Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Cryptocurrency price discrepancies under uncertainty: Evidence from COVID-19 and lockdown nexus

Meichen Chen, Cong Qin, Xiaoyu Zhang

Article info
Article history: Available online 21 March 2022
JEL Classification: F21 G12 I18
Keywords: Price discrepancies Bitcoin Uncertainty COVID-19 Investor sentiment

Abstract
The past decades have witnessed recurrent price discrepancies in cryptocurrency markets across countries. In addition to prior explanations that generally attribute this phenomenon to domestic capital controls during normal periods, we provide another explanation that investors perceive cryptocurrency as an alternative (hedging) investment, especially under uncertainty. Using the emerging of the COVID-19 pandemic in 2020 and the subsequent lockdown policies implemented by a group of countries as natural experiments, we adopt a difference-in-difference framework to examine how the nexus affects Bitcoin price discrepancies. We find that price discrepancies are larger in countries with confirmed cases of COVID-19 and rigorously implementing lockdown policies. We then verify our “alternative investment” hypothesis on the mechanism by showing that countries with intensified exposure to media hype on COVID-19 topics and with more panic emotion among citizens during the pandemic generally experienced larger Bitcoin price discrepancies than their counterparts. We also find that domestic capital control, sanitary policy stringency, uncertainty aversion, individualistic culture, and governmental power could moderate the general effect.

1. Introduction

It was the best of times, it was the worst of times, regarding cryptocurrencies. The past decades have witnessed their fervent surging and subsequent sagging in terms of price and trading amount, as well as recent vibration during the COVID-19 pandemic. Despite the fluctuation, cryptocurrencies of various types remain attractive in the global financial market. As suggested, there are conservatively 50 million active investors involved in cryptocurrency-related transactions on more than 100 exchanges worldwide (Makarov and Schoar, 2020).

First discovered in the Chinese city of Wuhan in December 2019, and then declared as pandemic status by the World Health Organization (WHO) in March 2020, COVID-19 has induced (and probably will continue to cause) enormous costs in lives and economies worldwide (Goodell and Goutte, 2021; Mazur et al., 2021). Almost immediately after the declaration
of the WHO, global financial markets experienced one of their most dramatic crashes in history.\(^1\) Although in less severity, we have also observed a plunge in the gold market, which has long been considered a safe haven (Mariana et al., 2021). Unlike in traditional stock and hedging assets markets, where investors experienced large losses and became less active during the pandemic periods (Zhang et al., 2020; Ding et al., 2022), cryptocurrency markets retained their energy. Therefore, it raises the first legitimate academic question that quantitatively, to what extent does the pandemic-induced uncertainty affect price discrepancies in cryptocurrency markets? As a step further, another research question is that whether any hedging asset exists during the crashes. As such, it extends the prior burgeoning debate on the hedging ability of cryptocurrencies in normal period (Wu and Pandey 2014; Briere et al., 2015; Eisl et al., 2015; Bouri et al., 2017; Corbet et al., 2020; Klein et al., 2018; Shahzad et al., 2019) to the post-pandemic period (Goodell and Goutte, 2021; Nguyen, 2021; Raheem, 2021).

In this paper, drawing on the certainly unfortunate COVID-19 pandemic and the corresponding implementation of lockdown regulations in some countries, we first adopt an identification framework in a difference-in-difference (DID) format to explore the effects of uncertainty on Bitcoin price discrepancies. Using the preferable specification that includes a full set of controls and country- and date-fixed effects, we find that adopting the lockdown policy during the pandemic results in a statistically large effect of 1.21% further price discrepancies. Given the huge daily transaction amount, the effect is also economically significant.

Then, we show that our baseline results are robust to an extensive set of checks. First, we alternatively use an intensified DID strategy to further account for the severity of the pandemic (and hence uncertainty). Specifically, in lieu of the indicator of being affected by COVID-19, we respectively use the number of daily confirmed cases, accumulated confirmed cases, daily death cases, and accumulated deaths as alternative measures of the pandemic, and then re-estimate the results. Second, instead of using weighted average price in the benchmark, we rely on a simple average daily price to measure the price discrepancy. Third, we change the time spot from the first COVID-19 wave to the implementation of the lockdown policy to account for people’s potential lagged awareness of the pandemic severity. Fourth, we consider different fixed effects (accounting for week-fixed effects instead of date-fixed effects) and different cluster levels (clustering standard errors at a continental level instead of country level). Finally, we adopt a falsification strategy to address the potential endogeneity problem and find no clues on the existence of endogeneity. Altogether, the robustness check results provide confidence on the validity of our benchmark.

Another key research question of this paper is to understand the source of Bitcoin price discrepancies. Unlike conventional wisdom that attributes discrepancies to the exogenous cross-border capital controls, here we propose a potential endogenous channel wherein people outside the US might de facto consider cryptocurrency as an alternative investment hedging against uncertainty. To verify this conjecture, we examine whether intensive exposure to media hype on COVID-19 and the intensity of social panic due to the pandemic increased the price discrepancies. Because people under uncertainty are more inclined to purchase perceived safe assets, if we observe a co-movement of higher uncertainty and increased Bitcoin price discrepancies, it should imply that people indeed perceive cryptocurrency as hedging investments. Our results confirm this mechanism.

Additionally, we examine five heterogeneous effects on the effects of the pandemic and lockdown nexus. By including a triple interaction term, we find that (i) countries with stringent domestic capital controls generally respond more radically to the uncertainty nexus; (ii) countries with rigorous public health policies exhibit larger price discrepancies in the Bitcoin market; (iii) countries with higher uncertainty avoidance also have relatively higher price discrepancies in their Bitcoin market; (iv) people in countries with individualism culture do not positively respond to the nexus; and (v) Bitcoin markets in centralized countries present larger price discrepancies.

It is notable that, from a further perspective, this paper serves as a tether stone for future relevant studies. Bitcoin, among other cryptocurrencies, is nascent and subject to severe uncertainty. While this paper investigates the uncertainty derived from exogenous shocks, recent literature proposes another important source of uncertainty – model specification uncertainty (Qiu et al., 2021). As new techniques are rapidly embraced by the community of economists, nonlinear and even non-parametric modelling techniques are adopted to circumvent the potential model specification uncertainty. Therefore, future studies on the issues discussed in this paper could be extended by incorporating innovative modelling techniques (e.g., machine learning, ensemble learning, model averaging, and deep learning) and considering uncertainty from other possible sources.\(^2\)

The remainder of this paper is organized as follows: Section 2 reviews the literature and discusses the contribution of this paper. Section 3 introduces the data from which we draw upon to illustrate some novel stylized facts. Section 4 presents the empirical strategy and corresponding baseline results, robustness checks, and analyses on mechanisms and heterogeneity. Finally, Section 5 concludes the paper.

---

\(^1\) In the first trading day after the WHO’s declaration, we saw plunges of 9.51%, 10.87%, and 4.41%, respectively for the S&P500, FTSE-100, and Nikkei-225 (Mariana et al., 2021). Within four trading days, DJIA plunged 26% in U.S. (Mazur et al., 2021). The scenarios were similar in other stock markets including Europe, UK, Australia, and Asia (Zhang et al., 2020).

\(^2\) We are grateful to referee’s insightful suggestion to discuss model specification uncertainty here.
2. Literature review

The starting point of this work is the recent recognition of the existence of cryptocurrency price discrepancies and consequently arbitrage opportunities worldwide. The seminal work of Makarov and Schoar (2020) has addressed the phenomenon that the price deviation of cryptocurrency is larger in exchanges across countries than within countries and, more importantly, this deviation cannot be explained by the different features of exchanges. Emerging evidence was soon empirically and theoretically and country-specified and globally developed to confirm and explain this phenomenon (Borri and Shakhnov, 2021; Choi et al., 2021; Hautsch et al., 2021).

As a new example of the purchasing power parity (PPP) puzzle, the price discrepancy of cryptocurrencies has attracted increasing attention, largely because prior explanations for this puzzle in international economy seemed irrelevant in the new context (Choi et al., 2021). In particular, some macroeconomic factors that could explain the puzzle in traditional financial markets lost their explanation abilities for cryptocurrencies (Bianchi, 2020; Liu and Tsyvinksi, 2020). By far, among sporadic work on this topic, a plausible explanation attributes the presence of arbitrage opportunities to the rigorous domestic capital controls and, on the contrary, loose regulations on cryptocurrency transactions (Makarov and Schoar, 2020; Choi et al., 2021; Wang et al., 2021). The rationale is that if people in a country with rigorous capital controls want to evade the regulation, they may have to purchase cryptocurrencies at a higher price, thereby creating price discrepancies in some periods. Similar to this explanation, if investing in cryptocurrencies could induce diversification benefits (or mitigate potential risks), risk-averse arbitrageurs might also contribute to the price discrepancies (Borri and Shakhnov, 2021; Hautsch et al., 2021; Huang et al., 2021).

Therefore, it is related to the burgeoning debate on whether cryptocurrencies played a role as a diversifier or shelter. Theoretically, cryptocurrencies could provide diversification benefits and serve as an alternative (hedging) investment mainly because of their low correlation with traditional financial assets (e.g., stock and bond) and their role as a store of value (Huang et al., 2021). The advocates have shown that the inclusion of cryptocurrencies diversifies the traditional asset portfolio by increasing average returns and enhancing aggregated effectiveness (Wu and Pandey 2014; Briere et al., 2015). Although including cryptocurrencies in portfolios might concurrently involve higher risk, the high returns could compensate for the additional risk and result in a better risk-return ratio (Eisl et al., 2015). Subsequent mechanism analyses revealed that cryptocurrencies did so because they responded little to stock and bond investments (Briere et al., 2015; Bouri et al., 2017; Corbet et al., 2020) and their store of value (Conlon and McGee, 2020). However, opponents have found clues that cryptocurrencies were devoid of the ability to serve as a safe haven (Klein et al., 2018; Shahzad et al., 2019; Ji et al., 2020). Specifically, Conlon and McGee (2020) observed a positive relationship between cryptocurrencies and stock returns and Baur et al. (2018) identified the weakened role of cryptocurrencies as a store of value.

The COVID-19 pandemic provides us with a valuable window to reconcile this debate (Goodell and Goutte, 2021; Nguyen, 2021; Raheem, 2021). On the one hand, because the COVID-19 pandemic has had a significant effect on the economic and social systems across the world, situations in the cryptocurrency market might have also been changed. On the other hand, understanding investors’ trading strategy on cryptocurrencies during a crisis is of both more academic importance and policy implications. Unfortunately, we are still far from reaching a consensus during the post-pandemic period. Mnif et al. (2020) investigated the performance of the cryptocurrency markets during the pandemic and found that market efficiency increased during this period. Mariana et al. (2021) pointed out that the daily return of Bitcoin and Ethereum presented a negative relation against S&P500 returns and hence argued that cryptocurrency could act as a short-term safe haven. In contrast, Corbet et al. (2020) found that the volatility between the stock market and Bitcoin was positively correlated and suggested that cryptocurrencies were not a de facto hedging asset. Moreover, Ji et al. (2020) compared several assets and concluded that rather than Bitcoin, forex currencies, and the crude oil commodity futures, gold and soybean commodity futures were more analogous to hedging assets.

In addition to the two major strands, other explanations on the determinants of cryptocurrency prices have been offered. Before the outbreak of the COVID-19 pandemic, the effective factors in cryptocurrency markets include public attention (Liu and Tsyvinksi, 2020), cryptocurrency past returns (Bianchi, 2020), the ability of monetary policy to modulate demand shock (Saleh, 2021), cryptocurrency production factors (Cong et al., 2021) and blockchain fundamentals (Bhambhwani et al., 2019; Pagnotta, 2022), among others. With the advent of the COVID-19 pandemic, a strand of literature highlighted the importance of social media (reflecting social panic) on the price of cryptocurrencies (Cafrerra, 2020; Chen et al., 2020; Corbet et al., 2020; Bejaoui et al., 2021). Usually using Google search volume as a proxy of panic sentiment, these studies measured the effects of social panic on the returns and trading volume in cryptocurrency markets. A higher extent of social panic generally resulted in higher market volatility and extensive trading volume.

The aforementioned review suggests that the current (but burgeoning) understanding of cryptocurrency might just be the beginning. In this paper, we attempt to add new insights into three aspects. First, we contribute to the understanding of cryp-

---

3 In an attempt to better understand the set of stylized facts revealed by Makarov and Schoar (2020), Borri and Shakhnov (2021) and Hautsch et al. (2021) built theoretical models to explain the Bitcoins’ price differences across countries. Despite the variations in modeling framework, they introduced risk averse behavior/intention of investors in the model. As for additional empirical evidence, unlike Makarov and Schoar (2020)’s broad attention on global markets, Choi et al. (2021) focused on the price premium of Bitcoin between Korea and United States.

4 We notice that there are debates on the effectiveness in determining cryptocurrency prices of some aforementioned factors. For example, Liu and Tsyvinksi (2020) questions the role of cryptocurrency production factors.
tocurrency price discrepancies. The conflicting results were raised for at least two reasons: (i) The use of inappropriate targets. Given that Bitcoin price discrepancies and arbitrage opportunities have been shown to be a global phenomenon (Makarov and Schoar, 2020), some following analyses based on a specific country might be misleading because of serious informational loss (Huang et al., 2021). (ii) The use of inappropriate methods. Because most previous studies ignored the potential endogeneity problem, the results should be interpreted more as correlation than causality. To address those issues, we conduct a cross-country analysis and exploit a DID identification framework based on the exogenous shock of the COVID-19 pandemic.

More directly, we contribute to the debate on whether cryptocurrencies played the role of diversifier or alternative hedging investments. Instead of focusing on the evolution directions between cryptocurrency prices and traditional financial assets, we explicitly concentrate on the investors’ trading strategies during the pandemic. We find that leaving aside the real functions, investors outside the U.S. perceived cryptocurrencies as valuable alternative investments and were inclined to include more cryptocurrencies in their portfolios under uncertainty. In this sense, this paper also contributes to a broader literature on the effects of the COVID-19 pandemic.

Finally, this paper sheds some light on the role of social media in financial markets during the pandemic. Prior literature generally used online search frequency, which is an active way to acquire information, as a proxy of social sentiment. However, we propose that the citizens are more likely to be affected by being passively exposed to social media. Therefore, we adopt a set of indicators of social media to measure social panic. In addition to previous findings that social media has a direct effect on cryptocurrency prices, we find that social media could interact with crises and indirectly affect cryptocurrency prices.

3. Data and stylized facts

We use a diverse set of datasets to examine the effect of the pandemic and lockdown nexus on Bitcoin price discrepancies. Below, we describe the data on COVID-19, lockdown interventions, Bitcoins, capital controls, and other country-specific characteristics. We also provide a detailed description of the variables used in this study in Table A1 in the appendix.

3.1. COVID-19 cases and deaths

We obtain the COVID-19 data from Coronavirus COVID-19 Global Cases Database, operated by Johns Hopkins Coronavirus Resource Center. The database tracks and integrates daily information on the new pneumonia from more than 180 economies (Ding et al., 2021). To provide reliable figures, the database relies primarily on official reports, then supplements the missing from other sources, and finally collates those figures with the records of some international health authorities. For each country-date pair, we retrieve the number of newly confirmed cases and accumulated confirmed cases, as well as the number of deaths and accumulated deaths due to COVID-19. In the baseline specification, drawing on the above information, we identify the time spot when the first confirmed case was announced as the beginning of a country exposed to the COVID-19 pandemic.

Table 1 provides the summary statistics for key variables. Fig. 1 illustrates the daily increment of confirmed COVID-19 cases over time for each exposed country to provide a clear pattern of the evolution of the disease. The x-axis depicts the period (year-month-date) between January 1, 2019 and January 1, 2021 and the y-axis represents the number (in logarithm) of newly confirmed cases. The evolution of COVID-19 in most countries generally follows a rising tendency (with fluctuation), indicating that the effects of the pandemic might be continuous. We also find substantial cross-economy and cross-time variations from the figure.

3.2. Lockdown policy

We collect the information on governmental regulations during the pandemic from Our World in Data (OWD), which is managed by Oxford Coronavirus Government Response Tracker (OxCGRGRT). According to the strictness of regulation, the OxCGRGRT team classifies countries into four categories: (1) countries with no official intervention are labeled as type 0; (2) countries that provided suggestive guidance of stay-at-home are labeled as type 1; (3) countries that have announced official requirements of stay-at-home except for necessary activities are labeled as type 2; and (4) countries that implemented compulsory requirements of stay-at-home with few exemptions are labeled as type 3. In this paper, we consider the type 2 and type 3 countries as those adopting lockdown policies, while others are not. As such, we construct a lockdown policy dummy, countries of types 2 and 3 equal one and the remaining equal zero.

3.3. Bitcoin price discrepancies

We retrieve data on tick-level Bitcoin trading from Bitcoincharts, a leading provider of data relevant to the Bitcoin network. Bitcoincharts provides a market application programming interface (API) in its website, through which we access its data. It initially collects all Bitcoin trading information. Then, for each currency, only the daily average trading amount in exchange above 50,000 deals is released to the public and thus included in our analysis. Table A2 in the appendix shows such
pairs being considered in this paper. Moreover, because this paper aims to investigate the effects of the pandemic on Bitcoin price discrepancies, the sample covers 24 months from January 1, 2019 to January 11, 2021, nearly following 1 year prior and post to the breakout of the COVID-19 pandemic.

We process the raw data in the following steps to construct our outcome variable, namely the Bitcoin price discrepancy. We first aggregate the original tick-level data at the daily level, that is, to calculate the daily Bitcoin price in each country. Specifically, the daily price in terms of each currency is calculated by taking the volume-weighted average price of all exchange among the currency-exchange pairs. Then, to increase comparability of Bitcoin prices across countries, we use the fiat currency exchange rate, obtained from Bloomberg, to convert Bitcoin prices in local currency into those in US dollars. Finally, with the Bitcoin price in the US as the benchmark, we compute the price difference between each country and the benchmark. This price ratio is the dependent variable of our study. Table 1 shows the sample mean of the Bitcoin price ratio equals 1.005 with a standard deviation of 0.024.

Fig. 2 provides visual evidence on the widespread existence of Bitcoin price discrepancies. The x-axis covers the entire sample period from January 1, 2019 to January 11, 2021 and the y-axis records the Bitcoin price ratio. Recall that we have transformed all country-specific Bitcoin prices in local currency into US dollars and use the price in the US market as a unified benchmark; hence, the Bitcoin price ratio is comparable across countries. Therefore, Fig. 2 implies the existence of Bitcoin price discrepancies and detectable variation in magnitude across countries. In particular, we observed some extreme peaks and troughs after the breakout of the COVID-19 pandemic, which are generally larger in magnitude than that in the pre-pandemic period. More importantly, we find a disparity in terms of price ratio that straddles the starting dates of a pandemic. Thus, it suggests to some extent that the uncertainty probably has an effect on Bitcoin price discrepancies and it is worth further rigorous analysis.

We also consider another way to compute Bitcoin price discrepancies. In the aforementioned process, we follow Makarov and Schoar (2020) to calculate Bitcoin price discrepancies using Bitcoin-fiat currencies pair. Here, we alternatively adopt the Bitcoin-Tether pair because of the increasingly important role of Tether in Bitcoin transactions (Wang, 2018; Ante et al., 2021). Tether, which was first authorized on October 6, 2014, has been the largest stable coin. Given that it is implicitly backed by US dollars reserves and free of banking connections, Tether has accounted for more Bitcoin trading volume than US dollars since 2017 (Griffin and Shams, 2020). Although it is reasonable to assume that the Bitcoin price ratio computed by the

---

**Table 1**

|                     | Mean | SD   | Median | P25  | P75  | No. of observations |
|---------------------|------|------|--------|------|------|---------------------|
| COVID-19            | 0.460| 0.498| 0      | 0    | 1    | 8,162               |
| New Cases           | 5.692| 23.009| 0      | 0    | 0.809| 8,162               |
| Total Cases         | 0.476| 1.903| 0      | 0    | 0.070| 8,162               |
| New Deaths          | 0.116| 0.405| 0      | 0    | 0.018| 8,162               |
| Total Deaths        | 14.851| 46.099| 0      | 0    | 1.831| 8,162               |
| Lockdown            | 0.182| 0.386| 0      | 0    | 0    | 8,162               |
| Price Ratio         | 1.005| 0.024| 1.001  | 0.997| 1.010| 8,162               |
| Price Ratio (Tether)| 1.005| 0.024| 1.002  | 0.996| 1.010| 8,162               |
| Price Ratio (Simple Average) | 1.002| 0.039| 1.001  | 0.996| 1.010| 8,162               |
| Capital Control     | 0.303| 0.282| 0.250  | 0    | 0.500| 8,027               |
| Capital Outflow Control | 0.370| 0.333| 0.500  | 0    | 0.500| 8,027               |
| Amount              | 5.311| 11.676| 0.601  | 0.138| 4.500| 8,162               |
| Volume              | 53.389| 157.609| 5.107  | 1.169| 42.479| 8,162               |
| Stock Index         | 0.988| 0.164| 0.967  | 0.893| 1.053| 8,162               |
| Fake News Index     | 1.358| 2.018| 0.800  | 0.480| 1.460| 3,955               |
| Media Hype Index    | 45.003| 17.339| 47.400  | 38.280| 56.980| 4,062               |
| Panic Index         | 5.296| 4.324| 4.070  | 2.753| 6.490| 4,007               |
| Sentiment Index     | -12.448| 17.942| -9.681  | -22.650| -0.090| 4,146               |
| Fake News Ratio     | 1.599| 1.867| 1      | 0.761| 1.730| 3,909               |
| Media Hype Ratio    | 1.367| 0.848| 1.224  | 1.055| 1.420| 4,035               |
| Panic Ratio         | 1.567| 1.315| 1.198  | 0.965| 1.732| 3,990               |
| Sentiment Ratio     | 0.602| 10.71| 0.406  | -0.722| 1.112| 4,048               |
| Health Policy Index | 26.800| 31.391| 0      | 0.462| 62.500| 7,962               |
| Uncertainty Avoidance Index | 66.700| 22.138| 62.500  | 48    | 92    | 7,420               |
| Individualism Index | 58.578| 27.570| 59.389  | 39    | 89    | 7,420               |
| Power Distance Index| 55.528| 18.325| 52.139  | 39    | 68    | 7,420               |

Note: This table presents the summary statistics of all the variables used in this paper. The unit is thousand for New Cases, New Deaths, Total Deaths, and Amount. The unit is million for Total Cases and Volume.

---

5 We are grateful to the referee, who suggested that we use the Bitcoin-Tether pair, in addition to Bitcoin-fiat currency pair, to re-calculate the Bitcoin price discrepancies.

6 Please refer to Griffin and Shams (2020) for a more comprehensive description on the history of Tether.

7 It is worth noting that despite Tether’s longstanding claims that it is backed by US dollars reserves or, according to its recent modification, by traditional currency and cash equivalents, some anecdotal evidence suggests that the cash reserves are not sufficient to fully support Tether’s instruments.
Bitcoin-fiat currencies pair is similar to that by Bitcoin-Tether pair because Tether is pegged to US dollars, we confirm this conjecture by re-calculating the Bitcoin price ratio relying on the Bitcoin-Tether pair. Specifically, we compare the country-specific daily Bitcoin price in Tether with that in the US market. The difference between the two prices is the new Bitcoin price discrepancy. We retrieve information on Bitcoin-Tether trading from CryptoDataDownload.com, including the two largest exchanges of such trade, namely, Binance and Kucoin.

The upper part of Fig. 3 depicts the exchange rate between Tether and US dollar. The ratio fluctuates around one, confirming Tether’s role as a stable coin and indicating that Bitcoin price ratios calculated by Tether and US dollars are likely to be similar. The lower part of Fig. 3 illustrates the evolution of trading volumes of Bitcoin using Tether and US dollars over time. Initially, the two volumes are similar. However, the volume using Tether surpasses that using US dollar in most periods after the burst of the COVID-19 pandemic. As such, it is necessary to re-calculate the Bitcoin price ratio using Tether.

Fig. 1. The evolution of newly confirmed COVID-19 cases. Note: In this figure, we plot the evolution of newly confirmed COVID-19 cases in our sample countries (and regions). The numbers are in the logarithm to make the trends comparable.
3.4. Capital controls

We obtain data on the level of country-specific capital controls from a database managed by Fernandez et al. (2016). This database includes 100 countries and has a recent update to 2019. It provides a rich set of annual capital control indices on inflows, outflows, and overall for ten assets categories. Among them, we primarily use two indices, the overall restrictions index and the overall outflow restrictions index, to examine the influence of capital controls on Bitcoin price discrepancies. Both indices range from 0 to 1 and a higher number of a country represents more serious capital controls there.

Following Makarov and Schoar (2020), capital controls and the variation in strictness across countries are the preconditions of the existence of price discrepancies in the cryptocurrency market. Therefore, in this study, we further restrict our attention to countries (or regions) where local fiat currencies are being actively used in Bitcoin transactions. This is because governmental capital controls mainly affect cross-border flows of local fiat currencies. Before the formal analysis, we first run a simple regression to show the difference in capital control stringency is positively related to the Bitcoin price discrepancies. Table 2 shows that the estimates of capital control on price ratio are unanimously significantly positive, thereby indicating that our study satisfies the precondition.

Fig. 2. The evolution of Bitcoin price discrepancies. Note: In this figure, we plot the evolution of Bitcoin price ratio in our sample countries (and regions). The Bitcoin price ratio is the ratio of volume-weighted average daily price between each country and the US.
Fig. 3. Comparison of the US Dollar and Tether. Note: In the upper part of this figure, we plot the price ratio of Tether (USDT) to the US dollar (USD). The lower part of this figure shows the trading volume of Bitcoins between USD and USDT. The data are from CoinMarketCap.com.

Table 2
Bitcoin price discrepancy and capital control.

| Dep.Var | Price Ratio |
|---------|-------------|
|         | (1) | (2) | (3) | (4) | (5) | (6) |
| Capital Control | 0.0445*** | 0.0708** | 0.0387* | 0.0222*** | 0.0354** | 0.0194* |
| (0.00984) | (0.0228) | (0.0174) | (0.00492) | (0.0114) | (0.00870) |
| Outflow Control | | | | 0.0222*** | 0.0354** | 0.0194* |
| (0.00492) | (0.0114) | (0.00870) | (0.00492) | (0.0114) | (0.00870) |
| Additional controls | NO | YES | YES | NO | YES | YES |
| Country FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | NO | YES | YES | NO |
| Date FE | NO | NO | YES | NO | NO | YES |
| R-squared | 0.274 | 0.285 | 0.490 | 0.274 | 0.285 | 0.490 |
| Observations | 8,027 | 8,027 | 8,027 | 8,027 | 8,027 | 8,027 |

Note: In this table, the dependent variables are the Bitcoin price ratio between each country and the US. Column (1)-(3) reports the estimates using capital control index as key variables on various control variables and fixed effects. Column (4)-(6) follows the specification by using capital outflow control index as the key variables. Additional controls include the logarithm of Bitcoins’ transaction volume, the logarithm of Bitcoins’ transaction amount, the logarithm of Bitcoins’ transaction number, and stock market index. Standard errors corrected for clustering at the country level are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.
3.5. Other country-specific characteristics

This paper also utilizes data from other sources. We collect stock market data for sample countries from Bloomberg to control for the effect of the capital market. We obtain media and sentiment information, such as Panic Index, Media Hype Index, Fake News Index, and Sentiment Index, from RavenPack’s coronavirus media monitor to explore how the pandemic and lockdown nexus influences investors’ behaviors and thereafter the Bitcoin prices. The Panic Index, which ranges from 0 to 100, measures the level of news that indicates panic and COVID-19. The Media Hype Index also ranges from 0 to 100 and measures the percentage of news that makes references to COVID-19. A larger number of Panic Index or Media Hype Index reflects that residents are more intensively exposed to negative news of COVID-19 and hence, panic more. The Fake News Index measures the level of media chatter about the novel virus that makes reference to misinformation or fake news alongside COVID-19. It falls into an interval from 0 to 100, where any value indicates the corresponding percentage of fake news about COVID-19. The Sentiment Index falls into an interval between −100 and 100, which gauges the degree of sentiment across all entities referred to in the news during the pandemic. A positive number represents a generally positive social sentiment during the pandemic, while a negative number represents the opposite. To understand the heterogeneous effect of some key features, we first obtain Health Policy Index from Johns Hopkins Coronavirus Resource Center. It measures the strictness of local government responses during the pandemic. A higher score indicates a higher level of public health regulation and control.

We then retrieve three culture indices based on Hofstede’s culture dimensions theory (Hofstede et al., 2010). Specifically, we use the Individualism Index, Uncertainty Avoidance Index, and Power Distance Index to capture different aspects of national culture: (i) Individualism Index measures the degree to which a society is integrated into groups and people’s obligation to groups. A higher score indicates that people place higher priority over attaining personal goals rather than the well-being of the group; (ii) Uncertainty Avoidance Index measures the extent to which a society accepts uncertainty and ambiguity. A higher index suggests low tolerance for uncertainty and ambiguity, and high tolerance for strict rules and regulations; and (iii) Power Distance Index represents the extent to which unequal distribution of power is accepted in society. A higher score implies high tolerance for concentrated power and inequality.

4. Empirical analysis

4.1. Empirical strategy

4.1.1. Effects of pandemic and lockdown nexus on Bitcoin price discrepancies

The existence of large and recurrent arbitrage opportunities in cryptocurrency markets across countries has recently been recognized (Makarov and Schoar, 2020). Some pioneering studies attributed this discrepancy to the stringency of domestic capital controls in normal periods. In this paper, we extend the analysis to the periods of uncertainty by first examining the effects of exposure to COVID-19 and the corresponding lockdown regulations on the price discrepancy of Bitcoins. Unlike the conventional perspective that uncertainty in the post-COVID-19 period comes mainly from the COVID-19 pandemic itself (e.g., Zhang et al., 2020; Mazur et al., 2021; Nguyen, 2021), recent studies emphasize the role of governmental responses (e.g., Ashraf, 2020; Zaremba et al., 2021). Therefore, we utilize the nexus of COVID-19 bear and governmental intervention to measure the uncertainty within a country.

Specifically, we explore a DID function with the form:

\[ Y_{it} = \beta_0 + \beta_1 COVID-19_{it} \times Lockdown_{it} + \beta_2 X_{it} + \varphi t + \omega_i + \epsilon_{it}. \]  

(1)

where \( Y_{it} \) is the outcome variable of interest, that is, the Bitcoin price ratio of country \( i \) to the US at date \( t \). We use exposure to COVID-19 and following governmental intervention nexus as the measure of the uncertainty extent faced by a country. In the baseline, \( COVID-19_{it} \) is an indicator of whether any confirmed cases of COVID-19 have been reported in country \( i \) by date \( t \). We adopt the number of daily confirmed cases, accumulated confirmed cases, daily death cases, and accumulated death cases as alternative measures of the intensity of uncertainty in robustness checks. \( Lockdown_{it} \) indicates the adoption of stringent lockdown policies for country \( i \) by date \( t \). We expect the estimate of \( \beta_1 \) to be positive because the implementation of lockdown policies during a pandemic should further impede capital flows, which theoretically leads to a wider arbitrage deviation (Makarov and Schoar, 2020).

We also consider a set of control variables \( X_{it} \), to avoid potential correlation with uncertainty and Bitcoin price discrepancies. Specifically, we include the logarithm of transaction volume, the logarithm of the transaction amount, the logarithm of transaction number, and the traditional financial market circumstances captured by the stock market index for country \( i \) at date \( t \). In addition to these covariates, our econometric model also includes a full set of country-specific fixed effect \( \varphi_i \) and

\(^8\) Conlon and McGee (2020) states that we are still in the very beginning of understanding Bitcoins and are devoid of knowledge on Bitcoins’ performance during the crisis. Thus, the outbreak of COVID-19 pandemic provides an opportunity to extend our insights on this topic.

\(^9\) As suggested by Zaremba et al. (2021), in modern society, citizens’ daily lives rely heavily on face-to-face interactions, which would be suspended by governments’ radical responses to the COVID-19 pandemic, for example, temporary closure of workplace. This suspension should account for uncertainty.

\(^10\) In equation (1), we initially include COVID-19 and Lockdown, but they are absorbed by fixed effects.
date fixed effects $\alpha_i$, which allows us to control for any time-invariant country unobservables that may affect the diffusion of COVID-19, governments’ attitude toward epidemic prevention, and domestic Bitcoin price discrepancies, along with other macro-economic shocks at the country level. $\epsilon_i$ is an idiosyncratic error term. We cluster standard errors at the country level to allow for an arbitrary serial correlation within-country over time.

Note that the validity of specification (1) relies on the underlying assumption that the Bitcoin price discrepancy of a country is caused by local traders whose behaviors are subject to domestic exposure to the pandemic and following lockdown policies. Otherwise, if overseas traders contribute most to the discrepancy, it might not be enough to connect country-wide lockdown policy with the associated Bitcoin price discrepancy. To address this concern, we collect the account verification requirements of each exchange. As summarized in Table A3 in the appendix, almost all exchanges in our dataset require their customers to submit a government-issued ID and proof of residency to verify they are domestic traders before trading. For exchanges allowing single fiat currency as trading cryptocurrencies, they unanimously require investors to provide a local phone number to receive short messages and submit documents to prove their local identity.\(^{11}\) Although other exchanges offer trading opportunities of using different fiat currencies, most merely require investors to trade on local fiat currency in their residing countries, and traders also have to provide a local phone number, proof of residency, and identity documents (Makarov and Schoar, 2020).\(^{12}\) As such, despite the lack of information on the exact location of traders of each transaction, it is reasonable to believe that the majority of traders against a fiat currency reside in the corresponding country (or region) because of the trading rules and restrictions posted by exchanges.

### 4.1.2. Role of social panic and media hype

Another key question is on the mechanism through which lockdown policies affect Bitcoin price discrepancies. Unlike conventional wisdom that attributes the discrepancies to exogenous cross-border capital controls, we propose a potential endogenous channel wherein people outside the US might de facto consider cryptocurrency as an alternative hedging investment against uncertainty. To verify this conjecture, we explore the specification as follows:

$$ Y_{it} = \beta_0 + \beta_1 \text{Lockdown}_{it} \times Hedge_{it} + \beta_2 X_{it} + \alpha_i + \epsilon_{it}, $$(2)

where $Hedge_{it}$ represents the inclination of holding hedge assets during a pandemic for country $i$ at date $t$. It is arguably difficult to find a direct measure, particularly at the daily level, to capture the extent to which investors value Bitcoins. However, it is plausible that if people perceive more uncertainty, they might feel more urgency to find shelters for their assets. Therefore, a co-movement of higher uncertainty and enlarged Bitcoin price discrepancies should support the proposed alternative investment mechanism.

Following this logic, we propose two sets of measures. The first set measures the intensity of media hype on COVID-19. Specifically, we calculate (i) *Fake News Index*, which is the percentage of fake news reported in the media alongside COVID-19; and (ii) *Media Hype Index*, which measures the percentage of news talking about COVID-19. The rationale is that the more people are exposed to intensified media hype on COVID-19, the more pessimistic they might feel about the economy and the more they favor the cryptocurrency. As such, we measure the coefficients of $\beta_1$ to be positive. More directly, we use the social panic during the pandemic as another proxy. *Panic Index* measures the level of news chatter references panic or hysteria alongside COVID-19 and *Sentiment Index* measures the level of sentiment mentioned in the news alongside COVID-19. Note that a higher *Panic Index* (values range between 0 and 100) means a more panicked society but a lower *Sentiment Index* (values range between −100 and 100, with negative signs meaning pessimistic) indicates a more panicked society. Thus, we expect the coefficient of $\beta_1$ to be positive for the former measure and negative for the latter.

### 4.2. Baseline results

In this subsection, we quantitively identify the effects of the nexus between COVID-19 pandemic and lockdown policies on Bitcoin price discrepancies. We present sophisticated evidence by estimating Eq. (1). Table 3 reports our baseline estimation results. In columns (1)–(3), the Bitcoin price ratio is calculated on the benchmark of US price. Column (1) provides a raw estimate, where we include no additional controls and only consider country-fixed effects. The effect of the uncertainty nexus on Bitcoin price discrepancies is 0.0141 (with a clustered standard error of 0.00242). After including a set of control variables in column (2), the coefficient remains statistically and economically significant, with an estimated coefficient of 0.0148 (with a clustered standard error of 0.00288). Finally, in our preferred specification that additionally considers date-fixed effects (shown in column (3)), the coefficient becomes 0.0121 (with a clustered standard error of 0.00507), implying that, on average, adopting a lockdown policy during the pandemic results in 1.21% further price discrepancies. Thus, it confirms the intuitive pattern uncovered by Fig. 2.

\(^{11}\) This cohort includes BTC markets, Btcoid (Indodax), bitFlyer, BitBox, Coincheck and Korbit. Specifically, BTC markets requires an Australian phone and an Australian passport or driver’s license; Btcoid (Indodax) requires non-Indonesian expatriates to provide a residence permit card (KITAS or KITAP); bitFlyer only offers services to residents in the local branch (Japan, Europe, or USA) and accounts management is separate across regions; BitBox and Coincheck only offer services to Japanese residents and customers need to provide proof of local residency to pass the account verification; Korbit requires customers to submit a phone number provided by a Korean carrier, proof of residency in Korea, and a bank account that can be used for trade in Korea.

\(^{12}\) This cohort contains Kraken, BitBay (Zonda), Bitstamp, Coinsbank, Coinfloor (Coincorner), BitX (Luno) and CEX. For example, BitX (Luno) has operations in different countries but investors in South Africa can only trade Bitcoins against ZAR.
As previously mentioned, we also compute the Bitcoin price ratio on the alternative benchmark of Tether. Columns (4)–(6) report the results using the new dependent variables. The coefficients of the variable of interest across columns remain similar both in significance and in magnitude with that in columns (1)–(3). It therefore provides further evidence that uncertainty explains the Bitcoin price discrepancies during the pandemic.

Moreover, columns (3) and (6) of Table 3 show that the coefficient of COVID-19 lacks statistical significance. It means that after including a nexus of COVID-19 bear and governmental intervention, the pandemic has little power to explain the Bitcoin price discrepancies. Therefore, it verifies our conjecture that rather than the pandemic alone, the uncertainty during the crisis should be attributed to the interaction of the pandemic and governments’ responses.

4.3. Robustness checks

This subsection provides robustness checks for our baseline results.

Accounting for the severity of the COVID-19 pandemic. – As a response to Goodell and Goutte (2021) who suggested that the price of Bitcoin co-moved with the severity of the pandemic, we additionally account for the effects of pandemic severity on Bitcoin price discrepancies. To do so, we draw upon an intensity DID framework by substituting the COVID-19 bear dummy13 with several severity measures in Eq. (1). Following Ding et al. (2021), the severity was first gauged by newly confirmed cases and accumulated confirmed cases on a given date. Then, to address the concern by Spiegel and Tookes (2021) that confirmed cases might be problematic because of the differentiation in testing capacity over time and across countries, we also measure the severity using daily death cases and accumulated death cases. Columns (1)–(4) of Table 4 present the results. The new estimates remain statistically significant, ensuring the robustness of our results. It also suggests that Bitcoin price discrepancies are co-moved with uncertainty level, thereby shedding light on the following analyses on the mechanisms of alternative investments.

Alternative price measure and time of policy shock. – An alternative method to calculate the Bitcoin price in a period is directly using the simple average of each deal (Makarov and Schoar, 2020). Hence, we employ a simple average daily price instead of weighted average price to measure the price discrepancy in column (1) of Table 5. An argument might be that the shock should start when the lockdown policy was implemented, which was the time most of the people realized the severity of the pandemic. We change the time spot from the first COVID-19 wave to the implementation of the lockdown policy and report the estimates in column (2). The results in both columns are still consistent with our benchmark results.

Alternative fixed effects and clusters. – In the benchmark, we consider geographic-fixed effects and allow for an arbitrary serial correlation at the country level. However, macro-economic shocks might also occur at the regional level and investors are likely to have imitative investment behaviors with those in neighboring countries. As such, in columns (3)–(4) of Table 5, we re-estimate Eq. (1) by respectively clustering standard error at continental level and including time-fixed effects at the week level. The new estimates still bear positively significant coefficients, thereby confirming the positive influence of uncertainty and lockdown interactions.

Dealing with potential endogeneity. – Endogeneity problem often arises because of reverse causality and omitted variables. In our context, reverse causality might not be a big issue. That is to say, for any country, neither its vulnerability to COVID-19 nor governmental decisions on implementing lockdown policies is likely to be determined by domestic Bitcoin price discrepancies. For one thing, whether a country is infected by COVID-19 is exogenous (Mazur et al., 2021; Rahman et al., 2021); for another thing, though the adoption of lockdown policy might be a trade-off between curbing disease and retaining economic activities (Fisman et al., 2021), given the independence of Bitcoin transactions from governmental regulation (Conlon and McGee, 2020), the Bitcoin market is less possibly to be involved within the trade-off.

---

13 Recall that in the baseline, a COVID-19 bear country is defined by a dummy, indicating whether any confirmed cases appeared there.
In this sense, the major (if not only) source of endogeneity would be the potential existence of omitted variables that simultaneously affect local uncertainty and domestic Bitcoin price discrepancies. As a step further, within the uncertainty nexus, because the infection of COVID-19 is exogenous, the only concern is that the implementation of lockdown policies is not random. As such, to ensure that our baseline results are not driven mainly by unobserved time-varying heterogeneity

| Dep.Var | Price Ratio |
|---------|-------------|
| (1)     | (2)         | (3)     | (4)     |
| New Cases | 0.0453     |           |         |
|          | (0.0507)   | (0.000899)|         |
| × Lockdown | 1.209***   | -2.037   |         |
|          | (0.236)    | (0.000776)|         |
| Total Cases | 0.0394*** | 82.569***|         |
| × Lockdown | (0.00729)  | (19.591) |         |
| New Deaths |           |         | -0.0405 |
| × Lockdown |           |         | (0.0315) |
| Total Deaths |         |         | 3.607***|
| × Lockdown |           |         | (0.729) |
| Additional controls | YES      | YES      | YES     |
| Country FE | YES       | YES      | YES     |
| Date FE | YES        | YES      | YES     |
| R-squared | 0.569      | 0.569    | 0.568   |
| Observations | 8,162    | 8,162    | 8,162   |

Notes: In this table, we estimate the effect of COVID-19 severity and lockdown nexus on Bitcoin price discrepancies. The dependent variables are the Bitcoin price ratio. Columns (1)-(4) respectively use the number of daily confirmed cases, accumulated confirmed cases, daily death cases, and accumulated death as alternative measures of pandemic. All regressions include the controls of the logarithm of Bitcoins’ transaction volume, the logarithm of Bitcoins’ transaction amount, the logarithm of Bitcoins’ transaction number, and stock market index. Country and date fixed effects are included in all specifications. Standard errors corrected for clustering at the country level are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

Fig. 4. Distribution of simulated treatment estimates. Note: This figure plots the empirical distribution of simulated treatment effects for the benchmark. The PDF is constructed from 500 estimates using the specification in column (3) of Table 3. No parametric smoothing is applied: the PDF appears smooth because of the large number of points used to construct it. The vertical line shows the benchmark estimate reported in column (3) of Table 3.

In this sense, the major (if not only) source of endogeneity would be the potential existence of omitted variables that simultaneously affect local uncertainty and domestic Bitcoin price discrepancies. As a step further, within the uncertainty nexus, because the infection of COVID-19 is exogenous, the only concern is that the implementation of lockdown policies is not random. As such, to ensure that our baseline results are not driven mainly by unobserved time-varying heterogeneity
that affects a country’s adoption of lockdown policies and Bitcoin prices, we conduct a falsification test. Following Chetty et al. (2009), we implement the test as follows: (i) within COVID-19 bear countries, we randomly select 7 countries (7 is the true number of countries implementing lockdown policies) to assume them to have implemented lockdown policies; (ii) we then artificially assign the true dates of implementing lockdown policies to those falsified COVID-19 bear countries; (iii) drawing on this new sample, we re-estimate Eq.(1) and repeat the exercise 500 times to increase the identification power. By doing so, if no omitted variables exist, the estimates from the above falsification should be close to zero.

The empirical density of the estimated coefficients of the falsification from the 500 simulation tests is presented in Fig. 4. As expected, the distributions of the estimated coefficients after the falsification are centered around zero with a small standard deviation, suggesting the absence of a significant effect with the randomly constructed experiment. Meanwhile, our baseline estimate is 0.0121, which is located far from the entire density range, indicating that our baseline estimate is unlikely to be driven by unobserved factors (if exist).

4.4. Mechanisms

In this subsection, we analyze the potential mechanism through which uncertainty affects Bitcoin price discrepancies. To this end, we particularly examine whether people perceive cryptocurrency as a shelter under uncertainty.

As previously discussed, we first examine whether intensive exposure to media hype on COVID-19 enlarged Bitcoin price discrepancies. We estimate Eq.(2) by measuring media hype exposure by the percentage of all entities reported in the media alongside COVID-19 and the percentage of fake news talking about COVID-19. Columns(1)–(2) of Table 6 provide the results. Because the coefficients of Lockdownit × Hedgeit are significantly positive, it suggests that countries exposed to intensified media hype on COVID-19 generally experienced higher Bitcoin price discrepancies. We also replicate the above procedure except that we scaled the two measures by US value (hence using the ratio). Columns (3)–(4) of Table 6 show the new estimates are consistent with those in Columns(1)–(2).

We then directly check whether social panic during the pandemic affects Bitcoin price discrepancies. We estimate Eq. (2) using the level of news chatter that makes reference to panic or hysteria alongside COVID-19 and the level of sentiment mentioned in the news alongside COVID-19 as proxies of social panic. The results are reported in columns (1)–(2) of Table 7. We obtain a significantly positive coefficient on our key variable for the former and a negative for the latter, implying that increments of uncertainty indeed stimulate the incentives of conducting hedging investment and enlarge Bitcoin price discrepancies. We also scaled the two measures by US value and re-estimate Eq. (2). The results, as shown in columns (3)–(4) of Table 7, remain consistent.

The results in this subsection suggest that hedging motivation is likely to be an important mechanism that explains the existence of price discrepancies in the Bitcoins market, especially during periods under high uncertainty.

4.5. Heterogeneous effect of regional characteristics

In this subsection, we examine several heterogeneous effects on the baseline estimation. First, we connect findings during the crisis on the role of uncertainty with previous knowledge on the role of capital controls. That is, we examine whether the

Table 5
The impact of uncertainty nexus on Bitcoin price ratio: robustness checks.

| Dep.Var | Price Ratio |
|---------|-------------|
|         | (1)         | (2)         | (3)         | (4)         |
| COVID-19 | -0.00473 (0.00755) | 0.00121 (0.00409) | 0.00178 (0.00252) |
| COVID-19 × Lockdown | 0.0127** (0.00410) | 0.0121** (0.00408) | 0.0140*** (0.00266) |
| Policy | 0.00431 (0.00351) | 0.0123*** (0.00354) |
| Policy × Lockdown | 0.0123*** |
| Additional controls | YES | YES | YES | YES |
| Country FE | YES | YES | YES | YES |
| Time FE | Date | Date | Date | Week |
| S.E. cluster level | Country | Country | Continental | Country |
| R-squared | 0.274 | 0.569 | 0.568 | 0.471 |
| Observations | 8,162 | 8,162 | 8,162 | 8,162 |

Notes: In this table, we perform a set of robustness checks. Column (1) uses simple average daily price ratio as alternative dependent variable. Column (2) uses policy implementation as the time of shock. Column (3) clusters standard error at continental level. Column (4) changes time fixed effects to week level instead of date level. All regressions include the controls of the logarithm of Bitcoins’ transaction volume, the logarithm of Bitcoins’ transaction amount, the logarithm of Bitcoins’ transaction number, and stock market index. Country fixed effects are included in all specifications. *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.

14 Because we included country fixed effects in the specification, we have controlled for any time-invariant heterogeneity.
The stringency of capital control has an effect on the effects of the pandemic and lockdown nexus. Specifically, we interact an indicator measuring the stringency of capital control in 2019 (a higher number means more rigorous regulation) with the term of interest, $\text{COVID-19}_{it} \times \text{Lockdown}_{it}$, in the Eq. (1) framework. Column (1) of Table 8 presents the results. The estimate
of the triple interacted term is significantly positive, implying that capital control remains important during the crisis, the uncertainty would be amplified in a more capital-regulated country, thereby resulting in larger Bitcoin price discrepancies.

Second, we detect how containment and health policies affect the effects of the uncertainty. To do so, (i) we adopt an aggregated containment and health policy index to measure the strictness of local government responses during the pandemic, that is, a higher Health Policy Index indicates stricter public health regulations and controls; and (ii) interact this indicator with \( COVID-19 \times Lockdown \times \) Capital Control and re-estimate the results. As shown in column (2) of Table 8, the estimate of the triple interacted term is significantly positive, indicating that people in a society with stricter public health regulations are more likely to purchase Bitcoins during the pandemic and the following lockdown periods.

Third, we examine how people’s attitude towards uncertainty affects our baseline results. Because we found that Bitcoin is perceived as an important alternative investment under uncertainty, it is plausible that people that are more uncertainty averse would purchase more Bitcoins during the pandemic. To verify this conjecture, we repeat the above strategy, except that we interact an indicator of Uncertainty Avoidance that measures the tolerance of uncertainty with \( COVID-19 \times Lockdown \times \) Uncertainty Avoidance Index and re-estimate the results. As presented in column (3) of Table 8, the estimate of the triple interacted term is significantly positive, indicating that people in a society with stricter public health regulations are more likely to purchase Bitcoins during the pandemic and the following lockdown periods.

Fourth, enlightened by Fernandez-Perez et al. (2021), which states that culture has a deep influence on the way of investors’ response to the pandemic, we examine how individualism/collectivism affects our benchmark pattern. We use the Individualism Index to measure the extent of individualism within a country. A larger indicator implies a higher degree of individualism. Then, we add a triple interaction term of \( Individualism_i \times COVID-19_{it} \times Lockdown_{it} \) in Eq. (1) and re-conduct the analysis. Column (4) of Table 8 reports the new results. The coefficient of the triple interaction term is significantly negative, suggesting that a culture of individualism would mitigate the willingness to buy Bitcoins under uncertainty. A plausible explanation is that individualistic people might not perceive governmental lockdown policies as a signal of uncertainty because they usually do not comply with this regulation, and thus, social interaction remains.

Finally, we delve into an important aspect of state capacity, which is the ability to effectively implement governmental policy. It is reasonable to assume that a more centralized (in terms of power) government is more likely to penetrate society. In this paper, we use the Power Distance Index as a proxy for power concentration and verify our conjecture by interacting it with \( COVID-19_{it} \times Lockdown_{it} \). Column (5) of Table 8 reveals the results. As expected, the estimate of the triple interaction term is significantly positive, indicating that a powerful government can indeed shut down the internal movements and consequently increase the level of uncertainty.

### Table 8
The heterogeneity effects on Bitcoin price ratio.

|                | (1)         | (2)         | (3)         | (4)         | (5)         |
|----------------|-------------|-------------|-------------|-------------|-------------|
| COVID-19       | -0.0252**   | 0.00292     | -0.0131     | 0.0185***   | -0.00832    |
|                | (0.0113)    | (0.0169)    | (0.00798)   | (0.00548)   | (0.00737)   |
| COVID-19 × Capital Control | -0.00959 | 0.0501**     | (0.0177)    |             |             |
| COVID-19 × Lockdown × Capital Control |             |             |             |             |             |
| COVID-19 × Health Policy Index |             | 0.00973     |             | (0.00609)   |             |
| COVID-19 × Lockdown × Health Policy Index |             |             | 0.0207***   | (0.00524)   |             |
| COVID-19 × Uncertainty Avoidance Index |             |             |             | 0.00799     |             |
| COVID-19 × Lockdown × Uncertainty Avoidance Index |             |             |             | (0.00603)   |             |
| COVID-19 × Individualism Index |             |             |             | -0.00570    |             |
| COVID-19 × Lockdown × Individualism Index |             |             |             | (0.00644)   |             |
| COVID-19 × Power Distance Index |             |             |             | 0.0212**    |             |
| COVID-19 × Lockdown × Power Distance Index |             |             |             | (0.00718)   |             |
| Additional controls | YES | YES | YES | YES | YES |
| Country FE | YES | YES | YES | YES | YES |
| Data FE | YES | YES | YES | YES | YES |
| R-squared | 0.571 | 0.564 | 0.298 | 0.297 | 0.297 |
| Observations | 8,162 | 7,942 | 7,420 | 7,420 | 7,420 |

**Note:** In this table, we present the heterogeneity analyses results. The dependent variables are the Bitcoin price ratio. All regressions include the controls of the logarithm of Bitcoins’ transaction volume, the logarithm of Bitcoins’ transaction amount, the logarithm of Bitcoins’ transaction number, and stock market index. Country and date fixed effects are included in all specifications. Standard errors corrected for clustering at the country level are reported in parentheses. *** denotes significance at the 1% level, ** at the 5% level, * at the 10% level.
5. Conclusions

Undoubtedly, the unprecedented COVID-19 pandemic has re-shaped the global economy. Unlike traditional financial markets that have experienced huge plunges, we observed active trading and recurrent price discrepancies in cryptocurrency markets across countries during the post-pandemic period. Using the beginning of the COVID-19 pandemic in 2020 and subsequent lockdown policies as natural experiments, along with a DID identification strategy, this paper examines how the uncertainty nexus affects Bitcoin price discrepancies. We find that price discrepancies are larger in countries with confirmed cases of COVID-19 and rigorously implementing lockdown policies. Our results are robust based on a set of tests. By showing that countries with intensified exposure to media hype on COVID-19 topics and with more panic emotion among citizens during the pandemic generally experienced larger Bitcoin price discrepancies than their counterparts, we attribute the emergence of such discrepancies to investors’ perception of Bitcoin as an alternative hedging investment under uncertainty. Finally, we conduct several heterogeneity analyses and show that countries with stringent domestic capital control, strict public health regulations, higher uncertainty aversion, collective culture, and a powerful government are more likely to be engaged in Bitcoin transactions. At last, since recent literature proposes that model specification uncertainty is also notable for the study of cryptocurrency, further steps to extend this paper could be taken to utilize new modelling techniques (e.g., machine learning) and consider uncertainty from other possible sources.

CRediT authorship contribution statement

Meichen Chen: Conceptualization, Validation, Resources, Data curation, Writing – original draft, Funding acquisition. Cong Qin: Methodology, Validation, Writing – original draft, Writing – review & editing, Project administration, Funding acquisition. Xiaoyu Zhang: Conceptualization, Methodology, Software, Formal analysis, Investigation, Validation, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors thank the anonymous referee of the Journal of International Money and Finance for the very helpful comments and suggestions. Cong Qin thankfully acknowledges financial support from the Fundamental Research Funds for the Central Universities and the Research Funds of Renmin University of China [Grant number: 19XNF009] and the National Natural Science Foundation of China [Grant number: 72003187]. Meichen Chen is sponsored by Shanghai Pujiang Program [2020PJ028] and the Fundamental Research Funds for the Central Universities [JKN0120022001]. Xiaoyu Zhang gratefully acknowledges support from the Fundamental Research Funds for the Central Universities and the Research Funds of Renmin University of China [19XNF009], the National Natural Science Foundation of China [no. 72003187], the Foundation of Shanghai International Studies University [no. 2020114086], and the Innovative Research Team of Shanghai International Studies University [no. 2020114047]. Authorship is alphabetical – the three authors have contributed equally. All remaining errors are our own.
## Appendix

See Tables A1–A3.

### Table A1
Variable definitions.

| Variable                  | Definition                                                                                                                                 |
|---------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| COVID-19                  | Dummy variable that equals 0 before the pandemic outbreak in a country, and 1 afterward.                                                    |
| New Cases                 | Count number of daily new COVID-19 cases.                                                                                                 |
| Total Cases               | Cumulative number of COVID-19 cases.                                                                                                       |
| New Deaths                | Count number of daily death cases due to COVID-19.                                                                                         |
| Total Deaths              | Cumulative number of death cases due to COVID-19.                                                                                           |
| Lockdown                  | Dummy variable that equals 1 if a country implements stay-at-home policy, and 0 otherwise.                                                 |
| Price Ratio               | The ratio of Bitcoin price in a country to its price in the US.                                                                             |
| Price Ratio (Tether)      | The ratio of Bitcoin price in a country to the Bitcoin-Tether price in the US.                                                             |
| Price Ratio (Simple Average) | The ratio of Bitcoin price in a country to its price in the US. The tick-level Bitcoin price is averaged to daily by equal weight.                 |
| Capital Control           | Index ranges from 0 to 1. A large number represents high level of overall capital controls in a country.                                      |
| Capital Outflow Control   | Index ranges from 0 to 1. A large number represents high level of capital outflow controls in a country.                                       |
| Amount                    | The number of Bitcoins traded in a country.                                                                                                 |
| Volume                    | The volume of Bitcoins traded in a country in US dollar terms.                                                                             |
| Stock Index               | The daily stock market return in a country.                                                                                                 |
| Fake News Index           | Index ranges from 0 to 100 and indicates the percentage of fake news about COVID-19 in all the pandemic related news.                         |
| Media Hype Index          | Index ranges from 0 to 100 and indicates the percentage of the news about COVID-19 in all the news.                                            |
| Panic Index               | Index ranges from 0 to 100 and measures the level of news that indicates panic related to COVID-19.                                           |
| Sentiment Index           | Index ranges from –100 to 100. A positive number represents optimal social sentiment during the pandemic, while a negative number represents the opposite. |
| Fake News Ratio           | The ratio of fake news index in a country to that in the US.                                                                               |
| Media Hype Ratio          | The ratio of fake news index in a country to that in the US.                                                                               |
| Panic Ratio               | The ratio of fake news index in a country to that in the US.                                                                               |
| Sentiment Ratio           | The ratio of fake news index in a country to that in the US.                                                                               |
| Health Policy Index       | Index ranges from 0 to 100. A high score indicates a high level of public health regulation and control.                                   |
| Uncertainty Avoidance Index | Index ranges from 0 to 100. A high score suggests low tolerance for uncertainty and ambiguity.                                           |
| Individualism Index       | Index ranges from 0 to 100. A high score indicates that people place high priority on attaining personal goals rather than the well-being of the group. |
| Power Distance Index      | Index ranges from 0 to 100. A high score indicates unequal distribution of power in a society.                                               |

### Table A2
Bitcoin data coverage and source.

| Currency | Country/Region  | Exchange | Currency | Country/Region | Exchange |
|----------|-----------------|----------|----------|----------------|----------|
| AUD      | Australia       | BTC Markets | JPY      | Japan          | Bitflyer |
| CAD      | Canada          | Kraken   | Japan    | Japan          | Bitbox   |
| EUR      | Eurozone        | BitBay   | Japan    | Japan          | Coincheck |
| EUR      | Eurozone        | Bitstamp | KRW      | South Korea    | Korbit   |
| EUR      | Eurozone        | Coinsbank | PLN      | Poland         | BitBay   |
| EUR      | Eurozone        | Kraken   | RUB      | Russia         | CEX      |
| GBP      | United Kingdom  | Coinfloor | USD      | United States  | Bitstamp |
| GBP      | United Kingdom  | Coinsbank |         | United States  | Coinbase |
| IDR      | Indonesia       | BitX     | United States | United States  | Gemini   |
| IDR      | Indonesia       | Bitoid   | United States | United States  | Kraken   |
|          |                 |          |          | ZAR            | BitX     |

M. Chen, C. Qin and X. Zhang Journal of International Money and Finance 124 (2022) 102633
### Table A3
Account verification requirements of each exchange.

| Exchange          | Allowed currency | Account Verification                                                                 |
|-------------------|------------------|--------------------------------------------------------------------------------------|
| BTC Markets       | AUD              | Local phone to receive SMS                                                           |
|                   |                  | Identity document: Australian Passport or Driver License                              |
| Kraken            | USD, EUR, GBP, CAD, JPY, CHF, AUD | Phone to receive SMS                                                                 |
|                   |                  | Identity document: ID card, passport or driver’s license.                            |
| BitBay(Zonda)     | USD, EUR, GBP, PLN | Identity document                                                                     |
|                   |                  | Proof of residency: mails or bills.                                                   |
| Bitstamp          | USD, EUR, GBP    | Identity document: ID card, passport or driver’s license.                            |
|                   |                  | Proof of residency: mails or bills.                                                   |
| Coinsbank         | USD, EUR, GBP    | Identity document: official photo ID                                                 |
|                   |                  | Proof of residency: mails or bills.                                                   |
| Coindoor (Coincorner) | EUR, GBP     | Identity document: ID card, passport or driver’s license.                            |
|                   |                  | Proof of residency: mails or bills.                                                   |
| BitX(Luno)        | EUR, GBP, AUD, IDR, MYR, NGN, SGD, UGX, ZAR | Local phone to receive SMS (level 1)                                                  |
|                   |                  | Government issued ID (level 2)                                                        |
|                   |                  | Proof of residency (level 3)                                                          |
| Btcoid (Indodax)  | IDR              | Local phone to receive SMS                                                            |
|                   |                  | Identity document                                                                     |
|                   |                  | Proof of residency: mails or bills.                                                   |
| bitFlyer          | JPY, EUR, USD    | (each fiat currency is only allowed in the (corresponding branch))                   |
|                   |                  | Local phone to receive SMS                                                            |
|                   |                  | Identity document: ID card, passport or driver’s license.                            |
|                   |                  | Proof of residency: mails or bills.                                                   |
| Btcbox            | JPY              | Local phone to receive SMS                                                            |
|                   |                  | Identity document: ID card, passport or driver’s license.                            |
|                   |                  | Proof of residency: mails or bill                                                    |
|                   |                  | Proof of residency: send postcard to verify the residence information                |
| Coincheck         | JPY              | Local phone to receive SMS                                                            |
|                   |                  | Identity document: ID card, passport or driver’s license.                            |
| Korbit            | KRW              | Local phone to receive SMS                                                            |
|                   |                  | Identity document: ID card, passport or driver’s license.                            |
|                   |                  | Proof of residency: mails or bill                                                    |
| CEX               | GBP, USD, RUB    | Phone to receive SMS                                                                  |
|                   |                  | Identity document: ID card, passport or driver’s license.                            |
|                   |                  | Proof of residency: mail or driver’s license.                                         |
|                   |                  | Address verification: ID card, passport or driver’s license.                         |
|                   |                  | Enhanced verification: Address verification (stage 2)                                 |
|                   |                  | Enhanced verification: Address verification (stage 3)                                 |

References

Ante, L., Fiedler, L., Strehle, E., 2021. The Influence of Stablecoin Issuance on Cryptocurrency Market. Financ. Res. Lett. 41, 101867.
Ashraf, B.N., 2020. Economic Impact of Government Interventions during the Covid-19 Pandemic: International Evidence from Financial Markets. J. Behav. Exp. Finance 27, 100371.
Baur, D.G., Dimpfl, T., Kuck, K., 2018. Bitcoin, Gold and the US Dollar—A Replication and Extension. Financ. Res. Lett. 25, 103–110.
Bhambhwani, S., Delikouras, S., Korniotis, G., 2019. The Fundamental Drivers of Cryptocurrency Prices. Working Paper.
Briere, M., Oosterlinck, K., Szafarz, A., 2015. Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoin. J. Asset Manag. 16, 365–373.
Bejaoui, A., Mgadmi, N., Moussa, W., Sadraoui, T., 2021. A Short-and Long-term Analysis of the Nexus between Bitcoin, Social Media and Covid-19 Outbreak. Heliyon 7, e07530.
Caferra, R., 2020. Good Vibes Only: The Crypto-Optimistic Behavior. J. Behav. Exp. Finance 28, 100407.
Chen, C., Liu, L., Zhao, N., 2020. Fear Sentiment, Uncertainty, and Bitcoin Price Dynamics: The Case of Covid-19. Emerg. Markets Finance Trade 56, 2298–2309.
Chetty, R., Looney, A., Kroft, K., 2009. Salience and Taxation: Theory and Evidence. Am. Econ. Rev. 99, 1145–1177.
Choi, K.J., Lehar, A., Stauffer, R., 2021. Bitcoin Microstructure and the Kimchi Premium. Working paper.
Conlon, T., McGee, R., 2020. Safe Haven or Risky Hazard? Bitcoin during the COVID-19 Bear Market. Financ. Res. Lett. 35, 101607.
Cong, L., Li, Y., Wang, N., 2021. Tokenomics: Dynamic Adoption and Valuation. Rev. Financ. Stud. 34, 1105–1155.
Corbet, S., Larkin, C., Lucey, B., 2020. The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies. Financ. Res. Lett. 35, 101554.
Ding, W., Levine, R., Lin, C., Xie, W., 2021. Corporate Immunity to the Covid-19 pandemic. J. Financ. Econ. 141, 802–830.
Ding, H., Fan, H., Lin, S., 2022. COVID-19, Firm Exposure, and Firm Value: A Tale of Two Lockdowns. China Econ. Rev. 71, 101721.
Eis, A., Gasser, S.M., Weinmayer, K., 2015. Caveat Emptor: Does Bitcoin Improve Portfolio Diversification? Working Paper.
Fernandez, A., Klein, M.W., Reubelt, A., Schinder, M., Uribe, M., 2016. Capital Control Measures: A New Dataset. IMF Econ. Rev. 64, 548–574.
Fernandez-Perez, A., Gilbert, A., Indriawan, L, Nguyen, N.H., 2021. Covid-19 Pandemic and Stock Market Response: A Culture Effect. J. Behav. Exp. Finance 29, 100454.
Fisman, R., Lin, H., Sun, C., Wang, Y., Zhao, D., 2021. What Motivates Non-democratic Leadership: Evidence from Covid-19 Reopenings in China. J. Public Econ. 196, 104389.
Griffin, J.M., Shams, A., 2020. Is Bitcoin Really Untethered? J. Finance 75, 1913–1964.
Goodell, J., Goutte, S., 2021. Co-movement of Covid-19 and Bitcoin: Evidence from Wavelet Coherence Analysis. Finance Res. Lett. 38, 101625.
Hautsch, N., Scheuch, C., Voigt, S., 2021. Building Trust Takes Time: Limits to Arbitrage in Blockchain-Based Markets. Working paper.
Hofstede, G., Hofstede, G.J., Minkov, M., 2010. Cultures and Organizations: Software of the Mind. McGraw Hill, New York.
Huang, Y., Duan, K., Mishra, T., 2021. Is Bitcoin Really More Than a Diversifier? A Pre- and Post-Covid-19 Analysis. Financ. Res. Lett. 102016.
Ji, Q., Zhang, D., Zhao, Y., 2020. Searching for Safe-haven Assets during the COVID-19 Pandemic. Int. Rev. Financ. Anal. 71, 101526.
Klein, T., Thu, H.P., Walther, T., 2018. Bitcoin Is Not the New Gold—A Comparison of Volatility, Correlation, and Portfolio Performance. Finance Res. Lett. 59, 105–116.
Liu, Y., Tsyvinskii, A., 2020. Risks and Returns of Cryptocurrency. Rev. Financ. Stud. 34, 2689–2727.
Makarov, I., Schoar, A., 2020. Trading and Arbitrage in Cryptocurrency Markets. J. Financ. Econ. 135, 293–319.
Mariana, C.D., Ekaputra, I.A., Husodo, Z.A., 2021. Are Bitcoin and Ethereum Safe-havens for Stocks during the COVID-19 Pandemic? Financ. Res. Lett. 38, 101798.
Mazur, M., Dang, M., Vega, M., 2021. Covid-19 and the March 2020 Stock Market Crash: Evidence from S&P1500. Finance Res. Lett. 38, 101690.
Mnif, E., Jarboui, A., Mouakhar, K., 2020. How the Cryptocurrency Markets Has Performed during COVID 19? A Multifractal Analysis. Financ. Res. Lett. 36, 101647.
Nguyen, K.Q., 2021. The Correlation between the Stock Market and Bitcoin during Covid-19 and Other Uncertainty Periods. Financ. Res. Lett. 102284.
Pagnotta, E.S., 2022. Decentralizing Money: Bitcoin Prices and Blockchain Security. Rev. Financ. Stud. 35, 866–907.
Qiu, Y., Wang, Z., Xie, T., Zhang, X., 2021. Forecasting Bitcoin Realized Volatility by Exploiting Measurement Error under Model Uncertainty. J. Empirical Finance 62, 179–201.
Raheem, I.D., 2021. Covid-19 Pandemic and the Safe Haven Property of Bitcoin. Quart. Rev. Econ. Finance 81, 370–375.
Rahman, M.L., Amin, A., Mamun, M.A.A., 2021. The Covid-19 Outbreak and Stock Market Reactions: Evidence from Australia. Financ. Res. Lett. 38, 101832.
Saleh, F., 2021. Blockchain without Waste: Proof-of-stake. Rev. Financ. Stud. 34, 1156–1190.
Shahzad, S.J.H., Bouri, E., Rouboua, D., Kristoufek, L., Lucey, B., 2019. Is Bitcoin a Better Safe-haven Investment than Gold and Commodities? Int. Rev. Financ. Anal. 63, 322–330.
Spiegel, M.L., Toolks, H., 2021. Business Restrictions and COVID Fatalities. Rev. Financ. Stud. 34, 5266–5308.
Wang, C.W., 2018. The Impact of Tether Grants on Bitcoin. Econ. Lett. 171, 19–22.
Wang, Y., Chen, Y., Deng, S., Wattenhofer, R., 2021. Cyclic Arbitrage in Decentralized Exchange Markets. Working paper.
Wu, C.Y., Pandey, V.K., 2014. The Value of Bitcoin in Enhancing the Efficiency of an Investor’s Portfolio. J. Financ. Plann. 27, 44–52.
Zhang, D., Hu, M., Ji, Q., 2020. Financial Markets under the Global Pandemic of COVID-19. Finance Res. Lett. 36, 101528.
Zaremba, A., Aharon, D.Y., Demir, E., Kizys, R., Zawadka, D., 2021. Covid-19, Government Policy Responses, and Stock Market Liquidity around the World. Rev. Int. Business Finance 56, 101359.