Bitcoin Reveals Exchange Rate Manipulation and Detects Capital Controls

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Abstract

Many countries manipulate the value of their currency or use some form of capital control, yet the data usually used to detect these manipulations are low frequency, expensive, lagged, and potentially mis-measured. I demonstrate that the price data of the internationally traded cryptocurrency Bitcoin can approximate unofficial exchange rates which, in turn, can be used to detect both the existence and the magnitude of the distortion caused by capital controls and exchange rate manipulations. However, I document that bitcoin exchange rates contain problematic bitcoin-market-specific elements and must be adjusted before being used for this purpose. As bitcoin exchange rates exist at a daily frequency, they reveal transitory interventions that would otherwise go undetected. This result also serves as verification that Bitcoin is used to circumvent capital controls and manipulated exchange rates.

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

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

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1. INTRODUCTION

This paper is a contribution to timely, high-frequency, accurate measurement of unofficial exchange rates, *de facto* exchange rate regimes, and *de facto* capital controls. While policies that result in manipulated exchange rates—such as capital controls—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) estimate that fewer than one half of *de jure* floats were *de facto* floats. Similar to *de jure* exchange rate regimes, *de jure* capital controls may be misleading as countries could impose undeclared barriers, or may fail to effectively enforce declared barriers.

I show bitcoin price data can be used to construct a dataset of daily unofficial exchange rates, which, when combined with official exchange rate data can detect *de facto* exchange rate regimes and *de facto* capital controls even if such controls are transitory—"gates" or "walls" in Klein (2012) classification.[2] In addition to detecting the existence of exchange rate manipulation or capital controls, the bitcoin exchange rate generates a quantified measure of the effective impact—given that a distortion exists, does it have a large or small impact on exchange rates?

Prior papers that use unofficial exchange rates to detect *de facto* regimes or capital controls across multiple countries, such as Reinhart and Rogoff (2004), use unofficial exchange rate data from the same source: *World Currency Yearbook*.[3] Data from the World Currency Yearbook 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

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

[3] The *World Currency Yearbook* was formerly known as *Pick's Currency Yearbook*. Some cite Reinhart and Rogoff (2004) as their data source—their dataset was constructed using *World Currency Yearbook* data.

prices can be observed at the minute frequency, removing potential bias from reporting agents and allowing the detection of short-lived interventions.

Papers that do not use the *World Currency Yearbook* as a source for unofficial exchange rate data are usually restricted to only a few currencies: for example, the exchange rate data Huett, Krapf, and Uysal (2014) obtain from an unofficial exchange rate website consider only the Belarusian ruble to the US dollar, euro, and Russian ruble, and the market stopped existing once the Belarusian ruble was allowed to float. Given bitcoin's use as an investment vehicle, prices are available even if the exchange rate is floating.

Using bitcoin to construct an unofficial exchange rate is most similar to papers that use prices of globally traded commodities to construct unofficial exchange rates—for example, Ferraro, Rogoff, and Rossi (2015) use oil prices. However, unlike any commodity, currency, or financial asset, Bitcoin is completely virtual, with no physical transportation costs that could impact prices across markets, and Pieters and Vivanco (2017) show that it faces no effective national regulations on its cross-border trade or prices. Bitcoin does not have an originating source country — unlike oil, gold, or similar commodities where countries may impose trade barriers. These factors all facilitate global purchases of bitcoins across multiple currencies and countries. 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.

It may seem trivial that bitcoin prices should yield the unofficial exchange rates: Akram, Rime, and Sarno (2008) study global contracts using official exchange rates and find that most price deviations across markets are quickly arbitraged away. Given 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), data from any bitcoin exchange should yield the same deviations and therefore detect the same regime. However, an early study of US dollar bitcoin price behavior by Yermack (2015) concluded that the daily US dollar-bitcoin exchange rate exhibited nearly zero correlation with the exchange rate of US dollar to euro, Japanese yen, Swiss franc, or gold. This finding is consistent with the known issues in bitcoin prices, users, and markets.

Bitcoin prices are highly volatile. Baek and Elbeck (2015), Bouoiyour and Selmi (2015), and Cheah and Fry (2015) find that bitcoin prices are consistent with a speculative market, with Cheung, Roca, and Su (2015) documenting multiple bubble episodes that result in significant price distortions. However, existing alongside this bubbly, speculative behavior, Bouoiyour, Selmi, Tiwari, and Olayeni (2016) find evidence of long-term (above one year) fundamental components in prices. Additionally, Bouoiyour and Selmi (2016) find that Bitcoin prices react to negative rather than positive news, and is not yet a mature market.

Ciaian, Rajcaniova, and Kancs (2016) find that market forces and Bitcoin attractiveness for investors and users have a significant, although time varying, impact on Bitcoin price. However, Bitcoin users themselves are not necessarily representative of the population, as Yelowitz and Wilson (2015) document that interest in computer programming or illegal activity are correlated with interest in Bitcoin. It is therefore feasible that the constructed bitcoin exchange rates are unrelated to a currency's unofficial exchange rate, instead reflecting the expectations of the global online 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.

Bitcoin exchanges—the markets where bitcoins are bought and sold—may have specific issues as well, potentially creating issues with any collected data. Pieters and Vivanco (2017) document persistent differences in US dollar bitcoin prices and trends across bitcoin exchanges—arbitrage forces fail even in the simplest case of a single currency. Urquhart (2016) finds evidence that bitcoin markets are not efficient, although they also find evidence that it is becoming more so.

Section 2 of this paper shows that these concerns about bitcoin prices, users, and markets are relevant and apply to bitcoin-based exchange rates: The exchange rates created using bitcoin prices vary across data sources and contain regions where behavior seems to be driven by bitcoin dynamics—not the currency studied. Section 3 confirms that most Bitcoin price data cannot be directly used to approximate unofficial exchange rates, even for well behaved and liquid currencies such as the US dollar and the euro. However, section 4 and section 5 show that a normalization removes these distortions, respectively yielding capital control and exchange rate regime classifications for each currency consistent with their current classification in the literature, with remaining deviations explained by the higher frequency of the bitcoin data.

I use the lack of a stationary difference between the official and bitcoin exchange rate to detect capital controls in section 4. This approach is related to that of Levy-Yeyati, Schmukler, and Horen (2009), who show that capital controls cause a failure in the Law of One Price in price of stocks sold in multiple markets. While their stock-price-based data can be as high frequency as bitcoin prices, it requires data from the sale of the same company's stock in two different stock markets (a foreign and domestic stock market). This implicitly limits attention to larger economies that contain a functioning stock market, and with companies that can enter a foreign stock market, a restriction not imposed by bitcoin data.

Given concerns about the quality of Bitcoin price data, I verify the validity of the bitcoin capital controls 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. KAOPEN is an annual measure constructed from the weighted values of four binary dummy variables sourced from the International Monetary Fund's (IMF) Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

Other measures of capital controls 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 indexes can be found in Quinna, Schindler, and Toyoda (2011). All these measures terminate several years prior to the time period in this study, and so they cannot be compared to the bitcoin results. Fernndez, Klein, Rebucci, Schindler, and Uribe (2016), like the Chinn and Ito (2006) measure of capital controls, build a measure from AREAER, however, they consider capital controls disaggregated by type (equities, direct investment, etc.). While Bitcoin can provide high frequency data, it cannot disclose the originating sector of the capital movement. However, unlike AREAER-based measures, bitcoin can detect the magnitude of distortions created by capital controls.

Ilzetzki, Reinhart, and Rogoff (2017) observes that the *de facto* exchange rate literature often ignores capital controls even though the two are related through the trilemma. The trilemma states that a country cannot simultaneously have a managed exchange rate regime, free movement of capital, and independent monetary policy; it can only choose two of the three. This requirement forms the basis of the indirect methods developed to detect the *de facto* exchange rate regime given fear-of-floating and the lack of unofficial exchange rate data: a smooth exchange rate accompanied by a volatile policy instrument is interpreted as evidence of a non-floating exchange rate. Calvo and Reinhart (2002) use interest rates, while Levy-Yeyati and Sturzenegger (2005) use foreign exchange reserves. Alternatively, Shambaugh (2004) uses the volatility of the official exchange rate, while Quéré, Coeuré, and Mignon (2006) use a stability criteria against a market basket of currencies.

However, Kim (2016) suggests that these approaches suffer from a simultaneity problem—policy instruments may be reacting to a domestic event with a smoothed exchange rate as a side effect, rather than the goal, therefore leading to over-estimates of *de jure* deviations. In contrast, Klein and Shambaugh (2015) show that under-detection of *de jure* deviations by these methods is possible because economies can successfully mix and match policies to smooth exchange rates. Under-detection could also result if capital controls are temporary—gates instead of walls as characterized in Klein (2012). I verify the existence of both the over- and under-estimation errors identified by Klein and Shambaugh (2015), Kim (2016) and Klein (2012).

Following Reinhart and Rogoff (2004) and Kiguel and O'Connell (1995), who argue that the deviation between the unofficial and official rates should be greater for managed exchange rates than it is for market exchange rates, I compare the size of the difference between the official and bitcoin exchange rate to detect exchange rate regimes in section 5. I compare the bitcoin exchange regime classification to the current classification of the currency in IMF Annual Report on Exchange Arrangements and Exchange Restrictions (2014), and again find that the appropriately adjusted bitcoin exchange rate can replicate the official classification.

The ability to use bitcoin—or similar cryptocurrencies—has powerful implications for future empirical research or policy work on business cycles, event studies, international finance, macroeconomics, or trade, as bitcoin data are publicly available at no charge on a daily basis—even as events unfold—and cannot be manipulated by bad reporting. Even if governments temporarily cease to gather data due to political or economic upset, the bitcoin data continue to exist and accrue.

Currently, 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. High-frequency exchange rates constructed from bitcoin data 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 other economic data; therefore, the high-frequency data allow us to identify specific intervals when economic data are more likely to be misreported. Finally, Esaka (2014) shows that fear-of-floating countries have a higher probability of a currency crisis than countries of similar economic profile, implying use for currency crisis literature.

2. A VISUAL INTRODUCTION TO BITCOIN EXCHANGE RATES

2.1. Defining Bitcoin Exchange Rates

Bitcoin is a cryptocurrency[4] with no central monetary authority, country of origin, or physical representation, designed and created by the entity Nakamoto (2008).[5] The interested reader should consult Böhme, Christin, Edelman, and Moore (2015) for a technical overview of Bitcoin, while Brandvold, Molnar, Vagstad, and Valstad (2015) include a brief discussion of major events in Bitcoin history. White (2015) considers the market for cryptocurrencies more broadly.

The bitcoin studied in this paper are bought and sold for currency on an online trading website known as an "exchange". Once acquired, a bitcoin can be held for investment purposes, used for retail purchases, or to facilitate international money transfers by selling it for a different currency. Dwyer (2015) explores why the ability to use bitcoin for these purposes could result in a cryptocurrency 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 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. In the bitcoin markets, trades clear in an average of 10 minutes, though users with higher balances or willing to pay higher fees may trade prior to this. Therefore, buying and selling can be treated as immediate. 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 bitcoin-based exchange rate, ($E^{B,C}_{m,t}$) and between currency (C) and the US dollar is

[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 cryptocurrencies, such as Bitcoin or Ethereum.

[5]The name Satoshi Nakamoto is a pseudonym. The identity and nationality of Satoshi (person or persons) is currently unknown.

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. Unlike traditional vehicle currencies, access to bitcoin and its associated exchange rate to other foreign currencies is difficult to restrict because it requires preventing individuals from accessing websites. Hendrickson, Hogan, and Luther (2016) consider governmental efforts to discourage bitcoin use, while Pieters and Vivanco (2017) show that such efforts are easily circumvented. Some exchanges have implemented systems for direct currency trades. However, these systems are still in their infancy and have poor data availability, so transactions of this nature will not be considered; however, they should only improve the ability of bitcoin to represent a *de facto* exchange rate.

2.2. Potential And Limitation Of Bitcoin Exchange Rates

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 similar, indicating that subsequent calls to further devalue the Chinese yuan may be misplaced.

(Figure 1 about here)

Figure 1 contradicts the analysis of Ju, Lu, and Tu (2016) who find that the People's Bank of China (PBC), China's central bank, successfully halted illicit capital outflows via Bitcoin after announcing cryptocurrency regulations on December 5, 2013. The reason that their finding contradicts Figure 1, which clearly shows a difference between the bitcoin and official exchange rates, is that their empirical method did not adjust for bitcoin-specific trends, which were significant during the time of their study. Shortly after the PBC made their announcement the worlds largest bitcoin exchange, Mt. Gox, declared bankruptcy which significantly decreased Bitcoin trading around the world. This event is discussed further in section 3.1.

The limitations of bitcoin exchange rates are reflected in Figure 2, which charts the official, unofficial, and bitcoin exchange rates for Argentina. Argentina is widely known to have a long-established crawling peg regime to 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)

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 as an estimate of the level-value of the unofficial exchange rate. The behavior during the two-month periods in Region 1 and Region 2 indicates more serious reasons to pause, as they indicate that the deviations consist of more than shift a level shift. In Region 1, the bitcoin exchange rate remains level while the unofficial exchange rate is changing, whereas in Region 2 the unofficial exchange rate decreases while the bitcoin exchange rate increases. Section 3.2 and 4.1 establish that these deviations are significant even for open markets such as the US dollar to Euro exchange rate, which is why despite its promise, Bitcoin cannot be directly used as an estimate of unofficial exchange rates. An empirical contribution of this paper is to show that the adjustment needed to correct for these deviations is simple, and the result fulfills the promise of bitcoin-based exchange rates.

2.3. Capital Controls and Managed Exchange Rate Regimes Look Different

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 stationary mark-up, as the demand for bitcoin relative to official channels should be stable as discussed Reinhart and Rogoff (2004) and Kiguel and O'Connell (1995). A free floating exchange rate with capital controls would have a volatile, non-stationary mark-up as demand for bitcoin ebb and flow with unofficial capital flows, as discussed in Levy-Yeyati, Schmukler, and Horen (2009). These movements can be readily observed in the constructed bitcoin exchange rates.

Although the South African rand (ZAR) has a floating exchange rate, there are—as in Argentina—many capital controls in place. This is revealed in Figure 3 in the typically small difference between the official and bitcoin exchange rate—indicating that exchange rates are not highly managed—with the exception of two episodes where bitcoin exchange rates move without any corresponding movement in the official exchange rate: April 17, 2015, and May 21, 2015. The timing of these bitcoin deviations is linked to domestic events that received only limited international attention—on April 17 there were 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 increase in the number of ZAR required to buy 1 USD is consistent with an episode capital flight—a sentiment that could not be revealed in the official exchange rate data given capital controls.

(Figure 3 about here)

Unlike the preceding figures which showed the bitcoin and official exchange rates, Figure 4 plots the mark-up for the Polish zloty (PLN), calculated according to equation 4. Figure 4 contains regions of large exchange rate mark-ups, similar to the large differences between the Chinese or Argentinian official and bitcoin exchange rate in Figures 1 and 2 respectively. It contain multiple episodes (three are highlighted in the Figure 4) where the mark-up suddenly changes. The large mark-ups indicate that the Polish zloty is a currency with a managed exchange rate, while the non-stationarity of those mark-up reveals that has capital controls.

(Figure 4 about here)

Sections 4 and 5 formalize the visual analysis in this section, detecting capital controls by lack of mark-up stationarity and exchange rate regimes by size of mark-ups, using econometric techniques suitable to the properties of bitcoin prices.

3. EMPIRICAL APPROACH

3.1. Data Sources

I obtain daily transaction-weighted bitcoin prices from the aggregation website Bitcoin Charts [bitcoincharts.com], which provides data from 72 exchanges trading 31 currencies. Minute-by-minute data are available but are not used to reduce missing observations. 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.

To create a comparable cross-currency study, I only use data from exchanges where users can buy or sell bitcoin in at least three different currencies, of which two must be the US dollar and the euro. Finally, I focus on a period of 487 days from June 1, 2014, to September 30, 2015, with each selected currency containing a minimum of 440 price observations.[6] This restricts focus to 17 of the 31 currencies and four of the 72 exchanges.[7] Official exchange rate

[6]Given the volatility of bitcoin price data, I examine exchange rates changes that are greater than 20% or 4 standard deviations from the mean. If the exchange rate approximately returns to its preceding level the following day, the outlier is replaced by the average of its neighbors. For example, the middle value of three observation values {5,9,5} may be replaced, but {5,9,13} or {5,9,9} would not. I use linear interpolation to estimate missing values, resulting in 487 daily observations per bitcoin exchange and currency. This procedure reduces volatility and reduces the probability that the methods used in this paper would detect a barrier. As the bitcoin-constructed exchange rates detect all the barriers reported in KAOPEN, there is no evidence that results of this paper are distorted.

[7]The price series for the Hong Kong dollar from ANXBTC and the price series for Australian dollars, Swiss francs, British pounds, Hong Kong dollars, Indian rupees, New Zealand dollars, and Russian rubles on LocalBitcoins either exhibit persistent residual autocorrelation or fail to yield a single direction of causality,

data for each currency 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.

There are two reasons this period of time is chosen. The primary reason is that part of this papers contribution is verifying that bitcoin-based exchange rates can be used to detect capital controls and exchange rate regimes, and therefore all results must be compared to existing exchange rate regime and capital control classifications. Due to the lagged nature of the standard classification systems, the most recent years for which these classifications exist are 2014 and 2015. The specific date within 2014 is deliberately chosen to avoid distortions at the beginning of the sample. In February 2014 Mt. Gox, which handled up to 80% of the world's bitcoin trade, declared bankruptcy and announced a theft of 850,000 bitcoins from the exchange, amounting to about 7% of the worlds bitcoin supply at the time. This caused rapidly decreasing prices and high price volatility.[8] By June 1, 2014, the bitcoin market had stabilized.

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 those that do usually have only standard money-laundering or counterterrorism 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.[9] The lack of a global regulatory framework means that any restrictions are difficult to enforce because countries cannot regulate bitcoin trades that occur in their currency outside of their borders (for example, someone in Canada buying

and therefore do not satisfy the empirical requirements for the tests in section 4.2. For sample consistency, they are removed from consideration.

[8]CoinDesk (www.coindesk.com/companies/exchanges/mtgox) provides more details surrounding this event.

[9]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/

bitcoin with Russian rubles). The results of this paper confirm anecdotal evidence that these regulations are easy to circumvent.

(Table 1 about here)

Table 1 summarizes the average daily volume of trade in either units of bitcoin (BTC) or in the currency indicated on each exchange. 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 both the global bitcoin markets and the four exchanges studied—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 dollars and euros is comparable, while on LocalBitcoins US dollar trade volume is eight times bigger than euro trade volume. Trade volume measured in Bitcoin can 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, the Polish zloty trade volume of "8 bitcoin" on LocalBitcoin could indicate 8 hundred million trades.

The table shows that four exchanges that have resulted from the selection procedure differ greatly in trade volume and in the variety of currencies traded. As the success of bitcoin exchange rates are successful across exchanges, this paper show that, at least among exchanges that satisfy the levels of activity required for selection, data can be used from any source. However, the price of a bitcoin in any given currency 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 while data can be obtained from any active exchange, data from different exchanges should not be mixed: I adjust each exchange using data from only that exchange. Pieters and Vivanco (2017) find that these differences result from differences in fees, exchange liquidity, and legal adherence.

3.2. Removing Bitcoin Trends in Exchange Rates

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-EUR 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 USD-EUR 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 5 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 the long-run trends.

(Figure 5 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 LocalBitcoins 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 reflect the individual bitcoin exchange, not the currency.[10]

[10] Graphs of all bitcoin and official exchange rates, and their differences, are available in the online appendix.

4. CAN BITCOIN DETECT BARRIERS TO ACCESSING FOREIGN CURRENCY?

4.1. Determining Capital Controls

Both the official and bitcoin exchange rate series for each currency are found to be nonstationary, with some exchange rate series integrated at different orders. This would lead to bias in an OLS regression, therefore, I instead 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 $E_{m,t}^{B,C}$ and $E_t^{O,C}$—means that a currency's official and bitcoin exchange rates are unrelated, suggesting the existence of a substantial barrier to accessing official international exchange markets.[11] If the series are cointegrated, I determine their cointegrating relationship—the two exchange rate series should share the same trend, indicated by a cointegrating parameter of $\hat{\beta} = 1$. Details are discussed in Appendix A.

I test for cointegration and calculate the cointegrating parameter across the four bitcoin exchanges for the USD-EUR exchange rate in Table 2. The official and bitcoin USD-EUR 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, $\hat{\beta}_m^{Euro}$, varies greatly. While ANXBTC reports the expected result of $\hat{\beta}_{\text{ANXBTC}}^{EUR} = 1$, LocalBitcoins reports $\hat{\beta}_{\text{LocalBitcoins}}^{EUR} = 0.76$, which implies that LocalBitcoins trend is to increase by only 0.76 cents for every dollar increase in the official exchange rate: a long-run divergence.

(Table 2 about here)

Table 2 therefore verifies Figure 5: there are non-negligible trends within either bitcoin or the bitcoin exchange. However, if these bitcoin trends are consistent across currencies

[11]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.

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.

$$\hat{\rho}^C = \begin{cases} ||\hat{\beta}_m^C - \hat{\beta}_m^{EUR}||, & \text{if cointegrated} \\ 1 & \text{otherwise} \end{cases} \tag{2}$$

The lowest value of $\hat{\rho}^C = 0$ indicates a barrier equivalent to that of the USD-EUR exchange rate (low barriers). The effective impact of a country's barrier in its exchange rate 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 unofficial and official exchange rates).

4.2. Does Bitcoin Reveal Barriers?

Table 3 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 the value 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. Only three countries differ from their KAOPEN classification: Mexico, Russia, and Norway.

(Table 3 about here)

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 the finding of lower barriers for Russia in 2014/2015 using bitcoin relative to the 2013 KAOPEN results is the continuation of this trend.

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 the 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). The Mexican exchange rate had become highly volatile, causing the central bank to intervene through an auction to provide liquidity to the market. This intervention matches the timing of the divergence of official and unofficial exchanges rates. This is not to imply that the intent was to intentionally appreciate or depreciate the exchange rate. This intervention does, however, represent an example of a short-lived policy intervention considered in Klein (2012) that would not be detected using more aggregated data.

Among low-barrier currencies, one currency differs from its KAOPEN classification: The Norwegian krone (NOK). Table 1 shows that the Norwegian krone has the second lowest volume of trade among currencies on LocalBitcoins—the lowest, the Polish zloty (PLN), is classified by both KAOPEN and bitcoin cointegration tests as an intermediate-barrier currency. Therefore, one explanation of the NOK classification difference is that it reflects liquidity issues on LocalBitcoins. 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 is close to Eurozone countries, which may be the source of the bitcoin capital flows. It is not feasible to determine in which country NOK was being purchased or sold for bitcoin, and so the source of the activity is unknown.

5. CAN BITCOIN DETECT EXCHANGE RATE REGIMES?

5.1. Detecting Exchange Rate Regimes

To identify exchange rate regimes, I consider the mean of the premium, or mark-up, between the official and bitcoin exchange rate, $M^C_{m,t}$:

$$M^C_{m,t} = \frac{E^{B,C}_{m,t}}{E^{O,C}_t} - 1 \tag{3}$$

Figure 5 shows that this mark-up exists, even for the euro, and varies across exchanges. The average euro mark-up across the time period is 0.06% for ANXBTC, 1.43% for BTC-e, 0.13% for itBit, and -7.08% for LocalBitcoins. I therefore introduce a simple adjustment: I reduce the bitcoin-exchange mark-up for all currencies by the value of the euro mark-up for the exchange

$$\tilde{M}^C_{m,t} = M^C_{m,t} - M^{EUR}_{m,t} \tag{4}$$

5.2. Exchange Rate Regime

Table 4 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). Consequent to the findings of Calvo and Reinhart (2002), the current standard reference for exchange rate regime, IMF Annual Report on Exchange Arrangements and Exchange Restrictions (2014), incorporates both the country's official statement and the behavior of its official exchange rate.

For some currencies and exchanges, bitcoin is a mark-up, while for others it is a mark-down. With no clear pattern to this deviation, I focus only on the size of deviation from zero in the year 2014. With the exception of four currencies discussed below, low bitcoin mark-ups are associated with exchange rate arrangements labeled as floating by the IMF, with results consistent across the multiple exchanges when applicable. This implies that the adjustment method in equation 4 is sufficient to ensure that bitcoin can be used to detect exchange rate regimes, regardless of data source. While most currencies have consistently low or high mark-ups from 2014 to 2015, some—specifically CNY, MXN, NOK, RUB, and ZAR—do change substantially, highlighting the importance of having timely data.

(Table 4 about here)

While the IMF classifies the Thai bhat (THB) as having a floating exchange rate, the currency 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.

The Polish zloty (PLN) has higher mark-ups than expected for a free floating exchange rate, however, this period is marked by informal capital flows as discussed in Section 2. 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 4 also confirms results in Table 4: 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.

Finally, bitcoin and the IMF disagree regarding the Singapore dollar (SGD) and the Chinese yuan (CNY), which both have low mark-ups even though neither are considered floating by the IMF. Figure 1 and the associated discussion in section 2 show 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 (low mark-ups) before diverging again in 2015.

Singapore has declared that it manages its exchange rate, yet the finding of low-mark-ups is confirmed across two bitcoin exchanges. Additionally, the high volatility of bitcoin data biases it to false detections of manipulation due to large deviations and mark-ups, not the low mark-ups found for the SGD. This bitcoin finding implies that the official, managed exchange rate is not significantly different from the underlying market rate for the period studied. 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.

6. CONCLUSION

The paper confirms that bitcoin price data can be used to construct measures of exchange rate regime and capital controls by comparing the results to the current standard indexes in the literature. The benefit of using Bitcoin is that it can detect transitory interventions that would be undetectable using lower frequency data—such as Mexico's auction—and it can reveal whether an existing policy actually has any impact on the market—such as Singapore's managed exchange rate.

However, I confirm that bitcoin price data are subject to their own trends—with trends differing across different bitcoin markets—and therefore any data must be adjusted prior to use. This paper shows that normalization by a major currency pair is sufficient to correct for these trends. This is a reason to be cautious in using an index of bitcoin prices to construct exchange rates, as these indexes may combine prices from different bitcoin markets, and thus it may not be possible to correct for bitcoin-market exchange rate behavior.

Since the time period of the data used in this paper, the number of exchanges that allow the purchase and sale of bitcoin has increased, with additional cryptocurrencies entering the market as competitors. The results, obtained across exchanges with different characteristics, imply that it may be possible to use any of these exchanges or currencies, assuming the data are appropriately adjusted.

The success of the bitcoin exchange rate in revealing capital controls and exchange rate regimes confirms that bitcoin is being used to circumvent capital controls and exchange rate restriction. This is suggestive evidence that Bitcoin has begun to become a new global currency, described in Weber (2016), eroding a country's ability to control their own exchange rates without sacrificing monetary policy independence.

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] (referred to as unit root, first-difference stationary, or having order of integration one), 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 rerun the ADF and KPSS tests on the first difference of the series. I consistently find that ADF is rejected and KPSS is accepted, indicating that the first difference is stationary and therefore the original series was fractionally integrated. Results are reported in the Online Appendix.

A.2. Are the series cointegrated?

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]. 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.

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, $\mathbf{E}^C_{m,t} = [E^{B,C}_t, E^{O,C}_{m,t}]$ (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 3.

Table A1: Bitcoin Estimates of Capital Controls

Currency	Market	Lag SBIC	ℓ	Johansen Trace Test $r=0$	$r=1$	PSS Test F-stat	C?	Barrier Size $\hat{\beta}^C_m$	$\hat{\rho}^C$	2013 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; $\hat{\beta}^C_m$: Cointegrating Coefficient; C?: Are Official and Bitcoin Exchange Rates Cointegrated?; KAOPEN: 1- 2013 Chinn-Ito Financial Openness Index value; $\hat{\rho}^C_m$: Bitcoin barrier estimate adjusted for bitcoin market trends, normalized to range from zero to one, equation (2); PSS: Pesaran-Shin-Smith; SBIC: Lag according to Schwarz Bayesian information criterion.

B. Appendix: Official, Unofficial, and Bitcoin Exchange Rates for Argentina

Table A2 reports the results from the cointegration test and mark-up (section 4.2 and 5) for the three Argentinian exchange rates. No cointegration—no relationship—exists between the official exchange rate and either the unofficial or bitcoin exchange rate. This is expected given the strict capital controls and the extent of exchange rate manipulation. A cointegrating relationship does exist for the unofficial and bitcoin exchange rates. Furthermore, the VECM coefficient is consistent with a result of low barriers between the unofficial and bitcoin exchange rate. This indicates that bitcoin exchange rates can be used to determine the dynamics of unofficial exchange rates.

Table A2 confirms that even though unofficial and bitcoin exchange rates are cointegrated, there is a significant negative mark-up, even after adjusting the mean for the bitcoin-specific mark-up (-6.31%). This difference—which persists after normalizing by the Euro exchange rate—must reflect an element that is not found in the euro exchanges. An example may be considerations of convenience and safety when using online bitcoin exchanges relative to street vendors in Argentina—this consideration does not exist for euro currency transactions or similar floating-exchange-rate regimes. This indicates that bitcoin should not be used to estimate the level-value of the unofficial exchange rate.

Table A2: Relationship among Three Sources of Argentinian Exchange Rates

	Official and Unofficial	Official and Bitcoin	Unofficial and Bitcoin
ℓ	11	6	5
Cointegration Test			
Johansen: $r = 0$	4.07***	4.90***	39.36
Johansen: $r \leq 1$	1.14	0.93	0.55***
Cointegrated?	No	No	Yes
Barrier			
$\hat{\beta}^C$	–	–	0.78***
$\hat{\rho}^C$	1.00	1.00	0.02
Low barrier?	No	No	Yes
Mark-Up			
Mean (%)	55.19	41.41	−6.31

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

Abbreviations: $\hat{\beta}^C_m$: Cointegrating Coefficient; $\hat{\rho}^C_m$: Bitcoin barrier estimate adjusted for bitcoin market trends, normalized to range from zero to one, equation (2); ℓ: Lag.
Note: Argentina's official and unofficial exchange rates are not cointegrated, indicating a barrier to capital flows, with large mark-up, consistent with the known fixed exchange rate. Similar results are obtained for the official and bitcoin exchange rate. In contrast, unofficial and bitcoin exchange rates are cointegrated with low barriers, indicating the bitcoin can approximate the dynamics of the unofficial exchange rate. However, a sizable mark-up remains—although it is smaller than the mark-up relative to the official exchange rate—indicating that bitcoin exchange rates cannot reveal the level.

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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 currencies. Most currencies have no legal restrictions placed on Bitcoin.

Table 2: Trends in the Bitcoin Mark-Up Exist: 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 (2).

Note: The table shows the results of a cointegration test between the bitcoin and official EUR-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 parameter $\hat{\beta}_m^{Euro} = 1$. This result 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 2, adjusts for market-specific effects.

Table 3: 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 (2).

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

Table 4: Bitcoin Mark-Up Provides Information About the De-Facto Exchange Rate Regime

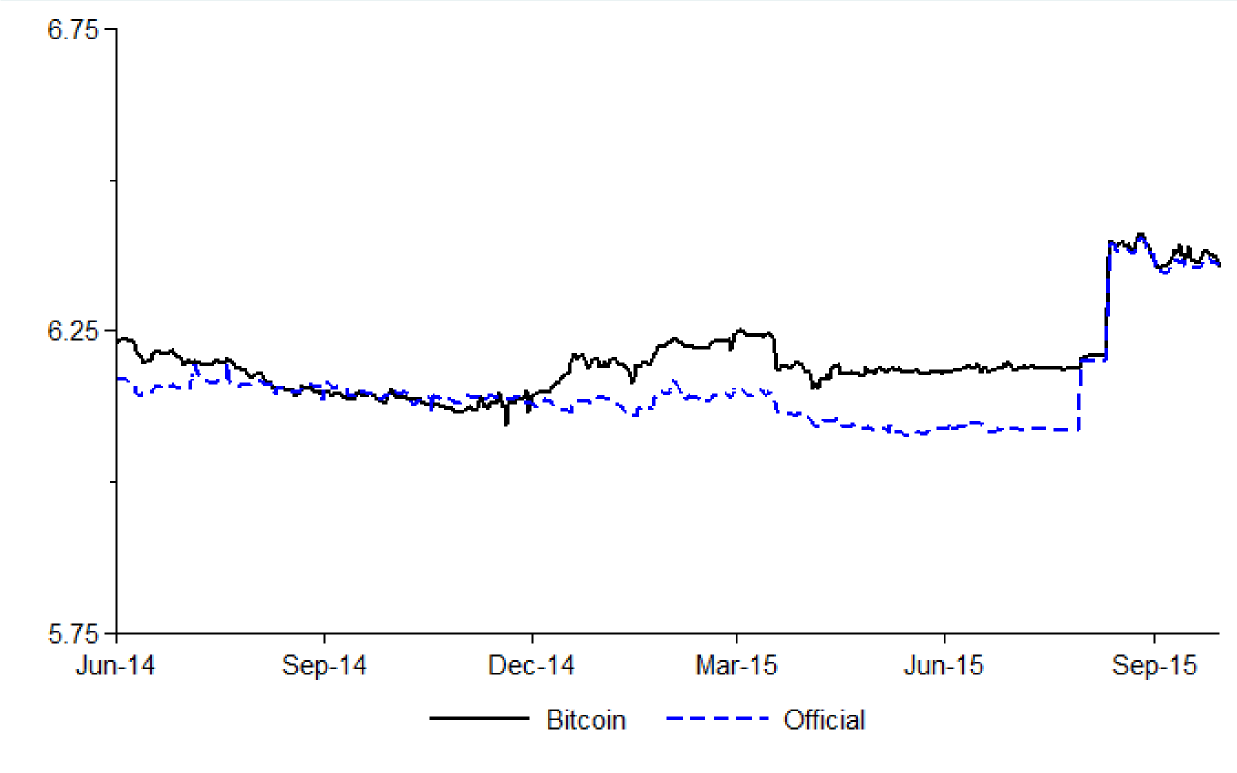
Currency	Market	2014 IMF Classification	Mark-Up (Adjusted, %) 2014	2015	Full Sample
		IMF Classification: Free Floating or Floating Exchange Rate			
Low Bitcoin Mark-up in 2014 (0-2%)					
AUD	ANX	Free Floating	0.02	0.05	0.04
CAD	ANX	Free Floating	-0.01	0.01	0.00
	Local	Free Floating	1.07	-0.25	0.33
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 (Above 5%)					
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 (0-2%)					
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 (Above 5%)					
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, LocalBitcoins.

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).

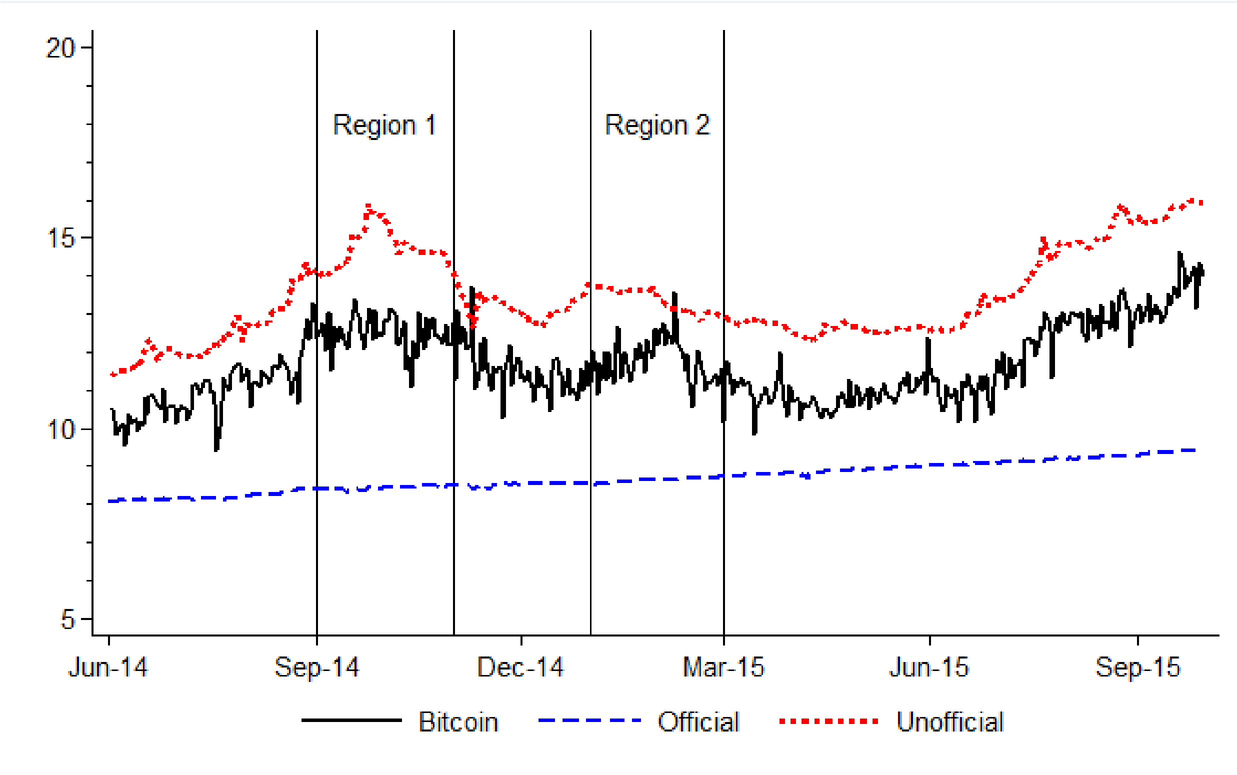
Adjusted Mark-Up calculated according to equation 4; IMF Classification is currency exchange rate regime classification from 2014 IMF Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

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



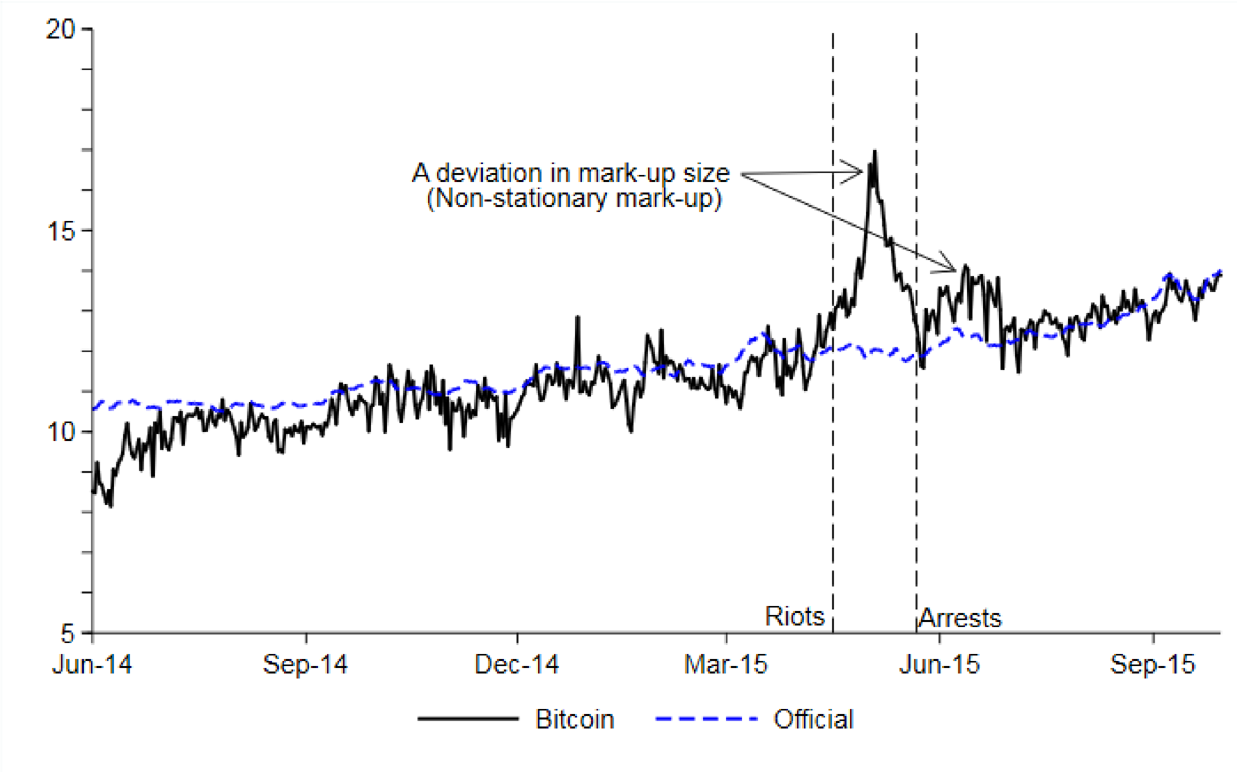
Note: Daily CNY-USD exchange rates: bitcoin-based (solid) and official (dashed) between 1 June 2014 and 30 September 2015. Official exchange rate data from Oanda.com. Bitcoin exchange rate is the ratio of CNY and USD bitcoin prices on ANXBTC, obtained from www.bitcoincharts.com. After China devalued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

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



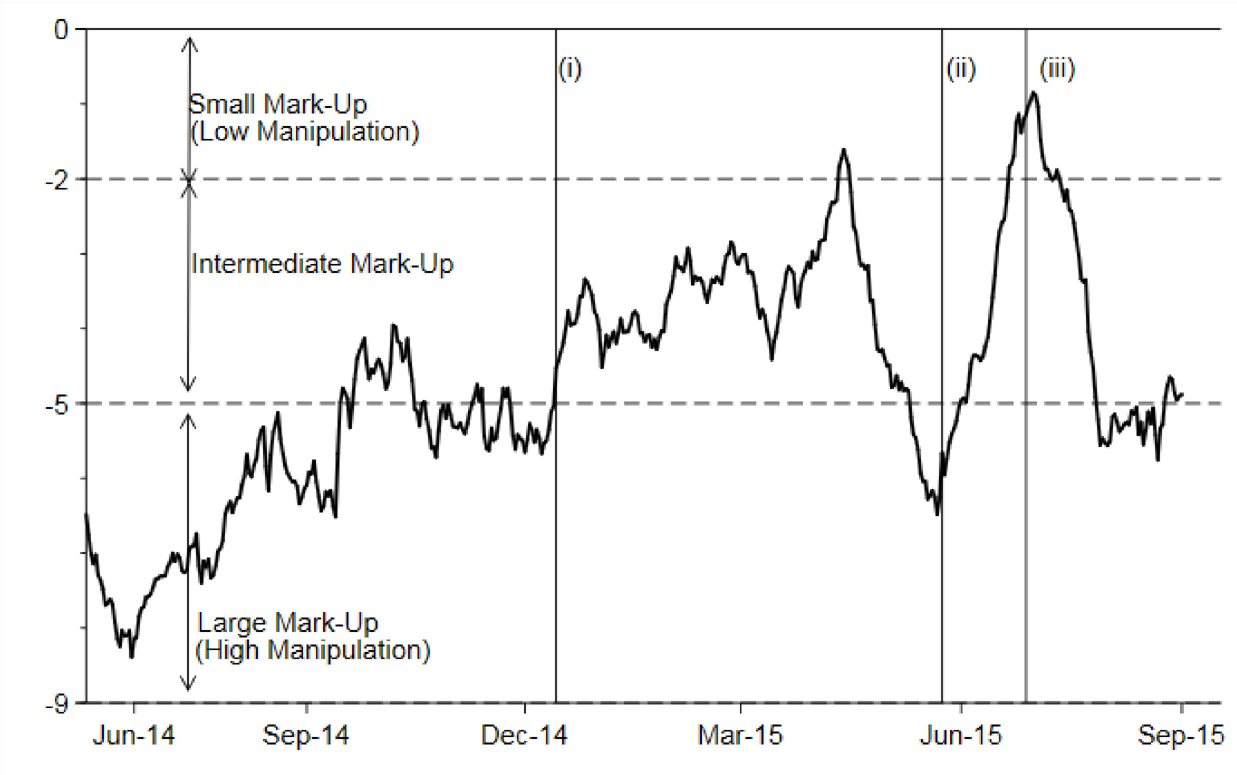
Note: Daily ARS-USD exchange rates: bitcoin-based (solid), official (dashed), and unofficial (dot) between 1 June 2014 and 30 September 2015. Official exchange rate data from Oanda.com; unofficial exchange rate from *Ámbito Financiero*. Bitcoin exchange rate is the ratio of ARS and USD bitcoin prices on LocalBitcoins, 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. Bitcoin exchange rate is the ratio of ZAR and USD bitcoin prices on LocalBitcoins, obtained from www.bitcoincharts.com. Multiday riots began on April 17, 2015, and 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 reflects the capital control barriers to capital flight faced by domestic bitcoin users.

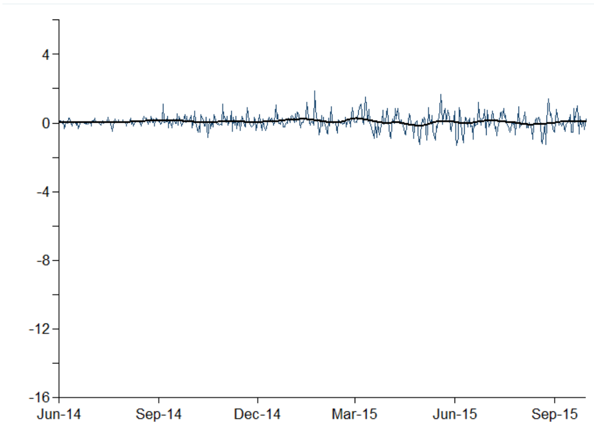
Figure 4: Bitcoin Mark-ups Reveal High Frequency and Temporary Changes from Global Events



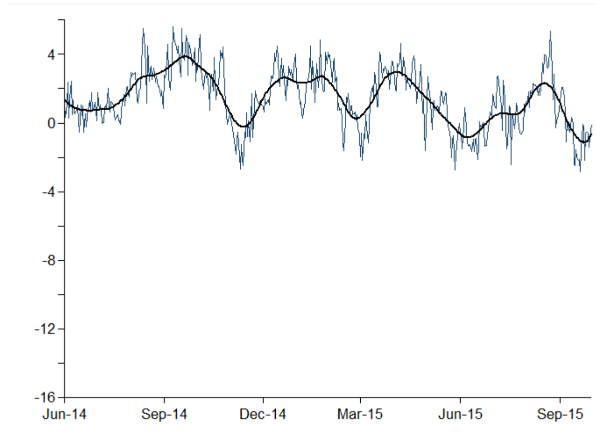
Note: Graph shows the 30-day rolling average of the percent deviation between bitcoin and the official PLN-USD exchange rate between 1 June 2014 and 30 September 2015 calculated according to equation 4. Mark-up within 3% is consistent with low mark-ups, while greater than 5% is a large mark-up. Three 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.

Figure 5: Bitcoin Euro-USD Exchange Rates Contain Market-Specific Premiums, Need Market-Specific Adjustment

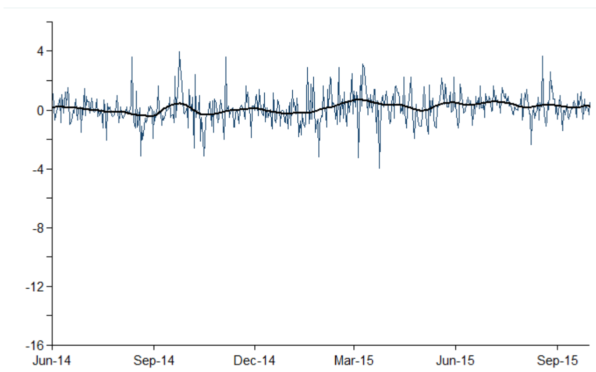
(a) ANXBTC



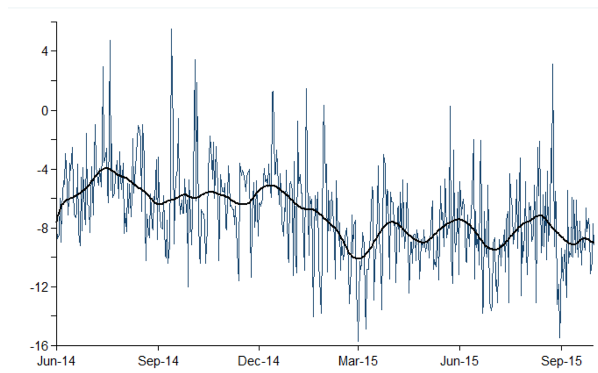
(b) BTC-e



(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 0.06%. BTC-e average deviation is 1.43%, itBit average deviation is 0.13%, LocalBitcoins average deviation is -7.08%. In addition to different levels of deviations, LocalBitcoins 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-based 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).