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Bitcoin Price Growth and Indonesia's Monetary System

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ABSTRACT

Concerned by the volatility of Bitcoin price growth (BPG), Bank Indonesia—Indonesia's central bank—discourages trading cryptocurrencies. We examine the relationship between Bitcoin price growth (BPG) and Indonesia's monetary aggregates (inflation, real exchange rate, and money velocity). In doing so, we develop the conceptual link between Bitcoin and monetary aggregates. We find strong and robust evidence that BPG leads to inflation growth, currency appreciation, and a reduction in money velocity. Our results have policy implications for other central banks in terms of achieving stability of the monetary system if BPG is indeed a concern for those countries.

Keywords: *Bank Indonesia*; *Monetary Aggregates*; *Bitcoin*; *Volatility*.

I. Introduction

Cryptocurrencies have a market capitalisation of at least 3 billion USD.[1] They have also created market volatility. Their presence is tracked by policymakers in almost every country of the world where they are likely to impact markets. The main source of this attractiveness for cryptocurrencies has roots in the unusually high returns from bitcoin investments. Phillip, Chan and Peiris (2018), for example, note that a USD1000 investment in Bitcoin in July 2010 would have returned USD81 million after 7 years. This is extraordinary; hence, its volatility is just as expected. Given this, how Bitcoin will impact the exchange rate market, inflation and money velocity is not something that can be predicted. It is this unpredictability that prompted Bank Indonesia (the central bank of Indonesia) to warn Indonesians not to invest in Bitcoin. Several efforts, both by Bank Indonesia and regulatory authorities (such as the Police), have been made to prevent Bitcoin trading in Indonesia.[2] That cryptocurrencies are active in Indonesia is a cause for concern because they can potentially influence the monetary system. Given these potentially harmful effects, Bank Indonesia's policy stance on Bitcoin trading may likely negate the effects of Bitcoin prices.[3] The objective of our paper is to understand whether Bitcoin price growth (BPG) has impacted Indonesia's monetary system.

To-date, there is no knowledge and understanding of the dynamic behaviour of the Indonesian currency (the Rupiah (IDR), inflation rate, and money velocity when exposed to cryptocurrencies. Understanding this dynamic behaviour has implications for prudent

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[1] The five main cryptocurrencies that together make up almost 85% of the total cryptocurrency capitalisation are Bitcoin, Ethereum, Ripple, Bitcoin Cash, and Litecoin. Of these Bitcoin, created in 2008, is the most popular (Peters, Chapelle, and Panayi, 2016; Hughes and Middlebrook. 2015; Neguriță, 2014). Unlike money, crypto currencies are not backed, regulated, or monitored by a country, region or its governments or private organisations and have been circulated in the real economy through a process called mining (which involves solving a complex mathematical problem), beyond the reach of regulation and monetary policy (Peters, Chapelle, and Panayi, 2016). It should be noted that while money (or currency) has three main characteristics (medium of exchange, unit of account, and store of value) cryptocurrencies do not currently inherit all these characteristics of money. Hughes and Middlebrook (2015) note that cryptocurrencies are a subset of the virtual currencies and Bitcoin is a decentralised and convertible virtual currency.

[2] The information is obtained from Jakarta Post: see http://www.thejakartapost.com/news/2018/01/15/bank-indonesia-police-prevent-bitcoin-transactions-in-bali.html

[3] For an excellent Islamic perspective on Bitcoin, see Meera (2018).

monetary policy formulation. Our paper offers a first attempt at understanding the role of cryptocurrencies in shaping Indonesia's monetary system. Against this background, the hypothesis developed in this paper is that cryptocurrencies, because of the stance taken by Bank Indonesia on cryptocurrencies, do impact Indonesia's monetary system. Cryptocurrencies can de-stabilize payment systems and currencies (Gandal, Hamrick, Moore, and Oberman, 2018)[4]; yet, there is lack of knowledge on how, if at all, cryptocurrencies impact the monetary system. Countries have demonstrated mixed reactions to the acceptance of cryptocurrencies as a medium of exchange. For example, while Japan has (from April 2017) accepted cryptocurrencies as a medium of exchange, India and Indonesia have not. Indonesia is unique because the concerns about cryptocurrencies have been led by the country's central bank. The cryptocurrency concern in practice should be of relevance to other countries because, like the hypothesis we develop in this paper, BPC can impact inflation, money velocity, and exchange rates regardless of country. The lessons learned from the Indonesian experience therefore should have far reaching implications for debate and decision making in other countries regardless of whether they are emerging economies.

To test this hypothesis, we utilise a range of econometric methods. We begin with a GARCH type model and estimate theoretical models that motivate the determinants of inflation, real exchange rate and money velocity. Our novelty is that we develop the conceptual link between Bitcoin and key monetary aggregates and augment traditional theoretical models with the BPG variable.

To these models (see Section II.B), we fit monthly data over the period 2011 to 2018. We do find strong evidence that BPG influences Indonesia's monetary aggregates. Our analysis shows that when BPG increases, inflation increases, exchange rate appreciates, and money

[4] There are studies on Indonesia currency though from different perspectives; see Fitrianti (2017) and Muntasir (2015).

velocity declines. Overall, from these results, we conclude that BPG matters to Indonesia's monetary system, implying that the policy stance of Bank Indonesia is justified and has implications for other countries which maybe facing (or likely to face) the repercussions of the sudden extraordinary growth and emergence of the Bitcoin market.

We subject our hypothesis test to multiple robustness tests. First, we use multiple controls, dictated by economic theory, as determinants of monetary aggregates, in estimating how BPG affects those aggregates. We reach the conclusion that BPG is an important channel through which inflation, real exchange rate and money velocity seem to be impacted. Second, we use a different GARCH model to reach the same conclusion about the role of Bitcoin. Third, we are aware that structural breaks in the data can distort empirical results. We formally obtain structural breaks and embed them in the empirical framework. The results corroborate those obtained from models without structural breaks. Our main conclusion that BPG influences monetary aggregates holds.

Our main contribution to the literature is twofold. First, with the emergence of cryptocurrencies, an active academic interest has developed. The focus on this literature (see, *inter alia*, Gkillas and Katsiampa, 2018; and Phillip, Chan, and Peiris, 2018a/b) has been to understand the dynamic behaviour of cryptocurrencies, in particular Bitcoin—the currency that has garnered most interest; see, also Corbet, Meegan, Larkin, Lucey and Yarovaya (2018), who study volatility spillovers amongst a range of financial assets. See Section II.A for a summary of this literature. No study has considered how, if at all, cryptocurrencies have impacted exchange rate, inflation, and velocity of money in a manner consistent with our proposal. Our paper is the first to investigate the empirical association between BPG and monetary aggregates. In so doing, our paper offers a different channel through which one can understand the association between BPG and the monetary system.

Our second contribution is related to public policy. Bank Indonesia's policy stance has been to discourage Indonesians from trading Bitcoin. Other countries, such as India, follow a similar policy stance. Several policy announcements have been made by Bank Indonesia on cryptocurrencies with the aim of reining in market instability that cryptocurrencies can potentially create. Our hypothesis is aimed at testing the relevance of Bank Indonesia's policy stance on cryptocurrencies. If indeed BPG matters to the Indonesian monetary system then it is a signal that Bank Indonesia's policy stance is relevant and justified. We discover sufficient evidence supporting a clear role of BPG in shaping Indonesia's inflation, real exchange rate, and money velocity. These findings are important because (a) forecasts of inflation matter directly to economic growth, exchange rate expectations, and investment decisions, (b) the stability of Indonesia's money demand is imperative for effective monetary policy making, and (c) velocity of money, its trend, if not rising suggests that money is idle and not active which hinders the growth of inflation, having implications for short-term interest rates. Because cryptocurrencies are a recent phenomenon, there is limited understanding of how they influence those monetary aggregates. By documenting the empirical relationship between BPG and monetary aggregates, our paper sets the foundation for not only understanding the type of effect cryptocurrencies have on the monetary system but also on the effectiveness of central bank policies on cryptocurrencies such as those adopted by Bank Indonesia.

The rest of the paper has the following orientation. Section II provides a discussion on the status of the literature and the motivating theory. Section III discusses the data and some key features and messages emerging from the data. Section IV presents the empirical framework and discusses results. The final section provides concluding remarks.

II. Status of literature and motivating theory

This section has two objectives. First, we take a stock take of the literature on cryptocurrencies to give context to our research question/hypothesis. Within this literature, we highlight our key contribution. This literature is at a nascent stage and evolving. As we discuss here, we bring to this literature a different perspective on Bitcoin from the point of view of the monetary system. Second, we provide a theoretical motivation for the hypothesis we develop, where we establish the conceptual link between BPG and monetary aggregates.

A. A summary of the literature

The literature can be divided into multiple strands.[5] Broadly, one set of studies examines the efficiency (or otherwise) of the Bitcoin market. A preponderance of studies (see Al-Yahyaee, Mensi and Yoon, 2018; Cheah, Mishra, Parhi and Zhang, 2018' Almudhat, 2018; Yonghong, He and Weihua, 2017) argue that the Bitcoin market is inefficient.[6] These studies are complemented by papers showing that the Bitcoin market is highly speculative; see Baek and Elbeck (2015), Baur, Hong and Lee (2018) Katsiampa (2017), Dyhrberg (2016a), Cheah and Fry (2015), and Balcombe and Fraser (2017). This evidence is further complemented by Corbet, Lucey, and Yarovya (2017) and Cheung, Roca and Su (2015), who show cryptocurrency bubbles.

A second strand of studies investigates the diversification benefits of Bitcoin. In this regard, studies (see Bariviera, 2017; and Phillip, Chan and Peiris, 2018) show evidence of volatility clustering. Baur, Dimpfl and Kuck (2017) show that Bitcoin's statistical (first and second order moments and correlation) properties are different to gold and the US dollar. Dyhrberg (2016) argues that Bitcoin has diversification benefits. The strength of Bitcoin being

[5] There is a large volume of studies on this subject and it is not practical to cite every paper; we choose selected papers, which we believe is representative of the literature. Interested readers should consider other papers not cited here.
[6] Sensoy (2018) shows that efficiency is conditional on data frequency.

a strong hedge and safe heaven is shown in the work of Bouri, Jalkh, Molnar and Roubaud (2017), Bouri, Molnar, Azzi, Roubaud, and Hagfors (2017), Feng, Wang and Zhang (2018), Dyhrberg (2016b), and Śmiech and Papież (2017).

The third strand of the literature investigates what precisely predicts Bitcoin prices. This literature though is at a nascent stage. The work of Balcilar, Bouri, Gupta, and Roubaud (2017) finds that trading volume predicts Bitcoin price returns while Demir, Gozgor, Lau and Vigne (2018) show that the economic policy uncertainty index is a useful predictor.[7]

The key gap in this literature is about the role of cryptocurrencies in shaping monetary aggregates. This is what is unknown. Our study fills this gap. In doing so, we also develop the conceptual link between BPG and monetary aggregates. Using this as a motivation, we augment the theoretical models of exchange rate, inflation and money velocity with BPG. Our work, therefore, lays the foundation for future studies on this subject.

B. Motivating theory

Modelling the determinants of exchange rates, inflation, and money velocity constitutes traditional subjects of enquiry that occupy a large volume of studies in monetary and international economics. The theories that motivate the relationship between each of these variables and their determinants are well understood. Here, we provide a brief discussion of the theories that motivate modelling these monetary aggregates. We begin with the velocity of money.

Traditionally, the velocity of money has been studied using the framework of the quantity theory of money under which the circulation of money (MV) depends on its demand covering all transactions in an economy (PY) and is represented by $MV = PY$, where M is the

[7] A related literature has tested for price discovery in the Bitcoin market; see Brandvold, Molnar, Vagstad and Valstad (2015) and Btauneis and Mestel (2018).

nominal money supply defined as $M1$, which is money in circulation and demand deposits, or $M2$, which is $M1$ plus time deposits; V is velocity; P is prices; and Y is real output. This implies $V = PY/M$. The quantity theory of money in its classical form postulates that velocity is constant and that any changes in M fuels P, a result that is possible under conditions of full employment. However, if real money demand is seen as being determined by interest rate (r) and output (Y) rather than price, as per the Keynesian view, then higher short-term interest rate, r, and output may be seen as increasing velocity.[8] Brunner and Meltzer (1963) provide initial support for this positive association between nominal interest rate and velocity in the short-run. Recent studies typically use GDP and short-term interest rates to examine the velocity of money. Bordo and Jonung (1981) use over hundred years of data to estimate the velocity of M2 for selected OECD nations and find that V decreases with monetization and increases with financial innovation over time. Bitcoin, a financial innovation, which to an extent is also a substitute for money (in terms of the role of money as a store of value), is predicted to be negatively associated with V.

The effect of the adoption of Bitcoin, if seen as replacing money or inheriting one or more of the roles of money, should see a reduction of the circulation of money. In an extreme scenario, replacement of money with Bitcoin should see the demise of the quantity theory of money. This means that the ability of Y and r to affect the circulation of money can be expected to weaken with increased usage of Bitcoin relative to money.

Next, we examine the link between inflation and Bitcoin within versions of the New Keynesian Phillips Curve (NKPC) framework, where inflation is a function of: (1) marginal cost of production, which is proxied using labour share; (2) lags of inflation to allow for the

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[8] Money demand is defined as $\left(\frac{M}{P}\right)^d = f(Y, r)$; where P is price level; $\left(\frac{M}{P}\right)^d$ is real money demand; Y is real output; and r is the interest rate. Through simple manipulation, this can be re-written as $V = \frac{PY}{M} = \frac{Y}{f(Y,r)}$, where an increase in Y or r increases V.

formation of inflation through expectations built by backward looking agents; and (3) leads of inflation to allow for forward looking agents (see Lannet and Luoto, 2014; Chritiano, Eichenbaum, and Evans, 2005; Gali and Gertler, 1999). This model is also augmented to include external factors that may influence marginal cost in an open economy, such as import prices relative to domestic prices, and oil prices (see Gordon, 1997, 2001; Gali and Monacelli, 2005; Blinder and Rudd, 2008). The traditional versions of the NKPC explain inflation in terms of expected inflation and unemployment rate or output gap (see Roberts, 1995; Sbordone, 2002; Gali and Gertler, 1999). We propose that BPG may influence the marginal cost component through an indirect channel. In particular, Bitcoin is used for investment and is now perceived as a store of value; hence, its effect on inflation via the marginal cost channel may come indirectly in the form of the wealth effect.

Owners of Bitcoin experience an increase in their wealth as Bitcoin increases, which may stimulate their demand for goods and services and put pressure on prices of inputs of these goods and services. As more individuals invest in Bitcoin, the same wealth effect will exert upward pressure on prices of inputs. And if Bitcoin is not within the realms of the monetary policy, any policy action other than regulation to ban Bitcoin to defuse increasing inflation would fail. We, therefore, predict that BPG will create inflationary pressures.

Finally, we examine real exchange rate movements for the Indonesian Rupiah vis-a-vis the US dollar against Bitcoin. Our models include other determinants of real exchange rate, namely, real interest rate differential between the US and Indonesia, inspired by the uncovered real interest rate parity; productivity differentials, explained in the well-known Balassa-Samuelson model (see Meese and Rogoff, 1988); and oil prices (see Camarero and Tamarit, 2002; Narayan, 2013; and Chen and Chen, 2007). This model is augmented with BPG. It is expected that a higher BPG will create a wealth effect on trade with an ambiguous effect on exchange rate. On these arguments, we predict that exchange rate could either appreciate or depreciate in response to BPG.

II. Data and preliminary features

This section discusses our dataset. To test our proposed hypothesis, we combine two different types of data. First, we have the Bitcoin price data. Second, we have data on macroeconomic indicators relating to Indonesia (and the US), namely, the exchange rate, short term interest rate, velocity of M1 and M2 (V1, V2), inflation (INF), industrial production (IP), consumer price index (CPI), and gross domestic product (GDP). In the case of the exchange rate model, we calculate additional variables, namely, real exchange rate (RER); short-run interest rate differential between the US and Indonesia (RIR1 and RIR3); productivity differential between the two countries (DY); and the real GDP (RGDP). Data on V1 and V2 and Indonesia's macroeconomic data are sourced from the *Bank Indonesia* while all other economic data are sourced from the *Global Financial Database*. Full details on each variable (its source, description and calculation) are available in Table I.

These macroeconomic indicators are available for many decades; however, because the Bitcoin price data is only available from a recent period, our final dataset spans the period September 2011 to April 2018. We also run models without the BPG over a longer time span to mainly provide a basis for testing the appropriateness of the choice of the control variables which are the traditional determinants of monetary aggregates.

Before testing our hypothesis, it is important to understand this data and appreciate the preliminary implications the data offer. To begin with, we examine the plot of the time-series data. Figure I suggests several important messages. The first point is directly related to the theme of this research—that is, the stability or otherwise of Indonesia's exchange rate, inflation, and velocity of money. All these three variables show serious movements: there are phases of instability witnessed in all these series, suggesting factors that matter to them. One source of this instability could be Bitcoin, which is what we test in Section IV. Pictorial evidence also points to potential heteroskedasticity. If formally true (which is what is tested later in this section), this would have implications for the choice of our econometric modelling techniques, for testing our hypothesis would need to account for heteroskedasticity. The second feature of the data relates to structural breaks. It is obvious that all data series have undergone structural changes. The important one is Bitcoin price—our variable of interest. The implication is that in testing our hypothesis, to ensure that we do not obtain spurious outcomes, we need to account for these structural changes in the Bitcoin price.

Table II formally looks at the pictorial story that we have told so far. For example, skewness and kurtosis statistics imply a non-normal distribution of the growth rate series of macroeconomic indicators and indeed of the BPG. Non-normal distributions imply heteroskedasticity. We undertake an autoregressive conditional heteroskedasticity (ARCH) Lagrange multiplier test for heteroskedasticity. This amounts to running an AR(12) ordinary least squares regression model of each of the main growth variables and subjecting the residuals to a null hypothesis of "no ARCH" test. For BPG, we obtain an *F*-statistic of 0.534 (*p*-value = 0.88); for velocity of money series, *F*-statistic = 2.04 (*p*-value = 0.03) and 0.33 (*p*-value = 0.98) for V1 and V2, respectively. For inflation, we find that *F*-statistic = 1.87 (*p*-value = 0.99) and for exchange rate growth, the *F*-statistic = 0.44 (*p*-value = 0.93). Overall, except for V1 we reject the null of "no ARCH", suggesting that heteroskedasticity is a feature of the growth series we have. The implication is that we need to adopt an econometric approach that specifically models heteroskedasticity. Given this, we choose to use a generalised ARCH (GARCH) model for testing our hypothesis.

We also test for unit roots. This is important because it has implications for the econometric modelling specification. We find that most variables are non-stationary in their level form. The exception is V1 and inflation, which turn out to be stationary: that is, the null hypothesis of a unit root is rejected at the 5% level or better. The growth form of all other variables is unit root stationary; that is, the null hypothesis is comfortably rejected. The implication is that if variables are non-stationary their stationary form (either in first difference or growth form) is then used in regression models.

III. Empirical framework and results

This section has two objectives. The first is to establish the econometric framework and the second is to empirically test our hypothesis that BPG influences Indonesia's monetary aggregates.

A. Empirical framework

The preceding section emphasised that our empirical framework should be one that takes account of data heteroskedasticity. An ideal model in this regard is a GARCH framework. We, therefore, propose the following model to test whether BPG effects Indonesia's monetary system. The mean equation has the following representation:

$$MI_t = a_0 + \rho BITCOIN_t + \pi X_t + \varepsilon_t \quad (1)$$

Here, MI_t is one of the monetary indicators (namely, *INF*, *RER* and *MV*) and $BITCOIN$ is the first difference of the Bitcoin price (or BPG) or the GARCH variance of the BPG. Finally, X_t represents a vector of control variables. When *MI* is MV, X_t includes GDP and interest rates; When *MI* is *INF,* the controls are leads and lags of inflation, output gap or unemployment rate, import price, and oil price; and when *MI* is *RER,* we use real interest rate differential, productivity differential, and oil price as controls. In this setup, ε_t, follows the first-order GARCH model (GARCH (1, 1)), written as:

$$\varepsilon_t = \eta_t \sqrt{h_t}\,, \;\; \sigma_t^2 = \varkappa + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (2)$$

Here, $\varkappa > 0, \alpha \geq 0, \beta \geq 0,$ and η_t is a sequence of independently and identically distributed random variables with zero mean and unit variance. We assume errors behave normally and use the maximum likelihood to estimate the parameters.

B. First set of results

We have a wide range of results including robustness test results. We organise the presentation and discussion as follow. We first test and report results from each of the models relating to inflation, real exchange rate, and money velocity. We augment all these three theoretical models with the BPG variable inspired by the conceptual framework presented in Section II. In the second part of this section, we focus on the robustness of our results. Mainly, we focus on two aspects; sensitivity of our results to (a) a different econometric model and (b) the presence of structural breaks.

B1. Main results

For each monetary aggregate (*INF*, *RER*, and *MV*), we begin explaining their determinants through estimating conventional models of inflation, real exchange rate and velocity—that is, models without the BPG (and its volatility). The literature on inflation is sensitive to the chosen variables. As a result, several alternative empirical models are presented for the purpose of comparison and robustness. The results reported in Table III-X reveal the following. In summary, we find strong evidence that BPG had a significant effect on all the three macroeconomic variables. However, except for V2, BPG volatility had no effect on monetary aggregates. Now we will consider the results in detail.

Tables III-V explain inflation in Indonesia with (2012-2017) and without (2000-2017) BPG or its volatility. Notice also that the sample period shrinks with the inclusion of BPG, hence it becomes important to check the robustness of the traditional model of inflation used here against a longer sample period. Across all the empirical models estimated within the NKPC framework, the lags and leads of inflation are found to be statistically significant drivers of inflation. Unemployment has the theoretically correct negative sign and is statistically significant in model (5) (see Table III). The introduction of BPG did not affect the relationship that the traditional NKPC factors had with inflation in Indonesia. However, we notice from Table IV that BPG has a statistically significant and positive effect on inflation in models (1) and (6). This suggests that an increase in BPG fuels inflation in Indonesia. Results reported in Table V are based on inflation models that instead of BPG include its volatility, which is, as explained earlier, measured as a GARCH(1,1) process. We find across all five models that volatility of BPG has no statistically significant effect on Indonesia's inflation rate.

In Tables VI-VIII, we present the real exchange rate (*RER*) models with (2012-2017) and without (1993-2017) BPG or its volatility. Real interest rates (*RIR1* and *RIR3*) are found to be the most important traditional determinants of the *RER*. Oil price and *DY* are weakly significant (Table VI). These traditional relations are unaffected when BPG is introduced in the model. However, BPG is found to be an important determinant of the *RER* (see models (3) -(9) in Table VII). The BPG and the *RER* are found to be positively related, which means that higher BPG leads to an appreciation of the Rupiah against the US dollar. On the other hand, BPG volatility has no statistically significant effect on *RER* (see Table VIII).

Finally, we examine models relating to the velocity of money (Tables IX-X). In Panel A of Table IX, the traditional velocity of money models are presented. Of the two factors, *RGDP* is found to be a statistically significant determinant of the velocity of money across the two definitions of velocity (*V1* and *V2*). That higher *RGDP* increases velocity of money is a theoretically sound finding. Velocity is weakly associated with the one-month interbank rate and the effect is negative. The introduction of BPG did not affect the importance of the traditional factors determining velocity; however, BPG becomes a statistically important determinant of velocity (V1). As a financial innovation, Bitcoin is a substitute for money when it comes to its role as a store of value, hence it is not surprising that there is a negative effect on velocity of money, suggesting that BPG leads to a reduction in the velocity of money. What is surprising is that the significant and negative effect of Bitcoin is confined to the *V1* and not to *V2*. BPG volatility, on the other hand, is found to be associated with *V2* and the effect is negative (Table X), however, this result is not robust.

B2. Robustness tests

We have estimated the effects of BPG on Indonesia's monetary aggregates with theoretical models of inflation, real exchange rate, and money velocity. We find strong evidence that BPG matters to those aggregates and, therefore, the implication is that whatever happens to Bitcoin prices is of interest to monetary authorities and other policy makers. These results also imply that if the goal of policymakers is to forecast inflation, real exchange rate and/or money velocity, the role of BPG should be modelled through augmentation of conventional theoretical models as shown in this paper. Ignoring the role of BPG will be costly because it does influence Indonesia's monetary aggregates.

With such a strong policy connection of our work, we attempt to confirm the robustness of our results along two additional lines: namely, by (a) using a different type of GARCH model (exponential GARCH, known as EGARCH) and (b) accounting for structural breaks in the Bitcoin price. With (a) we aim to confirm that our results are insensitive to the choice of model and with (b) we aim to test whether structural breaks, given that they are obvious (as can be seen from Figure 1), influence our results. Estimates from EGARCH (1,1) model, not reported here, suggest results are consistent with those obtained from the GARCH (1,1) model. This implies that BPG influences monetary aggregates regardless of the form of GARCH model we employ.

Next, we check whether results are sensitive to structural breaks. To obtain break dates endogenously, we employ the Narayan and Popp (NP, 2010) structural break unit root test. This test is preferred because Monte Carlo evidence presented in NP (2013) suggests that the test identifies the break dates most accurately compared to other tests. Using this test, we find the break dates in Bitcoin price series to be 2013:02 and 2013:10. We then create a dummy variable (DV), which takes a value 1 on the two break date months and a value of 0 otherwise. We then re-estimate the main regression models to test whether controlling for breaks in Bitcoin price influences the effect of BPG on inflation, real exchange rate and money velocity. For the inflation model, for instance, we re-estimate model (6) from Table IV and find that while the slope efficient on BPG is small (0.182), it is still statistically significant with a *p*-value of 0.04. The slope dummy variable turns out to be 0.456 (*p*-value = 0.000), suggesting that breaks in the Bitcoin price increased inflation by around 46% in that month. From the exchange rate models, we re-estimate model (5) from Table VII and find the slope coefficient on BPG to be unchanged (0.017, *p*-value = 0.008) and a DV coefficient of 0.0003 (*p*-value =0.995), suggesting that in the RER model, the break dates in the bitcoin price are unimportant.

Finally, we model the effect of DV on velocity regressions. Essentially, we augment regressions reported in Panel B (Table IX) with DV. When the dependent variable is V1 the slope coefficient on the DV variable is statistically insignificant (*p*-value = 0.884) but the slope coefficient of BPG retains its statistical significance (*p*-value = 0.002) with only a slight decline in the magnitude of the slope coefficient (-0.031). When the dependent variable is V2 neither DV nor BPG are statistically different from zero. On the whole, therefore, the conclusion from these additional tests is that structural breaks in the Bitcoin price do matter but only to Indonesia's inflation rate; however, the effect of BPG on Indonesia's monetary aggregates is insensitive to structural breaks in the Bitcoin price. In this regard, our results on the effects of BPG on monetary aggregates are robust.

IV. Concluding remarks

Cryptocurrencies are a global phenomenon with Bitcoin being the main driver of this market. Given their impressive debut amongst cryptocurrencies and phenomenal growth (in prices), they can have a de-stabilizing effect on a country's monetary system. This concern sparked a strong policy response from Bank Indonesia, which discourages trading cryptocurrencies (Bitcoin). It is this policy stance, and the implications this policy can have on policy directions of other central banks, that motivated the present study.

Specifically, we examine how, if at all, BPG impacts inflation, real exchange rate, and money velocity in Indonesia over the 2011 to 2018 period based on monthly data. Employing a range of theoretical models that we augment with BPG (through developing the conceptual link between BPG and monetary aggregates), we find ample evidence that BPG influences Indonesia's monetary aggregates. More specifically, our findings suggest that BPG increases inflation, appreciates Indonesia's currency, and reduces money velocity. These findings tend to provide support for the policy stance taken by Bank Indonesia with respect to cryptocurrency trading in Indonesia. Our study, therefore, will be useful to other central banks where the objective is to control the effects of cryptocurrencies on the monetary system.

Our results also have implications for modelling and forecasting Indonesia's monetary aggregates. The message is that in any such econometric exercise the role of Bitcoin should not be ignored. Finally, our study contributes to the broader literature on cryptocurrencies by telling a story about how they potentially influence the monetary system in the case of an emerging country, Indonesia. Our work, as a result, lays the foundation for future research on this subject.

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Figure I: A time-series plot of data

This figure plots time-series variables from our dataset. Both the levels (original form) of the variables and their growth form (where the original series is non-stationary) are plotted. The first-row plots are bitcoin price (BITCOIN), consumer price index (CPI), the USD/IDR exchange rate—number of USD per home currency (Rupiah) (ER), and gross domestic product (GDP). The second-row plots money velocity (V1 and V2), inflation rate (growth rate of CPI, denoted INFLATION), and the growth rate of ER (GER). The last row plots the 1-month and 3-month interest rate (IR_1 and IR_3), and the Bitcoin price growth (GBITCOIN).

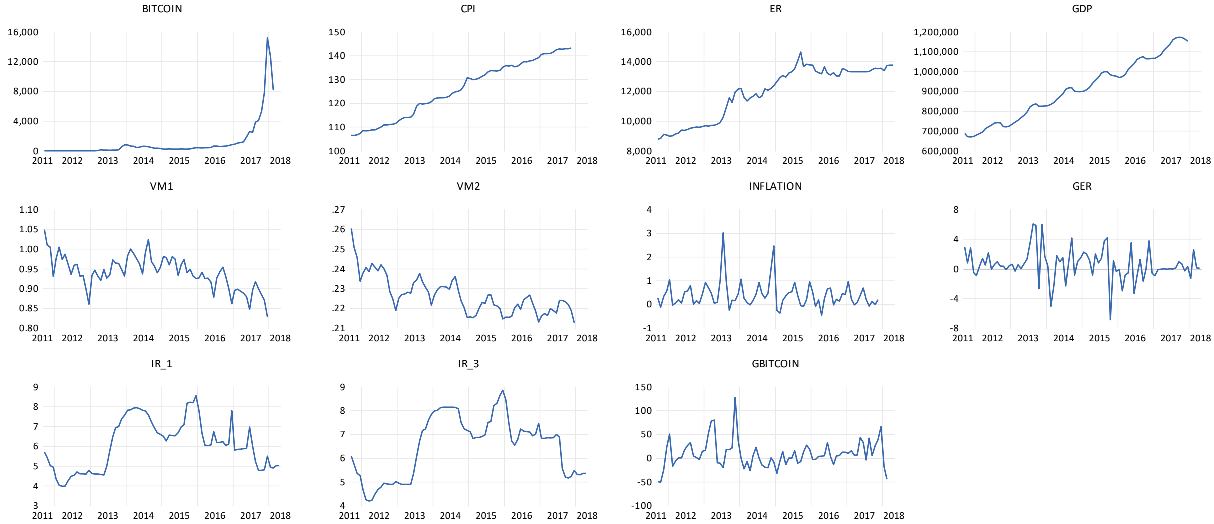

Table I: Data definition and sources

This table describes each variable, its calculation (where applicable) and its source used in estimating the inflation model (Panel A), exchange rate model (Panel B), and the money velocity model (Panel C).

Panel A: Inflation Model			
Variables	Definition	Author's Calculations	Source
Bitcoin	This does not include Bitcoin cash. It captures closing price of bitcoin		coinmarketcap.com
INF	Inflation rate	Year-on-year percentage change in the consumer price index (CPI, of all items) Indonesia	CPI – International Financial Statistics; Author's calculations
MP	Import Price Index		Global Financial Database
UM	Unemployment rate for Indonesia		Bank Indonesia
OP	Crude Oil Prices: West Texas		Global Financial Database
GAP	Output gap	Computed from a trend model	Bank Indonesia
Panel B: Exchange Rate Model			
Variables	Definition	Calculations	Source
RER	Real exchange rate, expressed as the number of foreign currency units per home currency unit.	$RER_t = \frac{Rupiah}{USD} * \frac{CPI_{Indo}}{CPI_{US}}$	Nominal exchange rate ($\frac{Rupiah}{USD}$) is sourced from Global Financial Database; ticker: USDIDR; RER is calculated by the author.
RIR1 and RIR3	Difference between United States and Indonesian 1-month Interbank Rate	$RIR_{i,t} = Nominal\ \ interbank\ rate_{i,t} - inflation\ rate\ _{i,t}$, where i is the US or Indonesia; $RIR1_t = RIR_{Indo,t} - RIR_{US,t}$	Nominal interest rate: Global Financial Database; CPI – International Financial Statistics; Inflation – author's calculations
DY	Difference of the logarithm of industrial production (IP) of the US and Indonesia	$LOG(IP_{INDONESIA}) - LOG(IP_{US})$	IP_{US}: Global Financial Database; $IP_{INDONESIA}$: International Financial Statistics; IP_DIFF – author's calculations
Panel C: Velocity model			
V1 and V2	Velocity of M1 and M2	$V = PY/M$ where M is M1 and M2	Bloomberg/International Financial Statistics (IFS)/ Bank Indonesia
RGDP	Real GDP	$RGDP = GDP/CPI$	Global Financial Database
IR_1 and IR_3	One-month and three-month Inter-bank rate		Global Financial Database

Table II: Descriptive statistics of data

This table reports selected descriptive statistics of the data. The sample period depicts the maximum observations captured in the empirical analysis. For each of the 15 time-series data, we report mean, standard deviation (SD), maximum. Minimum. Skewness, kurtosis, and ADF test statistics. The ADF test is based on a model with a constant only. The optimal lag length used to control for serial correlation is obtained using the Schwarz information criteria. We set the maximum lag length to 8. The p-values testing the null hypothesis of a unit root are reported.

	Sample period	Mean	Maximum	Minimum	SD	Skewness	Kurtosis	ADF
Bitcoin	2011:08-2018:02	1105.10	15235.02	2.97	2571.98	3.89	18.70	0.99
V1	2011:01-2017:12	0.94	1.08	0.00	0.11	-6.49	54.24	0.17
V2	2011:01-2017:12	0.23	0.26	0.21	0.01	1.07	3.43	0.00
INF	1990:01-2017:11	9.83	82.40	-1.10	11.89	4.40	23.60	0.00
IR_1	2011:01-2018:04	6.12	8.55	3.98	1.21	0.03	1.95	0.07
IR_3	2011:01-2018:05	6.52	8.86	4.21	0.01	-0.23	1.92	0.29
OP	1990:01-2018:04	46.99	133.88	11.35	29.86	0.77	2.39	0.23
RER	1993:12-2017:11	0.00	0.00	0.00	0.00	-0.34	2.68	0.18
RGDP	2011:01-2017:12	704276.50	821357.40	577427.90	58942.48	0.08	2.33	0.98
RIR1	1993:12-2018:04	-26.77	42.56	-106.25	41.10	-1.12	2.68	0.56
RIR2	1993:12-2018:04	3.50	107.82	-40.00	15.07	5.23	38.56	0.85
DY	1998:01-2013:03	-0.11	0.17	-0.68	0.16	-0.61	3.49	0.03
UM	2000:01-2017:12	7.76	10.75	5.82	1.67	0.32	1.58	0.43
MP	1991:01-2018:03	0.78	1.18	0.29	0.23	-0.14	2.01	0.65
GAP	2000:01-2017:12	0.000	151692.7	-104737.9	62435.1	0.481	2.379	0.32

Table III: Inflation models: 2000-2018

The table presents results relating to inflation models without the Bitcoin price variable. The models include: (1) appropriate lag structure of inflation (INF) to capture inflation expectations by backward looking economic agents; (2) appropriate leads of inflation to capture inflation expectations of forward looking economic agents; and (3) marginal cost defined as output gap (GAP), unemployment (UM), oil prices (OP) and/or import prices (MP). Inflation is captured as the year-on-year rate of growth in CPI of all items; UM, MP and OP appear in logarithmic first difference form. Panel B provides results from the variance equation. In row 1, numbers 1 to 7 denote the different regression models. Finally, *,**, *** denote levels of significance at the 10%, 5% and 1%, respectively.

Models	1		2		3		4		5		6		7	
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Panel A: Mean equation														
α_0	-0.038	0.109	-0.025	0.495	-0.027	0.515	-0.025	0.540	0.116	0.266	0.487	0.044	-0.007	0.876
$lnINF_{t-1}$	0.854***	0.000	0.714***	0.000	0.716***	0.000	0.712***	0.000			1.079***	0.000	0.712***	0.000
$lnINF_{t-2}$	-0.449***	0.000	-0.317***	0.000	-0.326***	0.000	-0.316***	0.000			-0.151	0.103	-0.317***	0.000
$lnINF_{t-3}$	0.120***	0.000	0.097**	0.019	0.098***	0.000	0.094***	0.000					0.094***	0.000
$lnINF_{t-4}$			-0.002	0.913										
$lnINF_{t+1}$	0.735***	0.000	0.752***	0.000	0.762***	0.000	0.753***	0.000	1.405***	0.000			0.749***	0.000
$lnINF_{t+2}$	-0.337***	0.000	-0.326***	0.000	-0.324***	0.000	-0.318***	0.000	-0.556***	0.000			-0.313***	0.000
$lnINF_{t+3}$	0.082***	0.000	0.067***	0.000	0.078***	0.000	0.080***	0.000	0.237***	0.000			0.076***	0.000
$lnINF_{t+4}$			0.021***	0.000					-0.104***	0.002				
ΔGAP_t			0.000	0.711										
$\Delta lnUM_t$					0.935	0.580	-0.081	0.960	-13.068***	0.002	19.579	0.127	0.398	0.822
$\Delta lnMP_t$							0.052	0.911	0.495	0.784	2.335	0.555	0.887	0.288
$\Delta lnOP_t$									-0.888	0.112	-0.387	0.743	-0.322	0.143
Panel B: Variance Equation														
$\varkappa$	0.038***	0.000	0.043***	0.000	0.049***	0.000	0.047***	0.000	0.280***	0.000	0.495	0.329	0.049***	0.000
ε_{t-1}^2	1.044***	0.000	1.172***	0.000	1.052***	0.000	1.091***	0.000	1.010***	0.000	-0.014***	0.000	1.025***	0.000
σ_{t-1}^2	0.055	0.158	-0.043	0.574	-0.056	0.498	-0.046	0.547	-0.004	0.916	0.562	0.222	-0.048	0.549
$\bar{R}^2$	0.995		0.964		0.964		0.964		0.907		0.911		0.964	

Table IV: Inflation models augmented with Bitcoin price: 2011-2018

This table presents results relating to the inflation models augmented with Bitcoin price growth. Panel A includes results from the mean models. Models (1) - (6) include leads and/or lags of inflation to capture inflation expectations of forward and backward-looking agents. These models, including model (7), capture other variables namely unemployment (UM), oil prices (OP) and/or import prices (MP). Inflation is captured as year-on-year rate of inflation estimated using the CPI of all items; UM, OP, MP and bitcoin appear in logarithmic first difference form. Panel B provides results from the variance equation. In row 1, numbers 1 to 7 denote the different regression models. Finally, *,**, *** denote levels of significance at the 10%, 5% and 1%, respectively.

Models	1		2		3		4		5		6		7	
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Panel A: Mean equation														
α_0	0.035	0.538	0.075	0.339	0.346***	0.000	0.062	0.593	0.265***	0.000	0.128***	0.004	4.073***	0.000
$\Delta lnUM_t$	13.48*	0.094	18.056*	0.060	-7.459	0.794	-0.832	0.965	-3.892	0.886	-1.958	0.907	-40.65*	0.057
$\Delta lnMP_t$	0.672	0.239	-0.085	0.955	1.781	0.684	-0.384	0.828	4.330	0.369	1.946	0.316	-6.993**	0.010
$\Delta lnOP_t$			-0.150	0.643					-1.266	0.073	-0.909	0.124	-0.512	0.564
$\Delta lnBitcoin_t$	**0.151*** **	**0.000**	0.086	0.430	0.046	0.903	0.277	0.158	0.020	0.955	**0.295** **	**0.039**	0.225	0.285
$lnINF_{t-1}$	0.613***	0.000	0.685***	0.000			0.966***	0.000			0.953***	0.000		
$lnINF_{t-2}$	-0.170***	0.000	-0.187***	0.000	1.214***	0.000								
$lnINF_{t+1}$	0.772***	0.000	0.691***	0.000	-0.287***	0.000			1.248***	0.000				
$lnINF_{t+2}$	-0.218***	0.000	-0.198***	0.000					-0.297***	0.000				
Panel B: Variance Equation														
$\varkappa$	0.000	0.957	0.022	0.098	0.011	0.231	0.076	0.010	0.009	0.292	0.060	0.004	0.082	0.100
ε_{t-1}^2	2.766	0.000	1.264	0.001	-0.121	0.000	1.818	0.000	-0.116	0.000	2.266	0.000	1.410	0.000
σ_{t-1}^2	0.023	0.26	-0.034	0.488	1.119	0.000	-0.021	0.725	1.123	0.000	-0.026	0.586	-0.069	0.568
$\bar{R}^2$	0.943		0.944		0.844		0.830		0.840		0.825		-0.405	

Table V: Inflation models augmented with Bitcoin volatility: 2011-2018

This table presents results relating to the inflation models augmented with Bitcoin price volatility which is computed as an AR(8) GARCH (1,1) model of bitcoin price returns. Panel A includes results from the mean models. Models (1) - (2) include leads and models (4) – (5) include leads of inflation to capture inflation expectations of forward and backward-looking agents, respectively. These models, including model (7), capture other variables namely unemployment (UM), oil prices (OP)and/or import prices (MP). Inflation is captured as year-on-year rate of inflation estimated using the CPI of all items; UM, OP, MP and bitcoin appear in logarithmic first difference form. Panel B provides results from the variance equation. In row 1, numbers 1 to 5 denote the different regression models. Finally, *, **, *** denote levels of significance at the 10%, 5% and 1%, respectively.

	1		2		3		4		5	
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Panel A: Mean Equation										
α_0	-0.032	0.814	-0.028	0.756	3.814***	0.000	0.005	0.965	0.430*	0.086
$lnINF_{t-1}$	0.709***	0.000	0.708***	0.000			0.982***	0.000		
$lnINF_{t-2}$	-0.282***	0.004	-0.281***	0.002						
$lnINF_{t-3}$	0.070	0.311	0.076	0.209						
$lnINF_{t+1}$	0.723***	0.000	0.719***	0.000					1.210	0.000
$lnINF_{t+2}$	-0.301***	0.000	-0.302***	0.000					-0.278	0.000
$lnINF_{t+3}$	0.089**	0.013	0.089**	0.014						
$\Delta lnUM_t$	14.08	0.509	14.55	0.428	-195.9***	0.000	17.12	0.695	46.67	0.457
$\Delta lnMP_t$	-0.031	0.989	-0.565	0.802	-5.992	0.148	2.250	0.548	3.762	0.408
$\Delta lnOP_t$			-0.178	0.743	-1.411*	0.059	-0.835	0.389	-2.046**	0.009
σ_t^2	-0.116	0.765	-0.267	0.353	0.376	0.583	0.258	0.846	0.355	0.789
Panel B: Variance Equation										
$\varkappa$	0.035	0.101	0.029	0.092**	0.049	0.434	0.142	0.023**	0.016	0.139
ε_{t-1}^2	1.203**	0.032	1.269**	0.038	1.308***	0.000	1.119***	0.007	-0.131***	0.000
σ_{t-1}^2	-0.102	0.431	-0.084	0.529	0.044	0.739	-0.039	0.819	1.149***	0.000
$\bar{R}^2$	0.943		0.942		-0.646		0.816		0.831	

Table VI: Real Exchange rate (RER) model with traditional determinants: 1993-2018

This table reports results from the real exchange rate determinants model, which includes as determinants the difference in the short-term real interest rate between Indonesia and the US (RIR1, RIR3), oil prices (OP), and the difference in log of industrial production between Indonesia and the US (DY). The RER appears in the model as the number of foreign currency units per home currency unit. Hence, an increase in the RER is an appreciation of the RER. Variables RER, OP, and DY are in logarithmic first difference form. Panel B provides results from the variance equation. In row 1, numbers 1 to 6 denote the different regression models. Finally, *, **, *** denote levels of significance at the 10%, 5% and 1%, respectively.

	1		2		3		4		5		6	
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Panel A: Mean Equation												
α_0	0.002*	0.079	0.003**	0.029	0.003**	0.030	0.003***	0.005	0.006***	0.001	0.003	0.170
$\Delta RIR1_t$	-0.000*	0.082			-0.000*	0.052	-0.002***	0.000	0.000	0.983	-0.004***	0.000
$\Delta RIR3_t$			-0.002***	0.000								
$\Delta lnOP_t$					-0.017	0.313	-0.019*	0.093	-0.037	0.146	0.021	0.409
ΔDY_t									-0.028	0.885	-0.048	0.355
Panel B: Variance Equation												
$\varkappa$	0.000***	0.000	0.000***	0.000	0.000***	0.000	0.000***	0.001	0.000	0.146	0.000**	0.021
ε_{t-1}^2	0.527***	0.000	0.571***	0.000	0.571***	0.000	0.646***	0.000	0.689***	0.000	0.247**	0.013
σ_{t-1}^2	0.603***	0.000	0.589***	0.000	0.589***	0.000	0.567***	0.000	0.512***	0.000	0.712***	0.000
$\bar{R}^2$	-0.011		0.014		-0.018		0.006		-0.021		0.039	

Table VII: Real Exchange rate model with Bitcoin price: 2011-2018

This table reports results from the real exchange rate determinants model, which includes as determinants the difference in the short-term real interest rate between Indonesia and the US (RIR1, RIR3), oil prices (OP), and the difference in log of industrial production between Indonesia and the US (DY). The model is augmented with the first difference (log of) of the Bitcoin price variable (Panel A). The RER appears in the model as the number of foreign currency units per home currency unit. Hence, an increase in the RER is an appreciation of the RER. Variables RER, OP, and DY are in logarithmic first difference form. In row 1, numbers 1 to 9 denote the different regression models. Panel B provides results from the variance equation. Finally, *, **, *** denote levels of significance at the 10%, 5% and 1%, respectively.

	1		2		3		4		5		6		7		8		9	
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Panel A: Mean Equation																		
α_0	-0.005**	0.032	-0.005**	0.028	-0.006**	0.002	-0.006**	0.016	-0.005***	0.006	-0.008***	0.005	-0.005**	0.013	-0.006	0.113	-0.005*	0.075
$\Delta RIR1_t$			0.000	0.954			0.000	0.960			-0.002	0.868	0.010***	0.000	-0.002	0.864		
$\Delta RIR3_t$					0.007***	0.002			0.006***	0.007							0.003***	0.000
$\Delta lnOP_t$							-0.019	0.522	-0.030	0.294					-0.054	0.247	-0.045	0.311
ΔDY_t											0.244	0.822	0.058	0.102	0.230	0.847	0.026	0.536
$\Delta lnBitcoin_t$	0.013	0.166	0.015	0.133	0.018***	0.007	0.017*	0.071	0.017***	0.007	0.029***	0.001	0.032***	0.000	0.028***	0.000	0.026***	0.000
Panel B: Variance Equation																		
$\varkappa$	0.000***	0.010	0.000**	0.019	0.000	0.153	0.000**	0.021	0.000	0.164	0.000	0.245	0.000	0.142	0.000	0.794	0.000	0.727
ε_{t-1}^2	0.325**	0.018	0.329**	0.018	0.666**	0.022	0.351**	0.020	0.623*	0.055	-0.706	0.529	-0.386*	0.069	-0.197	0.767	-0.205	0.662
σ_{t-1}^2	0.544***	0.000	0.542***	0.000	0.438***	0.000	0.542***	0.000	0.466***	0.001	1.228	0.201	0.699	0.320	0.610	0.728	0.613	0.680
$\bar{R}^2$	-0.048		-0.069		-0.182		-0.097		-0.183		0.172		0.128		0.103		0.166	

Table VIII: Exchange rate model with Bitcoin volatility: 2011-2018

This table reports results from the real exchange rate determinants model, which includes as determinants the difference in the short-term real interest rate between Indonesia and the US (RIR1, RIR3), oil prices (OP), and the difference in log of industrial production between Indonesia and the US (DY). The model is augmented with the Bitcoin price volatility variable which is estimated as an AR(8) GARCH(1,1) model (Panel A). The RER appears in the model as the number of foreign currency units per home currency unit. Hence, an increase in the RER is an appreciation of the RER. Variables RER, OP, and DY are in logarithmic first difference form. Panel B provides results from the variance equation. Finally, *, **, *** denote levels of significance at the 10%, 5% and 1%, respectively.

Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Panel A: Mean Equation														
α_0	-0.001	0.864	-0.000	0.932	-0.001	0.892	0.001	0.530	0.003	0.175	0.002	0.391	0.000	0.975
$\Delta RIR1_t$			-0.000	0.933			0.000	0.976			0.000	0.970		
$\Delta RIR3_t$					-0.002	0.687			-0.003	0.328			-0.001	0.973
ΔDY_t							-0.052	0.909	-0.022	0.397	-0.052	0.888	-0.018	0.509
$\Delta lnOP_t$											-0.010***	0.000	-0.045	0.778
σ_t^2	-0.029	0.473	-0.039	0.318	-0.029	0.467	-0.049	0.679	-0.111	0.289	-0.064	0.501	0.022	0.932
Panel B: Variance Equation														
$\varkappa$	0.000	0.017	0.000	0.009	0.000	0.041	0.000	0.756	0.000	0.714	0.000	0.754	0.000	0.572
ε_{t-1}^2	0.305**	0.034	0.318**	0.034	0.328**	0.034	0.094	0.838	0.040	0.962	-0.019	0.929	-0.143	0.721
σ_{t-1}^2	0.565	0.000	0.547	0.000	0.562	0.000	0.542	0.469	0.637	0.627	0.685	0.127	0.571	0.422
$\bar{R}^2$	0.001		-0.016		-0.014		-0.436		-0.477		-0.710		-1.181	

Table IX: Velocity of money estimates

This table reports estimates of the velocity of money covering the entire sample for which data is available on traditional determinants of velocity (Panel A) and for the sample for which data is available for all variables including Bitcoin price data (Panel B). Two proxies are used as money velocity (which is the dependent variable), namely, $V1$ and $V2$, where $V = RGDP/M$ and M is either $M1$ or $M2$. The independent variables are first difference of real GDP (RGDP); and the inter-bank one-month (IR_1) or three-month (IR_3)' rates. All variables are in logarithmic form. Panel B augments the traditional model with the Bitcoin price variable. Both panels display results for mean and variance equations. The model with V1* is an augmented AR(2)MA(2) GARCH(1,1) model. This specification obviates any autocorrelation. For the rest of the models, a GARCH(1,1) specification is free of autocorrelation. Finally, ** and *** denote levels of significance at the 5% and 1%, respectively.

Panel A: The traditional model of velocity of money model: 2000-2018								
Mean eq.	V1				V2			
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
α_0	-0.112***	0.000	-0.109***	0.000	-0.005***	0.000	-0.005***	0.000
$\Delta lnRGDP_t$	0.333*	0.054	0.436**	0.017	0.997***	0.000	0.998***	0.000
ΔIR_1_t	-0.089*	0.063			-0.021	0.113		
ΔIR_3_t			-0.086	0.220			0.002	0.886
Variance Eq.								
K	0.000**	0.032	0.001**	0.033	0.000***	0.000	0.000***	0.000
ε_{t-1}^2	1.021***	0.000	0.965***	0.000	0.455***	0.010	0.406**	0.016
σ_{t-1}^2	0.046	0.435	0.065	0.304	0.000	0.998	0.002	0.988
$\bar{R}^2$	-0.186		-0.156		0.457		0.452	
Panel B: The traditional model of Velocity with BITCOIN: 2011-2018								
Mean Eq.	V1*				V2			
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
α_0	-0.169	0.657	-41.188	0.885	-0.004	0.000	-0.004	0.000
$\Delta lnRGDP_t$	0.399	0.231	0.430	0.194	0.863***	0.004	0.788***	0.000
$\Delta RIR1_t$	-0.114***	0.000			-0.073***	0.002		
$\Delta RIR3_t$			-0.190**	0.011			-0.009	0.802
$\Delta lnBitcoin_t$	-0.040***	0.000	-0.040***	0.001	-0.003	0.639	-0.007	0.276
AR(2)	0.977	0.000	1.000	0.000				
MA(2)	-0.672	0.000	-0.710	0.000				
Variance Eq.								
K	0.000	0.189	0.000	0.160	0.000	0.781	0.000	0.201
ε_{t-1}^2	0.317	0.112	0.365	0.145	-0.137*	0.117	-0.117**	0.036
σ_{t-1}^2	0.166	0.744	0.145	0.777	1.110	0.000	1.086	0.000
$\bar{R}^2$	0.480		0.468		0.373		0.326	

Table X: Velocity of money and Bitcoin volatility

This table reports results from the money velocity regression which is augmented to test the effect of bitcoin price volatility (σ_t^2). The GARCH variance series is estimated with an AR(8) GARCH (1,1) model of bitcoin price returns. Panel A has these results. The dependent variables are $V1$ and $V2$, where $V = RGDP/M$ and M is either $M1$ or $M2$. The independent variables are the first difference of real GDP (RGDP); and the first difference of the inter-bank one-month (IR_1) or three-month (IR_3) interest rates. Model with V2 (4)` is estimated with a AR(3)MA(3) GARCH (1,1) specification in order to obviate autocorrelation. For the rest of the models, a GARCH(1,1) specification is robust. In row 3, numbers 1 to 4 denote the different regression models. Panel B presents results from the variance equations. Finally, ** and *** denote level of significances at the 5% and 1%, respectively.

Panel A: Mean Equation								
Mean eq.	V1				V2			
	(1)		(2)		(3)		(4)`	
Variable	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
α_0	-0.055***	0.000	-0.055***	0.000	-0.003	0.156	0.000	0.954
$\Delta lnRGDP_t$	-0.041	0.868	0.035	0.873	0.827***	0.000	0.795***	0.000
ΔIR_1_t	-0.040	0.461			-0.060**	0.000		
ΔIR_3_t			0.010	0.897			0.000	0.993
σ_t^2	0.002	0.912	0.010	0.752	-0.026	0.417	-0.035**	0.038
AR(3)							-0.524***	0.007
MA(3)							0.381	0.116
Panel B: Variance Equation								
K	0.000*	0.095	0.000**	0.055	0.000	0.956	0.000***	0.003
ε_{t-1}^2	0.916**	0.038	0.908**	0.020	0.107	0.344	-0.142***	0.000
σ_{t-1}^2	-0.070*	0.092	-0.066*	0.605	0.891***	0.000	0.949***	0.000
$\bar{R}^2$	-0.129		-0.138	0.039	0.438		0.366	