Bitcoin Reveals Unofficial Exchange Rates and Detects Capital Controls

G.C. Pieters*

Trinity University, Economics Dept, 1 Trinity Place, San Antonio, Texas, 78212.

Abstract

Managed exchange rates and capital controls impact international trade and finance flows, yet data used to detect these manipulations are of low frequency, expensive, lagged, and potentially mis-measured. The timely, high frequency, free-of-charge prices of Bitcoin offer a solution to this problem. I demonstrate that the internationally traded crypto-currency can estimate unofficial exchange rates, detect exchange rate regimes; and detect capital controls at a daily frequency. However, Bitcoin prices may contain bitcoin-specific dynamics that must be removed prior to being used for this purpose, and Bitcoin-based exchange rates approximate the dynamics, but not the level, of unofficial exchange rates.

Keywords: Bitcoin; Exchange Rates; Black Market; Unofficial; Financial Integration; Capital Controls

JEL Codes: F30, F31, F38, E42, G15, O17

*Corresponding author

Email address: gpcpieters@gmail.com (G.C. Pieters)

[1]I am grateful for helpful comments and suggestions from Christoffer Koch, participants at the 2015 Southern Economic Association Conference in New Orleans, and the 2016 International Trade and Finance Association Conference at Occidental College.

1. INTRODUCTION

This paper is a contribution to timely, high frequency, accurate measurement of unofficial exchange rates, *de facto* exchange rate regimes, and capital controls. While exchange rate manipulation may seem like a problem that distorts the trade and finance flows of only a few countries, Calvo and Reinhart (2002) found that governments display "fear of floating": officially declaring they allow their exchange rates to float (a *de jure* floating regime), while still actively manipulating their exchange rates (a *de facto* managed regime). Alesina and Wagner (2006) document that only 157 out of 601 *de jure* floats were *de facto* floats, with countries declaring a floating regime to signal their virtuousness.

In the absence of accurate official data, economists use indirect methods to detect the *de facto* exchange rate regime. Calvo and Reinhart (2002) and Levy-Yeyati and Sturzenegger (2005) use volatility of a policy instrument – such as interest rates or foreign exchange reserves – and interpret a smooth exchange rate accompanied by a volatile policy as a non-floating exchange rate regime. However, Klein and Shambaugh (2015) show that economies can successfully "mix-and-match" policies to smooth exchange rates – such as a temporary capital control accompanied by only a small adjustment to interest rates – confounding these detection systems and leading to under-detection of *de jure* deviations. In contrast, Kim (2016) shows that these approaches suffer from a simultaneity problem—policy instruments may be reacting to a domestic event instead of attempting to smooth a exchange rate, suggesting over-estimation of *de jure* deviations.

I show that the timely, high frequency, free-of-charge price data from bitcoin sales can be used to construct a dataset of daily unofficial exchange rates and detect *de facto* regimes.[2] Unlike commodities-based analysis of exchange rate behavior – such as the oil prices used in Ferraro, Rogoff, and Rossi (2015) – Bitcoin's lack of regulations and lack of transportation costs (as a virtual good) facilitates purchases across multiple currencies and countries.

[2] I use to the term "unofficial exchange rates" to broadly include what others call the market, black market, parallel, or de facto exchange rates.

Moreover, because bitcoin has an alternative use as an investment and purchasing vehicle bitcoin prices exist across a variety of regimes, even currencies with unmanipulated exchange rates.

Prior attempts to use unofficial exchange rates to detect *de facto* regimes for multiple countries, such as Reinhart and Rogoff (2004), use data from the same source: *World Currency Yearbook*.[3] This consists of a monthly observation reported by "Central Bank and Ministries of Finance who may be reluctant to provide the true data", or "foreign correspondents or informed currency dealers" [Bahmani-Oskoee, Miteza, and Nasir (2002)]. In contrast, Bitcoin prices are directly observed and therefore potential bias from reporting agents is removed. The prices are available regardless of the state of the economy or government. Bitcoin prices are available at a high frequency, by the minute, and so can detect the transitory interventions detailed in Klein and Shambaugh (2015).

Similar to *de jure* exchange rate regimes, *de jure* capital controls may be misleading as countries impose undeclared barriers or declared barriers are circumvented. Even though the trilemma implies the two are closely related, Ilzetzki, Reinhart, and Rogoff (2017) note that the *de facto* exchange rate literature often ignores capital controls. While constructed measures of capital controls may be robust to the specific concerns above, these measures are usually annual. They also lag in availability: even though current year is 2017, the broadly used capital controls index, the Chinn-Ito Index, ends in 2013. I verify that the high-frequency Bitcoin exchange rates can also be used to detect capital controls, even if the impact is transitory.

The daily measures of effective capital controls and unofficial exchange rates compiled in this paper will prove to be a key input into future empirical work in business cycle or event study papers, and research on international finance, macroeconomics, or trade. Currently,

[3]The *World Currency Yearbook* was formerly known as *Pick's Currency Yearbook*. Some cite Reinhart and Rogoff (2004) as their data source—this dataset was built using *World Currency Yearbook*. Papers that do not use the *World Currency Yearbook* are usually restricted to only one exchange rate: for example, while Huett, Krapf, and Uysal (2014) use online data the prices are only for the Belarusian ruble to the US dollar, euro, and Russian ruble.

business cycle or event study papers, such as Fernández, Rebucci, and Uribe (2015) who examine whether capital controls are countercyclical, use annual capital control data. It can be used in empirical work to detect the magnitude of unofficial capital flows or the dynamics of unofficial exchange rates. Bitcoin is a sovereign-less vehicle currency, so it can decompose exchange rate effects between economies in macroeconomic models, as Yang and Gu (2016) demonstrate for trade. Michalski and Stoltz (2013) find that among countries of similar economic profiles, fear-of-floating countries are more likely to misreport economic data. The high-frequency data allows us to identify specific intervals when the economic data is to be misreported —for example, unemployment or inflation.

2. THE PROMISE AND LIMITS OF BITCOIN EXCHANGE RATES

Bitcoin is a crypto-currency[4] with no central monetary authority, country of origin, or physical representation, designed and created by the entity Nakamoto (2008).[5] Once acquired, a bitcoin can be held, used for retail purchases, or bought and sold on a bitcoin trading website, known as an "exchange".[6] Dwyer (2015) explores why the ability to use Bitcoin for these purposes could result in a crypto-currency with a positive price, while Luther (2016) examines conditions under which a positive price may not result even if Bitcoin is superior to existing monies.

Every account on an exchange has at least one virtual "wallet". Currency in a wallet can

[4] I use the term "currency" to refer exclusively to a currency issued by a central monetary authority (e.g., the US dollar) as opposed to crypto-currencies, such as Bitcoin or Ethereum.

[5] The name Satoshi Nakamoto is a pseudonym. The identity of Satoshi (person or persons) is currently unknown. Nakamoto designed the Bitcoin system to create 21 million bitcoin, automatically issued as rewards to users who are the first to successfully solve a mathematical algorithm in a process known as "mining". Böhme, Christin, Edelman, and Moore (2015) wrote an accessible technical review of Bitcoin, while Brandvold, Molnar, Vagstad, and Valstad (2015) contains a brief discussion of major events in Bitcoin history. White (2015) considers the market for crypto-currencies more broadly.

[6] The online nature and pseudo-anonymity of Bitcoin has resulted in its well-known use in online criminal transactions. The "Silk Road" market is the most widely known example. Silk Road was an online marketplace (not a bitcoin exchange) for the sale of drugs and other illegal activities where transactions were conducted in bitcoin to reduce the ability of law enforcement to trace payments. Bitcoin has a variety of legal purchase uses as well. Major companies, such as Dell and Amazon both allow the purchase of items using bitcoin, either directly or through the purchase of a gift card. Websites such as coinmap (http://coinmap.org) or usebitcoins (usebitcoins.info) maintain lists of businesses—both online and physical—that accept bitcoin.

be directly deposited into or withdrawn from a connected bank account, an online payment system (such as PayPal), or a different wallet. The currency can be used to buy a bitcoin, which can then be sold for a different currency.[7] Using bitcoin prices in the currency of interest ($B^{C}_{m,t}$) and the US dollar ($B^{USD}_{m,t}$) for exchange (m) on day (t), the implied bitcoin exchange rate, ($E^{B,C}_{m,t}$) and between currency (C) and the US dollar is given by:

$$E^{B,C}_{m,t} = B^{C}_{m,t}/B^{USD}_{m,t} \tag{1}$$

This treats bitcoin as a vehicle currency, a role traditionally held by the US dollar.[8] Unlike traditional vehicle currencies, access to bitcoin and its associated exchange rate to other foreign currencies is very difficult to restrict as it requires preventing individuals from accessing websites.[9]

Bitcoin – with its virtual nature and global, unregulated, online markets – may appear the perfect instrument with which to obtain unofficial exchange rates and measures of capital controls. Figure 1 uses the Chinese yuan exchange rate to show this potential. The bitcoin exchange rate reveals devaluation pressure building prior to the official devaluation on August 10, 2015. After the official devaluation, the exchange rates become very similar indicating that calls to further devalue the Chinese Yuan may be misplaced.

(Figure 1 about here)

However, Pieters and Vivanco (2017) document persistent differences in bitcoin prices and trends across Bitcoin markets —arbitrage forces fail even in the simplest case of a single currency. It is feasible that the constructed bitcoin exchange rates are unrelated to a currency's unofficial exchange rate, instead reflecting the expectations of the global online

[7]In the bitcoin markets, trades clear every 10 minutes, though users with higher balances or willing to pay higher fees may trade prior to this. Therefore, the buying and selling can treated as immediate.

[8]Systems for direct currency trades have recently been implemented by some exchanges. As these systems are still in their infancy (having poor data availability), transactions of this nature will not be considered, however they should only improve the ability of bitcoin to represent an exchange rate.

[9]Hendrickson, Hogan, and Luther (2016) consider governmental efforts to discourage bitcoin use, while Pieters and Vivanco (2017) show that such efforts are easily circumvented.

Bitcoin community – many of whom may not live in the country that uses the currency – and not the unofficial "street value" of the currency, especially in countries with low internet penetration rates. An early study of U.S. dollar bitcoin price behavior by Yermack (2015) concluded that the daily U.S. Dollar-Bitcoin exchange rate exhibited nearly zero correlation with the exchange rate of U.S. Dollar to Euro, Japanese Yen, Swiss Franc, or Gold.

This limitation of bitcoin exchange rates is shown in Figure 2 using the official, unofficial, and bitcoin exchange rates for Argentina. Argentina is widely known to have a long-established crawling peg regime with the US dollar with many capital controls. It is unique in that its unofficial exchange rate is reported daily by various sources (including Argentinian newspapers), reducing many of the concerns typically associated with estimates of the unofficial exchange rate. I obtain unofficial exchange rate data from *Ámbito Financiero*, a daily newspaper based in Buenos Aires.

(Figure 2 about here)

It is immediately obvious that the bitcoin exchange rate (middle solid line) is highly volatile, and resembles the unofficial exchange rate (top dotted line) but not the official exchange rate (bottom dashed line). The bitcoin exchange rate is lower than the unofficial exchange rate, which may reflect considerations of convenience and safety when using online bitcoin exchanges relative to street vendors in Argentina, and indicates that bitcoin should not be used to estimate the level-value of the unofficial exchange rate. The behavior during the two-month periods in Region 1 and Region 2 indicate more serious reasons to pause. In Region 1, the bitcoin exchange rate remains level while the unofficial exchange rate is changing, while in Region 2 the unofficial exchange rate decreases while the bitcoin exchange rate increases. However, Figure 3 shows that the behavior in Region 1 and Region 2 cannot be dismissed as a disconnect between Bitcoin and "street-level" market sentiments in Argentina.

(Figure 3 about here)

While the South African rand (ZAR) is a floating exchange rate there are many capital controls in place. Figure 3 shows two episodes where bitcoin exchange rates change without any corresponding movement in the official exchange rate: April 17, 2015 and May 21, 2015. The timing of these bitcoin deviations are linked to domestic events that received only limited international attention – on April 17 there was mass anti-migrant riots and violence, and on May 21 there were nationwide police raids, which resulted in approximately 4,000 arrests in connection to the riots. The bitcoin exchange rates are consistent with capital flight – a sentiment that would not be revealed in the official exchange rate data given capital controls. Therefore, the behavior of the bitcoin exchange rate in Figure 2 do not necessarily reflect a disconnect between bitcoin and Argentinian exchange rate markets, but a property of the Bitcoin market that must first be accounted for when using bitcoin exchange rates.

3. EMPIRICAL APPROACH

3.1. DATA SOURCES

I obtain daily transaction-weighted bitcoin prices from the the aggregation website Bitcoin Charts [bitcoincharts.com], which provides data from 72 exchanges trading 31 currencies.[10] Bitcoin prices on Bitcoin Charts are available immediately, without charge or subscription, enhancing arbitrage flows. Because exchanges do not close for trading, each day is defined as starting at midnight Coordinated Universal Time (UTC) regardless of exchange location or currency traded, so there is no time difference between exchanges.

I focus on a period of 487 days between June 1, 2014, to September 30, 2015.[11] To create a comparable cross-currency study, I examine only exchanges where users can buy or sell

[10]Minute-by-minute data is available, but is not used to reduce missing observations.

[11]The beginning and end dates are deliberately chosen as bookends to a calm period in bitcoin history. In February 2014 an exchange that handled up to 80% of the world's bitcoin trade, Mt. Gox, failed and declared bankruptcy, causing rapidly decreasing prices and high price volatility. CoinDesk (www.coindesk.com/companies/exchanges/mtgox) provides more details surrounding this event. By June 1, 2014 the bitcoin market had stabilized. September 30, 2015 marks the beginning of a sustained rapid increase in prices: in September Bitcoin was declared a commodity for USA tax purposes, in October the EU ruled there would by no VAT on Bitcoin transactions and Bitcoin was featured in front page article in the Economist. Most importantly, by October it was clear that an attempt to change Bitcoin, called the XT fork, was going to fail. This lead to infighting, ultimately resulting in the exit of a prominent developer, Mike Hearn, in January 2016 whereupon he wrote a viral opinion piece declaring Bitcoin dead.

bitcoin in at least three different currencies, of which two must be the US dollar and the euro, with each selected currency containing a minimum of 440 price observations.[12] This restricts focus to seventeen of the 31 currencies and four of the 72 exchanges.[13] Official exchange rate data come from Oanda.com, which reports the average exchange rate over a 24-hour period of global trading, seven days a week—a structure similar to the exchange rate created by bitcoin data.

Table 1 lists summary details of each price series and any Bitcoin restrictions imposed by the currency's country of origin. Most countries have no laws regarding bitcoin trading, and when they do it is usually only to require standard money-laundering or counter-terrorism laws, or ban financial firms or banks – but not individuals – from trading bitcoin. Russia and Thailand are the only two countries that appear to have banned bitcoin trades, yet statements by Russian politicians have contradicted this position, and bitcoin-based businesses have received licenses in Thailand.[14] The lack of a global regulatory framework means that any restrictions are difficult to enforce as countries cannot regulate bitcoin trades that occur in their currency outside of their borders (for example, someone in Canada buying bitcoin with Russian Rubles). Pieters and Vivanco (2017) show that the regulations surrounding USD trades are easy to circumvent, so I assume regulations have a minimal impact on the global bitcoin market.

[12] I use linear interpolation to estimate missing values, resulting in 487 daily observations per bitcoin exchange and currency. There is no evidence that results are distorted due to sample size. Given the volatility of bitcoin price data, I examine exchange rates changes that are greater than 20% or are 4 standard deviations away from the mean. If the exchange rate approximately returns to its preceding level the following day, the outlier exchange rate is replaced by the average of its neighbors. For example, an exchange rate that lists 3 observation values of {5,9,5} may have the 9 value replaced, but an exchange rate that lists {5,9,13} or {5,9,9} would not. This replacement reduces bitcoin exchange rate volatility, and reduces the probability that the bitcoin exchange rate reports a barrier. As the bitcoin constructed exchange rates detect all the barriers reported in KAOPEN, this does not distort results.

[13] The price series for the Hong Kong dollar from ANXBTC, and the price series for Australian dollars, Swiss franc, British pounds, Hong Kong dollars, Indian rupees, New Zealand dollars and Russian rubles on LocalBitcoins also satisfy the selection criteria. However, these series either exhibit persistent residual autocorrelation or fail to yield a single direction of causality and cannot be tested in later sections. For sample consistency, they are removed from consideration.

[14] Russia's history of stances on Bitcoin is reviewed here: http://bravenewcoin.com/news/russias-bitcoin-winter-may-be-thawing/ while Thailand's history is discussed here: http://themerkle.com/legal-status-bitcoin-thailand/

(Table 1 about here)

The average daily volume of trade summarizes trades either in units of bitcoin (BTC) or in the currency indicated.The volume of currency traded, measured in bitcoin, varies by currency and by exchange. During this period the US dollar was the most traded currency on bitcoin markets —exceeding a quarter million dollars even on the smallest exchange. The difference between US dollars trade volume and the next most used currency varies. On ANXBTC the volume of trade in US dollar's and Euro's is comparable, while on LocalBitcoins US dollar trade volume is 8 times bigger than Euro trade volume. Bitcoin measures of trade volume is misleading because a bitcoin is highly divisible: the smallest bitcoin unit is the bitcoin-satoshi, which equals 10^{-9} bitcoin (a hundred-millionth of a bitcoin). Therefore, a trade volume of "1 bitcoin" could indicate a hundred million trades. The price of a bitcoin in any given currency also varies across exchanges. On BTC-e the average price of bitcoin in US dollars is \$341.53, while on LocalBitcoins it is \$382.89. The volume and price differences imply that data from different exchanges should not be mixed.[15]

3.2. IDENTIFYING TRENDS IN BITCOIN MARKETS

Conversions between the US dollar and the Euro face minimal financial barriers in the official exchange rate market, so I assume that the official USD-Euro exchange rate also represents the unofficial USD-EUR exchange rate. As the US dollar and the Euro are the most traded currencies on each bitcoin exchange, the bitcoin US dollar-Euro exchange rate should represent the least distorted bitcoin exchange-rate. I will therefore use the deviation between the official and bitcoin USD-EUR exchange rate to identify bitcoin-specific trends in each market.

Figure 4 shows the percent deviation between the official and bitcoin exchange rates constructed from equation 1 for each bitcoin market, $\frac{E_{m,t}^{B,Euro} - E_t^{O,Euro}}{E_t^{O,Euro}}$. It also shows a trend line constructed using a Lowess smoother with a bandwidth of 10% to facilitate analysis of

[15] The cause of these arbitrage deviations are examined in Pieters and Vivanco (2017).

the long run trends.

(Figure 4 about here)

The bitcoin exchange rate constructed from ANXBTC and itBit data is almost indistinguishable from the official exchange rate, unlike those calculated using BTC-e and LocalBitcoins data. The difference between the bitcoin and official exchange rate is not constant, with LocalBitcoin trending away from the official exchange rate. This visual analysis demonstrates why determining how to appropriately compare bitcoin exchange rate to official exchange rate data is highly relevant: while bitcoin data can theoretically be used for easy inference about exchange rates, there are clearly trends in the bitcoin-derived exchange rate that reflects the individual bitcoin exchange, not the currency.

In the sections that follow I use the relative bitcoin and official exchange rate to detect exchange rate regimes and a currency's capital barriers. I find that this approach yields the same result as the current classification systems if a bitcoin adjustment term, based on the Euro exchange rate difference, is incorporated, and allowance is made for the higher frequency of the bitcoin data.

4. BITCOIN AND UNOFFICIAL EXCHANGE RATES

4.1. Detecting Exchange Rate Regimes

The inconsistency between the declared and actual exchange rate regimes has led to many attempts to classify exchange rate regimes based on observed behavior. Levy-Yeyati and Sturzenegger (2005) construct a classification based on official exchange rates and international reserves; Shambaugh (2004) use the volatility of the official exchange rate; while Quéré, Coeuré, and Mignon (2006) used a stability criteria against a market basket of currencies. Consequent to the findings of Calvo and Reinhart (2002), the IMF regime classification now considers both the country's official statement and the behavior of the exchange rate.

Reinhart and Rogoff (2004) use the existence of a parallel exchange rate, which is not suited for bitcoin data which exists regardless of regime. However, both they and Kiguel and O'Connell (1995) argue that the difference between the market and official rates should be greater for managed exchange rates than it is for market exchange rates. Akram, Rime, and Sarno (2008) study global (official) exchange rate contracts and find that most price deviations are quickly arbitraged away, evidence that floating exchange rates comply to this theory. Bitcoin's global simultaneity (exchanges never close) and ease of comparison of prices across bitcoin markets (bitcoin prices in all currencies are globally and simultaneously available to the public at no charge) imply that arbitrage opportunities should be found and exploited even more quickly and easily. To identify exchange rate regimes I consider the mean of the premium, or mark-up, between the official and bitcoin exchange rate, $M^C_{m,t}$:

$$M^C_{m,t} = \frac{E^{B,C}_{m,t}}{E^{O,C}_t} - 1 \tag{2}$$

Because Figure 4 shows that this mark-up even for the Euro, I adjust the mark-up by the value of the euro mark-up for the exchange:

$$\tilde{M}^C_{m,t} = M^C_{m,t} - M^{EUR}_{m,t} \tag{3}$$

4.2. Exchange Rate Regime

Table 2 lists the adjusted mark-up for each currency and bitcoin exchange, grouped by exchange rate regime identified by IMF Annual Report on Exchange Arrangements and Exchange Restrictions (2014). For some currencies and exchanges, bitcoin is a mark-up, while for others are a mark-down. With no clear pattern to this deviation, I focus only the size of deviation from zero.[16] With the exception of four currencies discussed below, once adjusted low bitcoin mark-ups are associated with exchange rate arrangements labeled as floating by the IMF. This implies that bitcoin can be used to detect exchange rate regimes.

Bitcoin and the IMF disagree regarding the Singapore dollar (SGD) and the Chinese

[16] The average mark-up for the Euro is 0.06% for ANXBTC, 1.43% for BTC-e, 0.13% for itBit, and -7.08% for LocalBitcoin.

(Table 2 about here)

Yuan (CNY), which both have low mark-up's even though neither are considered floating by the IMF. The SGD finding is confirmed across both of the bitcoin exchanges that trade in Singapore dollars. Figure 1 shows why the reported CNY mark-up is low despite the IMF classification —for the portion of 2014 covered by Bitcoin data the official and bitcoin exchange rates are very similar before diverging again in 2015. This is a unique aspect of using Bitcoin to identify exchange rate regimes: It allows inference about the extent to which a government control is impacting the exchange rate. In these two cases, for the later half of 2014, the exchange rate controls were not distorting the markets much.

While the IMF classifies the Thai bhat (THB) as floating exchange rate it has a high bitcoin mark-up. Thailand underwent a political coup by the military in May 2014 (detailed in Human Rights Watch (2015)), so the persistent high mark-up may reflect underlying uncertainty and unofficial capital flight.

Finally, the Polish zlotly (PLN) has higher mark-ups than expected for a free floating exchange rate. However, Poland is known to have barriers to capital flow as I will discuss in Section 5. The mark-up reflects capital movements in unofficial Bitcoin channels that are not occurring in the official channels, causing a divergence in the relative exchange rates. Figure 5 identifies three specific events corresponding to large changes in the mark-up: a decrease in mark-up size after a financial crisis starts in Russia (potentially interpreted as a decrease in likelihood of further aggression), a decrease after a successful Polish election, and an increase with the re-appearance of the threat of Grexit. Figure 5 also confirms results in Table 2: the deviation between official and bitcoin exchange rates generally decreased in 2015, though transitory large swings in capital flows still occurred. This detail would not be observed in annual data.

5. BARRIERS TO ACCESSING FOREIGN CURRENCY

Bitcoin can fulfill two functions in international markets: an alternative way to obtain a foreign currency, and a way to circumvent capital controls. A fixed exchange without capital controls (for example, a currency board) would have a large but stable mark-up, as relative demand for bitcoin to official channels should be stable. A free floating exchange rate with capital controls would have a volatile, non-stationary mark-up as bitcoin purchases ebb and flow with unofficial capital flows —the riots and arrests in Figure 3, or the various events in Figure 5. Figure 5 also reveals that Bitcoin can detect how binding barriers may be at deterring capital flows through official channels in response to specific events. I will use the lack of mark-up stationarity to detect capital regulations. My mark-up-based estimate of capital controls is related to Yeyati, Schmukler, and Horen (2009), who examine the length of the half-life price premium of stocks sold across markets in different currencies resulting *from* known cross-border capital regulations.

I test the validity of my results against an ubiquitous measure of capital controls: the Chinn-Ito Financial Openness index (KAOPEN), originally developed by Chinn and Ito (2006) and currently updated to 2013.[17] Other measures exist: For example Bekaert and Harvey (2005) construct a binary index based on the date of financial liberalization and Lane and Milesi-Ferretti (2007) use measures of a country's exposure to international financial markets. A comparison of the various indices can be found in Quinna, Schindler, and Toyoda (2011), however, as all these measures terminate several years prior to the time period in this study they cannot be compared to the Bitcoin results.

[17]KAOPEN is constructed from the values of four annual binary dummy variables from the International Monetary Fund's (IMF) Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). Specifically, it is based on four dummy variables that indicate the presence of multiple exchange rates, restriction on current account transactions, restrictions on capital account transactions, or a requirement of the surrender of export proceeds.

5.1. Determining Capital Controls

Both the official and bitcoin exchange rate series for each currency are found to be nonstationary, therefore I test whether the official and bitcoin exchange rates are cointegrated to determine if the mark-up is stationary. A failure to find cointegration – no statistically significant linear relationship between $E^{B,C}_{m,t}$ and $E^{O,C}_{t}$ – means that a currency's official and bitcoin exchange rates are unrelated, suggesting the existence of a substantial barrier to access official international exchange markets.[18] If the series are cointegrated, I determine their cointegrating relationship —the two exchange rates series should share the same trend, indicated by a cointegrating parameter of 1.

I use either the Johansen trace test or the Pesaran-Shin-Smith (PSS) bounds testing procedure to test for cointegration. The Johansen trace test is the default test for cointegration but requires that all tested series be I[1] (referred to as unit root, first-difference stationary, or having order of integration one). However, some series in this sample are fractionally integrated (between I[0] and I[1]) and because the fractional integration of a series could result from the exchange rate regime or barriers to access, these series should not simply be removed. Unlike the Johansen trace test, the PSS bounds test allows for fractional integration, but is more restrictive as it requires the series to display a single direction of causality. Details are discussed in Appendix A.

I test for cointegration and calculate the cointegrating parameter across the four bitcoin exchanges for the Euro in Table 3. The official and bitcoin USD-Euro exchange rates are cointegrated for all four bitcoin markets – the expected result for an exchange rate with minimal restrictions – however the estimated coefficient of the cointegrating equation, $\hat{\beta}^{Euro}_{m}$, varies greatly. While ANXBTC reports the expected result of $\hat{\beta}^{EUR}_{\text{ANXBTC}} = 1$, LocalBitcoins reports $\hat{\beta}^{EUR}_{\text{LocalBitcoins}} = 0.76$ which implies that LocalBitcoin's trend is to increase by only

[18] Cointegration tests are biased against finding cointegration if one of the series contains a structural break. Within this setting, however, the exchange rate series should share the timing and magnitude of a structural break if there are no barriers, so a finding of no cointegration in this setting is consistent with the interpretation of a barrier. Therefore, I do not include controls for structural breaks.

0.76 cents for every dollar increase in the official exchange rate: a long run divergence.

(Table 3 about here)

Table 3 therefore again verifies Figure 4: there are non-negligible trends within either bitcoin or the bitcoin exchange. However, if these bitcoin-trends are consistent across currencies on an exchange it is feasible to use $\hat{\beta}_m^{EUR}$ to normalize the remaining estimates and remove bitcoin-specific effects for any currency to estimate the magnitude of barriers relative to the Euro.

$$\hat{\rho}^C = \begin{cases} ||\hat{\beta}_m^C - \hat{\beta}_m^{EUR}||, & \text{if cointegrated} \\ 1 & \text{otherwise} \end{cases} \tag{4}$$

The lowest value of $\hat{\rho}^C = 0$ indicates a barrier equivalent to that of the USD-EUR exchange rate (low barriers). The effective size of a country's barrier can then be ranked based on its distance from $\hat{\rho}^C = 0$, with $\hat{\rho}^C = 1$ indicating the maximum barrier (complete dissociation of the two exchange rates).

5.2. Does Bitcoin Reveal Barriers?

Table 4 presents results from the cointegration tests, the unadjusted trend coefficients $\hat{\beta}_m^C$, the estimated barrier magnitude $\hat{\rho}_m^C$, and a currency's barrier status based upon the 2013 KAOPEN classification. Traditionally, a KAOPEN value of zero implies zero capital flows (high barriers) and one means no barriers, but for ease of comparison to bitcoin results I transform KAOPEN so that ranges from zero (no barriers) to one (high barriers) by taking the difference from one. I sort currencies into three broad categories based upon their 2013 KAOPEN classification: High, Intermediate, and Low Barriers to facilitate comparison with bitcoin results.

(Table 4 about here)

Amongst low barrier currencies one currency differs from its KAOPEN classification: The Norwegian Krone (NOK). Table 1 shows that the Norwegian krone has among the lowest volume of trade among low-barrier testable currencies on LocalBitcoin (the Polish Zloty (PLN) is classified by KAOPEN as an intermediate barrier currency). Therefore, one explanation of the difference is that it reflects liquidity issues on LocalBitcoin. However, a structural break analysis reveals a break in the bitcoin NOK exchange rate series on December 8, 2014. Examining the series before and after this break yields the same low barrier classification as KAOPEN, therefore failure originates entirely from the exchange rate activity of a single day. While I could find no news originating in Norway that could explain timing, Norway, like Poland, is close to Eurozone countries which may be the source of the bitcoin capital flows.[19]

Relative to their KAOPEN classification, Mexico is found to have significantly more capital restrictions, while Russia has lower barriers. Several events could explain a change in the Mexican exchange rate – the fall of oil prices; implementation of austerity cuts; a political scandal – observed in both the official and bitcoin exchange rate. However none of these events can explain the divergence between the official and bitcoin exchange rates visible at the beginning of October 2014. A likely cause can be found in last paragraph on page 53 of the Banco de Mexico January–March 2015 Quarterly Report (Banco De Mexico, 2015), detailed in more depth by Cardenas (2015). Mexico moved out of the acceptable band for its exchange rate, causing the central bank to intervene through an auction. This intervention matches the timing of the divergence of official and unofficial exchanges rates.

Recall that the bitcoin data I use for this study are based on 2014 and 2015 information, while KAOPEN is based on 2013 data. Since 2008, KAOPEN has documented a trend of decreased barriers in Russia. It therefore seems feasible that finding of lower barriers for Russia in 2014/2015 using bitcoin relative to the 2013 KAOPEN results is the continuation of this trend.

[19] It is not feasible to determine in which country NOK was being purchased or sold for bitcoin.

6. CONCLUSION

Table 5 contrasts the exchange rate regime and capital controls for each currency. A floating (low mark-up) exchange rate usually has a low barrier, and a managed (high mark-up) exchange rate usually has an intermediate of high mark-up. However, the results also confirm that a fixed exchange rate may exist without capital controls, that capital controls can exist without a fixed exchange rate, and that intermediate combinations exist —all detected with unofficial exchange rates constructed using Bitcoin prices.

This method of identification has powerful implications for future applied and policy work, as bitcoin data are publicly available at no charge on a daily basis–even as events unfold–and cannot be manipulated by bad reporting. Additionally, even if governments temporarily cease to gather data due to political or economic upset, the bitcoin data continue to exist and accrue. However, bitcoin data is subject to its own trends – with trends differing across different bitcoin markets – and therefore any data must be adjusted prior to use. This is a reason to be cautious in using any of the various bitcoin price indexes to construct exchange rates, as these indexes may combine prices from different bitcoin markets, and it may therefore not be possible to correct for bitcoin-market exchange rate behavior.

A. Appendix: Method for Determining Barriers

A.1. Are the series I(1)?

I use tests with opposing nulls for robustness. The null of augmented Dickey-Fuller test (ADF; Dickey and Fuller, 1979) is that the series is I[1], while the null of Kwiatkowski-Phillips-Schmidt-Shin (KPSS; Kwiatkowski et al., 1992) test is that the series is I[0] (stationary or having order of integration zero). A series that is truly I[1] should both accept the ADF test and reject the KPSS test at the lag value, ℓ. I select the initial lag according to the Schwarz Bayesian information criterion (SBIC) for the two series. After running the VECM or CECM described below at lag ℓ, a Lagrangian multiplier (LM) test is used to test for autocorrelation in the residuals. If the null of no autocorrelation is rejected at the 5% level, the lag is incremented by one and all the tests are repeated.

Series that accept both ADF and KPSS could be either fractionally integrated or integrated to an order higher than I[1]. To differentiate, I re-run the ADF and KPSS tests on the first difference of the series. I consistently find that ADF is rejected and KPSS is accepted, indicated that the first difference is stationary and therefore the original series was fractionally integrated.

A.2. Are the series cointegrated?

If both the official and bitcoin exchange rate series for a given currency are I(1) at lag ℓ, Johansen trace test requirements are satisfied. The Johansen test iteratively tests the null hypothesis that the trend relationship between the two exchange rate series can be described by no more than r equations. With two series, a cointegrating relationship is indicated by significant results for $r = 1$.

If at least one series is not I(1), I use the PSS test. A significant restriction of PSS method is that it requires a single direction of causality. Given series that are not I(0), I use Toda and Yamamoto (1995) (TY) to determine Granger causality, first estimating a vector autoregression model (VAR) on the data with lags $\ell + 1$ using a vector of the bitcoin and official exchange rate for a given market and currency, $\mathbf{E}_{m,t}^{C} = [E_t^{B,C}, E_{m,t}^{O,C}]$ (where market and currency notations are suppressed in future equations for clarity):

$$\mathbf{E}_t = c + \sum_{i=1}^{\ell+1} \Psi_i \mathbf{E}_{t-i} + \epsilon_t \tag{5}$$

where $\mathbf{E}_{t-(\ell+1)}$ is an exogenous variable. If I find residual autocorrelation at either ℓ or $\ell+1$, the lag is incremented and the procedure repeated, with each series order of integration once again verified. If I establish a single direction of causality between the bitcoin and the official exchange rate series, I apply the PSS bounds test for cointegration.

A.3. Determining the cointegrating parameter

The Johansen trace test is based on a vector error correction model (VECM), which estimates

$$\Delta\mathbf{E}_t = \alpha + \sum_{i=1}^{\ell} \Gamma_i \Delta\mathbf{E}_{t-i} + \gamma\Pi'\mathbf{E}_{t-1} + \epsilon_t \tag{6}$$

where $\Delta E_t = E_t - E_{t-1}$, ℓ is the lag, and ϵ_t are standard mean zero, independent, identically distributed shocks.

The PSS bounds test is based on the unrestricted conditional error-correction model (CECM):

$$\Delta E_t^y = \alpha + \sum_{i=1}^{\ell} \Gamma_i \Delta\mathbf{E}_{t-i} + \gamma\Pi' \log \mathbf{E}_{t-1} + \omega'\Delta E_t^x + \epsilon_t \tag{7}$$

where y refers to either the bitcoin or official exchange rate, and x refers to the exchange rate not used in y. In Equation (7), E_t^x causes E_t^y, or in the parlance of PSS, E_t^x is the forcing function for E_t^y. Which series is the forcing function depends on the outcome of the causality test.

The cointegrating relationship between the two series is captured in Π, where $\Pi = [1, -\hat{\beta}]$. Among cointegrated series, $\hat{\beta}$ is the variable of interest because a failure to find $\hat{\beta} = 1$ implies that the bitcoin exchange rate growth (the long-run trend) is either larger ($\hat{\beta} > 1$) or smaller ($\hat{\beta} < 1$) than the official exchange rate. Table A1 shows the detailed results associated with the construction of Table 4.

Table A1: Bitcoin Estimates of Capital Controls

		Lag		Johansen Trace Test		PSS Test		Barrier Size		2013
Currency	Market	SBIC	ℓ	$r=0$	$r=1$	F-stat	C?	$\hat{\beta}_m^C$	$\hat{\rho}^C$	KAOPEN
				KAOPEN Classification: High Barriers (0.80-1.00)						
Bitcoin Classification: High Barrier (0.50-1.00)										
ARS	Local	3	6	4.90***	0.93	–	N	–	1.00	1.00
CNY	ANX	2	3	3.28***	0.40	–	N	–	1.00	0.84
THB	Local	2	2	–	–	2.06	N	–	1.00	0.84
ZAR	Local	2	2	–	–	11.57***	Y	1.45***	0.69	0.84
				KAOPEN Classification: Intermediate Barriers (0.20-0.80)						
Bitcoin Classification: High Barrier (0.50-1.00)										
MXN	Local	2	7	13.22***	0.04	–	N	–	1.00	0.31
Bitcoin Classification: Intermediate Barrier (0.10-0.50)										
PLN	Local	2	2	–	–	79.46***	Y	0.86***	0.10	0.55
Bitcoin Classification: Low Barrier (0.00-0.10)										
RUB	BTC-e	2	3	25.62	1.30***	–	Y	0.93***	0.04	0.29
				KAOPEN Classification: Low Barriers (0.00-0.20)						
Bitcoin Classification: Intermediate Barrier (0.10-0.50)										
NOK	Local	2	7	36.44	0.87***	–	Y	0.93***	0.17	0.00
Bitcoin Classification: Low Barrier (0.00-0.10)										
AUD	ANX	1	1	1318.27	0.05***	–	Y	1.00***	0.00	0.19
CAD	ANX	1	1	1154.12	0.02***	–	Y	1.00***	0.00	0.00
	Local	2	2	–	–	77.10***	Y	0.67***	0.09	0.00
GBP	ANX	1	1	1152.45	2.13***	–	Y	1.00***	0.00	0.00
JPY	ANX	2	2	164.82	2.58***	–	Y	1.00***	0.00	0.00
NZD	ANX	2	2	246.05	0.03***	–	Y	1.00***	0.00	0.00
SEK	Local	2	2	–	–	53.21***	Y	0.81***	0.05	0.00
SGD	ANX	2	2	231.17	0.00***	–	Y	1.00***	0.00	0.00
	itBit	2	5	72.93	0.00***	–	Y	0.95***	0.08	0.00

****1%, ** 5%.*

Abbreviations: ANX, ANXBTC; $\hat{\beta}_m^C$: Cointegrating Coefficient; C?, Are Official and Bitcoin Exchange Rates Cointegrated?; KAOPEN, 1- 2013 Chinn-Ito Financial Openness index value; $\hat{\rho}_m^C$: Bitcoin barrier estimate adjusted for bitcoin market trends, normalized to range from zero to one, equation (4); PSS, Pesaran-Shin-Smith; SBIC, Lag according to Schwarz Bayesian information criterion.

References

Akram, Q. F., Rime, D., Sarno, L., December 2008. Arbitrage in the Foreign Exchange Market: Turning on the Microscope. Journal of International Economics 76 (2), 237–253.

Alesina, A., Wagner, A., 2006. Choosing (and reneging on) exchange rate regimes. Journal of the European Economic Association 4 (4), 770–799.

Bahmani-Oskoee, M., Miteza, I., Nasir, A., August 2002. The long-run relation between black market and official exchange rates: evidence from panel cointegration. Economics Letters 76 (3), 397–404.

Banco De Mexico, 2015. Informe Trimestal: Enero - Marzo 2015. Retrieved at: www.banxico.org.mx/publicaciones-y-discursos/publicaciones/informes-periodicos/trimestral-inflacion/

Bekaert, G., Harvey, C., 2005. Does Financial Liberalization Spur Growth? Journal of Financial Economics 77.

Böhme, R., Christin, N., Edelman, B., Moore, T., Spring 2015. Bitcoin: Economics, Technology, and Governance. Journal of Economic Perspectives 29 (2), 213–238.

Brandvold, M., Molnar, P., Vagstad, K., Valstad, O. C. A., May 2015. Price discovery on Bitcoin exchanges. Journal of International Financial Markets, Institutions and Money 36, 18–35.

Calvo, G. A., Reinhart, C. M., May 2002. Fear of Floating. Quarterly Journal of Economics 107 (2), 379–408.

Cardenas, S. N., 2015. Banxico, ¿engordndole un cochinito a SHCP? El Financiero. Retrieved at: www.elfinanciero.com.mx/opinion/banxico-engordandole-un-cochinito-a-shcp.html.

Chinn, M. D., Ito, H., October 2006. What Matters for Financial Development? Capital Controls, Institutions, and Interactions. Journal of Development Economics 81 (1), 163–192.

Dickey, D. A., Fuller, W. A., 1979. Distribution of the estimators for autoregressive time series with a unit root. Journal of the American Statistical Association 74, 427–431.

Dwyer, G. P., April 2015. The economics of Bitcoin and similar private digital economies. Journal of Financial Stability, 81–91.

Fernández, A., Rebucci, A., Uribe, M., November 2015. Are capital controls countercyclical? Journal of Monetary Economics 76.

Ferraro, D., Rogoff, K., Rossi, B., 2015. Can oil prices forecast exchange rates? An empirical analysis of the relationship between commodity prices and exchange rates. Journal of International Money and Finance 54 (C), 116–141.

Hendrickson, J., Hogan, T., Luther, W., 2016. The Political Economy of Bitcoin. Economic Inquiry 54 (2).

Huett, H., Krapf, M., Uysal, D., September 2014. Price Dynamics in the Belarusian black market for foreign exchange. Journal of International Economics (1), 169–176.

Human Rights Watch, 2015. World Report 2015: Thailand, events of 2014. Retrieved at: https://www.hrw.org/world-report/2015/country-chapters/thailand.

Ilzetzki, E., Reinhart, C. M., Rogoff, K. S., February 2017. Exchange arrangements entering the 21st century: Which anchor will hold? Working Paper 23134, National Bureau of Economic Research.

IMF Annual Report on Exchange Arrangements and Exchange Restrictions, October 2014. Tech. rep., International Monetary Fund, Washington.

Kiguel, M. A., O'Connell, S. A., 1995. Parallel Exchange Rates in Developing Countries. The World Bank Research Observer 10, 21–52.

Kim, S., December 2016. What Is Learned from a Currency Crisis, Fear of Floating, or Hollow Middle? Identifying Exchange Rate Policy in Crisis Countries. International Journal of Central Banking 12 (4), 105–146.

Klein, M. W., Shambaugh, J. C., October 2015. Rounding the Corners of the Policy Trilemma: Sources of Monetary Policy Autonomy. American Economic Journal: Macroeconomics 7 (4), 33–66.

Kwiatkowski, P. D., Phillips, P., Schmidt, P., Shin, Y., 1992. Testing the null of stationarity against the alternative of a unit root: How sure are we that the economic time series have a unit root? Journal of Econometrics 54, 159–178.

Lane, P., Milesi-Ferretti, G., 2007. The External Wealth of Nations Mark II: Revised and Extended Estimates of Foregin Assets and Liabilities, 1970-2004. Journal of International Economics 73.

Levy-Yeyati, E., Sturzenegger, F., August 2005. Classifying exchange rate regimes: Deeds vs. words. European Economic Review 49 (6), 1603–1635.

Luther, W., 2016. Cryptocurrencies, Network Effects, and Switching Costs. Contemporary Economic Policy 34 (3).

Michalski, T., Stoltz, G., May 2013. Do Countries Falsify Economic Data Strategically? Some Evidence That They Might. The Review of Economics and Statistics 95 (2), 591–616.

Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System. http://bitcoin.org/bitcoin.pdf.

Pieters, G. C., Vivanco, S., 2017. Financial Regulations and Price Inconsistencies across Bitcoin Markets. Information Economics and Policy.

Quéré, A. B., Coeuré, B., Mignon, V., March 2006. On the identification of de facto currency pegs. Journal of the Japanese and International Economies 20 (1), 112–127.

Quinna, D., Schindler, M., Toyoda, A. M., 2011. Assessing Measures of Financial Openness and Integration. IMF Economic Review 59 (3).

Reinhart, C. M., Rogoff, K. S., February 2004. The Modern History of Exchange Rate Arrangements: A Reinterpretation. Quarterly Journal of Economics 119 (1), 1–48.

Shambaugh, J., 2004. The effect of fixed exchange rate on monetary policy. Quarterly Journal of Economics 119, 301–352.

Toda, H., Yamamoto, T., 1995. Statistical inferences in vector autoregressions with possibly integrated processes. Journal of Econometrics 66, 225–250.

White, L., 2015. The Market for Cyryptocurrencies. Cato Journal 35 (2).

Yang, G., Gu, Q., 2016. Effects of exchange rate variations on bilateral trade with a vehicle currency: Evidence from China and Singapore. Journal of International Money and Finance 68 (C), 50–73.

Yermack, D., 2015. Is bitcoin a real currency? An economic appraisal. In: Lee, D. K. (Ed.), The Handbook of Digital Currency. Elsevier, pp. 31–44.

Yeyati, E. L., Schmukler, S. L., Horen, N. V., 2009. International Financial Integration through the Law of One Price: The Role of Liquidity and Capital Controls. Journal of Financial Intermediation 18 (3).

Tables

Table 1: Bitcoin Average Daily Trade Volume, Price, and Legal Status by Exchange and Currency

			Average Daily Volume			
Symbol	Currency	Obs.	BTC	Currency	Price	Bitcoin Legal Status
ANXBTC (https://anxbtc.com)						
USD	US dollar	480	911	319,186	344.56	
EUR	Euro	480	909	259,909	282.12	
AUD	Australian dollar	480	908	377,218	409.85	
CAD	Canadian dollar	480	908	370,269	401.73	AML and CT
CNY	Chinese yuan	480	908	1,974,069	2,134.54	Financial firms forbidden
GBP	British pound	480	908	198,727	215.60	
JPY	Japanese yen	480	908	35,591,785	38,765.43	
NZD	New Zealand dollar	480	908	408,896	445.12	Banks need approval
SGD	Singapore dollar	480	908	414,723	449.60	
BTC-e (https://btc-e.com)						
USD	US dollar	476	7,555	2,355,088	341.53	
EUR	Euro	481	114	32,251	284.17	
RUB	Russian ruble	480	309	4,878,342	16,861.43	May be illegal
itBit (https://www.itbit.com)						
USD	US dollar	487	2,787	819,135	344.76	
EUR	Euro	476	352	80,574	280.17	
SGD	Singapore dollar	484	237	88,561	448.39	
LocalBitcoins (https://localbitcoins.com)						
USD	US dollar	487	1,705	552,005	382.89	
EUR	Euro	487	209	54,930	292.98	
ARS	Argentinian peso	448	13	51,045	4,400.49	
CAD	Canadian dollar	487	47	17,599	418.46	AML and CT
MXN	Mexican peso	487	15	71,073	5,127.63	AML and AF
NOK	Norwegian krone	474	11	25,564	2,510.87	
PLN	Polish zloty	468	8	8,530	1,151.59	
SEK	Swedish krona	487	44	102,628	2,747.46	
THB	Thai bhat	487	35	368.493	11,177.79	May be illegal
ZAR	South African rand	487	52	193,765	4,293.01	

Abbreviations: AF, anti-fraud laws; AML, anti-money laundering; (blank), No restrictions on bitcoin trades; BTC, units of bitcoin; CT, counterterrorism laws; Obs., observations.
Note: USD and Euro are the most frequently traded currenciess. Most currencies have no legal restrictions placed on Bitcoin.

Table 2: Bitcoin Mark-Up Provides Information About The De-Facto Exchange Rate Regime

Currency	Market	2014 IMF Classification	Mark-Up (Adjusted, %) 2014	2015	Full Sample
		IMF Classification: Free Floating or Floating Exchange Rate			
Low Bitcoin Mark-up in 2014					
AUD	ANX	Free Floating	0.02	0.05	0.04
CAD	ANX	Free Floating	-0.01	0.01	0.00
	Local	Free Floating	1.07	-0.25	0.33
GBP	ANX	Free Floating	0.01	-0.02	-0.01
JPY	ANX	Free Floating	0.03	-0.04	-0.01
MXN	Local	Free Floating	-0.95	3.15	1.34
NOK	Local	Free Floating	-0.47	2.21	1.04
NZD	ANX	Floating	0.03	0.10	0.07
SEK	Local	Free Floating	1.15	1.56	1.38
ZAR	Local	Floating	0.56	10.83	6.32
High Bitcoin Mark-up in 2014					
PLN	Local	Free Floating	-5.91	-3.84	-4.75
THB	Local	Floating	-5.16	-3.42	-4.18
		All Other IMF Exchange Classifications			
Low Bitcoin Mark-up in 2014					
CNY	ANX	Crawl-like arrangement	0.20	1.12	0.72
SGD	ANX	Stabilized arrangement	0.00	-0.00	0.00
	itBit	Stabilized arrangement	0.07	-0.63	-0.32
High Bitcoin Mark-up in 2014					
ARS	Local	Crawl-like arrangement	44.02	39.37	41.41
RUB	BTC-e	Other managed arrangement	4.42	0.06	1.98

Abbreviations: ANX, ANXBTC; Local, LocalBitcoin.

Note: This table shows that Free or Floating Regimes have lower bitcoin mark-ups than other regimes. The four deviations (PLN, THB, CNY, and SGD) are discussed in text. Most currencies are consistent from 2014 to 2015, although large changes can happen (CNY, MXN, NOK, RUB, ZAR)

Adjusted Mark-Up calculated according to equation 3, IMF Classification is currency exchange rate regime classification from 2014 IMF Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

Table 3: Trends in the Bitcoin Mark-Up exists: Normalization is needed

	Lag		Johansen Trace Test		PSS Test		Barrier Estimate	
Market	SBIC	ℓ	r=0	r=1	F-stat	Cointegrated?	$\hat{\beta}_m^{Euro}$	$\hat{\rho}_m^{\text{Euro}}$
ANXBTC	2	2	242.64	2.05***	–	Yes	1.00***	0.00
BTC-e	2	3	21.39	2.04***	–	Yes	0.97***	0.00
itBit	2	2	166.80	2.20***	–	Yes	1.03***	0.00
LocalBitcoins	2	4	–	–	54.72***	Yes	0.76***	0.00

****1%, ** 5%.*

Abbreviations: $\hat{\beta}_m^{Euro}$: Cointegrating Coefficient; Cointegrated?, Are Official and Bitcoin EUR-USD Exchange Rates Cointegrated?, $\hat{\rho}_m^{Euro}$: Bitcoin barrier estimate adjusted for bitcoin market trends, normalized to range from zero (low barrier) to one, equation (4).

Note: The table shows the results of a cointegration test between the bitcoin and official Euro-USD exchange rate. A finding of cointegration – implying the existence of a shared long run linear trend – is expected given the liquidity of these two currencies in the bitcoin market, and the lack of capital controls in the official market. If the trends are perfectly shared then the cointegrating paramter $\hat{\beta}_m^{Euro} = 1$. This results occurs for ANXBTC, but clearly not for LocalBitcoins. Given that this failure occurs for the same exchange rate, during the same time period, the cause must be market-specific effects, implying that the estimates cannot be directly used to measure capital controls. The normalized barrier measure, $\hat{\rho}_m^{\text{Euro}}$, defined in equation 4, adjusts for market-specific effects.

Table 4: Bitcoin Estimates of Capital Controls Agree with the Chinn-Ito Index of Financial Openness (KAOPEN)

Currency	Market	Cointegrated?	Cointegrating Parameter, $\hat{\beta}_m^C$	Bitcoin Barrier, $\hat{\rho}^C$	2013 KAOPEN Barrier
		KAOPEN Classification: High Barriers (0.80-1.00)			
Bitcoin Classification: High Barrier (0.50-1.00)					
ARS	Local	No	–	1.00	1.00
CNY	ANX	No	–	1.00	0.84
THB	Local	No	–	1.00	0.84
ZAR	Local	Yes	1.45***	0.69	0.84
		KAOPEN Classification: Intermediate Barriers (0.20-0.80)			
Bitcoin Classification: High Barrier (0.50-1.00)					
MXN	Local	No	–	1.00	0.31
Bitcoin Classification: Intermediate Barrier (0.10-0.50)					
PLN	Local	Yes	0.86***	0.10	0.55
Bitcoin Classification: Low Barrier (0.00-0.10)					
RUB	BTC-e	Yes	0.93***	0.04	0.29
		KAOPEN Classification: Low Barriers (0.00-0.20)			
Bitcoin Classification: Intermediate Barrier (0.10-0.50)					
NOK	Local	Yes	0.93***	0.17	0.00
Bitcoin Classification: Low Barrier (0.00-0.10)					
AUD	ANX	Yes	1.00***	0.00	0.19
CAD	ANX	Yes	1.00***	0.00	0.00
	Local	Yes	0.67***	0.09	0.00
GBP	ANX	Yes	1.00***	0.00	0.00
JPY	ANX	Yes	1.00***	0.00	0.00
NZD	ANX	Yes	1.00***	0.00	0.00
SEK	Local	Yes	0.81***	0.05	0.00
SGD	ANX	Yes	1.00***	0.00	0.00
	itBit	Y	0.95***	0.08	0.00

****1%, ** 5%.*

Abbreviations: ANX, ANXBTC; $\hat{\beta}_m^C$: Cointegrating Coefficient; Cointegrated?, Are Official and Bitcoin Exchange Rates Cointegrated?; KAOPEN Barrier, 1- 2013 Chinn-Ito Financial Openness index value; $\hat{\rho}_m^C$: Bitcoin barrier estimate adjusted for bitcoin market trends, normalized to range from zero to one, equation (4).

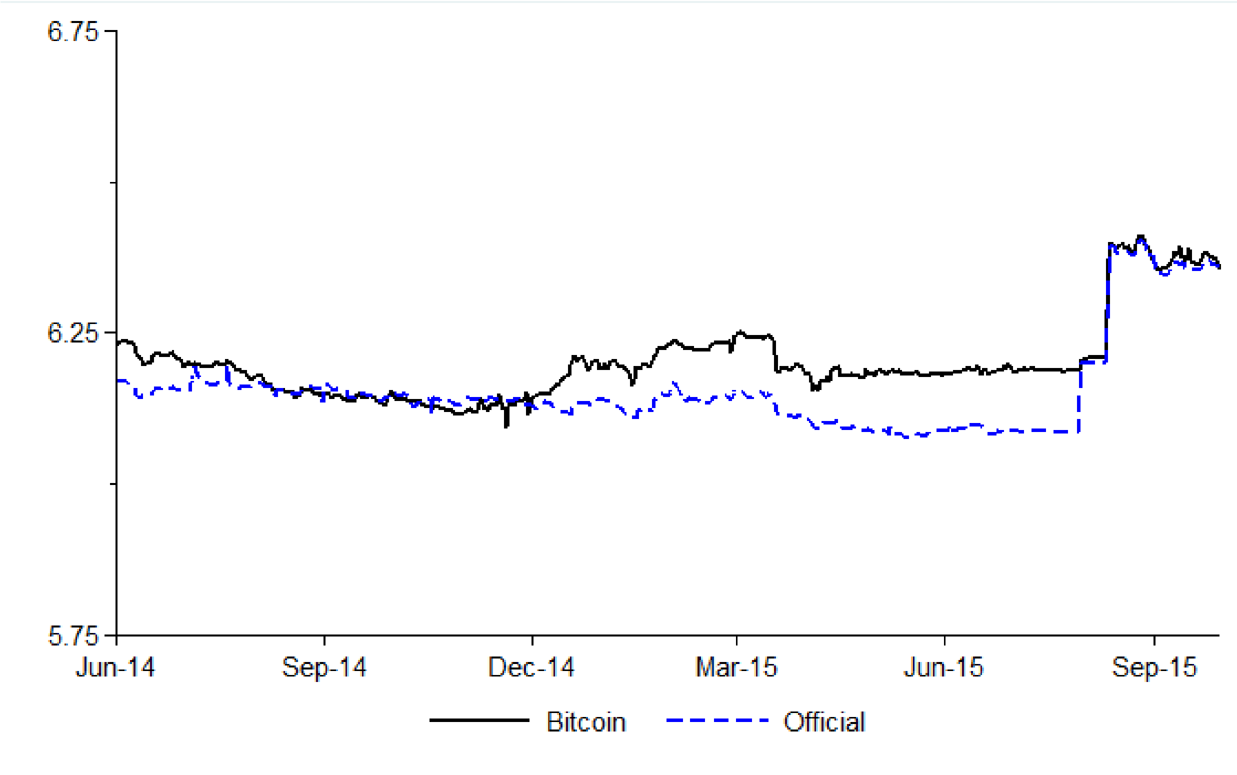
Note: Out of the ten bitcoin measures across these Low Barriers currencies, six report a barrier of 0.00. Two of non-zero bitcoin measures are duplicate measures – CAD and SGD – with one bitcoin market indicating a zero barrier and the other reporting a non-zero barrier. Given the results for CAD and SGD, any $\rho_m^C < 0.10$ shall be identified as a low barrier currency.

Table 5: Mark-Up (Exchange Rate Regime) and Barriers (Capital Controls) Are Correlated—But Not Perfectly

	Low Barrier (8)	Intermed. Barrier (2)	High Barrier(5)
Low Mark-Up (11)	AUD, CAD, GBP, JPY, NZD, SEK, SGD	NOK	CNY, ZAR, MXN
High Mark-Up (4)	RUB	PLN	ARS, THB

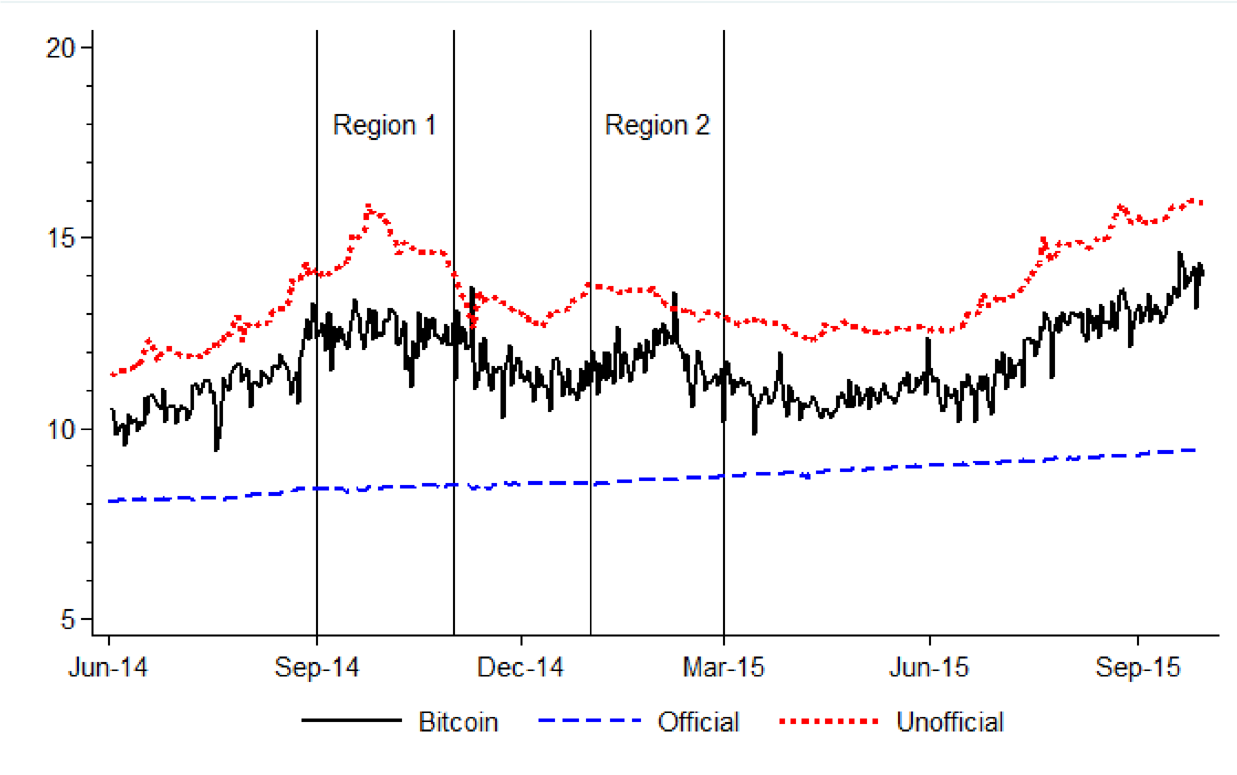
Note: A floating exchange rate regime is likely to have low barriers, and a manipulated exchange rate regime is likely to have a high barrier—but exceptions and intermediate cases exist.

Figure 1: Bitcoin Exchange Rates Reveal Information About Currency Pressures and Devaluations



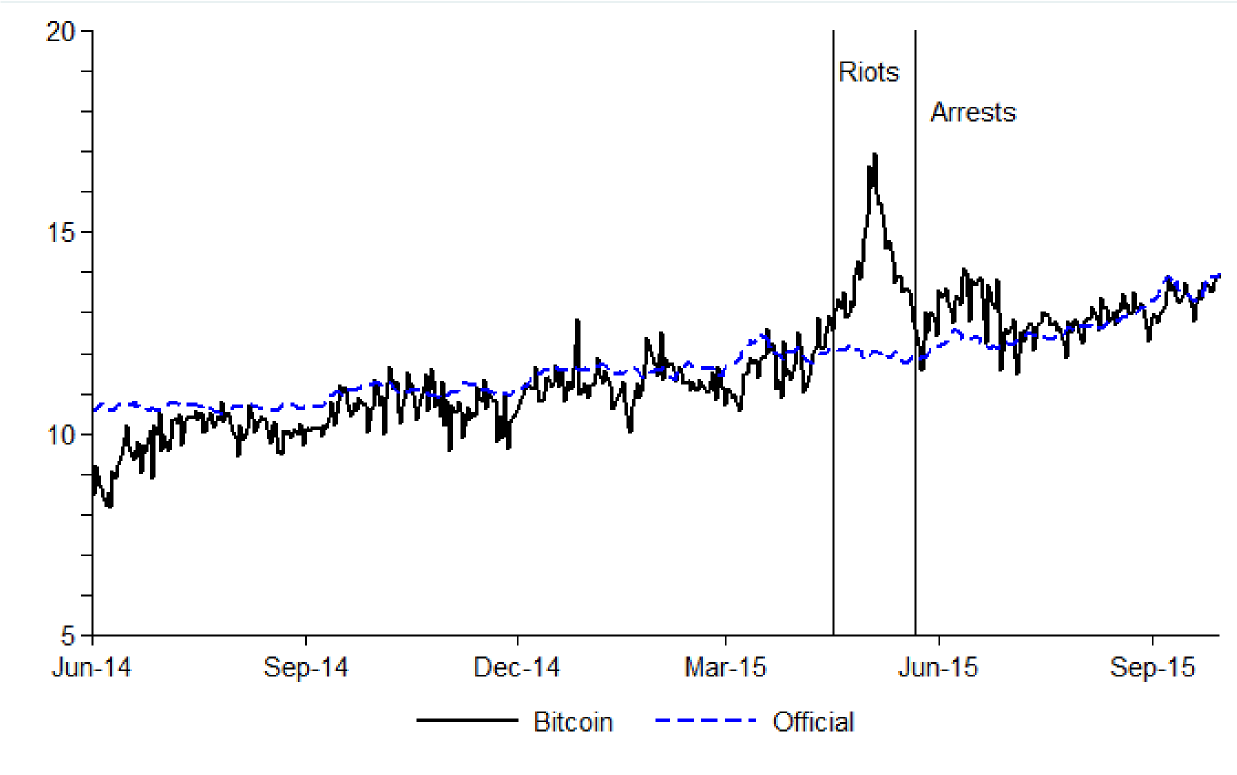
Note: Daily CNY-USD exchange rates: Bitcoin-based (solid) and Official (dashed) between 1 June 2014 and 30 September 2015. Official exchange rate data from Oanda.com, and Bitcoin exchange rate is the ratio of CNY and USD Bitcoin prices on ANXBTC, obtained from www.bitcoincharts.com. China devalued the Yuan by 1.9% on August 10,2015.

Figure 2: Bitcoin Exchange Rates Resemble Unofficial Exchange Rates in Argentina



Note: Daily ARS-USD exchange rates: Bitcoin-based (solid), Official (dashed), and Unofficial (dot) between 1 June 2014 and 30 September 2015. Official exchange rate data from Oanda.com, Unofficial exchange rate from *Ámbito Financiero*, Bitcoin exchange rate is the ratio of ARS and USD Bitcoin prices on LocalBitcoin, obtained from www.bitcoincharts.com. Region 1 and Region 2 indicate two regions where bitcoin and unofficial exchange rates deviate.

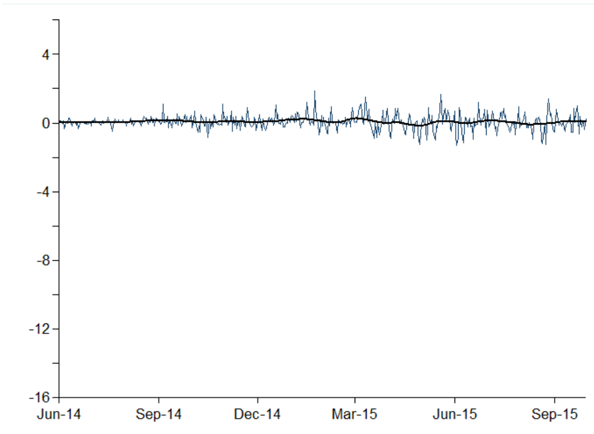
Figure 3: Bitcoin Exchange Rates Are Not Disassociated From Local Events



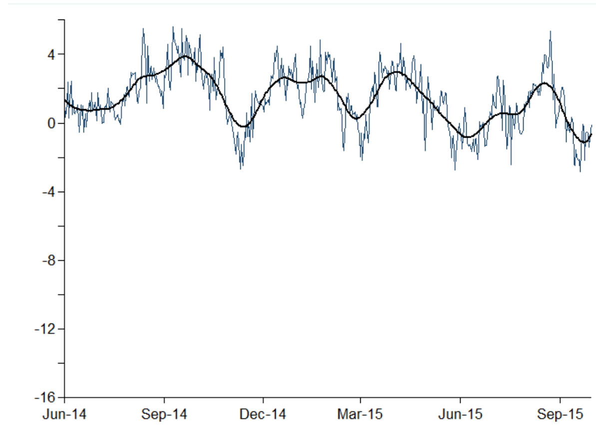
Note: Daily ZAR-USD exchange rates: Bitcoin-based (solid) and Official (dashed) between 1 June 2014 and 30 September 2015. Official exchange rate data from Oanda.com, and Bitcoin exchange rate is the ratio of CNY and USD Bitcoin prices on LocalBitcoins, obtained from www.bitcoincharts.com. Multiday Riots began on April 17, 2015, while the arrest of 4,000 people in connection with the riots began on May 21, 2015. Both events received limited international attention, making it likely that the difference in exchange rates reflect the capital control barriers to capital flight faced by domestic Bitcoin users.

Figure 4: Bitcoin Euro-USD Exchange Rates Contain Market-Specific Premiums, Need Market-Specific Adjustment

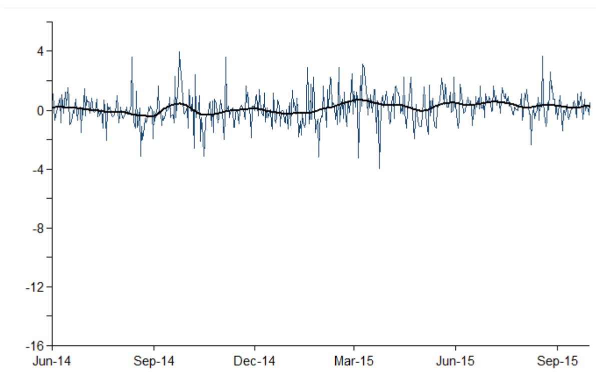
(a) ANXBTC



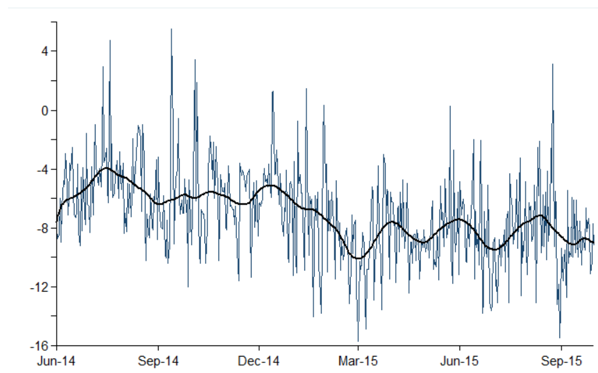
(b) BTC-e



(c) itBit

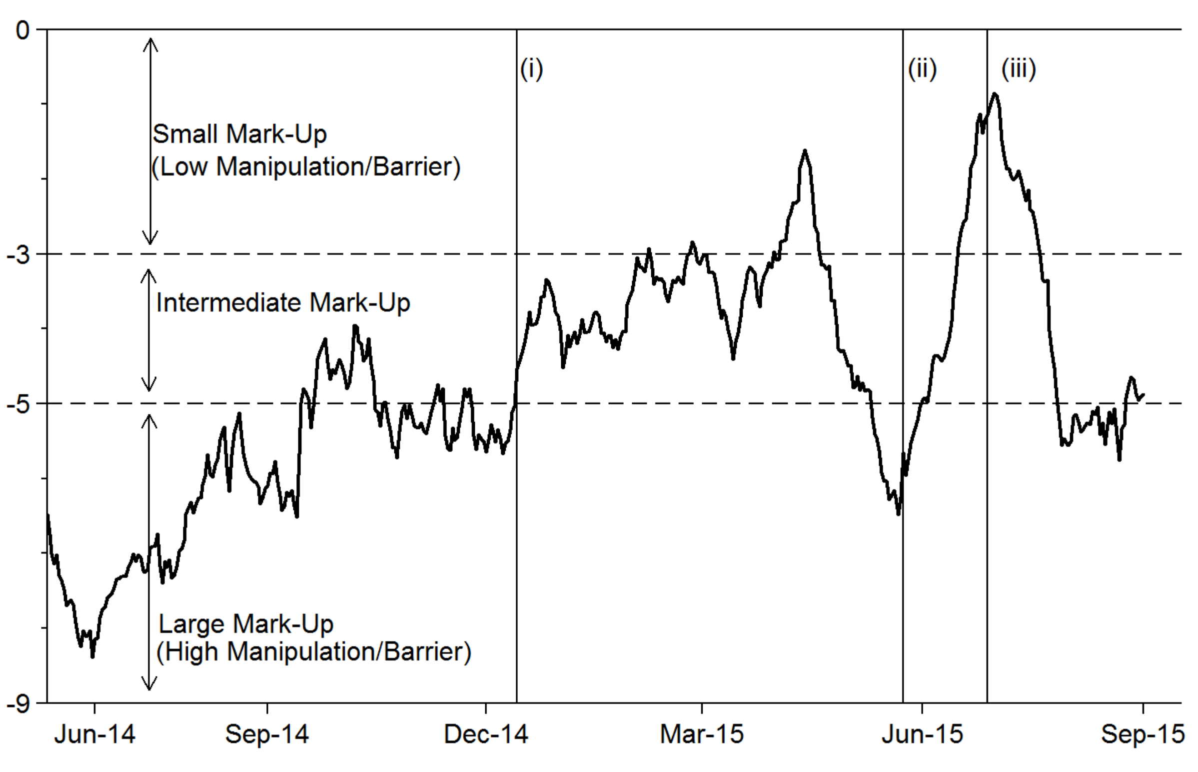


(d) LocalBitcoins



Note: Percent deviation from official daily EUR-USD exchange rates and corresponding trend line between 1 June 2014 and 30 September 2015. The bitcoin exchange rate from ANXBTC follows the official exchange rate closely, with an average deviation of 0.05%. BTC-e average deviation is 1.43%, itBit average deviation is 0.13%, LocalBitcoin average deviation is -7.08%. In addition to different levels of deviations, LocalBitcoin exchange rate is trending away from zero, indicating greater difference from official exchange rate over time, that is not shared by the other exchanges. Official exchange rate data from Oanda.com, and Bitcoin exchange rate is the ratio of EUR and USD Bitcoin prices on ANXBTC, BTC-e, itBit, and LocalBitcoins, obtained from www.bitcoincharts.com. Trend line is constructed using a Lowess least-squares-based smoothing with a 10% bandwidth (48 days).

Figure 5: Bitcoin mark-ups reveal high frequency and temporary changes from global events



Note: Graph shows the 30 day rolling average of the percent deviation between Bitcoin and the Official PLN-USD exchange rate between 1 June 2014 and 30 September 2015 calculated according to equation 3. Mark-up within 3% is consistent with low mark-ups, while greater than 5% is a large mark-up. Three events are shown: (i) 16 December: Crash in Russian Financial Markets (ii) 24 May: Second round of Polish elections successful (iii) 27 June: Announcement of Greek referendum vote raises concern about Grexit.