Skidmore College
Creative Matter

Economics Student Theses and Capstone Projects

Economics

2018

The Value of Bitcoin: A Closer Look at How Investor Attention Affects the Value of Bitcoin

Joseph Warner
Skidmore College, jwarner1@skidmore.edu

The Value of Bitcoin: A Closer Look at How Investor Attention Affects the Value of Bitcoin.

By

Joseph Warner

A Thesis Submitted to

Department of Economics

Skidmore College

In Partial Fulfillment of the Requirement for the B.A Degree

Thesis Advisor: Qi Ge

May 1, 2018

Abstract

This paper looks at two measure of the value of Bitcoin (the price and volume traded in the last month of Bitcoin) and sees if investor attention causes any changes in the values of Bitcoin. This paper also adds exchange rates, the S&P 500, and the price of gold as other possible explanations for the value of Bitcoin. This paper examines the variables at a worldwide level and at the countries with the top 10 GDP in the world. The results of this paper find that investor attention has a significant positive relationship with the value of Bitcoin. Specifically at the country level, Russia consistently has a significant relationship with the value of Bitcoin.

A. Introduction

Bitcoin is a cryptocurrency that has gained attention due to its incredibly high volatility and possibility of high returns. In 2013, bitcoin was 142% more volatile than the USD, Euro, Yen, British Pound, and Swiss Franc. (Yermack 2014). On February 1, 2018, the total amount of Bitcoin transactions were 297,182,366 and seem destined to grow. The price of Bitcoin has grown from $0.06 in June 30, 2010 to a height of $13850.40 USD in December 1, 2017 a 230,839% growth in the price. It is important to study the determinants of Bitcoins value since the factors that cause changes in the value of Bitcoin are currently unclear. The implications of finding an accurate way to value Bitcoin could lead to more accepted use throughout the world.

Bitcoin is a very interesting type of currency. On one hand, Bitcoin is a decentralized currency that is used in transactions and the sending of money without country regulations and fees. On the other hand, Bitcoin is a financial asset that is very risky and yields large returns. The media has focused on the extreme growth and volatility of Bitcoin causing many misinformed investors to flock to Bitcoin. As the media hype has grown so has the value of Bitcoin, thus it is interesting to study how the value of Bitcoin reacts to investor attention.

In this paper, I use two measures of the value of Bitcoin on a monthly basis from June 30, 2010 until February 1, 2018. My two measures for the value of Bitcoin are the price and volume traded in the last month. These two measures of the value of Bitcoin allow me to examine if investor attention causes rises in price and volume due to hype and awareness. My investor attention variable is gathered from Google Trends, because it has been found as a viable proxy for thoughts and intentions of a population (Stephens-Davidowitz 2014). Additionally, I examine investor attention at a worldwide level and at country level of the top 10 GDPs. Using this data, I examine the effects of investor attention on the value of Bitcoin similar to Li et al (2016), using similar empirical frameworks of Stephens-Davidowitz (2014) and Dyhrberg (2016). Additionally, I add a measure of the price and volume traded of the S&P 500 to check if the financial market has an effect on Bitcoin. I also add the price of gold to check the relationship between the value of gold and Bitcoin that was identified by Dyhrber (2016). I add exchange rates in USD for all the countries that I examine in the study to check how the currency market affects Bitcoin. The final regression I run looks to see if what the lagged variables of volume of Bitcoin traded and investor attention have on the price of Bitcoin.

My finding provide evidence that investor attention has an effect on the value of Bitcoin. My year fixed effects for year show that the volume and price of Bitcoin has grown since 2010 until 2018. At the worldwide level, investor attention has an effect on the volume, as investor attention grows by 1% the volume traded grows by 0.03%. Worldwide investor attention also effects the price of Bitcoin as investor attention grows by 1% the price of Bitcoin rises by 0.02%. Worldwide investor attention was consistent even when the variables of the S&P 500 and the price of gold were added to the regression. The only country that had investor attention effect both volume and price of Bitcoin was Russia. I assume that the reasons that Russia has such an impact on the value of Bitcoin is because Russia was one of the first mover in the acceptance of Bitcoin. When the Russian currency began to fail, the people of Russia found that Bitcoin was a smarter safer alternative. Therefore this caused Russia to accumulate more Bitcoins through lots of transactions leading to why it has such a large effect on the value of Bitcoin. Japan had a negative effect on the volume of Bitcoin. The contributions of my work is that I add to the literature of Bitcoin in two ways. I add to the literature that Bitcoin is a financial asset and to the literature of what causes the price of Bitcoin. Additionally, I also add to the literature of investor attention and how it effects the value of financial assets and the Google Trend literature.

The rest of the paper is organized as follows. Section B examines the related literature. Section C and D displays and explains the data used in this paper and introduces the models used to examine the effect of investor attention on value of Bitcoin. Section E introduces expected results from my models. Section F and G present and discuss the main findings of this paper. Concluding remarks are offered in Section H.

B. Literature Review:

1. Bitcoin

1.1 Bitcoin Origins

In 2008, Satoshi Nakamoto first introduced the idea of Bitcoin. Bitcoin was created as a type of electronic cash that could be used from peer-to-peer payments (Nakamoto 2008). Before the introduction of Bitcoin, online payments had to rely on a third party financial institution to makes sure the payments were legitimate. These third party financial institutions would charge some sort of transaction fee. Nakamoto stated that these institutions prevented "small casual transactions" from occurring frequently due to the transaction fee. Since third party financial institutions were previously needed to prevent any double-spending of online payments, Nakamoto suggested," an electronic payment system based on cryptographic proof instead of trust" (Nakamoto 2008). Bitcoin's electronic payment system would allow a transaction to occur without a trusted third party financial institution. Nakamoto's new method would protect buyers and sellers by offering a timestamped public ledger of transaction in chronological order. Nakamoto's proposition in theory would then make Bitcoin a completely decentralized currency. Nakamoto's innovations would eventually lead to block chain technology and the development of miners.

1.2 Bitcoin History

On January 3, 2009, Nakamoto mined the first 50 Bitcoin to show the method of mining to an online audience (Yermack 2013). Bitcoin mining is the process in which transaction are verified. Ma et al. (2018) refers to the act of mining as a "game," the goal of this "game" is to solve a computational puzzle which to leads to transactions adding on to the blockchain. A new block, a group of transactions, is added to the blockchain on average every 10 minutes (Ma et al. 2018). The blockchain is a decentralized public ledger of transactions, where miners, solvers of the puzzle, are continuously accessing and confirming transactions on the public ledger. The puzzle is not solved through strategy but through a set number of commutations in a puzzle. The more difficult a problem is; the more guesses are needed to solve the puzzle. As the price of Bitcoin has grown the difficulty has also grown. Once the puzzle is complete, it requires only one calculation to see if the miner is correct. For this reason, the computational strength in order to compete in mining is very high and requires a lot of power. It is estimated that the energy used for mining operation makes mining the 56th largest consumer of energy in the world and 75 times higher than the Visa network. (Ma et al. 2018). Due to this energy use, China decided to tax the energy usage of miners in 2018. The incentives for the miners are newly issued Bitcoin and sometimes a transaction fee. Ma et al. (2018) states that mining solves two important issues: mining ensures that only one block of transactions will be added and verified on the blockchain. Secondly, it prevents doubling spending on transactions that already have been verified and spent. In October of 2009, New Liberty Standard published the first United States Dollar (USD)-Bitcoin exchange rate of one Bitcoin for 0.076 of a penny (Crane 2017). One week later Martti Malmi made the first sale of Bitcoin to New Liberty Standard via PayPal. New Liberty Standard sent Martti Malmi $5.02 USD in exchange for 5,050 bitcoins raising the price to of Bitcoin to

0.099 of one penny (Crane 2017). On May 22, 2010 the first bitcoin transaction occurred. The first transaction was for two pizzas, costing 10,000 bitcoins, which, equaled to $25 USD at the time (Bonneau 2015). As the interest around Bitcoin began to grow, Jeb McCaleb started Mt. Gox in July 2010; an online platform for the trading of Bitcoin based out of Japan. The first day of trading showed that 20 bitcoins traded for 4.951 cents each (Yermack 2013). The first Bitcoin security issue occurred on August 15, 2010 when users hacked into Bitcoin and created over 184 billion bitcoins in one transaction, the hack and transaction were quickly spotted and then nullified (Miller 2015). This was the first of many security breaches with Bitcoin and Bitcoin trading websites.

Bitcoin saw substantial growth in 2011 as 5.25 million Bitcoins had been generated and Bitcoin had reached parity with the USD. In April 2011, the first article in mainstream press about Bitcoin was published by *TIME* magazine. This exposure lead Bitcoin to reach a price of $10 USD (Miller 2015). The growth and use of the Silk Marketplace, an online marketplace that sells illegal items, sparked growth in the price of Bitcoin. It was speculated that the majority of Bitcoin transactions occurred on this illegal platform due to the anonymous characteristics of Bitcoin (Yermack 2013). The FBI shut down the Silk Road marketplace in 2013 and the FBI seized around 26,000 BTC (Miller 2015). In July 2011, the first Bitcoin app created for iPhones was released. Finally, in 2011, the first Bitcoin Conference and first European Bitcoin Conference was held (Miller 2015).

In 2012, Bitcoin-Central was formed as the first Bitcoin exchanged that waslicensed as a financial institution in Europe. Bitcoin's market cap surpassed $1 billion for the first time in April of 2013. Mt. Gox saw some issues in May of 2013 when Financial Crimes Enforcement Network (FinCEN) established new regulatory rules for "decentralized virtual currencies." This classified Bitcoin miners and exchanges to register as Money Service Business (MSBs). These other regulations for MSBs were "to disclose large transactions and suspicious activity, comply with money-laundering regulations, and collect information about their customers" (Miller 2015). Mt. Gox did not register as a MSBs so they faced legal repercussions of the government seizing $5 million from US accounts (Miller 2015). Once Mt. Gox received its MSBs license in July of 2013, customers throughout the world were experiencing delays of weeks and months during transactions. Mt. Gox announced their bankruptcy on February 23, 2014. Another problem that Bitcoin faced was that China decided it would not allow their banks to use Bitcoin or to use Bitcoin as a currency, although Chinese individuals could still trade Bitcoin as an asset in December 2013 (Miller 2015). Even with the restrictions and issues, the commercial use of Bitcoin started to become more evident. The first Bitcoin ATM was founded in Canada. Websites like OkCupid, Reddit and Overstock.com began to accept Bitcoin as payment (Miller 2015). The total supply of Bitcoin is 21 million bitcoins, which are released every 210,000 blocks at half the number of bitcoins that were released in the prior period.

1.3 Bitcoin Currency Problems

Gervais et al. (2014) examine the possible risks associated with Bitcoin by examining if Bitcoin was truly a decentralized currency. The three ways the authors identify that Bitcoin is not a decentralized currency are mining pools, coin tainting, and web-wallets. These could pose potential risks in the future of Bitcoin with those who are unfamiliar with the power that these entities hold.

Mining pools were the first entities that Gervais et al. (2014) examine. Since the mining of Bitcoin has become so lucrative and difficult due to computation power needed, mining became very expensive which led to mining pools. Mining pools are establishments of miners who share their computational power to create one large entity with higher combined computational power. Under these mining pools, miners work together to corroborate and check the creation and validity of the block chain. Every time a miner successfully mines a Bitcoin, they are rewarded with a fractional amount of the Bitcoin. Therefore, to create a steady amount of payouts mining pools have been formed. Gervais et al. find that in 2013, 75% of the entire computing power (checking and validating) of Bitcoin was controlled by six mining pools (Gervais et al. 2014). This is significant because it requires only 50% of the computing power to confirm a transaction, therefore if these mining pools were ever to collude or come together they could completely control the transactions of Bitcoin (Gervais et al. 2014).

Ma et al. (2018) examine how miners would succeed in different forms of competition. The models that Ma et al. use look at different aspects of the mining process such as technology of the miners, size of the miners, how many computations are needed to solve the puzzle, payoff of the solution of the puzzle, and Nash equilibrium of the miners to find the equilibrium of different scenarios of competition. In the current "game" of mining, the authors find when holding technology constant for other miners, an increase in a miners technology does not guarantee the miner will reach the K computations first. The authors then examine the competition of mining in a free entry market where all miners must use the same technology. The results in this style of competition in mining would lead to expected profits of zero in the long run. In a free market where the difficulty of solving decreases as the number of miner increase the authors find that probability of solving the puzzle drops, lowering expected value of winning. Finally, the authors examine what the effect of a monopoly would be on competition, as mentioned in Gervais et al. (2014) the possibility of a monopoly exists if all mining pools were to combine or form a cartel. In a scenario where there is a mining monopoly, they would decrease technology to as low as possible to cut costs and lower the difficulty of solving the puzzle. A monopoly would result in a public centralized ledger. Although, they would not be able to double spend bitcoins owned by others, they would have the ability to spend their own bitcoins as many times as they would want. This would lead to coin tainting, since anyone can see the misuse of bitcoins on the public ledger, these coins end up being devalued. Ma et al. (2018) offer some very interesting insight on the competition of mining but finds most of its results through theory so it is hard to judge how accurate these situations would turn out.

Coin tainting is a second way that does not qualify Bitcoin as a decentralized currency. Coin tainting is the method in which Bitcoin tries to "achieve accountability and prevent theft." When coins are tainted it can lead to the devaluation of Bitcoin and less transactions taking place. Gervais et al. (2014) run an experiment looking at the block chain to see if this is indeed true. The results show that a single coin tainting affects a large amount of transactions and that coin tainting leads to a decrease in the price. Consequently, coin tainting affects both the transactions and price.

Finally, the last reason that Bitcoin was not a decentralized currency is web-wallets. Since most people do not have the power and technology to create their own ways to store Bitcoin, many web-wallets have emerged. These web-wallet holds the bitcoins of thousands of people and do not offer any type of insurance or security. Therefore if there is a hack into theses web-wallets, which has happened on multiple occasions, your bitcoins can basically disappear (Gervais et al. 2014). Instawallet, a web-based Bitcoin wallet, was hacked in April 2012 and resulted in the loss of 35,000 BTC which was valued at more than $4.6 million USD (Miller 2015).

If Bitcoin is not considered a decentralized currency, it must be examined if Bitcoin acts like a bona fide currency. Yermack (2013) examined if Bitcoin has the capabilities to become a real currency. Yermack came to the conclusion that Bitcoin does not have the characteristics of a bona fide currency including medium of exchange, a store of value, and a unit of account.

The first reason that the author claims Bitcoin is not a *bona fide* currency is due to its limited commercial use. Coinbase estimated in 2013 that only about 15,000 Bitcoin transactions per day are made for goods or services. Coinbase, founded in 2012, is a digital currency wallet and platform where merchants and consumer can trade digital currencies based out of San Francisco, California[1]. They have over 10 million users and have traded over $50 Billion USD. Overstock.com was the only established business that was accepting Bitcoin (Yermack 2013). The way that goods and services would be priced was another reason that Bitcoin could not be a bona fide currency. As the price of Bitcoin continues to rise, it becomes harder and harder to put a price on a normal daily good. If something were to be priced normally for only $5 USD, it would then mean that the Bitcoin valuation of this good would have multiple decimal places before you would be able to see the price. This would be a nuisance for people who have normal price reference points.

The volatility that is associated with Bitcoin is another reason that prevents Bitcoin from being a bona fide currency. Bitcoin has been known to have large jumps and drops that make it very hard to keep its value at the time of the purchase. It also means that the price of goods/services is constantly changing. Finally, the last reason mentioned on why Bitcoin is not a bona fide currency, is security. People are constantly trying to hack and steal Bitcoin, which has led to many worries in the Bitcoin industry (Yermack 2013). Unlike most bona fide currencies it

[1] https://www.coinbase.com/about

is not backed by any type of insurance so if one were to lose their bitcoins, they would not be guaranteed any of their money returned. For example, in August of 2011 MyBitcoin, an online exchange, was hacked into. The hack caused the exchange to shut down- the exchange was only able to refund 49% of customer deposits and other customers ended up losing nearly $800,000 due to the hack. The biggest example of this loss was the bankruptcy of Mt. Gox losing somewhere around 750,000 bitcoins (Miller 2015).

The literature reviewed in this section makes it hard to view Bitcoin as a currency. The literature offers multiple issues associated with considering Bitcoin as a currency like issues of security and volatility. It is also very hard to use Bitcoin as a unit of exchange for normal commodities. Since there are many issues with linking Bitcoin as currency, additional literature has claimed that Bitcoin has more characteristics of a financial asset rather than a currency.

1.4 Bitcoin as a Financial Asset

On March 25, 2014, the IRS announced that Bitcoin would not be taxed as a currency. Instead it would be taxed as a capital asset and subject to capital gains taxes once sold. Stocks and other financial securities are also subject to this tax; thus the IRS must view Bitcoin as similar to a financial asset. Yermack (2013) compares to the volatility of exchange rates of multiple proven currencies and Bitcoin in terms of USD. The author looked at the daily exchange rates in 2013 of the Euro, Yen, British Pound, and Swiss Franc in addition to Bitcoin. The results showed that the exchange rate volatility in 2013 was 142%, while the other currencies volatility were between 7% and 12% (Yermack 2013). The author then compares Bitcoin's volatility to widely traded stocks volatility, which is between 20% and 30%. The author then examines the correlation of the daily changes of Bitcoin compared to the other currencies. The results showed that Bitcoin has practically zero correlation with the other currencies. Conversely all currencies except Bitcoin have strong positive correlation with other currencies. The author concludes that Bitcoin is not affected in a positive or negative way when there are macroeconomic factors that would affect currencies. The author suggests that Bitcoin has similar behaviors to a risky investment rather than a currency.

Dyhrber (2016) explores if Bitcoin could be used in a similar manner to gold in hedging against stocks and USD. The author expresses that Bitcoin shares some characteristics that make gold a financial asset. These characteristics include "scarcity of supply, supply is not controlled by a government but independent agents, both assets have high price volatility and total supply is finite" (Dyhrber 2016). The author uses the daily prices Financial Times Stock Exchange (FTSE) Index and the daily USD-Euro and USD-Sterling exchange rates from July 19, 2010 until May 22, 2015. The author uses an OLS regression to examine the effects that the lagged daily FTSE and lagged daily USD-Euro and USD-Sterling exchange rates have on the price of Bitcoin. The author's results suggested that Bitcoin returns are not affected by changes in the FTSE, which would allow investors to hedge the risk of the market. The results are very similar to the results of Baur and Lucey (2010), who looked at the hedging capabilities of gold in the FTSE. The author's results show that there is a very small correlation that the exchange rates positively lead the Bitcoin returns. The author suggests that since the correlations are so small the relationship could be short-term and may have to question their significance. Capie et al (2005) find similar results when comparing gold to exchange rates of the sterling-dollar and yen-dollar. The author concludes that Bitcoin can be used in a similar manner to gold when hedging investments to minimize risks of a portfolio.

The literatures in this section show that Bitcoin may have characteristics and act like a financial asset rather than a currency. One paper argues that it has the characteristics of gold while another suggests that it is more like a stock. This allows me to consider Bitcoin as a financial asset allowing me to use investor attention as a determinant of Bitcoin's value. Additionally, the model that is used is Dyhrber (2016) is similar to the model used in this paper because it examines how different variables affect the price of Bitcoin.

2. Google Trends

Google Trends is a database that records and analyzes all the of the Google search data into one platform. A user of Google Trends can search a term or phrase and the result will show the interest that Google users have shown on 0-100 scale. The 0-100 scale can cause limitations in research due to the way the data is adjusted. The Google Trends data for a specific search term is adjusted by dividing the total amount of a specific search term by the total amount searches in the selected geography and time period. This number is then scaled from 0-100 based off the specific search terms proportion to all search terms.[2] This only allows Google Trends data to be examined with relative popularity instead of total search numbers making it very hard to compare. Google Trends data is anonymized, categorized, and aggregated allowing users to view interest of a certain topic at a global level or even at city-level.

Stephens-Davidowitz (2014) reveals that Google Trends can used as a viable proxy for the behaviors of individuals. Stephens-Davidowitz (2014) compares racial animus to President Barack Obama's vote shares during the presidential election. The author affirms that Google Trends is an accurate measure in this study due to the lack of self-reporting bias and that people

[2] https://support.google.com/trends/answer/4365533?hl=en

are more forthcoming with Google Searches. In previous surveys exploring racism during the presidential election, the possibility of self-reporting bias could be present due to the nature that the respondent did not want to seem racist. The author states that Google users are more forthcoming with their searches due to interest of a number of searches for things like pornography that otherwise would not be discovered in other ways. The author looked at Google Trends data from 2004-2007. In order to measure the racially charged search rate in an area, the author looked at the amount of Google searches using a derogatory racial term towards African Americans over the total Google searches in an area. The data encompassed all 50 states and more than 99% of American voters. The author also used data from white democratic presidential election to make sure a person's political affiliation did not affect the results. The model that the author uses is an OLS regression where the dependent variables are the results of percentage of people who voted for Obama and results of turnout during the presidential election and the independent variable is the Google Trends data results of racially charged words. The results showed that areas with high racially charged search rate supported Obama more than a previous white democrat. The author also finds that racially charged search rate is a robust negative predictor of Obama's vote share in the area. Finally, the racial prejudices against Obama resulted in around 4.2% decrease in the national popular vote.

Stephens-Davidowitz's (2014) study shows that Google Trends can be used as an accurate proxy for the behaviors and thoughts of individuals because the Google Trend data accurately depicted the voting results of racist people during the President Obama's presidential election. Due to the accuracy of being a proxy, Google Trends has commonly been used in finance to see how investors care about different financial questions or issues. In this paper, Google Trends will be used to see how attentive the general public is to Bitcoin and if it affects

Bitcoin's value. The model in this paper also uses aspects of the model in Stephens-Davidowitz (2014) by also using the Google Trends data as the independent variable.

3. Investor Attention Measure in the Financial Market

3.1 Investor Attention Measure without Google Trends

Investor attention was once considered not important in the performance of stocks due to the Efficient Market Hypothesis. This hypothesis states that all investors are rational and pay attention to all news in a timely manner (Li et al. 2016). The Efficient Market Hypothesis predicts that all prices in the financial markets accurately describe all available information. However, this has not been found to be the accurate scenario in financial markets (Wu and Shamsuddin, 2014). Instead there is the gradual information diffusion hypothesis, discovered by Daniel Kahneman in 1973, which states that attention is a scare resource. This means that focusing on one item will diminishes the resources available to focus on other items. For example, if someone were to completely focus on one item of information they would not be able to focus on anything else until that information is digested. This can then lead to price-delay effects or a lead-lag effects in financial markets which is why investor are constantly trying to beat the market (Wu and Shamsuddin, 2014). This is important in the market because there is a lot of information readily available for most investors. Investors must pick and choose which information they value most and which information they do not consider as valuable to be successful in markets.

The way in which investors decide to allocate their attention in the market leads to the information to gradually be processed by the whole entire market. Wu and Shamsuddin (2014), examines how different stock factors lead to investor attention and how the way investors perceive information affects stock returns. The authors use very in depth data by looking at all individual stocks actively traded for 29 years starting in 1990 on the Australian Stock Exchange. In addition to the stock information, the authors creates three proxies to represent investor attention from the Institutional Brokers Estimate database (IBES). The proxies the author creates for investor attention are based on industry size, the liquidity, and the number of times that a stock is traded in a certain timeframe. The model the authors use is an OLS regression that looks at predicative capabilities of high and low investor attention on the market returns of stock. The model that was used by the authors uses the proxy variables for investor attention to see if they have a direct effect on stocks returns or if information is slowly diffused throughout the market causing a delayed effect on the stocks returns. The results find that depending on the characteristics of a stock, investor attention and the information related to the stock had different effects. For example, the findings show that in prices of stocks that are in small and illiquid industries it takes a while for the information to be incorporated into the stock's returns (Wu and Shamsuddin, 2014). On the other hand, stocks that come from large and liquid industries see their returns affected directly with the release of information (Wu and Shamsuddin, 2014). These results support that gradual information diffusion hypothesis because in large, liquid industries there is a lot of investor attention so the information is processed quickly, while in small, illiquid industries there is much less investor attention leading to information to slow diffuse into the market. The authors finding will be used in this paper to see if the country-by-country value of investor attention will have an effect on the value of Bitcoin if attention is high or low.

Li et al. (2016) examine how investor attention may affect the returns on stock but also looks at trading volume and volatility. In addition, to using new variables to examine the effects of investor attention on financial assets, the authors use Twitter as a way to measure investor attention. The authors look at two different type of tweeting behaviors when examining investor attention; the first being to see which stock the user was tweeting about and how long it had been since the user had mentioned this stock. Therefore, in order for tweets to qualify, the Twitter user had to have tweeted no less than 2 times about a certain stock in the time frame of May 17, 2011 and October 2, 2012. In addition to these specification, the stock also must have had more than 1500 different people tweet about it, which lead to 90 different stock being used (Li et al. 2016). These stocks were then deemed the nature of their investor attention to be either active or passive.

The model that Li et al. (2016) create examines if the amount of investor attention co-evolves with trading volume along a lead-lag relationship using a cross-correlation function. The results show that investor attention does indeed have an effect on stocks. When the authors examine what effects investor attention has on the volume traded, they find that no matter passive or active nature of investor attention, if the amount that a stock was traded changed in a positive or negative way it was a preceded by a change in a similar manner in investor attention. The authors note that there was a stronger relationship between the two variables for stocks with active investor attention than passive investor attention (Li et al. 2016). Stock returns have a different outcome than volume trade. If there is a change in passive investor attentions in a stock it usually does not precede unusual return, whereas, a change in active investor attention can be seen at least three days before unusual returns (Li et al. 2016). Finally the volatility of stocks with high investor attention are closely related to growth and decline in the price movements of a stock. On the other hand, stocks with passive investor attention experience changes in volatility with little to no warning signs (Li et al. 2016). The authors find that investor attention is highly correlated with trading volumes, stocks return, and volatility.

3.2 Investor Attention Measure Using Google Trends

Welagedara et al. (2017) examine investor attention using Google Trends. The authors explore the affects that an analyst's recommendation has on investor attention and price discovery. The data the authors use was collected from Google Trends on the scale of 0-100 on a monthly basis using stock tickers only in the United States. The analyst recommendations were collected from Thomas Reuters' IBES database. Finally, the stocks were selected from the Russell 3000 on December 31, 2012. The results that are found were similar to the previous papers discussed. Once an analyst offered an upgrade recommendation high attention stocks rose on average 0.6% higher than stocks with low attention. The authors find that when there is a downgrade recommendation by an analyst there is little difference between the stocks of high and low attention after 10 days, but when looked at 5 days they were very different. In the first five days stocks with attentive investors had a large decrease in the price before correcting itself in the next five days. The authors suggest that this could be explained by investors regret aversion (Welagedara et al. 2017).

Preis et al. (2013) explore to see if there is a relationship between Google Trends search data and the current market conditions. The authors pick 98 terms; some were related to the financial markets like debt, inflation, profit, and short sell. While the other terms were more generic search terms like cancer, water, and marriage. To measure the current market conditions the author uses the closing prices of Dow Jones from 2004 until 2011. The results of the paper show that when Google Trends search terms that are "keywords" in the financial markets increased it was followed by a fall in the stock market. This author suggest that this was the case because trends to sell their positions at lower prices are preceded by a period of concern. During this period, investors may gather more research about the state of the market. The authors also conclude that Google Trends are able to reflect the current condition of the market. There is also some evidence that Google Trends may be able to provide insight in future market trends.

Instead of looking if Google Trends could reflect current market conditions, Basistha et al. (2017) examine if Google Trends would be able to predict realized volatility in the financial market. The authors used S&P 500 and DJIA to measure realized volatility in the financial market. For the Google Trends data, the authors uses the search terms 'S&P' and 'DJIA' as their basis of the terms they used. The authors uses the top five search queries that contained 'S&P' and 'DJIA'. The data collected spanned from January 4, 2004 until August 28, 2015 on a weekly frequency to avoid the missing data points of the daily Google Trends results. There is a positive and significant correlation with Google Trends search volume and realized volatility in the S&P 500 and DJIA. Google Trends correlation with the S&P 500 was 0.33 while it was 0.75 with the DJIA (Basistha et al. 2017). An interesting side note that the authors observe was that Google Trends search volumes usually decreases after an increase in the stock prices. They suggest that this is because bad news tends to attract more attention than good news. This is a similar finding to Preis et al. (2013). The results of the paper find that Google Trends does have predictive capabilities in financial markets. The authors also look at if the effects of implied volatility would lead to a better predictive measure for the financial markets. To measure implied volatility, the authors introduce the CBOE VIX for the S&P 500 and CBOE VXD to measure the DJIA. These indices are designed to reflect investors' thoughts on the stock market volatility in 30 days. The results show that implied volatility has better predictive powers than Google Trends search volumes. When implied volatility is added the significance of Google Trends is not present. The results suggest that implied information reflects relevant information faster than

Google Trends. Another explanation for these results are that Google Trends are based of the search history of the general public, who are often times not experienced traders or observers of financial markets. Whereas the implied volatility indices are meant for investors and are derived from the option prices.

The two sections of literature regarding investor attention show that certain degrees of investor attention have clear impacts in the financial market. It also shows that investor attention has some degree of predicting financial markets. Additionally, it shows that Google Trends can be used a measure of investor attention, which is what will be used in this paper. Finally, these papers allow me to conclude my expectations in section D about how investor attention will affect Bitcoin.

4. My Contribution

My study will add to literature in a couple ways. First, the literature that considers Bitcoin as a financial asset is very limited. The previous literature shows that Bitcoin shares more characteristics with a financial asset then with a currency. Since Bitcoin is rarely thought of as a financial asset and is relatively new it is important to provide a basis for what drives the value of Bitcoin. Since investor attention in Bitcoin and the value of bitcoin have not been studied at this point and both have seen ramped growth recently this is a good place to start my analysis of the value of Bitcoin. I will also add to the literature of Google Trends using it once again as a proxy for a population. This paper will build of previous investor attention literature as I see if Bitcoin and investor attention have any relation.

C. Data.

The data in this study is monthly data spanning from June 30, 2010 to February 1, 2018. There are 92 observations for each one of the variables. The monthly Bitcoin price in USD is collected from CoinDesk. Bitcoin is priced on the CoinDesk Bitcoin Price Index (XBP), which calculates the average Bitcoin price from a variety of global exchanges that meet the criteria set by the XBP[3]. The four exchanges that meet the criteria of the XBP are Bitstamp, Coinbase, itBit, and Bitfinex. Using XBP in this study is very useful for an accurate worldwide price. The price of Bitcoin for the roughly seven and two-thirds years timespan is illustrated in Figure 1.

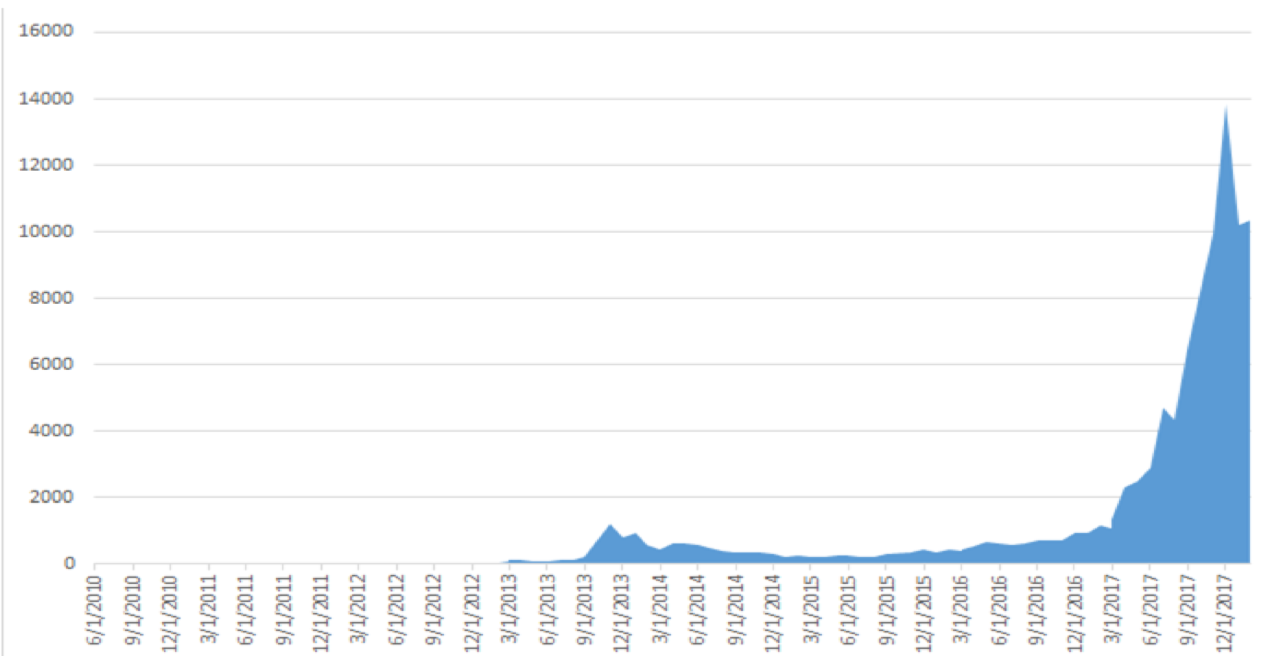

Figure 1. Bitcoin Price

Figure 1 displays the wide variety in Bitcoin price which ranges from $.06 USD to $13850.40 USD. Additionally, it offers a visualization of the recent explosion in price.

[3] https://www.coindesk.com/price/bitcoin-price-index

The monthly worldwide volume of Bitcoin is collected from Yahoo Finance. The monthly volume shows the amount of times that Bitcoin has been bought and sold in the past month. Figure 2 shows the volume that has been traded in the month before.

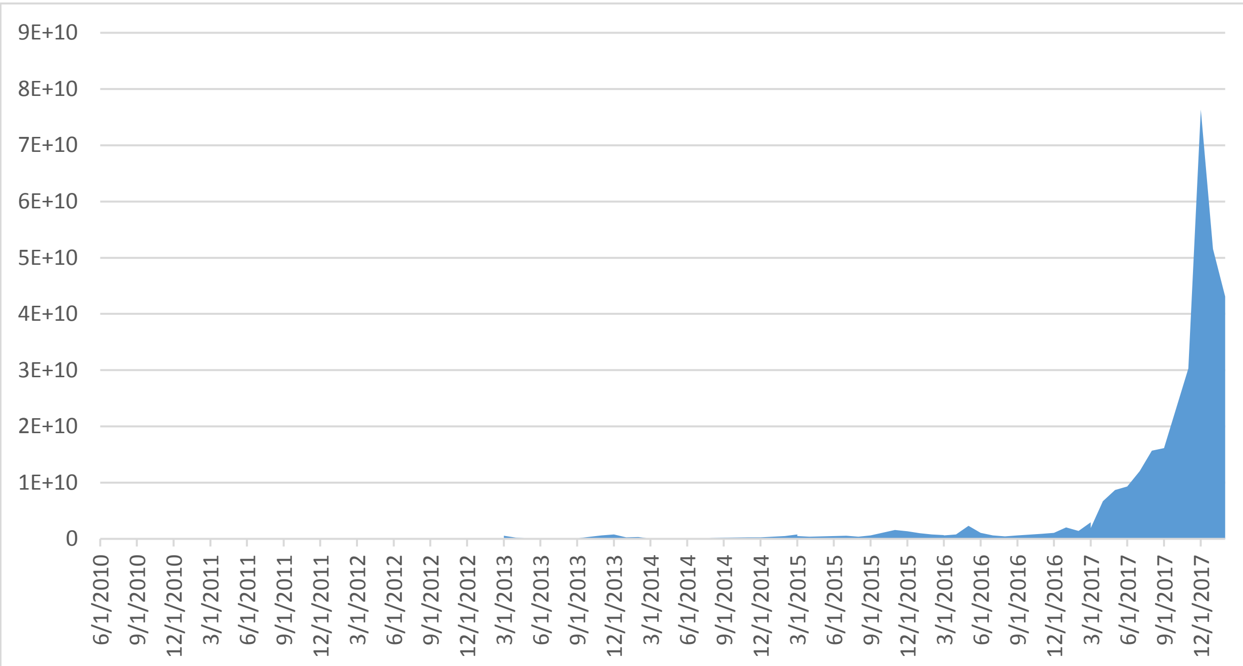

Figure 2. Volume of Bitcoin Trading in the Previous Month

Figure 2 seems to show that the volume of Bitcoin traded has a relationship with the price of Bitcoin. Both Figure 1 and Figure 2 share that incredible growth into a very high peak.

For my dependent variable, I am using the log of prices and volumes of trading in the last month. Since the variance of the data is so high, using the log of these variable normalize the data and account for the skewness of my data. Logs create data that is normally distributed. Figure 3 shows the results of taking the log for prices and volume. It can be seen that the data is much more normalized.

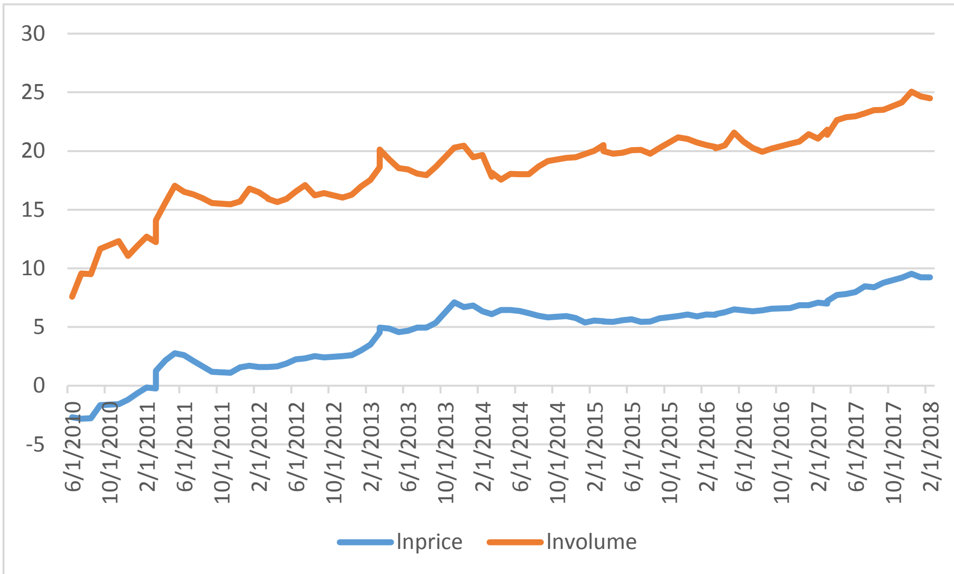

Figure 3. Log of Price and Volume of Bitcoin

My measure for investor attention is collected from Google Trends. As the literature discussed Google Trends can be used as an accurate proxy to measure the attention and thinking patterns of a population. The search term used to collect the data was *Bitcoin*. There are many search terms that could be used in this study but I choose to keep it directly with correlated with Bitcoin. Other search terms like *cryptocurrency* could be related to other currencies than Bitcoin. The first Google trend variable is for the worldwide search inquiries. With the options that Google Trends offers, country-by-country data is able to be collected. Given the different stances of countries on the acceptance of Bitcoin, the investor attention by country must be considered. As mentioned in the history of Bitcoin, China has been associated with Bitcoin from the beginning. The data from China has to be taken with a grain of salt since Google is banned in mainland China so the data mostly comes from Hong Kong. A lot of the early exchanges and the mining of Bitcoin is done in China. Russia is another country that has been closely associated with Bitcoin. A large population of Russia has been aware of Bitcoin for the last several years. Additionally, after an announcement, in January 2018 about of the regulation of Bitcoin in Russia, the price of Bitcoin saw dramatic decrease, ergo it is important to examine the possible effects of Russian investor attention may have on Bitcoin. The central bank of Japan has also announced that it approves of Bitcoin as a financial asset. Since these countries have been associated with Bitcoin and also part of the world's top 10 GDP, I use all 10 countries in the world's top 10 in GDP. The reason for adding the 7 other countries to this study is because it can be assumed that these countries are more active investors and have a larger effect on the value of financial assets. Furthermore, since Bitcoin is very volatile, it must be considered if a certain country's investor attention could impact the value of Bitcoin. Additionally, Wu and Shamsuddin (2014) found that high investor attention in firms cause an immediate change in stock price when there are shifts in the market, a lag in the change of stock price is found for firms with low investor attentions.

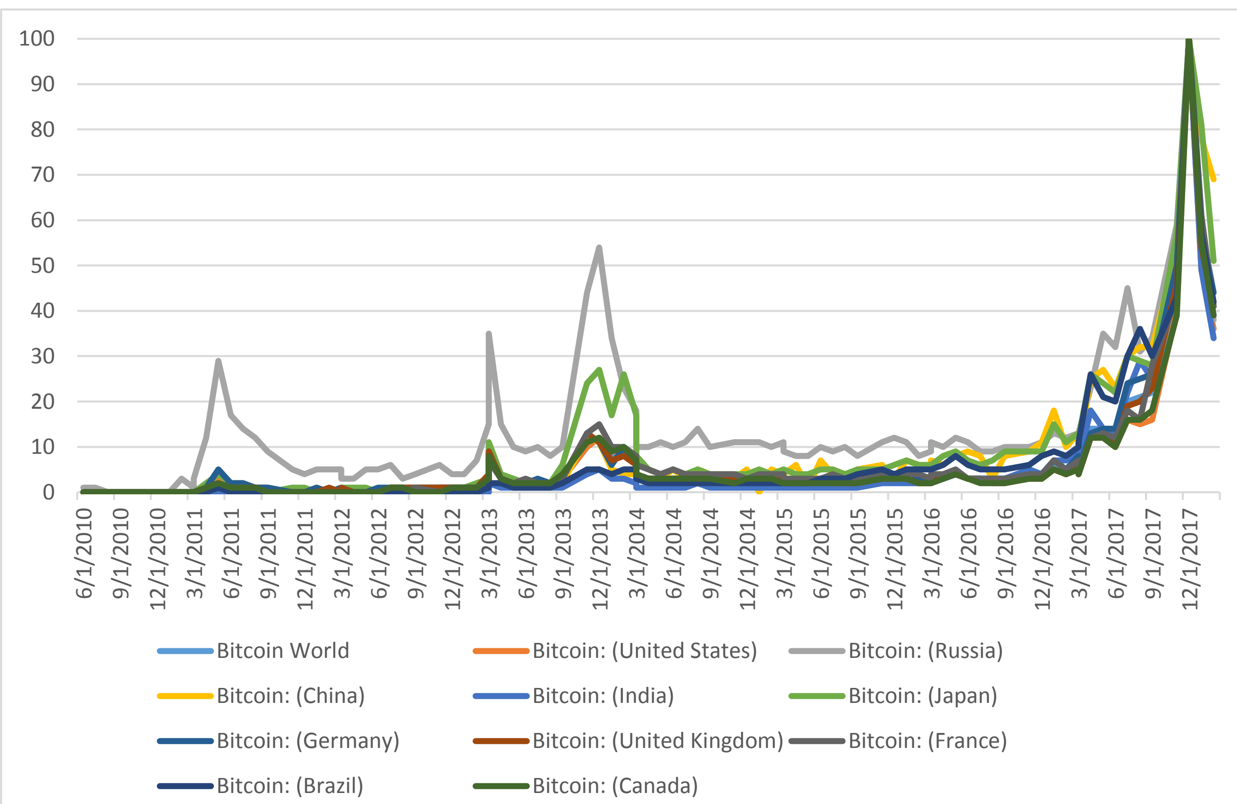

Figure 4. Google Trends for Bitcoin of the World and Countries with the Top 10 GDP

Figure 4 shows the changes in the investor attention based off Google Trends for the world and the countries with the top 10 GDP in the world. Figure 4 shows that most of the countries have very similar Google Trends for Bitcoin as the world does. It is important to note that the Google Trends for Russia deviates from the world quite noticeably. Early on the Google Trends for Russia is higher than the world and other countries with some noticeable spikes. Additionally, in late 2013 and early 2014 Japan also spikes well above other countries and the world. These two countries have been closely associated to Bitcoin so it will be important to see how they affect the value of Bitcoin. Finally it is important to note that all Bitcoin data is on a 0-100. Therefore, when all the countries reach a Google Trends of 100 in 12/1/2017, there is no additional measure to see which country was using the search term the most. For my time fixed effect variables, I use the month and the year. Months are denoted 1 to 12 starting with January as 1 and ending in December as 12. Years are denoted from 1 to 9, starting with 2010 as 1 and ending with 2018 as 9 in chronological order.

In this study, I add more independent variables to test how investor attention affects the value of Bitcoin in different conditions. The first independent variable that is added to this study is the price and volume traded in the last month of the S&P 500 Index. I once again use the log of these values to normalize the data and account for the skewness. This data was collected from Yahoo Finance. I use the S&P 500 Index because it is a good indicator of how the financial market is preforming (Basistha et al. 2017). Therefore, I use the S&P 500 to see if the state of the financial markets affects the value of Bitcoin. Another independent ant variable is the price of an ounce of gold. I pick to use this variable due to Dyhrber's (2016) findings that Bitcoin and gold have similar hedging capabilities in financial markets. Since they have similar hedging capabilities, the prices of the two assets could have a relationships. This data was collected from Federal Reserve

Economic Database. I use the log of the price of an ounce of gold to account for the skewness. The final independent variable that I use in this study is the exchange rate of all 10 countries that are examined. I use the value of the different currencies in terms of US dollars. This data is collected from the Data-Planet. I decide to use the currency exchange control variable to see if currency markets have an effect on the value of Bitcoin (since Bitcoin is technically a type of currency). Additionally, if a currency is losing value a country can decide to invest in other currencies which could affect the value of these currencies.

Table 1. Summary Statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Price	92	1,000	2,412	0.0600	13,850
Volume	92	3.283e+09	1.108e+10	1,963	7.634e+10
World Attention	92	5.935	13.26	0	100
United States Attention	92	5.446	12.67	0	100
Russia Attention	92	14.12	15.41	0	100
China Attention	92	8.141	16.42	0	100
India Attention	92	5.043	13.40	0	100
Japan Attention	92	9.304	16.02	0	100
Germany Attention	92	6.370	13.91	0	100
U.K. Attention	92	5.826	13.36	0	100
France Attention	92	6.337	13.58	0	100
Brazil Attention	92	6.533	14.30	0	100
Canada Attention	92	5.511	13.02	0	100
S&P 500 Price	92	1,816	444.4	1,049	2,824
S&P 500 Volume	92	7.686e+10	9.808e+09	5.813e+10	1.080e+11
Price of Gold	92	1,363	189.6	1,068	1,772
China-USD	92	6.415	0.240	6.051	6.920
Japan-USD	92	99.80	15.23	76.64	123.7
Canada-USD	92	1.141	0.141	0.955	1.421
Brazil-USD	92	2.550	0.723	1.563	4.056
India-USD	92	58.61	7.650	44.30	68.24
Euro-USD	92	0.810	0.0770	0.692	0.948
Russia-USD	92	44.46	15.35	27.36	75.46
UK-USD	92	0.650	0.0517	0.585	0.817

Table 1 shows the summary statistics of the data that is used in this study. Although, the mean of the price of Bitcoin is $1,000, this value does not accurately represent the price due to the price of Bitcoin being so low for an extended period. It is important to notes the differences in the means of investor attention in the different countries. Russia has a mean investor attention that is 5 points higher than the next highest country, Japan. This shows that over the course of time period in this study, the investor attention in Russia was consistently higher than the other countries. The second highest mean of investor attention is Japan. It is interesting to note that these two countries also have the two highest standard deviations in their exchange rates into USD, meaning that the currency in Russia and Japan has seen the most fluctuation.

D. Methodology

The current literature has found that investor attention has effects on the value of financial assets. The effects of investor attention change with which type of measure is used for the value of the financial asset, therefore it is important to have multiple measures of value when examining Bitcoin. Li et al. (2016) find that there is a strong positive relationship between the change in the trading volume of financial assets and the change in the investor attention. Wu and Shamsuddin (2014) find that the price of financial assets can be affected by the amount of investor attention in the financial asset. These two studies are the basis of the study in this paper to examine what type of relationship investor attention will have. These studies found that investor attention has effects on price and volume, therefore these variable must be considered when looking at the effects of investor attention on Bitcoin value I follow Li et al. (2016) model of using a proxy for investor attention specific to a financial asset instead of Preis et al. (2013) model of a proxy for investor attention in the whole market. Stephens-Davidowitz's (2014) found that Google Trends is a viable use of a proxy for the thought and behaviors of individuals. Stephens-Davidowitz's model also uses Google Trends data as the independent variable. Additionally, Welagedara et al. (2017), Preis et al. (2017), and Basistha et al. (2017) all use Google Trends as a proxy for investor attention when examining the implications of investor attention on financial assets.

The current literature examines the effects of investor attention on the value of financial asset have used regression in order to capture unusual or unexpected features of the data. My first model regresses $lnprice_{it}$, which is the log price of Bitcoin, by $world_{it}$, which is the Google Trends result for the search term for Bitcoin in the world. I also include a time fixed effects variable τ_t to account for the month and year. To account for error I use the variable ε_{it}. This model looks at the unknown relationship between price of bitcoin and Google Trends results for the world where β_0 and β_1 are unknown parameters.

$$1)\ lnprice_{it} = \beta_0 + \beta_1 world_{it} + \tau_t + \varepsilon_{it}$$

My second model builds off my first model by using $lnprice_{it}$ as the dependent variable. This model uses the country level Google Trends results for the search term of Bitcoin as the independent variables. These variables are denoted by the $(name\ of\ the\ country)_{it}$. The fixed effects variable and error term variable are the same as Model 1.

$$\begin{aligned}2)\ lnprice_{it} = \beta_0 &+ \beta_1 unitedstates_{it} + \beta_2 russia_{it} + \beta_3 china_{it} + \beta_4 india_{it} + \beta_5 japan_{it} \\ &+ \beta_6 germany_{it} + \beta_7 unitedkingdom_{it} + \beta_8 france_{it} + \beta_9 brazil_{it} \\ &+ \beta_{10} canada_{it} + \tau_t + \varepsilon_{it}\end{aligned}$$

My third model has the same structure as Model 1 but uses $lnvolume_{it}$ as the dependent variable instead of $lnprice_{it}$ as the measure of value for Bitcoin. The variables $world_{it}$, τ_t, and ε_{it} are the exact same as Model 1.

$$3)\ lnvolume_{it} = \beta_0 + \beta_1 world_{it} + \tau_t + \varepsilon_{it}$$

My fourth model is a combination of Model 2 and 3. This model uses $lnvolume_{it}$ as my dependent variable and $(name\ of\ the\ country)_{it}$ as my independent variables. The fixed effects and error term are the same as the previous models

$$4)\ lnvolume_{it} = \beta_0 + \beta_1 unitedstates_{it} + \beta_2 russia_{it} + \beta_3 china_{it} + \beta_4 india_{it} + \beta_5 japan_{it} + \beta_6 germany_{it} + \beta_7 unitedkingdom_{it} + \beta_8 france_{it} + \beta_9 brazil_{it} + \beta_{10} canada_{it} + \tau_t + \varepsilon_{it}$$

My fifth and sixth models are very similar to Model 1 and 3. In Model 5, I add the variable of $lns\&p500price_{it}$ to Model 1. In Model 6, I add the variable of $lns\&p500volume_{it}$ to Model 3.

$$5)\ lnprice_{it} = \beta_0 + \beta_1 world_{it} + \beta_2 lns\&p500price_{it} + \tau_t + \varepsilon_{it}$$

$$6)\ lnvolume_{it} = \beta_0 + \beta_1 world_{it} + \beta_2 lns\&p500volume_{it} + \tau_t + \varepsilon_{it}$$

Model 7 is similar to Model 5. In this model I use the variable of $lnpricegold_{it}$ instead of $lns\&p500volume_{it}$ used in Model 5.

$$7)\ lnprice_{it} = \beta_0 + \beta_1 world_{it} + \beta_2 lnpricegold_{it} + \tau_t + \varepsilon_{it}$$

Models 8 and 9 is similar to Model 2. In Model 8 I add the variable $exchangerates_{it}$ to Model 2. In Model 9 I add $lns\&p500price$ to Model 8.

$$8)\ lnprice_{it} = \beta_0 + \beta_1 unitedstates_{it} + \beta_2 russia_{it} + \beta_3 china_{it} + \beta_4 india_{it} + \beta_5 japan_{it} + \beta_6 germany_{it} + \beta_7 unitedkingdom_{it} + \beta_8 france_{it} + \beta_9 brazil_{it} + \beta_{10} canada_{it} + \beta_{11} exchangerates_{it} + \tau_t + \varepsilon_{it}$$

$$9)\ lnprice_{it} = \beta_0 + \beta_1 unitedstates_{it} + \beta_2 russia_{it} + \beta_3 china_{it} + \beta_4 india_{it} + \beta_5 japan_{it} + \beta_6 germany_{it} + \beta_7 unitedkingdom_{it} + \beta_8 france_{it} + \beta_9 brazil_{it} + \beta_{10} canada_{it} + \beta_{11} exchangerates_{it} + \beta_{12} lns\&p500price_{it} + \tau_t + \varepsilon_{it}$$

Model 10 is similar to Model 1. In Model 10 $world_{it-1}$ is lagged one month prior to $lnprice_{it}$. Additionally, I add $lnvolume_{it-1}$ which is also lagged one month.

$$10)\ lnprice_{it} = \beta_0 + \beta_1 world_{it-1} + \beta_2 lnvolume_{it-1} + \tau_t + \varepsilon_{it}$$

E. Hypothesis

My expectations for the effect of investor attention on the value of Bitcoin follows the work of Li et al. (2016). I think that there will be a positive effect on Bitcoin value as the measure of investor attention rises. Specifically, for Model 1 I believe that an increase in $world_{it}$ would result in an increase of $lnprice_{it}$. Based off Figure 1 and Figure 4, it appears that is a positive correlation between price and world Google Trends data results so I believe that the results will confirm this. In Model 2, I think that $unitedstates_{it}$, $russia_{it}$, $china_{it}$, and $japan_{it}$ will have the greatest positive effects on $lnprice_{it}$. These countries have been associated with awareness and acceptance of Bitcoin, therefore I think the investors will be more attentive with great influence.

I think that investor attention will have a greater effect on $lnvolume_{it}$ than $lnprice_{it}$ due to the results of Li et al. (2016) that investor attention's greatest effect is on the volume of trades for a financial asset. I think that the results of Models 3 and 4 will be very similar to Model 1 and 3 but the coefficient for $world_{it}$ and $(name\ of\ the\ country)_{it}$ will be larger. I also think that there will be more countries that have a statistically significant effect on the volume of Bitcoin traded because these countries are able to invest more than other countries with lower GDP. Similar to Model 2, I believe that $unitedstates_{it}$, $russia_{it}$, $china_{it}$, and $japan_{it}$ will have positive effects on $lnprice_{it}$.

In Models 5 and 6, I think that the addition of the variables $lns\&p500price_{it}$ and $lns\&p500volume_{it}$ will cause the coefficient for $world_{it}$ to not be as high as it is in Model 1 and 3. I think this will be the case because some of the value of Bitcoin will be explained by the conditions of the financial markets because if the conditions are bad people are less likely to invest in financial assets.

In Model 7, I believe that adding $lnpricegold_{it}$ will cause the coefficient of $world_{it}$ to once again not be as high. This is due to findings of Dyhrber (2016) that Bitcoin and Gold have similar hedging capabilities in financial and currency markets. This could mean that the factors that cause the value of gold to change could also cause changes in the value of Bitcoin.

In Model 8, I think that the addition of $exchangerates_{it}$ will add some variables that are significant. I think the $exchangerates_{it}$ of Russia and Japan will have a significant effect on $lnprice_{it}$ because they have currencies that are somewhat unstable and the people in these countries are looking for better ways to store their money. In Model 9, I believe the addition $lns\&p500price_{it}$ will have a positive effect on $lnprice_{it}$ with similar results for the other variables to Model 8.

Finally, when looking at Model 10, I believe that $world_{it-1}$ and $lnvolume_{it-1}$ will have positive significant coefficients on the $lnprice_{it}$. I base this predictions off the results of Basistha et al. (2017), which found that investor attention is a good predictor for the S&P 500. Additionally, as more people pay attention and trade more Bitcoin, I believe this will cause an increase in the $lnprice_{it}$.

F. Results

When examining the results of the models it is important to note the results of the year dummies. The results show that the year has a statistically significantly positive impact and increasing on the value of Bitcoin with $p<0.01$. The coefficients for year in all the models grow in their impact of the value in Bitcoin from 2011 until 2018. In Model 1 year has a cumulative growth rate of 18.79% from 2011-2018 compared to 2010. Model 2 year had a cumulative growth rate of 22.46%. Model 3 year had a cumulative growth rate of 16.46%. Finally, Model 4 year had a cumulative growth rate of 21.16%. The models that examined the worldwide investor attention the fixed effect of the year on price and volume was larger than the models that used country-by country data in all years except 2018.

Table 2. Results for Year Fixed Effects in Models 1-4

	(1)	(2)	(3)	(4)
VARIABLES	lnprice	lnprice	lnvolume	lnvolume
2.year	3.667***	3.123***	4.926***	3.994***
	(0.290)	(0.227)	(0.463)	(0.421)
3.year	4.449***	4.172***	6.286***	5.854***
	(0.290)	(0.212)	(0.463)	(0.393)
4.year	7.244***	6.315***	8.640***	7.335***
	(0.292)	(0.242)	(0.467)	(0.448)
5.year	8.503***	7.922***	8.514***	7.862***
	(0.292)	(0.238)	(0.468)	(0.442)
6.year	7.946***	7.618***	10.13***	9.637***
	(0.291)	(0.239)	(0.465)	(0.443)
7.year	8.676***	8.595***	10.46***	10.19***
	(0.291)	(0.279)	(0.466)	(0.517)
8.year	9.901***	9.829***	12.12***	11.50***
	(0.335)	(0.482)	(0.535)	(0.894)
9.year	11.25***	12.14***	13.76***	14.71***
	(0.301)	(0.222)	(0.964)	(2.398)
R-squared	0.971	0.987	0.946	0.968

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

First, I examine to see if it was affected by investor attention was the price of Bitcoin. Model 1 finds that $lnprice_{it}$ and $world_{it}$ are highly correlated with an r-squared of 0.971. The results show that $world_{it}$ is a statistically significant variable for $lnprice_{it}$ at p<0.01. The coefficient for world is 0.0223 meaning that an increase of 1% in the world Google Trends data results in an increase of 0.0223% in the price of Bitcoin. Model 2 yield very interesting results. The only country that has a coefficient that is statistically significant was $russia_{it}$at p<0.01. As I state earlier Russia has a strong association with Bitcoin. The coefficient for $russia_{it}$ was 0.0595, which is more than double the coefficient found in Model 1 for the world. My expectations for Japan, China, and United States were incorrect as they were negative and insignificant. Table 3 shows the complete results for Models 1 and 2 minus the fixed effect variables.

Table 3. Results for lnprice

Model VARIABLES	(1) lnprice	(2) lnprice	(5) lnprice	(7) lnprice
unitedstates		-0.158		
		(0.125)		
russia		0.0595***		
		(0.0142)		
china		-0.0526**		
		(0.0262)		
india		-0.0221		
		(0.0644)		
japan		-0.0170		
		(0.0172)		
germany		0.0757		
		(0.0553)		
unitedkingdom		0.00660		
		(0.0834)		
france		-0.00592		
		(0.0498)		
brazil		-0.0100		
		(0.0384)		
canada		0.140		
		(0.150)		
world	0.0223***		0.0202**	0.0220***
	(0.00817)		(0.00785)	(0.00828)
lnsp500price			2.635	
			(2.133)	
lnozau				0.713
				(1.530)
Constant	-3.127***	-3.085***	-21.51	-8.230
	(0.417)	(0.332)	(14.89)	(10.89)

Month FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	92	92	92	92
R-squared	0.971	0.987	0.972	0.971

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Models 3 and 4 use volume as the measure of value of Bitcoin. The results from Model 3 show that world and $lnvolume_{it}$have an r-squared of 0.946. This shows that there is less correlation between $lnvolume_{it}$ and $world_{it}$ than $lnprice_{it}$ and $world_{it}$. Like in Model 1, $world_{it}$ is statistically significant at p<0.01 with a coefficient of 0.0305. The results suggest that $world_{it}$ has a greater effect on volume than price. The results from Model 4 show that two countries investor attention effects the volume. Similar to the results in model 2 $russia_{it}$ is statistically significant at p<0.01. The coefficient for $russia_{it}$ is 0.103 in Model 4, which is almost double the coefficient of $russia_{it}$ in Model 2. Additionally, coefficient of $russia_{it}$ in Model 4 is more than 3 times the coefficient of $world_{it}$ for $lnvolume_{it}$. The coefficient $japan_{it}$ is also statistically significant at p<0.1. The coefficient of $japan_{it}$ -0.0765 means that an increase of one unit in the Google Trends data results lead to a decrease of 0.0765% in the volume of Bitcoin traded in the last month. This is the opposite of the expectation I had for Japan. Although it is not significant it is interesting to note that Canada has the largest coefficient out of all the countries. My expectations of the United States and China having positive significant effects of the volume of Bitcoin were not true. In fact, although there were not significant both the United States and China investor attention have negative relationships with the volume of Bitcoin failing to meet my expectations

Table 4. Results for lnvolume

Model VARIABLES	(3) lnvolume	(4) lnvolume	(6) lnvolume
unitedstates		-0.189	
		(0.194)	
russia		0.103***	
		(0.0244)	
china		-0.0306	
		(0.0416)	
india		-0.0183	
		(0.115)	
japan		-0.0765**	
		(0.0370)	
germany		0.164	
		(0.117)	
unitedkingdom		-0.147	
		(0.151)	
france		-0.103	
		(0.0706)	
brazil		0.0211	
		(0.0703)	
canada		0.307	
		(0.238)	
world	0.0305***		0.0314***
	(0.00929)		(0.00913)
lnspvol			1.951**
			(0.924)
Constant	9.319***	9.523***	-39.92*
	(0.781)	(0.729)	(23.02)
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	92	92	92
R-squared	0.946	0.968	0.949

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In Models 5 and 6, I examine the effects of adding data from the S&P 500 to the regressions run in Model 1 and 3. The results from Model 5 are shown in Table 2. The results are similar to Model 1. The added variable of $lns\&p500price_{it}$ is not statistically significant. In Model 5, $world_{it}$ is significant at P<0.05 compared to being significant at P<0.01 in Model 1. Additionally, the coefficient for $world_{it}$ in Model 5 is 0.0202 compared to 0.0223 in Model 1. The results from Model 6 are seen in Table 4. In Model 6, $lns\&p500volume_{it}$ has a positive relationship statistically significant at p<0.05. If the volume traded of S&P 500 in the last month increase by 1% it leads to an increase of 1.9% in the volume of Bitcoin traded in the last month. Compared to Model 3, $world_{it}$ in Model 6 is very similar. The coefficient for $world_{it}$ in Models 3 and 6 are both statistically significant at p<0.01 and the difference in the coefficient is 0.0009. In Model 7, the price of gold is added as an independent variable to Model 1. The results of Model 7 are in Table 3. The results show that the added variable of $lnpricegold_{it}$ is not statistically significant and the coefficient for $world_{it}$ is almost identical to the result of Model 1.

In Models 8 and 9 examine the effect of country by country investor attention and exchange rates in these countries on the price of Bitcoin. Model 9 adds S&P 500 data to the regression. Model 8 is consistent with the previous country level data. Once again, the only country that has a statistically significant coefficient is $russia_{it}$. In Model 8, there are no $exchangerates_{it}$ that are statistically significant. When $lns\&p500price_{it}$ is added to the equation in Model 9 there results are very different except for one thing. Once again in Model 9, the coefficient of investor attention in Russia is statistically significant at p<0.01. The other coefficient that is statistically significant at p<0.01 is $lns\&p500price_{it}$. The coefficient for $lns\&p500price_{it}$ of 4.468 is the highest that is seen across all model. This coefficient mean that a 1% increase in the price of the S&P 500 will lead to 4.468% increase in the price of Bitcoin. After having zero exchanges rates that were statistically significant in Model 8, Model 9 has three coefficients of $exchangerates_{it}$ that are statistically significant. The exchange rate of Japanese Yen to USD and Indian Rupee to USD were significant at $p<0.1$. The exchange rate of the Euro to USD is significant at $p<0.05$. The results of Models 8 and 9 are displayed in Table 5.

Table 5. Results with Exchange Rates

VARIABLES	(1) lnprice	(2) lnprice
lnsp500price		4.468***
		(1.656)
unitedstates	-0.136	-0.149
	(0.132)	(0.127)
russia	0.0564***	0.0582***
	(0.0120)	(0.0112)
china	-0.0299	-0.0318
	(0.0241)	(0.0262)
india	-0.0643	-0.0661
	(0.0657)	(0.0633)
japan	-0.0234	-0.0292
	(0.0194)	(0.0182)
germany	0.0936	0.0769
	(0.0667)	(0.0643)
unitedkingdom	-0.0197	0.0114
	(0.0928)	(0.0869)
france	0.0215	0.0185
	(0.0501)	(0.0475)
brazil	0.0166	0.0210
	(0.0480)	(0.0494)
canada	0.105	0.106
	(0.168)	(0.169)
chinausd	-0.337	-0.390
	(0.817)	(0.812)
japanusd	-0.0188	-0.0337*
	(0.0195)	(0.0171)
canadausd	-1.314	1.868
	(3.202)	(2.853)
brazilusd	-0.313	-0.246
	(0.408)	(0.397)
indiausd	0.0578	0.0851*
	(0.0433)	(0.0461)
eurousd	2.309	5.554**
	(2.453)	(2.682)
russiausd	-0.00711	-0.0229

	(0.0175)	(0.0186)
ukusd	-2.346	-1.908
	(3.206)	(2.855)
Constant	-0.0848	-36.70**
	(7.200)	(15.49)
Observations	92	92
R-squared	0.989	0.990

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

My final model explores the relationship between two lag variable and the price of Bitcoin. The results of Model 10 show that $world_{it-1}$ is not statistically significant. This is the first model in which world investor attention is not statistically significant. The coefficient for $lnvolume_{it-1}$ is statistically significant at p<0.01 and shows that a 1% change in the volume of Bitcoin traded in $t-1$ would cause a 0.488% change in the price. The results from Model 10 are in Table 6. The results for all models warrant further discussion specifically the results that Russia produces.

Table 6. Results for Lagged Variables

Model VARIABLES	(10) lnprice
worldlag	0.00432
	(0.00505)
lnvolumelag	0.488***
	(0.0667)
Constant	-8.125***
	(0.742)
Month FE	Yes
Year FE	Yes
Observations	91
R-squared	0.981

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

G. Discussion

The takeaways from the results were that the year and $world_{it}$ had a significant positive effect on both values of Bitcoin. Additionally, $russia_{it}$ was the only other variable to have a significant effect on both values of Bitcoin. The only other variable that is statistically significant in my models is $japan_{it}$ in terms of $lnvolume_{it}$. It is very interesting to see how the later the year, the larger the impact on the value of Bitcoin. This could be related to the huge growth phase that Bitcoin has seen in the past years. Figure 1 and Figure 2 shows that starting in 2016, the value of Bitcoin rose at an exponential rate. This can be seen in the results for year as in all four models the coefficient in 2018 is more than tripled the effect on Bitcoin value than in 2011. If the coefficient for year continues to grow in the same matter, as the years go on it will describe a large amount of the price in Bitcoin, for example in 2018 defined 12.14% of Bitcoin price in Model 2 and 14.71% of the volume of Bitcoin traded in Model 4.

The coefficients for $world_{it}$ shows that investor attention has a positive effect on the value of Bitcoin. This follows the results from the previous literature how a positive investor attention has a positive effect on the value of a financial asset. I assume the reason that $lnvolume_{it}$ is affected more by world investor attention is because as more people become interested in a financial asset it would lead to more trading of the asset. Due to all the speculation surrounding Bitcoin returns, as more investors pay attention it would make sense that more trading would occur. The results of investor attention for the world effects on the Bitcoin price is very intriguing. Since Bitcoin does not have very clear specifications which lead to its price, the results in Model 1 show that investor attention causes price changes with no other variables included. Model 5 and 7 add extra variables to check if investor attention causes price changes or if there is another possible effect. Model 5 finds the same results as Model 1 with the same significance and very similar coefficients for $world_{it}$ when adding the price of the S&P 500. The results of Model 5 suggest that the Price S&P 500 does not have a significant effect on $lnpirce_{it}$ at the world level. This is important since the S&P 500 is a good measure of financial markets, so I assume that prices in the financial markets do not affect the price of Bitcoin. Model 7 attempts to see the relationship of the price of Gold and world investor attention on $lnpirce_{it}$. This results continue to show that $world_{it}$ has a positive relationship to $lnpirce_{it}$ with similar results to Models 1 and 5. Once again the added variable, $lnpricegold_{it}$ does not have a significant relationship with $lnpirce_{it}$. Model 7 allows me to conclude that the price of gold and the price of Bitcoin do not have a relationship even though Dyhrber (2016) found that they share hedging capabilities. Models 1, 5, and 7 show that the worldwide investor attention and the price of Bitcoin have a positive significant relationship. This is important to note because the reasons that the investor attention has grown so much could be correlated to the hype that surrounds the possible returns that people have earned in the past. This is in turn could lead to the price of Bitcoin to be overvalued similar to the way of the early 2000's tech bubble. If hype and speculation are the reasons for investor attention to effect the price of Bitcoin, this could lead to the eventual crash of the price of Bitcoin. It is also very interesting to note that the price of Bitcoin does not share a relationship with what literature has attributed with. It was created as a currency, yet there is no relationship between exchanges rates and price in Model 8. Dyhrber (2016) found that Bitcoin shares characteristics of gold yet in Model 7 there is no relationship between the price of Bitcoin and the price of Gold.

The results for $russia_{it}$ in Models 2, 4, 8 and 9 show that the investor attention in Russia effect the value of Bitcoin. In Model 2, 8, and 9 $russia_{it}$ is the only country that has a statistically significant effect on $lnpirce_{it}$. I assume this can be explained by Russia becoming one of the first countries to use Bitcoin widely throughout the country. In wake of the rapid weakening of the Russian currency in 2013, many Russians used Bitcoin as a way to store their money in a safer manner. I was surprised to see in both Models 8 and 9 that the Russian exchange rate to USD did not have a significant effect. This may be due to the gradual information diffusion hypothesis, that the people of Russia first paid attention to the currency then Bitcoin after the currency was troubled (Rowley). In additions to storage Russians used Bitcoin as a form of payment as it became widely accepted. The increased usage and the Russian government speaking out against Bitcoin rose the relative investor attention throughout the country, which led to hype and speculation of a safer way to store and spend money. As I mention in the previous paragraph, the price of Bitcoin may be affected by the hype and speculation of investors. So, due to the longer duration of time that Russia has had a larger amount of relative investor attention towards Bitcoin compared to other countries it is reasonable to assume that their effect would be larger than countries would have only recently started paying attention. This is similar to the findings of Wu and Shamsuddin (2014), where in firms that have low investor attention there is a lag in the change of stock price whereas firms with high investor attention see immediate changes in their stock prices. Additionally it supports the gradual information diffusion hypothesis, where investors must pick at choose where to use their scarce amount of attention. In Russia's case they paid attention to Bitcoin while other countries focused on other financial assets. The results from Model 4 can also be attributed to the length of time that Russia has been aware of Bitcoin. Following the findings of Model 1, I assume that an increase in investor attention will lead to a rise in the volume of Bitcoin traded. In this scenario, since Russia has had higher investor attention for a longer period of time they have been able to collect more Bitcoins than other countries. Since Russia has a large amount of Bitcoin compared to other countries du, the amount of attention that their investors pay to Bitcoin has a much larger effect on volume of Bitcoin traded than other countries.

The only other country to have a statistically significant coefficient was Japan in Model 4. In this case $Japan_{it}$ had a negative effect on $lnvolume_{it}$. My expectations predicted that Japan would have a positive effect due to the Bank of Japan's announced acceptance of Bitcoin. I assumed that failing currency and more accepted use of Bitcoin would lead to similar results to Russia. Although Russia and Japan seem to be similar scenarios, they are not. In Russia's case in addition to using it as a safer alternative to their currency, they also continued to trade Bitcoin throughout the country. In Japan's scenario, the people of Japan are buying Bitcoin and then solely using it as a form of storage for money. Therefore, once someone buys a Bitcoin in Japan, it is often held for a longer period than the normal use of Bitcoin. As Japanese awareness of the use of Bitcoin as a storage of money increases so would investor attention but since Bitcoins are being held in Japan the volume is slowed down. This leads to the results found in Model 4 between $japan_{it}$ and $lnvolume_{it}$. The effects of a weak Japanese currencies can also be seen in Model 9. The relationship between Japanese Yen-USD and the Price of Bitcoin is negative and show that a decrease of 1 yen need to purchase 1 USD would cause the price of Bitcoin to rise by 0.03%. I assume that this is caused by the people of Japan being able to buy more Bitcoin if there currency strengthens rather than invest in an unstable currency.

The last relationship that I explore in my paper is the lagged effect of volume of Bitcoin traded and world investor attention on the price of Bitcoin. The results show that investor attention lagged one period does not have a significant relationship with the price of Bitcoin. This is the only model in which world investor attention does not have a significant relationship with the price of Bitcoin. This shows that the effect of world investor attention is a current effect.

H. Conclusion

In this paper, I use two measures of value for Bitcoin from June 30, 2010 until February 1, 2018. By using the worldwide and country data of Google Trends data as investor attention I study the how investor attention effects the value of Bitcoin. I find that an increase in worldwide investor attention causes an increase in the price and volume of Bitcoin. Russia is the only country where a rise in investor attention cause a positive change in the price and volume of Bitcoin. Additionally, I find that Japan has an effect on the volume of Bitcoin. My findings suggest that Russia is the only country that can cause changes in price and volume of Bitcoin

Although there are some implications that are found in this paper, there is a lot that needs to be studied in the relationship of investor attention and Bitcoin. There are a few limitations that I face with the use of Google Trends. As previously mentioned, since the data from Google Trends are scaled from 0-100 instead of the actual number of searches conducted, therefore, it is very difficult to compare two different countries with similar results, which may lead to multicollinearity. Additionally, Google Trends provides monthly data. This only allowed me to look at the value of Bitcoin at the monthly levels instead of a daily value of Bitcoin levels, which is extremely accessible. Google Trends results from China also have to be questioned, due to the ban of Google in mainland China in 2010. China has also banned all Bitcoin foreign Bitcoin exchanges in mainland China. Although Google Trends was used for investor attention, it may not be the most accurate measure for investors. Google Trends collects all data from all the searches that are done on Google, therefore, Google Trends may capture people who are simply trying to find out what Bitcoin is rather than their investor attention. Another limitation is the length of data in this paper. Values for Bitcoin only dated back to 2010 because of how new

Bitcoin is. This did not allow me to get a very large sample size and was during a time of rapid growth for Bitcoin and investor attention. It would be very interesting to see the effect of investor attention has on the value of Bitcoin during a much less volatile time for both variables.

There are many possibilities for future research. One of the possibilities is to use another proxy for the investor attention. Li et al. (2016) found significant data from using Twitter activity as a proxy for investor attention. Additionally, future research could use multiple proxies for the measure of investor attention to get a more accurate measure. Another suggestion for future research is to examine the volatility of Bitcoin similar to Basistha et al. (2017) did in their paper examining predicted and realized volatility. Another avenue that future research could follow is looking at more types of Bitcoin value on a daily level to see if those are effected by investor attention. Finally, it would be very interesting to use detailed country level transaction data to check which countries affect Bitcoin transactions.

Despite being called a currency, Bitcoin shares a lot of characteristics of a financial asset. My study shows the price and volume of Bitcoin will respond to changes in investor attention at the worldwide and country level. This study begins to look what causes the value of Bitcoin to change, which is currently fairly unknown.

Works Cited:

Basistha, A., Kurov, A., & Wolfe, M. (2017). Volatility forecasting: The role of Internet search activity and implied volatility. Working Paper.

Bonneau, J., Miller, A., Clark, J., Narayanan, A., Kroll, J. A., & Felten, E. W. (2015, May). Research perspectives and challenges for bitcoin and cryptocurrencies. In *Security and Privacy (SP), 2015 IEEE Symposium on* (pp. 104-121). IEEE.

Crane, J. (2017, December 28). How bitcoin got here: A mostly complete timeline of bitcoin's highs and lows. Retrieved from http://nymag.com/selectall/2017/12/bitcoin-timeline-bitcoins-record-highs-lows-and-history.html

Dyhrberg, A. H. (2016). Hedging capabilities of Bitcoin. Is it the virtual gold?. *Finance Research Letters*, *16*, 139-144.

Gervais, A., Karame, G., Capkun, S., & Capkun, V. (2014). Is Bitcoin a decentralized currency?. *IEEE security & privacy*, *12*(3), 54-60.

Kristoufek, L. (2013). Can Google Trends search queries contribute to risk diversification?. *Scientific reports*, *3*, 2713.

Li, X., Hendler, J. A., & Teall, J. L. (2016). Investor attention on the social web. *Journal of Behavioral Finance, 17*(1), 45-59.

Nakamoto, S., Bitcoin: A peer-to-peer electronic cash system (2008)

Ma, June and Gans, Joshua S. and Tourky, Rabee, Market structure in bitcoin mining (January 16, 2018). *Rotman School of Management Working Paper No. 3103104.*

Miller, M. (2015). *The ultimate guide to Bitcoin*. Indianapolis, IN: QUE.

Preis, T., Moat, H. S., & Stanley, H. E. (2013). Quantifying trading behavior in financial markets using Google Trends. *Scientific reports*, *3*, 01684.

Rowely, E. (2013). Russians most interested in Bitcoin, searches show. Retrieved from https://www.telegraph.co.uk/finance/economics/9976524/Russians-most-interested-in-Bitcoin-searches-show.html

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics*, *118*, 26-40.

U.S. Department of the Treasury. Internal Revenue Service. (2014). *IRS Virtual Currency Guide* (Cat. No. 2014-21). Washington, DC: U.S. Government Publishing Office.

Welagedara, V., Deb, S. S., & Singh, H. (2017). Investor attention, analyst recommendation revisions, and stock prices. *Pacific-Basin Finance Journal, 45*, 211-223.

Wu, Q., & Shamsuddin, A. (2014). Investor attention, information diffusion and industry returns. *Pacific-Basin Finance Journal, 30*, 30-43.

Yermack, D. (2013). Is Bitcoin a real currency? An economic appraisal. *National Bureau of Economic Research.* Working Paper (No. w19747)