Do economic crises cause trading in Bitcoin?

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Abstract

The paper provides new evidence for Bitcoin's safe haven property by examining the relationship between currency price, return and Bitcoin trading volume. Using a unique dataset from a person-to-person (p2p) exchange, the paper demonstrates that local economic crises are positively associated with increased Bitcoin trading. Using currency returns to identify local economic crises, the 8 crisis affected currencies are Venezuela Bolivar (VES), Iranian Rial (IRR), Ukrainian Hryvnia (UAH), Argentine Peso (ARS), Egyptian Pound (EGP), Nigerian Naira (NGN), Turkish Lira (TRY) and Kazakhstani Tenge (KZT). Specifically, there is a negative association between trading volume and currency value (and return), suggesting low currency price and currency depreciation are accompanied with increased Bitcoin trading. The results not only hold for the crisis affected currencies but also currencies of advanced economies. Granger causality test also reinforces the negative association results. This finding indicates some forms of flight-to-safety have occurred during local market crises when capital flight from domestic markets to Bitcoin, strengthening Bitcoin's hedging asset status. However, trading volume declines after the start of the COVID pandemic, suggesting that Bitcoin is still regarded as a speculative asset. Overall, the findings show that Bitcoin is a hedging asset to protect against local currency depreciation, but not a safe haven asset for the global crisis.

Key words: Bitcoin, cryptocurrency, economic crisis, currency devaluation

JEL classification: G01, G10, G28

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1. Introduction

The rapid rise of price in 2017 and 2020 has popularized Bitcoin into the mainstream. Now news about Bitcoin is as common as stock market reports. As a newly created digital asset (Nakamoto, 2008), Bitcoin is often compared to gold for its unique property as a store of wealth. It also attracts considerate academic attention. A few key questions surround Bitcoin has already been extensively investigated, for example, whether Bitcoin is a real currency (Yermack, 2015); whether Bitcoin prices are manipulated (Gandal et al, 2019; Griffin and Shams, 2019). The consensus is that Bitcoin exhibits features of currency but behaves like a speculative asset. Its prices are also manipulated during period of fast appreciation.

More relevantly, Bitcoin creates a new class of assets that is completely isolated to the current financial system. This leads to claim that Bitcoin is a safe haven asset like gold and treasury bills. For example, the S&P 500 index went down 2.4% on 13th May 2019, the highest single day drop since January 2019 due to uncertainty surround the US-China trade war. Incidentally, Bitcoin price went up 15% on the same day. The digital currency industry calls this movement "flight to safety of Bitcoin",[2] some media even refer to Bitcoin as a hedge against global financial risk.[3] While price co-movement in a single day is hardly evidence of hedging properties or even evidence of flight to safety, these incidents are occurring more and more often.[4] This leads to several academic research to explores Bitcoin's hedging and safe haven properties, e.g., Corbet et al (2018), Urquhart and Zhang (2019), Platanakis and Urquhart (2020). They confirm that Bitcoin return has zero or low correlation with most financial assets and can serve as a hedging and safe haven asset under normal market condition. However, Bitcoin is not a safe haven asset during the COVID crisis, e.g., Chen, Liu and Zhao (2020), Conlon and McGee (2020). Though all results come from well-established financial assets in developed economy.

In addition, these studies do not directly examine the flight to safety property of Bitcoin. For an asset to be a financial safe haven, it must have the properties of flight to safety where investors abandon other assets to buy into the safe haven during time of distress. Luther and Salter (2017) who look at the 2013 bank bailout in Cyprus, in expectation that the

[2]Barry Silbert, CEO of Digital Currency Group, twitted on 19th May 2019, "Flight to safety of Bitcoin".
[3] As CNBC put it, "Bitcoin emerges as a global hedge while stocks tumble in US-China trade war". https://www.cnbc.com/2019/05/13/Bitcoin-emerges-as-a-global-hedge-while-stocks-tumble-in-us-china-trade-war.html
[4]Another example is the conflict between US and Iran in January 2020 when an Iranian general was assassinated, and a Ukraine civilian airplane was shot down. During this period between 2nd and 10th January, Bitcoin price appreciated 17%.

announcement of bailout would encourage adoption of Bitcoin (or some form of flight to Bitcoin). They find Bitcoin adoption (based on app downloads) has increased in the US but not in Cyprus. They did not find evidence of flight to safety. But Bitcoin's market capitalization was comparatively small, and it is not well known at the time of the event. Bitcoin's market capitalization has increased 100-fold since then.

In this paper, I employ a new approach to investigates the safe haven property of Bitcoin, focusing on Bitcoin's main difference to traditional financial asset: decentralisation. Instead of examining relationship between Bitcoin returns and returns of financial assets, I test the association between currency price/return and Bitcoin trading volume. Since Bitcoin is directly traded in every currency, impact of local economic crisis can be studied. The idea is simple, currency price and return are two indicators of a country's economic health. In economic distress, currency depreciates and currency return can serve as a proxy for economic crisis.[5] If Bitcoin is perceived as a safe asset in a local market, a spike in Bitcoin trading volume should be observed during major currency devaluation. As locals flight to safe assets in crisis, trading in Bitcoin should intensify. In other words, economic crises should lead to increased trading in Bitcoin. A local crisis may not have enough impact on Bitcoin price, so there may be minimum correlation change between Bitcoin returns and returns of affected financial assets. But it can create a volume surge in the local market signalling some forms of flight-to-safety. Volume in a local market captures trading activities which reflects perceived risk profile of Bitcoin in the local market. If Bitcoin is regarded as a safe asset, then consistent volume spikes should be observed in many distressed currencies. Trading volume in local currency contains information that is not present in Bitcoin price.

To examine the relationship between Bitcoin volume and currency price, I collect currency prices between 2014 and 2020 for 48 currencies. The sample includes major currencies like USD, EUR, GBP and JPY, etc, but also 8 currencies that suffered economic crisis. The 48 currencies are selected based on activeness of the local Bitcoin market. The 8 currencies have lost over 60% of its value against USD between 2014 and 2019. They are Venezuela Bolivar (VES), Iranian Rial (IRR), Ukrainian Hryvnia (UAH), Argentine Peso (ARS), Egyptian Pound (EGP), Nigerian Naira (NGN), Turkish Lira (TRY) and Kazakhstani Tenge (KZT). These crisis

[5] In standard macroeconomic models an appreciating real exchange rate is seen as a loss of competitiveness that will be followed by a widening current account deficit and may require future adjustment processes that reverse the initial appreciation (Lommatzsch and Tober, 2004). This means currency depreciation does not necessarily imply economic crisis. However, the crisis currency in the sample depreciated significantly (more than 60%) during the sample period, it is unlikely the depreciation was caused solely by loss of competition.

currencies are selected as they are the worst performing currencies in the sample between 2014 and 2019. Currency price data are matched with volume data from LocalBitcoins.com to find Bitcoin trading volume for each currency. LocalBitcoins.com (hereafter LBTC) is a person-2-person trading platform which allows users to exchange Bitcoin into a wide range of currencies. Some lesser-known currencies, which are not available in major cryptocurrency exchanges, are also traded there. Data from LBTC provide a viable avenue to study Bitcoin trading volume and its interaction with a local currency.

The main findings of the paper are as follow: First, panel regression results show that there is a negative association between currency value (and return) and Bitcoin trading volume. The results suggest that the lower the currency value (and return) the higher the trading volume in a local market. The finding not only hold for volume in local currency but also for volume denominated in Bitcoin. It appears that locals are more interested in trading Bitcoin when their currency is depreciating. Subsample analysis show that the negative association between currency value (and return) and Bitcoin volume not only hold for crisis affected currencies but also currencies of advanced economy. In fact, the negative association is even stronger for advanced economy. Trading in these countries is more responsive to changes in their currency value. The result provides evidence for Bitcoin's safe haven property.

Second, I conduct Granger style causality test to investigate the direction of the causality between volume and currency value (and return). I find that the causality between volume measured in local currency and currency value (and return) is mutual. In some cases, volume increase precedes currency depreciation. It is likely that Bitcoin trading rises in anticipation of impending currency depreciation. When trading volume is measure in number of Bitcoins, the causality runs from currency value (and return) to volume. While these results do not offer evidence of true causality, they confirm the negative statistical association between Bitcoin trading volume and currency value.

Third, trading volume declined during the COVID pandemic, and the decline is consistent cross all subsamples. Furthermore, the association between volume and currency value (and return) did not change during the pandemic. If Bitcoin is perceived as a safe asset, then the negative association between currency value (and return) should strengthen (compare to normal market condition) during the pandemic. But regression results show that the association did not change during the pandemic. Overall, these results do not support Bitcoin's hedging and safe haven property. It appears that the market systematically reduced trading in Bitcoin during the global pandemic, a behaviour consistent with trading speculative asset.

The paper contributes to the literature in the following ways: First, using currency data from developing and crisis affected economies, I offer new evidence on Bitcoin's safe haven property. While Bitcoin is a borderless asset which can be traded anywhere without physical boundary. Most studies only consider relationship between Bitcoin and well-established assets/currencies in developed economy, e.g., S&P 500, Euro, etc. Developing economies also trade Bitcoin and is an important part of Bitcoin's overall market. Even though their price impact is smaller than that of developed economies. My results show that Bitcoin is traded like a hedging asset in many local markets, reactive to local currency fluctuation.

Second, the paper demonstrates the importance of data from p2p exchange, which is overlooked by the literature. Due to capital restriction and foreign sanction, Bitcoin trading in some lesser-known currencies is not observable in major exchanges. One example is Iranian Rial which is sanctioned by the US and cannot be freely exchanged in the FX market. Bitcoin trading is also explicitly banned in Iran. However, data from LBTC shows that small number of Bitcoins are still bought and sold in Rial every week. This example extends to a few other countries (e.g., EGP) that had economic crisis. In other words, p2p exchange allows direct Bitcoin trading for these lesser-known currencies. My results show that trading in these crisis-affected economies is very much alive despite restrictions and local economic problems.

The rest of paper is organised as follow: Section 2 reviews related literature and develops the main hypothesis. Section 3 discusses the two types of exchanges for trading Bitcoin. Section 4 explains the sample and data used in the paper. Section 5 outlines the simple panel regression model used for testing the main hypothesis. Section 6 presents panel regression results. Section 7 employs a Granger-styled causality test, providing further evidence to support results in section 6. Section 8 concludes the paper.

2. Related literature and hypothesis development

The paper is related to several literatures examining various properties of Bitcoin. The relationship between trading volume and Bitcoin price/return is the most relevant. Balcilar et al. (2017) shows that volume can predict Bitcoin returns under normal market condition. Their results reveal that volume cannot help predicting volatility of Bitcoin price return. Gemici and Polat (2019) conduct a causality test between volume and Bitcoin price and found a causality relationship was determined from price to volume. Their findings are very interesting: a unilateral causality relationship was determined from negative shocks in Bitcoin prices to negative shocks in trading volume, the same is observed from positive shocks in trading volume to positive shocks in prices. This result suggests a positive association between Bitcoin price and trading volume. Similarly, Bouri et al. (2019) also find that trading volume carry useful information to predict extreme returns in cryptocurrencies. Enoksen et al. (2020) detect multiple periods of Bitcoin price bubble, particularly in 2017 and 2018. They find that trading volume, volatility and transaction are good predictors of price bubble. In short, these studies suggest that volume convey useful information about Bitcoin's price and return.

The literature examining Bitcoin's safe haven property is also relevant. Dyhrberg (2016) find that Bitcoin is uncorrelated to US dollar and UK stock market hence can be used as a hedging asset like gold. Using VIX index data from 14 countries, Bouri, et al. (2017) show that Bitcoin act as a hedge against global uncertainty. Shahzad, et al. (2019) employ a new definition of weak and strong safe haven, they find that Bitcoin can be regarded as a weak safe-haven asset. Feng et al. (2018) evaluate the downside risk of cryptocurrencies using an extreme-value-theory-based method. Their results suggest that Bitcoin can be a good diversifier, and its hedging property is similar to gold. Platanakis and Urquhart (2020) demonstrate that including Bitcoin in a conventional financial portfolio can substantially improve its risk adjusted return. Zeng et al. (2020) investigate the relationship between Bitcoin and conventional financial assets from a perspective on the connectedness of asset networks. They find that the connectedness between Bitcoin and conventional assets is weak and suggesting Bitcoin is an uncorrelated asset. Overall, previous studies find supporting evidence of Bitcoin's safe haven properties. All these studies are conducted under normal market condition, this is because there is only one major crisis since the inception of Bitcoin, and its impact are still being analysed. Conlon and McGee (2020) investigate the effect of the COVID-19 pandemic on the price of Bitcoin. They find that Bitcoin is not a safe haven asset during market selloff in March 2020. This is because Bitcoin decreases in price in lockstep with the S&P 500 as the crisis develops.

The literature on gold is relevant to the paper. Gold is also traded across the global and have localised price in each individual market. If Bitcoin is traded like gold, then prices should exhibit similar feature to gold prices, e.g., local trading does not necessarily affect global gold price but is reflective of local sentiment. When crisis erupt in a local market, Gold trading also surges in the local market.[6] While economic crisis on a global scale occurs only once every few years, local crisis is very common. For example, gold volume in Turkey doubled in mid-2018. But the increased volume in the local market had minimum effect on gold price. Gold is traded for centuries, unlike Bitcoin it has undergone every economic and financial crisis, and its price properties are extensively studied. Baur and Lucey (2010) study time-varying relation between stock, bond and gold returns, they find that gold is a hedge for US, UK and German stocks and a safe haven against extreme negative market condition. They also show gold's safe haven property only last 15 days after a market crash. O'Connor *et al.* (2015) conduct a comprehensive review of the gold market and their findings suggest that gold increasingly behaves like a speculative asset. This is because more and more gold are hold in investment vehicle like ETFs. Yet, gold still display safe haven property as Ciner, et al. (2013) show, gold can serve as a safe haven for US dollar from 2000 onwards. Overall, the literature appears to suggest that gold could behave as a speculative as well as a safe haven asset, depends on market condition and sample period. If Bitcoin follows the history of gold, its price should exhibit both speculative and safe haven properties.

The flight to safety literature is also relevant as media increasingly report capital flying to Bitcoin during market stress.[7] During financial crisis capital flight to safe haven (or quality) assets to prevent further losses. Safety assets could be US dollar if the crisis is local and domestic currency suffered huge losses, it could be government bonds (e.g. German bunds, US treasuries) if the crisis is in equity. It could also be gold if the crisis is global which affect even the US dollar and treasuries. Safe haven assets are defined as assets that are uncorrelated or negatively correlated with another assets in times of market stress or turmoil (Baur and Lucey, 2010; Urquhart and Zhang, 2019).

While the definition does not mention flights to safety, it is not difficult to understand the implication on correlation. If flight to safety is of small scale, there would be minimum price impact on the safe haven asset. Hence, the correlation between the safe asset and stressful assets does not change. If the flight to safety is of large scale, i.e., a market wide reaction, then prices of the safe haven asset increase due to large influx of capital. This creates a negative correlation

[6]Walt and Rowling (2018) "Gold Trading Volumes Double in Turkey Amid Currency Crisis", Bloomberg News, available from: https://www.bloomberg.com/news/articles/2018-08-15/turkey-s-gold-futures-trading-doubled-during-the-currency-crisis
[7]Again, see the CNBC article, "Bitcoin emerges as a global hedge while stocks tumble in US-China trade war". https://www.cnbc.com/2019/05/13/Bitcoin-emerges-as-a-global-hedge-while-stocks-tumble-in-us-china-trade-war.html

between stressful and the safe haven asset. In other words, trading volume in safe haven assets jump up under market stress, and a range of behaviour changes are also observed. For example, Baur and Glover (2015) find gold price exhibit properties similar to speculative assets during 2002-2008. If Bitcoin is a safe haven asset, trading volume in a local market should also shoot up during a local crisis. This should hold true across many local markets for Bitcoin to be recognised as a safe asset. Due to small scale and limited impact, many local crises have little effect on prices of safe haven assets.

The increased trading may not directly affect prices but provides evidence that some form of flight to safety has occurred. If Bitcoin is regarded as a safe haven asset, trading volume in Bitcoin should increase whenever a country undergoes economic crisis. This should also be true when economic problems are small and have mild impact on a country's economy, e.g., a mild currency devaluation. Bitcoin trading volume in a currency should increase when the currency experiences a devaluation. On the other hand, if Bitcoin is used for speculation, volume should have positive correlation with Bitcoin price and volume should decrease during market stress as investors reduces risk taking. Here comes the safe haven hypothesis,

H_1: *If Bitcoin is regarded as a safe haven (speculative) asset, trading volume in a currency should be negatively (positively) associated with the currency value and returns.*

Figure 1 visually demonstrates this hypothesis. The figure plots currency price (in units of local currency per USD), Bitcoin price and Bitcoin trading volume in the same graph. All variables in the graph are log-transformed. The two currencies shown in the figure, ARS and TRY, demonstrates the two opposite results of the hypothesis. Both currencies depreciated significantly against the USD as the currency price keeps rising on the graph. While currency price is rising (which means currency value is declining), Bitcoin trading volume in ARS is also rising. Visually, trading volume in ARS tracks currency price almost perfectly. But trading volume in ARS shares no similarity with Bitcoin price. It appears that Bitcoin is traded to mitigate currency depreciation rather than an asset for speculation. On the other hand, trading volume in TRY tracks Bitcoin price quite nicely and share no similarity with TRY currency price. Bitcoin trading in TRY seems to be dictated by Bitcoin price. It appears that Bitcoin is a hedging asset in ARS and a speculative asset in TRY. Data in Figure 1 is only a small part of the sample period and it only includes two currencies. It is unclear which version of the hypothesis will prevail in the full sample.

[Insert Figure 1 here]

Previous studies provide evidence that Bitcoin is uncorrelated to major currency prices (Urquhart, 2018), volume data in each currency can provide new evidence about Bitcoin's safe haven properties. Since increased trading volume does not necessarily influence price, the hypothesis capture behaviors that is not observable by using Bitcoin price alone. For example, during domestic market turmoil Bitcoin price may not change due to small size of the local market, but Bitcoin trading volume in the currency could have changed substantially. Capital may flight to Bitcoin in the local market, but they are too small to impact Bitcoin's price.

This is especially true on peers-to-peers exchanges where Bitcoin volumes in developing countries' currencies are very small. Trading volume in Bitcoin should increase during market stress if Bitcoin is a safe haven/hedging asset. Hence further strengthens the negative association between currency value (return) and volume. Here comes the second hypothesis.

H_2: *If Bitcoin is regarded as a safe haven (speculative) asset, the negative association between Bitcoin trading volume and currency value/return grows stronger (weaker) during market turmoil.*

While regional crisis is common among developing countries, a systemic market meltdown which involves every country in the world is rather rare. The last major crisis occurred in 2008 when Bitcoin was not yet invented. The pandemic in 2020 offers an opportunity to test this hypothesis. If Bitcoin is a hedging asset, then association between currency prices and Bitcoin trading volume should change as market flight to safe asset during the pandemic. The increased market stress should reinforce Bitcoin's safe haven status. On the other hand, if Bitcoin is used primarily for speculation, the market would turn risk averse during turmoil and the association between volume and currency price/return would be weakened.

With volume data, it is straightforward to further examine Bitcoin's speculative properties. Here comes the third hypothesis, which is complementary to H_1 and H_2,

H_3: *If Bitcoin is regarded as a speculative asset, Bitcoin trading volume in a currency should be positively associated with Bitcoin's price and returns.*

One of the most discussed topics about Bitcoin on media outlets is price. As Bitcoin price appreciates, media attention also rises. Urquhart (2018) shows price volatility is one of the key drivers of next day investor attention proxied by Google keyword trends. The increased investor attention and media coverage then drives even more speculative trading. So, Bitcoin trading in a currency could increase simply because prices are rising. The same applies when

Bitcoin price crashes, though the impact on volume would be reduced as negative news cannot attract new speculators. H_3 is complementary to H_1 and H_2, so they are not mutually exclusive. Bitcoin can be a speculative and safe haven asset at the same time. This type of behaviors is not unique to Bitcoin, Gold also exhibits period of rapid appreciation where price behaves like a speculative asset. Baur and Glover (2015) even question the safe haven status of gold after detecting bubble-like characteristics in gold prices.

3. Bitcoin exchanges

There are primarily two type of exchanges that facilitate Bitcoin trading, centralized and decentralized exchanges. Due to overwhelming popularity, Bitcoin's prices and returns properties are mostly examined using data from centralized exchanges. A notable exception is Matkovskyy (2019) who investigates price characteristics of Bitcoin on both centralized and decentralized exchanges. Decentralized exchanges can offer insights that are usually not available in centralized exchanges. As I will discuss below, they provide unique data that underlying the main findings of the paper.

3.1 Centralized exchanges

The term "centralized" means all trades are centrally matched and executed, where exchanges act as the middleman between buyers and sellers. For the middleman function to work, exchanges need to hold both buyers' fund and sellers' Bitcoin. In other words, all assets for all transactions are hold by exchanges. Hence the word "centralized", to denote the fact that fund and Bitcoin needs to be sent to exchanges for trading, e.g., a central point for all transactions. Centralized exchanges are the fastest ways of trading Bitcoin and also process the most trading volume. It is also the best place for Bitcoin price discovery, Bitcoin prices used for research comes mostly from quotes in centralized exchanges. A prime example is Luxembourg based exchange Bitstamp, which also makes trading data available free to the public. While centralized trading is fast and can process large volume, there are also clear disadvantages. For example, most exchanges only have a few currency pairs which are usually between major currencies and Bitcoin, e.g., USD, EUR, GBP, JPY etc. For lesser-known currencies such as IRR, EGP, trading would not be possible without some difficult workarounds. This limitation also means trading on small currencies are not readily available. A large part of Bitcoin's trading activities is simply not observable in centralized exchanges, decentralized exchanges on the other hand can fill this gap.

3.2 Decentralized exchanges

Decentralisation means that exchanges do not hold users' funds nor their Bitcoin. Instead, trades occur directly between users (peer-to-peer or person-to-person) through an automated process. LocalBitcoins.com (LBTC) is the oldest decentralised p2p exchange for Bitcoin. The platform is available in many countries, even in countries where Bitcoin is officially banned. For example, Bitcoin is illegal in Egypt (as of January 2019) but weekly trading volume between Bitcoin and Egyptian pound is frequently over 400,000 EGP (approximately 25,000 USD). Since LBTC does not hold customers/users' fund and essentially is a matching website, it is not regulated by financial authorities.[8] This feature facilitates trading even in period of financial restriction. LBTC can provide valuable trading data during economic crisis.

Contrary to centralized exchanges, peer-to-peer transactions are usually slow as buyer/seller requires transactions to be confirmed on the blockchain before exchanging funds. It also involves more risk as one party can run away without completing a transaction. Also, volume on p2p platforms is usually small, liquidity in some currencies is very low and trading always comes with a higher cost due to high spread. For this reason, p2p exchanges are never good places for price discovery. For the same reason, prices on p2p exchanges usually lag prices on centralised exchanges, and it is very unlikely that Bitcoin price is moved by transactions on p2p exchanges. P2p exchanges simply do not have enough volume to influence Bitcoin's price.

While there are clear disadvantages of using p2p exchanges, their main attraction is also obvious. They provide an avenue to trade Bitcoin in developing countries where there is no major cryptocurrency exchange. This is especially useful when financial restrictions are imposed in the economy, e.g., Iran, Venezuela, Russia, etc. Take Iran as an example, Iranian Rial (IRR) is not listed in any major cryptocurrency exchanges. Buying Bitcoin using IRR is a rather complex process which involves converting IRR to USD (or other major currencies) then send the fund to an exchange aboard. The first part of the process has to be carried out in a black market, probably on streets. As official IRR rates are not reflective of the real market condition. To get access to more reasonable rates, locals must go to "unofficial" channels. The second part is even harder due to US sanction, which prohibits sending/transfer money overseas through banking systems. Iranian nationals cannot open foreign bank account either, due to the sanction. Once IRR is converted to USD or other major currencies for trading Bitcoin, much

[8] Regulations on p2p exchanges are gradually introduced since 2019, though regulations are very different across countries.

of information between IRR and Bitcoin are already lost. LBTC offers an easy avenue to buy and sell Bitcoin in Iran, most importantly it also provides valuable trading data between IRR and Bitcoin.

4. Sample and data

4.1 The sample

I collect all 146 time-series of currency prices (in USD) from Bloomberg. The currencies are then matched against Bitcoin data from LBTC. There are 48 currencies/countries with active Bitcoin market, i.e., LBTC data is available. Hence the sample is reduced to 48 currencies. All currencies are priced in the USD, and USD is priced using the dollar index DXY, which values the USD against a basket of currencies. I also carry out analysis on a subgroup basis to examine impact of currency devaluation on Bitcoin trading. The 48 currencies are divided into 4 groups. The most important group is currencies that are affected by economic crisis. Naturally, the candidate currencies are the ones that suffered huge losses. I choose the worst performing currencies (against the USD) which have at least a weekly depreciation of more than 20% since 2014. This gives 8 currencies: Venezuela Bolivar (VES) is the worst performing currency in the sample with the largest weekly depreciation of 782%, Egyptian Pound (EGP) follows with a single week return of -71%, Ukrainian Hryvnia (UAH) ranks the third with -44%, Nigerian Naira (NGN) follows at -35%, Argentine Peso (ARS) is the fifth at -30%, then Kazakhstani Tenge (KZT), Turkish Lira (TRY) and Iranian Rial (IRR) each at -24%, -24% and -22%, respectively. Some other currencies in the sample also fared poorly against the USD but have less dramatic single week depreciation. In short, the crisis currencies are just developing country currencies as these countries are more likely to have economical/political problems than advanced economies.

Besides crisis affected currencies, I also investigate three other currency groups. The second group is the G11 group which represents the 11 most advanced economy and most traded currencies, they include: USD, EUR, GBP, JPY, AUD, NZD, CAD, CHF, NOK, SEK and DKK. The third group includes currencies that are in the G20 group which represents the largest 20 economies in the world. A few G20 currencies are already in the G11 group (e.g USD, EUR), and also in the crisis currency group (e.g., ARS, TRY). they are excluded from this group, so the G20 group only has 9 currencies: BRL, INR, RUB, SAR, ZAR, MXN, CNY, IDR, and KRW.

The last group includes all currencies that are not in the first three groups. This includes 20 currencies and a full list of them are reported in Table 2.

4.2 Data

Daily price data for currencies are collected from Bloomberg, except for IRR where daily prices are collected from Bonbast.com.[9] Dollar index (DXY) data is also collected from Bloomberg. Bitcoin prices are collected from CoinMarketCap.com. Bitcoin volume data are collected from CoinDance website which reports LBTC data every week. Due to limited liquidity, volume data are only available on a weekly basis. Currency and Bitcoin prices are then matched to Bitcoin trading volume. The sample covers 2014 to first half of 2020, and there are roughly 342 weekly observations for each currency. Table 1 shows the summary statistics for returns and prices of all currencies and Bitcoin, as well as Bitcoin trading volume. All currency prices are quoted in US dollars except USD which is quoted in the dollar index.

[Insert Table 1 here]

The sample consists of 48 currencies and 14,926 weekly return and price observations. The lowest currency price is merely $0.000004 and the highest is $667, which shows the vast diversity of currencies. The worst weekly return is -783%, this return comes from VES. The mean return for currency is -0.23% which suggests that currencies on average are depreciating against the USD. For Bitcoin, there are 342 weekly observations which is six and half years of data from 2014 to July 2020. Volume in both local currency and Bitcoin are reported. Maximum weekly trading volume, which is over 1 trillion, is very large in local currency, as some currencies suffered huge devaluation in the sample period. The lowest volume in Bitcoin is merely 0.002 Bitcoin. On the other hand, the highest volume is over 21,000 Bitcoins. Some countries' Bitcoin market is small and not very active, some are huge and have a heathy community.

Table 1 Panel B report correlations between the six variables. Bitcoin price and volume in local currency are positively correlated (6.24%) which suggests that price appreciation may attract more trading. Bitcoin price is negatively correlated (-12.92%) to volume quoted in Bitcoin, this is expected: The higher the price, the lower the amount of Bitcoin that can be bought. Currency

[9]Bloomberg does not have IRR price data after 2016, as the Iranian central bank imposed financial restriction which prohibit free exchange of IRR. Alternatively, Bonbast.com provides IRR exchange rate against all major currencies based on actual market rate. Whilst these are not official exchange rates, they are more reflective of real market condition in Iran.

price is negatively correlated to volume (-0.74%) and Bitcoin price (-7.45%). This is consistent with the hypothesis that Bitcoin is a hedging asset to protect currency devaluation. Finally, currency price is positively correlated to volume in Bitcoin (11.70%), this is consistent with the speculation hypothesis where higher trading volume associated with appreciating currency.

[Insert Table 2 here]

Table 2 break down observations on an individual currency basis. In addition, currencies are divided into 4 groups as defined previously. To save space, only means of each variable are reported for each currency. Mean returns are mostly negative except USD, AUD, SAR, AED, THB, and HKD, overall currencies depreciated against the USD. This is especially true for crisis currencies, which has the lowest mean returns. VES even has a mean return of -5.74% which indicates the currency depreciate about 6% every week in the last 6 and half years.

Mean volume is difficult to interpret in each local currency as every currency have their own price. But mean volume in Bitcoin convey interesting information. USD has the largest mean volume with over 5,000 Bitcoins per week, the second highest is Russian Ruble (RUB) at 2,298 Bitcoins. Some G11 countries have very low volumes, for example, Japan only has an average 4.4 Bitcoin every week. For advanced economies, there may be alternative avenues to buy/sell, so volume on LBTC is small. The same applies to developing economies where LBTC could be the only viable source of buying/selling Bitcoin, for example, Venezuela (VES), Russia (RUB) and Nigeria (NGN) all have large trading volumes.

Volumes from LBTC are very small compare to volumes from centralised exchanges. For example, the mean volume in USD is slightly under $6 million. In comparison, Bitstamp (a centralised cryptocurrency exchange) has more trading volume in the quietest day of the year, its USDBTC volume on 31 December 2019 is $19 million.[10] In addition, Bitcoin's daily total trading volume is $21 billion,[11] this volume is especially large as it takes into account trading in all fiat and cryptocurrencies. In short, volumes from LBTC are a very small part of Bitcoin's ecosystem. Despite the small volumes, LBTC is still the most active p2p platform with the highest p2p volumes.

5. Methodology

[10]Based on data from Bitcoincharts.com
[11]Based on data from Coinmarketcap.com

A simple and easy approach to investigate whether locals are trading Bitcoin during period of economic distress, is to regress Bitcoin trading volume against the depreciating currency price. If the market perceives Bitcoin as a safe asset, we should observe a positive (or negative if price is quoted in USD per local currency) and significant coefficient on the currency price. The panel regression equation is:

$$Vol_{it} = a_i + c\ CurrPrice_{it} + d\ CurrReturn_{it} + e\ BitPrice_t + f\ BitReturn_t + \varepsilon_{it} \tag{1}$$

Where Vol_{it} is Bitcoin trading volume for currency i at time t. Independent variables are self-explanatory: currency prices, currency return, Bitcoin price and Bitcoin return. Currency fixed-effect are included to control for omitted time-invariant variables. As countries are different in many ways and it is impossible to control for unobservable variables. Coefficients c and d are used to test H_1. If locals regard Bitcoin as a hedging asset, the coefficient, c and d, should be significant, and they would be positive (or negative) if prices are expressed in local currency per USD (or USD per local currency).[12] Bitcoin price is also included to test H_3. As Table 1 shows that trading volumes are correlated to Bitcoin prices, naturally, it should have significant explanatory power to variations in trading volume. Most importantly, Bitcoin prices capture the effect of market attention, as media coverage of Bitcoin increases during period of Bitcoin price appreciation. The rising media attention could encourage more people to trade. If H_3 is true and trading is motivated by speculation, then coefficient, e, should be significantly positive. If trading volumes are motivated by hedging, then currency price and return should explain most variations of trading volume.

The sample period spans the COVID-19 pandemic, so effects of the pandemic is also investigated using a modified version of the equation (1):

$$\begin{aligned} Vol_{it} = {} & a_i + c\ CurrPrice_{it} + d\ CurrReturn_{it} + e\ BitPrice_t + f\ BitReturn_t \\ & + g\ Post2020 + h\ Post2020 \times CurrPrice_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

[12]This is a rather simple setup. Directly investigating period of crisis (or using crisis dummy variables) may be an alternative approach. But that is problematic as well. This is because crisis usually unfold in an extended period, spanning many months even years. Identifying the starting and ending point of a crisis is not only difficult but also introduce selection bias. If currency price affects Bitcoin trading, then its effect should hold in the long term and across different markets.

The new variable “Post2020” is a dummy variable that equals to 1 if the observation occurs after 29th February 2020, or 0 otherwise. Since the worldwide spread of COVID-19 starts around March 2020, the dummy captures the effect of the pandemic on trading volume. An interaction term is also included to investigate the price and volume relationship after the pandemic. If Bitcoin’s safe haven property strengthens during the pandemic, then coefficient, *h*, should be positively (or negatively) significant when price is expressed in units of local currency per USD (or units of USD per local currency). On the other hand, if Bitcoin is a speculative asset, *h* would be negative (or positive) when price is in units of local currency per USD (or units of USD per local currency).

[Insert Table 3 here]

6. Regression results

This section examines the hypothesis outlined in section 2. Table 3 reports regression results for a few variations of Equation (1) and (2). The regressions include all currencies and the four subgroups of currencies. Currency prices are in local currency per USD, this is different from prices reported in Table 1 and 2. USD prices are reported as inverse of the dollar index, to be consistent with other currencies. In this case, price increase indicates currency depreciation, i.e., the higher the price, the lower the currency’s value. All prices are log-transformed. Positive coefficients on the currency price indicates negative association between currency value and Bitcoin volume.

Table 3 Panel A report results for the full sample, all currency prices have positive coefficients, and they are significant at 1%, t-statistics are based on robust standard error which clustered at currency level. The positive association suggests declining currency value and increasing Bitcoin trading, which is in line with the hedging asset hypothesis. The coefficients on currency returns are also positive, indicating deprecating currency value and increased trading volume, but they are not significant. The results hold for both measures of trading volume. Interestingly, volume in Bitcoin should be negatively associated with currency prices, i.e., the higher the currency price (hence lower value against USD), the fewer Bitcoin each person can buy and sell as same amount of Bitcoin worth more in USD. Rise in currency price (reduced value against USD) should decrease numbers of Bitcoin traded. However, Table 3 Panel A column 5-8 shows that number of Bitcoins traded increases with currency depreciation, suggesting that volumes are not only increase in nominal term (local currency) but also in absolute term

(Bitcoin). This is evidence that Bitcoin volume is associated with depreciating currency, reinforcing the hedging asset hypothesis of H_1.

Table 3 Panel A also report effect of the COVID-19 pandemic on trading volumes. While a few countries suffered economic problems on their own, the pandemic is the systemic crisis that affect the whole world. If Bitcoin is a safe haven asset, volume should spike during the pandemic. To investigate this, a dummy variable "Post2020" and interaction term "Post2020*CurrPrice", "Post2020*CurrReturn", are included in column 2 to 4 and 6 to 8. In Panel A of Table 3, coefficients on "Post2020" are negative and significant (column 2 to 4 and 6 to 8), suggesting reduced trading volume once pandemic erupted. The coefficients on all interaction terms are positive, suggesting the increased positive association between currency price (return) and trading volume. But they are not significant, the pandemic did not strengthen or weaken the positive association between currency price and Bitcoin volume. If Bitcoin is a safe haven asset, its safe haven feature should be strengthened during period of crisis. There should be increased trading during stressful time, but this is not observed in the data.

Expectedly, the coefficients on Bitcoin price are significant and positive when volume is measured in local currency. They are negative and insignificant when measured in number of Bitcoins. Bitcoin return is positively associated with both measures of volume, suggesting high Bitcoin return is associated with large trading interest, supporting the speculative property of H_3. Volume is still heavily influenced by Bitcoin price movement.

While the full sample results in Table 3 Panel A show that volume and price are positively associated, volume are not associated with currency return. Also, the pandemic reduces Bitcoin trading rather than increasing it, indicating capitals are flying away from Bitcoin. Similar to findings of Conlon and McGee (2020) that Bitcoin is not a safe haven during a crisis. But these results are for the full sample, it may not hold in subsamples of currencies.

6.1 Crisis currencies

Table 3 Panel B reports regression results for the crisis currencies group. As mention before, these 8 countries have economic problems and their currencies lost more than 60% against the USD in the last 6 year. As shown in Panel B, currency price is positively associated with volume. Coefficients on price (Table 3 Panel B column 1-8) are positive and significant. This applies to both measures of trading volume. This result supports the safe haven hypothesis of H_1. Volume and currency return are also positively associated when volume is measured in local currency (column 1 to 4) as coefficients are significantly positive. This again provides support to hedging asset of H_1. When volume is measured in Bitcoin, the coefficients are still positive, but they are no longer significant.

The pandemic has very little impact on the overall level of trading volume. As coefficients on Post2020 are positive for four regressions and negative for two, none of them are significant. Coefficients on the interaction term Post2020*CurrPrice are weakly significant, which indicates the volume-price association changed since the start of the pandemic. All coefficients are negative, suggesting that the positive association between currency price and Bitcoin volume is reduced. This result supports the speculative property of H_2.

Overall, the positive association between volume and currency price still stands in this subgroup. Since the 8 currencies suffered huge losses during the sample period, the results offer evidence of Bitcoin's safe haven property. For currency deprecation is always associated with increased Bitcoin trading. On the other hand, the positive association is weakened after the pandemic, suggesting that there is still speculative trading in Bitcoin.

6.2 G11 currencies

Table 3 Panel C reports regression results for the subsamples of G11 currencies. As discussed previously, these are currencies of the world's most advanced economy. The results are similar to that of Panel A. First, currency price is positively associated with volume. This is true for both measures of volume, all coefficients on currency price are positive and significant. Second, currency returns are also positively associated with volume, again this applies to both measures of trading volume. The result offers evidence that Bitcoin is traded like a safe haven asset. As positive price return (or negative return in currency value) is associated with more Bitcoin trading. Third, trading volume drops during the pandemic, as coefficients on the Post2020 dummy are all negative and statistically significant, indicating reduced trading in time of crisis. Association between price and volume strengthened as coefficients on the interaction term, Post2020*CurrPrice, (Table 3 Panel C column 3, 4, 7 and 8) are positive, and they are significant at 10%. Though the interaction term Post2020*CurrReturn is negative and insignificant. Overall, trading volume in the G11 currencies seems to be more reactive to the pandemic than the full sample does. While overall trading volume drops after the pandemic, the positive association between volume and currency price increased. Finally, Bitcoin price is still an important determinant of trading volume, as coefficients on Bitcoin price and return are all significant. Though the association is positive when volume is measured in local currency, and negative when measured in Bitcoin. This is expected as price increase attract speculation, but total number of Bitcoins traded drops as same amount of local currency can trade fewer Bitcoin.

To sum up, while Bitcoin price and return are still important determinant of trading volume. The results from the G11 subsample offer more evidence that Bitcoin behaves like a safe haven asset.

6.3 G20 currencies

Table 3 Panel D reports regression results for the G20 currencies. A few G20 currencies are already included in the G11 group (e.g. USD, EUR, etc) and in the crisis currencies (e.g. TRY and ARS), so the G20 group only has 9 currencies. Overall, currency price and returns are positively associated with volume as coefficients on currency price and returns are all positive and mostly significant, supporting the safe haven hypothesis H_1. The pandemic, again, reduces overall trading volume (positive and significant coefficients on Post2020) but increases the positive association between price and volume (positive and significant coefficients on Post2020*CurrPrice). Providing evidences for Bitcoin's speculative and hedging property. Expectedly, volume is still heavily influenced by Bitcoin price and return as coefficients on Bitcoin returns are all significant.

6.4 The rest of currencies

Table 3 panel E report the last currency group where the rest 20 currencies are grouped together. The results are again in support of the hedging asset version of H_1. Currency price and return are positively associated with volume as coefficients on price and return are all positive. Coefficients on the Post2020 dummy are all negative and significant. The pandemic reduces trading volume similar to other currency group. The association between price and volume did not change after the pandemic as coefficients on the interaction term are not significant. Overall, Table 3 Panel E depicts the same picture as the rest of results – Bitcoin trading volume is positively associated with currency price and return, and trading reduced since the start of the pandemic.

7. Causality tests

While previous section demonstrates the positive association between volume and currency price/return, it is still unclear whether currency depreciation causes trading in Bitcoin. In this section, I conduct a Granger type causality test to examine the effect of price/return over volume (Pereira et al, 2018), and explore the direction of causality. To be more precise, the following regression model is employed.

$$Vol_{it} = \alpha_i + b_0 Vol_{it-1} + b_1 CurrPrice_{it-1} + b_2 CurrReturn_{it-1} + b_3 BitPrice_t + b_4 BitReturn_t + \varepsilon_{it} \quad (3)$$

$$CurrPrice_{it} = \beta_i + c_0 Vol_{it-1} + c_1 CurrReturn_{it} + c_2 BitPrice_t + c_3 BitReturn_t + \varepsilon_{it} \quad (4)$$

$$CurrReturn_{it} = \gamma_i + d_0 Vol_{it-1} + d_1 CurrPrice_{it} + d_2 CurrReturn_{it-1} + d_3 BitPrice_t + b_4 BitReturn_t + \varepsilon_{it} \quad (5)$$

Similar to equation (1) and (2), all regressions run on weekly data. In equation (3), Bitcoin trading volume is a function of lagged currency price (CurrPrice_{it-1}), lagged currency return (CurrReturn_{it-1}) and lagged volume (Vol_{it-1}). If the coefficients, b_1 and b_2, are significant, then I conclude that currency price 'Granger causes' trading volume. Similarly, if coefficients c_0 and d_0 in equation (4) and (5) are significant, then I conclude that trading volume 'Granger causes' currency price and currency return. I expect to find currency prices cause trading volume.

[Insert Table 4 here]

Table 4 reports results of these causality tests. In Panel A, I run regression in equation (3). There is clear evidence of causality from lagged currency price to Bitcoin trading volume. The result suggests that high currency price (low currency value) leads to higher trading in Bitcoin. To a less extent, a similar pattern is found for currency returns, where causality runs from lagged return to trading volume. Panel B reports results from regression equation (4), there are evidence of causality from lagged trading volume to currency price as coefficients on the lagged volume are significant. This means that Bitcoin trading volume Granger cause higher currency price. The result indicates the causality between Bitcoin trading volume and currency price runs both ways. It is likely that the market anticipated a currency devaluation and starts pre-emptively trading Bitcoin. When volume is measure in Bitcoin, results are weaker as only 1 coefficient on currency price is significant. Panel C report regressions from equation (5). Similar to results in Panel B, there is also evidence of causality from lagged trading volume to currency return as coefficients on lagged volume are significant. The result confirms the mutual causality between currency return and Bitcoin trading volume. Again, when volume is measured in number of Bitcoins, the causality from volume to currency return is weaker with only 3 significant coefficients.

As a robustness check, I run the same causality test using changes in trading volume. These results are reported in Table 5. Two measures of volume change – absolute change (ΔVolCurr and ΔVolBTC) and percentage change (%ΔVolCurr and %ΔVolBTC) in Bitcoin trading volume, are used in Table 5. In panel A, absolute change in volume is used as the dependent variable in the upper part. There is evidence that causality runs from lagged currency price and return to absolute change in trading volume (ΔVolCurr) as the coefficients on lagged currency price for G11, G20 and the rest currency group are significant. When volume is measured in Bitcoin (ΔVolBTC), the causality results is weaker. None of the subgroup have significant coefficients on currency return, only two subgroups (crisis and G20 group) have significant coefficient on currency price.

[Insert Table 5 here]

On the second part of Panel A, dependent variable is percentage change in volume (%ΔVolCurr and %ΔVolBTC). There is some evidence that causality runs from lagged currency price to percentage change in volume (%ΔVolCurr), where the coefficient on the rest and G20 group are significant. But the overall causality results are even weaker as only two subgroups (Rest and G20 groups) have significant coefficients. For volume measured in Bitcoin (%ΔVolBTC), none of the subgroup have significant coefficient on currency price, only one subgroup (G20) has significant coefficient on currency return.

In Panel B of Table 5, currency price is the dependent variable. Five out of ten coefficients on the lagged absolute volume change ($\Delta VolCurr_{t-1}$ and $\Delta VolBTC_{t-1}$) are significant. This is evidence of causality from trading volume to currency price, suggesting that currency price and volume have mutual causality. However, none of the ten coefficients on the lagged percentage volume change ($\%\Delta VolCurr_{t-1}$ and $\%\Delta VolBTC_{t-1}$) are significant. Panel C of Table 5 paints a similar picture, in this panel dependent variable is currency return. Four out of the ten coefficients on the lagged absolute volume ($\Delta VolCurr_{t-1}$ and $\Delta VolBTC_{t-1}$) change are significant. Again, there are some evidence of causality from volume to currency return. All coefficients on the lagged percentage volume change ($\%\Delta VolCurr_{t-1}$ and $\%\Delta VolBTC_{t-1}$) are insignificant.

To sum up, results in Table 4 and Table 5 appears to suggest that the Granger causality is mutual between volume and currency price (return) and some subgroups results are stronger than other subgroups. Overall, the causality results are weaker in Table 5 than those reported in Table 4, but changes in volume still exhibit mutual causality in G20 and the rest current groups. At least, that is the case for absolute change in volume. While these results cannot prove true causality that currency depreciation causes Bitcoin trading, they confirm the positive statistical association between currency price/return and Bitcoin trading volume.

8. Conclusion

Using data from LocalBitcoins.com, a person-to-person exchange, I demonstrate that increase in Bitcoin trading volume is accompanied with local currency crises. To be more precise, I find positive (negative) association between currency price (currency value) and Bitcoin trading volume, this is presented in Table 3. The results not only hold for the 8 crisis affected currencies but also G11 currencies of advanced economies. There is also evidence of positive association between currency return (currency depreciation) and Bitcoin trading volume, though they are weaker than results in currency price. These results appear to suggest that some forms of flight-to-Bitcoin (measured in increased trading volume) have occurred during currency depreciation. It also indicates that Bitcoin is a hedging asset during local crises.

However, the result changed when I examine the effect of COVID-19. Trading volume declined in 2020, and this is consistent across all subgroups. On a global level, it appears that investors avoid trading Bitcoin due to risk aversion during the pandemic. This result is largely in line with prior literature, e.g., Conlon and McGee (2020) and Chen, Liu and Zhao (2020). In addition, the negative association between currency value and volume did not change during the pandemic. If Bitcoin is regarded as a safe haven asset, then the negative association between currency value and volume should strengthen in time of market distress. But that did not happen. The market seems to regard Bitcoin as a speculative investment and reduce exposure during the crisis. The duality of hedging and speculative properties is not unique to Bitcoin, gold is also known to have both safe haven and speculative properties, e.g., O'Connor et al. (2015) and Baur and Glover (2015).

While the results cannot prove currency prices (and returns) cause trading in Bitcoin, the causality test in section 7 (Table 4 and 5) reinforces the statistical association between currency price and volume. The association may simply be a coincident, as a result of declining currency value and increasing interest in Bitcoin. Currency value has been declining, as Table 2 shows most currency have negative returns in the last 6 years. At the same time, LBTC sees steady increase of volume on their platform.[13] Or the gradual decline of currency may spark slow but growing interest toward Bitcoin. At least the data cannot prove either case. A more robust setup based on natural experiment can offer evidence of actual causation. Though identify natural events that are truly exogenous is still challenging. That would be an interesting avenue for future research.

Another avenue for future research is examining influences of culture on trading behaviours, as Bitcoin is traded in almost every country in the world. Cross country variation may well be explained by cultural difference. Hoftstede cultural variables can be used in this regard to classify currencies into different cultural groups. It would be interesting to re-estimate equation (1) and (2) and see if the association between trading volume and currency prices are weakened or strengthen in different cultural group. The results could help us understand the impact of culture trading behaviours.

[13]See LBTC's total volume in USD since 2016 here: https://coin.dance/volume/localBitcoins

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Figure 1. Bitcoin trading volume and currency price. The figure plots currency prices, Bitcoin prices and Bitcoin trading volume in a single graph, for Argentine Peso (ARS) and Turkish Lira (TRY). Currency prices are in local currency per USD, rising currency price in the graph means the currency is depreciating against USD. Trading volumes are in local currency. All variables are log-transformed. The three time-series (currency price, Bitcoin price and volume) are under different y-axis which correspond to their respective line colour. The far-left y-axis, which is coloured in green, corresponds to natural logarithm of Bitcoin price. The second y-axis on the left, which is coloured in black, corresponds to logarithm of currency price. The y-axis on the right, which is coloured in red, corresponds to logarithm of Bitcoin trading volume in local currency.

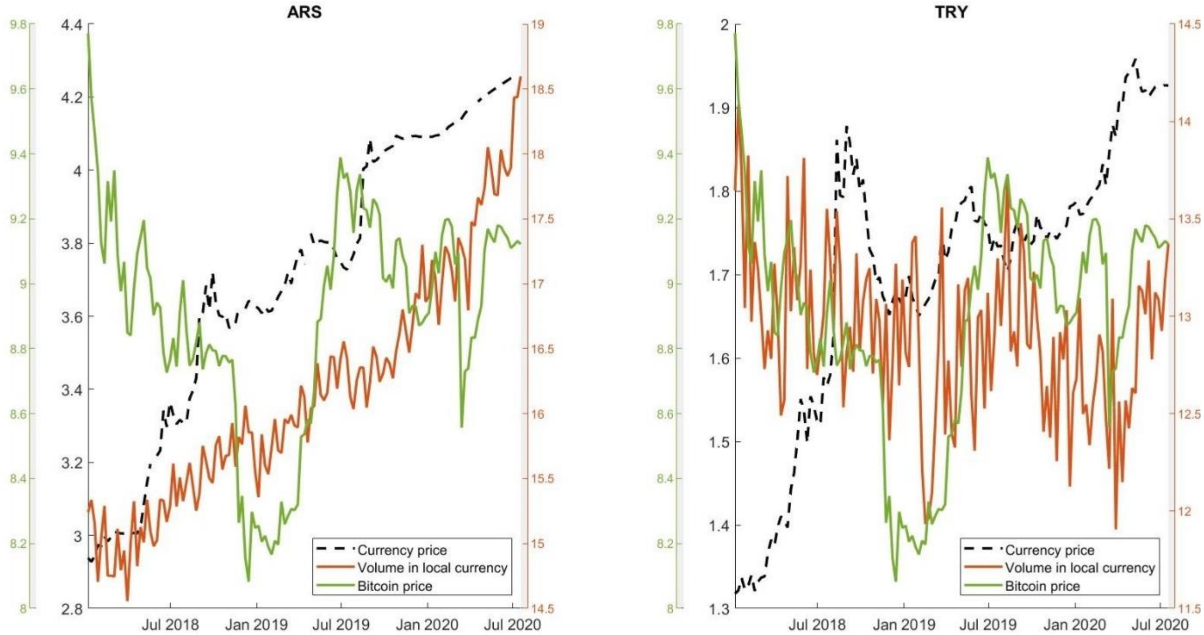

Table 1. Summary statistics and correlations. Panel A report summary statistics of the 6 variables: CurrPrice (currency price), CurrReturn (currency return), VolCurr (volume in local currency), VolBTC (volume in Bitcoin), Bitcoin price (BTC price) and Bitcoin return (BTC return). All returns are calculated based on $ln\left(\frac{P_i}{P_{i-1}}\right)$, where P_i is price at time i. All prices are expressed in dollars per unit of local currency. The data are collected on a weekly basis. The sample contains 48 currencies covering the period of January 2014 to July 2020. Panel B reports correlations between the 6 variables. The asterisks *, **, *** on correlations denote statistical significance at 10%, 5% and 1% level, respectively.

Panel A: Summary Statistics

	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis	N
CurrPrice	0.000004	666.67	9.43	64.37	8.65	81.52	14926
CurrReturn	-7.83	0.228	-0.0023	0.068	-103.78	11943.94	14926
VolCurr	0.0046	1091977902957	1594313443	28934350419	27.81	855.17	14926
VolBTC	0.00020	21574.9	343.56	1343.15	8.54	92.40	14926
BTC price	199.26	19497.4	3886.02	4008.26	0.86	2.90	342
BTC return	-0.54	0.350	0.0081	0.107	-0.28	5.67	342

Panel B: Correlation matrix

	CurrPrice	CurrReturn	VolCurr	VolBTC	BTC price
CurrReturn	0.22%				
VolCurr	-0.74%	-2.52%***			
VolBTC	11.70%***	0.05%	0.68%		
BTC price	-7.45%***	-0.70%	6.24%***	-12.92%***	
BTC return	-0.02%	1.42%	0.15%	0.96%	6.05%***

Table 2. Currency distribution. The table reports 4 variables for each of the 48 currencies. The four variables reported are mean of currency return (CurrReturn), mean of currency price (CurrPrice), mean of volume in local currency (VolCurr) and mean of volume in Bitcoin (VolBTC). Returns are calculated based on $ln\left(\frac{P_i}{P_{i-1}}\right)$, where P_i is currency price at time i. All prices are expressed in dollars per unit of currency except the USD, which is quoted using the dollar index, DXY. Currencies are divided into 4 groups: G11 is the most liquid currencies which also represents the most advanced economies, crisis currencies are currencies that have a minimum weekly return less than -20%, G20 are currencies of the largest economy excluding G11 and crisis currencies, the rest currencies are in the last group.

Curr	CurrReturn	CurrPrice	VolCurr	VolBTC	n
G11 currencies					
USD (DXY)	0.05%	94.28028	5863792	5780.7	342
EUR	-0.05%	1.15762	1307423	823.1	342
GBP	-0.08%	1.39276	2277899	1987.4	342
JPY	-0.01%	0.00905	1151334	4.4	322
AUD	-0.07%	0.70583	1012522	674.6	342
NZD	-0.06%	0.70771	307416	74.4	342
CAD	-0.07%	0.78544	551808	204.8	342
CHF	-0.02%	1.03316	42061	36.1	342
NOK	-0.12%	0.12471	1300699	69.1	342
SEK	-0.10%	0.11859	3188542	207.0	342
DKK	-0.05%	0.15527	120174	6.7	337
Crisis currencies					
VES	-5.74%	345.58382	62583083841	401.0	332
IRR	-0.81%	0.00002	6782733126	15.7	297
UAH	-0.38%	0.04247	7456863	59.2	310
ARS	-0.71%	0.06489	6981595	54.7	342
EGP	-0.42%	0.06223	380829	3.6	199
NGN	-0.29%	0.00365	691270283	391.6	311
TRY	-0.36%	0.27992	284031	19.3	320
KZT	-0.36%	0.00297	19841074	8.1	239
G20 currencies					
BRL	-0.26%	0.30256	793873	62.3	342
INR	-0.06%	0.01503	43323898	182.3	342
RUB	-0.22%	0.01749	453328185	2298.3	342
SAR	0.00%	0.26659	576861	23.7	313
ZAR	-0.13%	0.07523	8488466	344.7	342
MXN	-0.16%	0.05721	3360413	73.2	342
CNY	-0.04%	0.15193	18831906	754.1	342
IDR	-0.12%	0.00007	346619957	6.7	267
KRW	-0.05%	0.00088	34971713	5.8	272
The rest of currencies					
AED	0.00%	0.27226	617261	41.8	339
CLP	-0.11%	0.00152	82630847	26.6	341
COP	-0.21%	0.00036	2965007948	171.3	342
CZK	-0.05%	0.04360	351068	14.3	342
DOP	-0.13%	0.02045	3352314	10.7	245
HRK	-0.05%	0.15406	70973	12.4	342
KES	-0.07%	0.01008	22569913	51.9	340
MAD	-0.06%	0.10404	648647	15.1	238
MYR	-0.09%	0.25321	1319619	113.9	342
PEN	-0.07%	0.30902	1071423	55.1	329
PHP	-0.03%	0.02055	4022578	38.2	342
PKR	-0.15%	0.00846	26301331	51.5	287
RON	-0.08%	0.25310	412601	62.7	342
THB	0.01%	0.03030	10892540	170.0	342
TZS	-0.10%	0.00045	72784994	5.0	259
VND	-0.03%	0.00004	621109259	6.3	274
HKD	0.00%	0.12843	1895071	78.0	342
SGD	-0.03%	0.73798	177003	32.9	342
HUF	-0.11%	0.00366	1318376	3.5	342
PLN	-0.08%	0.27134	162224	27.6	342

Table 3. Regression results. The table reports result from panel regressions with currency fixed effect. Dependent variables are logarithm of Bitcoin trading volumes in both local currency (VolCurr) and Bitcoin (VolBTC). The independent variables are Bitcoin price (logarithm of Bitcoin prices), Bitcoin return (returns of Bitcoin prices), Currency Price (logarithm of currency prices) and Currency Return (returns of currency prices). Bitcoin prices are in USD. Currency prices are quoted in units of currency per USD. t-statistics are reported in the bracket below each coefficient and are based on robust standard errors that adjusted for heteroscedasticity and clustered by currency (White cross-section). The asterisks *, **, *** on coefficients denote statistical significance at 10%, 5% and 1% level, respectively. Panel A report results from the full sample. Panel B reports subsample results for the crisis currencies. The currencies are chosen based on their weekly currency returns – they have a minimum weekly return of -20%, i.e., these currencies have depreciated more than 20% in a week at least once in the sample period. There are 8 currencies in the group. Panel C reports results using data from the G11 subsample. G11 represents the 11 most liquid currencies in the world. Panel D reports subsample results for G20 currencies but excludes currencies that are already presented in the G11 and crisis subsample. This leaves only 9 currencies in Panel D. Panel E reports subsample results for the rest of currencies which are not included in the G11, crisis and G20 subsamples. There are 20 currencies in this group.

Panel A: Full sample

	VolCurr (Volume in local currency)				VolBTC (Volume in Bitcoin)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post2020		-0.528***	-0.753***	-0.756***		-0.558***	-0.769***	-0.772***
		(-4.133)	(-3.697)	(-3.748)		(-4.463)	(-3.670)	(-3.731)
Post2020*CurrPrice			0.066	0.069			0.062	0.065
			(0.797)	(0.851)			(0.727)	(0.784)
Post2020*CurrReturn		1.583		2.687		1.967		3.010
		(0.689)		(1.672)		(0.829)		(1.772)
CurrPrice	**1.136*****	**1.144*****	**1.133*****	**1.134*****	**0.243*****	**0.252*****	**0.241*****	**0.242*****
	(20.296)	(19.783)	(20.256)	(20.257)	(4.530)	(4.546)	(4.534)	(4.570)
CurrReturn	**0.374**	**0.376**	**0.374**	**0.355**	**0.125**	**0.125**	**0.127**	**0.105**
	(1.491)	(1.584)	(1.523)	(1.533)	(0.513)	(0.543)	(0.533)	(0.470)
BTC Price	0.928***	0.951***	0.953***	0.953***	-0.079	-0.054	-0.053	-0.053
	(11.425)	(11.642)	(11.647)	(11.650)	(-0.995)	(-0.680)	(-0.659)	(-0.662)
BTC Return	0.329**	0.289**	0.293**	0.289**	0.724***	0.681***	0.685***	0.681***
	(2.528)	(2.267)	(2.306)	(2.274)	(5.631)	(5.409)	(5.453)	(5.416)
Adj R^2	0.649	0.652	0.700	0.652	0.032	0.042	0.043	0.043
Currency number	48	48	48	48	48	48	48	48
Currency weeks	14926	14926	14926	14926	14926	14926	14926	14926

Panel B: Crisis currencies

	VolCurr (Volume in local currency)				VolBTC (Volume in Bitcoin)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post2020		-0.735	0.813	0.825		-0.748	0.939	0.944
		(-1.293)	(0.852)	(0.867)		(-1.372)	(1.090)	(1.094)
Post2020*CurrPrice			-0.279	-0.285*			-0.307**	-0.309**
			(-1.642)	(-1.698)			(-1.994)	(-2.015)
Post2020*CurrReturn		6.503		-1.993		8.296		-0.918
		(0.857)		(-0.690)		(1.196)		(-0.335)
CurrPrice	**0.979*****	**0.993*****	**1.021*****	**1.021*****	**0.100*****	**0.115*****	**0.145*****	**0.145*****
	(32.152)	(29.730)	(23.634)	(23.496)	(3.664)	(3.954)	(4.024)	(4.019)
CurrReturn	**0.298*****	**0.312*****	**0.358*****	**0.362*****	**0.059**	**0.071**	**0.124**	**0.125**
	(2.848)	(3.494)	(3.244)	(3.341)	(0.519)	(0.725)	(1.052)	(1.090)
BTC Price	1.570***	1.598***	1.581***	1.582***	0.494**	0.523**	0.505**	0.505**
	(6.437)	(6.422)	(6.323)	(6.317)	(2.190)	(2.289)	(2.182)	(2.183)
BTC Return	0.047	-0.006	-0.002	-0.002	0.317	0.260	0.265	0.265
	(0.093)	(-0.013)	(-0.004)	(-0.005)	(0.643)	(0.541)	(0.553)	(0.553)
Adj R^2	0.802	0.804	0.808	0.808	0.181	0.194	0.214	0.214
Currency number	8	8	8	8	8	8	8	8
Currency weeks	2170	2170	2170	2170	2170	2170	2170	2170

Panel C: G11 currencies

	VolCurr (Volume in local currency)				VolBTC (Volume in Bitcoin)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post2020		-0.442***	-0.537***	-0.536***		-0.502***	-0.598***	-0.597***
		(-2.632)	(-2.951)	(-2.952)		(-2.865)	(-3.193)	(-3.193)
Post2020*CurrPrice			0.162*	0.163*			0.165*	0.165*
			(1.843)	(1.851)			(1.695)	(1.701)
Post2020*CurrReturn		-1.918		-2.168		-1.876		-2.131
		(-1.315)		(-1.588)		(-1.242)		(-1.496)
CurrPrice	**1.945*****	**2.051*****	**1.947*****	**1.945*****	**1.240***	**1.360***	**1.255***	**1.253***
	(3.110)	(3.074)	(2.863)	(2.864)	(1.914)	(2.037)	(1.860)	(1.859)
CurrReturn	**2.533*****	**3.062*****	**2.492*****	**2.982*****	**2.180*****	**2.713*****	**2.150*****	**2.631*****
	(4.181)	(3.203)	(3.686)	(3.082)	(3.620)	(2.983)	(3.298)	(2.861)
BTC Price	0.468***	0.488***	0.489***	0.489***	-0.538***	-0.516***	-0.514***	-0.514***
	(6.797)	(7.075)	(7.105)	(7.105)	(-7.425)	(-7.180)	(-7.158)	(-7.160)
BTC Return	0.359***	0.333***	0.333***	0.336***	0.781***	0.750***	0.751***	0.754***
	(3.621)	(3.529)	(3.511)	(3.555)	(9.269)	(9.607)	(9.598)	(9.626)
Adj R^2	0.458	0.467	0.473	0.473	0.461	0.472	0.478	0.478
Currency number	11	11	11	11	11	11	11	11
Currency weeks	3737	3737	3737	3737	3737	3737	3737	3737

Panel D: G20 currencies

	VolCurr (Volume in local currency)				VolBTC (Volume in Bitcoin)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post2020		-0.797***	-1.654***	-1.655***		-0.807***	-1.644***	-1.643***
		(-3.219)	(-3.843)	(-3.836)		(-3.290)	(-3.826)	(-3.820)
Post2020*CurrPrice			0.215***	0.215***			0.210**	0.210***
			(2.756)	(2.752)			(2.680)	(2.680)
Post2020*CurrReturn		-0.731		-0.318		-0.351		0.051
		(-0.383)		(-0.190)		(-0.183)		(0.030)
CurrPrice	**3.724*** **	**4.124*** **	**4.209*** **	**4.208*** **	**2.731** **	**3.138*** **	**3.220** **	**3.220*** **
	(3.316)	(3.530)	(3.604)	(3.604)	(2.448)	(2.704)	(2.773)	(2.773)
CurrReturn	**3.168*** **	**2.912** **	**2.874*** **	**2.931** **	**2.485** **	**2.156**	**2.184* **	**2.175**
	(2.635)	(2.243)	(2.641)	(2.280)	(1.972)	(1.572)	(1.916)	(1.602)
BTC Price	1.013***	1.034***	1.034***	1.034***	0.019	0.040	0.040	0.040
	(7.144)	(7.210)	(7.126)	(7.125)	(0.137)	(0.286)	(0.278)	(0.278)
BTC Return	0.388***	0.312**	0.313**	0.313**	0.807***	0.729***	0.730***	0.730***
	(2.650)	(2.326)	(2.354)	(2.363)	(5.424)	(5.395)	(5.450)	(5.462)
Adj R^2	0.681	0.688	0.692	0.692	0.094	0.116	0.126	0.126
Currency number	9	9	9	9	9	9	9	9
Currency weeks	2762	2762	2762	2762	2762	2762	2762	2762

Panel E: The rest of currencies

	VolCurr (Volume in local currency)				VolBTC (Volume in Bitcoin)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post2020		-0.861***	-1.145***	-1.145***		-0.883***	-1.173***	-1.173***
		(-6.404)	(-3.501)	(-3.502)		(-6.546)	(-3.506)	(-3.506)
Post2020*CurrPrice			0.078	0.077			0.079	0.079
			(1.024)	(1.018)			(1.011)	(1.006)
Post2020*CurrReturn		-3.620		-3.429		-3.672		-3.477
		(-1.396)		(-1.372)		(-1.412)		(-1.387)
CurrPrice	**6.067*** **	**6.568*** **	**6.492*** **	**6.488*** **	**5.116*** **	**5.629*** **	**5.552*** **	**5.548*** **
	(3.732)	(4.120)	(4.118)	(4.121)	(3.114)	(3.496)	(3.486)	(3.488)
CurrReturn	**3.884*** **	**4.632*** **	**3.962*** **	**4.573*** **	**3.256** **	**4.016** **	**3.337** **	**3.955** **
	(3.014)	(2.915)	(3.215)	(2.892)	(2.485)	(2.498)	(2.668)	(2.473)
BTC Price	0.856***	0.887***	0.889***	0.889***	-0.137	-0.106	-0.104	-0.104
	(7.750)	(8.165)	(8.172)	(8.170)	(-1.236)	(-0.968)	(-0.953)	(-0.954)
BTC Return	0.206	0.130	0.132	0.135	0.633***	0.554***	0.556***	0.559***
	(1.049)	(0.677)	(0.689)	(0.709)	(3.237)	(2.904)	(2.928)	(2.961)
Adj R^2	0.593	0.604	0.604	0.604	0.103	0.128	0.197	0.129
Currency number	20	20	20	20	20	20	20	20
Currency weeks	6257	6257	6257	6257	6257	6257	6257	6257

Table 4: Granger causality test. The table reports result of testing reverse causality between Bitcoin volume and currency price/return. All regressions include currency fixed effect. Dependent variables are as follow: logarithm of Bitcoin trading volumes in both local currency (VolCurr) and Bitcoin (VolBTC), currency return, currency price. The independent variables are Bitcoin price (logarithm of Bitcoin prices), Bitcoin return (returns of Bitcoin prices), lagged currency price ($CurrPrice_{t-1}$), lagged currency return ($CurrReturn_{t-1}$), and lagged Bitcoin volume ($VolCurr_{t-1}$ and $VolBTC_{t-1}$). t-statistics are reported in the bracket below each coefficient and are based on robust standard errors that adjusted for heteroscedasticity and clustered by currency (White cross-section). The asterisks *, **, *** on coefficients denote statistical significance at 10%, 5% and 1% level, respectively. In Panel A, dependent variables are trading volume in local currency (VolCurr) and Bitcoin (VolBTC). In panel B, the dependent variable is currency price. In panel C, the dependent variable is currency return.

Panel A: Trading volume

	VolCurr (Volume in local currency)					VolBTC (Volume in Bitcoin)				
Dep variable	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
$CurrPrice_{t-1}$	**0.164*****	**0.546*****	**0.124*****	**0.759*****	**0.927*****	**0.036*****	**0.349*****	**0.015*****	**0.552****	**0.747****
	(5.033)	(3.846)	(2.757)	(2.666)	(2.414)	(3.822)	(2.416)	(2.623)	(2.245)	(2.079)
$CurrReturn_{t-1}$	**0.041**	**1.533*****	**0.017**	**0.717**	**1.290**	**0.060**	**1.782*****	**0.030**	**1.163***	**1.713****
	(0.880)	(3.016)	(0.651)	(1.069)	(1.525)	(0.994)	(3.636)	(1.344)	(1.888)	(2.027)
$VolCurr_{t-1}$	0.854***	0.722***	0.873***	0.786***	0.833***					
	(33.035)	(8.219)	(19.410)	(11.189)	(27.380)					
$VolBTC_{t-1}$						0.840***	0.713***	0.838***	0.781***	0.834***
						(34.894)	(8.027)	(21.987)	(11.241)	(28.449)
BTC price	0.125***	0.125**	0.189***	0.207***	0.133***	-0.023*	-0.159***	0.067**	-0.005	-0.032*
	(5.093)	(2.234)	(3.015)	(2.435)	(4.224)	(-1.853)	(-4.249)	(2.064)	(-0.188)	(-1.751)
BTC return	0.380***	0.327***	0.542***	0.485***	0.279***	-0.009	0.066	0.148	0.149	-0.103
	(7.452)	(3.589)	(3.265)	(4.217)	(3.795)	(-0.166)	(0.492)	(0.983)	(0.944)	(-1.427)
Adj R^2	90.84%	74.24%	95.44%	88.44%	87.75%	72.42%	74.23%	76.02%	65.48%	73.06%
n	14693	3682	2135	2719	6157	14693	3682	2135	2719	6157
F-statistic	29136.18	2125.03	8941.13	4159.91	8822.71	7727.51	2123.82	1355.71	1033.57	3343.90

Panel B: Currency price

CurrPrice	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
CurrReturn$_t$	-0.998***	-0.394***	-0.712***	-0.535***	-0.546***	-1.375***	-0.372***	-1.225***	-0.511***	-0.537***
	(-3.759)	(-10.32)	(-2.538)	(-4.189)	(-8.865)	(-109.2)	(-10.60)	(-6.922)	(-3.800)	(-8.661)
VolCurr$_{t-1}$	**0.351***	**0.017***	**0.619*****	**0.031***	**0.022*****					
	(1.931)	**(1.857)**	**(3.656)**	**(1.823)**	**(3.404)**					
VolBTC$_{t-1}$						**0.124**	**0.010**	**0.184**	**0.023**	**0.018*****
						(1.357)	**(1.241)**	**(1.062)**	**(1.494)**	**(2.893)**
BTC price	-0.255*	0.003	-0.689**	-0.000	-0.003	0.120*	0.018**	0.602	0.033***	0.018***
	(-1.652)	(0.572)	(-2.376)	(-0.002)	(-0.405)	(1.649)	(2.082)	(1.676)	(3.435)	(3.586)
BTC return	-0.038	0.029**	-0.145	0.038***	0.030***	-0.180	0.020	-0.586	0.016	0.012*
	(-0.607)	(2.240)	(-0.425)	(3.188)	(2.926)	(-1.091)	(1.183)	(-1.084)	(1.139)	(1.803)
Adj R^2	41.42%	8.07%	65.89%	26.01%	21.20%	6.19%	6.17%	16.46%	21.85%	17.99%
n	14693	3682	2135	2719	6157	14693	3682	2135	2719	6157
F-statistic	2609.64	84.28	1033.24	241.82	419.75	255.11	64.02	107.85	193.00	343.42

Panel C: Currency return

CurrReturn	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
CurrPrice$_t$	-0.009***	-0.012***	-0.011***	-0.010***	-0.011***	-0.008***	-0.011***	-0.008***	-0.009***	-0.010***
	(-29.35)	(-5.799)	(-12.54)	(-2.955)	(-6.475)	(-92.88)	(-5.594)	(-16.21)	(-2.639)	(-6.572)
CurrReturn$_{t-1}$	-0.000	-0.077***	-0.000	0.050*	-0.031	-0.000	-0.077***	0.001	0.051*	-0.030
	(-0.555)	(-6.638)	(-0.009)	(1.745)	(-1.436)	(-0.182)	(-6.700)	(1.140)	(1.765)	(-1.419)
VolCurr$_{t-1}$	**0.001*****	**0.001*****	**0.003*****	**0.000**	**0.000*****					
	(3.943)	**(3.216)**	**(2.629)**	**(1.607)**	**(3.396)**					
VolBTC$_{t-1}$						**0.000**	**0.000*****	**0.001***	**0.000**	**0.000*****
						(1.526)	**(2.805)**	**(1.878)**	**(1.431)**	**(3.221)**
BTC price	-0.000	-0.000	-0.005	-0.000	0.000	0.000	0.000***	-0.000	0.000**	0.000***
	(-1.323)	(-0.273)	(-1.071)	(-0.400)	(1.076)	(1.113)	(3.445)	(-0.260)	(2.301)	(4.984)
BTC return	0.008*	0.000	0.031	0.007***	0.004***	0.007	0.000	0.030	0.007***	0.003***
	(1.686)	(0.579)	(1.065)	(3.349)	(4.245)	(1.495)	(0.048)	(0.993)	(3.392)	(4.234)
Adj R^2	0.85%	0.96%	0.73%	0.65%	0.60%	0.80%	0.85%	0.63%	0.56%	0.55%
n	14502	3682	2075	2654	6091	14502	3682	2075	2654	6091
F-statistic	35.15	10.15	5.46	6.07	12.18	33.89	9.33	5.04	5.57	11.57

Table 5: Robustness check. The table reports the same causality test results as in Table 4 by using absolute change in Bitcoin trading volume (ΔVolBTC and ΔVolCurr) and percentage change in Bitcoin trading volume (%ΔVolCurr and %ΔVolBTC). All other variables are the same as in Table 4. In Panel A, dependent variables are ΔVolBTC, ΔVolCurr and %ΔVolCurr, %ΔVolBTC. In Panel B and C, dependent variables are currency price and currency return, respectively.

Panel A: Volume change

	Volume change in local currency (ΔVolCurr)					Volume change in Bitcoin (ΔVolBTC)				
	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
ΔVolCurr$_{t-1}$	-0.010***	0.278***	-0.011***	0.361***	0.390***					
	(-58.320)	(15.036)	(-8.829)	(6.023)	(11.420)					
ΔVolBTC$_{t-1}$						-0.006***	-0.004***	-0.008***	0.366***	-0.005***
						(-5.333)	(-4.432)	(-4.763)	-6.534	(-7.866)
CurrPrice$_{t-1}$	**3.485**	**0.887*****	**12.648**	**1.461*****	**2.583*****	**-46.68*****	**-4.352**	**-45.06*****	**0.839***	**-447.3**
	(1.245)	(2.540)	(1.016)	(3.071)	(3.669)	(-13.97)	(-0.111)	(-11.98)	(1.667)	(-1.325)
CurrReturn$_{t-1}$	**13.26**	**2.808****	**18.189**	**2.145*****	**1.581**	**20.962**	**-1138**	**25.991**	**1.047**	**-701.6**
	(0.743)	(2.101)	(0.700)	(4.847)	(1.049)	(0.900)	(-1.018)	(1.277)	(1.002)	(-0.504)
BTC price	-5.397	0.377***	-50.23	0.537***	0.409***	-28.08***	-15.38	-33.84	-0.089	-40.81**
	(-0.870)	(9.642)	(-0.949)	(9.705)	(7.237)	(-2.594)	(-1.085)	(-1.212)	(-1.419)	(-1.945)
BTC return	41.425	0.101	259.52	0.354	0.274	-213.1**	-99.4	-617.5	0.028	-217.7
	(1.017)	(0.656)	(1.080)	(1.259)	(1.631)	(-2.153)	(-1.046)	(-1.330)	(0.169)	(-1.474)
Adj R^2	-0.33%	30.96%	-0.44%	53.67%	46.81%	-0.17%	-0.33%	-0.17%	14.71%	-0.20%
n	14693	3682	2135	2719	6157	14693	3682	2135	2719	6157
F-statistic	0.71	333.14	0.54	632.44	1088.38	5.3	0.56	1.66	96.35	2.37

	% Volume change in local currency (%ΔVolCurr)					% Volume change in Bitcoin (%ΔVolBTC)				
	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
%ΔVolCurr$_{t-1}$	-0.418***	-0.433***	-0.372***	-0.432***	-0.42***					
	(-24.73)	(-20.84)	(-16.35)	(-13.39)	(-8.715)					
%ΔVolBTC$_{t-1}$						-0.417***	-0.436***	-0.370***	-0.432***	-0.415***
						(-24.41)	(-22.24)	(-17.51)	(-15.43)	(-7.814)
CurrPrice$_{t-1}$	**0.001*****	**-0.022**	**0.020**	**0.063***	**0.002***	**-0.001****	**-0.072**	**-0.004**	**0.019**	**-0.000**
	(3.187)	(-0.372)	(0.637)	(1.865)	(1.875)	(-2.294)	(-1.403)	(-0.148)	(0.531)	(-0.580)
CurrReturn$_{t-1}$	**-0.050**	**0.078**	**-0.153**	**0.453***	**-0.053**	**-0.002**	**0.406**	**0.377**	**0.808*****	**-0.015**
	(-1.308)	(0.091)	(-0.261)	(1.692)	(-1.212)	(-0.090)	(0.493)	(0.637)	(2.683)	(-0.490)
BTC price	-0.010***	-0.011***	-0.012***	-0.006***	-0.012*	-0.013***	-0.014***	-0.014***	-0.009***	-0.016***
	(-6.924)	(-5.923)	(-4.739)	(-4.727)	(-1.767)	(-9.742)	(-7.430)	(-5.509)	(-7.707)	(-2.678)
BTC return	0.409***	0.355***	0.551***	0.336***	0.489***	-0.145***	-0.204***	-0.001	-0.209***	-0.059
	(7.824)	(6.196)	(3.427)	(4.488)	(2.711)	(-2.993)	(-3.729)	(-0.010)	(-3.734)	(-0.357)
Adj R^2	17.72%	18.76%	14.30%	18.81%	18.04%	17.43%	18.93%	13.60%	18.63%	17.27%
n	14693	6157	2719	3682	2135	14693	6157	2719	3682	2135
F-statistic	643.26	289.19	93.28	173.51	96.33	630.61	292.36	88.19	171.53	91.51

Panel B: Currency price

	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
ΔVolCurr$_t$	0.000	0.003*	0.000	0.010*	0.008***					
	(1.533)	(1.824)	(1.605)	(1.892)	(3.662)					
ΔVolCurr$_{t-1}$	**0.000**	**0.002***	**0.000**	**0.010***	**0.007*****					
	(1.506)	(1.687)	(1.588)	(1.799)	(3.586)					
ΔVolBTC$_t$						-0.000	0.000**	-0.000***	0.006	-0.000
						(-1.292)	(2.103)	(-2.528)	(1.294)	(-1.412)
ΔVolBTC$_{t-1}$						**-0.000**	**0.000*****	**-0.000*****	**0.005**	**-0.000**
						(-1.293)	(4.185)	(-2.548)	(1.178)	(-1.448)
CurrReturn$_t$	-1.392***	-0.357***	-1.225***	-0.506***	-0.540***	-1.390***	-0.343***	-1.217***	-0.483***	-0.506***
	(-42.70)	(-8.699)	(-8.007)	(-3.684)	(-8.704)	(-45.91)	(-7.836)	(-7.938)	(-3.266)	(-7.481)
BTC price	0.112	0.009	0.706	0.017*	0.005	0.111	0.012*	0.700	0.037***	0.017***
	(1.611)	(1.284)	(1.547)	(1.733)	(1.051)	(1.617)	(1.781)	(1.548)	(3.983)	(3.060)
BTC return	-0.065	0.031***	-0.462	0.036***	0.026***	-0.067	0.031***	-0.468	0.032***	0.030***
	(-0.813)	(2.545)	(-1.133)	(3.117)	(2.635)	(-0.810)	(2.549)	(-1.118)	(3.041)	(2.970)
adj R^2	3.39%	5.68%	14.98%	20.74%	15.65%	3.53%	5.05%	15.25%	18.18%	9.81%
n	14693	3682	2135	2719	6157	14693	3682	2135	2719	6157
F-statistic	113.59	47.31	77.62	144.84	233.28	117.86	42.13	79.19	123.38	138.68

	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
%ΔVolCurr$_t$	0.004	0.001	0.022	0.000	-0.000					
	(0.936)	(1.339)	(1.168)	(0.359)	(-0.032)					
%ΔVolCurr$_{t-1}$	**0.002**	**0.001**	**0.012**	**0.000**	**0.000**					
	(1.153)	(1.205)	(1.047)	(0.238)	(0.504)					
%ΔVolBTC$_t$						-0.002	0.000	0.001	-0.000	-0.000
						(-1.261)	(0.440)	(0.251)	(-0.731)	(-1.025)
%ΔVolBTC$_{t-1}$						**-0.003**	**-0.000**	**-0.005**	**-0.000**	**-0.000**
						(-1.009)	(-0.044)	(-0.502)	(-0.841)	(-0.934)
CurrReturn$_t$	-1.392***	-0.346***	-1.224***	-0.473***	-0.504***	-1.392***	-0.345***	-1.225***	-0.474***	-0.504***
	(-42.63)	(-7.786)	(-8.048)	(-2.993)	(-7.732)	(-42.55)	(-7.806)	(-8.046)	(-2.993)	(-7.715)
BTC price	0.112	0.012*	0.705	0.036***	0.017***	0.112	0.012*	0.705	0.036***	0.017***
	(1.611)	(1.779)	(1.547)	(4.270)	(3.066)	(1.611)	(1.779)	(1.547)	(4.271)	(3.063)
BTC return	-0.067	0.031***	-0.460	0.038***	0.030***	-0.065	0.031***	-0.450	0.039***	0.030***
	(-0.813)	(2.502)	(-1.124)	(2.946)	(3.080)	(-0.810)	(2.571)	(-1.116)	(2.949)	(2.949)
adj R^2	3.39%	5.05%	14.96%	16.94%	9.75%	3.39%	5.04%	14.95%	16.94%	9.75%
n	14693	3682	2135	2719	6157	14693	3682	2135	2719	6157
F-statistic	113.52	42.15	77.46	113.43	137.83	113.51	42.03	77.43	113.45	137.88

Panel C: Currency return

	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
$\Delta VolCurr_t$	0.000***	0.000***	0.000	0.000	0.000**					
	(11.161)	(2.373)	(0.783)	(1.387)	(2.141)					
$\Delta VolCurr_{t-1}$	**0.000*****	**0.000*****	**0.000**	**0.000***	**0.000**					
	(4.713)	(0.246)	(0.116)	(1.665)	(0.709)					
$\Delta VolBTC_t$						0.000	-0.000***	0.000**	0.000	0.000
						(0.283)	(-103.7)	(2.171)	(0.841)	(0.422)
$\Delta VolBTC_{t-1}$						**-0.000**	**-0.000*****	**0.000****	**0.000**	**-0.000****
						(-0.373)	(-61.08)	(2.080)	(0.227)	(-1.906)
$CurrPrice_t$	-0.008***	-0.010***	-0.008***	-0.009***	-0.010***	-0.008***	-0.010***	-0.007***	-0.008**	-0.008***
	(-150.8)	(-4.748)	(-17.23)	(-2.701)	(-7.261)	(-161.3)	(-4.350)	(-17.05)	(-2.245)	(-6.799)
$CurrReturn_{t-1}$	-0.000	-0.076***	0.001	0.050*	-0.031	-0.000	-0.077***	0.001	0.051*	-0.029
	(-0.101)	(-6.717)	(1.108)	(1.769)	(-1.446)	(-0.099)	(-7.016)	(1.090)	(1.754)	(-1.373)
BTC price	0.000	0.000	-0.000	0.000	0.000***	0.000	0.000**	-0.000	0.000***	0.000***
	(1.076)	(1.264)	(-0.020)	(0.316)	(2.487)	(1.086)	(2.281)	(-0.016)	(3.011)	(6.215)
BTC return	0.008*	0.000	0.031	0.007***	0.004***	0.008*	0.000	0.031	0.007***	0.004***
	(1.661)	(0.640)	(1.023)	(3.368)	(4.238)	(1.663)	(0.640)	(1.026)	(3.389)	(4.330)
adj R^2	0.79%	0.70%	0.57%	0.53%	0.56%	0.79%	0.86%	0.57%	0.45%	0.46%
n	14502	3682	2075	2654	6091	14502	3682	2075	2654	6091
F-statistic	28.00	6.98	4.15	4.70	9.89	28.00	6.98	4.15	4.70	9.89

	Full	G11	Crisis	G20	Rest	Full	G11	Crisis	G20	Rest
$\%\Delta VolCurr_t$	-0.000***	-0.000	-0.002***	-0.000*	-0.000*					
	(-3.187)	(-0.604)	(-4.424)	(-1.770)	(-1.769)					
$\%\Delta VolCurr_{t-1}$	**-0.000**	**0.000**	**-0.000**	**-0.000**	**0.000**					
	(-0.208)	(0.537)	(-0.274)	(-1.440)	(0.817)					
$\%\Delta VolBTC_t$						-0.001***	-0.000	-0.003***	-0.000*	-0.000
						(-2.444)	(-0.335)	(-2.362)	(-1.724)	(-1.656)
$\%\Delta VolBTC_{t-1}$						**-0.000**	**0.000**	**-0.002**	**-0.000**	**0.000**
						(-1.053)	(0.797)	(-1.401)	(-1.435)	(0.874)
$CurrPrice_t$	-0.008***	-0.010***	-0.008***	-0.007***	-0.008***	-0.008***	-0.010***	-0.008***	-0.007***	-0.008***
	(-148.8)	(-4.323)	(-17.44)	(-2.014)	(-6.772)	(-147.9)	(-4.335)	(-17.43)	(-2.017)	(-6.808)
$CurrReturn_{t-1}$	-0.000	-0.074***	0.001	0.052*	-0.029	-0.000	-0.074***	0.001	0.052*	-0.029
	(-0.115)	(-6.687)	(1.128)	(1.763)	(-1.370)	(-0.103)	(-6.723)	(1.072)	(1.772)	(-1.364)
BTC price	0.000	0.000***	-0.000	0.000***	0.000***	0.000	0.000***	-0.000	0.000***	0.000***
	(1.058)	(2.382)	(-0.033)	(3.099)	(6.438)	(1.016)	(2.402)	(-0.045)	(3.099)	(6.438)
BTC return	0.008*	0.001	0.033	0.008***	0.004***	0.008	0.000	0.031	0.007***	0.004***
	(1.742)	(0.702)	(1.077)	(3.585)	(4.359)	(1.651)	(0.614)	(1.029)	(3.446)	(4.331)
adj R^2	0.79%	0.62%	0.59%	0.46%	0.45%	0.80%	0.62%	0.60%	0.45%	0.45%
n	14502	3682	2075	2654	6091	14502	3682	2075	2654	6091
F-statistic	28.20	6.49	4.21	4.40	8.75	28.20	6.49	4.21	4.40	8.75