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Does Bitcoin Reveal New Information About Exchange Rates and Financial Integration?*

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Abstract

I show that the prices of the internationally traded crypto-currency bitcoin can be used to estimate a currency's unofficial exchange rate and capital controls at a daily interval. Two important bitcoin features are documented: (1) Bitcoin-based exchange rates approximate the behavior, but not the level, of unofficial exchange rates, and (2) Bitcoin prices contain a bitcoin-trend term and must be appropriately normalized prior to being used for this purpose. Bitcoin-based exchange rates reveal that (3) there is no consistent pattern of Granger causality between unofficial rates and official rates by exchange rate regime or barriers at the daily frequency, and (4) that countries can engage in short-interval capital controls.

JEL codes: F31, F33, G15, O17

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1 INTRODUCTION

It is difficult to obtain accurate data for unofficial exchange rates.[1] Most papers examining unofficial exchange rate behavior rely on the same data source: the *World Currency Yearbook*.[2] Rates in the *World Currency Yearbook* "are provided by the Central Bank and Ministries of Finance who may be reluctant to provide the true data", or reported by "foreign correspondents or informed currency dealers". [Bahmani-Oskoee, Miteza, and Nasir [2002]]. This data consists of a single observation per month. Similar issues exist in attempting to quantify barriers to international financial flows, as countries may impose unofficial barriers or put in place official barriers that have no effect. Efforts to directly measure barriers, without relying on government reports, requires data that is usually released only annually, limiting the frequency at which the barriers estimates can be updated.[3]

Its virtual, online nature allows bitcoin to function both as a method to bypass restrictions on the acquisition of foreign currency and as an alternative to the official, potentially manipulated, exchange rate. I examine whether daily price data from bitcoin sales in various currencies can be used to both construct a meaningful alternative dataset of daily unofficial exchange rates, and be used to detect barriers to global financial integration.[4] Because bitcoin prices can be directly observed, this method requires no reporting agents, thereby removing potential reporting bias. Moreover, because bitcoin has an alternative use as an investment vehicle, bitcoin trades exist even if a currency is freely floating and therefore a bitcoin exchange rate for exists for currencies that are both floating and managed.[5]

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

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

[3] Literature that estimates international financial barriers is reviewed in Section 4.3.

[4] Minute-by-minute data is also available. However, to maintain a large sample size and reduce missing observations, daily data is used.

[5] For example, Huett, Krapf, and Uysal [2014] found that trading of the Belarusin ruble ceased once the currency was allowed to float.

The paper proceeds as follows. In Section 2 I provide a brief introduction to bitcoin, its history, and relevant terminology and literature. In Section 3 I discuss data collection and bitcoin exchange rate construction, and why the ratio of bitcoin prices does not trivially yield a usable exchange rate. In Section 4, I use a cointegration test (either the Johansen trace test or the Pesaran-Shin-Smith bounds testing procedure) and the results of a vector error correction model or conditional error correction model to identify barriers to the acquisition of foreign currency. I identify exchange rate manipulation by the magnitude of the bitcoin and official exchange rate ratio in Section 5. After showing that bitcoin reflects the trend (but not the level) of unofficial exchange rates in section 6.1, I update results in the literature regarding the relationship between official and unofficial exchange rates—previously focused on managed exchange rate regimes and using monthly observations—for the remainder of Section 6. Specifically, I show that (1) the proportionality restriction (required for many models of unofficial market exchange rates) exists for all exchange rate regimes as long as there are no restrictions to access of foreign currency; and (2) Granger causality between the official and bitcoin exchange rate follows no consistent pattern across regimes or barriers when using daily exchange rate data.

2 WHAT IS BITCOIN? A BRIEF HISTORY

The purpose of this section is to give the interested reader only as much information as needed to understand bitcoin for this paper. For a comprehensive overview of bitcoin, readers should consult Velde [2013]. Böhme, Christin, Edelman, and Moore [2015] wrote an accesible technical review of bitcoin, and 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.

Bitcoin is a crypto-currency designed and created by the entity Nakamoto [2008].[6] A crypto-currency is entirely digital, with no central monetary authority, country of origin, or physical representation. Nakamoto created 21 million bitcoin, which are discovered by solving mathematical algorithms in a process known as "mining". Once discovered, a bitcoin can be held, used for retail

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

purchases, or bought and sold on a bitcoin trading website in exchange for a variety of currencies.[7] 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.

A website where bitcoin can be bought and sold is known as an "exchange." Every account on an exchange has a virtual "wallet" in which the users can store both their bitcoin[8] and the currencies accepted by the exchange. Currency in a wallet can be directly deposited into or withdrawn from a connected bank account, an online payment system (such as PayPal), or into a wallet associated with a different exchange. An example of an exchange buy/sell interface is shown in Figure 1, using the exchange ANXBTC. An exchange user can buy bitcoin using currency in their wallet (in Figure 1, US dollars would be used to purchase bitcoin) and in a matter of seconds, sell the purchased bitcoin for a different currency (selecting EUR from the drop-down menu would sell the bitcoin for euros), which would be deposited back into their wallet. This illustrates why the bitcoin price in US dollars and in euros can be used to construct an exchange rate: bitcoin can function like a vehicle currency for foreign exchange swaps, a role traditionally held by the US dollar.[9] 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 any one of exchange websites.[10] Additionally, bitcoin prices in different currencies among various independent, globally established exchanges are publicly and instantaneously available to all agents without charge regardless of the agent's country of origin.

The online nature and pseudo-anonymity of bitcoin has resulted in its use in online criminal transactions.[11] The "Silk Road" market is the most widely known example. Silk Road was not

[7] 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 litecoin.

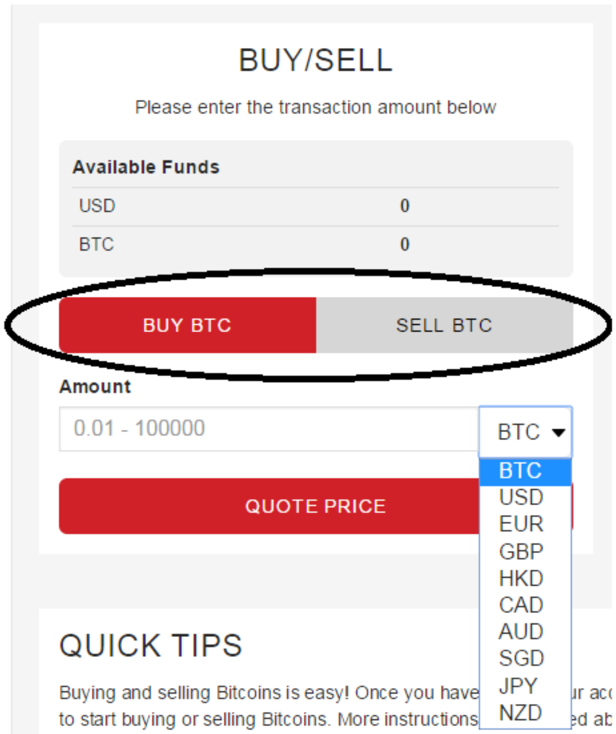
[8] Technically, the wallet does not actually "store a bitcoin," though from a user's perspective, this is functionally what occurs. For details, refer to Böhme, Christin, Edelman, and Moore [2015].

[9] 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.

[10] Hendrickson, Hogan, and Luther [2016] consider governmental efforts to discourage bitcoin use.

[11] Contrary to popular belief, bitcoin is not anonymous. The entire transaction history of a bitcoin travels with it in the bitcoin's publicly visible "blockchain"—equivalent to a digital ledger. Pieters and Vivanco [2015] have examined the implication of this on bitcoin pricing, finding that it contributes to the bitcoin market segmentation that is also

FIGURE 1
Buy/Sell Interface on the ANXBTC Bitcoin Exchange



a bitcoin exchange; rather, it was an online marketplace 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 uses as well—an investment asset, or as a means to purchase goods from major companies (Dell and Amazon both allow the purchase of items using bitcoin, either directly or through the purchase of a gift card). Because bitcoin has these other uses, even currencies with unrestricted capital markets and unmanipulated exchange rates have bitcoin trading activity, and therefore, a bitcoin price. These uses allow for the construction of a bitcoin exchange rate for currencies with a variety of exchange rate regimes, from the euro and Canadian dollar to the Chinese yuan and Argentinian peso.

A major structural change to the bitcoin market occurred after the sudden failure and bankruptcy of Mt. Gox, an exchange that handled up to 80% of the world's bitcoin trade, in February 2014.[12] Given the enormity of the changes that followed the Mt. Gox collapse, this paper only focuses

detected in this paper.

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

on the period after June 1, 2014, when the bitcoin market stabilized after nearly six months of instability and structural changes, even though the first bitcoin was traded in January 2009.[13]

3 EMPIRICAL APPROACH

3.1 DATA SOURCES

Bitcoin are bought and sold in many different currencies and exchanges (the aggregation website Bitcoin Charts [bitcoincharts.com] provides data from 72 exchanges trading 31 currencies). To create a comparable cross-country study, I will examine only exchanges that conduct transactions in at least three different currencies, of which two must be the US dollar and the euro. I obtain the daily transaction-weighted price from the Bitcoin Charts website, and include only currencies that report at least 400 transactions during the period of the study: June 1, 2014, to September 30, 2015.[14] This selection process yields an initial selection of 22 currencies traded across four exchanges, ANXBTC, itBit, BTC-e, and LocalBitcoin. The currencies and exchanges studied in this paper therefore only include a subset of all the transactions, and while some currencies appear only once in my sample, all currencies studied trade on multiple bitcoin exchanges, most of which are not included.

Table 1 lists current price observations, along with current restrictions on bitcoin trades applicable to each currency's country of origin during the period of study. Most countries in this sample have no bitcoin trading laws; the those that do mostly only apply standard money-laundering or counterterrorism laws, or ban financial firms or banks 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. As neither of these countries can regulate bitcoin trades that occur in their currency

[13] An early study of bitcoin price behavior by Yermack [2015] concluded that the bitcoin daily exchange rate exhibited nearly zero correlation with major currencies. This conclusion was based on an examination of correlations using Mt. Gox prices from July 17, 2010, to the day prior to its collapse (February 6, 2014). Even without the Mt. Gox collapse, this date range includes several dramatic events in bitcoin price history not discussed here that could bias results.

[14] Because bitcoin exchanges do not close for trading, each trading day is defined as starting at midnight Coordinated Universal Time (UTC) regardless of the location or currency traded on the exchange.

TABLE 1
Summary of Bitcoin Price, Volume, and Legal Status Across Exchanges and Currencies

Exchange Symbol	Currency	Obs.	Average Daily Volume BTC	Average Daily Volume Currency	Average Price	Bitcoin Trade Legal Status
ANXBTC (https://anxbtc.com)						
USD	US dollar	480	910.88	319,185.72	344.56	
EUR	Euro	480	908.86	259,909.33	282.12	
AUD	Australian dollar	480	908.12	377,217.71	409.85	
CAD	Canadian dollar	480	907.85	370,268.77	401.73	AML and CT
CHF	Swiss franc	418	12.93	3,862.03	345.10	AML
CNY	Chinese yuan	480	907.91	1,974,068.91	2,134.54	Financial firms forbidden
GBP	British pound	480	907.59	198,726.70	215.60	
HKD	Hong Kong dollar	480	908.76	2,472,351.55	2,671.54	AML and AF
JPY	Japanese yen	480	907.53	35,591,785.03	38,765.43	
NZD	New Zealand dollar	480	907.92	408,896.33	445.12	Banks need approval
SGD	Singapore dollar	480	907.57	414,722.76	449.60	
BTC-e (https://btc-e.com)						
USD	US dollar	476	7,554.94	2,355,088.31	341.53	
EUR	Euro	481	114.40	32,250.93	284.17	
RUB	Russian ruble	480	309.06	4,878,341.97	16,861.43	Unclear; appears to be illegal
itBit (https://www.itbit.com)						
USD	US dollar	487	2,787.36	819,134.79	344.76	
EUR	Euro	476	351.50	80,574.17	280.17	
SGD	Singapore dollar	484	236.83	88,561.27	448.39	
LocalBitcoins (https://localbitcoins.com)						
USD	US dollar	487	1,705.08	552,005.11	382.89	
EUR	Euro	487	209.19	54,929.90	292.98	
ARS	Argentinian peso	448	13.46	51,044.50	4,400.49	
AUD	Australian dollar	487	199.80	78,206.06	430.62	
BRL	Brazilian real	434	5.76	5,218.54	985.43	
CAD	Canadian dollar	487	47.15	17,598.88	418.46	AML and CT
CHF	Swiss franc	418	12.93	3,862.03	345.10	AML
CZK	Czech Republic koruna	401	2.91	20,330.17	7,871.56	
GBP	British pound	487	518.40	105,941.87	222.64	
INR	Indian rupee	487	17.72	322,911.44	21,748.92	
MXN	Mexican peso	487	15.31	71,072.77	5,127.63	AML and AF
NOK	Norwegian krone	474	11.17	25,563.80	2,510.87	
NZD	New Zealand dollar	485	10.37	4,596.90	462.47	Banks need approval
PLN	Polish zloty	468	8.25	8,529.66	1,151.59	
RUB	Russian ruble	487	148.26	2,298,994.40	17,007.64	Unclear, appears to be illegal
SEK	Swedish krona	487	43.51	102,627.89	2,747.46	
SGD	Singapore dollar	442	3.92	1551.87	478.31	
THB	Thai bhat	487	35.42	368.493.30	11,177.79	Officially illegal
ZAR	South African rand	487	51.97	193,764.97	4,293.01	

Abbreviations: AF, anti-fraud laws; AML, anti-money laundering; (blank), unrestricted trade; BTC, units of bitcoin; CT, counterterrorism laws; Obs., observations.

outside of their borders (for example, someone in Canada buying bitcoins with Russian Rubles), I assume the impact that these regulations have on the global bitcoin market is minimal.

The average daily volume of trade measures the bitcoin trades conducted in the indicated currency, either in units of bitcoin (BTC) or in the currency indicated. The volume of trades measured in bitcoin is slightly 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). US dollar trades are the most popular trades (as measured by BTC) for all exchanges in this sample. While trade volumes on bitcoin markets represent only a small fraction of the official currency markets, even the smallest exchange has a daily volume of over a quarter-million US dollars in USD-bitcoin trades.

Official exchange rate data come from Oanda.com. Oanda 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. I linearly interpolate each series to estimate missing values, resulting in 487 daily observations per bitcoin exchange and currency.

3.2 DEFINING BITCOIN EXCHANGE RATES

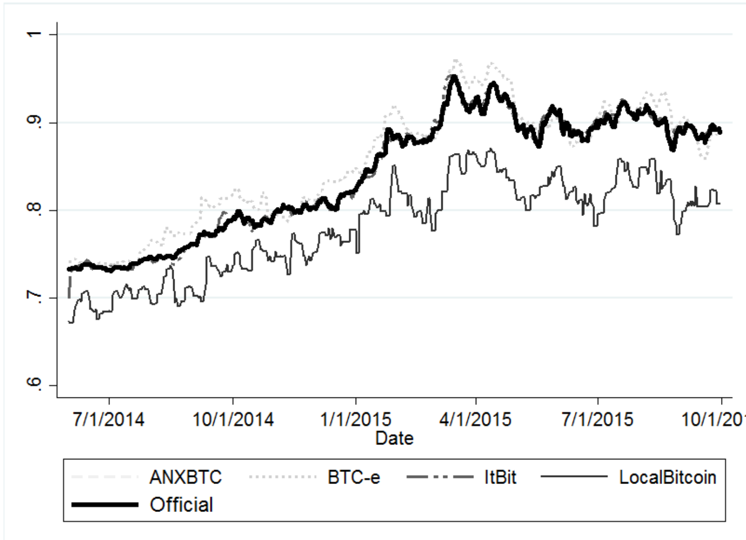
Using bitcoin prices in the currency of interest $(B^{C}_{m,t})$ and the US dollar $(B^{USD}_{m,t})$ the implied bitcoin exchange rate, $(E^{B,C}_{m,t})$, is given by:

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

for exchange (m) on day (t) between currency (C) and the US dollar. This equation uses bitcoin as a vehicle currency, buying bitcoin in one currency to sell it for another.

Figure 2 shows the bitcoin US dollar to Euro exchange rate constructed for the four selected exchanges, as well as the official exchange rate. The bitcoin exchange rate constructed from ANXBTC and itBit data almost indistinguishable from the official exchange rate, unlike the exchange rate calculated using BTC-E and LocalBitcoins data. As the USD-Euro exchange rate represents the most easily accessible official and bitcoin exchange rates across the various currencies, this figure shows why the question of how to appropriately compare bitcoin exchange rate to official exchange rate data is even asked, as the data from various exchanges do not appear to be

FIGURE 2
USD to Euro Exchange Rate for Four Exchanges



interchangeable. This is consistent with the findings of Pieters and Vivanco [2015], who show that arbitrage is not satisfied across the various bitcoin exchanges due to differences in the structure of the exchanges.

I assume the relationship between bitcoin and official exchange rates across the various exchange markets consists of two terms: a stationary, potentially non-zero, mark-up term, $(\varepsilon_{C,m})$, and a trend difference term, $(\rho_{C,m})$, and can be expressed in the form[15]:

$$E_{m,t}^{B,C} = \left(1+\rho_{C,m}\right) E_t^{O,C} + \varepsilon_{C,m} \tag{2}$$

The absolute Law of One Price (aLOP) requires that the bitcoin and official exchange rates are identical, $\rho_{c,m} = 0$ and $\varepsilon_{C,m} = 0$, while relative Law of One Price (rLOP) allows for a level differences and requires only that the two exchange rates follow the same trend, $\rho_{c,m} = 0$ and $\varepsilon_{C,m} \neq 0$. A failure of the absolute law of one price is expected because both the bitcoin exchanges and official currency vendors charge fees for currency trades, thereby introducing an arbitrage band, $\varepsilon_{C,m} \neq 0$, into the markets. This band can be identified in Figure 2 as the non-zero difference be-

[15] I refer to $\rho_{C,m}$ as a trend difference term as it captures the differences in the trend of the two series: $E_{m,t}^{B,C} - E_{m,t-1}^{B,C} = (1+\rho_{c,m})\left(E_t^{O,C} - E_{t-1}^{O,C}\right)$

tween the official and bitcoin exchange rates. The trend difference, $\rho_{c,m}$, is most easily be seen as the increasing distance between LocalBitcoin and the official exchange rate series (recall that $\varepsilon_{C,m}$ is stationary).

Akram, Rime, and Sarno [2008] studied global financial and exchange rate contracts of different durations, and found that most price deviations in exchange rate markets were quickly arbitraged away, implying that exchange rates across foreign exchange markets should adhere to rLOP. Relative to official exchange rate markets, the 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, and there are no exchange rate contracts of different lengths) imply that arbitrage opportunities caused by the difference between the official and unofficial exchange rates should be found and exploited by any participant even more quickly and easily than on the official markets studied in Akram, Rime, and Sarno [2008]. However, Yermack [2015] argues that bitcoin should not be thought of as a currency and should, therefore, be treated as a traded good. In examining the behavior of car prices across the eurozone after the introduction of the euro, Goldberg and Verboven [2005] found convergence to both the absolute and relative law of one price, while in a study examining consumer goods prices across European cities, Engel and Rogers [2004] found no evidence of convergence. It is therefore possible that some aspect of bitcoin or a bitcoin exchange—one that cannot be easily removed—could overwhelm convergence to the exchange rate causing rLOP between the official and bitcoin exchange rate to fail.

I assume that the trend difference term, $\rho_{c,m}$, can be decomposed into three components:

$$\rho_{C,m} = \rho^B + \rho^m + \rho^C \tag{3}$$

The deviation from the official exchange rate trend that occurs because of bitcoin—and is therefore shared across all bitcoin exchanges and currencies—is reflected in (ρ^B). The bitcoin-exchange-specific wedge—capturing differences in fees or structures specific to a bitcoin exchange—is reflected in (ρ^m). Finally, (ρ^C) denotes any deviations between the official and bitcoin exchange rates that are currency-specific.[16] All components can take positive or negative values. Given an estimate of $\rho_{C,m}$ for two different currencies, $C1$ and $C2$, on the same exchange m, the form assumed in Equation (3) allows a normalized currency-specific wedge to isolated, removing the impact of both bitcoin and the exchange:

$$\rho_{C1,m} - \rho_{C2,m} = \rho^{C1} - \rho^{C2} \equiv \rho^{C1,C2} \tag{4}$$

Studying the prices of stocks that trade on both domestic and international markets, Yeyati, Schmukler, and Horen [2009] showed that price segmentation resulted from cross-border capital regulations functioning as a barrier in international financial markets. Similarly, Goldberg and Verboven [2005] interpreted the reduction in car price segmentation across the eurozone as a reduction in the barriers in the international goods market. Therefore, irrespective of whether bitcoin should be thought of as a good or as money, $\rho^{C1,C2} \neq 0$ can be interpreted as implying the existence of a barrier in accessing official exchange rates from the bitcoin exchange rate market, while a finding of $\rho^{C1,C2} = 0$ is consistent with rLOP in exchange rates. After describing the method used to estimate $\rho^{C1,C2}$ in Section 3.3, I shall verify in Section 4.3 that estimates of $\rho^{C1,C2}$ reflect known barriers in the currency market, verifying that the bitcoin components are removed from $\rho^{C1,C2}$ in this normalization, as part of the contribution of this paper.

3.3 Testing for Cointegration

As both the official and bitcoin exchange rate series for each currency are found to be nonstationary, determining whether $\rho^{C1,C2} = 0$ requires care. First I test the official and bitcoin exchange rates for cointegration. A failure to find cointegration is inconsistent with flexible, market-based exchange rates because it implies that the official and bitcoin exchange rates do not share a trend. This failure is consistent with a barrier in access to international exchange markets (for example, capital

[16]Technically, equation 3 can be generalized, as all that is needed is for the currency component to be seperable.

controls or a lack of market access).[17]

I use either the Johansen trace test or the Pesaran-Shin-Smith (PSS) bounds testing procedure. The Johansen trace test is the default method to determine cointegration, however it requires that the series tested be integrated to the same order and be I[1] (also referred to as unit root, first-difference stationary, or having order of integration one). This requirement is not met by all exchange rates in this sample because some are fractionally integrated (between I[0] and I[1]), or one series of the pair is fractionally integrated, while the other is I[1]. Because the fractional integration of a series could be the result of the exchange rate regime or barriers to access, these series are not simply removed. The PSS bounds test allows for both fractional integration and for the two series to have different orders of integration, but it is more restrictive in that it requires the series to display a single direction of causality.

3.3.1 Order of Integration I test the order of integration of each exchange rate series at a given lag using tests with opposing nulls for robustness: an augmented Dickey-Fuller test [ADF; Dickey and Fuller, 1979], which has a null of the series being I[1], and a Kwiatkowski-Phillips-Schmidt-Shin [KPSS; Kwiatkowski et al., 1992] test, which has a null of the series being 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.

If both the official and bitcoin exchange rate series for a given currency accept ADF and reject KPSS, the requirements of the Johansen trace test are satisfied. 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 the first difference rejects ADF and accepts KPSS; therefore, the original series is fractionally integrated and the methods of the PSS bounds test are applied to that currency instead.

[17]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.

3.3.2 Johansen Trace Test. The Johansen test iteratively tests a null hypothesis that no more than r equations exist, which describe the trend relationship between n series (with $r = 0$ indicating no cointegration), accepting the first value of r for which the null is not rejected. As I consider only two series, there can be at most one cointegrating equation, so the test should obtain significant results for $r = 1$ if the two sources of exchange rates are to be cointegrated.

The trace test is based on a vector error correction model (VECM). Given the 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), the VECM estimates the following:

$$\Delta\mathbf{E}_t = \sum_{i=1}^{\ell} \Gamma_i \Delta\mathbf{E}_{t-i} + \gamma\Pi'\mathbf{E}_{t-1} + \alpha + \varepsilon_t \tag{5}$$

where $\Delta E_t = E_t - E_{t-1}$, ℓ is the lag, and ε_t are standard mean zero, independent, identically distributed shocks. I select the initial lag according to the Schwarz Bayesian information criterion (SBIC).

After running the VECM at lag ℓ, a Lagrangian multiplier (LM) test is used to test for autocorrelation in the residuals. If the LM test null of no autocorrelation is rejected at the 5% level, the value of the lag is incremented by one. The order of integration and the tests for residual autocorrelation are repeated. If the null is not rejected, the Johansen trace test is applied.

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.

3.3.3 PSS Bounds Test The PSS bounds test is based on the unrestricted conditional error-correction model (CECM), expressed in notation from Section 3.3.2 as:

$$\Delta E_t^y = \alpha + \sum_{i=1}^{\ell} \Gamma_i \Delta \mathbf{E}_{t-i} + \gamma \Pi' \log \mathbf{E}_{t-1} + \omega' \Delta E_t^x + \varepsilon_t \tag{6}$$

where y refers to either the bitcoin or official exchange rate, and x refers to the exchange rate not used in y, and ℓ is the lag (initially selected by SBIC or passed by the process in Section 3.3.2).

A significant restriction of the PSS method is that the CECM requires a single direction of causality, which I establish before proceeding. In Equation (6), I assume that E_t^x causes E_t^y, or in the parlance of PSS, E_t^x is the forcing function for E_t^y. Given the presence of series that are not I(0), I use the methodology of Toda and Yamamoto [1995] (TY) to determine Granger causality, first estimating a vector autoregression model (VAR) on the data with lags $\ell + 1$:

$$\mathbf{E}_t = c + \sum_{i=1}^{\ell+1} \Psi_i \mathbf{E}_{t-i} + \varepsilon_t \tag{7}$$

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 find that both series are unit root processes, the Johansen trace test (described in Section 3.3.2) is applied. Otherwise, causality is tested using the TY methodology described above.

If I establish a single direction of causality between the bitcoin and the official exchange rate series, I can use the PSS bounds test. The PSS bounds test evaluates the joint significance of the coefficients for lagged variables using a Wald test, comparing the resulting F-statistic to an upper and lower bound calculated by Pesaran, Shin, and Smith [2001]. For this paper, the bounds for the critical values (c.v.) are the following:

H0: No Cointegration	1% c.v.	5% c.v.	10% c.v.
Accept H0 if F$<$ c.v.	6.84	4.94	4.04
Reject H0 if F$>$ c.v.	7.84	5.73	4.78

If the F-statistic is lower (higher) than the lower (upper) critical bound, then the null hypothesis of no cointegration is rejected (accepted) regardless of the underlying series order of integration. If the F-statistic falls between the critical bounds, I must use information on the underlying series order of integration.

4 BARRIERS TO ACCESSING FOREIGN CURRENCY

4.1 ADJUSTING FOR BITCOIN-SPECIFIC BARRIERS

I compare the behavior of the bitcoin and official exchange rate across the four bitcoin exchanges for the euro in Table 2. The bitcoin exchange rate on LocalBitcoins is fractionally integrated, so I use the PSS bounds test after determining that causality occurs from the official exchange rate to the bitcoin exchange rate. I use the Johansen trace test for the other three exchanges. Across all four bitcoin exchanges, the official and bitcoin exchange rates are cointegrated, as would be expected for standard financial markets given an exchange rate with minimal restrictions on foreign currency trades.

TABLE 2
Euro-USD Cointegration Test

	Lag		Johansen Trace Test		PSS Test		Barrier Size	
Market	SBIC	ℓ	r=0	r=1	F-stat	C?	$\hat{\beta}^{EUR,M}$	$\tilde{\rho}^{EUR}$
ANXBTC	2	2	242.65	2.05***	–	Y	1.00***	0.00
BTC-e	3	4	25.19	2.06***	–	Y	0.96***	0.00
itBit	2	2	193.76	2.21***	–	Y	1.02***	0.00
LocalBitcoins	2	4	–	–	50.89***	Y	0.74***	0.00

****1%, ** 5%.*
Abbreviations: C, Cointegrated series

The VECM or CECM estimated trend coefficient of the cointegrating equation, $\hat{\beta}^{EUR,M}$ reported in Table 2, is more interesting as it is not true across all exchanges that $\hat{\beta}^{EUR,M} = 1$, even though the Euro exchange rate is a major, easily accessible market. The relationship between the estimated long-run cointegrating relationship, $\hat{\beta}^{EUR,M}$ and the trend difference introduced in Section 3.2 can be expressed as:

$$\hat{\beta}^{EUR,M} = 1 + \rho^B + \rho^M + \rho^{EUR} \tag{8}$$

The $\hat{\beta}^{EUR,ANX} = 1$ result of ANXBTC implies that the rLOP holds; the trend difference component is calculated to be $\rho^B + \rho^{ANXBTC} + \rho^{EUR} = 0$. As expected given Figure 2, this is not strictly true for the remaining three exchanges, with LocalBitcoins exhibiting a substantial deviation. Table 2 therefore verifies a significant result implied by the visual examination of Figure 2: while it may be tempting to assume that the rLOP should hold between bitcoin and official exchange rates trends, or that $\hat{\beta}^{C,M} = 1$ and $\left(\rho^B + \rho^m + \rho^C\right) = 0$, this may not be a valid assumption due to non-negligible trends within either bitcoin or the bitcoin exchange. Therefore, I use $\hat{\beta}^{EUR,M}$ to normalize the remaining estimates and remove bitcoin-specific (ρ^B) and exchange-specific (ρ^M) effects for any currency, using equation 4 to generate $\rho^{C1,C2}$ as defined in Section 3.2. This estimates the currency trend wedge relative to the euro trend wedge $(\hat{\rho}^C)$, normalized to range from zero to one:

$$\hat{\rho}^C = \hat{\rho}^{C,EUR} \begin{cases} ||\hat{\beta}^{C,M} - \hat{\beta}^{EUR,M}||, & \text{if cointegrated} \\ 1 & \text{otherwise} \end{cases} \tag{9}$$

This value is reported in the final column of Table 2. The highest value of $\hat{\rho}^C = 1$ indicates high barriers to access official exchange rate markets, while the lowest value of $\hat{\rho}^C = 0$ indicates a barrier equivalent to that of the USD-EUR exchange rate (low barriers), while the effective size of a country's barrier can then be ranked based on its distance from $\hat{\rho}^C = 0$.

4.2 Detecting Barriers in International Financial Markets

Assessing the extent of effective barriers to international currency flows is a difficult task, as restrictions may be mostly unofficial, or may only be occasionally binding. A standard measure of barriers to international capital movement is the Chinn-Ito Financial Openness index (KAOPEN), originally developed by Chinn and Ito [2006] and recently updated to 2013. The KAOPEN ranges from zero (no barriers) to one (high barriers), and 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. 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. The data underlying the KAOPEN ranking is therefore substantially different from the bitcoin-based estimate of barriers, which is based on non-binary daily pricing data.

While KAOPEN will be used as the point of comparison to evaluate whether bitcoin-based inferences can be considered accurate, it is not the only index that measures financial openness and integration. Bekaert and Harvey [2005] constructed a binary index based on the date of financial liberalization, while Lane and Milesi-Ferretti [2007] base their index upon measures of a country's exposure to international financial markets. The index constructed in a manner most similar to the bitcoin index is based on stock price differences and constructed by Yeyati, Schmukler, and Horen [2009].[18] A comparison of the various indices can be found in Quinna, Schindler, and Toyoda [2011].

4.3 Does Bitcoin Reveal Barriers to Official Exchange Rate Markets?

Table 3 presents results from the cointegration tests, the unadjusted trend coefficients $\hat{\beta}$, and estimated barrier $\hat{\rho}^C$.[19] I divide all results into three broad categories, and within each category currencies are sorted by their lowest value of $\hat{\rho}^C$. A "High Barriers" currency failed to find cointegration, while both the "Low Barriers" and "Intermediate Barriers" currency obtained cointegration results (indicated by values of "N" and "Y" respectively under the column heading "C?"). For currencies with cointegration results, there is the question of what value of ρ^C indicates a barrier that, while not significant enough to completely decouple the two markets, is sufficient to indicate a potential burden for users of official exchange rates of that currency. I use the results from CAD and SGD, which report $\hat{\rho}^C$ results from two exchanges, as a guide to an appropriate interval. Low barriers are defined as $\hat{\rho}^C$ in the interval $[0.0, 0.1]$, and intermediate barriers as $\hat{\rho}^C > 0.1$. Note that using the unadjusted coefficient, $\hat{\beta}$, that does not remove bitcoin-specific trends would yield a different ordering of barriers, illustrating the importance of adjusting for bitcoin-specific trends in

[18] Results are not compared to this index because it terminates in 2004.

[19] The bitcoin exchange rate data from ANXBTC for HKD, and LocalBitcoins for AUD, CHF, GBP, HKD, INR, NZD, RUB, and SGD, are problematic (either exhibiting residual autocorrelation, or failing to yield a single direction of causality); thus, they were removed.

the exchange rate market.

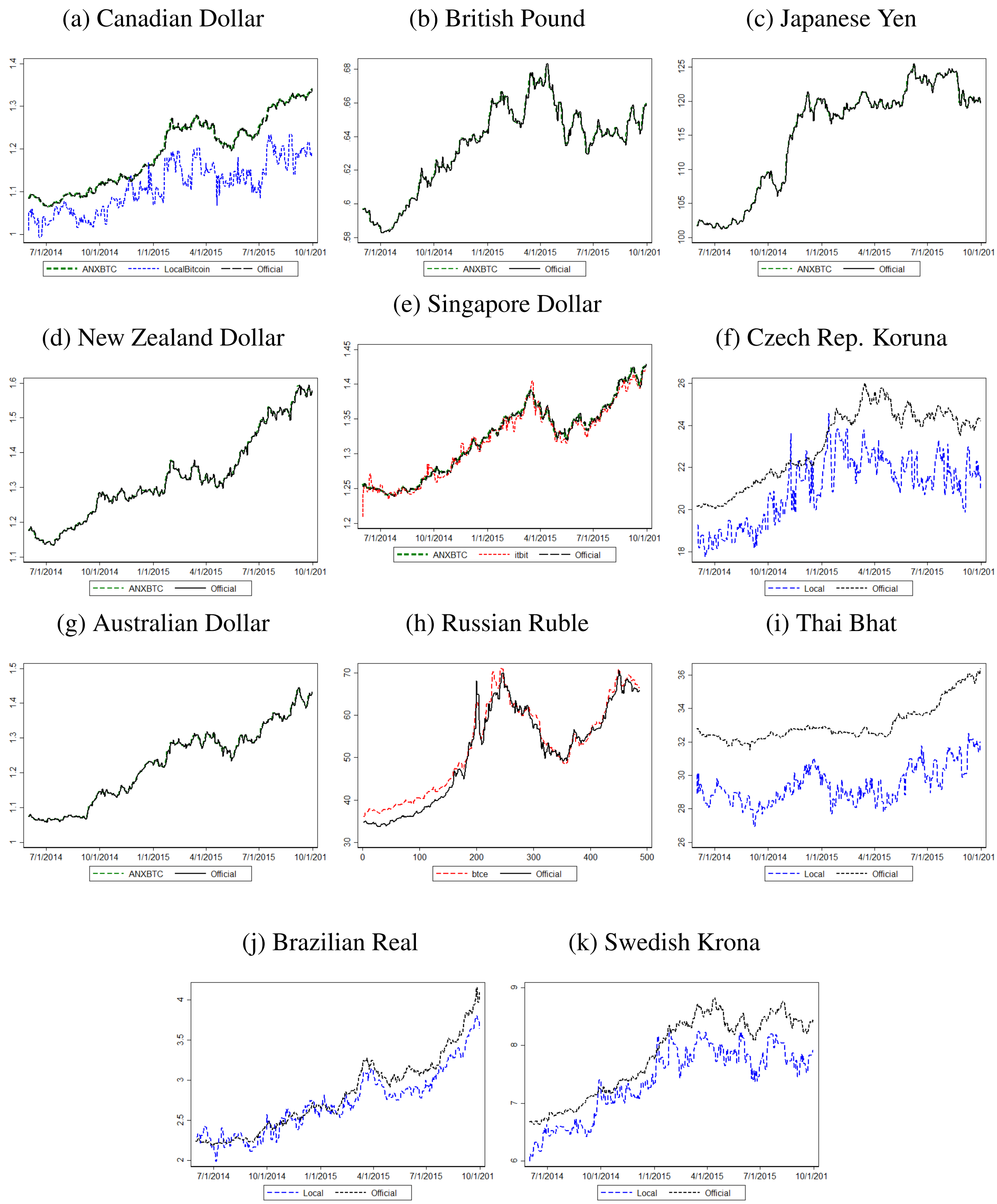
TABLE 3
Existence and Size of Exchange Rate Barriers

Currency	Market	Lag SBIC	ℓ	Johansen Trace Test $r=0$	$r=1$	PSS Test F-stat	C?	Barrier Size $\hat{\beta}$	$\hat{\rho}^C$	KAOPEN
Low Barriers										
CAD	ANX	1	1	1154.08	0.02***	–	Y	1.00***	0.00	0.00
	Local	2	2	135.40	0.02***	–	Y	0.65***	0.09	0.00
GBP	ANX	1	1	1152.46	2.13***	–	Y	1.00***	0.00	0.00
JPY	ANX	2	2	213.77	2.63***	–	Y	1.00***	0.00	0.00
NZD	ANX	2	2	224.07	0.03***	–	Y	1.00***	0.00	0.00
SGD	ANX	2	2	231.27	0.01***	–	Y	1.00***	0.00	0.00
	itBit	2	3	144.25	0.01***	–	Y	0.93***	0.09	0.00
CZK	Local	2	5	–	–	32.84***	Y	0.74***	0.00	0.00
AUD	ANX	1	1	1318.26	0.05***	–	Y	1.00***	0.00	0.19
RUB	BTC-e	2	2	31.91	1.23***		Y	0.93***	0.03	0.29
THB	Local	2	2	–	–	109.67***	Y	0.77***	0.03	0.84
BRL	Local	1	4	67.18	4.04***	–	Y	0.81***	0.07	0.59
SEK	Local	2	2	–	–	51.17***	Y	0.81***	0.07	0.00
Intermediate Barriers										
PLN	Local	2	3	–	–	61.25***	Y	0.86***	0.12	0.55
CHF	ANX	3	3	–	–	67.03***	Y	1.17***	0.17	0.00
NOK	Local	2	3	116.99	0.67***	–	Y	0.93***	0.19	0.00
High Barriers										
MXN	Local	2	2	14.04***	0.08	–	N	–	1.00	0.31
ZAR	Local	2	6	15.13***	0.37	–	N	–	1.00	0.84
CNY	ANX	2	3	3.59***	0.38	–	N	–	1.00	0.84
ARS	Local	6	6	5.44***	0.79	–	N	–	1.00	1.00

Abbreviations: ANX, ANXBTC; C, cointegrated series; KAOPEN, Chinn-Ito Financial Openness index; Local, LocalBitcoin; PSS, Pesaran-Shin-Smith; SBIC, Schwarz Bayesian information criterion.
****1%, ** 5%.*

With seven exceptions, the barriers of each of the currencies are in the same order as presented in KAOPEN. Four are found to have lower barriers relative to other countries than those reported by KAOPEN, and three have higher barriers than reported by KAOPEN. I examine the reasons for these seven deviations in Sections 4.3.1–4.3.3, and find them to reflect either the granularity of the data, or the newer nature of the bitcoin data. I therefore conclude that an alternative measure of barriers can be constructed using bitcoin data.

FIGURE 3
Comparison of Unadjusted Bitcoin and Official Exchange Rates: Minimal Barriers

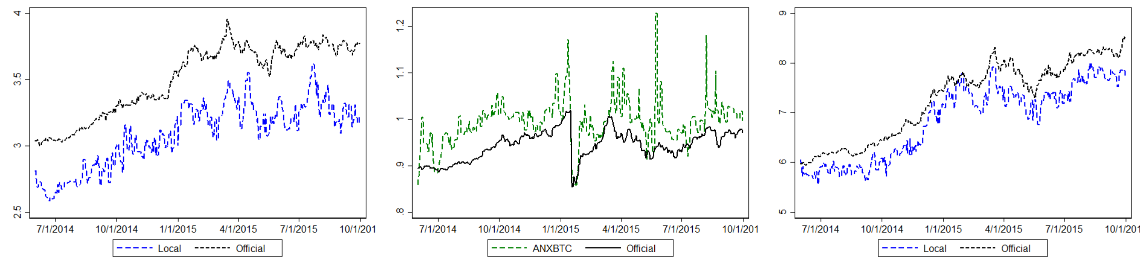


4.3.1 Low Barrier Currencies Among the 11 countries that bitcoin reports to have low barriers, four deviate from their KAOPEN ranking: Australia (AUD, Figure 3[g]), Russia (RUB, Figure

FIGURE 4

Comparison of Unadjusted Bitcoin and Official Exchange Rates: Intermediate Barriers

(a) Polish Zloty (b) Swiss Franc (c) Norwegian Krone



3[h]), Thailand (THB, Figure 3[i]), and Brazil (BRL, Figure 3[j]).

Recall that the bitcoin data I use for this study are based on 2014 and 2015 information, while KAOPEN is based on 2013 data. KAOPEN documents a trend of decreased barriers in both Australia (since 2011) and Russia (since 2008). It therefore seems likely that finding of lower barriers using bitcoin than the KAOPEN results from a continuation of this trend.

While I do not find evidence of barriers the remaining two countries, Thailand and Brazil, in section 5.2 I show that they appear to have managed exchange rates based upon the magnitude of the difference between the offical and bitcoin exchange rates, consistent with the findings of KAOPEN. The bitcoin-based results of Table 3 imply that during the period of this study, these two countries (which have managed exchange rate regimes in KAOPEN) did not maintain their exchange rate regimes by limiting access to foreign currency, but may instead use policies such as interest rate manipulation or monetary policy.

4.3.2 Intermediate Barrier Currencies Among currencies with intermediate barriers, both the Swiss franc (CHF) (Figure 4[b]), and the Norwegian krone (Figure 4[c]) are found by bitcoin to be more restricted than KAOPEN reports.

Prior to January 15, 2015, the Swiss National Bank (SNB) had a minimum exchange rate peg in place relative to the euro. Comparing the official and bitcoin exchange rates in Figure 4[b], it appears this peg had been binding as the two exchange rates do not share a similar trend. On

January 15, the SNB formally abandoned its peg (to the apparent surprise of all market participants given the reaction in both markets) and lowered its target interest rate further into negative territory.[20] After the removal of the peg, bitcoin and official exchange rates appear to share a trend. While the peg had been in place since September 2011 and is therefore in the data used to construct KAOPEN, it may not have been a binding minimum constraint during that time. For the Norwegian krone (NOK), a structural break in the bitcoin exchange was detected on December 8, 2014. Unlike the Swiss franc, no obvious event coincides with this date. However, given that Norway is physically proximate to eurozone countries that underwent great economic upheaval during this time period, it is possible that the NOK exchange rate anomaly reflects spillover from those economies.

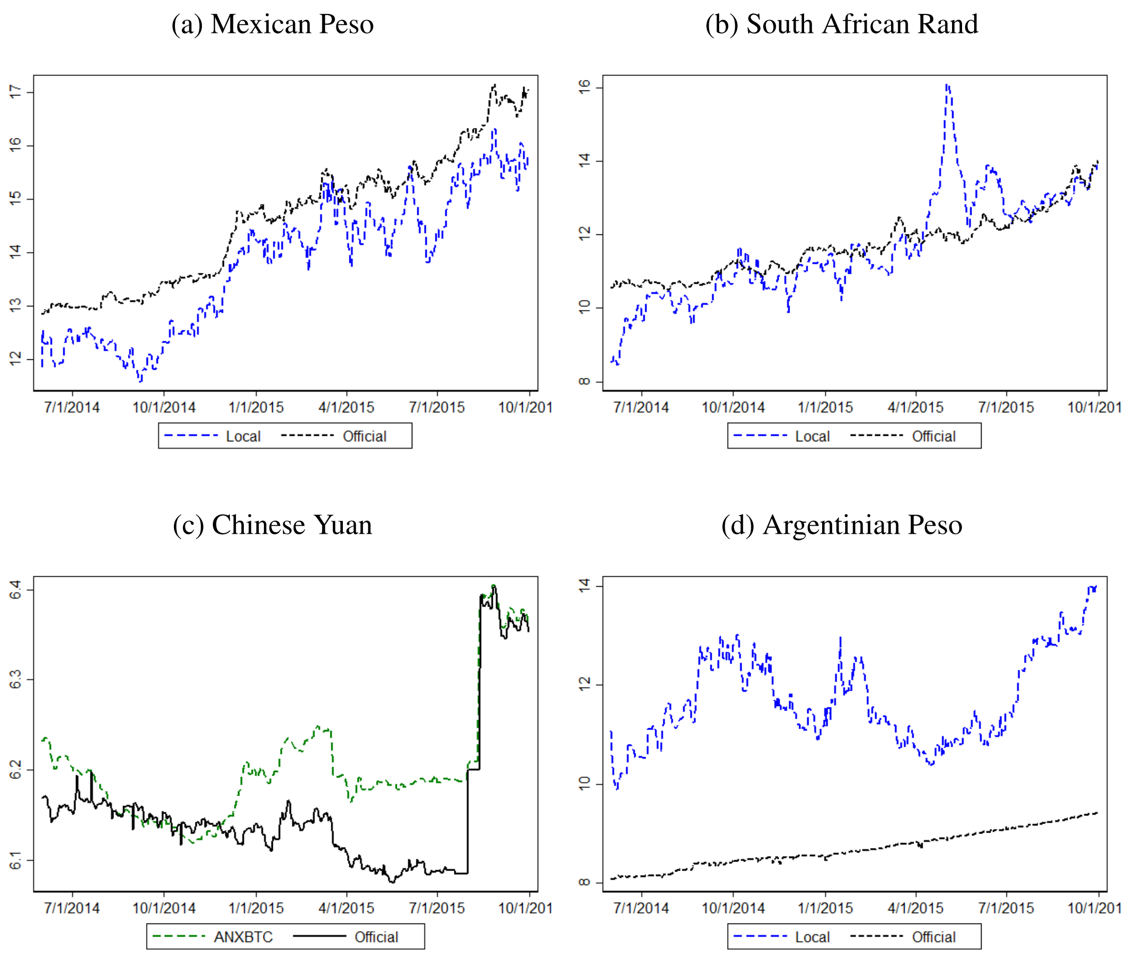
4.3.3 High Barrier Currencies Of the four countries that have high barriers, Mexico (Figure 5[a]) is found to have more capital restrictions than expected given KAOPEN. While Mexico is commonly classified as a freely floating exchange rate, it strongly rejects cointegration with the bitcoin exchange rate. Though several factors could explain a change in the exchange rate (the fall of oil prices; implementation of austerity cuts; a political scandal), none of these events can explain a divergence between the official and bitcoin exchange rates visible at the beginning of October 2014. 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], briefly mentions a possible cause. Informally, Mexico has an acceptable band for its exchange rate. The exchange rate moved out of this band, causing the central bank to intervene and manipulate its exchange rate through an auction. This intervention—which represented a change in the exchange rate regime—resulted in the divergence of the official and unofficial exchanges rates, beginning in October 2014.

4.4 Domestic Economic Events and Bitcoin Exchange Rates

In Figure 5[b], the South African rand (ZAR) shows two clear episodes where bitcoin exchange rates changed without any corresponding movement in the official exchange rate: on April 17,

[20] January 2015 SNB press release (www.snb.ch/en/mmr/reference/pre_20150115/source/pre_20150115.en.pdf).

FIGURE 5
Comparison of Bitcoin and Official Exchange Rates: High Barriers



2015, and on May 21, 2015. The timing of these bitcoin market 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 4000 arrests in connection to the riots the month before—suggestive evidence that the bitcoin exchange rates are not formed purely by international speculators.

Turning to the Chinese yuan (CNY), Figure 5(c) shows that the official and bitcoin exchange rates were slowly separating from each other. The eventual 1.9% exchange rate devaluation on August 10, 2015, represents a noticeable trend break in both series, and has resulted in a bitcoin and official Chinese exchange rate that is subsequently very similar in both trend and level (or more succinctly, an official CNY rate that reflects the bitcoin market rate) implying that the devaluation has succesfully realinged the Chinese and American currencies.

5 BITCOIN AND UNOFFICIAL EXCHANGE RATES

5.1 Detecting Exchange Rate Regimes

While the most common officially reported exchange rate regime is a free- or managed-float regime, Calvo and Reinhart [2002] found that the exchange rates of many countries resembled that of a fixed or highly managed exchange rate (a phenomenon they termed "fear of floating"). Crucially, Alesina and Wagner [2006] showed countries with relatively good institutions use a declaration of a floating regime to signal their virtuousness, rather than countries with poor political institutions (the typical suspects for bad or misreported data).

This inconsistency between the declared and actual exchange rate regimes has led to many attempts to find other systems of classifying exchange rate regimes based not on self-reporting but on observed behavior. Reinhart and Rogoff [2004] retroactively reclassified exchange rate regimes using the observed behavior of the official and parallel exchange rate data between 1946 and 1998; Levy-Yeyati and Sturzenegger [2005] constructed a classification based on official exchange rates and international reserves; Shambaugh [2004] used 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 takes into consideration the behavior of the exchange rate in addition to the country's official statement.

Kiguel and O'Connell [1995] argued that a significant difference between the market and official rates may signal fundamental macroeconomic misalignments; therefore, the difference should be greater for managed exchange rates than it is for market exchange rates. I define the premium between the official and bitcoin exchange rate, $M^C_{m,t}$, as:

$$M^C_{m,t} = \frac{E^{B,C}_{m,t}}{E^{O,C}_t} - 1 \tag{10}$$

$$= (\rho^C + \rho^B + \rho^m - 1) + \frac{\varepsilon^{C,m}}{E^{0,C}_t} \tag{11}$$

Because there is a bitcoin-exchange-specific premium (given that the exchanges charge different fees and have different structures), and Figure 2 showed that this premium was non-zero for some exchanges even for the Euro, I adjust the premium by the value of the euro premium for the exchange:

$$\tilde{M}^C_{m,t} = M^C_{m,t} - M^{EUR}_{m,t} \tag{12}$$

I consider the mean of this adjusted premium to classify exchange rates. Note that is possible for an exchange rate to have no barrier ($\rho = 0$), while still maintaining a positive premium ε^C. This is consistent with exchange rate pegs maintained by domestic policy, instead of international financial markets controls (which would have be detected using the methodology in Section 4.3).

5.2 Exchange Rate Regime

Table 4 lists the mean and standard deviation of the adjusted markup for each currency and bitcoin exchange. Three clear clusters emerge: markups between 0 and 0.5%, which I categorize as "Market" regimes; currencies with markups between 0.5 and 2%, which I categorize as "Mildly Managed"; and the remainder categorized as "Highly Managed." Within these three categories, the currencies are sorted by the size of their markup. I compare these categories with the 2014 exchange rate regime identified by the IMF Annual Report on Exchange Arrangements and Exchange Restrictions, which is based on the behavior of the official exchange rate. The range of the markup (as measured by the standard deviation) and the average markup both increase as the exchange rate becomes increasingly managed.

TABLE 4
Exchange Rate Regime and Markup

Currency	Market	Mean	SD	IMF Classification
Market (0.00%-0.50%)				
AUD	ANX	0.04	0.49	Free float
CAD	ANX	0.00	0.41	Free float
	Local	0.14	4.51	Free float
GBP	ANX	-0.01	0.37	Free float
JPY	ANX	-0.00	0.43	Free float
NZD	ANX	0.07	0.55	Float
	Local	0.49	4.79	Float
SGD	ANX	0.00	0.38	Stabilized arrangement
	itBit	-0.31	1.24	Stabilized arrangement
Mildly Managed (0.50%-2.00%)				
CNY	ANX	0.72	0.81	Crawl-like arrangement
NOK	Local	0.74	4.66	Free float
SEK	Local	1.21	4.31	Free float
MXN	Local	1.11	4.90	Free float
CZK	Local	-1.55	8.20	Other managed arrangement
RUB	btce	1.91	3.95	Other managed arrangement
Highly Managed (2.00%+)				
PLN	Local	-4.89	5.56	Free float
THB	Local	-4.36	4.45	Float
BRL	Local	4.16	9.11	Float
ZAR	Local	6.21	9.67	Float
CHF	ANX	7.19	12.01	Crawl-like arrangement
ARS	Local	41.37	10.39	Crawl-like arrangement

Abbreviations: ANX, ANXBTC; btce, BTC-e; Local, LocalBitcoin.

There are eight differences in classifications, with seven currencies found to be more managed that their IMF classification suggests and one currency found to be less managed. The differences are discussed in detail in Sections 5.2.1-5.2.3, and are similar to the reasons discussed in Section 4.3. Overall, once appropriately adjusted, bitcoin can be used to determined exchange rate regime.

5.2.1 Market Exchange Rate Regimes Bitcoin and the IMF disagree regarding the Singapore dollar (SGD, Figure 3[e]), with the IMF considering it a stabilized arrangement and bitcoin classifying it as a floating exchange rate. I found low premiums on both bitcoin exchanges that sell

Singapore dollars. This result implies that while Singapore is officially managing its currency, the resulting exchange rate is not substantially different from the market exchange rate.

5.2.2 Mildly Managed Exchange Rate Regimes The Norwegian krone (NOK) and the Swedish krona (SEK) are both found to be more managed than recognized by the IMF, with obvious premiums observable in Figures 4(c) and 4(k). These results may be a reflection of the political and economic turbulence in the eurozone during this time. The issues surrounding the remaining currency, the Mexican peso (MXN), were discussed in Section 4.3.

5.2.3 Highly Managed Exchange Rate Regimes The Polish zloty (PLN, Figure 4[a]) is classified by the IMF as a free float, but appears like a highly managed exchange rate when viewed by bitcoin. Again, this discrepancy seems likely to be the effect of the eurozone crisis. The South African rand (ZAR), a floating currency according to the IMF and a highly managed one according to bitcoin, was discussed in Section 4.4. Both the Brazilian real (BRL) and Thai bhat (THB) were found to be low barrier currencies: the IMF classifies them as floating, but they appear to be highly managed exchange rate regimes based on the bitcoin premium. As detailed in Human Rights Watch [2015], Thailand underwent a political coup by the military in May 2014, so the premium may reflect underlying uncertainty regarding the economic stability of the country. A similar explanation may also apply to Brazil, which faced a series of large protests in 2015 due to alleged political corruption within the state owned energy company Petrobas, the beginning of which is discussed in Prada [2015].

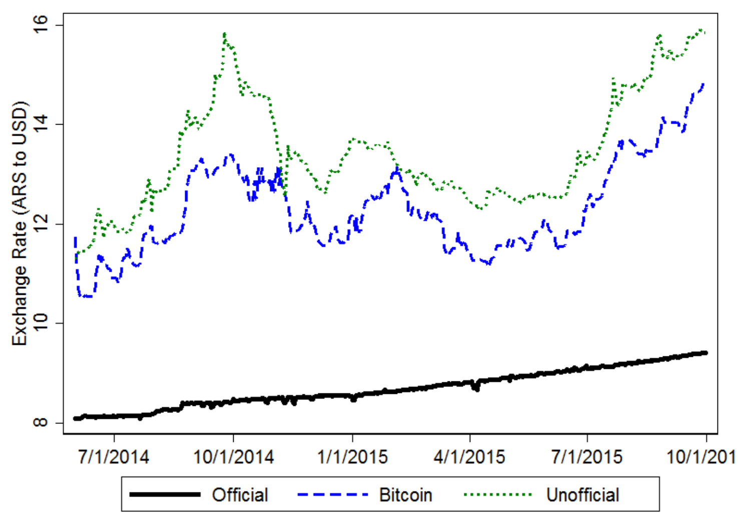
6 A COMPARISON OF OFFICIAL AND UNOFFICIAL EXCHANGE RATES

6.1 Do Bitcoin Exchange Rates Reflect Unofficial Exchange Rates?

It seems reasonable, given that the bitcoin exchange rate is determined by the market, that it provides an estimate of a currency's unofficial exchange rate, especially after controlling for bitcoin-specific trends. Historically, unofficial exchange rate data have been both expensive and difficult to obtain, and, because they are reported rather than directly observed the data are subject to quality concerns. The ability to use the bitcoin exchange rate as a free alternative source for unofficial exchange rate movement data could alleviate many of these concerns. The results in Section 4.1 (showing that there could be significant bitcoin and bitcoin exchange trends) should, however, invite pause because it implies that bitcoin-specific trends may distort the bitcoin exchange rate.

To test whether bitcoin can be interpreted as the unofficial exchange rate, I examine the behavior of bitcoin relative to that of the unofficial Argentinian exchange rate. Argentina is widely known to have a long-established crawling peg regime with the US dollar and a highly manipulated exchange rate, and 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.

FIGURE 6
Comparison of Argentinian Exchange Rates



I obtain unofficial exchange rate data from *Ámbito Financiero*, a daily newspaper based in Buenos Aires. The official, unofficial, and adjusted bitcoin exchange rate of the Argentian Peso to the US dollar are shown in Figure 6.[21] A visual examination reveals that the bitcoin exchange rate (dashed line) closely follows the time trend of the unofficial exchange rate (dotted line) but not the

[21] The bitcoin rate has been smoothed by a five-point smoothing filter to aid visual analysis.

official exchange rate (solid line).

Table 5 lists the corresponding cointegration test, VECM, and premium for the three exchange rates. There is no cointegrating relationship between the official exchange rate and either the unofficial or bitcoin exchange rate, as expected given the strict capital controls. A cointegrating relationship does exist for the unofficial and bitcoin exchange rates. Additionally, the VECM reveals that these two exchange rates obey the rLOP, reflecting the same information. These findings, together with the earlier discussion of the South African rand (ZAR) exchange rate that showed national domestic domestic events affecting the exchange rates suggests that bitcoin is not only being used by speculative foreign investors but also by residents of these countries.

TABLE 5
Relationship among Three Sources of Argentinian Exchange Rates

	Official and Unofficial	Official and Bitcoin	Unofficial and Bitcoin
SBIC	3	6	3
ℓ	11	6	5
Cointegration Test			
Johansen: $r = 0$	4.24***	5.44***	39.48
Johansen: $r \leq 1$	1.22	0.79	0.54***
Cointegrated?	No	No	Yes
Barrier			
$\hat{\beta}$	–	–	0.79***
$\hat{\rho}$	1.00	1.00	0.05
Low barrier?	No	No	Yes
Premium			
Mean (%)	54.53	34.50	−12.91
Adj. mean (%)	61.40	41.37	−6.04

Abbreviations: SBIC, Schwarz Bayesian information criterion.
****1%, ** 5%.*

Interestingly, the data in Table 5 reveal that even though unofficial and bitcoin exchange rates are cointegrated, there is a significant negative premium, even after adjusting the mean for the bitcoin-specific markup (−6.04%). This persistence, even after adjusting for an exchange-specific premium, must reflect an element that is not found in the bitcoin-based euro exchange rate and therefore cannot be normalized. It could reflect, for example, the convenience and relative safety of using bitcoin exchange rate channels that are not as relevant or significant 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. However, given the cointegration results bitcoin exchange rates can be used to determine trends of the unofficial exchange rate.

6.2 PROPORTIONALITY

The modeling approach of Dornbusch, Dantas, Pechman, Rocha, and Simoes [1983]—using a portfolio choice model as the starting point for a model of dual exchange rate markets where each exchange rate is the price of an asset (in this case, the currency)—is frequently used as a launching point to examine the relationship between official and unofficial exchange rates. This approach implies a long-run constant proportionality between the official and unofficial exchange rates (or a rLOP between identical assets). Papers using multiyear datasets have found only mixed evidence for a proportionality relationship: Caporale and Cerrate [2008] rejected a proportionality relationship, while Bahmani-Oskoee, Miteza, and Nasir [2002] and Kula, Aslan, and Ozturk [2014] found evidence in support of it.

TABLE 6
Relationship of Exchange Rate Regime and Barriers to Foreign Exchange

	Barriers		
Exchange Rate Regime	Low (11)	Intermediate (3)	High (4)
Market (6)	AUD, CAD, GBP, JPY, NZD, SGD	–	–
Mildly managed (6)	SEK, CZK, RUB	NOK	MXN, CNY
Highly managed (6)	THB, BRL	PLN, CHF	ZAR, ARS

Table 6 summarizes the regime and exchange rate classification results for each currency. Recall that a finding of a low or intermediate barriers requires cointegration, so any low or intermediate barrier result supports proportionality. Table 6 shows that all exchange rate regimes *can* satisfy the proportionality requirement. Given that my barrier index broadly reflects the ordering of KAOPEN, it implies that proportionality is more likely to be satisfied if countries do not implement barriers and therefore, the mixed findings in the literature could reflect the existence of unofficial barriers.

TABLE 7
Causality Tests

Currency	Exchange	Lag SBIC	ℓ	H0: O $\not\to$ B Test Value	H0: O $\not\to$ B *P* Value	H0: O $\not\leftarrow$ B Test Value	H0: O $\not\leftarrow$ B *P* Value	Causality
Floating								
—Minimal barriers								
CAD	ANX	1	2	4.63	0.10	3956.7	0.00	O $\leftrightarrow$ B
	Local	2	2	14.67	0.00	0.82	0.66	O $\to$ B
AUD	ANX	1	2	0.17	0.92	6102	0.00	O $\leftarrow$ B
GBP	ANX	1	3	4.74	0.19	3739.7	0.00	O $\leftarrow$ B
JPY	ANX	2	2	3.46	0.18	704.28	0.00	O $\leftarrow$ B
NZD	ANX	2	2	2.47	0.29	5297	0.00	O $\leftarrow$ B
SGD	ANX	2	2	1.70	0.43	2294.9	0.00	O $\leftarrow$ B
	itBit	2	3	28.92	0.00	10.46	0.02	O $\leftrightarrow$ B
Mildly Managed								
—Minimal barriers								
CZK	Local	2	5	11.71	0.04	1.93	0.86	O $\to$ B
SEK	Local	2	2	7.58	0.02	2.02	0.37	O $\to$ B
RUB	btce	2	2	4.54	0.10	99.87	0.00	O $\leftrightarrow$ B
—Intermediate barriers								
NOK	Local	2	3	11.81	0.01	14.22	0.00	O $\leftrightarrow$ B
—High barriers								
MXN	Local	2	2	6.31	0.04	10.16	0.01	O $\leftrightarrow$ B
CNY	ANX	2	4	1.81	0.77	128.6	0.00	O $\leftarrow$ B
Highly Managed								
—Minimal barriers								
THB	Local	2	2	2.08	0.35	15.44	0.00	O $\leftarrow$ B
BRL	Local	1	4	8.19	0.09	0.71	0.95	O $\to$ B
—Intermediate barriers								
PLN	Local	2	3	8.27	0.04	0.12	0.99	O $\to$ B
CHF	ANX	3	3	10.66	0.01	0.17	0.98	O $\to$ B
—High barriers								
ZAR	Local	2	6	14.61	0.02	11.85	0.07	O $\leftrightarrow$ B
ARS	Local	6	6	4.81	0.57	4.69	0.58	O $\not\leftrightarrow$ B

Note: x $\not\to$ y stands for "x does not Granger-cause y."
Abbreviations: ANX, ANXBTC; btce, BTC-e; Local, LocalBitcoin.

6.3 CAUSALITY

The unofficial exchange rate is thought to Granger-cause the official exchange rate in a managed exchange rate regime, as the unofficial exchange rate reflects current market information that may take time to be reflected in the official rate. Baliamoune-Lutz and Lutz [2008] and Baliamoune-Lutz [2010] documented that the black market exchange rate Granger-causes the official rates Tunisia and Morocco (managed exchange rate regimes), providing support for this hypothesis. However, Huett, Krapf, and Uysal [2014], found mutual causation between the official and unofficial exchange rates for the managed Belarusian ruble. Using the TY method described in Section 3.3.3, I test for Granger causality across all currencies. Unlike the aforementioned studies, I can compare both floating and managed exchange rates, *and* currencies with and without binding barriers to foreign exchange markets, over the same period and on a daily basis.

Table 7 presents the causality test results. There is no uniform pattern across barriers and exchange rate regimes. Half of the market regimes have causality from bitcoin to official exchange rates, half of the mildly managed regimes have bidirectional causality, and half of the highly managed regimes show causality from the official rate to bitcoin. A single direction of causality occurs for 10 out of 13 currencies with low barriers, and for 1 out of 4 currencies with the highest level of high barriers.

This result is not surprising if a change in the official exchange rate to an event that causes a change in the unofficial exchange rate occurs only infrequently, and takes multiple days or weeks to occur. This would weaken any causality relationship estimated on higher frequency daily data, instead of monthly data. Indeed, Huett et al. [2014], who also did not find causality from unofficial to official exchange rates, were also using daily data, lending support to this interpretation.

7 CONCLUSIONS

This work proposes a method to use bitcoin-transaction prices in various currencies to construct a currency's unofficial exchange rate, detect the size of barriers to the official exchange rate, and identify exchange rate regimes. Bitcoin-based exchange rates can be used to identify episodes of capital movement that, due to their transitory nature, current classification systems (such as the IMF or the Chinn-Ito index) cannot detect. 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 as could be the case with the *World Currency Yearbook* or, to a lesser extent, the IMF classification system. Additionally, even if governments temporarily cease to gather data due to political or economic upset, the bitcoin data continue to exist and accrue.

Findings from earlier work that show mixed evidence regarding Granger causality between official and unofficial exchange rates is re-examined over the same time period for a variety of regimes and barriers, and explained as causality is not found to consistently flow from the unofficial bitcoin rate to the official rate when using daily data. Even among highly managed regimes, Granger causality exists in all variationsd. Proportionality between unofficial and official exchange rates is possible for all regimes, but more likely to exist in the absence of barriers.

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