Economics Bulletin

Volume 43, Issue 3

How does Bitcoin react to economic discomfort? Evidence from the economic misery index

Sinda Hadhri
ESDES Lyon the Business School of UCLy, France

Abstract

Does Bitcoin love Misery? This paper answers this question by examining the relationship between Economic Discomfort as measured by the Barro (1999) misery index and Bitcoin fundamentals and finds that lagged Barro misery index significantly increases trading volume. The effect on Bitcoin volatility is positively significant with two month-delay but seems to revert as time elapses. Bitcoin returns are less predictable based on past misery. These findings are confirmed for the period of the Covid-19 pandemic.

Funding sources: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
Declaration of interest: none.
Citation: Sinda Hadhri, (2023) "How does Bitcoin react to economic discomfort? Evidence from the economic misery index", *Economics Bulletin*, Volume 43, Issue 3, pages 1235-1253
Contact: Sinda Hadhri - sinda.hadhri@yahoo.fr.
Submitted: October 02, 2022. **Published:** September 30, 2023.

1. Introduction

Fourteen years after Satoshi Nakomoto released Bitcoin, a fully decentralized cryptocurrency based on the blockchain technology, this new cryptocurrency has become a global phenomenon and its market capitalization increased from 1.374 billion $ in May 22nd, 2013 to 214.124 billion $ in August 12th, 2020.[1] Its innovative features, transparency and the rapid increase in its market capitalization are the most important factors explaining its increasing popularity (Garcia and Schweitzer, 2015; Urquhart, 2016). The academic literature on Bitcoin has exceeded its technical aspects and stylized facts (e.g., Dweyer, 2015; Feng et al., 2018) to speculative properties (Glaser et al., 2014; Cheah and Fry, 2015; Baur et al., 2018; Corbet et al., 2018; Bouri et al., 2019; Katsiampa et al., 2019) and hedging effectiveness (e.g., Dyhrberg, 2016; Bouri et al., 2017; Demir et al., 2018).

There is one question yet to answer: Does economic environment, as proxied by the economic discontent or misery, have an impact on Bitcoin? In examining this, there are two alternative hypotheses that can be tested. First, cryptocurrencies, as highly speculative assets, can be influenced by the economic environment as a result of changes in investors' perceptions and expectations thus shifting in investment choices and portfolio allocations. Alternatively, due to its unique decentralized payment based on a peer-to-peer electronic cash system that is not controlled by any financial institutions or third parties and the relatively isolated nature of this market from other asset classes (e.g., Baur et al., 2016), cryptocurrencies can exhibit a weak response to economic conditions.

2. Theoretical background

The literature related to our study can be divided into two main literature strands. First, this study is related to the literature on the relationship between Bitcoin and macroeconomic features, which has evolved considerably during the last years. Particularly, investors and some researchers consider Bitcoin as a viable hedge against inflation (e.g., Blau et al., 2021; Choi and Shin, 2022), especially during the recent pandemic.[2] According to Oudet (1973) and Fama and MacBeth (1974), an asset is considered as an inflation hedge if its returns are uncorrelated with the rate of inflation. Consistently, an asset presents strong safe-haven properties if a negative correlation is established between its rate of return and the rate of inflation (Bodie, 1976). The monetarization and the strong demand for Bitcoin has prompted some researchers to study potential hedging properties of Bitcoin (e.g., Bouri et al., 2017; Urquhart and Zhang, 2019; Wu et al., 2019). For instance, Schilling and Uhlig (2019) have examined the interactions between Bitcoin and a more traditional currency that is supplied by a central bank (the Dollar). They allow agents to infinitely live and the possibility of speculative holdings of currencies and show that Bitcoin can be considered as a viable albeit volatile medium of exchange. In the other hand, Peetz and Mall (2017) show that Bitcoin can not be considered as a transaction currency for a multitude of reasons such as the lack of intrinsic worth, its production and the limited transaction capacity. Narayan et al. (2019) find that Bitcoin price growth is correlated with Indonesia's inflation growth and that Bitcoin's volatility contributes to currency appreciation. Baur et al. (2018) demonstrate that Bitcoin is not correlated with traditional assets such as stocks, bonds and commodities. Their empirical findings suggest that Bitcoin is mainly used as a speculative asset. We contribute to this broad literature by examining the lead-lag relation between Bitcoin and the U.S. economic wellbeing, measured using changes in economic series.

---

[1] Source : https://www.coinmarketcap.com/

[2] Bloomberg News has reports that fund managers are responding to expansionary policies of central banks during the pandemic by raising their holdings of Bitcoin (Bloomberg, 2020).

Consistent with previous literature, we use the Barro misery index that provides a better measure of economic satisfaction than other existing proxies (Barro, 1999; Welsh, 2007; Ekren et al., 2017; Sergi et al., 2021).
A second strand of literature related to our study includes studies regarding the efficiency of Bitcoin. Mixed results characterize this literature stream, as some studies provide evidence of Bitcoin efficiency (e.g., Bariviera, 2017; Blau, 2017; Nadarajah and Chu, 2017; Tiwari et al., 2018) while some others find that Bitcoin returns are significantly inefficient (e.g., Urquhart, 2016; Kristoufek, 2018; Al-Yahyaee et al., 2018). The relation between Bitcoin and economic misery could stem from structural differences in the respective markets and, hence, provides an indication of market efficiency.

3. Data and construction of variables

We use data from Bitstamp exchange[3] since it is the world most popular and liquid Bitcoin exchange[4]. The period spans 2013:05- 2021:12. Data includes the close, high and low prices and the trading volume. Bitcoin returns (R_t) are computed as the natural logarithm of change in monthly settlement Bitcoin prices. Monthly volatility (VOL_t) is calculated as natural logarithm of the highest to lowest prices over month (*t*), and the monthly trading volume (TV_t) is calculated as the natural logarithm of average trading volume over month (*t*).

The Misery index that we use is the Barro (1999) Misery index *(BMI).* BMI measures the yearly relative performance of the economy. Barro (1999) suggests that, when examining BMI, we must use "the changes over the entire course" (p.22) instead of the levels. Hence, following this same methodology, we calculate BMI as the sum of the four following metrics on the basis of training periods over 12 months including month (*t*): the difference between the average inflation rate over a year and the average inflation rate during the last quarter of the previous year (*M1*); the difference between the average unemployment rate over a year and the unemployment rate from the last month of the previous year (*M2*); the change in the 30-year government bond yield during a year (*M3*); and the shortfall of the real rate of growth during a year from the trend rate of real GDP growth (*M4*).[5]

A summary of Bitcoin variables and Misery proxies in the full sample is reported in Table 1. The mean return of Bitcoin for the sample is 5.73% with an average volatility of 29.75%. The mean trading volume (in millions) is of about 374,978. The results indicate that returns are positively but moderately skewed, with excess kurtosis. The maximum/minimum values and standard deviations indicate a relatively high volatility of returns and trading volumes. The mean BMI for the studied period is -0.3469 with a standard deviation of 0.2426.

Table 1. Summary statistics of used variables

	Mean	St. dev	Skewness	Kurtosis	Minimum	Maximum
Bitcoin						
Return	0.0573	0.2426	0.9043	6.6140	-0.4527	1.2084
Volatility	0.2975	0.1897	0.5917	2.7874	0.0096	0.8030
Trading volume (in millions)	374,978.4000	544,226.7000	1.5791	4.8606	553.1023	2267,150

[3] www.bitcoincharts.com
[4] We also used data from Binance exchange for robustness check. The results are in the appendix part (Tables A.1 to A.6). Findings remain qualitatively the same with some minor differences mainly in terms of magnitude of the coefficients.
[5] We use data from the Federal Bank of *St Louis* database.

Barro's misery index and its components						
BMI	-0.3469	6.5097	-1.1104	6.8804	-30.084	13.4473
M1	0.2817	0.1234	-0.1404	2.6463	-0.0181	0.5418
M2	0.2609	1.045	2.5132	9.2134	-1.3417	4.4917
M3	-0.5880	6.5137	-1.0072	6.6299	-29.9597	13.7201
M4	-0.3016	0.2941	1.6612	4.7977	-0.5591	0.4352

Note: this table reports the summary statistics of monthly Bitcoin returns (R), volatility (VOL) and trading volume (TV), and Barro Misery index (BMI) as well as its four components (metrics) (M1, M2, M3 and M4). The full sample covers 2013:06-2021:12.

4. Methodology

In order to examine the dynamics between Bitcoin returns, volatility and trading volume and the misery index, we estimate a Vector AutoRegressive (VAR) model. Intuitively, changes in economic conditions could have an impact on asset prices and trading activity. On the other hand, we also consider the impact in the opposite direction where changes in Bitcoin returns, volatility and trading volume can influence economic misery. We use the following model specification:

$$x_t = \alpha_0 + \beta_{11}x_{11} + \cdots + \beta_{1n}x_{1n} + \gamma_{11}BMI_{11} + \cdots + \gamma_{1n}BMI_{1n} + \varepsilon_t \quad (1)$$
$$BMI = \alpha_0 + \beta_{11}BMI_{11} + \cdots + \beta_{1n}BMI_{1n} + \gamma_{11}x_{11} + \cdots + \gamma_{1n}x_{1n} + \varepsilon_t$$

Where x_t is a vector that contains the variable of interest (R_t, VOL_t or TV_t) and BMI refers to the Barro's misery index. α_0 is a vector of constants and ε_t is a vector of independent white noise innovations. The lag-length is determined using the Akaike Information Criterion (AIC).
VAR models for Bitcoin returns (R_t), volatility (VOL_t) and trading volume (TV_t) permit to determine the sign, the timing and how long the Misery effect remains. Then, we continue with the corresponding Granger causality tests and impulse response functions in order to investigate the reaction of Bitcoin to shocks in the Misery index (B*MI*) over time and vice-versa.

We, then, account for the effect of past returns on the relation between Bitcoin variables and BMI. We include in our initial specification (model 1) an interaction term between past misery index and a dummy variable that takes the value of 1 if the lagged return is negative and 0 otherwise. By doing this, we attempt to investigate whether there is a difference in the effect of economic discomfort when the past return is negative or positive. The model can be written as follows:

$$x_t = \varphi + \sum_{k=1}^{n} \alpha_k x_{t-k} + \sum_{k=1}^{n} \beta_k BMI_{t-k} + \sum_{k=1}^{n} \gamma_k BMI_{t-k} * D(R_{t-k} < 0) + \varepsilon_t \quad (2)$$

Where $D(x_{t-k} < 0)$ is a dummy variable that equals 1 if Bitcoin returns are negative and 0 otherwise. The coefficients of the interaction term measure the change in the coefficients β_k when the lagged return is negative. If the interaction terms are significant, the sign of past return has an impact on current return, volatility and trading volume and the magnitude of this impact depends on BMI.

Finally, to determine whether Bitcoin responds to the nonlinearity of economic discomfort. We consider the square effect of BMI using the following predictive model:

$$x_t = \varphi + \sum_{k=1}^{n} \theta_k x_{t-k} + \sum_{k=1}^{n} \vartheta_k BMI_{t-k} + \sum_{k=1}^{n} \rho_k BMI_{t-k} * BMI_{t-k} + \varepsilon_t \quad (3)$$

Where $(\rho + \theta)$ measures the combined impact of lagged BMI on Bitcoin variables.

5. Empirical results

5.1. The sign, the timing and the persistence of the misery impact

Table 2 summarizes the estimation results of VAR models for each Bitcoin's variable. Figures 1, 2 and 3 depict the impulse response functions where we use the Cholesky decomposition. The impulse response is not statistically different from zero at the 5% level for returns and volatility. When there is impulse in BMI, the response of TV is significantly positive at the first two responsive periods. The effect usually converges to zero after with some fluctuations with a reverse negative effect in longer periods for volatility.

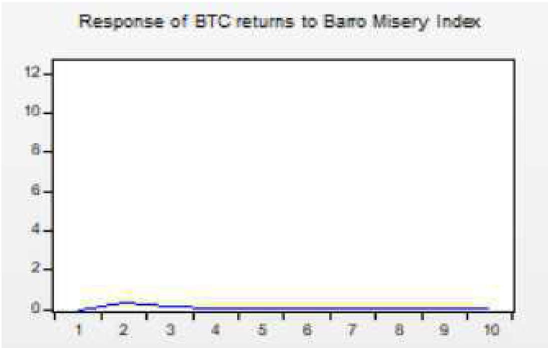

Figure 1: Impulse response function for Bitcoin returns after a shock in the Barro Misery Index (BMI)

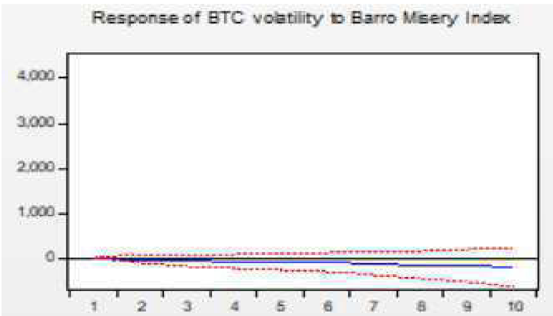

Figure 2: Impulse response function for Bitcoin volatility after a shock in the Barro Misery Index (BMI)

Figure 3: Impulse response function for Bitcoin trading volume after a shock in the Barro Misery Index (BMI)

The estimation results in Table 2 demonstrate that Misery has no significant impact on future Bitcoin returns and volatility. Interestingly, we find that the second lag of BMI is significantly positive for the trading volume at the 1% level. This suggests that when BMI is high, Bitcoin's trading volume increases but with a two-month delay.

Table 2. VAR analysis of BMI and Bitcoin

	$x = R$	$x = VOL$	$x = TV$
Panel A: VAR for Bitcoin			
x_{t-1}	0.1735* (0.0990)	0.4949*** (0.0868)	0.9879*** (0.0149)
x_{t-2}			0.5743** [0.0841]
BMI_{t-1}	-0.0018 (0.0037)	0.0001 (0.0025)	-0.0030 (0.0064)
BMI_{t-2}			0.01033*** [0.00399]
Constant	0.0484** (0.0247)	0.1534*** (0.0306)	0.2917*** (0.1634)
R²	0.0322	0.2564	0.9777
Panel B: VAR for economic misery			
x_{t-1}	-2.0940 (2.5622)	-2.1512 (3.3039)	0.0785 (0.2232)
x_{t-2}			0.0541 (0.2140)
BMI_{t-1}	0.3190*** (0.0949)	0.3285*** (0.0962)	0.3169*** (0.0953)
BMI_{t-2}			0.2274 (0.1025)
Constant	-0.1202 (0.6377)	0.3973 (1.1659)	-1.0751 (2.4390)
R²	0.1076	0.1054	0.1026
LM	0.8533	5.0103	2.5342
Obs.	102	102	102

Note: Panel A reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. Panel B reports VAR estimation results for BMI using Bitcoin variables as predictors. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

5.2. Granger causality between economic misery and Bitcoin

In Table 3, we report-values of the pairwise Granger causality tests of the relationship between BMI and its components and Bitcoin variables. The *p-values* in brackets from the Granger causality test reported in Panel A indicate that we can reject the null hypothesis that BMI does not Granger cause TV at the 5% level. Also, results indicate a significant Granger causality from the unemployment component of the misery measure to Bitcoin volatility. The change in the long-term government bonds seems to Granger cause Bitcoin trading volume at the 5% level. The reverse direction, however, is not pronounced.

Table 3. Granger causality between BMI and its metrics and Bitcoin

	$x = R$	$x = VOL$	$x = TV$
Panel A: Granger causality tests for BMI and Bitcoin			
H0: BMI does not Granger cause x	0.2368 [0.6265]	0.1441 [0.7042]	0.0222** [0.0376]
H0: x does not Granger cause BMI	0.6679 [0.4138]	0.4239 [0.5150]	0.1236 [0.7252]

Panel B: Granger causality tests for M1 and Bitcoin			
H0: M1 does not Granger cause x	0.5981 [0.4393]	3.3814 [0.1844]	0.8478 [0.3572]
H0: x does not Granger cause M1	0.0131 [0.9088]	0.5138 [0.7734]	0.1478 [0.7006]
Panel C: Granger causality tests for M2 and Bitcoin			
H0: M2 does not Granger cause x	0.9749 [0.3235]	6.1313** [0.0466]	0.0377 [0.8461]
H0: x does not Granger cause M2	0.3521 [0.5529]	0.7077 [0.7020]	0.0116 [0.9139]
Panel D: Granger causality tests for M3 and Bitcoin			
H0: M3 does not Granger cause x	0.3861 [0.5343]	0.1320 [0.7163]	0.2120** [0.0270]
H0: x does not Granger cause M3	0.8017 [0.3706]	0.4451 [0.5047]	0.0030 [0.9557]
Panel E: Granger causality tests for M4 and Bitcoin			
H0: M4 does not Granger cause x	0.0196 [0.8886]	0.5656 [0.4520]	0.2971 [0.5857]
H0: x does not Granger cause M4	0.6569 [0.4176]	0.5048 [0.4774]	0.6521 [0.4193]

Note: Panel A reports for Granger causality test results for the Misery index (BMI) and Bitcoin. Panels B to D report for Granger causality test results for BMI components and Bitcoin variables. P-values are in brackets. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

5.3. The influence of past returns

Table 4 presents the results of the regression that includes the interaction term of BMI and past returns. We find no significant effect of the above interaction on Bitcoin variables. Hence, we can conclude that there is no significant connection between past BMI and current returns, volatility and trading volume when the returns of the past period are negative. This finding suggests that the sign of past returns is not a determinant of the magnitude of the impact of economic misery on Bitcoin in the long-run. This result is in line with previous studies that find that returns are less predictable based on past information when there are negative lagged returns (Han et al., 2017).

Table 4. The influence of past returns on the BMI-Bitcoin relationship

	$x = R$	$x = VOL$	$x = TV$
x_{t-1}	0.1747* (0.0980)	0.5018*** (0.0870)	0.9876*** (0.01505)
BMI_{t-1}	0.0007 (0.0044)	-0.0001 (0.0031)	-0.0058 (0.0079)
$BMI_{t-1} * D_{t-1}$	-0.0001 (0.0077)	0.0055 (0.0053)	0.0081 (0.0136)
Constant	0.0492** (0.0243)	0.1507*** (0.0307)	0.1939 (0.1643)
R^2	0.0303	0.2645	0.9778
LM	0.3523	12.1423	7.3768
Obs.	102	102	102

Note: the table reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. We include an interaction term to examine the effect of lagged negative returns on current BMI-Bitcoin relation. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

5.4. The nonlinear effect of the economic misery on Bitcoin

Table 5 reports the results of equation (3). The interaction terms are significant for Bitcoin volatility only, with a positive sign at the second-lag and a negative sign at the fourth lag meaning that the sign of the nonlinear relationship between Misery and Bitcoin's volatility changes with time. The effect is a U-shape at the first two lags then, the relation reverted to an inverted U-shape at the fourth lag.

Table 5. The nonlinear effect of BMI on Bitcoin

	$x = R$	$x = VOL$	$x = TV$
x_{t-1}	0.1729* (0.0994)	0.4943*** (0.0871)	0.9855*** (0.0151)
x_{t-2}		0.1505 (0.1052)	
x_{t-3}		0.1326 (0.1062)	
x_{t-4}		-0.0012 (0.0991)	
BMI_{t-1}	-0.0005 (0.0042)	0.0018 (0.0029)	0.0008 (0.0074)
BMI_{t-2}		0.0007 (0.0030)	
BMI_{t-3}		-0.0027 (0.0030)	
BMI_{t-4}		-0.0017 (0.0029)	
$BMI_{t-1} * BMI_{t-1}$	0.0002 (0.0003)	0.0001 (0.0001)	0.0005 (0.0004)
$BMI_{t-2} * BMI_{t-2}$		0.0002* (0.0004)	
$BMI_{t-3} * BMI_{t-3}$		0.0002 (0.0009)	
$BMI_{t-4} * BMI_{t-4}$		-0.0003** (0.0011)	
Constant	0.0418 (0.0268)	0.1491*** (0.0315)	0.1978 (0.1638)
R^2	0.0361	0.3097	0.9779
LM	4.3887	8.6723	5.5307
Obs.	102	102	102

Note: Note: the table reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

5.5. The relation during Covid-19

Based on the initial proposal to explore the Bitcoin-BMI relationship and to better enhance our analysis, we estimate equation (1) for the period of the Covid-19 pandemic that starts from 2019:11, the date of its outbreak in China. The use of the VAR model is allowed, in our case, since the number of parameters is smaller than the number of data points (the sample size minus the lag-length) used in the different estimations of return, volatility and trading volume.
Table 6 summarizes the estimation results for the pandemic period. We find that the economic misery measure contains relevant information that help predict Bitcoin volatility. More particularly, we find a significantly positive impact of one-lag BMI. The relationship seems to

revert at the third lag. Sergi et al. (2021) find the same result of one-lag BMI on stock volatility for both developed and emerging stock markets during the pandemic period. This result indicates that the overall economic discomfort level could induce heavy trading by incorporating more information into prices. The inverse effect for Bitcoin at longer lags, here, could be understood as an indirect consequence of the familiarization of households with such conditions.

Table 6. VAR analysis of BMI and Bitcoin during the Covid-19 pandemic period

	$x = R$	$x = VOL$	$x = TV$
Panel A: VAR for Bitcoin			
x_{t-1}	0.2347 (0.2454)	-0.0795 (0.1992)	0.7002*** (0.1777)
x_{t-2}		-0.0192 (0.1973)	
x_{t-3}		-0.1874 (0.1993)	
x_{t-4}		0.1539 (0.2040)	
BMI_{t-1}	0.0041 (0.0110)	0.0297*** (0.0084)	0.0012 (0.0136)
BMI_{t-2}		0.0060 (0.0082)	
BMI_{t-3}		-0.0162* (0.0083)	
BMI_{t-4}		-0.0179** (0.0086)	
Constant	0.0502 (0.0581)	0.3111** (0.1455)	4.1785* (2.4756)
R^2	0.0460	0.7455	0.4921
H0: BMI does not Granger cause x	0.1629 [0.6870]	10.3550** [0.0350]	0.0095 [0.9220]
Panel B: VAR for economic misery			
x_{t-1}	1.0782 (4.5880)	-4.1096 (5.6597)	0.3243 (2.7482)
x_{t-2}		9.5049 (5.6058)	
x_{t-3}		-9.2940 (5.6638)	
x_{t-4}		-6.5465 (5.7975)	
BMI_{t-1}	0.3304 (0.2066)	0.3742 (0.2389)	0.3044 (0.2095)
BMI_{t-2}		0.0909 (0.2322)	
BMI_{t-3}		-0.3045 (0.2351)	
BMI_{t-4}		-0.2005 (0.2452)	
Constant	0.5247 (1.0863)	1.1816 (4.1350)	-3.8748 (38.2848)
R^2	0.1233	0.6908	0.1214
H0: x does not Granger cause BMI	0.0639 [0.8000]	5.3283 [0.2550]	0.0161 [0.8990]
LM	3.5633	1.8432	7.6765
Obs.	26	26	26

Note: Panel A reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. Panel B reports VAR estimation results for BMI using Bitcoin variables as predictors. The sample period is 2019:11-2021:12. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

Finally, as an additional robustness check, we study the differential impact of Covid-19 on the relationships between Bitcoin variables and BMI. Hence, equation (1) is also estimated with a differential intercept using a dummy variable that equals one starting from November 2019 and zero otherwise. Results reported in Table 7 confirm the robustness of our results for the Bitcoin equations and suggest that the effect of economic misery index on Bitcoin variables is not significantly different after November 2019. However, the reverse effect is significantly positive during the pandemic period with respect to trading volume, meaning that the effect of Bitcoin's trading volume on BMI is significantly higher during Covid-19. This finding is interesting and joins previous findings for increasing trading activity in periods of economic discomfort. Specifically, based on behavioral and psychological explanations (Erber and Tesser, 1992), this result could be understood as individuals try to overcome their economic discomfort by increasing their trading on Bitcoin.[6]

Table 7. The differential effect of the Covid-19 pandemic on the relation between BMI and Bitcoin

	$x = R$	$x = VOL$	$x = TV$
Panel A: VAR for Bitcoin			
x_{t-1}	0.1731* (0.0977)	0.4888*** (0.0858)	1.0857*** (0.0985)
x_{t-2}			-0.0998 (0.0995)
BMI_{t-1}	-0.0019 (0.0037)	0.0006 (0.0026)	-0.0051 (0.0068)
BMI_{t-2}			0.0068 (0.0068)
$Covid-19$	0.0073 (0.0557)	0.0259 (0.0380)	-0.0066 (0.1431)
Constant	0.0465 (0.0557)	0.1485*** (0.0309)	0.211 (0.2058)
R^2	0.0324	0.2599	0.9779
Panel B: VAR for economic misery			
x_{t-1}	-2.2208 (2.4989)	-2.6662 (3.2358)	-0.7892 (1.4524)
x_{t-2}			0.4347 (1.4667)
BMI_{t-1}	0.2849*** (0.0953)	0.2955*** (0.0962)	0.2983*** (0.0998)
BMI_{t-2}			-0.1102 (0.1006)
$Covid-19$	2.112 (1.4252)	2.1921 (1.4329)	3.9669* (2.1108)
Constant	-0.6629 (0.7213)	-0.01977 (1.1679)	2.4992 (3.0354)
R^2	0.1264	0.1255	0.1391
LM	1.0034	3.2452	2.8975
Obs.	102	102	102

Note: Panel A reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. Panel B reports VAR estimation results for BMI using Bitcoin variables as predictors. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

[6] Results reported in Table (A.6) in the appendix using Binance data suggest that the effect of economic misery index on Bitcoin variables is not significantly different after November 2019. However, the reverse effect is significantly positive during the pandemic period, meaning that the effect of Bitcoin on BMI is significantly higher during Covid-19. Results of the BMI equations also suggest that Bitcoin volatility (trading volume) exert a significantly positive (negative) one-lag impact on economic misery.

6. Conclusion

This paper investigates whether Misery or Economic Discomfort matters for the movements of Bitcoin fundamentals. Specifically, we employ a VAR-based framework that uses the Barro's (1999) misery index and we test for its significant impact on subsequent Bitcoin variables. We contribute to the literature on the predictability of cryptocurrencies markets in two main ways. First, we introduce the economic misery index as a predictor of trading on Bitcoin market by formulating a misery-based predictive model. Second, we explore whether changes in economic performance and wellbeing could affect Bitcoin, and vice-versa.

The empirical findings indicate that misery contains information that positively influences Bitcoin's trading volume with a two-month delay. A nonlinear relationship exists between misery and Bitcoin's volatility. Particularly, changes in economic misery as measured by the Barro misery index seems to have a long-lasting effect (up to four lags). This effect is significantly positive at the second-lag but reverts as time elapses. Conversely, Bitcoin does not seem to have a significant impact on economic wellbeing.

Our results support those of some empirical studies that have presented Bitcoin as a hedging asset during episodes of economic turmoil (e.g., Shahzad et al., 2019; Blau et al., 2021). Bitcoin fundamentals are not correlated with inflation shocks, consistent with its inflation-hedging property. Interestingly, Bitcoin prices do not seem to decrease aftershocks in economic conditions, confirming the notion of its independence from government authorities. Rather, trading volume seems to increase with the increase of economic discomfort. This result suggests that, when economic ill-being increases, crypto-investors tend to trade more to overcome this negative setting. The effect is, particularly, significant for the period of the Covid-19 pandemic.

References:

Al-Yahyaee, K.H., W. Mensi and S.M. Yoon (2018) Efficiency, multifractality, and long-memory property of the Bitcoin market: A comparative analysis with stock, currency, and gold markets. *Finance Research Letters* 161, 1-4.

Barro, R.J. (1999) Reagan vs. Clinton: Who's the economic champ? Business Week 22. February 22. https://scholar.harvard.edu/barro/publications/reagan-vs-clinton-whos-economic-champ.

Baur, D. G., K.J. Hong, and A.D. Lee (2016) Bitcoin: Currency or asset?. Melbourne Business School, 2016 Financial Institutions, Regulation & Corporate Governance (FIRCG) conference.

Baur, D.G., K. Hong and A.D. Lee (2018) Bitcoin: medium of exchange or speculative assets. *Journal of International Financial Markets, Institutions and Money* 54, 177-189.

Blau, B.M. (2017) Price dynamics and speculative trading in bitcoin. *Research in International Business and Finance* 41, 493-499.

Blau, B.M., T.G. Griffith and R.J. Whitby (2021) Inflation and Bitcoin: A descriptive time-series analysis. *Economics Letters* 203, 109848.

Bodie, Z. (1976) Common stocks as a hedge against inflation. *Journal of Finance* 31(2), 459-470.

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

Bouri, E., S.J.H. Shahzad and D. Roubaud (2019) Co-explosivity in the cryptocurrency market. *Finance Research Letters* 29, 178-183.

Cheah, E.T., and J. Fry (2015) Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters* 130, 32-36.

Choi, S., and J. Shin (2022) Bitcoin: An inflation hedge but not a safe haven. *Finance Research Letters* 46(B), 102379.

Corbet, S., B. Lucey and L. Yarovaya (2018) Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters* 26, 81-88.

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

Dweyer, G.P. (2015) The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability* 17, 81-91.

Dyhrberg, A.H. (2016) Hedging capabilities of Bitcoin. Is it the virtual gold? *Finance Research Letters* 16, 139-144.

Ekran, N., E.A. Alp and M.H. Yagmur (2017) Macroeconomic performance index: A new approach of calculation of economic wellbeing. *Applied Economics* 49(53), 5462-5476.

Fama, E.F., J.D. Macbeth (1974) Tests of the multiperiod two-parameter model. *Journal of Financial Economics* 1(1), 43-66.

Feng, W., Y. Wang and Z. Zhang (2018) Informed trading in the Bitcoin market. *Finance Research Letters* 26, 63-70.

Garcia, D., and F. Schweitzer (2015) Social signals and algorithmic trading of bitcoin. *Royal Society Open Science* 2 (9), 1–13.

Glaser, F., K. Zimmermann, M. Haferkorn, M.C., Weber, and M. Siering (2014) Bitcoin-Asset or currency? Revealing users' hidden intentions. *Twenty second European Conference on Information Systems.*

Katsiampa, P., S. Corbet, and B. Lucey (2019) Volatility spillover effects in leading cryptocurrencies: A Bekk-Mgarch Analysis. *Finance Research Letters* 29, 68–74.

Kristoufek, L. (2018) On Bitcoin markets (in)efficiency and its evolution. *Physica A* 503, 257-262.

Nadarajah, S. and J. Chu (2017) On the inefficiency of Bitcoin. *Economics Letters* 150, 6-9.

Narayan, P.K. S. Narayan, R.E. Rahman and I. Setiawan (2019) Bitcoin price growth and Indonesia's monetary system. *Emerging Markets Review* 38, 364-376.

Oudet, B.A. (1973) The variation of the return on stocks in periods of inflation. *Journal of Financial and Quantitative Analysis* 24, 7-258.

Peetz, D. and G. Mall (2017) Why Bitcoin is not a currency but a speculative real asset. SSRN working paper 3098765.

Schilling, L. and H. Uhlig (2019) Some simple bitcoin economics. *Journal of Monetary Economics* 106, 16-26.

Sergi, B.S., M.A. Harjoto, F. Rossi and R. Lee (2021) Do stock markets love misery? Evidence from the Covid-19. *Finance Research Letters* 42, 101923.

Shahzad, S.J.H., E. Bouri, D. Roubaud, L. Kristoufek and B. Lucey (2019) Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis* 63, 322-330.

Tiwari, A.K. R.K. Jana, D. Das, and D. Roubaud (2018) Informational efficiency of Bitcoin – An extension. *Economics Letters* 163, 106-109.

Urquhart A. (2016) The inefficiency of Bitcoin. *Economics Letters* 148, 80-82.

Urquhart A. and H. Zhang (2019) Is Bitcoin a hedge or safe haven for currencies? An intraday analysis. International Review of Financial Analysis 63, 49-57.

Welsch, H. (2007) Macroeconomics and life satisfaction: Revisiting the "Misery Index". *Journal of Applied Economics* 10(2), 237-251.

Wu, S. M. Tong, Z. Yang and A. Derbali (2019) Does gold or Bitcoin hedge economic policy uncertainty? *Finance Research Letters* 31, 171-178.

Appendix:

Table A.1. VAR analysis of BMI and Bitcoin

	$x = R$	$x = VOL$	$x = TV$
Panel A: VAR for Bitcoin			
x_{t-1}	0.0704 (0.0998)	0.3691*** (0.0921)	0.7307*** (0.0969)
x_{t-2}			0.1911** (0.0966)
BMI_{t-1}	0.0017 (0.0042)	-0.0040 (0.0043)	-0.0085 (0.0106)
BMI_{t-2}			0.0188* (0.0106)
Constant	0.0563** (0.0282)	0.2462*** (0.0461)	1.1924* (0.6447)
R^2	0.0620	0.1503	0.8284
Panel B: VAR for economic misery			
x_{t-1}	1.2720 (2.2384)	3.4089* (1.9843)	-1.7506** (0.9019)
x_{t-2}			1.7094* (0.8983)
BMI_{t-1}	0.3221*** (0.0943)	0.3356*** (0.0934)	0.3163*** (0.0986)
BMI_{t-2}			-0.0510 (0.0984)
Constant	-0.3240 (0.6323)	-1.5880* (0.9909)	0.3944 (5.9953)
R^2	0.1044	0.1271	0.1389
LM	1.8432	6.2881	3.0215
Obs.	102	102	102

Note: Panel A reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. Panel B reports VAR estimation results for BMI using Bitcoin variables as predictors. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

Table A.2. Granger causality between BMI and its metrics and Bitcoin

	$x = R$	$x = VOL$	$x = TV$
Panel A: Granger causality tests for BMI and Bitcoin			
H0: BMI does not Granger cause x	0.1720 [0.6780]	0.8507 [0.3560]	3.2377* [0.0920]
H0: x does not Granger cause BMI	0.3329 [0.5700]	2.9514 [0.0860]	3.8897 [0.1430]
Panel B: Granger causality tests for M1 and Bitcoin			
H0: M1 does not Granger cause x	0.5314 [0.4660]	0.0434 [0.8350]	0.6852 [0.7100]
H0: x does not Granger cause M1	0.5405 [0.4660]	0.0177 [0.8940]	1.7734 [0.4120]
Panel C: Granger causality tests for M2 and Bitcoin			
H0: M2 does not Granger cause x	1.2079 [0.2720]	0.4975* [0.0680]	1.2320 [0.5400]
H0: x does not Granger cause M2	0.0282 [0.8670]	0.3380 [0.5610]	4.5813* [0.1000]
Panel D: Granger causality tests for M3 and Bitcoin			
H0: M3 does not Granger cause x	0.0757 [0.7830]	0.5920 [0.4420]	3.6450 [0.1620]
H0: x does not Granger cause M3	0.2212 [0.6380]	3.5086* [0.0610]	3.2486 [0.1970]
Panel E: Granger causality tests for M4 and Bitcoin			
H0: M4 does not Granger cause x	0.1929 [0.6600]	1.0274 [0.3110]	0.6242 [0.7320]
H0: x does not Granger cause M4	0.0063 [0.9370]	0.0150 [0.9020]	0.2498 [0.8830]

Note: Panel A reports for Granger causality test results for the Misery index (BMI) and Bitcoin. Panels B to D report for Granger causality test results for BMI components and Bitcoin variables. P-values are in brackets. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

Table A.3. The influence of past returns on the BMI-Bitcoin relationship

	$\boldsymbol{x = R}$	$\boldsymbol{x = VOL}$	$\boldsymbol{x = TV}$
x_{t-1}	0.0651 (0.1022)	0.3864*** (0.0935)	0.8919*** (0.0430)
BMI_{t-1}	0.0045 (0.0068)	0.0047 (0.0070)	0.0247 (0.0163)
$BMI_{t-1} * D_{t-1}$	-0.0046 (0.0088)	-0.0142 (0.0089)	-0.0434** (0.0211)
Constant	0.0559** (0.0287)	0.2373*** (0.0467)	1.6246** (0.6506)
R^2	0.0191	0.1718	0.8246
LM	1.3362	6.8875	3.5696
Obs.	102	102	102

Note: the table reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. We include an interaction term to examine the effect of lagged negative returns on current BMI-Bitcoin relation. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

Table A.4. The nonlinear effect of BMI on Bitcoin

	$x = R$	$x = VOL$	$x = TV$
x_{t-1}	0.0699 (0.0995)	0.2969*** (0.0944)	0.9099*** (0.0455)
x_{t-2}		-0.0304 (0.1022)	
x_{t-3}		0.3277*** (0.0972)	
BMI_{t-1}	0.0038 (0.0048)	-0.0006 (0.0051)	-0.0049 (0.0121)
BMI_{t-2}		-0.0039 (0.0053)	
BMI_{t-3}		-0.0062 (0.0049)	
$BMI_{t-1} * BMI_{t-1}$	0.0003 (0.0003)	0.0001 (0.0003)	-0.0005 (0.0008)
$BMI_{t-2} * BMI_{t-2}$		0.0001* (0.0003)	
$BMI_{t-3} * BMI_{t-3}$		-0.0005* (0.0003)	
Constant	0.0458 (0.0306)	0.1725*** (0.0570)	1.3804** (0.6795)
R^2	0.0137	0.2717	0.8177
LM	1.9925	6.5322	4.4421
Obs.	102	102	102

Note: Note: the table reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

Table A.5. VAR analysis of BMI and Bitcoin during the Covid-19 pandemic period

	$x = R$	$x = VOL$	$x = TV$
Panel A: VAR for Bitcoin			
x_{t-1}	0.1866 (0.1969)	-0.1782 (0.1917)	0.2870 (0.2096)
x_{t-2}		0.5273*** (0.1362)	0.2027 (0.2082)
x_{t-3}		0.2733*** (0.0725)	0.0257 (0.2117)
x_{t-4}		0.0654 (0.0599)	0.3600* (0.2171)
x_{t-5}		0.2741*** (0.0582)	
x_{t-6}		-0.3216*** (0.0837)	
x_{t-7}		-0.4932*** (0.1282)	
BMI_{t-1}	0.0073 (0.0086)	-0.0177*** (0.0039)	-0.0013 (0.0400)
BMI_{t-2}		-0.0295*** (0.0034)	0.0076 (0.0392)
BMI_{t-3}		-0.0021 (0.0056)	0.0425 (0.0371)
BMI_{t-4}		-0.0154*** (0.0039)	-0.0057 (0.0363)
BMI_{t-5}		-0.0313*** (0.0061)	
BMI_{t-6}		0.0054** (0.0027)	
BMI_{t-7}		0.0021 (0.0025)	
Constant	0.0411 (0.0490)	0.4229*** (0.0530)	1.6033 (2.5963)
R^2	0.0540	0.9667	0.6602
H0: BMI does not Granger cause x	0.7155 [0.3980]	364.6200*** [0.0000]	1.9568 [0.7440]
Panel B: VAR for economic misery			
x_{t-1}	-5.0304 (3.9156)	15.3425*** (5.2816)	1.7399* (1.0202)
x_{t-2}		2.0141 (3.7521)	1.9967** (1.0133)
x_{t-3}		9.6581*** (1.9960)	-1.9597* (1.0303)
x_{t-4}		-8.9497*** (1.6525)	-0.9626 (1.0569)
x_{t-5}		-1.4984 (1.6030)	
x_{t-6}		-9.6439*** (2.3082)	
x_{t-7}		5.4553 (3.5319)	
BMI_{t-1}	0.3534** (0.1709)	-0.0736 (0.1092)	0.2644 (0.1949)
BMI_{t-2}		-0.5465*** (0.0931)	0.0722 (0.1909)
BMI_{t-3}		0.1136 (0.1551)	-0.2589 (0.1807)
BMI_{t-4}		-0.4113*** (0.1066)	-0.2328 (0.1765)
BMI_{t-5}		0.3851** (0.1685)	
BMI_{t-6}		-0.1513** (0.0739)	

BMI_{t-7}		0.3861*** (0.0686)	
Constant	1.5500 (0.9748)	-3.3476** (1.4619)	-10.0969 (12.6377)
R^2	0.2126	0.9546	0.5040
H0: x does not Granger cause BMI	1.6532 [0.1990]	203.8900*** [0.0000]	10.2480** [0.0360]
LM	2.8865	1.0320	5.5524
Obs.	26	26	26

Note: Panel A reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. Panel B reports VAR estimation results for BMI using Bitcoin variables as predictors. The sample period is 2019:11-2021:12. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.

Table A.6. The differential effect of the Covid-19 pandemic on the relation between BMI and Bitcoin

	$x = R$	$x = VOL$	$x = TV$
Panel A: VAR for Bitcoin			
x_{t-1}	0.0708 (0.0999)	0.3650*** (0.0923)	0.7344*** (0.0967)
x_{t-2}			0.2044** (0.0974)
BMI_{t-1}	0.0018 (0.0044)	-0.0034 (0.0045)	-0.0063 (0.0108)
BMI_{t-2}			0.0214** (0.0109)
$Covid-19$	-0.0052 (0.0651)	-0.0346 (0.0669)	-0.1504 (0.1736)
Constant	0.0576* (0.0328)	0.2569*** (0.0504)	0.9778 (0.6884)
R^2	0.0063	0.2892	0.8296
Panel B: VAR for economic misery			
x_{t-1}	1.1083 (2.2062)	3.7382** (1.9538)	-1.8331** (0.8835)
x_{t-2}			1.4157 (0.8900)
BMI_{t-1}	0.2779*** (0.0962)	0.2890*** (0.0946)	0.2686*** (0.0992)
BMI_{t-2}			-0.1069 (0.0999)
$Covid-19$	2.5493* (1.4367)	2.8098** (1.4170)	3.3367** (1.5859)
Constant	-0.9853 (0.7256)	-2.4579** (1.0666)	5.1549 (6.2880)
R^2	0.1315	0.1598	0.1754
LM	1.0034	3.2452	2.8975
Obs.	102	102	102

Note: Panel A reports VAR estimation results for Bitcoin returns (R), volatility (VOL) and trading volume (TV) using Barro Misery index (BMI) as a predictor. Panel B reports VAR estimation results for BMI using Bitcoin variables as predictors. The number of lags for each VAR specification is selected according to AIC. Robust standard errors are in parentheses. *,** and *** denote significance at the 10%, 5% and 1%, respectively.