Bitcoin in Brazil: Law of One Price and Price Discovery in an Emerging Market

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Abstract

We study the bitcoin market in Brazil, a large emerging economy with an unregulated bitcoin market. First we test if the Law of One Price (LOOP) is valid for bitcoin prices in Brazil, conducting tests with data from three Brazilian exchanges. We find a common trend within bitcoin prices among these exchanges, with cointegration tests between the price series indicating that LOOP is valid in Brazilian markets in the long run. Next, we document bitcoin price dynamics in the short run by studying the price discovery mechanism in these exchanges. We use Information Share and Component Share, combining the two measures to obtain an Information Leadership Share (ILS) measure. ILS indicates that, for closing prices, the most liquid exchange (Foxbit) leads discovery, while the least liquid (Local Bitcoin) lags, with Mercado Bitcoin in the middle both in terms of discovery and liquidity. Our research brings the first evidence of a price discovery mechanism for exchanges in Brazilian Reais. Although LOOP is valid in the long run, existing inefficiencies in bitcoin markets potentially create arbitrage opportunities in the short run.

Keywords: Bitcoin; Law of one Price; Price Discovery; Cryptocurrencies.

Resumo

Estudamos o mercado de bitcoins no Brasil, uma grande economia emergente com um mercado de bitcoins não regulamentado. Primeiro, testamos se a Lei do Preço Único (LOOP) é válida para os preços do bitcoin no Brasil, realizando testes com dados de três bolsas brasileiras. Encontramos uma tendência comum nos preços de bitcoin entre essas bolsas, com os testes de cointegração entre a série de preços indicando que o LOOP é válido nos mercados brasileiros no longo prazo. Em seguida, documentamos a dinâmica dos preços do bitcoin no curto prazo, estudando o mecanismo de descoberta de preços nessas bolsas. Usamos Information Share e Component Share, combinando as duas medidas para obter uma medida de Information Leadership Share (ILS). O ILS indica que, para os preços de fechamento, a bolsa mais líquida (Foxbit) lidera a descoberta, enquanto a menos líquida (Local Bitcoin) fica atrás, com o Mercado Bitcoin no meio, tanto em termos de descoberta quanto de liquidez. Nossa pesquisa traz a primeira evidência de um mecanismo de descoberta de preços para as trocas em reais. Embora o LOOP seja válido no longo prazo, as ineficiências existentes nos mercados de bitcoin criam potencialmente oportunidades de arbitragem no curto prazo.

Palavras-chave: Bitcoin; Lei de um preço; Descoberta de Preços; Criptomoedas.

JEL: C10; G15

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1 Introduction

Digital currency was an technology put in practice in the 1990s in the form of stored value cards for peer-to-peer (P2P) payments that did not require bank authorization. Bitcoin is an online communication protocol based on cryptography and information technology to facilitate P2P transactions. Despite some similarities with traditional digital payment methods (e.g. medium of exchange and store of value), two characteristics make it distinct: transactions can be made anonymously and decentralized (Nguyen et al., 2018). Kristoufek (2015) has pointed out some bitcoin advantages, such as low or no fees, a controlled and known algorithm for currency creation, and an informational transparency for all transactions. On the other hand, bitcoin suffers from some shortfalls such as the scalability problem and high energy consumption from mining (Karame, 2016; Poon and Dryja, 2016; Narayanan et al., 2016).[1] However, the factor that attracts more attention both to media and investors is bitcoin price (Nguyen et al., 2018). The first study to address bitcoin price formation was conducted by Ciaian et al. (2016), who considered both the traditional determinants of currency price – supply and demand forces – and digital currency specific factor for investor's attractiveness.

Investors around the globe have witnessed an impressive growth in cryptocurrencies markets. Focusing on bitcoin, the first ever cryptocurrency and the most well-known in the market (Nguyen et al., 2018) displays a market cap surpassing US$ 100 billion. Although the magnitude of the volume arouses the curiosity of many scholars, bitcoin's price volatility is quite peculiar. It went from zero value at the time of its inception, in 2009, to around $1100 4 years later. Then, the price dropped to around $250 at the end of 2014, before another exponential growth curve until almost reaching $20.000 in December, 2017. Such price movements are unusual for traditional currencies, suggesting that the determinants for price formation do not follow rules established in previous theories (Ciaian et al., 2016), or in the words of Mai et al. (2018) traditional explanatory variables for currency valuation fall short. We approach the problem by studying the bitcoin market in Brazil, a large emerging economy with an unregulated bitcoin market.

If information flows freely, we should observe an equilibrium in price among exchanges, independently of the geographical location. Under some market efficiency, bitcoin prices should follow the Law of One Price (LOOP, hereafter). However, Pieters and Vivanco (2017) find evidence indicating violations of LOOP for bitcoin. After analyzing 11 distinct markets, representing 26% of the global market, evidence indicates that LOOP is not verified in markets where no compliance policy, such as mandatory user identification, is in place. This is the case we study, since in Brazil bitcoin exchanges are not subject to any regulation (BCB, 2017).

The study of financial markets has brought evidence that emerging economies have different markets from developed economies. In particular, Bekaert and Harvey (2002) review the empirical evidence and argue that emerging markets are relatively inefficient due to slow adjustment to new information. In addition, Cole et al. (2011) presents some evidence that high fixed costs of financial services can be a barrier to financial development. The market of cryptocurrencies has the potential to overcome such costs, since to operate in these markets one only needs access to the internet. Moreover, there is evidence that bitcoin markets can be efficient (Tiwari et al., 2018). Therefore, testing LOOP in the Brazilian bitcoin market can shed light on our knowledge about financial markets in emerging economies, and also on the behavior of bitcoin markets per se. Brazil is a particularly interesting case, as according to

[1]Bitcoin mining is the process of confirming transaction by writing then in a block to be added to the *Blockchain*. For more details on Bitcoin mining see Narayanan et al. (2016).

Bitcoin Average (`https://bitcoinaverage.com`) the Brazilian bitcoin market was ranked 4$^{\text{th}}$ in the world in 2017.

Following the method of Pieters and Vivanco (2017), we conduct tests using data from three Brazilian exchanges to check whether bitcoin prices satisfy LOOP, even though no user identification rule is imposed through regulation, and some Brazilian bitcoin exchanges do not mandate it. We find a common trend within bitcoin prices among these different exchanges. First, we identify that prices are non-stationary in Brazilian markets. Next, we verify that the price series are cointegrated. The cointegration tests between the price series indicate that LOOP is valid in Brazilian markets in the long run.

However, there remains the question about bitcoin price dynamics in the short run. Mai et al. (2018) raise a relevant concern about bitcoin price formation: what determines its value? The answer concerns investors, who can profit from estimating future price swings and calculating expected returns. Bitcoin can be converted virtually to any fiat currency, such as USD, EUR, GBP, JPY, or BRL. With exchanges all over the globe operating 24/7, with little to no regulation, can there be opportunities of arbitrage? Such opportunities could arise between countries, and between exchanges within the same country. Therefore, we also study the price discovery mechanism in Brazilian exchanges. Price discovery happens when new information is impounded into the implicit, efficient price, leading to a permanent change of its level (Hasbrouck, 1995). In the short run, one exchange could lead the other is price discovery, opening up opportunities for arbitrage between Brazilian exchanges. We use two distinct and complementary measures for price discovery (Baillie et al., 2002), Information Share (Hasbrouck, 1995), and Component Share (Gonzalo and Granger, 1995). We combine the two measures to obtain an Information Leadership Share (ILS) measure (Putniņš, 2013). ILS indicates that, for closing prices, the most liquid exchange (Foxbit) leads discovery, while the least liquid (Local Bitcoin) lags, with Mercado Bitcoin in the middle both in terms of discovery and liquidity.

To the best of our knowledge, our research brings the first evidence of a price discovery mechanism for exchanges in Brazilian Reais. The evidence we bring show that LOOP is valid in the long run, but reinforces existing evidence that inefficiencies in bitcoin markets still exist, potentially creating arbitrage opportunities (Köchling et al., 2018; Sensoy, 2018). We contribute to the growing literature of bitcoin prices with novel evidence from a large emerging economy.

The remaining parts of this paper are organized as follows. Section 2 describes the data and presents some characteristics of Brazilian Bitcoin exchanges. Section 3 presents the test we use in order to identify LOOP and price discovery of Bitcoin price. Section 4 discusses and evaluates the empirical results. Finally, section 5 presents our final remarks.

2 Data

We use daily bitcoin price data spanning from December 11th, 2014 to October 17th, 2017, yielding 1013 days. The initial date corresponds to the beginning of Foxbit exchange's price series. The end date is the last day available for all exchanges on the date of data collection. We use Quandl's API to retrieve the prices. Quandl is a platform that collects several economics and finance time series, collecting bitcoin prices reported to Bitcoincharts.

The data we obtain come from 3 Brazilian exchanges: Local Bitcoin, Mercado Bitcoin, and Foxbit (see Table 1). Although there are other exchanges in Brazil, like NegocieCoins, Arena Bitcoin, and Bitcointoyou, we do not have access to their data. They do not report daily prices to Bitcoincharts, a platform that aggregates bitcoin data from all over the world, nor provide any means of getting daily prices directly from them.

Table 1: Selected Brazilian bitcoin exchanges

Exchange	Num.Obs	URL
Foxbit	1013	https://foxbit.exchange
Mercado Bitcoin	1013	https://www.mercadobitcoin.com.br
Local Bitcoin	1013	https://localbitcoins.com.pt

All exchanges have daily prices from December 11th, 2014 to October 17th, 2017.

Of the 3 exchanges, Mercado Bitcoin does not clearly state whether it adopts some kind of know-your-customer (KYC) or anti-money-laundering (AML) policy. These are important features for the validity of the Law of One Price (LOOP) (Pieters and Vivanco, 2017). In turn, both Local Bitcoin and Foxbit report to comply with KYC and AML policies. Table 2 presents the main characteristics of these exchanges regarding customer policies.

Table 2: Summary of exchanges' characteristics

Exchange	Trading fee	Deposit fee	Withdrawal fee	KYC	AML
Foxbit	0.25% to 0.50%	0%	1.39% or 1.39% + R$9.50	Yes	Yes
Mercado Bitcoin	0.30% to 0.70%	R$2.90 + 1.99%	R$ 2.90 $ + $ 1.99%	?	?
Local Bitcoin	0% to 1%	0.50%	0.50%	Yes	Yes

KYC is know-your-customer policy, AML is anti-money-laundering policy. "?" indicates the exchange does not deny nor confirm enforcing a policy. R$1 is approximately US$0.27 as of Feb/2019.

Table 3 shows the averages for the data Quandl provides. There are opening and closing prices, highest and lowest intraday prices, and transaction volume. Unlike stock exchanges, bitcoin exchanges do not really have opening and closing times, since they operate 24h per day, 7 days a week, non-stop. Therefore, closing price is the last trade recorded until 23h59min59sec UTC, and the opening price is the first negotiation recorded from 0h00min00sec, UTC (Coordinated Universal Time).

Note how average prices differ from one exchange to another. In particular, the High and Low prices of Local Bitcoin present a sizable difference when compared to the other exchanges. It may be a liquidity problem, as the average traded volume is much lower in Local Bitcoin. However, the other two exchanges also show signs of different prices, although to a smaller degree. Also note that Open and Close prices are potentially less than 1 second away from each other, and even so there are non-negligible differences within the same exchange. In conjunction, these numbers indicate a highly dynamic and volatile market, in which pricing can quickly change.

Figure 1 plots the opening price series for each of the exchanges. Their overall shapes are quite similar, with little visual differences. All of the series start at about R$1,000, and fluctuate around this value until May/2017. On this month prices begin escalating, and reached about R$18,000 in October 17th, 2017, in all exchanges. One difference worth noting is the larger volatility of Local Bitcoin, corroborating the analysis of Table 3. The graphs also show similar trends and behaviors: the series apparently are non-stationary, and seem to display

Table 3: Average prices and volume

Exchange	Open	Close	High	Low	Volume (BTC)
Foxbit	7488.72	7512.95	7764.94	7149.39	310.32
Mercado Bitcoin	7497.07	7524.90	7787.28	7125.75	204.01
Local Bitcoin	7793.94	7875.94	11400.54	6788.45	12.14

Open is the "opening" price, the first trade recorded at 0h00min00sec UTC, Close is the "closing" price, the last trade recorded at 23h59min59sec UTC, High is the highest intraday price, Low is the lowest intraday price, and Volume (BTC) is the total sum of all trades within the day, in bitcoins. All prices are in BRL per bitcoin.

comovement, indicating that these series may have a unit root and be cointegrated. Next we discuss how we formally test these properties.

3 Methodology

3.1 LOOP

We use only the opening and closing prices series. The high and low prices can occur at different times of the day on each exchange, thus defeating the purpose of our study, since prices at different times can be related to different information sets. This rationale is especially true for bitcoin, since the cryptocurrency is traded continuously around the globe.

We use three distinct unit root tests. One of them uses the opposite null hypothesis of the others, thus increasing the power of our tests and reducing concerns of wrong inference (Kwiatkowski et al., 1992). The Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) test the null hypothesis of a unit root (Dickey and Fuller, 1979; Phillips and Perron, 1988). The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests the null of stationarity (Kwiatkowski et al., 1992).

If the tests detect the existence of a unit root, the series can be tested for cointegration (Johansen, 1995). The test checks the existence of cointegration vectors, and indicates whether the series move in tandem in the long run. The cointegration test is applied to each pair of price series. We fixate the type of price (opening or closing) and then compare the same series across exchanges. The test can be generalized to several series at the same time, but our question is about the LOOP and the pair by pair test suffices. To select the number of lags of the Johansen procedure we use the AIC (Akaike information Criterion) (Johansen, 1995).

The cointegration tests if a linear combination between two price series from different exchanges, x_1 and x_2, is able to form a third, stationary series. Consider Equation 1. P_t^y is the bitcoin price in period t, exchange y. β is a parameter, and ε_t is the linear combination of prices. Formally, the cointegration test checks if a β exists so that ε is stationary. If such β exists and is close to 1, it is evidence that LOOP is valid for prices from x_1 and x_2.

$$P_t^{x_1} - \beta P_t^{x_2} = \varepsilon_t, \tag{1}$$

3.1.1 Price discovery

Returning to Equation 1, suppose that $\beta = 1$ and therefore LOOP is valid. Since cointegration is a long run relation, we can have a disturbance at the price among different markets in the

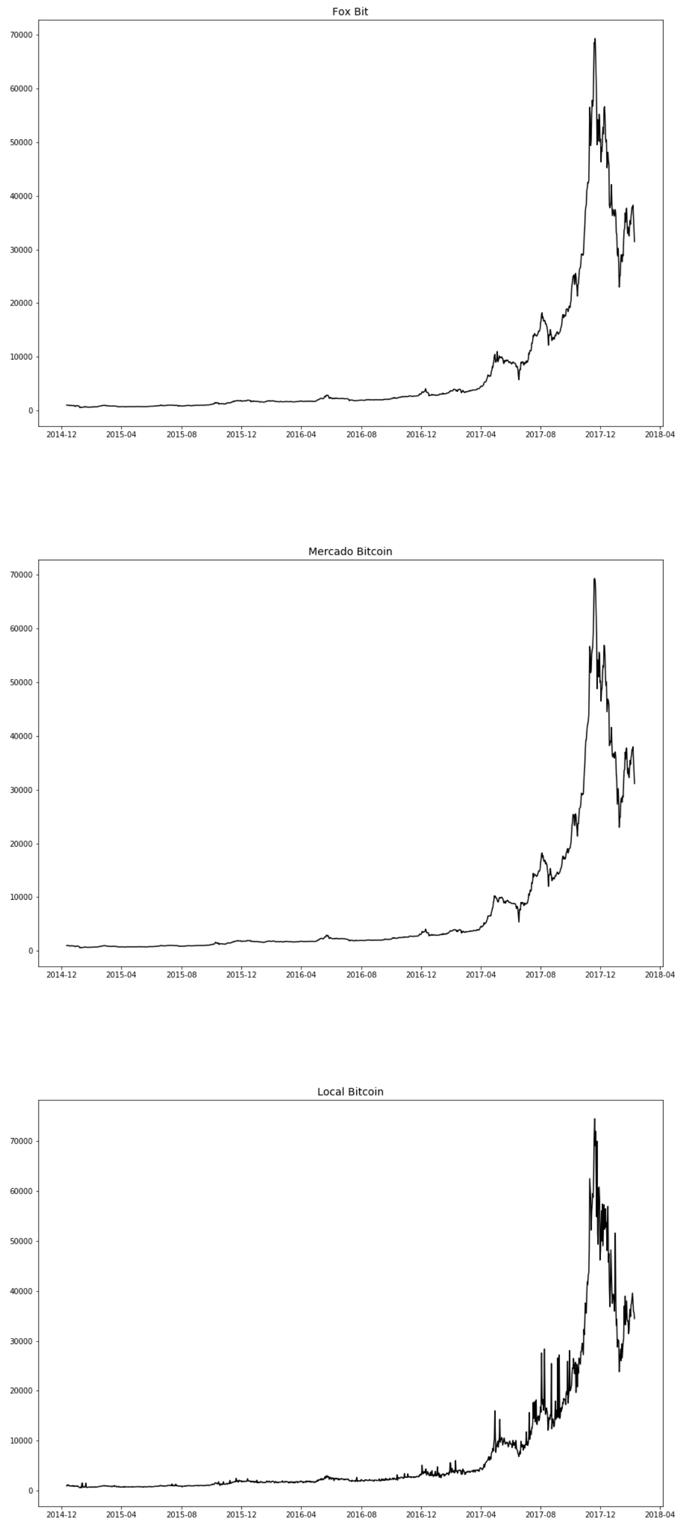

Figure 1: Bitcoin prices in Brazilian exchanges

short run. Moreover, cointegration implies causality between the prices at least in one direction. Then, one of the markets can lead price changes in the Brazilian market. There remains the question where price discovery occurs. Within the framework of Hasbrouck (1995), there is a common, implicit efficient price for the same asset traded in different markets. Same asset is defined broadly as assets "closely linked by arbitrage or short-term equilibrium considerations", such as an asset traded in different exchanges, or an asset and its derivative (Hasbrouck, 1995).

Price discovery happens when new information is impounded into the efficient price, leading to a permanent change in its level (Hasbrouck, 1995; Harris et al., 2002; Aggarwal and Thomas, 2018). One way of measuring it is through Information Share (IS), "defined as the proportion of the efficient price innovation variance that can be attributed" to one market (Hasbrouck, 1995). Implementation details can be found in Hasbrouck (1995) and Aggarwal. We use it to test which exchange dictates price discovery by doing all permutations possible to estimate the upper and lower bounds of IS for each market.

Another way of measuring price discovery is through Component Share (CS). The measure is based on Gonzalo and Granger (1995)'s approach of obtaining common factors that are integrated of order 1. As Baillie et al. (2002) argue, CS complements IS, providing a different view of the price discovery process. Both models are based on VECMs (Vector Error Correction Models). However, the IS model works with variance, while the CS model is based on the contribution given by the market's error correction coefficients to the common factor (Baillie et al., 2002; Harris et al., 2002). One important feature of CS is that it "isolates the dynamics following a synchronous event of price divergence (...) and the subsequent readjustment to a common stochastic trend" (Harris et al., 2002).

Baillie et al. (2002) exemplify this isolation property of CS. Consider an asset traded in two different markets, with highly correlated and cointegrated prices. The first market's price responds to deviations from the second market's price, but the opposite is not true: the second market's price does not respond to the first. According to the CS model, price discovery happens on the second market. However, the IS model suggests the two markets contribute to price discovery, since they are highly correlated.

Yan and Zivot (2010) discuss what IS and CS really measure. One result is that IS can yield ambiguous interpretations, as Baillie et al. (2002) discuss. However, Yan and Zivot (2010) also show that CS "measures the relative response to contemporaneous transitory frictions", concluding that CS does not measure responses to new information but the level of noise in one price series relative to the other (Putniņš, 2013). To overcome these issues, we follow Putniņš (2013) and calculate the Information Leadership Share (ILS), defined as in Equation 3.

$$IL_1 = \left| \frac{IS_1}{IS_2} \cdot \frac{CS_2}{CS_1} \right|, \qquad IL_2 = \left| \frac{IS_2}{IS_1} \cdot \frac{CS_1}{CS_2} \right| \tag{2}$$

$$ILS_1 = \frac{IL_1}{IL_1 + IL_2}, \qquad ILS_2 = \frac{IL_2}{IL_1 + IL_2} \tag{3}$$

In which IL_k, IS_k, and CS_k are market's k Information Leadership metric, Information Share, and Component Share, respectively. As IS_k depends on the ordering of the price series, we also follow Baillie et al. (2002) and use the simple average between IS and Reverse IS as IS_k. Note that $IL_k \in [0, \infty)$, unlike IS_k and CS_k, which lie in the interval $[0, 1]$. Therefore, we normalize to an Information Leadership Share (ILS_k).

4 Results

Table 4 presents results for the unit root test. They indicate both opening and closing price series are non-stationary. The only exception is the PP test for the Local Bitcoin exchange closing price series. Therefore, we consider that prices exhibit non-stationarity in all exchanges.

Table 4: Unit root tests

Closing prices			
	Foxbit	Mercado Bitcoin	Local Bitcoin
Lags	1	1	6
ADF	−2.40	−2.07	−2.13
PP	−2.186	−2.109	−5.318*
KPSS	2.6*	2.58*	2.62 *
Opening prices			
	Foxbit	Mercado Bitcoin	Local Bitcoin
Lags	1	1	7
ADF	−2.12	−2.03	−1.95
PP	−2.146	−2.076	−3.247
KPSS	2.6*	2.58*	2.6 *

* is significant at 1%. All tests include a constant and a deterministic trend. ADF is the Augmented Dickey-Fuller test and PP is the Phillips-Perron test. These two test the null hypothesis of a unit root (non-stationarity). KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test, which has a null of no unit root (stationarity).

We also test whether the first difference series has a unit root (Table 5). Note how all series are stationary in all tests. In conjunction with Table 4, we conclude that all the bitcoin price series we use are integrated of order 1, $I(1)$. Therefore, we can proceed to test their cointegration (Johansen, 1995).

Table 6 shows the cointegration test. Note that we test the three exchanges in pairs, yielding $C(3,2) = 3$ test statistics. The test for $Rank = 0$ rejects the null of no cointegration, while the test for $Rank = 1$ does not reject the null that the pair is cointegrated, both for the closing and opening prices. Therefore, we conclude all pairs of series are cointegrated.

More important, closing price series, as well as the opening price series, share one common trend and consequently, move in tandem in the long term. Note that the cointegration test between Mercado Bitcoin and Local Bitcoin prices is not necessary, since they both share a trend wit Foxbit (Stock and Watson, 1988). However, we conduct the test anyway, since our question is not about cointegration only. We also want details on the cointegration vectors, to recover the estimated β from Equation 1, shown in Table 7. The evidence indicates that the Law of One Price is valid between these three Brazilian bitcoin exchanges, since all of the $\hat{\beta}$s are close to 1. Therefore, in the long term prices converge to the same value between these exchanges. However, this may not be true in the short term, which we explore next.

4.1 Price discovery in Brazil

Table 8 shows results using Information Share (IS) and Component Share (CS) techniques with the three possible pairs combining the three exchanges. Since IS depends on the ordering of

Table 5: Unit root tests: first difference

Closing prices			
	Foxbit	Mercado Bitcoin	Local Bitcoin
Lags	7	2	10
ADF	-30.469 *	-29.630 *	-55.074*
PP	-30.459 *	-29.717 *	-83.512*
KPSS	0.043	0.043	0.018
Opening prices			
	Foxbit	Mercado Bitcoin	Local Bitcoin
Lags	1	2	8
ADF	-29.113 *	-29.296 *	-48.227*
PP	-29.075 *	-29.385 *	-54.268*
KPSS	0.042	0.043	0.031

* is significant at 1%. All tests include a constant and a deterministic trend. ADF is the Augmented Dickey-Fuller test and PP is the Phillips-Perron test. These two test the null hypothesis of a unit root (non-stationarity). KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test, which has a null of no unit root (stationarity). The first difference is the series $FD_t^y = P_t^y - P_{t-1}^y$ for each exchange y.

Table 6: Johansen cointegration test

Closing price				
	Foxbit as reference		**Local Bitcoin as reference**	
	Mercado Bitcoin	Local Bitcon	Mercado Bitcoin	
Rank	Test statistic	Test statistic	Test statistic	Critical value (1%)
0	239.80	315.06	304.08	20.04
1	4.31	4.42	4.21	6.65
Opening price				
	Foxbit as reference		**Local Bitcoin as reference**	
	Mercado Bitcoin	Local Bitcon	Mercado Bitcoin	
Rank	Test statistic	Test statistic	Test statistic	Critical value (1%)
0	168.31	291.73	297.98	20.04
1	4.23	4.29	4.19	6.65

The test statistic is Johansen's trace statistic, λ_{trace}, under the null hypothesis that the rank of the matrix of coefficients of the vector auto-regression is 0 (no cointegration) or 1 (cointegraton between two series). Series are tested in pairs: (Foxbit, Mercado Bitcoin), (Foxbit, Local Bitcoin), and (Local Bitcoin, Mercado Bitcoin). Critical values come from Johansen (1995).

Table 7: Cointegration and Law of One Price

	Closing price		
	Foxbit as reference		Mercado Bitcoin as reference
	Mercado Bitcoin	Local Bitcoin	Local Bitcoin
Cointegrate?	Yes	Yes	Yes
$\hat{\beta}$	1.00*	0.99*	1.00*
LOOP?	Yes	Yes	Yes
	Opening price		
	Foxbit as reference		**Mercado Bitcoin as reference**
	Mercado Bitcoin	Local Bitcoin	Local Bitcoin
Cointegrate?	Yes	Yes	Yes
$\hat{\beta}$	1.00*	1.00*	0.99*
LOOP?	Yes	Yes	Yes

* is significant at 1%. Cointegrate? indicates if the series cointegrate according to the Johansen test; $\hat{\beta}$ is the estimated β from Equation 1; LOOP? indicates if Law of One Price is valid.

price variables (Aggarwal; Baillie et al., 2002), Table 8 also shows the Reverse IS. The IS value we use to calculate the ILS advocated by Putniņš (2013) is the simple mean between IS and Reverse IS.

The Mean IS estimate indicates that Mercado Bitcoin (MB) leads price discovery. Ordering the inequalities, we obtain that MB leads, Foxbit (FB) stands in the middle, and Local Bitcoin (LB) lags discovery. CS tells a similar story, with Mercado Bitcoin leading discovery in Brazil. This is consistent with LB being by far the less liquid exchange, with a volume less than a tenth of MB or FB (see Table 3). The difference between FB and MB is much lower, with FB trading 1.5 times the volume of MB. However, in this case, the less liquid exchange leads price discovery.

Results taking into account for IS and CS simultaneously through ILS tell us a different story. For the closing prices, the ordering is inconsistent. ILS implies LB both leads and lags the other exchanges. Opening prices tell a more consistent story, although different from IS and CS. Both FB and MB lead LB, consistent with IS and CS. But here FB leads MB, resulting in FB – MB – LB ordering of price discovery. Thus, ILS estimates for closing prices follow the ordering of liquidity with the most liquid exchange leading and the least liquid lagging discovery.

The disagreement between the isolated measures, IS and CS, and the integrated measure, ILS, is consistent with Putniņš (2013) and Yan and Zivot (2010) suggestions that IS can be ambiguous, and CS measures level of noise. For the opening prices, there is a correlation between liquidity and price discovery as measured by ILS. It indicates that arbitrageurs might use Foxbit's price to generate opportunities. However, as the LOOP test indicates, these opportunities disappear over time.

Our findings go in line with Brandvold et al. (2015), who document that certain exchanges lead others in price discovery, but they only include exchanges denominated in US Dollars, Chinese Yuans, Polish Złotys, and Canadian Dollars. To the best of our knowledge, our result is the first to point a price discovery mechanism for exchanges denominated in Brazil-

Table 8: Price discovery

Closing price					
Exchange	**IS**	**Reverse IS**	**Mean IS**	**CS**	**ILS**
Mercado Bitcoin	0.943	0.281	0.612	0.697	0.319
Foxbit	0.056	0.718	0.387	0.302	**0.681**
Mercado Bitcoin	0.986	0.981	0.984	0.963	**0.849**
Local Bitcoin	0.013	0.018	0.016	0.036	0.151
Local Bitcoin	0.045	0.001	0.023	0.013	**0.762**
Foxbit	0.954	0.998	0.976	0.986	0.238
Opening price					
Exchange	**IS**	**Reverse IS**	**Mean IS**	**CS**	**ILS**
Mercado Bitcoin	0.883	0.312	0.598	0.622	0.449
Foxbit	0.116	0.687	0.402	0.377	**0.551**
Mercado Bitcoin	0.911	0.976	0.944	0.859	**0.885**
Local Bitcoin	0.088	0.023	0.056	0.140	0.115
Local Bitcoin	0.078	0.049	0.064	0.110	0.231
Foxbit	0.921	0.950	0.936	0.889	**0.769**

IS is Information Share (Hasbrouck, 1995). Reverse IS the same as IS, but reversing the price order (Aggarwal; Baillie et al., 2002). Mean IS is the arithmetic mean between IS and Reverse IS (Baillie et al., 2002). CS is Component Share (Baillie et al., 2002; Harris et al., 2002; Gonzalo and Granger, 1995). ILS is Information Leadership share, calculated as in Equation 3 aggregating both IS and CS measures (Yan and Zivot, 2010; Putniņš, 2013). A larger ILS indicates that the series leads price discovery, as indicated by numbers in bold.

ian Reais. Our result is also consistent with Makarov and Schoar (2018), who find that arbitrage opportunities can persist for days or even weeks in the US, Japan, and Korea. We document that the same opportunities may exist in the Brazilian market, reinforcing evidence that the bitcoin market still has inefficiencies, although it has been improving (Köchling et al., 2019; Sensoy, 2018).

5 Final Remarks

This research adds to the growing literature on bitcoin (Halaburda and Sarvary, 2016). We contribute to the knowledge of bitcoin price behavior in a large emerging market, Brazil. Bitcoin evidence in non-developed markets is relatively scarce, despite the importance of such markets (Carrick, 2016; Ferreira Frascaroli and Carvalho Pinto, 2016). To the best of our knowledge, our research brings the first evidence of a price discovery mechanism for exchanges in Brazilian Reais. The evidence we bring show that LOOP is valid in the long run, but reinforces existing evidence that inefficiencies in bitcoin markets still exist, potentially creating arbitrage opportunities (Köchling et al., 2018; Sensoy, 2018).

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