of blockchain platforms [28]. The second reason is that the differences in Bitcoin prices on different exchanges are highly correlated while trading volumes vary greatly.

We examine three behavioural determinants of VOL. The first determinant is the Consumer Confidence Index (CCI), which is gathered from OECD. The CCI is a survey-based indicator that assesses consumers' expected financial position, their views on the general economic climate in the country, unemployment, and their propensity to save. The CCI index is normalized to have a long-term mean of 100, so CCI values above 100 should indicate above-average propensity to consume and invest. Garner [18] found CCI to be a useful tool for predicting changes in consumer spending but points out that it should not be used in isolation in forecasting economic outcomes, but should be considered together with other economic indicators.

The second determinant is the Economic Policy Uncertainty (EPU) Index which is obtained from https://www.policyuncertainty.com/. The US version of the EPU Index is a text-based indicator that proxies uncertainty based on the frequency of news articles containing specific keywords, such as 'uncertainty' or 'uncertain', 'economic' or 'economy' and some of the related terms: 'Congress', 'deficit', 'Federal Reserve', 'legislation', 'regulation' or 'White House' etc. [4]. Like the CCI, the EPU Index is also normalized for easier interpretation. For other countries in our studied sample, the selection of keywords is slightly modified to reflect the idiosyncrasies of each economy [4]. The existing literature using the EPU index to study Bitcoin trading is mainly considered with Bitcoin returns [14, 17] and price [**?**] while we focus on Bitcoin trading volume.

As the third class of indicators, global measures of uncertainty (VIX_UN) and risk aversion (VIX_AV) [7] are collected from https://mariehoerova.net/. These indices are obtained as a decomposition of the VIX index. Previous literature found it to have a negative impact on Bitcoin trading [10], while more recent research finds a positive relationship [19, 36].

In addition to the three behavioural determinants, we also include some control variables in the model. We collect the total equity market volumes related to each country (EQ) from https://statistics.world-exchanges.org and the industrial production year-on-year growth rates (IND) are used as proxies for economic fundamentals (source: OECD and FRED database). Previous research has not shown that macro variables significantly affect Bitcoin trading, however there is some evidence that the crypto market is a proxy for equity markets [30], so a negative sign of the relationship could be expected. By including additional variables as control variables in our model, we implement a comprehensive approach to ensure the validity and reliability of our results and provide a deeper understanding of the relationships between the variables.

We analyse the causal relationship between the stationary variables VOL and x (their behavioural determinant) using the following dynamic fixed effect model:

$$VOL_{it} = \sum_{k=1}^{K} \gamma_k VOL_{i,t-k} + \sum_{k=1}^{K} \beta_k x_{i,t-k} + \alpha_i + \epsilon_{it}, \qquad i = 1, \ldots, N; t = 1, \ldots, T \tag{1}$$

where VOL_{it} is the dependent (explained) variable, $VOL_{i,t-k}$ are the lagged dependent variables, $x_{i,t-k}$ are the lagged values of the strictly exogenous independent (explanatory) variable, γ_k and β_k are regression coefficients, α_i is an unobserved individual specific effect fixed in time and ϵ_{it} is an unobserved white noise error term. Under the null hypothesis, we test for homogenous non-causality, implying that x does not Granger-cause VOL:

$$\begin{aligned} &H_0 : \beta_k = 0, \forall k \in \{1, \ldots, K\} \\ &H_1 : \exists k \in \{1, \ldots, K\} \beta_k \neq 0 \end{aligned} \tag{2}$$

The test is performed using a conventional Wald statistic. In addition to the short-run Granger causality test, we also examine the long-run coefficients, which are obtained as follows:

$$\theta = \frac{\sum_{k=1}^{K} \beta_k}{1 - \sum_{k=1}^{K} \gamma_k} \tag{3}$$

As a robustness check we extend our bivariate model to include the control variables IND and EQ (4) and prun the same test.

$$\begin{aligned} VOL_{it} = \sum_{k=1}^{K} \lambda_k VOL_{i,t-k} + \sum_{k=1}^{K} \beta_k x_{i,t-k} + \sum_{l=1}^{L} \gamma_l IND_{i,t-l} + \sum_{m=1}^{M} \delta_m EQ_{i,t-m} + \alpha_i + \epsilon_{it}, \\ i = 1, \ldots, N; t = 1, \ldots, T. \end{aligned} \tag{4}$$

To avoid choosing too few or too many lags we follow Kónya [27] approach and allow for the number of lags to vary with regard to the independent variable but remain the same across countries. Namely, choosing the right number of lags is very important because by using too few lags some important variables may be omitted. On the other hand, by including too many lags, additional observations are lost and the results become less precise.

Finally, to conduct the Granger causality test it was necessary to choose an adequate panel data estimator. Including the lagged dependent variable $VOL_{i,t-1}$, correlates it with α_i and introduces bias into the OLS estimate. To solve this problem, different estimators for dynamic panel data are developed. The most popular and commonly used estimators are difference GMM developed by Arellano and Bond [3] and system GMM developed by Blundell and Bond [9]. Both estimators use instruments for the lagged dependent variable $VOL_{i,t-1}$ to avoid bias. The estimator of Arellano and Bond [3] uses second and earlier lags of the dependent variable $VOL_{i,t-2}, VOL_{i,t-3}, \ldots$.

Blundell and Bond [9] estimator uses lagged values of dependent variable and the value of the dependent variable in the first differences $\Delta VOL_{i,t-1}$. However, both estimators are appropriate for datasets with large N and small T. Therefore, they are not suitable for our data. On the other hand, due to the fact that the bias of the lagged dependent variable decreases with the growth of time dimension [26], we decide to employ Least Squared Dummy Variables (LSDV) estimator. Judson and Owen [24] have shown that the LSDV estimator outperforms the GMM estimators in the case of $T = 30$. Moreover, Beck et al. [6] found that when T is greater than 40, there is no harm in estimating dynamic model with LSDV estimator. The attractive property of this estimator is the lower variance than other dynamic panel data estimators [26].

However, if we divide our dataset into two sub periods, before and during COVID-19, the second subsample has 24 observations and the LSDV estimator tends to be biased because of the correlation of the lagged dependent variable with ϵ_{it}. The magnitude of this bias depends on the size T and is particularly large at a low T value [12]. For this reason, we employ another estimator as an additional robustness check for the period after the COVID shock. Namely, we use the Least Squares Dummy Variable Corrected (LSDVc) estimator developed by Kiviet [26]. We found additional support for our decision in the work of Škrabić Perić [33]. She found that for samples with smaller values of N and T, where T is larger than N such as $N = 10$, $T = 15$ and $N = 10$, $T = 30$; LSDVc tends to have lower bias and Root Mean Squared Error not only in comparison to LSDV but also to GMM estimators.

This estimator consists of three steps. In the first step LSDV estimates are obtained. Kiviet [26] derived an equation to calculate the bias of the estimate by using the results of one of the unbiased estimators of Anderson and Hsiao [2] or one of the above mentioned GMM estimators.In the following step, the calculated bias is subtracted from the LSDV estimate. Regardless of the chosen estimator, the initial results are very similar. However, in the empirical part of this paper, we use Arellano and Bond [3] and Blundell and Bond [9] as initial estimators.

4. Results

Before performing an econometric analysis, it is recommended to check the data for the presence of a unit root. Therefore, to assess the stationarity of our variables, we employ two different unit root tests. Specifically, we utilize the second generation Cross-sectionally Augmented Dickey Fuller (CADF) unit root test for country-specific variables, as well as the ADF unit root test for global variables (VIX_UN and VIX_AV). The results of these tests (Table 1) reveal that only the CCI index has a unit root, and therefore we model it in first differences ($DCCI$), while all other variables are modelled in levels.

Variable	ADF test	CADF test	First difference CADF test
VOL	-	0.000	-
CCI	-	0.559	0.000
EPU	-	0.000	-
VIX_UN	0.000	-	-
VIX_AV	0.000	-	-

Note: Table entries are p-values

Table 1: *Unit root test results*

To obtain the optimal lag order K in equation (1), we use the Bayesian Information Criterion (BIC). In equation (4), for each variable we use the number of lags obtained from the bivariate model. Since the impact of economic sentiment usually intensifies in turbulent economic periods

[34], we also perform a sub-sample analysis by splitting the period under study into the pre-pandemic period and the period after the initial COVID shock. We set March 2020 as the break date since that is when the World Health Organization declared COVID-19 a pandemic. This allows us to examine any differences in the relationship between Bitcoin volume and economic sentiment before and after the pandemic outbreak. The results of the determined optimal lag order of the variables for all time periods studied are presented in Table 2.

Variable	EPU	DCCI	VIX_UN	VIX_AV	EQ	IND
Entire period	5	2	2	2	4	5
Before COVID	4	4	4	4	4	4
After COVID	4	4	4	4	4	1

Table 2: *Lag orders of the variables*

		EPU			DCCI		
		Entire period	Before COVID	After COVID	Entire period	Before COVID	After COVID
$x \to VOL$ causality (p-value)		0.3266	0.0316	0.0001	0.5383	0.2776	0.1737
Long-run	Coefficient	7031.89	11410.6	46101.22	4193617	1.32E+07	-1575585
	p-value	0.675	0.599	0	0.267	0.107	0.491
		VIX_UN			VIX_AV		
		Entire period	Before COVID	After COVID	Entire period	Before COVID	After COVID
$x \to VOL$ causality (p-value)		0.4496	0.0324	0.0483	0.5264	0.0026	0.0369
Long-run	Coefficient	-51057.5	-939781.1	120695.1	-48658	-2053813	176041.8
	p-value	0.521	0.004	0.021	0.575	0	0.005
		EQ			IND		
		Entire period	Before COVID	After COVID	Entire period	Before COVID	After COVID
$x \to VOL$ causality (p-value)		0.0124	0.6937	0.0058	0.441	0.9144	0.0057
Long-run	Coefficient	-5.623	-5.131	-9.992	-412123	131509.2	-132016.6
	p-value	0.013	0.305	0.006	0.188	0.82	0.005

Table 3: *Bivariate model test results*

The results presented in Table 3 show that $DCCI$ does not Granger-cause VOL in any period, while EPU (at conventional significance levels) Granger-causes VOL both before and after COVID-19, but not in the entire period. In addition, VIX_UN and VIX_AV exhibit a similar pattern. Moreover, their long-run coefficients reveal a shift from a negative to a positive relationship. This change has roots in the COVID-induced contagion effect [19]. As the investors began to perceive traditional financial markets as overly uncertain, they shifted to digital currencies, such as Bitcoin, which took on the role of a safe haven asset [19].

The safe haven effect during the pandemic is also confirmed by the relationship between macroeconomic variables and VOL. Our analysis shows that both EQ and IND Granger-cause VOL in the post-COVID period, with a negative long-run coefficient.

Interestingly, these findings are in contrast to prior research, which has suggested that Bitcoin is not influenced by macroeconomic fundamentals. Previous studies by Shen et al. [32] and Bouri et al. [10] have indicated that Bitcoin is not subject to the same macroeconomic forces that affect traditional financial assets. However, our results paint a different picture and suggest that the COVID shock has altered this relationship. This highlights the importance of re-evaluating traditional assumptions and theories in the face of unforeseen global events such as the COVID-19 pandemic. Our findings confirm that the pandemic has disrupted the functioning of financial markets.

For behavioural variables that were significant in the previously discussed model, we perform a robustness check by extending our bivariate model. This is done by adding IND and EQ as control variables to the specification of the model as shown in (4). The results are presented in Table 4 and Table 5.

		$EPU \to VOL$		$IND \to VOL$		$EQ \to VOL$	
		Before COVID	After COVID	Before COVID	After COVID	Before COVID	After COVID
$x \to VOL$ causality (p-value)		0.0309	0.0146	0.8974	0.045	0.6893	0.0618
Long-run	Coefficient	10107.06	32267.78	170277.2	-140635	-5.18308	-6.12491
	p-value	0.645	0.002	0.766	0.065	0.297	0.025

Table 4: *Robustness check for EPU*

Table 4 leaves the results qualitatively intact. Economic uncertainty remains a strong driver of Bitcoin trading. However, the influence of VIX_AV and VIX_UN largely fades in the period following the COVID outbreak when fundamentals are taken into account (Table 5). Nevertheless, there are some significant relationships found for IND (at 10% significance level) and EQ, which argue for the macro hedge hypothesis.

Covariates: VIX_AV, IND, and EQ				Covariates: VIX_UN, IND, and EQ			
		Before COVID	After COVID			Before COVID	After COVID
VIX_AV→VOL (p-value)		0.0032	0.07455	VIX_UN→VOL (p-value)		0.043	0.4012
Long-run	Coefficient	-2063691	56148.4	Long-run	Coefficient	-922792	1075.68
	p-value	0.001	0.441		p-value	0.005	0.986
IND→VOL (p-value)		0.9011	0.2841	IND→VOL (p-value)		0.9333	0.0976
Long-run	Coefficient	-161618	-62456	Long-run	Coefficient	-22630	-99883
	p-value	0.768	0.287		p-value	0.968	0.099
EQ→VOL (p-value)		0.7604	0.0143	EQ→VOL (p-value)		0.7582	0.0106
Long-run	Coefficient	-2.4255	-8.0115	Long-run	Coefficient	-2.8396	-8.8224
	p-value	0.61	0.016		p-value	0.563	0.01

Table 5: *Robustness check for VIX_AV and VIX_UN*

Results for the period after COVID using the LSDVc estimator with both Arellano and Bond

(AB) and Blundell-Bond (BB) as initial estimators are presented in Table 6 and Table 7.

		Initial estimator: AB					
		EPU	DCCI	VIX_UN	VIX_AV	EQ	IND
$x \to$ VOL (p-value)		0.001	0.2166	0.1357	0.0859	0.0136	0.0128
Long-run	Coefficient	46161.78	-2076036	120594.3	174166.1	-9.87361	-132668
	p-value	0	0.471	0.044	0.015	0.041	0.011
		Initial estimator: BB					
		EPU	DCCI	VIX_UN	VIX_AV	EQ	IND
$x \to$ VOL (p-value)		0.0015	0.2455	0.1329	0.0833	0.0175	0.0264
Long-run	Coefficient	47738.1	-1919051	124739.1	180639.3	-10.3485	-140425
	p-value	0	0.502	0.043	0.015	0.046	0.024

Table 6: *LSDVc estimator results for the period after COVID*

		After COVID			
		Initial estimator: AB		Initial estimator: BB	
		Covariates: VIX_AV, IND and EQ	Covariates: VIX_UN, IND and EQ	Covariates: VIX_AV, IND and EQ	Covariates: VIX_UN, IND and EQ
VIX_AV/VIX_UN→VOL (p-value)		0.8716	0.4104	0.8883	0.454
Long-run	Coefficient	30551	-10489.98	32042.73	-1033.59
	p-value	0.725	0.881	0.725	0.888
IND→VOL (p-value)		0.3711	0.1675	0.4006	0.191
Long-run	Coefficient	-235624.5	-285634.3	-233188	-283712
	p-value	0.087	0.041	0.098	0.048
EQ→VOL (p-value)		0.0557	0.0438	0.0663	0.0543
Long-run	Coefficient	-7.626622	-8.180785	-7.92488	-8.48196
	p-value	0.074	0.061	0.081	0.068

Table 7: *Robustness check using LSDVc for the period after COVID*

The results remain qualitatively unchanged for EPU, $DCCI$, EQ and IND with similar long-run coefficients, while VIX_UN and VIX_AV lose some of their significance.

Using the LSDVc estimator, VIX_UN is no longer significant for the period after COVID, but since the VIX variables lost significance in our first robustness check when control variables were included (Table 5) this was now reasonably expected using a more appropriate estimator (for smaller T). VIX_AV remained significant but now at the 10% level. When the control variables were included (Table 7), IND became significant in the long run for the period after COVID, which now further confirms the macro hedge hypothesis.

5. Conclusion

This paper aims to test the predictive accuracy of three distinct classes of behavioural constructs with regard to Bitcoin trading volume. We reveal that the EPU index outperforms other proxies in this context. Our findings also provide a new perspective on previous research that had suggested that macroeconomic variables do not have a significant impact on Bitcoin trading. We have shown that there was a shift where Bitcoin was influenced by macroeconomic fundamentals during the pandemic. These findings are robust to several specifications of Granger causality tests, involving the inclusion of control variables and the use of different panel data estimators (LSDV and LSDVc), which are more appropriate for the period following the COVID-19 outbreak since it has a smaller T size.

From an academic and policy perspective, fully comprehending the driving forces behind Bitcoin trading volume is a crucial step for the development of appropriate valuation models and calculation of the intrinsic value of Bitcoin [11]. On the other hand, traders often use technical analysis when developing their investment strategies, which in turn uses trading volume as one of their key inputs [11].

Apart from the utilitarian value of our results for traders and policy analysts, we believe this paper provides valuable insights for academics dealing with applied panel analysis, Granger causality testing in particular. We address several empirical questions, including the advantages and disadvantages of panel data estimators, that are often overlooked in the existing literature. In our study we did not consider possible heterogeneity across the different economies of the world, so this remains a potential matter to be explored in future research.

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Data availability

Stata code and data used in this paper are available at:
https://figshare.com/s/230363cf01e0566afe39

References

[1] Al-Yahaee, K. H., Rehman, U. M., Mensi, W. and Al-Jarrah, I. M. W. (2019). Can uncertainty indices predict Bitcoin prices? A revisited analysis using partial and multivariate wavelet approaches. The North American Journal of Economics and Finance, 49, 47-56.

[2] Anderson, T. W. and Hsiao, C. (1982). Formulation and estimation of dynamic models using panel data. Journal of Econometrics, 18(1), 47–82. doi: 10.1016/0304-4076(82)90095-1

[3] Arellano, M. and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. Review of Economic Studies, 58(2), 277–297. doi: 10.2307/2297968

[4] Baker, S., Bloom, N. and Davis, S. J. (2016). Measuring Economic Policy Uncertainty. The Quarterly Journal of Economics, 131(4), 1593–1636. doi: 10.1093/qje/qjw024

[5] Basher, S. A. and Sadorsky, P. (2022). Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility? Machine Learning with Applications, 9(15): 10035. doi: 10.1016/j.mlwa.2022.100355

[6] Beck, N. L., Katz, J. N. and Mignozzetti, U. G. (2014). Of Nickell Bias and its Cures: Comment on Gaibulloev, Sandler, and Sul. Political Analysis, 22(2), 274–278. doi: 10.7910/DVN/24503

[7] Bekaert, G., Hoerova, M. and Lo Duca, M. (2013). Risk, uncertainty and monetary policy. Journal of Monetary Economics, 60(7), 771–788. doi: 10.1016/j.jmoneco.2013.06.003

[8] Ben Khelifa, S., Guesmi, K. and Urom, C. (2021). Exploring the relationship between cryptocurrencies and hedge funds during COVID-19 crisis. International Review of Financial Analysis, 76: 101777. doi: 10.1016/j.irfa.2021.101777

[9] Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115–143. doi: 10.1016/S0304-4076(98)00009-8

[10] Bouri, E., Gupta, R., Tiwari, A. K. and Roubaud, D. (2017). Does Bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 23, 87–95. doi: 10.1016/j.frl.2017.02.009

[11] Bouri, E., Lau, C. K. M., Lucey, B. and Roubaud, D. (2019). Trading volume and the predictability of return and volatility in the cryptocurrency market. Finance Research Letters, 29(C), 340–346. doi: 10.1016/j.frl.2018.08.015

[12] Bun, M. J. G. and Carree, M. A. (2005). Bias-Corrected Estimation in Dynamic Panel Data Models. Journal of Business & Economic Statistics, 23(2), 200–210. doi: 10.1198/073500104000000532

[13] Burggraf, T., Huynh, T. L. D., Rudolf, M. and Wang, M. (2020). Do FEARS drive Bitcoin? Review of Behavioral Finance, 13(3), 229–258. doi: 10.1108/RBF-11-2019-0161

[14] Cheng, H.-P. and Yen, K.-C. (2020). The relationship between the economic policy uncertainty and the cryptocurrency market. Finance Research Letters, 35: 101308. doi: 10.1016/j.frl.2019.101308

[15] Choi, S. and Shin, J. (2022). Bitcoin: An inflation hedge but not a safe haven. Finance Research Letters, 46(B): 102379. doi: 10.1016/j.frl.2021.102379

[16] Critien, J. V., Gatt, A. and Ellul, J. (2022). Bitcoin price change and trend prediction through twitter sentiment and data volume. Financial Innovation, 8(1), 1-20. doi: 10.1186/s40854-022-00352-7

[17] Demir, E., Gözgör, G., Lau, C. K. and Vigne, S. A. (2018). Does economic policy uncertainty predict the Bitcoin returns? An empirical investigation. Finance Research Letters, 26, 145–149. doi: 10.1016/j.frl.2018.01.005

[18] Garner, C. A. (1991). Forecasting consumer spending: Should economists pay attention to consumer confidence surveys? Economic Review, 76(3), 57-71. Retrieved from: kansascityfed.org

[19] Ghorbel, A. and Jeribi, A. (2021). Investigating the relationship between volatilities of cryptocurrencies and other financial assets. Decisions in Economics and Finance, 44(2), 817–843. doi: 10.1007/s10203-020-00312-9

[20] Gradojevic, N., Kukolj, D., Adcock, R., and Djakovic, V. (2023). Forecasting Bitcoin with technical analysis: A not-so-random forest?. International Journal of Forecasting, 39(1), 1-17. doi: 10.1016/j.ijforecast.2021.08.001

[21] Grobys, K. (2020). When Bitcoin has the flu: on Bitcoin's performance to hedge equity risk in the early wake of the COVID-19 outbreak. Applied Economics Letters, Vol 28(10), 860–865. doi: 10.1080/13504851.2020.1784380

[22] Gurrib, I. and Kamalov, F. (2022). Predicting bitcoin price movements using sentiment analysis: a machine learning approach. Studies in Economics and Finance, 39(3), 347-364. 10.1108/SEF-07-2021-0293

[23] Huang, Y., Duan, K. and Mishra, T. (2021). Is Bitcoin really more than a diversifier? A pre- and post-Covid-19 analysis. Finance Research Letters, 43(C), 102016. doi: 10.1016/j.frl.2021.102016

[24] Judson, R. A. and Owen, A. L. (1999). Estimating dynamic panel data models: a guide for macroeconomists. Economics Letters 65(1), 9–15. doi: 10.1016/S0165-1765(99)00130-5

[25] Keramiyan, M. and Gokmenoglu, K. K. (2023). Bitcoin, uncertainty and internet searches. Studies in Economics and Finance, 40(1), 24-42. doi: 10.1108/SEF-12-2021-0536

[26] Kiviet, J.F. (1995). On bias, inconsistency, and efficiency of various estimators in dynamic panel data models. Journal of Econometrics, 68(1), 53–78. doi: 10.1016/0304-4076(94)01643-E

[27] Kónya, L. (2006). Exports and growth: Granger causality analysis on OECD countries with a panel data approach. Economic Modelling, 23, 978–992. doi: 10.1016/j.econmod.2006.04.008

[28] Lahmiri, S., Bekiros, S., and Bezzina, F. (2022). Complexity analysis and forecasting of variations in cryptocurrency trading volume with support vector regression tuned by Bayesian optimization under different kernels: An empirical comparison from a large dataset. Expert Systems With Applications, 209, 118348. doi: 10.1016/j.eswa.2022.118349

[29] Nguyen, K. Q. (2022). The correlation between the stock market and Bitcoin during COVID-19 and other uncertainty periods. Finance Research Letters, 46(A), 102284. doi: 10.1016/j.frl.2021.102284

[30] Nie, W.-Y., Cheng, H.-P. and Yen, K.-C. (2020). Investor sentiment and the cryptocurrency market. The empirical economics letters: a monthly international journal of economics, 19(11), 1253-1262. Retrieved from: eel.my100megs.com

[31] Parvini, N., Abdollahi, M., Seifollahi, S., and Ahmadian, D. (2022). Forecasting Bitcoin returns with long short-term memory networks and wavelet decomposition: A comparison of several market determinants. Applied Soft Computing, 121, 108707. 10.1016/j.asoc.2022.108707

[32] Shen, D., Urquhart, A. and Wang, P. (2020). A three-factor pricing model for cryptocurrencies.

Finance Research Letters, 34, 101248. doi: 10.1016/j.frl.2019.07.021

[33] Škrabić Perić, B. (2019). Do the most frequently used dynamic panel data estimators have the best performance in a small sample? A Monte Carlo comparison. Croatian Operational Research Review, 10(1), 45–55. doi: 10.17535/crorr.2019.0005

[34] Sorić, P. (2018). Consumer confidence as a GDP determinant in New EU Member States: a view from a time-varying perspective — SpringerLink. Empirica 45, 261–282.

[35] Sovbetov, Y. (2018). Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero. Journal of Economics and Financial Analysis, 2(2), 1-27. doi: 10.1991/jefa.v2i2.a16

[36] Škrabić Perić, B., Rimac Smiljanić, A. and Jerković, I. (2023). Crypto-asset market development: the role of country's institutional quality. Journal of Money Laundering Control. ahead-of-print. doi: 10.1108/JMLC-02-2023-0038

[37] Virk, N. (2022). Bitcoin and integration patterns in the forex market. Finance Research Letters, 44, 102092. doi: 10.1016/j.frl.2021.102092

[38] Xia, Y., Sang, C., He, C., and Wang, Z. (2023). The role of uncertainty index in forecasting volatility of Bitcoin: Fresh evidence from GARCH-MIDAS approach. Finance Research Letters, 52, 103391. doi: 10.1016/j.frl.2022.103391