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Trading Cryptocurrencies as a Pandemic Pastime: COVID-19 Lockdowns and Bitcoin Volume

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Abstract: This paper examines the impact of COVID-19 lockdowns on Bitcoin trading volume. Using data from Apple mobility trends and several time-series econometric models, we find that investors became active participants during the COVID-19 pandemic period and traded more bitcoins on days with low mobility associated with lockdown mandates. These results remain robust after controlling for stocks and gold returns, the VIX index, and the level of attention and sentiment toward Bitcoin, as measured by Google search frequencies and the tone of Tweets discussing Bitcoin. These results suggest that when individual investors have ample free time on their hands, they trade cryptocurrencies as a pastime and use the Bitcoin market as a form of entertainment. Moreover, our results have important implications concerning investors' herding behavior and overconfidence leading to noise trader risks and bubbles typically accompanied by high trading volume in cryptocurrency markets.

Keywords: Bitcoin; trading; volume; COVID-19; lockdowns; investor attention

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1. Introduction

Bitcoin is the most popular open-source digital currency. The Bitcoin network is decentralized, private, and anonymous (or pseudonymous), and eliminates the need for any financial intermediaries like banks. Bitcoin is built on a network known as the blockchain, a decentralized and open ledger that enables peer-to-peer and cryptographically secured transactions. Blockchain is one of the most interesting emerging technologies nowadays. Martinez et al. (2020) [1] provide an excellent review of the cryptographic tools necessary to understand the fundamentals of blockchain technology. These mathematical tools include hash functions, digital signatures, elliptic curves, and Merkle trees.

Bitcoin has attracted great attention in recent years, and it has undeniably taken an important position in global financial markets. Bitcoin in its position as the virtual currency with the largest market capitalization has been found to have a weak correlation with other risky financial assets, making it a valuable financial instrument to hedge economic uncertainty and part of a suitably diversified portfolio [2–7]; however, one of its major criticisms is that trading bitcoins is used as a speculative investment similar to gambling [8–10].

In stock markets, prior research suggests that some investors trade stocks as a fun and exciting gambling activity. Kumar (2009) [11] shows that the propensity to gamble is correlated with investment decision-making and shows that state lotteries and lottery-type stocks attract similar socioeconomic clientele. Gao & Lin (2015) [12] also postulate that individual investors use the stock market as a means of gambling. The authors show that individual investors trade less on large jackpot days or, equivalently, that there is a substitution effect between stock trading and lottery participation. Recent literature has also documented that some investors are only seeking risk and excitement when they trade cryptocurrencies [13,14].

The lottery-like features of Bitcoin returns together with the COVID-19 pandemic shock provide an interesting setting to examine the predictions from previous literature proposing that some people trade for fun and excitement. The financial literature defines lottery-like stocks as those with high return volatility and kurtosis. Bitcoin possesses some lottery-like features. For instance, Baek & Elbeck (2015) [9] show that Bitcoin is 26 times more volatile than the S&P 500. The authors also show that Bitcoin returns are quite positively skewed and have positive excess kurtosis that causes fat tails, suggesting more opportunity for extreme values to occur.

During the year 2020, most countries imposed movement restrictions or mandatory lockdowns to contain the spread of the virus. Live sports and entertainment events were canceled, and gambling venues were temporarily shut down. An obvious result of this home confinement is that many people had an inordinate amount of free time available. Many of these individuals turned to trade as a replacement activity. One example can be found in the U.S. The trading app Robinhood and other online brokerages saw record trading volume and new accounts (see, for instance, https://www.wsj.com/articles/everyones-a-day-trader-now-11595649609, accessed on 6 January 2021) resulting in greater retail stock market participation and trading activity throughout the lockdown period. Ozik, Sadka, and Shen (2021) [15] find that the number of Robinhood trading accounts was significantly larger during lockdowns than during normal periods, especially among stocks with high COVID-19-related media coverage. Pagano et al. (2021) [16] also examine the role of Robinhood investors during the pandemic and their impact on market quality. The authors show that retail investors were actively engaged in both momentum and contrarian trading strategies, resulting in Robinhood investors negatively impacting market quality during the early weeks of the pandemic in the U.S. Meanwhile, Chiah & Zhong (2020) [17] document large spikes in trading volume during the COVID-19 pandemic in the international equity markets. Furthermore, Harjoto et al. (2021) [18], using data across 53 emerging and 23 developed countries from 14 January to 20 August 2020, find that COVID-19 cases and deaths adversely affect stock returns and increase volatility and trading volume.

In this paper, we study Bitcoin trading activity during the pandemic, taking the above observations as its foundation. We address the following question: Did the movement restrictions and stay-at-home mandates put in place across most of the world increase the traded volume of Bitcoin? Using mobility indicators provided by Apple, we find that Bitcoin trading significantly increased during the pandemic lockdowns. In particular, we see that a driving mobility index is negatively correlated to Bitcoin trading in major cryptocurrency exchanges during 2020. These results are consistent with the hypothesis that individual investors traded bitcoins as a pandemic pastime and as a form of exciting gambling activity when they were confined at home.

These results are built on a variety of time-series econometric models, ranging from ordinary least square (OLS) regressions to vector autoregressive (VAR) regressions. We partially base our model selection on the experience of previous literature. Other studies analyzing trading volume dynamics in equity markets during COVID-19 have mostly used OLS models (see, for example, [15–18]). Meanwhile, VAR models are commonly used in the financial literature to examine the dynamic relations among Bitcoin returns and trading activity (see, for instance, [19–21]).

We believe our results will help cryptocurrency investors to better understand the financial effects of extreme events, such as a pandemic. We contribute to the literature by showing how the COVID-19 shock can be used to prove some of the theoretical predictions proposing that people trade for fun and excitement. We stand apart from previous studies examining trading volume in equity markets during the pandemic. Instead, we study the dynamics of trading volume in cryptocurrency markets. To our knowledge, this is the first study to show how reductions in mobility across the world increased traded volume of Bitcoin during the Coronavirus pandemic lockdowns.

2. Materials and Methods

2.1. Methodology

We use a multivariate setting to examine the impact of mobility on Bitcoin trading. We first regress trading volume on the driving mobility index and control variables using ordinary least squared (OLS) regressions with Newey–West heteroskedasticity and autocorrelation consistent (HAC) covariance estimator [22]. The following is the baseline model:

$$\ln(\text{Bitcoin volume})_t = \alpha + \beta \quad \text{Mobility}_t + \gamma' \ \text{ Bitcoin return}_t + \delta' Z_t + \mu_t. \tag{1}$$

The main dependent variable is daily Bitcoin trading volume. We measured Bitcoin trading volume as the natural logarithm of total Bitcoin trading volume (in number of bitcoins). We control for contemporaneous and lagged values of Bitcoin returns. The vector Z_t contains additional control variables. We control for CBOE volatility index (VIX) returns, gold returns, and S&P 500 returns. Previous studies have shown that the level of attention and sentiment to Bitcoin in social networks can be used to provide additional insight on Bitcoin activity [20,23–25], therefore we also control for the level of attention and sentiment toward Bitcoin using Google search frequencies for the key term "Bitcoin" and the tone of Tweets discussing Bitcoin. All variables are defined in Appendix A.

To check the robustness of the results, we then use autoregressive moving-average models with independent variables included in the specifications (often called ARMAX models) and controlling for heteroskedastic disturbances. The autoregressive-moving average process is the basic model for analyzing stationary time series. We consider a first-order autoregressive moving-average process and estimate the structural Equation (1) by using maximum likelihood estimates and modeling the disturbance (μ_t) using the following ARMA (1,1) process:

$$\mu_t = \rho\mu_{t-1} + \theta\epsilon_{t-1} + \epsilon_t, \tag{2}$$

where ρ is the first-order autocorrelation parameter, θ is the first-order moving-average parameter, and ϵ_t is a white-noise disturbance.

Previous literature has also suggested a dynamic relationship between Bitcoin volume and returns [19–21,26,27]. Therefore, as an additional robustness check, we control for contemporaneous as well as lagged relationships between Bitcoin trading volume and Bitcoin returns. In particular, we study the dynamics between Bitcoin trading volume and returns by estimating vector autoregressive (VAR) models with exogenous variables (known as VARX). VARX is used to capture more complex dynamics of multiple time series. The VARX model we estimate in this study consists of the following two equations:

$$\begin{aligned} \ln(\text{Bitcoin volume})_t & \\ &= \alpha + \beta \quad \text{Mobility}_t + \sum_{j=1}^{p} \lambda' \quad \ln(\text{Bitcoin volume})_{t-j} \\ &+ \sum_{j=1}^{p} \gamma' \quad \text{Bitcoin return}_{t-j} + \delta' Z_t + \mu_t \end{aligned} \tag{3}$$

$$\begin{aligned} \text{Bitcoin returns}_t \quad &= \alpha + \beta \quad \text{Mobility}_t + \sum_{j=1}^{p} \lambda' \quad \ln(\text{Bitcoin volume})_{t-j} \\ &+ \sum_{j=1}^{p} \gamma' \quad \text{Bitcoin return}_{t-j} + \delta' Z_t + \mu_t, \end{aligned} \tag{4}$$

where α is a vector of constants, β is our coefficient of interest, λ is a vector of coefficients on the first endogenous variable (the natural logarithm of daily Bitcoin trading volume), γ is a vector of coefficients on the second endogenous variable (daily Bitcoin price returns), Z_t is the vector of exogenous control variables, δ is a vector of coefficients on the control exogenous variable, and μ_t is a vector of independent white noise innovations. The model is estimated using the maximum likelihood procedure. Hamilton (1994) [28] shows that the log-likelihood (LL) for a vector autoregression model is

$$\mathrm{LL} = -\left(\frac{T}{2}\right)\{\ln(|\Sigma|) + K\ln(2\pi) + K\}, \tag{5}$$

where T is the number of observations, K is the number of equations, and Σ is the maximum likelihood estimate of $E[\mu_t \mu_t']$, where μ_t is the $K \times 1$ vector of disturbances.

In Equations (3) and (4), the value p denotes the number of optimal lags determined by several information criteria, including the Akaike information criterion (AIC), Hannan–Quinn information criterion (HQIC), Schwarz-Bayesian information criteria (SBIC), and final prediction error (FPE). We use the Lütkepohl (2005) [29] versions of the information criteria, which differ from the standard definitions in that they drop the constant term from the log-likelihood. The Lütkepohl versions of the information criteria are defined as follow:

$$\mathrm{AIC} = \ln(|\Sigma|) + \frac{2}{T}pK^2 \tag{6}$$

$$\mathrm{SBIC} = \ln(|\Sigma|) + \frac{\ln(T)}{T}pK^2 \tag{7}$$

$$\mathrm{HQIC} = \ln(|\Sigma|) + \frac{2\ln\{\ln(T)\}}{T}pK^2 \tag{8}$$

$$\mathrm{FPE} = |\Sigma| + \left(\frac{T+\overline{m}}{T-\overline{m}}\right)^K, \tag{9}$$

where $\overline{m}$ is the average number of parameters over the K equations. In all models, we set the mobility index and the control variables (the vector Z_t) as exogenous variables.

2.2. Data

We collected daily Bitcoin trading volume and Bitcoin prices between 13 January 2020, and 31 December 2020, from coinmarketcap.com (accessed on 6 January 2021). This data source has been widely used in Bitcoin research (see, for example, [26,30,31]). Driving mobility trends around the world come from the Apple Mobility Trends Reports (https://covid19.apple.com/mobility, accessed on 6 January 2021). Using 13 January 2020 as the baseline, Apple calculates driving, walking, and public transit mobility trend indexes based on the relative volume of requests made to Apple Maps for directions in each location. An important caveat is that Apple Maps are not necessarily representative of usage against the overall population. In the empirical section, we only report results for the driving mobility index. However, results remain robust when we use the walking and transit indexes. VIX index, S&P 500 index, and gold prices are from Yahoo Finance (https://finance.yahoo.com, accessed on 6 January 2021). Twitter sentiment indicators toward Bitcoin are from IntoTheBlock (https://app.intotheblock.com, accessed on 2 April 2021). Google search activity for the keyword "Bitcoin" is available from Google Trends (https://trends.google.com/, accessed on 20 May 2021). Total population by country is taken from the World Bank. Finally, levels of cryptocurrency adoption for each country are from the Chainalysis 2020 Global Crypto Adoption Index (https://markets.chainalysis.com/#geography-index, accessed on 27 May 2021).

We begin by creating a global mobility indicator calculated as a weighted average of countries' driving mobility trends from Apple. In this calculation, each country's weight is obtained by multiplying its total population by its level of cryptocurrency adoption according to Chainalysis. Figure 1 plots the global driving mobility index and total Bitcoin trading volume (in natural logarithm) between 13 January 2020, and 31 December 2020. The figure shows significant declines in global driving mobility around 15 March 2020, returning to near-normal levels around 5 June 2020. During this period, there were large spikes in the total number of bitcoins traded. As the mobility index started to recover its pre-COVID-19 level, Bitcoin trading fell. As can be seen in Figure 1, mobility and Bitcoin trading volume appear to move in opposite directions. Further, we use the Bai and Perron test for structural breaks, as implemented by Ditzen, Karavias, and Westerlund (2021) [32], to examine the presence of structural breaks in trading volume on 15 March and 5 June 2020. We find a test statistic of 223.87 for the null hypothesis of no break against the hypothesis of breaks in these two dates. The critical values provided in Bai & Perron (1998, 2003) [33,34] suggest that we can confidently reject the null hypothesis of no breaks in the series of Bitcoin trading volume. In light of this relationship, we would expect a significant correlation between mobility and Bitcoin trade volume.

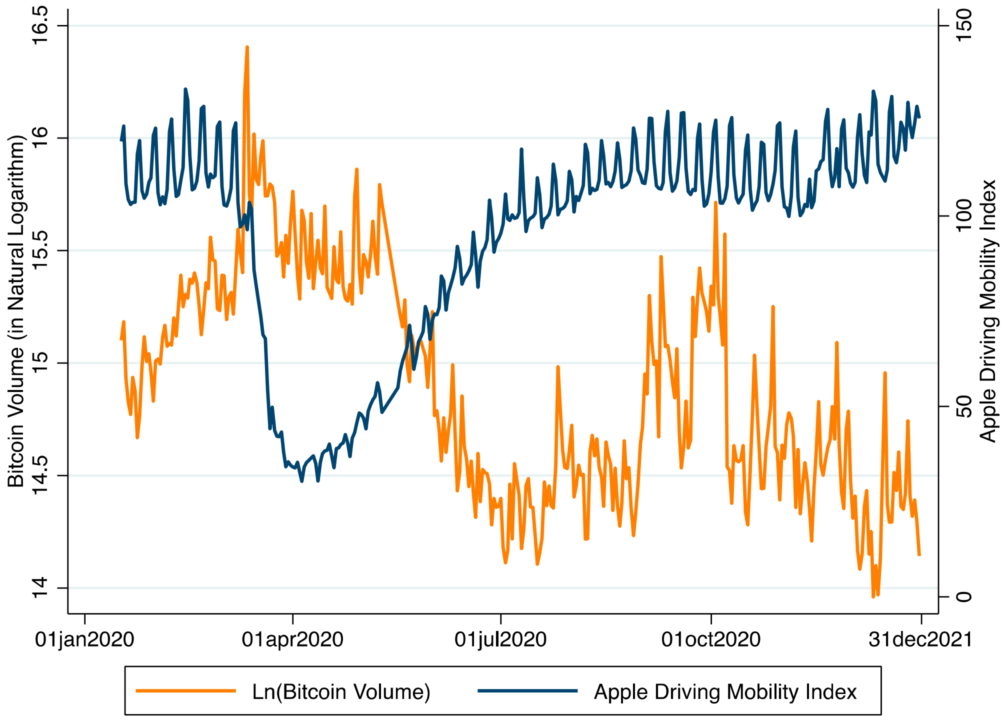

Figure 1. This figure represents the evolution of the natural logarithm of total Bitcoin trading volume (axis on the left) and the Apple driving mobility index (axis on the right) and between 13 January 2020, and 31 December 2020.

Table 1 provides descriptive statistics for the final sample. The results show that the average mobility index throughout 2020 was 96, with a minimum of 30.34 on 5 April. The average natural logarithm of Bitcoin trading volume was 14.88 (the average daily Bitcoin trading volume was 3.3 millions of bitcoins or USD 33.1 trillion). The average daily return and standard deviation for Bitcoin were 0.31% and 4.05%, respectively. The average daily return and standard deviation for the S&P 500 were 0.04% and 1.86%, respectively. The average abnormal Google search volume is 3.2. Meanwhile the average Twitter sentiment 0.17, with a maximum on 25 October, the week in which PayPal announced that will enable its customers to buy, sell, and hold bitcoins.

Table 1. Descriptive statistics of key variables.

	Observations	Mean	Media	SD	Min	Max	Skewness	Kurtosis	ADF Test
World mobility	344	96.00	105.61	27.11	30.34	133.34	−1.12	3.09	−2.26
US mobility	344	112.59	116.25	27.98	37.42	170.75	−0.54	2.81	−5.23 ***
Russia mobility	344	121.95	114.39	36.91	45.98	244.69	0.17	2.60	−2.36
Europe mobility	344	110.42	105.31	42.87	36.65	208.25	0.38	2.37	−1.4
Latin America mobility	344	76.55	79.15	24.41	22.90	137.58	−0.27	2.46	−4.84 ***
Africa mobility	344	87.34	101.16	30.94	15.99	131.87	−0.90	2.41	−1.72
Asia mobility	344	79.16	81.45	18.42	37.89	128.11	−0.59	2.94	−3.96 ***
Bitcoin return (%)	344	0.31	0.25	4.05	−46.47	16.71	−4.19	54.74	−20.99 ***
Ln(Bitcoin volume)	344	14.88	14.78	0.48	13.96	16.41	0.37	2.25	−3.94 ***
VIX return (%)	344	0.14	0.00	7.43	−26.62	39.17	1.87	11.37	−21.12 ***
Gold return (%)	344	0.05	0.00	1.18	−5.11	5.78	−0.28	8.20	−18.57 ***
S&P 500 return (%)	344	0.04	0.00	1.86	−12.77	8.97	−0.99	15.92	−24.13 ***
Google search volume	344	3.20	0.50	10.61	−12.50	41.50	1.32	5.43	−2.81 *
Twitter sentiment	344	0.17	0.18	0.08	0.00	0.48	0.71	3.79	−4.7 ***

Note: This table reports summary statistics for the dependent, independent, and control variables used in this study. The last column shows augmented Dickey-Fuller (ADF) tests to examine the stationarity of time-series data. All variables are defined in Appendix A. *** and * indicate that the coefficient is significantly different from zero at the 1% and 10% levels, respectively.

We begin our analysis by examining the stationarity of our time-series variables. This analysis is important as the use of non-stationary data could potentially lead to spurious regression results. We employ augmented Dickey–Fuller tests (ADF) to examine the stationarity of time-series data. The augmented Dickey–Fuller test fits a model of the form

$$\Delta Y_t = \alpha + \beta Y_{t-1} + \mu_t. \tag{10}$$

Testing β = 0 in this equation is equivalent to testing that Y_t follows a unit root process. In other words, the null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process. The results reported in Table 1 show that we cannot reject the null hypothesis that some of the series are not stationary. In particular, unit roots are present in most of the Apple mobility indicators. To normalize and detrend these series, we use the first differences of mobility indicators in all regression models in the subsequent sections. The null hypothesis of the existence of a unit root is discarded in the Bitcoin volume (in natural logarithm) series and Bitcoin returns. The rest of the series used as control variables are all stationary according to the ADF test.

3. Results

Table 2 presents the parameters estimated from OLS with HAC covariance estimator and ARMAX regressions for the total amount of daily Bitcoin trading volume taken from coinmarketcap.com. Columns 1 to 3 report the results from using OLS models on the natural logarithm of total Bitcoin trading volume (in number of bitcoins). As we hypothesize, driving mobility has a negative correlation with Bitcoin trading volume across all models. Columns 4 to 6 present the results from ARMAX (1,1) models. We find that driving mobility has a statistically significant (at the 1% level) and negative effect on Bitcoin trading volume across all models. In general, there is little theoretical guidance on how large the number of lags in ARMAX models should be. To keep the models parsimonious, we decided to report results when using only one lag for both the autoregressive and moving-average components of the disturbances. We have tested several alternative specifications with up to seven lags, as suggested by correlograms and partial correlograms of the natural logarithm of total Bitcoin trading volume (unreported), and the results remain robust. Consequently, the hypothesis that movement restrictions and stay-at-home mandates across the world increased the volume traded of Bitcoin is supported.

Table 2. The impact of mobility on Bitcoin trading volume.

	OLS Newey-West			ARMAX (1,1)		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ΔWord mobility	−0.0072 *	−0.0075 *	−0.0069 **	−0.0033 ***	−0.0034 ***	−0.0035 ***
	(1.8209)	(1.8579)	(1.9696)	(2.8693)	(2.9246)	(3.0179)
Controls:						
Bitcoin return	−0.0134	−0.0138 *	−0.0073	−0.0031	−0.0029	−0.0025
	(1.5554)	(1.7696)	(1.0221)	(0.5721)	(0.5651)	(0.4934)
Bitcoin return lagged	−0.0109	−0.0082	−0.0026	−0.0012	0.0007	0.0007
	(0.9719)	(0.7001)	(0.2544)	(0.2746)	(0.1647)	(0.1745)
VIX return		−0.0038	−0.0051		−0.0001	−0.0005
		(0.6393)	(1.1744)		(0.0850)	(0.3272)
Gold return		0.0016	−0.0036		0.0058	0.0058
		(0.0498)	(0.1653)		(0.7814)	(0.7885)
S&P500 return		−0.0290	−0.0304		−0.0102	−0.0108 *
		(0.9714)	(1.4620)		(1.5826)	(1.6615)
Google attention			−0.0038			0.0008
			(1.2747)			(0.2889)
Twitter sentiment			−2.8511 ***			−0.6063 **
			(6.3156)			(2.2756)
Constant	14.8902 ***	14.8912 ***	15.3730 ***	14.8498 ***	14.8497 ***	14.9408 ***
	(416.8204)	(414.9843)	(204.4701)	(84.8699)	(85.2502)	(87.7765)
ARMA:						
AR(1)	-	-	-	0.9662 ***	0.9658 ***	0.9660 ***
				(52.0875)	(51.9022)	(49.8298)
MA(1)	-	-	-	−0.3821 ***	−0.3750 ***	−0.3988 ***
				(2.6489)	(2.5799)	(2.9622)
Sigma	-	-	-	0.1939 ***	0.1927 ***	0.1912 ***
				(19.3300)	(19.1877)	(19.2389)
Observations	343	343	343	343	343	343
R^2	0.0291	0.0349	0.2765	-	-	-

Note: This table presents the parameter estimates from OLS and ARMAX models for Bitcoin returns and trading volume (in natural logarithm). The key independent variable is the global mobility index calculated from mobility trends provided by Apple. *t* values (in parentheses) are computed with Newey–West's heteroscedasticity and autocorrelation consistent (HAC) covariance estimators. All variables are defined in Appendix A. ***, **, and * indicate that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Table 3 shows the estimated results for VARX models. Columns (1) and (3) of Panel A report results without exogenous control variables. Columns (2) and (4) of Panel A report results controlling for CBOE Volatility Index (VIX) returns, gold returns, and S&P 500 returns. Columns (2) and (4) of Panel A report results for the full model that incorporates Google search frequency and Twitter sentiment. Panel B of Table 3 reports the AIC, HQIC, SBIC, FPE criteria we use to select the four lags used in the series of vector autoregressions presented in Panel A. Our results show that reduced mobility driven by Coronavirus is positively correlated with Bitcoin trading volume. These results further support the previous findings showing that reductions in mobility associated with lockdown mandates will lead to higher Bitcoin trading volume. Concerning the relationship between mobility and returns, we found no statistically significant results using vector autoregressive models. We also employ Granger causality tests to investigate the causal relationships between Bitcoin returns and trading volume. We present Granger causality tests for each VARX model at the bottom of Panel A. For this sample period, we cannot reject the null hypothesis that Bitcoin returns do not Granger-cause Bitcoin volume or vice versa.

Table 3. Dynamic relationships among mobility, Bitcoin returns, and trading volume.

Panel A. Vector Autoregressive Models						
	Ln(Bitcoin Volume)$_t$			**Bitcoin Return$_t$**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
ΔWord mobility$_t$	−0.0057 ***	−0.0060 ***	−0.0059 ***	−0.0288	−0.0306	−0.0288
	(3.5488)	(3.7024)	(3.6834)	(0.8465)	(0.8971)	(0.8461)
Controls:						
Bitcoin volume$_{t-1}$	0.6503 ***	0.6395 ***	0.6228 ***	0.4958	0.6511	0.8128
	(12.4377)	(12.1995)	(11.7283)	(0.4497)	(0.5867)	(0.7221)
Bitcoin volume$_{t-2}$	0.0846	0.1070	0.1049	−0.3671	−0.4895	−0.4914
	(1.3019)	(1.6360)	(1.6108)	(0.2678)	(0.3537)	(0.3561)
Bitcoin volume$_{t-3}$	0.0519	0.0467	0.0464	−0.2537	−0.3375	−0.3120
	(0.8249)	(0.7473)	(0.7449)	(0.1914)	(0.2550)	(0.2365)
Bitcoin volume$_{t-4}$	0.1631 ***	0.1548 ***	0.1563 ***	−0.5174	−0.5089	−0.3342
	(3.0525)	(2.9013)	(2.9220)	(0.4591)	(0.4507)	(0.2947)
Bitcoin return$_{t-1}$	0.0004	0.0027	0.0026	−0.1010 *	−0.1211 **	−0.1293 **
	(0.1556)	(0.9555)	(0.9026)	(1.8678)	(1.9994)	(2.1278)
Bitcoin return$_{t-2}$	0.0005	−0.0003	−0.0002	0.0758	0.0678	0.0610
	(0.2087)	(0.1144)	(0.0886)	(1.4002)	(1.2193)	(1.0963)
Bitcoin return$_{t-3}$	−0.0028	−0.0029	−0.0030	−0.0529	−0.0546	−0.0584
	(1.0917)	(1.1323)	(1.1619)	(0.9755)	(1.0096)	(1.0800)
Bitcoin return$_{t-4}$	−0.0029	−0.0030	−0.0030	0.1297 **	0.1282 **	0.1246 **
	(1.1329)	(1.1862)	(1.1959)	(2.4040)	(2.3811)	(2.3186)
VIX return$_t$		−0.0000	−0.0002		−0.0642	−0.0616
		(0.0060)	(0.1032)		(1.4975)	(1.4372)
Gold return$_t$		0.0020	0.0018		0.0765	0.0914
		(0.2194)	(0.2014)		(0.3964)	(0.4744)
S&P500 return$_t$		−0.0136 *	−0.0135		−0.1665	−0.1518
		(1.6449)	(1.6292)		(0.9495)	(0.8664)
Google attention$_t$			0.0007			0.0209
			(0.7158)			(1.0133)
Twitter sentiment$_t$			−0.2259			3.2519
			(1.5712)			(1.0670)
Constant	0.7435 **	0.7729 **	1.0706 ***	9.8762	10.5304	4.5660
	(2.2096)	(2.3065)	(2.6747)	(1.3918)	(1.4844)	(0.5381)
Observations	340	340	340	340	340	340
R^2	0.8502	0.8523	0.8536	0.0559	0.0622	0.068
H0: Bitcoin returns do not Granger-cause Bitcoin volume	2.2864	3.3739	3.359	-	-	-
H0: Bitcoin volume does not Granger-cause Bitcoin returns	-	-	-	2.2951	2.7505	1.1297

Panel B. Lag Order Information Criteria for Vector Autoregressive Models								
Lags	**LL**	**LR**	**df**	***p***	**FPE**	**AIC**	**HQIC**	**SBIC**
0	−1184.8100	0.0000	0.0000	0.0000	3.9261	1.3558	1.3558	1.3558
1	−889.0600	591.5100	4.0000	0.0000	0.6950	−0.3757	−0.3576	−0.3304 *
2	−881.3830	15.3550	4.0000	0.0040	0.6800	−0.3975	−0.3614	−0.3068
3	−872.3150	18.1350	4.0000	0.0010	0.6599	−0.4276	−0.3734	−0.2916
4	−861.9010	20.8290	4.0000	0.0000	0.6352 *	−0.4657 *	−0.3934 *	−0.2843
5	−860.3760	3.0499	4.0000	0.5500	0.6446	−0.4510	−0.3606	−0.2243
6	−855.1340	10.4830 *	4.0000	0.0330	0.6399	−0.4583	−0.3499	−0.1863
7	−851.5810	7.1060	4.0000	0.1300	0.6417	−0.4557	−0.3292	−0.1383

Note: Panel A of this table presents the parameter estimates from vector autoregressive (VAR) models for Bitcoin returns and trading volume (in natural logarithm). The key independent variable is the global mobility index calculated from mobility trends provided by Apple. *t* values (in parentheses). Panel B reports the final prediction error (FPE), Akaike's information criterion (AIC), Schwarz's Bayesian information criterion (SBIC), and the Hannan and Quinn information criterion (HQIC) lag-order selection statistics for the series of vector autoregressions presented in Panel A. All variables are defined in Appendix A. ***, **, and * indicate that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

Finally, we examine the relationship between global Bitcoin trading volume and mobility in some specific countries and regions. Given that the previously reported VARX models and Granger causality tests do not support the hypothesis of a dynamic relationship between Bitcoin volume and returns during this period, for this last test we prefer to use the relatively simpler ARMAX model. Table 4 shows the results estimated from ARMAX regressions for the total amount of daily Bitcoin trading volume taken from coinmarketcap.com on mobility in the U.S. (column 1), Russia (column 2), Europe, excluding Russia (column 3), Latin America (column 4), Africa (column 5), and Asia (column 6). We find that mobility trends in the U.S., Latin America, and Asia have statistically significant and negative effects on Bitcoin trading volume. Mobility clearly comes through as a significant factor in Bitcoin trading volume during pandemic lockdowns in these regions.

Table 4. The impact of mobility on Bitcoin trading volume, by country and region.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔUS mobility	−0.0014 **					
	(2.5331)					
ΔRussia mobility		−0.0002				
		(0.2782)				
ΔEurope mobility			−0.0007			
			(0.5973)			
ΔLatin America mobility				−0.0020 ***		
				(3.0477)		
ΔAfrica mobility					−0.0027	
					(1.6347)	
ΔAsia mobility						−0.0053 ***
						(4.7766)
Controls:						
Bitcoin return	−0.0025	−0.0024	−0.0024	−0.0027	−0.0026	−0.0027
	(0.4883)	(0.4628)	(0.4746)	(0.5437)	(0.5158)	(0.5287)
Bitcoin return lagged	0.0007	0.0001	0.0001	0.0005	0.0009	0.0001
	(0.1706)	(0.0128)	(0.0200)	(0.1234)	(0.2370)	(0.0187)
VIX return	−0.0001	−0.0002	−0.0002	0.0000	0.0003	−0.0009
	(0.0625)	(0.0937)	(0.1332)	(0.0152)	(0.1576)	(0.5722)
Gold return	0.0055	0.0076	0.0074	0.0047	0.0071	0.0064
	(0.7400)	(1.0219)	(0.9896)	(0.6366)	(0.9676)	(0.8937)
S&P500 return	−0.0095	−0.0093	−0.0094	−0.0083	−0.0079	−0.0108 *
	(1.4759)	(1.4421)	(1.4514)	(1.2961)	(1.2262)	(1.6775)
Google attention	0.0005	0.0007	0.0006	0.0005	0.0004	0.0010
	(0.1573)	(0.2295)	(0.2034)	(0.1814)	(0.1423)	(0.3547)
Twitter sentiment	−0.6530 **	−0.5804 **	−0.5825 **	−0.6668 **	−0.6101 **	−0.5867 **
	(2.4384)	(2.1036)	(2.1234)	(2.4527)	(2.1670)	(2.2015)
Constant	14.9501 ***	14.9362 ***	14.9368 ***	14.9522 ***	14.9468 ***	14.9366 ***
	(89.5029)	(87.3749)	(87.5147)	(89.3800)	(90.5221)	(87.2841)
ARMA:						
AR(1)	0.9654 ***	0.9671 ***	0.9670 ***	0.9653 ***	0.9642 ***	0.9665 ***
	(49.4701)	(50.9420)	(50.8447)	(49.2592)	(45.8633)	(50.7596)
MA(1)	−0.3968 ***	−0.4130 ***	−0.4126 ***	−0.3950 ***	−0.3904 ***	−0.3965 ***
	(2.9716)	(3.1436)	(3.1360)	(2.9518)	(2.6711)	(2.9786)
Observations	343	343	343	343	343	343

Note: This table presents the parameter estimates from ARMAX models for Bitcoin returns and trading volume (in natural logarithm). The key independent variable is the country or regional mobility index calculated from mobility trends provided by Apple. t values (in parentheses) are computed with heteroscedasticity consistent covariance estimators. All variables are defined in Appendix A. ***, **, and * indicate that the coefficient is significantly different from zero at the 1%, 5%, and 10% levels, respectively.

4. Discussion and Concluding Remarks

Despite the growing literature examining the effect of COVID-19 on the Bitcoin market [21,35–40], the direct effects of movement restrictions have received scant attention in cryptocurrency research. The COVID-19 lockdowns and the Bitcoin market represent a proper setting to test the proposition concerning investors trading as a form of entertainment and a substitute for gambling activities.

In this article, we show that reductions in mobility across the world increased the traded volume of Bitcoin during the pandemic. High Bitcoin volatility provides great gambling opportunities for individual investors. Thus, the results of this study suggest that some investors resort to the Bitcoin market as a substitute for gambling. The results also confirm prior literature documenting that some investors are seeking risk and excitement when they trade cryptocurrencies [13,14].

Moreover, Bitcoin has been historically characterized by explosive behavior due to its multiple bubbles since its inception in 2009 as an open-source digital currency. For instance, Cheung et al. (2015) [41], documented three Bitcoin bubbles during 2011–2013. Fry (2018) [42] showed the existence of bubbles in Bitcoin prices during 2015–2018. Further, Cheah and Fry (2015) [43], in addition to finding evidence to suggest that Bitcoin prices are prone to substantial bubbles, empirically estimate the value of a Bitcoin to be zero. Meanwhile, Corbet et al. (2018) [44] and Bouri et al. (2019) [30] provide evidence of bubbles in Ethereum and other large cryptocurrencies. In Appendix B, we show that Bitcoin price bubbles can be predicted by an increase in trading volume. This result is consistent with the predictions from Barberis et al. (2018) [45] and Scheinkman and Xiong (2003) [46] that financial bubbles in equity markets will be accompanied by high trading volume. Considering the documented history of Bitcoin bubbles and their relation to trading activity, our results contribute to the literature that examines the occurrence of speculative bubbles in the Bitcoin market.

Our results also have implications for the literature that examines investors herding behavior and overconfidence leading to systematic noise trader risk in cryptocurrency markets. Regarding investor herd behavior, Lux (1995) [47] describes the formation of expectations by those who are not fully informed about fundamentals. Abundant empirical evidence has challenged the hypothesis that financial markets are efficient, and several studies have shown that prices are not entirely driven by news, but also by irrational or uninformed trading [48–52]. The expectations of uninformed traders depend mainly on the behavior and expectations of others leading to a process of mutual mimetic contagion among speculators. According to Lux, this contagion may also lead to the existence of bubbles, that is, stationary states where actual prices exceed fundamental values or are below them [47]. Regarding the relation between COVID-19 and investors herding in cryptocurrency markets, recent literature offers contrasting evidence. Yarovaya et al. (2021) [53] show that COVID-19 does not amplify herding in leading cryptocurrencies. Meanwhile, Vidal-Tomás (2021) [54], using network analysis, shows that from 12 March, 2020 to 1 April 2020 there was a remarkable increase in market synchronization.

Overconfidence could also lead investors to overreact to private information, underreact to public information, trade more aggressively in subsequent periods, underestimate risk, and contribute to excessive volatility [55]. Scheinkman and Xiong (2003) [46] posit that the existence of bubbles is positively associated with the degree of the agents' overconfidence and the fundamental volatility of the asset. In this sense, overconfidence investors with ample free time on their hands and the presence of the "fear of missing out" (FOMO) psychological effect in the highly volatile Bitcoin market could create the conditions needed for speculative bubbles typically associated with high trading volume.

Considering that Bitcoin has taken an important position in global financial markets, the above observations together with our findings and empirical implications should be of interest to all investors, but in particular, institutional investors that are increasingly incorporating Bitcoin in their portfolio allocations. Professional investors should design investment strategies to tackle the volatility of Bitcoin. These strategies should be designed to properly manage risks and avoid potentially large financial losses when bubbles created by the speculative behavior of individual investors burst.

Several important questions still need to be addressed. Future research expanding on similarities and differences between retail and institutional trading volumes would further elucidate which kind of investor is behind the meaningful increase in overall Bitcoin trading volume. Such research should also provide international evidence regarding the effects of lockdowns and the trading volume of cryptocurrencies other than Bitcoin. Further research should also model possible nonlinearity and accounting for tail behaviors when analyzing dynamic relationships among Bitcoin trading volume, returns, investors' free time, and level of attention to cryptocurrency markets as forms of entertainment.

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Appendix A

Table A1 defines dependent, independent, and control variables used in this study.

Table A1. Definitions of variables.

Variable Name	Definition
Ln(bitcoin volume)	Is the main dependent variable in the regressions. It is measured as the natural logarithm of the total number of bitcoins traded in a day. This information is taken from coinmarketcap.com.
Bitcoin return (%)	Bitcoin return in percentage is defined as $\left[\ln\left(\frac{\text{bitcoin price}_t}{\text{bitcoin price}_{t-1}}\right) - 1\right] * 100$. Bitcoin price on day t is taken from coinmarketcap.com, accessed on 6 January 2021.
World mobility	Is the main independent variable in the regressions. It is calculated by taking each country driving mobility trend from Apple on a day and multiplying it, first, by the country's total population from the World Bank, and then, by the country's level of cryptocurrency adoption according to Chainalysis. World mobility is then measured as the daily average of these countries' weighted mobility trends. To normalize and detrend these series, we use in all regressions the first differences of this mobility indicator.
VIX return (%)	VIX index return in percentage is defined as $\left[\ln\left(\frac{\text{VIX index}_t}{\text{VIX Index}_{t-1}}\right) - 1\right] * 100$. VIX index on day t is taken from Yahoo Finance.
Gold return (%)	Gold return in percentage is defined as $\left[\ln\left(\frac{\text{gold price}_t}{\text{gold price}_{t-1}}\right) - 1\right] * 100$. Gold price on day t is taken from Yahoo Finance.
S&P 500 return (%)	S&P 500 index return in percentage is defined as $\left[\ln\left(\frac{\text{S\&P500 index}_t}{\text{S\&P500 index}_{t-1}}\right) - 1\right] * 100$. S&P 500 index on day t is taken from Yahoo Finance.
Google search volume	Abnormal weekly time series measuring the frequency of Google search volumes for the topic "Bitcoin" at the worldwide level. The Google search index ranges between 0 and 100. We calculated abnormal search volume by taking the Google search index for a particular week and subtracting the median Google search index value for the previous four weeks.
Twitter sentiment	Twitter sentiment is measured as $\left(\frac{\text{positive tweets}_t - \text{negative tweets}_t}{\text{Total tweets}_t}\right)$. Positive tweets, negative tweets, and the total number of tweets discussing Bitcoin on day t are obtained from IntoTheBlock.
Bubble	It is a dummy variable set to 1 if there is a Bitcoin bubble on day t and set to 0 otherwise. We define a bubble occurrence on day t when the Phillips-Shi-Yu (PSY) statistic for the respective observation exceeded the 95% bootstrapped critical value.

Appendix B

Previous financial research has shown that price bubbles are typically accompanied by high trading volume. In this appendix, we examine possible predictors of bubble periods in Bitcoin markets. Using price data from 1 January 2015, to 31 December 2020, we confirm that trading volume is a significant predictor of Bitcoin price bubbles. To detect Bitcoin bubbles, we use Phillips et al. (2015a,b) [56,57] (PSY) methodology, as implemented in the *psymonitor* package of the statistical software R. Several papers have used the PSY framework to detect bubbles in cryptocurrencies. Enoksen et al. (2020) [58] study which variables can predict bubbles in the prices of eight major cryptocurrencies. The authors find that volatility, trading volume, and transactions are positively associated with the presence of bubbles across major cryptocurrencies, while the VIX index is negatively related to bubble occurrences. References [30,41,44] also use the PSY framework to date-stamp price explosivity in leading cryptocurrencies. Figure A1 illustrates the PSY test when applied to the Bitcoin price from 1 January 2015, to 31 December 2020. The solid line represents the Bitcoin price. The identified bubble periods are shaded in orange. The PSY procedure detects one major bubble episode between November and December 2020. We also identify bubble events in June 2019 and July 2019, and a long bubble period starting in April 2017 and finishing in January 2018.

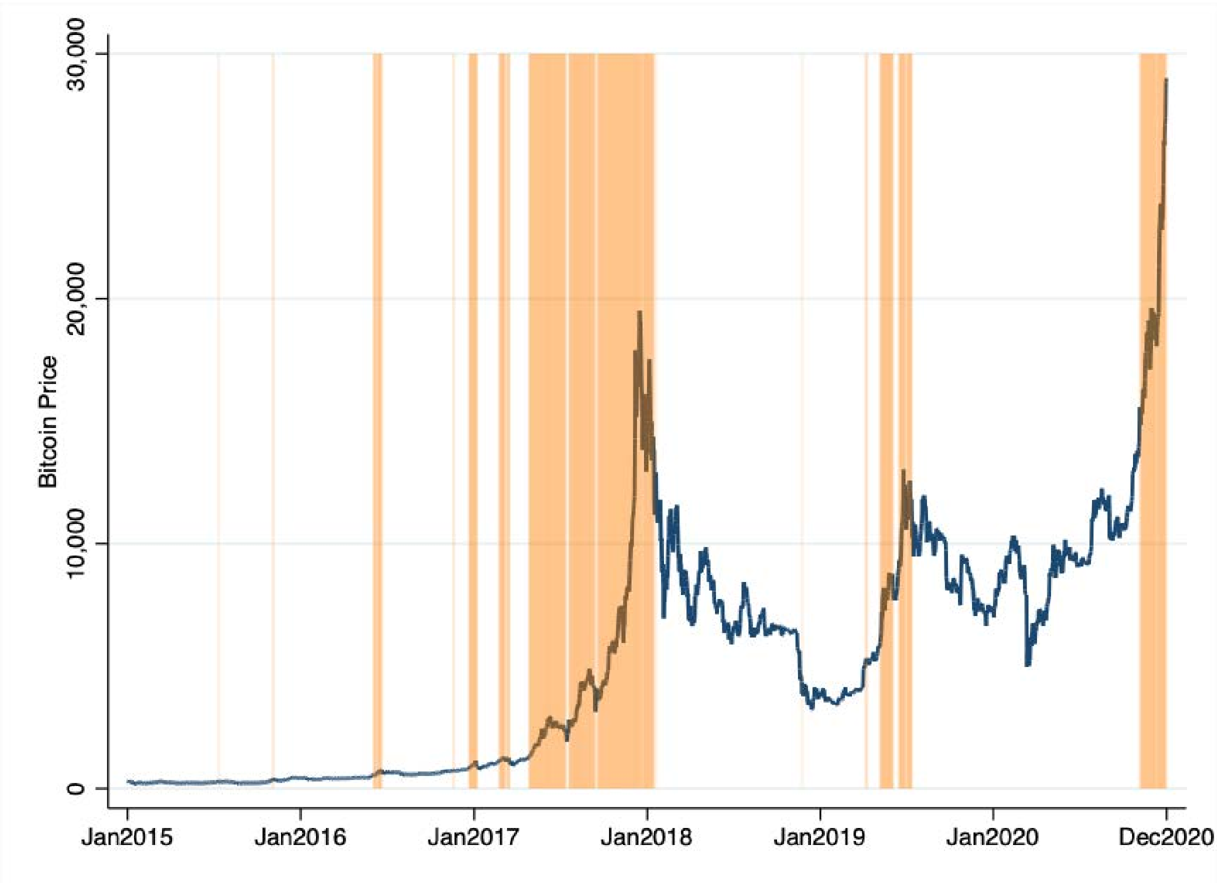

Figure A1. This figure represents the evolution of Bitcoin price and bubble periods between 1 January 2020, and 31 December 2020. The solid line is the Bitcoin price, and the shaded areas are the bubble periods (days when the PSY statistic exceeds its 95% bootstrapped critical value).

Next, we perform a probit analysis to evaluate whether trading volume can predict Bitcoin bubbles. The following is the baseline model:

$$\Pr\left[\text{Bubble}_t = 1\right] = \alpha + \lambda \quad \ln(\text{Bitcoin volume})_t + \delta' Z_t + \mu_t. \tag{A1}$$

The dependent variable is an indicator variable that takes a value of 1 if there is a Bitcoin bubble on day t. We define a bubble occurrence on day t when the PSY statistic for the respective observation exceeded the 95% bootstrapped critical value. We measured Bitcoin trading volume as the natural logarithm of total Bitcoin trading volume (in bitcoins). The vector Z_t contains additional control variables. We control for CBOE Volatility Index (VIX), gold returns, S&P 500 returns, and attention to Bitcoin using Google search frequencies for the key term "Bitcoin." All variables are defined in Appendix A. We do not control for Twitter sentiment because of data limitations.

Table A2 provides the probit model results when we regress the incidence of a bubble on trading volume and the control variables. As we expected, trading volume is a significant predictor of Bitcoin price bubbles. The ability of Bitcoin trading volume to predict bubbles highlights the importance of understanding the relation between trading activity, individual investors spare time, and their attitudes toward cryptocurrencies as a form of exciting gambling activity.

Table A2. The impact of Bitcoin trading volume on the probability of price bubbles.

	(1)	**(2)**	**(2)**
Bitcoin volume	0.0906 ***	0.0818 **	0.3752 ***
	(2.8610)	(2.4953)	(8.5473)
Controls:			
Bitcoin return		0.0872 ***	0.0859 ***
		(4.5409)	(4.4408)
Bitcoin return lagged		0.0913 ***	0.0916 ***
		(4.8431)	(4.7003)
VIX			−0.2447 ***
			(9.5236)
Gold return			0.0885
			(0.8171)
S&P500 return			−0.2177 **
			(2.0338)
Google attention			0.0425 ***
			(4.1362)
Constant	−2.5751 ***	−2.5587 ***	−2.8143 ***
	(6.0520)	(5.8680)	(4.3732)
Observations	2087	2087	2059
Pseudo R^2	0.0023	0.035	0.2

Note: This table presents the parameter estimates from probit models for Bitcoin price bubbles and trading volume (in natural logarithm). The key independent variable is an indicator variable that equals 1 if there is a Bitcoin bubble on day t, and 0 otherwise. t values (in parentheses) are computed with robust standard errors. All variables are defined in Appendix A. *** and ** indicate that the coefficient is significantly different from zero at the 1% and 5% levels, respectively.

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