The impact of inflation, credit risk and corruption on local bitcoin prices: A panel data analysis

Aleksander Bjørnå Spade
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Preface

Acknowledgements

A special thanks to my supervisor, professor Yikai Wang for many interesting discussions about the subject and for steering me in the right direction. Also I would like to thank my former professor in time-series econometrics, Ragnar Nymoen for valuable input and motivation. I would also like to thank my fellow students, friends and family who were all patient and supportive, especially the last few weeks. It has been truly fun and interesting to write this thesis. The idea to write about this subject came from personal observations after having been fortunate to live several semesters abroad, in Shanghai, Paris and Buenos Aires. All remaining errors are my own.

Aleksander Bjørnå Spade
May 11 2018
Abstract

This thesis analyzes whether inflation rates, government bonds and corruption levels have an impact on the difference between local prices of bitcoin and prices on the most liquid exchanges globally. Bitcoin may act as a preferred alternative to local currencies in countries with high levels of financial uncertainty, hence people who live in these countries might be willing to pay a premium to purchase bitcoin as they reduce the risk related to the future value of their own fiat currency. Daily average prices on bitcoin, in 15 different fiat currencies, are downloaded from LocalBitcoins and converted to USD at official exchange rates. The data covers the period of Jan.2015-Dec.2017. By calculating daily deviations from the BNC Liquid Index and aggregating to monthly observations, we consider three different panel data models: the static- and dynamic fixed effects and a within-between random effects model. The results suggest that countries with higher average inflation rates has a higher premium, while a within increase in monthly inflation has a negative impact. If the premium on 10Y government bonds increases, the premium increases significantly, but when comparing across countries, the average bond rate is not significant, but positive. A within increase in corruption levels has a positive impact on the premium, but surprisingly we get a negative relationship at country level. Countries with poor economic performance and high levels of uncertainty seems to be willing to pay a premium to acquire Bitcoins

Keywords: bitcoin, inflation, emerging markets, government bonds, corruption.
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1 Introduction

There is no doubt that bitcoin prices differ between countries. This thesis will investigate if inflation, government bond rates and corruption levels in different countries have an impact on the difference between the local price of bitcoin and the BNC Liquid Index, which is a bitcoin index designed for institutional use. For the less informed reader, Bitcoin acts as an alternative to the current financial system. Briefly explained, Bitcoin is a decentralized digital payments system, that is not governed by any central authority, which allows people to store, transfer and receive the digital currency bitcoin without the need for any third-parties to be involved. What makes Bitcoin rather unique is that Bitcoin has no location. If a person sends a bitcoin to another person who lives on the other side of the globe, bitcoin does not change location at all, it is simply an update in the ledger. The reason why prices differ between countries is mainly due to the fact that bitcoin prices are determined separately on each exchange and that triangular arbitrage is costly, due to transaction fees, withdrawl limits and the fact that international money transfers are costly, especially in emerging economies, where people do not necessarily have a bank account. Even so, there might be other explanations for why prices differ as well.

The value of fiat currencies essentially relies on decisions made by a few selected policymakers. When policymakers act irresponsible and focus on increasing their own private wealth, or try to benefit in the short-term by increasing the chance for re-election, better outcomes could have been realized. This is a common problem, even in developed countries. However, in countries where people constantly are affected by implementation of poor economic policies, people have little or no trust in the incumbent government, whose policies often result in high inflation rates, unstable currencies that depreciate over time, and in general high financial uncertainty levels. Therefore it would be reasonable to assume that people in those countries would be willing to pay a higher price to acquire bitcoin in order to reduce their exposure to decisions made by the government, as an alternative to other safe havens.
On the other hand, bitcoin is also commonly known for being used by criminals to operate under the radar of the government. Hence, in countries with high corruption rates, one can expect that the demand for bitcoin is high for two reasons, namely that the law abiding citizens are looking for alternative ways to store their wealth and that a substantial amount of tax embezzled money ends up in bitcoin.

When India’s Prime Minister, Narendra Modi, on November 8, 2016, announced that all 500- and 1000 Rupee notes would become worthless the next day, and that people could exchange their old notes into new ones, but capped at a daily limit in the range of 2000-4500 Rupees, the local premium on bitcoin in India, on the OTC platform LocalBitcoins, increased from almost nothing to 29% in less than a month. Even though the intention was to reduce the amount of criminal cash in the economy, people were not very pleased as all those notes combined accounted for 86% of the cash circulating in the economy. In the end, the project failed miserably, as 99% of all cash were returned.

1.1 Research questions and hypothesis

In this thesis I will try to determine why such local price deviations occur, but instead of focusing on single events that lead to sudden changes in local market conditions, I will aggregate to monthly data to get a more broad overview of local price differences. More specifically I will consider price observations from 15 different areas/countries over a three year period, from January 1, 2015 - December 31, 2017.

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2017. The data will be described in Section 4. We will investigate how month-on-month inflation rates, 10 year government bond rates and corruption levels affect the average monthly price deviations from global markets. Even though bitcoin is considered a highly speculative asset in developed countries, we can have reason to believe that Bitcoin offers something more for people in countries where the economy is unstable and where people have little trust in government officials. The three variables of interest provides a solid overall picture of a country’s financial stability and challenges related to trust issues. In other words, problems that arise from high levels in any of these variables, are the kind of problems that Bitcoin intends to solve.

Therefore, I propose the following hypothesis:

- Higher inflation leads to higher local price deviation
- Higher government bond rates leads to higher local price deviation
- Higher corruption levels leads to higher local price deviation

<table>
<thead>
<tr>
<th>Variable</th>
<th>Impact on local price difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Month-on-month inflation</td>
<td>+</td>
</tr>
<tr>
<td>Government Bonds (10Y)</td>
<td>+</td>
</tr>
<tr>
<td>Corruption Level</td>
<td>+</td>
</tr>
</tbody>
</table>

Table 1: Hypothesis

1.2 Outline

This thesis will include many references from online sources, as a lot of important information is very hard to find in the literature, especially covering the most recent events. The next section gives more detailed introduction to Bitcoin, which is necessary to understand why bitcoin can be appealing for people in countries with an unstable economy and trust-issues. Section 3 covers relevant literature about what might affect our results. Then we move on to describe the data that has been
gathered from 15 different countries, where data is presented both with summary statistics and visually. Section 5 will then present three different panel data models; the static fixed effects, dynamic fixed effects and within-between random effects model. All models have been estimated in STATA. Results will be presented after each model consecutively, then followed by appropriate specification tests. Section 6 will discuss and conclude and lastly limitations and policy recommendations is presented in section 7.
2 The Bitcoin Network

2.1 What is Bitcoin?

Bitcoin is a purely decentralized peer-to-peer electronic cash system that allows for online payments without the need for any financial intermediaries to be involved.\(^4\) Peers on the network can send and receive units of the digital currency, called bitcoin, directly between each others, while nodes provide the computational power needed to operate and maintain the network in line with the Bitcoin protocol.

People holding bitcoins have a certain level of anonymity. Every Bitcoin wallet has a private- and public key, where the private key is a randomly generated string, and the public key is mathematically derived from the private one. The private key allows bitcoins to be spent. In order to receive bitcoins, it is generated a wallet address (from the public key) safe to share with other peers. Regarding the level of anonymity, anyone can create a Bitcoin wallet, without revealing information about their identity. However, the Bitcoin network is a public ledger giving full transparency for anyone to view the complete transaction history.

Nodes compete to verify transactions that are stored in the next "block" on the Bitcoin block chain. For this activity, often called mining\(^5\), they are awarded in terms of new bitcoins that are generated, which is their incentive to contribute to the network. Anyone with access to the Internet can do this, by running the Bitcoin protocol on computers with a special type of computer hardware that are powerful enough to run mathematical difficult puzzles. A process requiring a lot of electricity. As there are no central authority in the network to issue currency, the growth rate in total bitcoins is pre-determined by an algorithm. Approximately every four years, the number of bitcoins that miners are rewarded is reduced by 50%. This implies a maximum limit on how many bitcoins that will ever exist, capped at approximately 21 million units. However, this limit will not

\(^4\)Bitcoin.org (2008) ”Bitcoin: A Peer-to-Peer Electronic Cash System”

\(^5\)This expression can be compared with gold miners, who discover new gold.
be reached within the next 100 years. The difficulty rate of mining is adjusted approximately every two weeks depending on the number of miners, to ensure a decreasing growth rate. More miners will result in higher difficulty rates, which will reduce their profits because electricity consumption increases. Thus, miners located in countries with relatively cheap electricity have a comparative advantage, as their marginal cost is lower. In March 2018, according to Elite Fixtures, South-Korea was the most expensive country to mine bitcoin and Venezuela the cheapest, where estimates based on electricity prices suggests that mining one bitcoin in those countries costs USD 26,170 and USD 531 respectively.

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6BitcoinWiki (2017) "Protocol Rules"  
7EliteFixtures (2018) "Bitcoin Mining Cost Throughout the World"  
https://www.elitefixtures.com/blog/post/2683/bitcoin-mining-costs-by-country/, accessed 10/05-2018
2.2 Bitcoin as currency and financial asset

2.2.1 Historical price development

The historical global daily average price of bitcoin is illustrated in figure 1, based on data from the BNC Liquid Index, together with the total supply of bitcoin, extracted from Bitcoin.com. The vertical lines indicate when mining rewards has been halved, which explains why the slope rate of total supply is reduced consecutively. Initially, bitcoin was trading at less than a cent, and in December 2017 it reached an all-time-high slightly below 20,000.00 U.S. dollars.

![Figure 1: Historical global price of bitcoin (in USD) and total supply](image)

2.2.2 The rationale for investing in Bitcoin

"Chancellor on Brink of Second Bailout for Banks" (The Times, January 3, 2009), reveals what was probably the true intention behind the creation of Bitcoin. It is the headline of the front page of The (London) Times newspaper, from January

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10The Times (2009) "Genesis Block Newspaper" https://www.thetimes03jan2009.com/, accessed 10/05-2018
3. 2009, and was quoted in the first block that was mined, the genesis block, on the Bitcoin network the same day\footnote{Blockchain (2017) "Transaction info" https://blockchain.info/tx/4a5e1e4baab89f3a32518a88c31be87f618f76673e2cc77ab2127b7afda33b?show_adv=true, accessed 10/05-2018}. This was in the aftermath of the the global financial crisis, which had led to a reduction in trust in the financial system.

As mentioned, bitcoin has a predictable growth rate and finite supply. Bitcoin serves as an alternative to the current financial system. By investing in bitcoin, people can reduce financial uncertainty related to the short- and long term value of their local currencies, whose value depends on economic policies. Thus, in countries governed by poor institutions, it is reasonable to assume that bitcoin may act as a safe haven, rather than simply being a speculative investment.

As bitcoin is a decentralized network without any central authority, a transfer on the network is simply a change in the ledger. The digital currency bitcoin does not change location or cross any boarders itself, but allows value to be transferred anywhere in the world. Therefore, bitcoin is a solution to circumvent capital controls while remaining relatively anonymous.

All these factors will probably not be able to explain the massive surge in the market capitalization of bitcoin, that seems more of a speculative bubble.

### 2.3 Market structure

Considering the fact that Bitcoin has no location, one would expect that the price would be determined by global demand and supply. However, the Bitcoin market is still immature, as prices seem to differ persistently between exchanges in different regions. If one searches for "arbitrage opportunities bitcoin", on Google, you will immediately find many pages that present live arbitrage opportunities. One can consider the Bitcoin market as several bottlenecks. Every person holding fiat currency, either in cash or in a bank account, need to connect with a seller willing to accept their currency. Hence, in order to get access to the benefits that
the Bitcoin network has to offer, you have to convert your fiat currency to bitcoin in some way or another. If local demand increases in a country that has capital controls, the price will naturally be pushed upwards, as the supply is determined locally.

2.3.1 Cryptocurrency exchanges

According to CryptoCoinCharts, there were 193 different cryptocurrency exchanges globally, on May 10. 2018. The top 10 exchanges in terms of trading volume represented 85% of the 24 average trading volume of all different kinds of trading pairs, not only limited to trading of bitcoin. Most notably, the trading volume of the two largest exchanges, Binance and Bitfinex, constitutes of 29% and 24% of all trading, respectively.

Cryptocurrency exchanges allow their customers to trade bitcoin and other digital currencies through their centralized trading platforms, and charge transaction fees. Customers can deposit and withdraw fiat currency on most exchanges, even though some only accept digital currencies, and are therefore the most common place to go for people who wants to buy bitcoin. As these exchanges are financial intermediaries, they need to comply with the jurisdiction where they are located, regarding know-your-customer and anti-money-laundering processes. This combination of centralized trading platforms and KYC/AML processes is a source of price discrepancies, since the price of bitcoin is determined separately on each exchange. Considering the fact that the top 2 exchanges handle more than 50% of the trades, there are a lot of small exchanges were markets are not as liquid.

Currently there are no well developed interoperability between exchanges, so in order to profit through arbitrage trading, each person has to register on all exchanges where one wish to exploit price differences, which is a time consuming process.

Different exchanges operate with different trading-, deposit- and withdrawal fees,
as well as deposit- and withdrawal limits. The most popular exchanges typically have an easy to use interface and charge higher transaction fees, especially if customers buy directly with their credit cards.

2.3.2 Over-the-counter

An alternative to register on an exchange is to trade over-the-counter (OTC). OTC-platforms simply connect buyers and sellers within an area, like any other marketplace online, and facilitates easy conversion from local fiat currency to bitcoin, or the other way around, under no regulation. This thesis will use data from the largest OTC platform "LocalBitcoins", as will be described in section 4. As in any other market where ID is not required to interact with other potential sellers or buyers, the existence of OTC platforms makes it hard for the government to regulate, and especially attractive for criminals who wish to operate under the radar. For this reason, the prices tend to deviate from the most liquid exchanges, as found in Pieters and Vivanco (2017). 13

2.4 Regulation.

Bitcoin, and cryptocurrencies in general, are assets that regulators are struggling to regulate, due to its decentralized nature. It limits their ability to track transfers related to criminal activities, but on the other hand, fiat currency is even harder to track, because those transactions are typically not reported anywhere at all. There are several instances of countries trying to regulate bitcoin exchanges, but the consequence is simply that OTC trading increases. As an example, early in February 2017, China issued a one month suspension of withdrawals from domestic exchanges and forced them to strengthen anti-money-laundering and

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know-your-customer procedures. As a result, the volume of bitcoins traded through LocalBitcoins increased from 1.340 BTC in January to 13.466 BTC in February, and reached an all time high of 28.726 BTC in March. Hence, imposing restrictions on cryptocurrency exchanges can make it even harder for regulators to regulate.

2.5 Case example: India and Venezuela

India

On November 8, 2016, bitcoin in India was trading, on average, at 50,151 Rupees or USD 754 on LocalBitcoins, only 45 dollars above the average price globally. The same day, India’s Prime Minister, Narendra Modi, announced on national television that all 500 and 1000 Rupee notes circulating in the economy would become invalid past midnight. These notes accounted for 86% of cash circulating in the economy. The intention was to reduce the amount of criminal cash circulating in the economy, as cash was leaking out of the system through tax embezzlement. People were allowed to exchange old notes into new ones, but limited in the range of 2,000-4,500 Rupees over-the-counter at all banks. In theory, this would make large fraction of criminal cash worthless, while the average Indian could expect to exchange a considerable amount of their wealth. However, the policy failed as 99% of the banned notes was returned. During this period, local


\[17\] Forbes (2016) ”How India’s Demonetization is Affecting it’s start-ups” https://www.forbes.com/sites/krnkashyap/2016/12/15/how-indias-demonetization-is-affecting-its-startups/#7d93430a2c2, accessed: 10/5-18

bitcoin prices in India surged as Indians, especially criminals, looked for alternative ways to store their wealth. 18 days after the announcement, the local premium on bitcoin in India had surged to 215.88 USD or 29.33%, relative to the global markets.

**Venezuela**

Venezuela provides a unique example of how bitcoin suddenly became a preferred value of exchange as a result of continuous poor economic policies that made their economy extremely vulnerable to a drop in the oil-price and highly dependent on imports. Recently, year-on-year inflation hit 13,379.00% in April 2018, according to their central bank, and the Venezuelan bolivar has basically become worthless abroad.\(^\text{19}\) Price controls and strict capital controls have lead to a lack of access to several necessities to survive. As mentioned, Venezuela is the cheapest place on earth to mine bitcoin, as electricity is heavily subsidized by the government. Therefore, bitcoin mining has gained popularity in times of desperation, as Venezuelan bitcoin miners convert electricity into bitcoin, which allows them to increase their purchasing power. Through third parties that accept bitcoin, they can purchase gift cards and use them to purchase goods abroad, for example canned food at Amazon. A good way to put it is to say that miners have "turned socialism against itself" (Epstein, J. 2017)\(^\text{20}\). Naturally, the government cracked down on this activity, claiming it was theft of electricity. Police officers confiscate bitcoin mining rigs frequently, for their own personal use or they blackmail miners to claim a share of the profits. As a result, bitcoin mining has become a relatively dangerous affair, and therefore Venezuelan miners have turned to mining of other cryptocurrencies, such as Zcash and Ethereum, which requires another type of computer hardware less recognized by government officials\(^\text{21}\).

Bitcoin is increasingly preferred over the dollar in Venezuela, not only because it


allows people to purchase goods abroad, but also because even though the U.S. dollar is attractive, most people do not have a bank account that accepts it. In addition, high crime rates makes the physical storage of dollars very risky. In other words, bitcoin does indeed have some appealing characteristics for people in Venezuela: a more secure way to store wealth, a safe haven to hedge against hyperinflation and a way to circumvent capital controls.

As Venezuela is a rather special case, it is excluded from the analysis in this paper, for several reasons. There were many missing observations both on LocalBitcoin prices, and large gaps in the reporting frequency of month-on-month inflation. Also, the official foreign exchange rate is so wrongly reported that it implies that bitcoin was trading at more than 9 times the price of global markets. This created extremely biased estimates in all models.

3 Literature review

There are more and more research about bitcoin, but still the availability is somewhat limited. Hence, many of the references throughout this thesis are references to web-sites, as the online Bitcoin community is large and most info can be found there. However, this section will discuss relevant academic literature that can give us an indication of what affects local bitcoin prices.

As the fundamental value of bitcoin is practically zero, the main driver behind the incredible price growth stems from speculation, as described in Cheah & Fry (2015). Even though the fundamental value of bitcoin is zero, the real value of bitcoin lies in its trust-less nature. Maurer & Nelms (2013) claim it is all about the fact that Bitcoin eliminates the need to trust governments and corporations, whose decisions in many cases are affected by personal gains. Blundell (2018)

confirms this and claims that the financial crisis of 2007-2008, that lead to a loss of trust in financial intermediaries, has probably helped pave the way for cryptocurrencies.\(^{24}\)

Böhme et al (2015) describes how the use-cases of bitcoin have developed over time and explains that a large fraction of early adopters used bitcoin as settlement when trading illegal goods on marketplaces on the dark web, such as the ”Silk-Road”, and as a way to circumvent capital controls.\(^{25}\) Today, bitcoin has become an alternative to current payment systems and as a speculative investment, rather than an asset used related to criminal activities. According to Brito & Castillo (2013), Bitcoin’s association with the Silk-Road destroyed its reputation, yet there is still a considerable amount of illicit trade with bitcoins.\(^{26}\) However, this is a problem with traditional cash as well, as they point out. Further, Moser et al. (2013) find that even though regulators impose anti-money-laundering procedures on exchanges, the existence of services that offer increased transaction anonymization which are very hard to track, makes it unlikely that know-your-customer procedures can be enforced in the whole Bitcoin network.\(^{27}\)

Carrick (2016) finds that Bitcoin has characteristics that make it well-suited to work as a complement to fiat currencies in emerging markets, even though the price volatility is high.\(^{28}\) Banks in emerging markets often charge huge transactions fees, especially for international transfers. For the unbanked, the total cost of engaging in financial transactions are significantly higher. By exchanging local currency into bitcoin and then a few seconds later initiate a transfer, this can almost eliminate


the volatility risk.

Pieters & Vivanco (2017) investigate how whether ID is required or not, is a source of higher prices. They find that bitcoin prices on exchanges that do not require ID are more likely to deviate from the global market price, hence countries with high corruption rates could likely have a higher deviation from the global price. In an earlier paper, Pieters & Vivanco (2015) suggest that bitcoin prices, that are easily accessible, can be used to derive a proxy of unofficial foreign exchange rates, in countries where no such data is available. The unofficial exchange rate, $\hat{E}_t$, is then given by the ratio between the local price of bitcoin $BTC_{LOCAL_t}$ (in local currency) and $BTC_{USD_t}$, the average price globally, at time $t$.

$$\hat{E}_t = \frac{BTC_{XXX_t}}{BTC_{USD_t}}$$

On the other hand, Holoub & Johnson (2018) document that the bitcoin price on LocalBitcoins in Australia is out of line with global market prices, not due to the presence of a black-market rate. There are substantial research within the field of how corruption has a negative impact on the real economy. Blackburn & Powell (2011) derives a theoretical framework on how corruption, through tax embezzlement, forces governments to rely on seigniorage to finance their expenditures, which increases inflation. Several empirical studies have proven this positive relationship between corruption and inflation, which is agreed upon in the literature, i.e. Al-Marhubi (2000), Ahmet

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To sum up the findings, we can have reason to believe that people living in countries with trust-issues likely are willing to pay a higher price to acquire bitcoin. Trust-issues will be higher in countries where the general public do not trust their policy makers. Additionally, countries with high corruption rates are also likely to have a higher demand for bitcoin since tax embezzlement are more widespread. Even though a larger fraction of people who possess bitcoin are not involved in criminal activities as before, bitcoin still acts as an appealing asset for criminals compared with fiat currency, as the literature suggests.

There are also the obvious challenges related to high inflation rates, that directly impacts people savings. High inflation rates itself, not necessarily connected with high corruption, will make bitcoin more attractive the higher it is.

4 Data

4.1 Sources and evaluation

This study combines daily, monthly and annual data covering the period from January 1. 2015 - December 31. 2017. Data has been collected from several trusted sources and daily data has been aggregated to monthly, while annual data remains the same for all monthly observations within the same year.

LocalBitcoins

24h-average local bitcoin prices and total daily bitcoin volume (in local currency) from 15 different currency pairs have been downloaded from the OTC platform


LocalBitcoins, through QUANDL. In total we have 14,628 daily observations for all 15 currency pairs where most of them have more than 1000 daily price observations, except South-Korea, Indonesia and Tanzania, with 294, 538 and 545 daily observations respectively. QUANDL extracts data from the LocalBitcoins API, and gathers all data for easy access. LocalBitcoins is the largest OTC platform, hence LocalBitcoins is a natural choice, as most trades occur on a local level, either through national bank transfers or by cash. Ideally one would include all currency pairs available from LocalBitcoins, but due to time constraints, 15 currency pairs were chosen, from countries(areas) with rather different economies. Instead of referring to the currency pair, I will refer to the country(area), respectively; Argentina, Brazil, Canada, Chile, China, India, South-Korea, Malaysia, Norway, Russia, South-Africa, Tanzania, Thailand, UK and lastly the Euro area.

**BNC Liquid Index.**

In order to calculate local premiums, we need a reference point for the global price of bitcoin. There are several alternatives, however the methodology for different indexes vary greatly. The BNC Liquid Index (BLX) was constructed to create a truly comprehensive and robust bitcoin price index for institutional use. BLX calculates a USD price for one bitcoin every 30 seconds, from the largest and most liquid exchanges around the world; Bitfinex, Bitstamb, Gemini, BTCC, BTC-e, Coinbase, itBit, OkCoin International, Kraken, Coinsetter and Mt.Gox. Data has been extracted from their API through a paid subscription. BLX constitutes of trading data.

**Foreign exchange rates**

Daily official foreign exchange rates for all 15 currencies has been downloaded from Oanda and then matched with the date of each transaction from LocalBitcoins, country-by-country, in order to convert the local price into U.S. dollars.

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36Quandl (2018) “Local Bitcoins”
https://www.quandl.com/data/LOCALBTC-Local-Bitcoins, accessed 10/05-2018

https://bravenewcoin.com/api/bitcoin-liquid-index/, accessed 10/05-2018

https://www.oanda.com/fix-for-business/historical-rates/, accessed 10/05-2018
is one of the most trusted providers of currency information and their historical rates are used by auditors and tax professionals. Their database covers up to 25 years of historical exchange rate data on more than 38,000 currency pairs.

**Inflation, government bonds (10Y) and corruption index**

Month-on-month inflation rates are downloaded from Tradingeconomics.\(^39\) Official source for each series can be found in Table 11 in the Appendix. The choice of month-on-month inflation rate versus year-on-year inflation, is that since we aggregate to monthly bitcoin prices, the inflation and price development is level with each other and therefore directly comparable, as both capture the current development.

Government 10 year bond rates are also collected from Tradingeconomics\(^40\) and the sources are reported in Table 12 in the Appendix. Government bonds are traded daily (excluding Saturdays and Sundays) and therefore the data has been aggregated to monthly, by simply taking the average of all observations within the same month for each country.

Corruption data is downloaded from Tradingeconomics and all observations refer to Transparency International Corruption (Perceptions) Index, which ranges from 0-100, where higher score indicates lower corruption.\(^41\) The index is reported annually, hence each observation in our monthly panel is equal for all months within the same year per country. Since we have included trading data on bitcoin in Euro from LocalBitcoins, the corruption index for the Euro area has been calculated by taking the average of all Euro area countries using the Euro, per year. A more detailed list with Euro area Corruption Index averages can be found in Table 14 in the Appendix. The regression models in this thesis will refer to the corruption index as TRANSP (Transparency), for easier interpretation, as the corruption index is inverted. A negative coefficient will translate to that higher levels of

\(^{39}\)Tradingeconomics (2018) “Inflation Rate Mom”
https://tradingeconomics.com/country-list/inflation-rate-mom, accessed 10/05-2018

\(^{40}\)Tradingeconomics (2018) "Markets - Bonds"
https://tradingeconomics.com/bonds, accessed 10/05-2018

\(^{41}\)Tradingeconomics (2018) "Corruption Index"
https://tradingeconomics.com/country-list/corruption-index

24
transparency (less corruption) has a a negative impact on the premium.

4.2 Summary statistics

In Table 2 we see summary statistics for the monthly aggregated data. The total number of observations is 540, as we have data from 15 countries over a period of 36 months. For inflation \((INF_{it})\), government bonds \((BONDS_{it})\) and the transparency index \((TRANSP_{it})\) we have no missing observations. However, due to lack of observations from South-Korea, Indonesia and Tanzania, we only have 528 observations of \(d_{it}\), a variable that measures the difference from the BLX in log terms.

\[
d_{it} = \log(BTCUSD_{it}) - \log(BLX_{it}) = \log\left(\frac{BTCUSD_{it}}{BLX_{it}}\right) \tag{2}
\]

It is calculated by taking the the average of all available daily observations of the local price in terms of USD, within each month, for each country. Then calculating the monthly average of all corresponding daily BLX prices, which means that the monthly average of BLX also differ between countries. Then we take the log of the ratio, which gives the premium.

<table>
<thead>
<tr>
<th>(d_{it})</th>
<th>(INF_{it})</th>
<th>(BONDS_{it})</th>
<th>(TRANSP_{it})</th>
<th>(\log(VOLUSD_{it}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>527</td>
<td>540</td>
<td>540</td>
<td>540</td>
<td>527</td>
</tr>
<tr>
<td>0.0534062</td>
<td>0.3781296</td>
<td>4.895521</td>
<td>51.94318</td>
<td>13.05701</td>
</tr>
<tr>
<td>0.0747141</td>
<td>0.7079197</td>
<td>3.880198</td>
<td>19.01815</td>
<td>2.523413</td>
</tr>
<tr>
<td>-0.128005</td>
<td>-1.6</td>
<td>-0.517205</td>
<td>29</td>
<td>1.617199</td>
</tr>
<tr>
<td>0.4863572</td>
<td>6.5</td>
<td>16.761</td>
<td>87</td>
<td>18.534</td>
</tr>
</tbody>
</table>

The max value is obtained from Argentina in September 2015, indicating a premium of almost 50%, while the minimum value is from South-Korea in November 2016.
We also see that the other variables differ substantially. In table 3 we see that the price difference is positively correlated with both inflation and government bond rates. Also it is negatively correlated with transparency, in other words that higher corruption is positively correlated with a higher deviation. Increased trading volume is negatively correlated, as expected. In addition, higher levels of transparency is negatively correlated with inflation and even more with bond rates. The summary statistics seems to be perfectly in line with our hypothesis.

<table>
<thead>
<tr>
<th></th>
<th>$d_{it}$</th>
<th>$\text{INF}_{it}$</th>
<th>$\text{BONDS}_{it}$</th>
<th>$\text{TRANS}_{it}$</th>
<th>$\log(\text{VOLUSD}_{it})$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_{it}$</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{INF}_{it}$</td>
<td>0.205</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{BONDS}_{it}$</td>
<td>0.396</td>
<td>0.210</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\text{TRANS}_{it}$</td>
<td>-0.227</td>
<td>-0.257</td>
<td>-0.654</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>$\log(\text{VOLUSD}_{it})$</td>
<td>-0.349</td>
<td>-0.122</td>
<td>-0.253</td>
<td>0.137</td>
<td>1</td>
</tr>
</tbody>
</table>

4.3 Visual inspection

By plotting all local price deviations per country, we see that they differ substantially in different areas. Canada, China, the Euro Area, Malaysia, Norway, Russia,
Thailand and the UK have a much lower variation than the rest of them, which needs to be considered in our regression model. The overall picture seems to be that less developed countries have a higher variance.

Figure 3: Average price deviation and MoM inflation

Figure 4: Average price deviation and government bond rates

Figure 5: Local price deviation by country

When plotting the average of the price deviation against inflation, bonds and corruption level, in figure 3, 4 and 5 respectively, we are able to get a better picture on a country level. We see that Argentina and Tanzania are outliers in all the three plots. However, Argentina has a much higher average month-on-month inflation than Tanzania, while there is an opposite relationship regarding for government
bonds. As the corruption index is inverted, we see there is a negative relationship between transparency levels, where Tanzania and Argentina have almost the same levels of both deviation from the global price of bitcoin and relatively high levels of corruption (low transparency). Norway, Canada and the UK have the highest transparency levels and among the lowest premiums, in line with the hypothesis. These illustrations speak for themselves and are quite interesting indeed, yet we need to see if we can find statistical significance.

5 Empirical model

The majority of the methodology builds on the frequently used fixed effects model, which will act as a benchmark model\textsuperscript{42}. Then we consider two alternative extensions: A dynamic fixed effects (DFE) model and a within-between random effects (WBRE) model.

5.1 The static fixed effects model

Consider the static fixed effects regression model:

\[
d_{it} = \beta_0 + \beta_1 \text{INF}_{it} + \beta_2 \text{BONDS}_{it} + \beta_3 \log(\text{TRANSP}_{it}) + \beta_4 \log(\text{VOLUSD}_{it}) + u_i + \epsilon_{it}
\]

(3)

For \(i = (1,2,...,15)\) and \(t = (1,2,...,36)\)

Where

\[
d_{it} = \log\left(\frac{\text{BTCUSD}_{it}}{\text{BLX}_{it}}\right)
\]

(4)

\[
\epsilon_{it} \sim N(0, \sigma^2_{\epsilon})
\]

(5)

\(u_i\) represents the unobservable fixed effects for each country \(i\) and \(\epsilon_{it}\) is the within-country error term. \(\text{INF}_{it}\) is the month-on-month inflation, \(\text{BONDS}_{it}\) the average monthly

market premium on 10 year government bonds, $TRANSP_{it}$ the corruption level and $VOLUSD_{it}$ the total monthly value of all bitcoin trading (in USD), all of them observations in country $i$ at time $t$.

A limitation of this static model is that it will not incorporate previous values of our dependent variable, $d_{it}$ that we almost know for sure is highly auto-correlated. We can expect that a large part of the variation in $d_{it}$ will not be explained by our model.

The choice of using a fixed effects model as benchmark instead of the RE is justified by the fact that our panel data seems to suffer from severe heterogeneity bias. This is the main reason why the FE model is preferred over the RE model in panels where the number of time observations ($T$) exceeds the number of groups ($N$). Fewer groups and more time observations increases the heterogeneity issue. Our panel data consists of observations from 15 countries ($N=15$) over a period of 36 months ($T=36$), hence $N< T$. In fact, we have documented that variation differs from country to country, both in the independent- and dependent variable(s). Thus an FE model is a natural choice as it allows the country specific error terms to have different variance.

For these reasons, we will estimate our model by using clustered robust standard errors to prevent our model from underestimating them. Intuitively, presence of heteroskedasticity seems very likely, for several reasons. As the market cap of bitcoin has surged, the market has become more liquid, which in theory should reduce the variation in price difference. Also, unobserved changes within each country will have an impact. As an example, we observed a dramatic increase in the OTC-trading of bitcoins in China when the government imposed restrictions. For comparison, a fixed effects model without robust standard errors will be estimated to compare coefficients. Also a random effects model with normal standard errors will be estimated to perform a Hausman test of the two models estimated with non-robust standard errors, to make sure that our model specification is in line with the arguments above. Even though we will discuss the results from the robust regression, the Hausman test will act as a specification test of the choice of a fixed
Another limitation is that since the FE model sterilizes variation between countries, we will only be able to analyze how within variation impacts the price ratio. Since the FE model performs poorly in situations where the explanatory variables do not change much over time, this can create problems. In the proposed model, $\text{TRANS}_d$ has the same value for all months in the same year and typically does not change much from year to year. Also, inflation- and bond rates in countries with a stable economy do not change much either. Hence, interpretation of results should take this into consideration.

The results presented in the next section will act as a benchmark for further extensions of the model.

5.1.1 Results - Static FE

The results from our benchmark model is reported in Table 4. Column one and two represent the fixed and random effects model with robust standard errors, while column three and four is with standard estimation procedures, for comparison.

As expected, we see that our explanatory variables are highly correlated with the country specific effects and that all robust error terms are adjusted upwards, which indicates presence of heteroskedasticity or auto-correlation, or both. The standard error of the inflation coefficient is the only one that does not change too much, but the others change dramatically. Nevertheless, significance remains for all coefficients of interest, but volume does not seem to affect the price ratio significantly anymore.

The impact of inflation is not in line with our hypothesis. It suggests if month-on-month inflation is one percent higher than it was the previous month, it leads to a -1.77% decrease in deviation from the global price of bitcoin. Even so, it does not tell us whether countries with high inflation, on average, pay a higher price of bitcoin,
Table 4: Regression table - Static fixed effects

<table>
<thead>
<tr>
<th></th>
<th>(FE_robust)</th>
<th>(RE_robust)</th>
<th>(FE)</th>
<th>(RE)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$d_{it}$</td>
<td>$d_{it}$</td>
<td>$d_{it}$</td>
<td>$d_{it}$</td>
</tr>
<tr>
<td>$INF_{it}$</td>
<td>-0.0177**</td>
<td>-0.0189**</td>
<td>-0.0177***</td>
<td>-0.0189***</td>
</tr>
<tr>
<td></td>
<td>(0.00431)</td>
<td>(0.00635)</td>
<td>(0.00379)</td>
<td>(0.00420)</td>
</tr>
<tr>
<td>$BONDS_{it}$</td>
<td>0.0180*</td>
<td>0.0127</td>
<td>0.0180***</td>
<td>0.0127***</td>
</tr>
<tr>
<td></td>
<td>(0.00694)</td>
<td>(0.00755)</td>
<td>(0.00199)</td>
<td>(0.00185)</td>
</tr>
<tr>
<td>log($TRANSP_{it}$)</td>
<td>-0.612*</td>
<td>-0.0368</td>
<td>-0.612***</td>
<td>-0.0368</td>
</tr>
<tr>
<td></td>
<td>(0.254)</td>
<td>(0.0566)</td>
<td>(0.0595)</td>
<td>(0.0261)</td>
</tr>
<tr>
<td>log($VOLUSD_{it}$)</td>
<td>0.00547</td>
<td>-0.00147</td>
<td>0.00547***</td>
<td>-0.00147</td>
</tr>
<tr>
<td></td>
<td>(0.00476)</td>
<td>(0.00377)</td>
<td>(0.00161)</td>
<td>(0.00161)</td>
</tr>
<tr>
<td>_cons</td>
<td>2.280*</td>
<td>0.160</td>
<td>2.280***</td>
<td>0.160</td>
</tr>
<tr>
<td></td>
<td>(0.923)</td>
<td>(0.230)</td>
<td>(0.229)</td>
<td>(0.109)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.3385</td>
<td></td>
<td>0.3385</td>
<td></td>
</tr>
<tr>
<td>$AIC$</td>
<td>-1771.7</td>
<td>.</td>
<td>-1769.7</td>
<td>.</td>
</tr>
<tr>
<td>$BIC$</td>
<td>-1754.6</td>
<td>.</td>
<td>-1748.4</td>
<td>.</td>
</tr>
<tr>
<td>Corr($u_{it},X$)</td>
<td>-0.9744</td>
<td>.</td>
<td>-0.9744</td>
<td>.</td>
</tr>
<tr>
<td>$F$</td>
<td>5.53***</td>
<td></td>
<td>64.86***</td>
<td></td>
</tr>
<tr>
<td>$N$</td>
<td>526</td>
<td>526</td>
<td>526</td>
<td>526</td>
</tr>
</tbody>
</table>

Standard errors in parentheses (Robust in column 1 and 2)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
since the coefficient only captures within effects. A direct effect of higher inflation is that peoples real income decreases, if interest rates and salaries are not adjusted accordingly. The result is that after covering necessary monthly expenses, people will have less savings per month, which reduces investments. Hence the negative coefficient is not that surprising.

Regarding government bond rates, we see that the coefficient is in line with our hypothesis. Higher average monthly rates on government bonds has a positive impact on the price ratio, at a 5% significance level. However, we see that if inflation and bond rates increase proportionally, the effect on the price ratio almost diminishes, as they drag in opposite directions with almost the same impact. If government bond rates increases from a monthly average of 1% in the previous month, to 2%, the estimated effect is a 1.8% increase in the local bitcoin price relative to the global price.

We also see that a 1% increase (decrease) in the transparency (corruption) index, from the previous month, reduces the price ratio with 0.612%. This is in line with our hypothesis, but since the index only changes two times in our dataset, from Dec 2015 to Jan 2016 and Dec 2016 to Jan 2017, the result is not as robust as the findings regarding inflation and bond rates. To fully understand the impact of corruption, we need another model where we can compare between countries, as within changes in the corruption index are relatively time invariant. Intuitively, the result makes sense. A decrease in corruption levels reflects more trust in the government and financial system, together with the fact that tax embezzlement is likely reduced, reducing local demand for alternative ways to store cash.

Trading volume of bitcoin does not seem to have significant within impact on the price ratio. In developed countries, bitcoin prices are more liquid and people have access to foreign markets to a higher extent. Thus a within increase in local volume would not necessarily be associated with a decrease or increase in the premium, instead the price would likely follow the global price, keeping the ratio somewhat equal. On the other hand, emerging markets have less access to foreign markets and trading occurs more locally. This means that if the local volume in emerging
markets increase more than it does globally, the price ratio will increase. This could be an explanation why our coefficient on volume is not significant, but indicates a positive relationship. However, this effect is rather low compared with the others, as a 1% increase in volume suggests a 0.55% increase in the price ratio.

According to the correlation matrix from the summary statistics, both inflation and bond rates are positively correlated with the price ratio and that the two of them are also positively correlated. Considering the static models poor ability to predict variation, as R-squared is only 0.338, our regression suffer from omitted variable bias. Actual and predicted values of the price ratio are reported in Figure 6 below and indicates that our model struggles to explain the price ratio, especially in countries where the ratio has high volatility.

Figure 6: Actual vs. predicted values of price deviation. S-FE, Robust
5.1.2 Hausman test

To be sure that the fixed effects model is the right approach, we perform a Hausman test in STATA, where the null hypothesis is that the random model is preferred. In our benchmark model, we estimated four coefficients and the test statistics is therefore a Chi-squared test with 4 degrees of freedom. Results from the Hausman test are presented in the table below and strongly rejects the random effects model, as expected. This is a specification test based on the estimates with non-robust errors.

<table>
<thead>
<tr>
<th>Table 5: Hausman test</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\chi(4)^2$</td>
</tr>
<tr>
<td>133.49</td>
</tr>
</tbody>
</table>

5.1.3 Woolridge test of autocorrelation

In the benchmark model, robust standard errors were calculated to prevent our standard errors from being underestimated. This yielded higher standard errors, as expected, and we should therefore test for auto-correlation, due to the fact that our coefficients will be biased if we do not include lagged values. By performing a Woolridge test of no first-order autocorrelation, we will be able to conclude whether the presence of autocorrelation is significant.

<table>
<thead>
<tr>
<th>Table 6: Woolridge test of no first-order autocorrelation</th>
</tr>
</thead>
<tbody>
<tr>
<td>F(1,14)</td>
</tr>
<tr>
<td>10.10</td>
</tr>
</tbody>
</table>

The Woolridge test rejects the null hypothesis of no first-order autocorrelation. Hence, a dynamic structure needs to be investigated.

---

5.2 Dynamic fixed effects model

Consider the dynamic fixed effects model:

\[ d_{it} = \beta_0 + \theta d_{i,t-1} + \beta_1 \text{INF}_{it} + \beta_2 \text{BONDS}_{it} + \beta_3 \log(\text{TRANSP}_{it}) + \beta_4 \log(\text{VOLUSD}_{it}) + u_i + \epsilon_{it} \]  

(6)

Where the only difference from the previous model is that we have included a lag of the price deviation as an explanatory variable.

Intuitively, a dynamic model makes more sense, as the price deviation in different countries seems to follow persistent patterns over a longer period of time, in other words, history matters, which was confirmed by the Woolridge test. We can expect that this lag will explain a large part of the deviation itself (large \( \theta \)), and therefore adjust the previously biased coefficients.

5.2.1 Results dynamic fixed effects

Regression results from the dynamic model is given in Table 7. We see that a 1% increase in the lag is associated with a 0.656% increase in the current value and the corresponding coefficient is strongly significant. The model performs much better compared with the benchmark model, as R-squared (within) has almost doubled, from 0.338 to 0.665. In addition, correlation between the country fixed effects and the explanatory variables remains high, but is adjusted slightly downwards.

Even when including a lag, we see that all coefficients drag in the same direction. The impact of inflation and bond rates are adjusted downwards and so is the effect of corruption which is reduced by a factor of three. Month-on-month inflation remains significant at the 1% level, while the significance level of government bond rates increases from 5% to 1%. We see that the intercept is reduced from 2.28 to 0.70, now that the lag explains a large part of the deviation itself. Monthly trading volume remains insignificant, and this coefficient is also adjusted downwards.
### Table 7: Regression table - Dynamic fixed effects

<table>
<thead>
<tr>
<th></th>
<th>(D-FE)</th>
<th>(Benchmark)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$d_{i,t-1}$</td>
<td>0.656***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0455)</td>
<td></td>
</tr>
<tr>
<td>$INF_{it}$</td>
<td>-0.0120**</td>
<td>-0.0177**</td>
</tr>
<tr>
<td></td>
<td>(0.00322)</td>
<td>(0.00431)</td>
</tr>
<tr>
<td>$BONDS_{it}$</td>
<td>0.00838*</td>
<td>0.0180*</td>
</tr>
<tr>
<td></td>
<td>(0.00304)</td>
<td>(0.00694)</td>
</tr>
<tr>
<td>$\log(TRANSP_{it})$</td>
<td>-0.200**</td>
<td>-0.612*</td>
</tr>
<tr>
<td></td>
<td>(0.0511)</td>
<td>(0.254)</td>
</tr>
<tr>
<td>$\log(VOLUSD_{it})$</td>
<td>0.00385</td>
<td>0.00547</td>
</tr>
<tr>
<td></td>
<td>(0.00204)</td>
<td>(0.00476)</td>
</tr>
<tr>
<td>cons</td>
<td>0.707**</td>
<td>2.280*</td>
</tr>
<tr>
<td></td>
<td>(0.207)</td>
<td>(0.923)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.665</td>
<td>0.3385</td>
</tr>
<tr>
<td>AIC</td>
<td>-2085.2</td>
<td>-1771.7</td>
</tr>
<tr>
<td>BIC</td>
<td>-2064.1</td>
<td>-1754.6</td>
</tr>
<tr>
<td>Corr($u_{i},X)$</td>
<td>-0.8225</td>
<td>-0.9744</td>
</tr>
<tr>
<td>F</td>
<td>145.6***</td>
<td>5.53**</td>
</tr>
<tr>
<td>N</td>
<td>509</td>
<td>526</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Hence, our previous coefficients were biased due to presence auto-correlation.

More interestingly, the coefficient on government bonds is reduced more than the coefficient on inflation. This is due to the fact that government bonds are almost twice as correlated with the price ratio than inflation, as presented in the summary statistics table.

There are mainly two factors determining government bond rates with long maturity, interest rates and credit risk. A temporary change in short-term interest rates, which affects month-on-month inflation, does not necessarily affect government bonds with long maturity. Hence an increase typically originates from an increase in long-term interest rates or credit risk, but we cannot directly differ between the two as we do not have data on long-term interest rates. The findings suggest that the short-term effect of inflation has a bigger impact on the local price ratio of bitcoin than the long term effect, which sounds reasonable.

Figure 7 graphs actual vs. predicted values of price ratios of different countries in the dynamic model, where prediction errors are reduced dramatically.
5.3 Within-between random effects model

Due to the fact that our panel data suffers from heterogeneity bias, the Hausman test will tell us to use the FE model because it simply eliminates the heterogeneity problem by making variation between countries irrelevant. Bell & Jones (2015) claim that the Hausman test is not really a test to decide between the FE or RE model. It is a test of the similarity in the between and within variation. Their argumentation is that by removing variation between countries, the FE model will often limit our ability to investigate what we are interested in. Since our data only covers a period of slightly more than 3 years, macroeconomic variables will rarely change too much, but they differ significantly between countries, which is an important aspect of this thesis. Thus, the most appropriate model for the purpose

---


Consider the model:

\[
d_{it} = \beta_0 + \beta_1(INF_{it} - \overline{INF}_i) + \gamma_1INF_i
+ \beta_2(BONDS_{it} - \overline{BONDS}_i) + \gamma_2BONDS_i
+ \beta_3(\log(TRANSP_{it}) - \overline{\log(TRANSP)}_i) + \gamma_3\log(TRANSP)_i
+ \beta_4(\log(VOLUSD_{it}) - \overline{\log(VOLUSD)}_i) + \gamma_4\log(VOLUSD)_i
+ \nu_{it}
\]

(7)

Where

\[
v_{it} = u_{it} + \epsilon_{it}
\]

(8)

\[
u_{it} \sim N(0, \sigma^2_u)
\]

(9)

\[
\epsilon_{it} \sim N(0, \sigma^2_e)
\]

(10)

\(INF_i, BONDS_i, CORRUPT_i\) and \(VOLUSD_i\) represent the clustered means in country \(i\), of the explanatory variables in our benchmark model. By subtracting the country specific mean from each of their respective current value at time \(t\), those differences become fully independent explanatory variables with expectation zero, but different variances in different countries, as in the FE model. Hence, the coefficients \(\beta_1, \beta_2, \beta_3\) and \(\beta_4\) will have the same interpretation as in the benchmark model, as they capture within effects. Most importantly, the coefficients \(\gamma_1, \gamma_2\) and \(\gamma_3\) capture between effects, as they represent the marginal effect of a change in any of the country specific means, which are time-invariant and of particular interest.

This model allows for comparison of different countries, yet still keep the properties of the fixed effects model, even though we are not able to directly measure the fixed effects, which are included in the overall residuals \(v_{it}\), expressed in equation 8. \(v_{it}\) is randomly distributed, by assumptions in the random effects model. The residuals
at within level, $\epsilon_{it}$, have the same properties as in the benchmark model.

### 5.3.1 Results WB-RE

Regression results are reported in Table 10 together with results from the static fixed effects benchmark model, both estimated with robust standard errors. By comparing results, we see that the hat variable coefficients, which represents deviation from the clustered means, are the same. Also the within R-squared in our WB-RE model is the same as the one reported in our benchmark model, but the between and overall are much higher, as we control for clustered means as well. Still the overall is less than the dynamic model. Actual vs. predicted values is illustrated in Figure 8. The constant term is not significant and close to zero and we basically have several fixed effects, instead of one per country.

The results suggest that countries with a higher average month-on-month inflation rate significantly pay a higher price for bitcoin compared with countries with lower average inflation. The significance level of monthly and average inflation has increased to a 0.1% level, indicating strong evidence that inflation indeed has an impact. Regarding average monthly inflation, we can compare Argentina with the UK, whose average monthly inflation rates were 2.033% and 0.128% respectively, from January 1, 2015 to December 31, 2017. The isolated effect suggests that the price ratio in Argentine markets relative to the UK should be 13.26% higher ($=\gamma_1(2.033-0.128)*100$). This is perfectly in line with the hypothesis, and would not have been captured in the FE model.

Country specific means of government bonds do not seem to have a significant impact at a 5% level. However, STATA reports a t-value of 1.88, indicating positive relationship at a 6% significance level. A within change in government bonds is now significant at a 1% level, compared with 5% in the benchmark model.

The results also provide evidence that higher average total trading volume have a significant negative impact on the price deviation at a 1% level, which is logical.
Table 8: Regression table - Within-between random effects

<table>
<thead>
<tr>
<th></th>
<th>(WB-RE)$^\dagger$</th>
<th>(Benchmark)$^\dagger$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$d_{it}$</td>
<td>$d_{it}$</td>
</tr>
<tr>
<td>$INF_{it}$</td>
<td>-0.0177$^{***}$</td>
<td>-0.0177$^{***}$</td>
</tr>
<tr>
<td></td>
<td>(0.00431)</td>
<td>(0.00383)</td>
</tr>
<tr>
<td>$INF_i$</td>
<td>0.0696$^{***}$</td>
<td>.</td>
</tr>
<tr>
<td></td>
<td>(0.00558)</td>
<td>.</td>
</tr>
<tr>
<td>$BONDS_{it}$</td>
<td>0.0180$^{**}$</td>
<td>0.0180$^*$</td>
</tr>
<tr>
<td></td>
<td>(0.00695)</td>
<td>(0.00694)</td>
</tr>
<tr>
<td>$BONDS_i$</td>
<td>0.00472</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00251)</td>
<td></td>
</tr>
<tr>
<td>$\log(TRANSP_{it})$</td>
<td>-0.612$^*$</td>
<td>-0.612$^*$</td>
</tr>
<tr>
<td></td>
<td>(0.255)</td>
<td>(0.254)</td>
</tr>
<tr>
<td>$\log(TRANSP_i)$</td>
<td>0.0360$^*$</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0170)</td>
<td></td>
</tr>
<tr>
<td>$\log(VOLUSD_{it})$</td>
<td>0.00547</td>
<td>0.00547$^{***}$</td>
</tr>
<tr>
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<td>(0.00478)</td>
<td>(0.00476)</td>
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<td>$\log(VOLUSD_i)$</td>
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<td>(0.00377)</td>
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<td>cons</td>
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<td>(0.923)</td>
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<td>$R^2$ (between)</td>
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<td>.1234</td>
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<td>.0797</td>
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<td>Wald $\chi^2$(8)</td>
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Robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

$^\dagger$ "Hat" variables refer to difference from clustered means
Our dataset covers countries with big differences in trading volume, where the cumulative volume of the top three countries constitutes more than 60% of total trading volume for all countries. Top countries are China, Russia and the UK, all of which average price ratios of bitcoin are below the average of all countries in our sample.

Regarding the effect of a country’s average transparency index, we obtain a rather surprising result. A higher transparency index (less corruption) leads to a higher price ratio at a 1% significance level. However, a within change drags in the other direction. Whether the effect of a within increase in transparency leads to a net positive relationship depends on the average level and the change.

**Figure 8:** Actual vs. predicted values of price deviation. WB-RE Robust

Finally, we have government bond rates, where a within increase has a positive impact. We also see that countries with higher average bond rates pay a higher premium. Thus, bond rates have a positive impact on local bitcoin prices, both dragging in the same direction.
6 Discussion and conclusion

Considering the never ending data availability on bitcoin prices, there are still a lot that can be done to expand the scope of this thesis. Further studies may expand the model to include more currency pairs and explanatory variables such as local electricity prices, mining activity, capital control measures and changes in the regulatory environment in different countries. The models should not only include lagged values of the dependent variable, but also of the explanatory variables.

Based on the findings in our very simplified models, we can say with a high level of confidence that our variables have an impact on the price deviation as explained above. Nevertheless, the local price differences have been calculated based on daily official exchange rates and will likely overestimate the premiums in the case where official rates differ substantially from the unofficial rates, as discussed in Pieters & Vivanco (2015). By including countries with black market exchange rates, such as Argentina, which is the country that deviates the most from the BLX, it will likely yield a biased result as it underestimates actual exchange rates.

The ability to reduce the exposure to financial uncertainty and thus being willing to pay a premium, seems logical from an economics perspective, even though the risk associated with Bitcoin is large as well. However, the downside risk of a fall in the bitcoin price can be somewhat mitigated if the only purpose of using the Bitcoin network is to transfer money abroad.

and we find evidence that month-on-month inflation, 10 year government bond rates and corruption levels affect the local price of bitcoin relative to global markets. First we estimated a benchmark model that allowed us to analyze within changes, but this model performed rather poor when predicting the local price deviation, as we were not able to capture the true data generating process.

Then we included a lag of the local price deviation to solve the auto-correlation issue that was documented. The dynamic fixed effects model found that our previous estimates had been biased, some more than others as the inflation coefficient

\[ 47 \text{Pieters, G., & Vivanco, S. (2015). Bitcoin arbitrage and unofficial exchange rates.} \]
did not change much. Some coefficients became even more significant and all signs remained, dragging in the same direction as in the benchmark. In other words, a large part of the local price deviation of bitcoin is explained by its previous value. The dynamic model performed much better, but our benchmark model was not too far off.

After investigating a dynamic structure, we took one step back instead of continuing with a lag. The within-between model provided us with valuable information on how country averages of the explanatory variables had an impact. Even though the estimates in this model is somewhat biased due to auto-correlation, we got a better understanding of the overall picture.

We found that higher average month-on-month inflation rates positively impacts the price deviation, but that a within increase affected the deviation negatively. Surprisingly, higher transparency was significantly associated with a higher premium, but a within change led to a decrease in premium. Bond rates were significantly affecting the price positively through an within change but not significant at a 5% level between countries.

7 Policy recommendations

Firstly, a realistic approach needs to be considered. The regulator should allocate resources to develop a good way to track transactions on the network the ability for criminals to operate under the radar of the government is still a challenge. Practically, it is impossible to prevent criminals from using the Bitcoin network. The only way to fully prevent criminal related transactions to occur on the network would be to eliminate all mining activity, which would require a global agreement that made sure a ban was enforced everywhere. This seems unlikely. However, the regulator should think twice before banning cryptocurrency exchanges, as this will lead to an increase in the volume of over-the-counter trading, making it even harder to follow developments. Higher OTC trading volume would
benefit criminals as it would be even easier for them to liquidate their bitcoin holdings into fiat. A better option would be to work closely with cryptocurrency exchanges and help them develop better anti-money-laundering processes.

Bitcoin and blockchain technology can provide easier conduct of money transfers to developing countries with high corruption rates and in addition be a better way to secure the value if high financial uncertainty. Easier to track transactions.
8 Bibliography


Maurer, B., Nelms, T. C., & Swartz, L. (2013). “When perhaps the real problem is money itself!”: the practical materiality of Bitcoin. Social Semiotics, 23(2),


URLs

• Blockchain (2017) "Transaction info" https://blockchain.info/tx/4a5e1e4baab89f3a32518a88c31bc87f618f76673e2cc77ab2127b7afdeda33b?show_adv=true, accessed 10/05-2018


- Bitcoin.org (2008) "Bitcoin: A Peer-to-Peer Electronic Cash System"
  https://bitcoin.org/bitcoin.pdf, accessed 10/05-2018
- BitcoinWiki (2017) "Protocol Rules"
- EliteFixtures (2018) "Bitcoin Mining Cost Throughout the World"
  https://www.elitefixtures.com/blog/post/2683/bitcoin-mining-costs-by-country/, accessed 10/05-2018
- Forbes (2016) "How India’s Demonetization is Affecting it’s start-ups"
- Medium (2017) "Venezuelans turns to ZCash & Ethereum Amidst Political Turmoil"
- Planet Money (2011): "What is Bitcoin?"
- The Times (2009) "Genesis Block Newspaper"
  https://www.thetimes03jan2009.com/, accessed 10/05-2018
- Quandl (2018) "Local Bitcoins"
  https://www.quandl.com/data/LOCALBTC-Local-Bitcoins, accessed 10/05-2018
- Tradingeconomics (2018) "Venezuela- Inflation rate"
- Tradingeconomics (2018) "Inflation Rate Mom"
  https://tradingeconomics.com/country-list/inflation-rate-mom, accessed 10/05-2018
- Tradingeconomics (2018) "Markets - Bonds"
  https://tradingeconomics.com/bonds, accessed 10/05-2018
- Tradingeconomics (2018) "Corruption Index"
  https://tradingeconomics.com/country-list/corruption-index
## 9 Appendix

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Table 9: Inflation Rate MoM - Tradingeconomics sources

Table 10: Government Bond 10Y - Tradingeconomics sources
# Table 11: Euro area - Corruption Index

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