Cryptocurrencies: An Economic Perspective

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In fulfillment of the requirement for the
Tepper School of Business Senior Honors Thesis in Economics

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May 2018
0 • Abstract

Are cryptocurrencies indeed currencies? Anecdotal evidence on the volatility of cryptocurrency prices suggest that these “currencies” are not a good store of value, and similarly the time delays in validating and publishing crypto-based transactions suggest that they are not a good medium of exchange either. Due to the context it is defined in, it seems to not follow social conventions of fiat currencies. In this thesis, we undertake a systematic evaluation of how much do cryptocurrency prices behave like fiat currency prices, focusing on the predominant cryptocurrency — Bitcoin. We test the usefulness of various time series and structural models to predict future changes in Bitcoin prices and conclude that when predicting out of sample, its price is as unpredictable as fiat currency prices. Since cryptocurrencies generally have no central authority and hence receive no regulation, we explore its country-dependent characteristics, and find that the overall conclusions apply. We also examine if nominal interest rate differentials denominated in fiat currencies versus Bitcoin predict exchange rate movements, and find that in addition to the persistent violation in short-run, interest parity suggest that Bitcoin price has not been rising fast enough. We conclude that we have to refine the definition of monetary parameters on cryptocurrencies to better capture its properties, but as far as our examination indicates, the price of the predominant cryptocurrencies behaves similarly to most fiat currencies. In our point of view, Bitcoin is a currency.

1 • Introduction

Cryptocurrencies emerged as a new form of asset, and has gained interest from various fields of studies since it was proposed in 2008. Not only are these cryptocurrencies backed with a set of carefully reasoned and integrated computer scientific theories, their digital nature also aligns perfectly with the Internet age, calling for scenarios where conventional fiat currencies performed badly or were completely powerless, for better or for worse. In particular, records show that they are often used to purchase digital goods, and plays an non-negligible role in the underground economy. From its launch in 2009, it has been the most famous and successful cryptocurrency, and cryptocurrencies are brought to the general public’s recognition. Along with its rapid growth in popularity, discussions ranging from algorithmic optimization to legal enforcement has escalated. Among them, a central debate is over whether cryptocurrencies are indeed currencies, or do they represent more of asset investment.

Despite the naming, cryptocurrencies differ from conventional fiat currencies in many aspects. Sure enough, they have an interesting form, but they are far from being the most bizarre form of currency. What really makes them special is their decentralized digital design, with Bitcoin being the first ever. The next section will cover the design of Bitcoin in more detail.
To answer whether or not cryptocurrencies are currencies, a simple starting point would be to ask if one can spend it. After all, the term currency specifically refers to money’s function as a medium of exchange. Unfortunately, most cryptocurrencies would not pass the check, because rather than having a central authority confirming a transaction, their decentralized design requires consensus from multiple entities to confirm a transaction. Take Bitcoin as an example: due to its majority consensus rule and increasing mining difficulty, it takes over an hour to validate each transaction at the time of writing of this paper. We might as well end the discussion here, but in order to provide a more systematic insight, we propose an alternative perspective. Since cryptocurrencies’ innovative form would not allow them to be spent like conventional fiat currencies anyways, we would like to dig down a layer and discuss if they inherit the market expectation of a currency. Specifically, we model and analyze cryptocurrencies’ economic and financial trends and behavior, in order to answer how closely they resemble currencies.

In this paper, we attempt to answer whether or not Bitcoin, in particular, resembles a currency. Bitcoin represents most of the innovations of cryptocurrencies, has been studied thoroughly enough, and provides the most amount of data for analysis. Throughout the paper, we use Bitcoin or BTC to refer to the currency, and bitcoin(s) or $\text{\textdollar}$ as a unit of account. In the second section, we provide some background knowledge of how Bitcoin is designed, and its features that draw our attention. The third section discusses the anecdotal aspects of Bitcoin, and why it is hard to conclude Bitcoin’s identity either as or not as a currency.

The fourth section models Bitcoin against three representative models of exchange rate that captures some important characteristics of conventional fiat currencies. We fit Bitcoin price against a univariate time series model, a multivariate time series model, and a structural model. Just like with fiat currencies, we find that the univariate time series model, the Random Walk model does the best job predicting changes in exchange rates out-of-sample. The fifth section further explores Bitcoin’s resemblance of conventional fiat currencies by predicting its in-sample changes. We test Bitcoin against Uncovered Interest Parity, and find it severely violated in the short-run. We end this paper by summarizing how sections four and five shed light on Bitcoin’s behavior as a currency, and suggesting drawbacks and improvements to our research.

2 • BITCOIN PRELIMINARIES

2.1 • A TIMELINE

Bitcoin is not the first digital currency proposed, nor is it special in its nature, but it is among the earliest practically operable digital currency. It was proposed in 2008 in the
paper “Bitcoin: A Peer-to-Peer Electronic Cash System”, under the pseudonym name Satoshi Nakamoto. The intent for a system so different from conventional currency systems, in Nakamoto’s words, is to establish “an electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party” (Nakamoto, 2009, p.1). Nakamoto sees a trusted third party as an unreliable intermediary, and hence calls for an alternative system whose transactions can be verified easily by any party, bypassing the need for an intermediary that operates purely on trust. Some call Nakamoto a cypherpunk for his intent to invoke political and social changes using cryptography, and whether or not it be so, Bitcoin definitely represents a potential innovative idea that leads way into the future.

The source code for Bitcoin was released in early 2009, but due to prior failures to carry out a working digital currency, Bitcoin did not draw much attention at the beginning. The first ever Bitcoin transaction took place a few days after the release, when Nakamoto sent 10 to Hal Finney, one of the first supporters and contributors, for testing purpose. After that, Bitcoin would continue to operate as a separate currency system, until its parallel relationship with the global economy broke down in May of 2010. In an attempt to spend Bitcoin, developer Laszlo Hanyecz offered to pay 10,000 for two pizzas, and 18-year-old Jeremy Sturdivant bought the pizzas for him at the price of $25 (“The first Bitcoin transaction bought two pizzas - today, it’s worth $150 million”, 2017). To give a sense of how far Bitcoin has come, at the time of this writing, those pizzas worth over $70 million.

In the upcoming years, more institutions started to accept Bitcoin, and its price started to take off, but not without frustrations. A major vulnerability in Bitcoin was exploited in August of 2010, which allowed transactions to be improperly verified, effectively removing the 21 million upper bound of Bitcoin issuance (Bitcoin History: The Complete History of Bitcoin [Timeline], n.d.). The vulnerability was quickly discovered and fixed, and even though this has been the only major one so far, cryptographic attacks continued. In early 2014, the largest Bitcoin exchange that hosted over 70% of global transactions at the time, Mt. Gox suspended its transactions. It reported a loss of over 850,000, and filed for bankruptcy shortly after (Takemoto, 2014). In fact, most of the large Bitcoin exchanges that still exist have all been hacked at some time, and have undergone the back-and-forth process of losing bitcoins and reclaiming part of them.

Recently, in August of 2017, Bitcoin split into two structures due to prolonged disagreement on handling scalability. This paper focuses on the original Bitcoin, or BTC, and does not get into detail with the forked Bitcoin Cash, or BCH. Technical details aside, the total number of bitcoins will converge to 21 million in 2140, and whether or not the Bitcoin community decides to remove the upper bound in the future, this event will impact Bitcoin price and transactions in the near future.
2.2 • A Technical Review

While our analysis does not require us to understand the complete set of theories behind Bitcoin, an overview of its mechanism would certainly help to understand its behavior. To begin, we note that there is no formal notion of ownership for Bitcoin, so all transactions are anonymous. The owner simply holds the cryptographic private key, which is required to sign the consequent transaction(s) upon hashing. Moving on, we introduce Bitcoin’s transaction criteria, consensus protocol, mining principals, and upper bound on issuance.

There is a global public ledger for Bitcoin, where each transaction is represented by a block. As every transaction depends on the state of its previous transaction, the blocks form a chain, called the blockchain. At any time, the longest blockchain is considered the consensus blockchain, with a caveat that we will discuss later. Each transaction generates an integer value representing the amount transacted, and a script snippet denoting the state of this transaction. Upon the next transaction, its input must match the outputs of its previous transaction. The scripts for both the previous and the current transactions must execute successfully, and the sum of amounts transacted must not exceed the sum of input amounts. The entire transaction would then be hashed using SHA-256, whose hash value eventually serves as the globally unique transaction ID.

Now that we have a set of rigorous transaction criteria, we also need to make sure that it works in a network setting. In particular, we need a protocol that deals with one of the greatest challenges in designing a digital currency: the double spending problem. For the case of Bitcoin, the double spending problem is that the same bitcoins could be spent more than once simultaneously. Bitcoin confronts the attack by making use of the global public ledger, admitting a transaction only if it is published to the global public ledger. By the criteria denoted earlier, the validity and state dependency of a transaction prevents other transactions of the same bitcoins from being appended to the blockchain. To successfully publish a transaction to the global public ledger, it needs to be valid not just to whoever proposed the transaction, but up to the consensus of the participants of the Bitcoin network, or miners as we call them.

Arguably the most innovative part of Bitcoin, its consensus protocol, often referred to as the Nakamoto consensus, integrates computational power to verify each transaction. Concurrency over a distributed setting is extremely difficult to manage, and Bitcoin avoids most of the conflicting concurrent publications by making its best to set aside publishing times. Bitcoin requires each publication to solve a cryptographic quiz, sometimes called a proof of work. The cryptographic quiz is adapted from Adam Back’s Hashcash proposed in 1997, and it requires the publishing party to solve for a hash value with a certain number of leading zeros \cite{Franco2015} p.164). The more leading zeros the quiz requires, the longer it takes to solve, and there is no unknown efficient algorithm, so the hashing difficulty is easily adjustable. As more computational power joins the Bitcoin network, and as the blockchain
branches out with more users transacting with each other, hashing difficulty is constantly adjusted upwards to keep conflicting concurrent publications low, as shown in Figure 1. The cryptographic quiz does not eliminate the possibility of having conflicting concurrent publications, so temporary forks of the same blockchain still take place. They usually converge to one consensus blockchain very quickly, but should the forks not converge soon enough, the system would reject all disagreeing blocks in an ad hoc fashion. In practice, each transaction block waits for six more “confirmation” blocks to append before announcing that it is published to the global public ledger (Bonneau et al., 2015, p.4). This practice, along with the increasing hashing difficulty, results in the lengthy verification time for each transaction.

![figure](image.png)

**Figure 1: Mining Difficulty Over Time**

Bitcoin Miners play a vital role in maintaining blockchains. After the first block that claims to have solved the cryptographic quiz is appended to the blockchain, they would inspect the block. If it doesn’t satisfy any of the aforementioned criteria, the block would be rejected, and miners would continue solving the same cryptographic quiz. Otherwise, they move on to solving the next cryptographic quiz. Their effort is not without returns, of course. A critical design of Bitcoin is to provide incentives for miners to maintain the blockchain. In particular, the protocol allows the first miner who solves the cryptographic quiz to a new block to insert a transaction of a specified amount of bitcoins to an address of their choosing. Among temporary forks of the same blockchain, miners need to choose a fork that they believe will eventually be the longest to work on, as rejected blocks’ rewards will be removed upon blockchain consensus.

The total amount of bitcoins that will ever be generated is captured by the total number of bitcoins generated as mining awards. It begins with \( B^{50} \) per block, and halves every 210,000
blocks, summing to

$$\sum_{i=0}^{\infty} 210,000 \cdot \frac{50}{2^i} = \$21,000,000$$

The exact total amount is $20,999,999.9769$, restricted by precision level, and we will reach this number some time in 2140 (Controlled supply, n.d.).

3 • CURRENCIES AND ASSETS

Of everything people think Bitcoin and every other cryptocurrency is, the arguments eventually run down to it being a currency and being a speculative asset. Some of Bitcoin's assumed identities, commodity for example, are out of plain misunderstanding, while other ones like collectible and fraud are more sarcastic than they are doubtful. Unsensible identities aside, it is reasonable that scholars find it hard to define Bitcoin as either of currency and speculative asset, and we too had to focus on its price-wise properties to be able to define it. In this section, we explore the anecdotal aspects of Bitcoin that resemble and contrast with currencies.

3.1 • BITCOIN AS MONEY

Before getting into currency, we first consider how much Bitcoin resembles money, in order to provide a well-rounded characterization of Bitcoin. As every economics textbook would write in its first chapters, economists define money by its functions as a medium of exchange, an unit of account, and a store of value. We explore each function separately.

Medium of exchange is what most people instantly think of money as. Every textbook would tell the story that before there were money, in a barter economy, each agent would hold some goods, and and they only trade with each other when a double coincidence of wants occurs. The story is, however, just Adam Smith’s view of the origin of money, and money dates back as far as trading itself. Just like its name indicates, money needs to act as a medium, so that people are willing to accept and use it as a means of payment. Since Bitcoin has no intrinsic value, whenever people accept it and use it, it is used as a medium. As more and more parties start to accept Bitcoin, its function as a medium of exchange would become even stronger. Some may argue against Bitcoin in claiming that, as we mentioned in the introduction, it takes over an hour to validate each transaction. Therefore, it cannot be used a form of instant payment, like we can with conventional fiat currencies. This argument
may serve well to refute the concern that Bitcoin may take over the money market, but says nothing about it being a medium of exchange.

To use an item as an unit of account, it first needs to dock in with some existing monetary measures. Since we can denote Bitcoin price in almost any major currency, we can use it to account for anything these currencies can, and so it is certainly a well-established unit of account. As a digital currency, Bitcoin features a much higher precision level than do fiat currencies, for better or for worse. On one hand, it can provide very accurate valuations, but then at the same time, it makes fiat currencies rougher unit of account, which may be less desirable. No matter which people take Bitcoin as, it is functional as an of account.

Money’s final function as a store of value is where Bitcoin falls short. Bitcoin’s price is highly volatile, so it falls short in preserving its value. To its credit, its price has been rising rapidly in the past few years, so for the most part its value would not be lost, but in preserving value we seek not a growing valuation, but a stable one. Moreover, Bitcoin holds no intrinsic value, so there is no assets backing it that secures its values. Once its price falls, there is no way to redeem the lost values (Yermack, 2013).

3.2 • Bitcoin as Currency

Currency refers, in particular, to the possession of purchasing power of money in a social context. More precisely, currency is only defined by some specific time and places. For example, USD is a currency in the US as of right now, but was not in the same geographic location 500 years ago. Similarly, it is not a currency in many other countries of the present world, but instead an asset convertible to their currencies. The anonymous design of Bitcoin makes it hard to establish an explicit social context, and in order to do so, we compare it with the Local Exchange and Trading System, or LETS.

LETS emerged and flourished in early 20th century, with the goal to develop a small, active economy to its members, at the cost of reduced contact with the outside economy. Its intent evolved over time, from resisting government taxation to counteracting job losses due to economic globalization, and finally to just providing convenience for a small community (Croall, 1997, p.11). A typical LETS has a public ledger that records each member’s balance, as a zero-sum system. Some LETS instances issue their own currencies, while others simply use working hours as measurements. Apparently, these local currencies are not backed, and despite the public ledger, it is the intimate relationship between community members that makes it operable.

If Bitcoin is on the extreme of not requiring trust, then LETS is on other extreme of relying heavily on trust, even more than fiat currencies do. Through LETS, we can see that currencies relying on trust are not defined by a social context, but to a social context, specifically the community that it serves. For this very reason, as soon as its members stop trading with
each other, the system ceases to exist. In fact, decay in activities is the primary reason why many LETS failed. On the other hand, by getting rid of trust, Bitcoin also frees itself from being constrained to a social context. If we have to appoint a context to it, it would be over the Internet, which extends globally. It is true that ultimately, it is those who use Bitcoin that decides its value relative to fiat currencies, but even if not so, it stays a robust currency system on its own.

3.3 • Anecdotally, then Systematically

Putting together the anecdotal aspects of Bitcoin, it becomes even harder to conclude whether or not it is a currency. It tries its best to fulfill the functions of money, and accomplishes them to some extent, but not satisfactory enough that we can close the case. After exploring its social context, we see that it establishes rules on its own that makes it a robust system, while at the same time being less familiar and flexible. Moving on, we explore how Bitcoin price behaves, with a systematic procedure according to previous literature in discovering monetary properties.

4 • Predictability with Empirical Models

In this section, we introduce three empirical economic models that have proved relatively effective in predicting the exchange rates of conventional fiat currencies: the random walk model, autoregression model, and Meese-Rogoff model. We examine how well fit they each fits Bitcoin data, and whether or not the conclusions on conventional fiat currencies apply.

4.1 • Models

The first model, the random walk (RW) model is an univariate time series model. It assumes no structure underlying exchange rates, and hence the best estimator of the exchange rate at any period is the exchange rate of the latest period preceding it. For our purpose, we adapt the model

\[
\Delta s_{t+1} = \varepsilon_{t+1} + \begin{cases} \Delta s_t & t \in (T_0, T_1] \\ 0 & \text{Otherwise} \end{cases}
\]

where we have data from period \(T_0\) to \(T_1\), \(\Delta s_t = s_t - s_{t-1}\), and \(s_t\) is the natural log of exchange rate at period \(t\). We assume \(\varepsilon_t \sim N(0, \sigma^2)\), where \(\sigma\) is an unknown constant. The lag in this model is simply 1, which, despite being a constant, is still up to how we define
the length of a period. When predicting out of sample, we would always predict the latest exchange rate in the data, so \( E[\Delta s_{t+1}] = E[s_{T_1} - s_{T_1}] = 0 \) in this case.

Expanding to a multivariate time series model, the autoregression (AR) model regresses the contemporaneous value against a lagged period of time. More specifically, we write

\[
\Delta s_{t+1} = \varepsilon_{t+1} + \alpha + \sum_{i=1}^{\ell} \beta_i \Delta s_{t+1-i}
\]

(2)

where \( \alpha \) and \( \beta_i \)'s are the intercept and coefficients, respectively. \( \Delta s_t \) and \( \varepsilon_t \) are defined the same way as before. This model has a degree of freedom of \( \ell + 1 \), and the lag here is \( \ell \), because we aggregate over the daily log differences of \( \ell \) periods into the past. Notice that this model is a generalized version of the RW model, and if the RW model is optimal, this model should give \( \alpha = 0, \beta_1 = 1, \) and \( \beta_i = 0 \) for \( i \geq 2 \).

The last model we adapt, the Meese-Rogoff (MR) model incorporates a more diverse set of predictors. The specification is as follows,

\[
\Delta s_{t+1} = \varepsilon_t + \alpha + \sum_{i=1}^{\ell} \left( \beta_{6(i-1)+1}\dot{\Delta}m_{t+1-i} + \beta_{6(i-1)+2}\dot{\Delta}y_{t+1-i} \\
+ \beta_{6(i-1)+3}\dot{\Delta}r_{t+1-i} + \beta_{6(i-1)+4}\dot{\Delta}\pi_{t+1-i} \\
+ \beta_{6(i-1)+5}\dot{T}B_{t+1-i}^{(1)} + \beta_{6(i-1)+6}\dot{T}B_{t+1-i}^{(2)} \right)
\]

(3)

where \( \alpha, \beta_i \)'s, and \( \varepsilon_t \) are as before. \( X^{(i)} \) gives quantity \( X \) according to currency \( i \), and \( m_t, y_t, r_t, \pi_t, \) and \( TB_t \) each denotes money supply, real income, short-term interest rate, expected long-term inflation differential, and cumulated trade balance for period \( t \), respectively, all in natural log scale. If \( s_t \) is the price of currency 2, or equivalently, the exchange rate of currency 2 in currency 1, then \( \Delta X_t = X_t^{(1)} - X_t^{(2)} \). This quantity can be interpreted as the difference in log terms, or the log of the ratio of the same quantity for two currencies. Just like for the AR model, we aggregate the data over \( \ell \) periods, so the lag is \( \ell \), but this time the degrees of freedom is \( 6\ell + 1 \), which is much larger than that of the AR model.

The MR model is perceivably the most complicated model of the three, and it provides a good example of the amount of research and theory that has been built on this topic. While there are more specific forms proposed for different scenarios (\textit{Meese & Rogoff} 1983, p.5), we stay with its general form as depicted in Equation (3).

Structural models like the MR model intend to capture the changes in exchange rates that stem from their monetary properties. For example, if the interest rate of a country rises faster than that of another country, then people would borrow from the low interest currency.
and lend to the high interest currency, which should decrease the price of the high interest currency relative to the price of the low interest currency. Since this model ties most closely to the characteristics of conventional fiat currencies, it is also the most difficult model to adapt for Bitcoin, because many of the quantities do not exist for it. A description of how the models are adapted is given in the next section.

4.2 • Purchasing Power Parity

To gain some insight into the significance of predicting exchange rate, consider the notion of Purchasing Power Parity (PPP). It conveys one simple idea, that the purchasing power should be preserved across currency swap. While there certainly are temporary deviation from PPP, evidence shows generally agree that it should hold in the long-run.

As a more concrete example, consider one of the more interesting and well-known variants of PPP established by The Economist in 1986 — the Big Mac Index. If we take the amount of USD to buy a big mac and convert it to EUR, then the converted amount should afford exactly one big mac. Otherwise, there would be arbitrage opportunities, and sellers would buy big macs in the currency with cheaper relative price and sell them in the other currency. Should that happen, equilibrium would shift in both currencies, and price levels would eventually be adjusted to follow PPP. Sellers would then be indifferent between buying big macs in either currency.

Contrary to the almost natural process depicted in the previous paragraph, researchers have been unable to confirm any convergence to PPP in the short-run. Despite years of research to propose reasonable structures that capture deviation from PPP, RW model still remains the most powerful. An abundance of models have been proposed, yet they hardly outperform the RW model out of sample, if at all.

More recent research suggests that if the convergence to PPP is slow enough, we need to extend to a much longer dataset to capture it. With 116 years of data between USD and EUR, there have been successful attempts to reject the RW model with high confidence. We need another century to perform the same test for BTC, so within the scope of what we can test, we may take the RW model as a strong candidate.

4.3 • Data

For the purpose of Section 4.4, we consider USD and EUR, because they are both major currencies in world economy. We fetch the data for both currencies from the Federal Reserve Economic Data (FRED).

Using notations specified in Equation 3, currency 1 is USD, and currency 2 is EUR. We have daily exchange rates, so the length of each period is one day.
We use M1 money supply, and since FRED only offers weekly data, we tabulate it to daily data by setting each date’s money supply to that of the latest available date preceding it. For short-term interest rate, we use monthly interest rate, which we tabulate to daily data in a similar fashion. The remaining quantities are missing in either or both of the currencies, so we have to leave them out. These adjustments make our model look more like the sticky-price monetary model (Dornbusch, 1976), and they certainly impact the performance of the MR model, but as we will see, doing so does make it easier to compare results to those of BTC.

All BTC data we use comes from Bitcomity.org, which fetches its data directly from major exchanges using their official APIs. We used daily price and trading volume in USD aggregated across all collected exchanges for Section 4.5 and inspect specific exchanges transacting in both USD and EUR for Section 4.6. These two currencies represent two distinct patterns, and the results for AUD, BRL, CAD, CNY, GBP, JPY, PLN, and RUB follow either of them. Among the exchanges that offer transactions in both USD and EUR, host a relatively large user base, and have operated for long enough, we pick Bit-X, Bitstamp, CEX.io, and Coinbase.

For each model with each pair of currencies, we fit with lag $\ell = 30$ days, 90 days, 180 days, and 365 days, which roughly equate 1 month, 3 months, half a year, and a year. Since the lag of the MR model is simply 1, we have to adjust the length of each period for each lag accordingly. Such adjustments may seem inconsistent if we compare by periods, but since we compare by lags instead, this is not a concern. Within each pair of currencies, we consider the same model across different lags, and different models on the same lag.

**4.4 • Modeling Conventional Fiat Currencies**

For USD and EUR, we use data from $T_0^{(EUR)} = 1999-01-04$ to $T_1^{(EUR)} = 2018-04-20$. We split data roughly in half, using dates up to 2009-01-01 as the training set, and the remaining dates as the testing set. Some might believe the global financial crisis between 2007 and 2008 would influence the coefficients in an unwanted way, or cause an unnecessarily large error out-of-sample, but we do not observe so in the results. Should we split the data at any time between 2006-01-01 and 2012-01-01, we would still end up with the same conclusions.

Table 1 lists the in-sample mean squared error (MSE) for the MR, AR, and MR model, with the aforementioned lags. We observe that the AR model and the MR model give decreasing sequences as lag increases, whereas the RW model gives an increasing sequence. Notably, the MR model outperforms the AR model at every lag, and does so by a margin that increases with lag. It seems as though a structural model does a better job capturing the features than do time series models, and recall that it has done so with several of its predictors dropped. It could, however, simply be due to the fact that a structural model has a higher degree of
As we have briefly mentioned, the MSEs out-of-sample do not resemble the MSE pattern we find in-sample. Table 2 lists MSEs when predicting out-of-sample, and upfront we observe an almost reverted ranking in the performance of the three models. All three models’ MSEs increase as lag increases, though at different rates, with the RW model increasing the slowest and the MR model increasing the fastest. The RW model beats the other two models at every lag, and the AR model beats the MR model at all lags but $\ell = 1$ month.

Note that the differences in MSEs for different lags of the RW model is purely referential, as the lags only affect its predictions in the first $\ell$ periods, while the remaining periods receive the uniform prediction $\Delta s_{t+1} = 0$, as depicted in Equation 1. If we discard lags and simply use the latest preceding rate differential, we would end up with a MSE of 0.89, which is slightly below the MSE with $\ell = 1$ month.

Figure 2 shows aggregated monthly MSE by $\ell = 3$ months, and the aggregated MSEs for the
other lags are attached to the appendix. When predicting in-sample, we see that the RW model often has the largest aggregated MSE, whereas the curve for the MR model usually has the lowest aggregated MSE. The two sudden spikes in the MR model are potentially sudden, unexpected changes that its structural predictors failed to capture, since different from the other two models, it has no predictors of previous response values. When predicting out-of-sample, however, we observe that the AR model and the MR model alternatively hold the highest aggregated MSE, while the curve for the RW model stays low the whole time.

Note that the shapes of the RW model and the AR model look very much alike, with the AR model stretched out towards the positive direction of aggregated errors. Recall from Section 4.1 that if the RW model is a better fit, the coefficient of the predictor with the most recent date should be close to 1, and all other coefficients should be around 0. Here, the 95% confidence interval for the coefficient of the nearest date is (1.01, 1.03), which does not include 1 but stays close enough to it. On the other hand, for the other coefficients we have a 95% confidence interval of (−0.0027, 0.0024), which includes and stays close to 0. Therefore, the AR model performs like a “noisy” RW model, hence their similarity in shape.

The results we stated above are representative of what we would otherwise get with slightly different setups. If we add a drift term for the RW model to fit, its MSEs would decrease at some lags and increase at others, but its ranking in performance still stays the same. If we include more predictors in the MR model, the in-sample MSEs would decrease by 0.39 on average, but the out-of-sample MSEs would increase by 1.03 on average. Meese and
Rogoff (1983) produce similar results with different currency combinations, and report that extensive constrained-coefficient experiments still cannot outperform the RW model. Other adjustments such as replacing M1 money supply with M2 money supply, and switching to a longer term interest rate hardly affect the results as well.

So far, our results resemble what most of the existing literature has found about fiat currency exchange rates. Of the greatest significance and perhaps confusion too, we see that the RW model tends to perform the worst in-sample, while being the best out-of-sample. Another unfortunate conclusion is that despite all the reasoning, adding complexity to a structural model often does not improve its performance out-of-sample, but worsens it.

4.5 • Modeling Bitcoin

With BTC, we use data from $T_0^{(BTC)} = 2010-07-17$ to $T_1^{(BTC)} = 2018-05-05$. Different from USD and EUR, whose establishment date back further than when their data became available, $T_0^{(BTC)}$ is not far from when BTC trading became more accessible than just between miners. Therefore, even though BTC provides as large a time span as any cryptocurrency can provide, it is more ideal to avoid its beginning years, when the data were highly volatile. Once again, we split the sample at roughly the middle point, this time at 2015-01-01.

In order to adapt the MR model for BTC, we need to define its quantities that correspond to $m_t$ and $r_t$. Other quantities are dropped, because arguably they do not exist for BTC, especially if we consider it a currency not bound by any country. For this reason, we would not expect the MR model to perform as well, as it fails to capture many of the structural properties of BTC. We use cumulative trading volume as money supply, and set interest rate to 0. Despite the fact that mining generate bitcoins, note that it is a reward mechanism for the miners, rather than interest for holders of existing bitcoins. Finally, recall that $\dot{\Delta}r_t$ can also be interpreted as the natural log of the ratio between the short-term interest rate of two currencies. We cannot have a denominator of exactly 0, so we shift both $r_t^{(Fiat)}$ and $r_t^{(BTC)}$ by the minimum $r_t^{(Fiat)}$ over $t \in [T_0^{(BTC)}, T_1^{(BTC)}]$. That is, we use

$$\dot{\Delta}r_t = \ln \left( \frac{r_t^{(Fiat)} + \min_{T_0^{(BTC)} \leq p \leq T_1^{(BTC)}} r_p^{(Fiat)}}{0 + \min_{T_0^{(BTC)} \leq p \leq T_1^{(BTC)}} r_p^{(Fiat)}} \right)$$

$$= \ln \left( r_t^{(Fiat)} + \min_{T_0^{(BTC)} \leq p \leq T_1^{(BTC)}} r_p^{(Fiat)} \right) - \ln \left( \min_{T_0^{(BTC)} \leq p \leq T_1^{(BTC)}} r_p^{(Fiat)} \right)$$

Table 3 lists the in-sample MSEs of the three models over the same lags as before. If we
Table 3: In-Sample Mean Squared Error with USD and BTC

<table>
<thead>
<tr>
<th>Lag \ Model</th>
<th>Random Walk</th>
<th>Autoregression</th>
<th>Meese-Rogoff</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>7.95</td>
<td>8.25</td>
<td>19.33</td>
</tr>
<tr>
<td>3 Months</td>
<td>9.29</td>
<td>7.81</td>
<td>13.06</td>
</tr>
<tr>
<td>6 Months</td>
<td>9.51</td>
<td>6.73</td>
<td>6.98</td>
</tr>
<tr>
<td>1 Year</td>
<td>9.38</td>
<td>3.98</td>
<td>4.25</td>
</tr>
</tbody>
</table>

Table 4: Out-of-Sample Mean Squared Error with USD and BTC

<table>
<thead>
<tr>
<th>Lag \ Model</th>
<th>Random Walk</th>
<th>Autoregression</th>
<th>Meese-Rogoff</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Month</td>
<td>1.37</td>
<td>2.61</td>
<td>4.64</td>
</tr>
<tr>
<td>3 Months</td>
<td>1.47</td>
<td>2.82</td>
<td>3.85</td>
</tr>
<tr>
<td>6 Months</td>
<td>1.75</td>
<td>2.98</td>
<td>2.43</td>
</tr>
<tr>
<td>1 Year</td>
<td>3.99</td>
<td>3.69</td>
<td>3.09</td>
</tr>
</tbody>
</table>

Interestingly, the MSEs out-of-sample given in Table 4 are substantially smaller than those in-sample. Since BTC was highly volatile in its first years, we would expect the MSEs in-sample to be somewhat larger compared to the MSEs in-sample with USD and EUR, but not so much so that they are larger compared to the MSEs out-of-sample. Such a contrast suggests that BTC is able to adjust to a relatively stabilized state that the models can better capture. This time, the RW model still performs the best out-of-sample, but the MR model no longer consistently performs the worst. In particular, it outperforms the AR model at \( \ell = 6 \) months and 1 year. On one hand, this may indicate that with enough lags long enough, the MR model can indeed capture some structure of the change in exchange rates, but on the other hand it still does so substantially worse than the RW model. Its improved performance could simply be out of its large number of degrees of freedom.

Since the RW model also outperforms the AR model, it is useful to check the coefficients of the AR model. The 95% confidence interval of coefficient of the latest preceding date is given by (1.27, 1.30), which, unlike with USD and EUR, is much larger than 1, which explains the
relatively larger gaps between the MSEs of the RW model and the AR model out-of-sample. The 95% confidence interval of the other coefficients is $(-0.0066, 0.0033)$, which still includes and stays close to 0. If the AR model is best characterized as a “noisy” version of the RW model for the case with USD and EUR, then here the AR model would better be described as a nosier and more extreme version of the RW model.

Figure 3: Aggregated Monthly MSEs at $\ell = 3$ Months for USD and BTC

Figure 3 gives aggregated monthly MSEs of the three models at $\ell = 3$ months. The curves in-sample fluctuate noticeably more drastically than they do out-of-sample, which is consistent with our earlier observations from Tables 3 and 4. Since the MR model does considerably worse than the other two models at the given lag, it often comes to the top over the whole time span. Most significantly, the aggregated MSEs seem to be close to 0 for the RW model out-of-sample. The spikes in-sample definitely play a role by stretching out the y-axis, but it is true that the aggregated MSEs after 2015-06-01 are extremely small, with a range of $(3.57 \cdot 10^{-5}, 9.43 \cdot 10^{-3})$.

Again, the results above are representative of similar configurations of the models. None of changing splitting time, adding a drift term to the RW model, switching from USD M1 money supply to M2, or switching from USD monthly interest rate to a longer term interest rate would change our conclusions. With BTC, the RW model still performs the worst for the most lags in-sample, and the best out-of-sample. The MR model performs significantly better at larger lags, and the worst by a relatively large margin at smaller lags. The AR model lies somewhere in between the two, but this time resembling less of the performance...
4.6 **Country-Dependent Bitcoin Behaviors**

Here we consider country-dependent behaviors of BTC by comparing USD data against EUR data. European currencies and CNY display patterns similar to EUR, whereas the remaining currencies we have looked at resemble patterns similar to that of USD. In order to control for possible differences by exchanges, we only consider exchanges that offer transactions in both USD and EUR, have a reasonable user base, and have operated relatively long. We pick Bit-X, Bitstamp, CEX.io, and Coinbase here.

None of the exchanges started to offer transactions in both currencies at the same time, so for each of them we discard dates where there are only data for one of the currencies, and only use dates when data for both currencies are available. After doing so, even the earliest starting date among all the exchanges dates only back to 2014-11-09, so we apply a slightly different splitting strategy, and use roughly the first two thirds of dates for training purpose. Table 5 gives the starting, splitting, and latest dates for each exchange. Note that we have the most dates for Bit-X, the least dates for Bitstamp, and comparably few dates for CEX.io and Coinbase.

<table>
<thead>
<tr>
<th>Exchange</th>
<th>Starting Date ($T_0$)</th>
<th>Splitting Date</th>
<th>Latest Date ($T_1$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bit-X</td>
<td>2014-11-09</td>
<td>2017-03-01</td>
<td>2018-05-06</td>
</tr>
<tr>
<td>Bitstamp</td>
<td>2016-05-29</td>
<td>2017-10-01</td>
<td>2018-05-06</td>
</tr>
<tr>
<td>CEX.io</td>
<td>2015-08-24</td>
<td>2017-06-01</td>
<td>2018-05-06</td>
</tr>
<tr>
<td>Coinbase</td>
<td>2015-05-01</td>
<td>2017-05-01</td>
<td>2018-05-06</td>
</tr>
</tbody>
</table>

Table 5: Splitting Dates for Different Exchanges

Table 7 gives the in-sample and out-of-sample MSEs for every exchange at each lag denoted in Section 4.3, for both USD and EUR. Despite the effort to allocate more dates to the training set, the AR model and the MR model still end up under-determined for most of the time at $\ell = 1$ year, as we observe zeros or very small MSEs in-sample. This also means that the models are underfit, so when predicting out-of-sample, we get absurdly large MSEs. Therefore, unless otherwise noted, the analysis ignores in-sample MSEs of 0 and out-of-sample MSEs on the scale of tens or larger.

The trends within each currency and model still applies generally, though not every case. In particular, the RW model’s MSEs form increasing sequences, whereas the AR model and MR model’s MSEs form decreasing sequences in-sample as lag increases, and all three models form increasing sequences out-of-sample as lag increases. This time, the MSEs in-sample
for the RW model is competitive with those of the other two models, and the MSEs out-of-sample for the MR model is competitive with those of the RW model. Unlike with previous subsections, the AR model performs the worst out-of-sample at every case. Inspecting its coefficients in Table 6, we see that for all exchanges, the coefficients of the latest preceding date are substantially greater than 1. Even though the 95% confidence intervals for the other coefficients all include 0, they no longer stay as close to 0. That is to say, the fitted AR models here are even more off the RW model than the previous subsections, hence their difference in performance.

The RW model and the MR model have competitive performances out-of-sample, so we compare them across exchanges for each currency. The RW model beats the MR model in every case for USD, but for EUR, the MR model outperforms the RW model at Bit-X and Bitstamp. Therefore, it seems that EUR has mixed best performing models across different exchanges, whereas USD consistently elects the RW model as its best performing model. Aggregating across all major exchanges, however, the best performing model for EUR is still the RW model.

Inspecting individual exchanges, we find that the RW model outperforms the other models by a smaller relative margin, sometimes even doing worse than the MR model. Recall that we mentioned earlier that the general conclusions for EUR applies to European currencies and CNY, so even though their individual choices differ, they have a mixed set of best performing models across exchanges, rather than consistently picking the RW model. With that said, the MSEs only vary by a minimal margin, so it seems plausible that these differences are more likely due to differences in how exchanges handle their transactions and determine prices. After all, when aggregating across all major exchanges, the RW model still performs the best.

As a last note, even though the exchanges we pick provide relatively large time spans, they are all too short to allow confident conclusions. We take these results as referential, and unless they stay in line with earlier results, we do not assume that they hold in general.
<table>
<thead>
<tr>
<th>Exchange</th>
<th>Currency</th>
<th>Lag</th>
<th>Random Walk In-Sample MSE</th>
<th>Random Walk Out-of-Sample MSE</th>
<th>Autoregression In-Sample MSE</th>
<th>Autoregression Out-of-Sample MSE</th>
<th>Meese-Rogoff In-Sample MSE</th>
<th>Meese-Rogoff Out-of-Sample MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bit-X</td>
<td>USD</td>
<td>1 Month</td>
<td>0.24</td>
<td>0.63</td>
<td>0.40</td>
<td>1.44</td>
<td>0.33</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>EUR</td>
<td>1 Month</td>
<td>0.30</td>
<td>0.78</td>
<td>0.37</td>
<td>1.42</td>
<td>0.43</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td>USD</td>
<td>1 Month</td>
<td>0.29</td>
<td>0.70</td>
<td>0.67</td>
<td>1.27</td>
<td>1.14</td>
<td>0.82</td>
</tr>
<tr>
<td>Bitstamp</td>
<td>EUR</td>
<td>1 Month</td>
<td>0.61</td>
<td>0.60</td>
<td>0.36</td>
<td>1.23</td>
<td>0.50</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>USD</td>
<td>1 Month</td>
<td>0.20</td>
<td>0.74</td>
<td>0.41</td>
<td>1.36</td>
<td>0.52</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>EUR</td>
<td>1 Month</td>
<td>0.20</td>
<td>0.71</td>
<td>0.42</td>
<td>1.38</td>
<td>1.32</td>
<td>1.30</td>
</tr>
<tr>
<td>CEX.io</td>
<td>USD</td>
<td>1 Month</td>
<td>0.25</td>
<td>0.81</td>
<td>0.35</td>
<td>1.50</td>
<td>0.58</td>
<td>1.17</td>
</tr>
<tr>
<td></td>
<td>EUR</td>
<td>1 Month</td>
<td>0.45</td>
<td>1.00</td>
<td>0.00</td>
<td>16.02</td>
<td>0.00</td>
<td>245.71</td>
</tr>
<tr>
<td>Coinbase</td>
<td>USD</td>
<td>1 Month</td>
<td>0.21</td>
<td>0.77</td>
<td>0.38</td>
<td>1.67</td>
<td>0.65</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td>EUR</td>
<td>1 Month</td>
<td>0.21</td>
<td>0.77</td>
<td>0.38</td>
<td>1.67</td>
<td>0.65</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Table 7: Out-of-Sample Mean Squared Error with USD and BTC versus EUR and BTC
5 • INTEREST PARITY

In addition to learning the out-of-sample behaviors, it would be helpful to see if the in-sample behaviors of Bitcoin price is similar to those of fiat currencies. For this section, we focus on the usefulness of interest rate spreads to predict in-sample exchange rate movements. We introduce the covered and uncovered interest parities, and discuss whether or not Bitcoin gives the same conclusions as conventional fiat currencies.

5.1 • INTEREST PARITY AND CARRY TRADE

Like PPP, the notion of interest parity also conveys a simple idea: that value should be preserved over interests of different currencies. When holding a currency, one has the option to earn interest in that currency, or convert it to another currency and earn its interest. The two options should end up holding the same value, or otherwise there would be arbitrage opportunities.

That being said, if we convert to another currency, we have to convert it back in the future, but the future exchange rate is unknown at the present, so this is a risky trading strategy. To reduce the risk, we can turn to a forward contract of currency swap. Say that we start with currency 1. Let \( r_{t}^{(1)} \), \( r_{t}^{(2)} \), \( s_{t} \) be the interest rates for currencies 1 and 2, and the exchange rate of currency 2 in currency 1, respectively. If the contract allows us to sell currency 2 in the future at the forward price \( f \), then Covered Interest Parity (CIP) states that we must have

\[
\left(1 + r_{t}^{(1)}\right) = \left(1 + r_{t}^{(2)}\right) \cdot \frac{f}{s_{t}}
\]  

(4)

Since all the prices are known at period \( t \) when the contract is created, one can determine its profitability beforehand. However, if \( s_{t+1} > f \), then we would have been better off applying the risky trading strategy. Therefore, we would still like to find some measures of the relationship

\[
\left(1 + r_{t}^{(1)}\right) = \left(1 + r_{t}^{(2)}\right) \cdot \frac{s_{t+1}}{s_{t}}
\]

\[
\frac{1 + r_{t}^{(1)}}{1 + r_{t}^{(2)}} = \frac{s_{t+1}}{s_{t}}
\]
and we can do so through the Uncovered Interest Parity (UIP),

\[
\frac{1 + r_t^{(1)}}{1 + r_t^{(2)}} = \mathbb{E}\left[ \frac{s_{t+1}}{s_t} \right]
\]

which we can evaluate by replacing the expectation with the average of exchange rate differentials.

With a carry trade strategy, one borrows money from a low-interest currency, and converts it to a high-interest currency to earn interest. If the future exchange rate stays almost unchanged, then we are earning a high interest while repaying a low interest. Of course, we cannot assume that the exchange rate plays out so nicely. In fact, UIP suggests that if \( r_t^{(1)} > r_t^{(2)} \), then we should expect \( s_t > \mathbb{E}[s_{t+1}] \), meaning that the low-interest currency would appreciate relative to the high-interest currency, which then indicates that the supposedly low interest to be repaid would become more expensive relatively, and the supposedly high interest earned would worth less relatively. Therefore, carry trades should be hardly profitable, if at all.

However, just like with PPP, while most economists agree that UIP holds in long-term, there can be very dramatic deviations over a shorter term. Despite our reasoning over UIP, the famous empirical anomaly “forward premium puzzle” depicts that in practice, the low-interest currency would often depreciate, rather than appreciating (Cavallo, 2006), making carry trades even more profitable. This anomaly also suggests that we should look for local carry trade strategies, rather than global ones.

An important note on BTC here is that we cannot short it. While there are authoritative sources of fiat currency borrowing, we do not have any for BTC. Therefore, for any carry strategy that we apply to BTC, we must hold a non-negative amount of BTC at any given moment.

5.2 • Data and Tests

We use the same sources of data as in Section 4.3. For the purpose of analyzing interest parities and carry trade, the length of a period needs to be set according to interest rate intervals. Therefore, instead of tabulating out monthly interest rates to daily values, we put together exchange rates and BTC prices to use their monthly values. Note that the interest rates are monthly rates, rather than annual rates.

In the upcoming sections, we test USD against EUR, and USD against BTC. Forward contracts for BTC is still in an very early stage, so we do not test for CIP here. We will test for UIP, and see which directions the two pairs each favor.
Then, using the direction of UIP, we apply two simple carry strategies. For the first naïve strategy, we buy $1 worth of the other currency whenever \( \frac{s_t}{s_{t-1}} > r_{t-1} \), and sell everything otherwise. Given the rapid rising in BTC prices, for the second strategy we apply a moving average of exchange rate differential with window sizes \( \ell = 1 \) month, 3 months, 6 months, and 1 year, buy $1 worth of the other currency when moving average is above price, and sell everything otherwise.

5.3 • USD AGAINST EUR

Figure 4 plots cumulative average of exchange rate differential along with the ratio of the interest of USD against EUR. Since the cumulative average is almost constant, switching to overall average hardly changes anything. We see that for 57.99% of the time, cumulative average of exchange rate differential is higher. If we switch to overall average, it is still higher 53.18% of the time. Both of them indicate a deviation of UIP in favor of exchange rate differential, but only by a small margin.

Given the shape of cumulative average of exchange rate differential, the two strategies perform extremely similarly. We can earn $77.14 for the first strategy, $77.16, $77.07, $78.03, and $80.00 for \( \ell = 1 \) month, 3 months, 6 months, and 1 year for the second strategy, respectively. These results all agree with our observation of the direction of UIP. Note that even
though we are fortunate enough to have the two strategies working globally, Figure 4 clearly shows regions when the cumulative average is below interest ratio.

5.4 • USD AGAINST BTC

Figure 5 gives cumulative average of exchange rate differential and interest ratio for USD and BTC, and it is in many ways opposite to Figure 4. Since the interest rate of BTC interest rate is set to 0, interest ratio here is simply USD interest, which would not fluctuate as much. On the other hand, monthly price of BTC changes dramatically, so it is not stable at all. Cumulative average of exchange rate differential is only above interest ratio 4.94% of the time, and if we switch to overall average, it would never be above interest ratio. For this case, the UIP deviation is almost entirely in the direction of interest ratio.

Not only is the cumulative average of exchange rate differential unstable for BTC, the rapid rise in BTC price would scale up our gains or losses from carry trades significantly. With the first strategy, we end up with earning $1,333.98, and with the second strategy, we would end up earning $1,340.54, $1,072.28, $2,4076.75, and $2,4076.75, for the four window sizes in increasing order.

Figure 6 plots moving averages for each window size, and we buy BTCs whenever the moving average is above interest ratio. With $\ell = 1$ month and 3 months, we get more spikes after...
2012, and they led us to make purchasing decisions that results in the lower profits compared to those of larger window sizes.

![Moving Averages of Exchange Rate Differential](image)

**Figure 6: Moving Averages of Exchange Rate Differential for USD and BTC**

Comparing AUD, CAD, CNY, GBP, and JPY against BTC would give similar results. In terms of UIP, interest ratio dominates cumulative and overall average of exchange rate differential most of the time, which is different from what we observe from fiat currencies. Even though we almost always get a positive profit out of the carry trade strategies, it only happens because we cannot short BTC in the strategies, and they often fail on randomly selected time intervals.

### 6 • Discussion and Conclusion

In answering whether or not cryptocurrencies are currencies, we focused on Bitcoin, the earliest, the most characteristic, and the most cryptocurrency to date. As a starter, we explored the anecdotal aspects of Bitcoin, and concluded that none of them were convincing enough to conclude or reject Bitcoin’s identity as a currency.

Turning to a systematic approach, we analyzed how its price behaves, and compared it to existing findings about fiat currencies. When predicting out-of-sample, we found that Bitcoin price was as unpredictable as fiat currency prices. We also found that structural
models performed better for Bitcoin than they did for fiat currencies, potentially due to the fact that Bitcoin receives no regulation, which allows it to freely adjust itself and its changes more easily captured by market factors. When examining Bitcoin price’s in-sample behaviors with UIP, we arrived at conclusions very different from what we had for fiat currencies. We observed that interest differentials dominated average exchange rate differentials the vast majority of time, which suggested that Bitcoin price was not rising fast enough. Before settling at a final conclusion on whether or not Bitcoin is a currency, we should take some time to discuss potential drawbacks and improvements to our testing methods.

6.1 • POTENTIAL DRAWBACKS AND IMPROVEMENTS

First and foremost, we should have tested against multiple cryptocurrencies, rather than just against Bitcoin. As much as we want to and should have, however, we hardly have sufficient data for even Bitcoin, let along newer cryptocurrencies. The first years of Bitcoin saw wild fluctuations in its price, and many newer cryptocurrencies are just as chaotic, which makes it less meaningful to test against them. Bitcoin too is in its early stage, and it could undergo dramatic changes in the upcoming years, as legal enforcements begin to take effects, and as mining reward decays.

We argued briefly in Section 4.5 that many predictors of monetary properties do not exist for Bitcoin, and it is true. Notions like trade balance cannot be applied to Bitcoin, because it has no country boundaries. We were still able to obtain satisfactory results from structural models, so for our purpose it may be fine to stop worrying about them. Nevertheless, should we take Bitcoin as a currency, it would be worthwhile to refine or rethink each of its monetary properties. Part of the reason why we observed such a large gap between interest ratio and cumulative average exchange rate differential in Figure 5 is that we set the interest rate of Bitcoin to 0. According to the definition of interest rate, this is the proper value, but then there is no interest rate to counteract fiat currency interest rates, so that the job of balancing UIP falls entirely on exchange rate differential, leading to the seemingly absurd conclusion that Bitcoin price is not rising fast enough.

As time goes by, so will the scope of analysis. For example, future inflation expectations such as Bitcoin Futures are in its experimental phase right now, but will mature and provide helpful measures. People would be able to interact with cryptocurrencies with a more abundant set of options, and cryptocurrencies would blend better into the global economy.

If cryptocurrencies would continue to operate for another century, we can also test against Frankel’s claim that a lengthier dataset is able to confirm the convergence to PPP [1986] and hence reject the RW model.
6.2 • An Answer

Finally, we back to the question: is Bitcoin a currency? Of course, Bitcoin does not resemble all characteristics we know about fiat currencies, but given its design, it probably never can. Our analysis seek not how Bitcoin behaves on the surface, but instead how it runs within the economy, and how it reacts to the market. From such an economic perspective, we end this paper by concluding that Bitcoin is a currency, but it is a currency unique to its own design.

7 • Appendix

7.1 • Aggregated Monthly MSEs with USD and EUR

![Graph](attachment:Aggregated_Monthly_MSE.png)

Figure 7: Aggregated Monthly MSEs at $\ell = 1$ Month for USD and EUR

7.2 • Aggregated Monthly MSEs with USD and BTC


Figure 8: Aggregated Monthly MSEs at $\ell = 6$ Month for USD and EUR

Figure 9: Aggregated Monthly MSEs at $\ell = 1$ Year for USD and EUR
Figure 10: Aggregated Monthly MSEs at $\ell = 1$ Month for USD and BTC

Figure 11: Aggregated Monthly MSEs at $\ell = 6$ Months for USD and BTC
8 • REFERENCES


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