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TITLE:

Bitcoin and payment systems

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Abstract

We study the relationship between Bitcoin and traditional payment systems and the financial sector. The payment systems we will do the study with are Visa, MasterCard, Western Union, American Express and PayPal. We study whether Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches have any relationship with the returns of the traditional payment companies. In addition we also study whether the same variables have any explanatory relationship with the financial sector. We find that the relationship between Bitcoin and payment systems is very weak, which indicates that investors that typically invest in these companies doesn't see Bitcoin as a serious competitor. However, number of unique Bitcoin addresses has a negative relationship with the abnormal returns of most of the payment companies.

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Preface

Bitcoin is the largest and most known cryptocurrency and experienced a huge increase in price and interest during 2017. Bitcoin was created in order to function as an alternative payment system without any trusted third party. We would like to research whether Bitcoin has any relationship with traditional payment systems and the financial sector. This is a very interesting topic with limited literature and will be a good indicator for whether Bitcoin is categorized as a competitor to the most known and used payment systems as well as the financial sector.

We would like to thank our supervisor Peter Molnar for all help during this writing process. He has been thorough in his feedback and been a great sparring partner. We would also like to thank Niaz Bashiri for the help with processing our data in Stata.

1. INTRODUCTION

Cryptocurrencies are a relative new phenomenon and has for the last few years rapidly increased in popularity. A cryptocurrency is digital or virtual currency that uses cryptography for security and is not issued by any central authority. In theory, this means that it is immune to government interference or manipulation. Today there are over a thousand different cryptocurrencies and the number is still increasing. The biggest cryptocurrencies have a market capitalization of several billion dollars. The total cryptocurrency market has a market capitalization of approximately $480 billions as of February 2018. The use and benefit of cryptocurrencies is to make it easier to transfer funds between two parties and with lower transaction fees. The biggest and the most known cryptocurrency is Bitcoin and in this paper we will use Bitcoin data in our analysis.

Most cryptocurrencies share a common set of transactional properties. The transactional properties of cryptocurrencies are that they are irreversible, anonymous, secure and permissionless (Blockgeeks, 2016). Being irreversible means that after confirmation, a transaction can't be reversed by anybody. Being anonymous means that neither transactions nor accounts are visibly connected to real-world identities. Cryptocurrency transactions are secure in the way that they are based on public-private key cryptography system and only the owner of the private key can send cryptocurrency. Cryptocurrency transactions are permissionless because you don't have to get permission from anybody to use cryptocurrency.

We are, to the best of our knowledge, the first to investigate whether abnormal returns for traditional payment companies are related various variables related Bitcoin. There are quite a few papers investigating and discussing whether Bitcoin can be categorized as a currency or money. Yermack (2013) investigates whether Bitcoin is a real currency. His study concludes for Bitcoin to be established as a bona fide currency its value needs to become more stable. Further he concludes that the volatile behavior of Bitcoin is more consistent with the behavior of a speculative investment. Baek & Elbeck (2015), Cheah & Fry (2015), Kristoufek (2015), Dyhrberg (2016), Blau (2017) and Corbet et al (2017) also agrees that Bitcoin primarily should be considered a speculative asset rather than a currency. Further Glaser et al (2014) investigates whether use of Bitcoin and digital currencies is driven by its appeal as a currency or as an asset. In their research they find strong indications that users approaching digital currencies are more interested to participate in an alternative investment vehicle rather than an alternative transaction system. Surda (2012) states that bitcoin can, hypothetically, eventually grow to become money. The building of credibility throughout the market participants is key factor for bitcoin to rise to an accepted exchange medium (Ciaian et al, 2016). Burniske & White (2017) explores Bitcoin as a whole new assets class and finds that Bitcoin exhibits characteristics of a unique asset class. Their study concludes that Bitcoin is differing substantially from other assets in terms of its politico-economic profile, price independence and risk-reward characteristics.

Bouoiyour & Selmi (2015) seeks to find out what bitcoin look like. Their findings conclude that Bitcoin has a very high speculative behavior and may be useful in trade transactions in a small degree. The uncertainty with what bitcoin will become as the year goes are many. Rogojanu & Badea (2014) is trying to see how Bitcoin both have advantages and disadvantages against alternative monetary systems. Bouri et al (2016) investigates whether Bitcoin can act as a hedge and safe haven. Their results indicate that Bitcoin is a poor hedge and is only suitable as a diversifier. Blundell-Wignall (2014) is separating the "currency" issues from the potential technology benefits with respect to cryptocurrencies.

We study whether Bitcoin returns, Bitcoin transaction volume, the number of unique Bitcoin addresses that is active each day and google searches for the term "Bitcoin" have any relationship with the abnormal returns for traditional payment systems that is widely used today and the financial sector. We find that the relationship between Bitcoin and payment systems is very weak, which indicates that investors that typically invest in these companies doesn't see Bitcoin as a serious competitor. However, unique Bitcoin addresses seems to have a negatively relationship with the abnormal returns of most of the payment companies.

The rest of the paper is organized as follows: Section 2 will give an overview of Bitcoin. Section 3 will give an overview over the payment companies. Section 4 presents the data. Section 5 describes the methodology. Section 6 presents the analysis and results. Section 7 we do a robustness check of our results. Section 8 concludes.

2. OVERVIEW BITCOIN

Bitcoin was created by Satoshi Nakamoto in 2009. Satoshi Nakamoto is a person or a group of persons that is unknown to the rest of the world. Bitcoin is a proposition of an electronic payment system that is based on cryptographic proof instead of trust. It allows any two willing parties to transact directly with each other without the need for a trusted third party. To protect sellers from fraud transactions cannot be reversed. Bitcoin is using a peer-to-peer distributed timestamp server to generate computational proof of the chronological order of transactions. This solves the double-spending problem where one digital currency can be spent twice. As long as the honest nodes control more computational power than any cooperating group of attacker nodes the system is secure. (Nakamoto, 2008)

Bitcoin have experienced an extraordinary development since the beginning. The interest and different opinions on Bitcoin have excelled the last few years. Some experts and crypto supporters believe that Bitcoin and other cryptocurrencies are the future while the critics believe that it's just a speculative bubble and will collapse sooner or later because there is no underlying value. Paul Krugman, a Nobel prize winning economist, went as far as stating "Bitcoin is evil" in an article in the New York Times. Sveriges Riksbank wrote a report on Bitcoin and cryptocurrencies in March 2018 (Söderberg 2018). Their conclusion is that cryptocurrencies cannot be assessed as money, but rather as assets. The reasoning for this conclusion is that cryptocurrencies are not primarily used as a payment method, but mostly as assets where the assets holders are speculating on an increase in value.

Bitcoins are created by a process called mining and individuals are rewarded by the network for their services. Bitcoin miners are processing transactions and securing the network. As a reward for their services the miners are collecting bitcoins in return. The more miners trying to find Bitcoin the more difficult it is. There will never be more than 21 million bitcoins in circulation. As of April 2018 there are nearly 17 million bitcoins in circulation which is approximately 80 % of the maximum number. Transactions can be denominated in smaller sub-units of a Bitcoin, such as bits. In one Bitcoin there are 1 000 000 bits which means that bitcoins can be divided up to 8 decimal places (Bitcoin.org, 2018).

In July 2010 the price of one Bitcoin was 0.05 USD. During 2017 the interest in Bitcoin and other cryptocurrencies exploded and this was reflected in the price. At its highest level in December 2017 the price of one Bitcoin was 19 193.72 USD. During the first months of 2018 the price has taken a huge fall and as of April 1 2018 the price is 6 946.3 USD. Bitcoin is still experiencing a high volatility in the price. The development in the price of Bitcoin is illustrated in Figure 1.

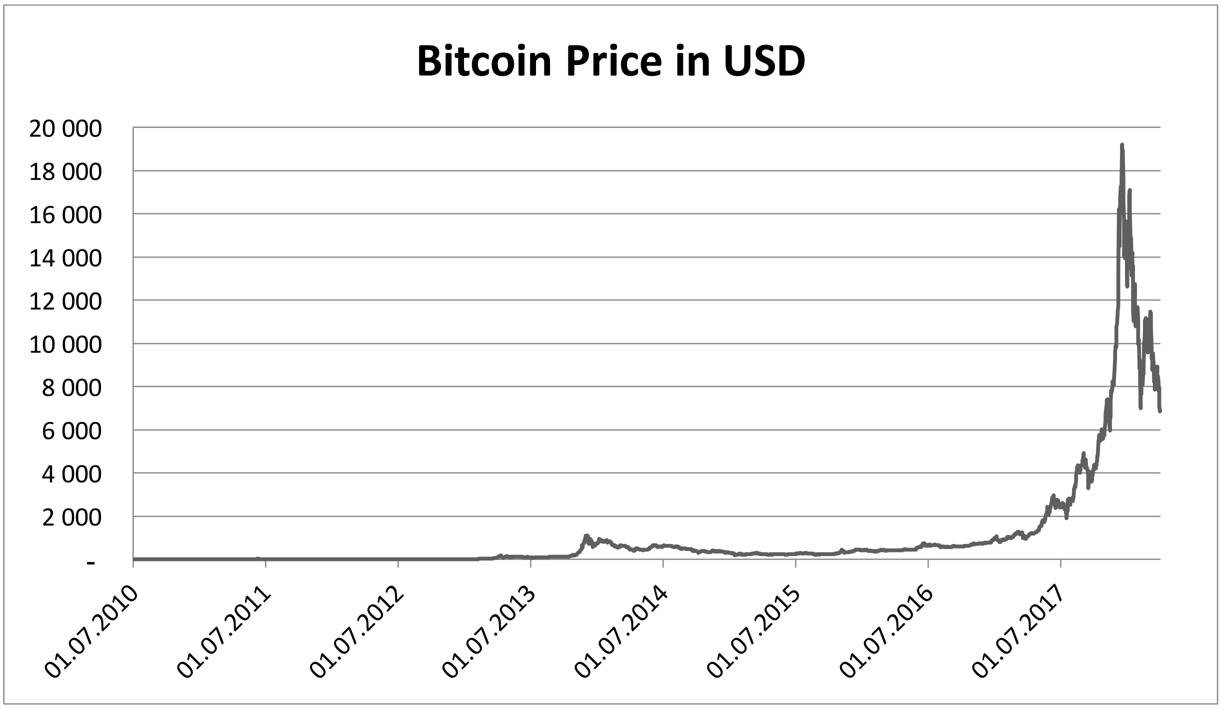

Figure 1: Bitcoin price in USD since 2010. Data retrieved from bitcoin.com.

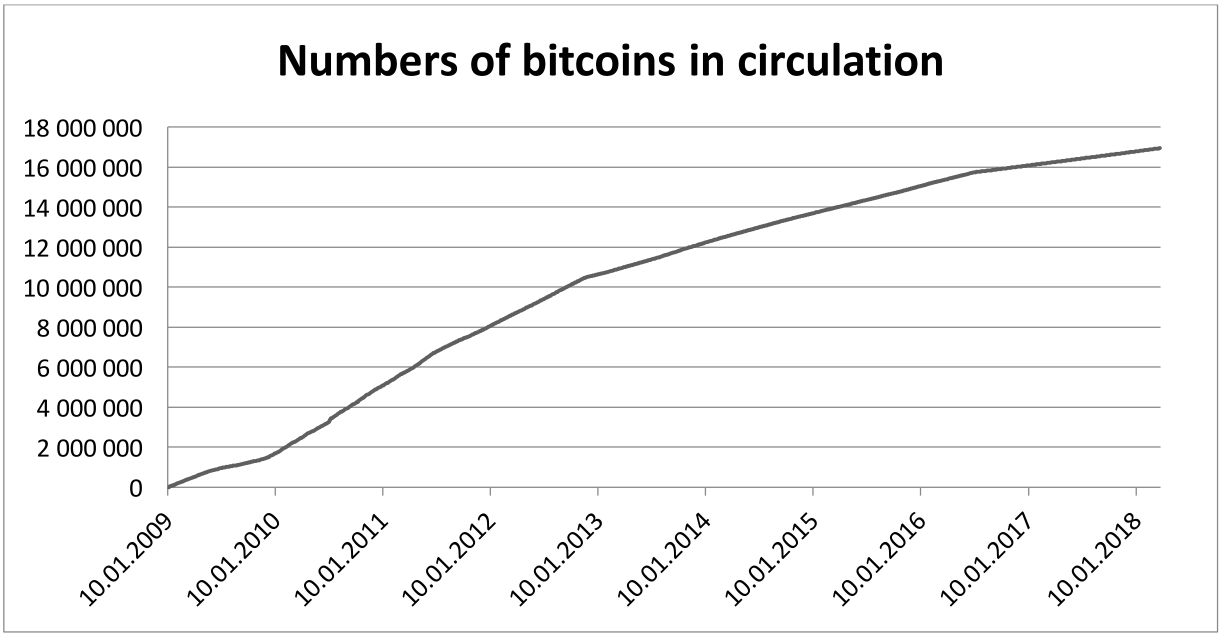

Figure 2: Numbers of bitcoins in circulation since 2009. Data retrieved from bitcoin.com.

In Figure 2 we can see the development in number of existing bitcoins. The maximal number of bitcoins is 21 million. In April 2018 the number of bitcoins was nearly 17 million. We can see that the growth in the graph is decreasing. This is because the more bitcoins that has been found the more difficult it is for miners to find new bitcoins. The cost and time required for mining is increasing.

During 2017 the market capitalization of Bitcoin have increased from approximately $15.5 billion to $321 billion in December 2017. This almost equals to an 2 000 % increase. After December 2017 the value of Bitcoin have decreased and in April 2018 the value is less than half of what it was at its highest.

The price of Bitcoin and other cryptocurrencies fluctuates a lot. It is not unusual that the price changes by 10% or more during a day or even just a few hours. There are several reasons why Bitcoin's price is so volatile. One likely reason is that all the Bitcoin in the world is owned by a small group of people. According to Amoros, R. (2017) about 95 % of all Bitcoins is owned by just over four per cent of people that owns Bitcoins. This makes the market very volatile because a few people controls a big portion of the market.

2.1 Bitcoin as a payment system

Today Bitcoin is mostly used as an investment object for investors and speculators even though it was originally planned as a payment system. Bitcoin is not issued by a central authority and differs a lot from traditional payment systems and banks. Once a transaction has been made it cannot be reversed. This can be perceived as both positive and negative. Irreversible transactions might increase fraud and the buyers might be more skeptic.

For merchants there might be a benefit by accepting Bitcoin as a payment method. The merchant does not pay anything to receive the funds because the transactions fees are paid by the sender (Bitconnect, 2018). There also isn't any subscription or monthly fees for using Bitcoin. Because of this merchants pay less in fees by using Bitcoin rather than the traditional payment system. The merchants also don't risk chargebacks because the transactions are irreversible.

There are also disadvantages in using Bitcoin as a payment system. The risk of fraud and the fact that it's not possible to chargeback if there is need is problematic. During times of high demand, transactions may be slow to be confirmed (Bitconnect, 2018). Bitcoin is not yet fully understood by governments and authorities which is also challenging. The high price volatility makes it very risky to use as a payment method. Bitcoin is also not yet accepted by most merchants globally.

By accepting bitcoins as a payment method merchants gets access to a broader market, and today there are merchants that is accepting bitcoins. However, the bitcoin volumes have generally not met the expectations at these outlets. As of January 2018 you can for instance use bitcoins to purchase flights, hotels, furniture, pizza, movies and music (Coindesk, 2018). At SpendBitcoins.com and Coinmap.org is it possible to check which stores that accepts bitcoins as payment.

The high volatility of Bitcoin makes it problematic for merchants to accept as payment. The largest payment processor for bitcoins is BitPay. BitPay was founded in 2011 and became the first Bitcoin payment processor (WeUseCoins, 2018). BitPay was founded in order to solve the volatility problem, and to make it easy for businesses to start accepting bitcoins as payment and not having to worry about price fluctuations. As of April 2018, BitPay serves more than 60 000 merchants worldwide and accepts both Bitcoin and Bitcoin Cash. BitPay charges a flat 1% fee per transactions which is lower than most traditional payment companies. At the end of each day or week the payments are settled in fiat currency. BitPay receives the bitcoin for each payment and locks in the dollar value for the merchant. At the end of each day or week the merchant receives a transfer equal to the fiat value of payments received.

3. OVERVIEW OF PAYMENT COMPANIES

3.1 VISA

Visa is a global payments technology company that enables electronic payments across more than 200 countries and territories. Visa is traded on the New York stock exchange. The company is most commonly known for their Visa cards (debit and credit). Visa have become one of the worlds largest electronic payments networks based on payment volume and number of transactions. (Visa Inc, 2018)

Every day Visa is connecting millions of consumers and businesses through their network. The Visa network involves issuers, acquirers, merchants and account holders. Worldwide there is

3.2 billon Visa cards and the network has a capacity to make more than 65 000 transactions per second. The Visa network has more than 46 million merchant locations and 16 300 financial institution clients. In 2017 Visa processed 111.2 billion transactions had a total transaction volume of $10.2 trillion. (Visa Inc, 2018)

Visa CEO, Alfred Kelly, told in an interview with CNBC (Belvedere, 2018) in January 2018 that he does not view Bitcoin as a payment system and that Visa won't process transactions in bitcoin. Kelly perceives Bitcoin more as a "speculative commodity" to invest in.

3.2 MasterCard

MasterCard is a global technology company in the payment industry. Through their global payments network MasterCard delivers payment transactions and related products and services in more than 210 countries and 150 currencies. MasterCard generates revenues based on the gross dollar volume, transaction fees and other payment-related products and services. In 2017 MasterCard processed 65.7 billion transactions and had a total transaction volume of $6.2 trillion. (Mastercard Incorporated, 2018). During an earnings call in May 2018 MasterCard's CEO, Ajay Banga, made it clear that cryptocurrencies are not a major part of their corporate strategy because of the unpredictability (Rooney, 2018).

3.3 Western Union

Western Union delivers ways to send money and make payments around the world for people and businesses. Western Union offers their services in more than 200 countries and territories. Approximately 90 % of these territories are outside the US. A big portion of Western Union's money transfer customers are migrants that has moved to countries with better economic opportunities than in their native country. Western Union was incorporated in 2006, and is listed on the New York Stock Exchange. In 2016 Western Union processed on average 31 transactions per second (The Western Union Company, 2017). Western Union have been evaluating blockchain technology and have been testing the cryptocurrency Ripple (Maranz, 2018). Ripple is the third biggest cryptocurrency based on market capitalization.

3.4 American Express Company

American Express Company offers charge and credit card products and travel-related services to consumers and businesses. American Express were founded in 1850 and incorporated in 1965. It is traded at the New York Stock Exchange. (American Express Company, 2017)

American Express Company have, together with Santander, partnered with Ripple (Browne, 2017). The incentive is that the project will speed up cross-border payments between the US and the UK using blockchain technology. Chief information officer at American Express, Marc Gordon, said in a statement in November 2017: "This collaboration with Ripple and Santander represents the next step forward on our blockchain journey, evolving the way we move money around the world".

3.5 PayPal

PayPal is a technology platform and digital payments company that enables digital and mobile payments on behalf of consumers and merchants worldwide. PayPal was founded in 1998 and was acquired by eBay in 2002. In 2015 eBay and PayPal became two independent publicly traded companies. The reason for the split was customary conditions (Ebay Inc, 2014). On July 20, 2015 PayPal's common stock started to be traded on the NASDAQ stock market.
PayPal is generating revenues by charging transactions fees and other payment-related services primarily based on the volume of activity. In 2016 PayPal had $197 million Active Customers Accounts, $6,1billion payment transactions and a total payment value of $354 billion. The average payment transaction was $58. (PayPal Holdings, Inc, 2017)

PayPal have decided not to take in use any cryptocurrencies in their businesses (Verhage, 2018). PayPal's CEO Dan Schulman said on an event on March 8: "Regulations need to be sorted out and a whole number of other things. It's an experiment right now that is very unclear which direction it will go." On the other hand, Shulman believes that blockchain will be an important part of the future. According to a PayPal spokeswoman PayPal currently have a team that is looking into potential ways to use blockchain in the future.

3.6 Financial sector

As a measurement for the financial sector we are using the iShares US Financials ETF (IYF). The iShares US Financials ETF is a fund which seeks to track the investment results of the Dow Jones U.S. Financial Index. The Dow Jones U.S. Financial Index is designed to measure the performance of U.S. companies in the financial sector. The correlation between the returns of the Dow Jones U.S. Financial Index and the iShares US Financials ETF for the last 5 years are 0.99. The top 10 holdings of the iShares US Financials ETF, which includes Visa, MasterCard and American Express, are presented in Table 1.

Table 1: Top 10 holdings of the iShares US Financials ETF as of June 2018

Berkshire Hathaway Inc B	7.09%
JPMorgan Chase & Co	7.07%
Bank of America Corporation	5.35%
Wells Fargo & Co	4.56%
Visa Inc Class A	4.53%
Mastercard Inc A	3.38%
Citigroup Inc	3.30%
Goldman Sachs Group Inc	1.54%
US Bancorp	1.51%
American Express Co	1.36%

3.7 Key numbers: Bitcoin vs VISA and MasterCard

Visa and MasterCard are the two largest and most known payment companies. These companies have the highest value, highest volume and the most transactions. Figure 3 is showing the market capitalization for Bitcoin, Visa and MasterCard at the end of each year from 2010 until 2017.

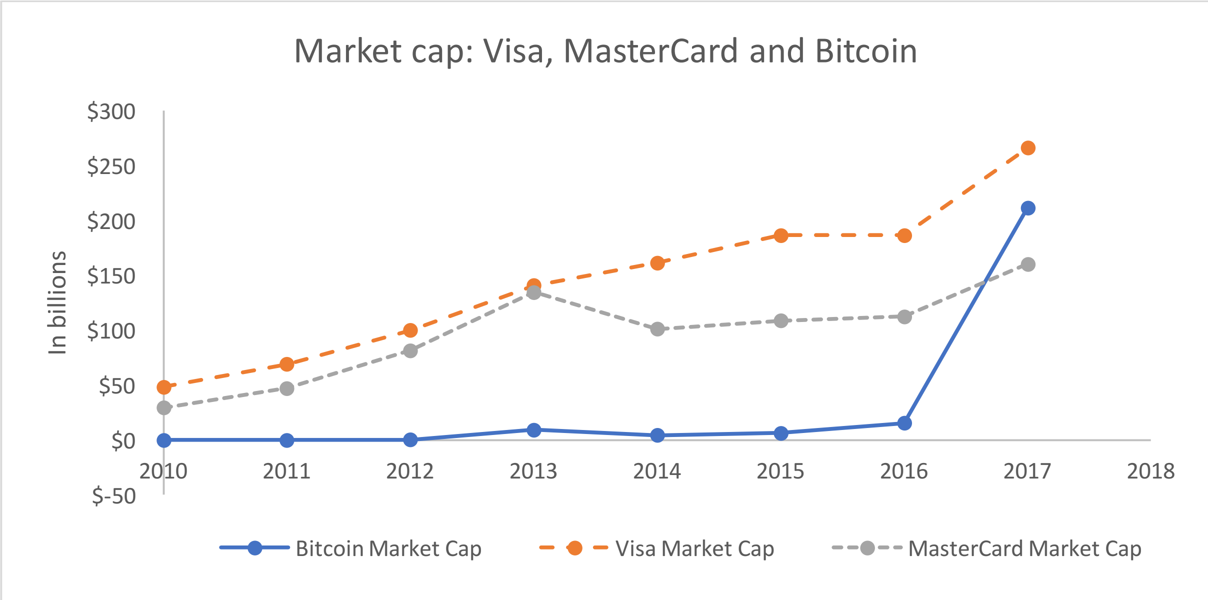

Figure 3: Market capitalization for Bitcoin, Visa and MasterCard from 2010 to 2017. Data is retrieved from bitcoin.com and ycharts.

Figure 3 is meant to illustrate the high growth in the value of Bitcoin. At the end of 2017, after a big increase in the Bitcoin price, Bitcoin had a market capitalization smaller than Visa, but larger than MasterCard. In 2018 Bitcoin have had a huge fall in price and as of the 1st of April 2018 the market capitalization of Bitcoin is $ 118 billions.

Comparing the number of transactions and volume Bitcoin has lower numbers than both Visa and MasterCard. Figure 4 is showing the number of transactions and figure 5 is showing the transaction volume for Bitcoin, Visa and MasterCard. In 2017 Visa and MasterCard processed respectively 111.2 billion (Visa Inc, 2018) and 65.7 billion transactions (Mastercard Incorporated, 2018) while Bitcoin processed 104 million transactions. The total volume for Visa and MasterCard was respectively $10.2 trillion (Visa Inc, 2018) and $6.2 trillion (Mastercard Incorporated, 2018) while Bitcoin had a volume of $3.7 trillion. This tells us that Bitcoin processes very few transactions compared to Visa and MasterCard, but on the other hand the average transaction value is much higher for Bitcoin. However, not all transactions processed by the bitcoin network are as straight forward as Visa or MasterCard transactions.

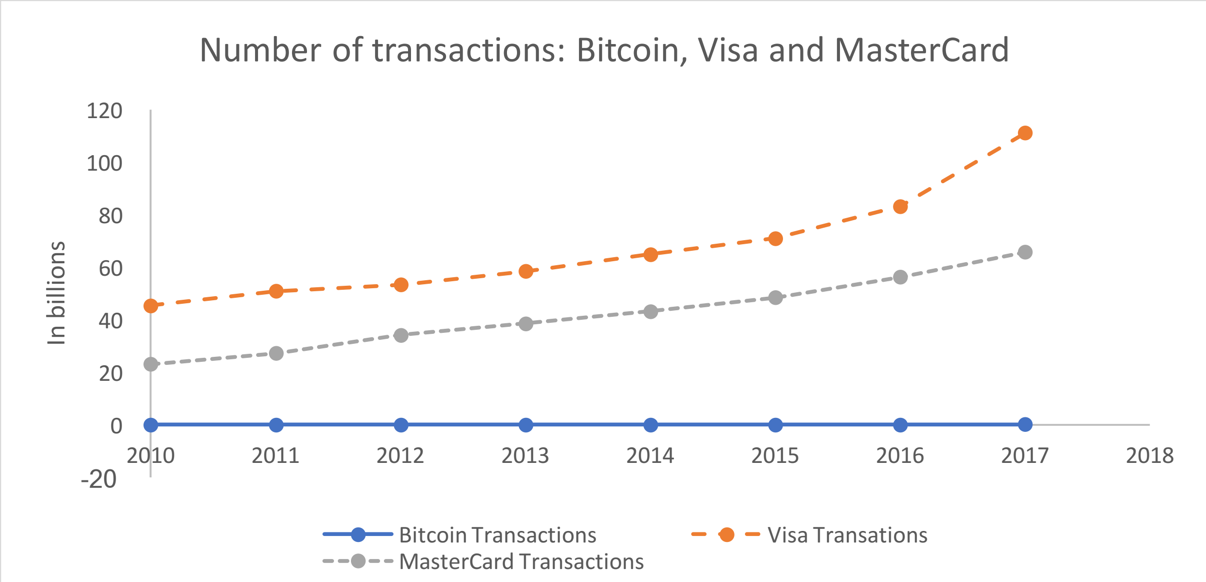

Figure 4: Number of transactions for Bitcoin, Visa and MasterCard

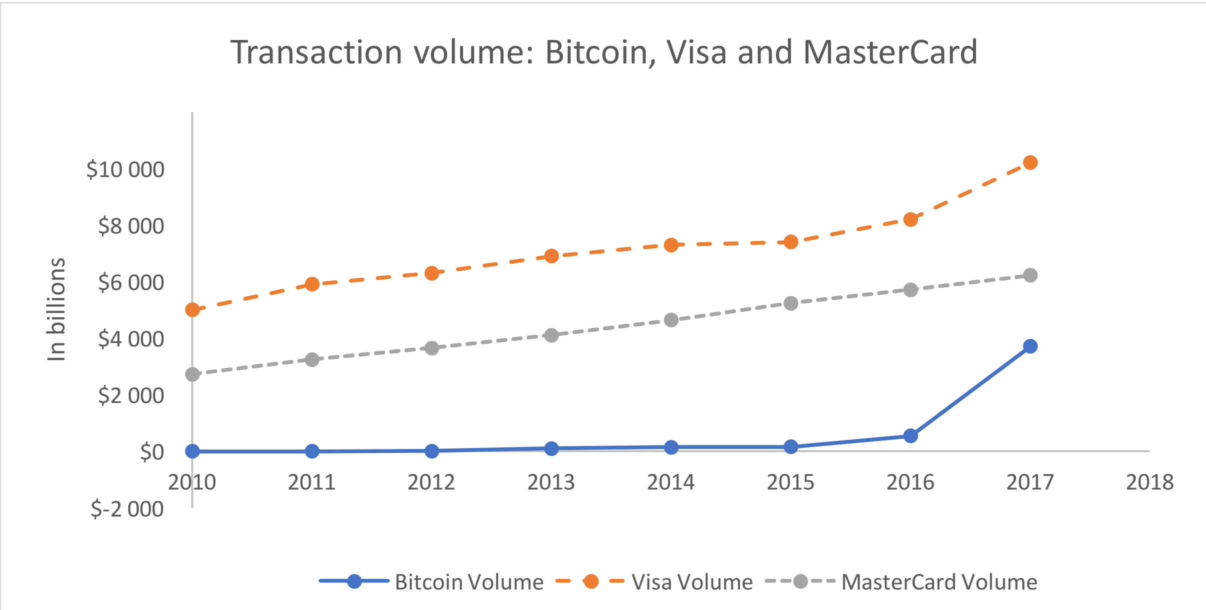

Figure 5: Transaction volume for Bitcoin, Visa and MasterCard

The number of transactions and transaction volume for Visa and MasterCard is collected from their respective annual reports from 2013 to 2017. The number of transactions and transaction volume for Bitcoin is collected from Bitcoin.com, see section 4.2.

4. DATA

The data used in this thesis is collected from different sources. In our collecting of data we have used Yahoo Finance, Bitcoin.com, Quandl, Federal Reserve Economic data (FRED) and Google Trends. In our analysis we use both weekly and monthly data. The time horizon for the collected data is from April 2013 until April 2018 for our weekly data and from February 2013 until February 2018 for our monthly data. For PayPal we only have available data from August 2015. Yahoo Finance is used to download prices for Bitcoin, all the comparable payment companies and the financial sector which we have used to calculate returns. Bitcoin.com provides various data for Bitcoin which we have used to collect number of transactions and transaction volume. Quandl was used to collect the number of unique bitcoin addresses used each day. FRED was used to collect the 3-month Treasury bill rate which was used as the risk-free rate. Google trend was used to collect data for the search frequency for the term "Bitcoin" on google.

4.1 Returns

From Yahoo Finance we downloaded weekly and monthly prices for Bitcoin, Visa, MasterCard, Western Union, American Express and PayPal. We downloaded the adjusted closed price. The weekly data is the closing price on Mondays. The monthly data is the closing price on the first day of each month. Prices were used to calculate logarithmic returns using equation (1).

(1) $r = \log\left(\frac{P_t}{P_{t-1}}\right)$

From the logarithmic returns we calculated the abnormal returns for the payment companies. Abnormal returns are the difference between actual returns and the expected returns from the market. The abnormal returns were calculated using equation (2):

(2) $AR = r - r_f - \beta(r_m - r_f)$

The 3-month Treasury bill rate is used as the risk-free rate. The returns on the S&P 500 is used as the market returns and is collected from Yahoo Finance. The company betas are obtained from Yahoo Finance. This equation was used for all the payment companies.

4.2 Transaction volume of Bitcoin

The transactions volume for Bitcoin is found by downloading daily transactions and transaction value from Bitcoin.com. Daily transactions are the number of transactions included in the blockchain each day. Transaction value is the average dollar value moved in each transaction. The transaction volume is found by multiplying the number of transactions and the transaction value for each day, as shown in equation (3). Then the daily transaction volumes are converted into weekly and monthly volumes.

(3) $Transaction\ volume = Transactions \times Transaction\ value$

To make the data stationary we calculated the logarithmic change in transaction volume for our weekly and monthly data using equation (4).

(4) $\Delta TransactionVolume = log\left(\frac{TransactionVolume_t}{TransactionVolume_{t-1}}\right)$

4.3 Unique Bitcoin addresses

From Quandl we downloaded data for unique bitcoin addresses. This data gives us the number of unique bitcoin addresses used per day. Bitcoin addresses represents one person's account and all addresses make up the total Bitcoin network. This data gives us information about how many persons are using the bitcoin network each day. To make the data weekly and monthly we summarized the number of unique Bitcoin addresses used each day for the last week and month respectively. To make the data comparable with our other variables we calculated the logarithmic change for each period using equation (5).

(5) $\Delta Unique\ addresses = Log\left(\frac{Addresses_t}{Addresses_{t-1}}\right)$

4.4 Google searches Bitcoin

Data for google searches on the term "Bitcoin" is downloaded from Google Trends. Google Trends is a search tool that allows us to see how often a specific term or keyword have been searched for on Google. This can be a good indicator on the interest and popularity for specific topics. The Google Trends data represents the search interest relatively to the time with highest search interest within the specified time. A value of 100 shows when the term was the most popular. A value of 50 means that the term was half as popular compared to when the term was at its most popular.

We retrieved the data the following way:

(6) $Trend_t = \log(Trendvalue_t) - log[Median\ (Trendvalue_{t-1}, \ldots, Trendvalue_{t-12})]$

Because google trend data are always reported as integers, we downloaded data in two separate periods to obtain better precision. Since the search frequency for Bitcoin sky rocketed during the last few months of 2017 we decided to transform the last year of data separately from the first 4 years of data. By doing this we get more precise values because we can capture the changes in the search frequency the first 4 years more precisely. To obtain transformed monthly data from 01.02.2013-01.04.2017 we downloaded data from 2012 to April 2017. To transform monthly data from 01.04.2017-01.02.2018 we downloaded data from 2013 to February 2018.

To transform the weekly data we transformed every year of the data separately by downloading 2 years of data at the time. When transforming the data for one year, we downloaded data for the respective year and for the previous year. The data is downloaded with two years at the time to make the data more precise. Like for the monthly data, we can capture more of the changes in the search frequency by transforming one year at the time. Then we used the same equation to transform the data using the median for the last 12 weeks.

Figure 6 and 7 are illustrating the raw google trend data and the transformed google trend data, respectively, at a weekly level.

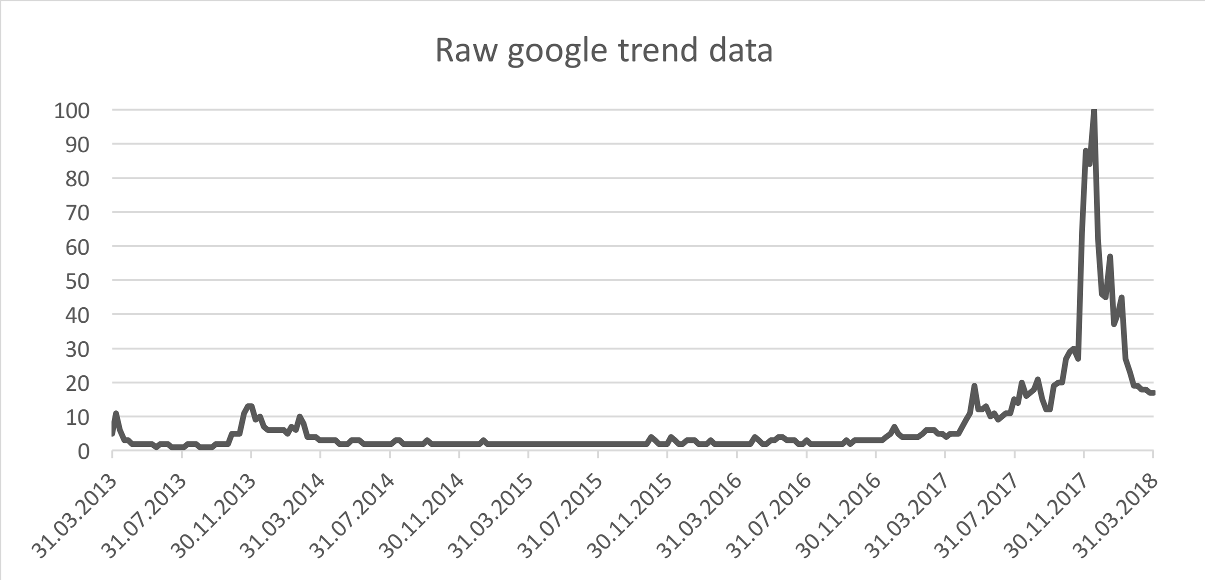

Figure 6: Raw data from google trends for the search term “Bitcoin”

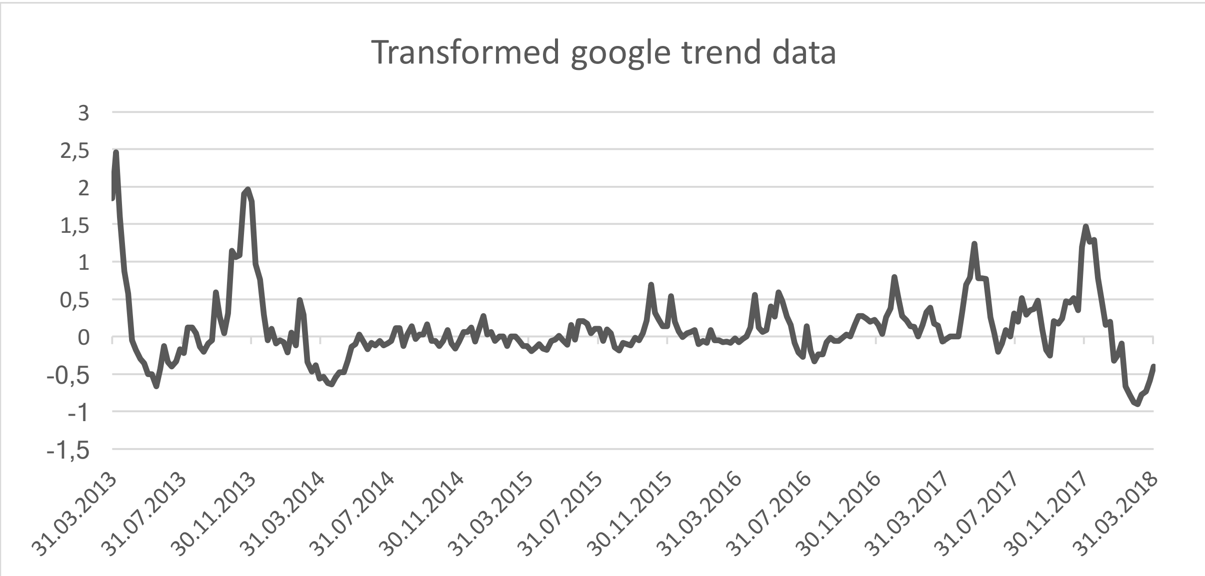

Figure 7: Transformed google trend data for the search term “Bitcoin”

4.5 Summary statistics

In table 2 we have presented the descriptive statistics for our weekly variables. In table 3 we have presented the correlation matrix for our weekly variables. In table 4 we have presented the descriptive statistics for our monthly variables. In table 5 we have presented the correlation matrix for our monthly variables.

Table 2: Descriptive statistics for weekly variables

Variable	Obs	Mean	Std. Dev	Min	Max
Returns Visa	262	0.002	0.018	-0.06	0.09
Returns Mastercard	262	0.003	0.018	-0.06	0.10
Returns WesternU	262	-0.001	0.024	-0.10	0.07
Returns AmericanExp	262	-0.001	0.022	-0.14	0.11
Returns PayPal	143	0.003	0.046	-0.13	0.16
Returns Bitcoin	262	0.016	0.147	-0.79	0.56
Financial sector	262	0.0001	0.009	-0.02	0.04
Addresses	262	0.007	0.622	-2.15	2.53
Google searches	262	0.105	0.464	-0.91	2.46
Volume	262	0.013	0.765	-2.46	2.61

Table 3: Correlation matrix for weekly variables

	Returns Visa	Returns Mastercard	Returns WestU	Returns AmerExp	Returns PayPal	Returns Bitcoin	Financial sector	Addresses	Google searches	Volume
Returns Visa	1.00									
Returns MastCard	0.49	1.00								
Returns WestU	0.02	0.07	1.00							
Returns AmerExp	-0.05	0.08	0.02	1.00						
Returns PayPal	-0.03	0.08	0.15	0.03	1.00					
Returns Bitcoin	-0.03	-0.08	-0.09	-0.02	0.05	1.00				
Financial sector	-0.04	-0.07	-0.01	0.37	0.11	0.02	1.00			
Addresses	-0.05	-0.02	-0.07	-0.03	0.02	-0.04	-0.14	1.00		
Google searches	-0.03	-0.09	-0.08	0.01	0.02	0.21	0.02	0.03	1.00	
Volume	-0.02	0.04	0.02	-0.11	0.12	-0.07	-0.07	0.85	0.10	1.00

Table 4: Descriptive statistics for monthly variables

Variable	Obs	Mean	Std. Dev	Min	Max
Returns Visa	61	0.010	0.036	-0.10	0.10
Returns Mastercard	61	0.011	0.037	-0.09	0.10
Returns WesternU	61	-0.001	0.046	-0.12	0.09
Returns AmerExp	61	0.000	0.048	-0.21	0.09
Returns PayPal	31	0.014	0.056	-0.10	0.10
Returns Bitcoin	61	0.102	0.336	-0.49	1.74
Financial sector	61	0.002	0.02	-0.03	0.05
Addresses	61	0.038	0.145	-0.08	0.47
Google searches	61	0.516	0.683	-0.55	2.56
Volume	61	0.094	0.462	-0.89	1.87

Table 5: Correlation matrix for monthly variables

	Returns Visa	Returns Mastercard	Returns WesternU	Returns AmerExp	Returns PayPal	Returns Bitcoin	Financial sector	Addresses	Google searches	Volume
Returns Visa	1.00									
Returns MastCard	0.76	1.00								
Returns WestU	-0.10	-0,04	1.00							
Returns AmerExp	-0.12	0.25	-0.08	1.00						
Returns PayPal	0.53	0.49	0.12	-0.23	1.00					
Returns Bitcoin	0.02	-0.09	-0.40	0.02	0.20	1.00				
Financial sector	-0.16	0.01	0.24	0.61	-0.29	-0.04	1.00			
Addresses	-0.19	-0.35	-0.15	-0.11	0.02	0.45	-0.13	1.00		
Google searches	0.12	0.12	-0.24	0.02	0.19	0.36	-0.06	0.05	1.00	
Volume	-0.02	-0.23	-0.29	-0.26	0.06	0.31	-0.04	0.64	0.20	1.00

We are seeing some correlation between some of the Bitcoin variables, which is expected because they are all an activity measure of Bitcoin. Visa and MasterCard also seems to be correlated.

5. METHODOLOGY

In our analysis we have used both Panel Data regressions and time-series regressions. Panel Data regression is chosen when we study whether various Bitcoin variables have an explanatory relationship with abnormal returns of payment companies collectively as a sector. The reason why we estimate the Panel Data regression is because we want to investigate the impact of

Bitcoin on the traditional payment companies in general. Time-series regression is used when we study whether various Bitcoin variables have an explanatory relationship with the abnormal returns of payment companies individually and the financial sector. The reason why we estimate time-series regression independently for each payment company is because we want to investigate whether the impact of Bitcoin varies among the different payment companies. The views on cryptocurrencies differs among the payment companies, some are considering implementing cryptocurrencies in their business while some are not. In our analysis and robustness check we conducted regressions based on both weekly and monthly data. We decided that weekly and monthly data would give us more precise results because of the high volatility in the Bitcoin price.

We are using robust standard errors in our regressions. Using robust standard error will remove the problem with heteroscedasticity and serial correlation (Arellano,1987). One important factor when using robust standard errors is that the time series are stationary (Vogelsang, 2011).

Before running our regressions we tested our variables for stationarity. A non-stationary variable can create problems in the analysis of the estimated model. To be able to use Panel Data and multiple regression analysis we need to create evidence that there is stationarity in the time series. In the data chapter we have explained what we are doing to make the different variables stationary. In Panel Data we used Im-Pesaran-Shin test and Fisher-type test to check for stationarity. In multiple regression we used the Dickey-Fuller test to check for stationarity. All our variables were stationary.

The Hausman test tells us what estimator is the best fit for the Panel Data regressions. We used the results from the Hausman test when we decided whether to use random or fixed estimator. In all our models the random estimator where the best fit. In our analysis the Panel Data regressions is presented with random estimator. The regressions with random and fixed estimator gave very similar results.

6. ANALYSIS AND RESULTS

We investigate whether various Bitcoin variables can explain weekly abnormal returns for different payment companies and whether the same variables can explain the returns for the financial sector. The analysis is conducted in weekly data. In the next section of the thesis we are doing robustness checks where we investigate the same models at a monthly frequency. We are also doing univariate regressions, in addition to multivariate regressions, because the model might be too complex given the relatively small number of observations and we might get insignificant results because of correlation between the variables. Every model presents 4 univarate regressions and 1 multivariate regression.

6.1 Panel Data

First we investigate whether various Bitcoin variables can explain the abnormal returns for payment companies in general. Our Panel Data regression investigates whether the weekly abnormal returns for payment companies can be explained by the various Bitcoin variables. The weekly abnormal returns for the payment companies is the dependent variable in this model. Our weekly Panel Data regression is shown in equation (7):

$$AR_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (7)$$

The independent variables in this model are the weekly Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (7) are presented in Table (6).

Table 6: Weekly Panel Data regressions results. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is weekly data from April 2013 – April 2018.

Panel Data weekly	Dependent variable: Abnormal returns payment companies				
Model	(7.1)	(7.2)	(7.3)	(7.4)	(7.5)
Intercept	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bitcoin returns	-0.0015				-0.003
	(0.007)				(0.006)
Volume		0.00004			0.005
		(0.001)			(0.004)
Addresses			-0.001**		-0.007*
			(0.001)		(0.004)
Google searches				-0.0009	-0.001
				(0.001)	(0.001)
Observations	1191	1191	1191	1191	1191
rho	0.0012	0.0012	0.0012	0.0012	0.0012
R^2					
within	0.0001	0.0000	0.0012	0.0006	0.0070
between	0.3456	0.3456	0.3456	0.3456	0.3456
overall	0.0005	0.0000	0.0012	0.0004	0.0069

In model 7.1, 7.2 and 7.4 none of the variables are significant. In model 7.3 unique Bitcoin addresses is significant at 5% and in model 7.5 unique Bitcoin addresses is significant at 10%. This result indicates that unique Bitcoin addresses have a negatively relationship with the abnormal returns of the payment companies. The variables Bitcoin returns, Bitcoin transaction volume and Bitcoin google searches are insignificant in all of our models which indicates that these variables doesn't have any relationship with the abnormal returns of the payment companies.

6.2 VISA

Next we investigate whether abnormal returns for Visa can be explained by various Bitcoin variables. In this model our dependent variable is the weekly abnormal returns for Visa. Our model can be shown in equation (8):

$ARVISA_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t$ (8)

The independent variables in this model are the weekly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (8) are presented in Table (7).

Table 7: Weekly multiple regression results for Visa. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is weekly data from April 2013 – April 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: VISA weekly abnormal log returns

Model	(8.1)	(8.2)	(8.3)	(8.4)	(8.5)
Intercept	0.002*	0.002**	0.002**	0.002**	0.002**
	(-0.001)	(0.01)	(0.001)	(0.001)	(0.001)
Bitcoin returns	0.0003				-0.0007
	(-0.007)				(0.006)
Volume		-0.0011			0.003
		(0.001)			(0.003)
Addresses			-0.002		-0.006*
			(0.002)		(0.003)
Google searches				-0.001	-0.001
				(0.002)	(0.002)
Observations	262	262	262	262	262
R^2	0.000	0.002	0.006	0.006	0.01

In model 8.1, 8.2, 8.3 and 8.4 none of the variables are significant. In model 8.5 the variable unique Bitcoin addresses is significant at 10%. This result indicate that the number of unique Bitcoin addresses that is active in the blockchain can have a negative effect on the abnormal returns for Visa. The variables Bitcoin returns, Bitcoin transaction volume and Bitcoin google searches does not have any effect on the abnormal returns of Visa. The R^2 of model 8.5 is 0.01

which means that the model can explain 1% of the variation of Visa abnormal returns.

6.3 MasterCard

Next we investigate whether abnormal returns for Mastercard can be explained by various Bitcoin variables. In this model our dependent variable is the weekly abnormal returns for Mastercard. Our model can be shown in equation (9):

$$ARMastercard_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (9)$$

The independent variables in this model are the weekly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (9) are presented in Table (8).

Table 8: Weekly multiple regression results for Mastercard. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is weekly data from April 2013 – April 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: MasterCard weekly abnormal log returns					
Model	(9.1)	(9.2)	(9.3)	(9.4)	(9.5)
Intercept	0.003**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.01)	(0.001)	(0.001)	(0.001)
Bitcoin returns	0.006				0.004
	(0.006)				(0.006)
Volume		-0.0009			0.006*
		(0.001)			(0.003)
Addresses			-0.003**		-0.009**
			(0.0013)		(0.004)
Google searches				-0.001	-0.002
				(0.002)	(0.002)
Observations	262	262	262	262	262
R^2	0.002	0.002	0.011	0.001	0.026

In model 9.1, 9.2 and 9.4 none of the variables are significant. In model 9.3 and 9.5 the variable unique Bitcoin addresses is significant at 5%. This result indicates that an increase unique Bitcoin addresses is negatively related with the abnormal returns of MasterCard. The variable Bitcoin transaction volume is signaficant at 10% in model 9.5. The R^2 of model 9.5 is 0.026 which means that the model can explain 2.6% of the variation in the abnormal returns of MasterCard. The variables Bitcoin returns and Bitcoin google searches aren't significant in any of our models which indates that none of these variables have any explanatory relationship with the abnormal returns of MasterCard.

6.4 Western Union

Next we investigate whether abnormal returns for Western Union can be explained by various Bitcoin variables. In this model our dependent variable is the weekly abnormal returns for Western Union. Our model can be shown in equation (10):

$$ARWesternUnion_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (10)$$

The independent variables in this model are the weekly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (10) are presented in Table (9).

Table 9: Weekly multiple regression results for Western Union. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is weekly data from April 2013 – April 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: Western Union weekly abnormal log returns					
Model	10.1	10.2	10.3	10.4	10.5
Intercept	-0.0005	-0.0009	-0.0009	-0.0002	0.00
	(0.001)	(0.01)	(0.001)	(0.001)	(0.001)
Bitcoin returns	-0.024***				-0.023**
	(0.009)				(0.01)
Volume		-0.0004			0.004
		(0.002)			(0.004)
Addresses			-0.0009		-0.005
			(0.002)		(0.005)
Google searches				-0.006*	-0.005
				(0.004)	(0.0035)
Observations	262	262	262	262	262
R^2	0.023	0.0001	0.0006	0.0145	0.036

Bitcoin returns is significant at 1% level in model 10.1 and at 5% level in model 10.5. This result indicates that the Bitcoin returns have a negatively relationship with the abnormal returns of Western Union. Bitcoin google searches is significant at 10% in model 10.4 which indicates that there might be a negatively relationship between this variable and the abnormal returns of Western Union. The R^2 of the model 10.5 is 0.036 which means that the model explains 3.6% of the variation of the abnormal returns of Western Union. The variables Bitcoin transaction volume and unique Bitcoin aren't significant in any of our models which indicates that there is no relationship with the abnormal returns of Western Union.

6.5 American Express

Next we investigate whether abnormal returns for American Express can be explained by various Bitcoin variables. In this model our dependent variable is the weekly abnormal returns for American Express. Our model can be shown in equation (11):

$$ARAmericanExpress_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (11)$$

The independent variables in this model is the weekly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (11) are presented in Table (10).

Table 10: Weekly multiple regression results for American Express. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is weekly data from April 2013 – April 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: American Express weekly abnormal log returns

Model	11.1	11.2	11.3	11.4	11.5
Intercept	-0.0008	-0.0007	-0.0007	-0.0009	-0.001
	(0.001)	(0.01)	(0.001)	(0.001)	(0.001)
Bitcoin returns	0.005				0.005
	(0.007)				(0.007)
Volume		-0.0013			-0.004
		(0.002)			(0.006)
Addresses			0.0013		0.003
			(0.002)		(0.007)
Google searches				0.0016	0.002
				(0.002)	(0.002)
Observations	262	262	262	262	262
R^2	0.001	0.002	0.0007	0.001	0.006

None of the variabels are significant in any of our models which indicates that these variables doesn’t have any relationship the the abnormal returns of Amercian Express.

6.6 PayPal

Next we investigate whether abnormal returns for PayPal can be explained by various Bitcoin variables. In this model our dependent variable is the weekly abnormal returns for PayPal. Our model can be shown in equation (12):

$$ARPayPal_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (12)$$

The independent variables in this model are the weekly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (12) are presented in Table (11).

Table 11: Weekly multiple regression results for PayPal. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is weekly data from August 2015 – April 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: PayPal weekly abnormal log returns

Model	12.1	12.2	12.3	12.4	12.5
Intercept	0.003	0.003	0.003	0.003	0.003
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
Bitcoin returns	0.019				0.028
	(0.035)				(0.037)
Volume		0.007			0.023
		(0.004)			(0.009)
Addresses			0.002		-0.024*
			(0.006)		(0.013)
Google searches				0.002	-0.003
				(0.009)	(0.009)
Observations	143	143	143	143	143
R^2	0.002	0.014	0.0005	0.0002	0.04

Unique Bitcoin addresses is the only significant variable in this model. In model 12.5 is unique Bitcoin addresses is significant at 10% and indicates a negatviely relationship with the abnormal returns of PayPal. Model 12.5 has a R^2 of 0.04 which means that the model can explain 4% of the variation in the PayPal returns. The variables Bitcoin returns, Bitcoin transaction volume and Bitcoin google searches aren't significant in any our models which indicates that they don't have an relationship with the abnormal returns of PayPal.

6.8 Financial sector

Next we investigate whether returns for the iShares US Financials ETF can be explained by various Bitcoin variables. In this model our dependent variable is the weekly returns for iShares US Financials ETF. Our model can be shown in equation (13):

$$FinancialSectorReturns_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (13)$$

The independent variables in this model are the weekly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (13) are presented in Table (12).

Table 12: Weekly multiple regression results for the financial sector. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is weekly data from April 2013 – April 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: iShares US Financials ETF weekly abnormal log returns					
Model	13.1	13.2	13.3	13.4	13.5
Intercept	0.0001	0.0001	0.0001	0.0001	0.0001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bitcoin returns	0.003				0.001
	(0.003)				(0.003)
Volume		-0.001			0.003
		(0.001)			(0.002)
Addresses			-0.002**		-0.01***
			(0.001)		(0.002)
Google searches				0.001	0.001
				(0.001)	(0.001)
Observations	262	262	262	262	262
R^2	0.002	0.01	0.02	0.0004	0.04

In model 13.1, 13.2 and 13.4 none of the variables are significant. In model 13.3 and 13.5 unique Bitcoin addresses is significant at 5% and 1% level respectively. This indicates that and unique Bitcoin addresses have a negative effect on the financial sector returns. Model 13.5 have a R^2 of 0.025 which means that 2.5% of the variation of the abnormal returns of the financial sector can be explained by the model. The variables Bitcoin returns and Bitcoin google searches aren't significant in any of our models. This indicates that these variables don't have a relationship with the abnormal returns of the financial sector.

To summarize the results from our weekly models for the payment companies we see that the variable unique Bitcoin addresses is negatively related and significant at least at 10% for all payment companies except Western Union and American Express. Bitcoin returns is only significant for Western Union and is negatively related to the abnormal returns. Bitcoin transaction volume is only significant for MasterCard and is positively related to the abnormal returns. Bitcoin google searches was significant at 10% for Western Union and American Express, negatively related to the abnormal returns of Western Union and positively related to the abnormal returns of American Express. The abnormal returns of the financial sector seems to have an negatively relationship with unique Bitcoin addresses.

7. ROBUSTNESS CHECK – MONTHLY FREQUENCY

In this section we will do robustness checks of our results by using some alternative models. We will do the same regressions at a monthly level to investigate whether the results differ from our weekly analyisis.

7.1 Panel Data

First we investigate whether the abnormal returns for payment companies can be explained by the various Bitcoin variables. The monthly abnormal returns for the payment companies is the dependent variable in this model. Our monthly Panel Data regression is shown in equation (14):

$$AR_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (14)$$

The independent variables in this model are the monthly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (14) are presented in Table (13).

Table 13: Monthly Panel Data regressions results. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is monthly data from February 2013 – February 2018.

Panel Data monthly	Dependent variable: Abnormal returns payment companies				
	(14.1)	(14.2)	(14.3)	(14.4)	(14.5)
Intercept	0.006**	0.006**	0.007**	0.006	0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Bitcoin returns	-0.001				0.009
	(0.01)				(0.01)
Volume		-0.007			-0.001
		(0.005)			(0.006)
Addresses			-0.035***		-0.045***
			(0.012)		(0.012)
Google searches				0.001	0.001
				(0.003)	(0.003)
Observations	275	275	275	275	275
rho	0.0024	0.0025	0.0027	0.0024	0.0026
R^2					
within	0.000	0.0049	0.0130	0.0002	0.0170
between	0.3291	0.3291	0.3291	0.3291	0.3291
overall	0.000	0.0047	0.0135	0.0001	0.0174

In model 14.1, 14.2, 14.4 and 14.5 none of the variables are significant. In model 14.3 and 14.5 the variable unique Bitcoin addresses is significant at 1% which indicates that this variable has a negatively relationship with the abnormal returns of payment companies. The variables Bitcoin returns, Bitcoin transaction volume and Bitcoin google searches aren't significant at any level which indicates that these variables doesn't have any explanatory relationship on the abnormal returns of payment companies.

In our Panel Data regressions the only significant variable is unique Bitcoin addresses both at weekly and monthly level. Panel Data regression at monthly level gave the most significant results. At weekly level unique Bitcoin addresses was significant at 10% level in model 7.5. At monthly level unique Bitcoin addresses was significant at 1% level in model 14.3 and 14.5.

7.2 VISA

Next we investigate whether abnormal returns for Visa can be explained by various Bitcoin variables. In this model our dependent variable is the monthly abnormal returns for Visa. Our model can be shown in equation (15):

$$ARVISA_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (15)$$

The independent variables in this model are the monthly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (15) are presented in Table (14).

Table 14: Monthly multiple regression results for Visa. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is monthly data from February 2013 – February 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: VISA monthly abnormal log returns					
Model	(15.1)	(15.2)	(15.3)	(15.4)	(15.5)
Intercept	0.010**	0.01**	0.011**	0.01	0.011*
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Bitcoin returns	-0.005				-0.004
	(0.001)				(0.018)
Volume		-0.002			0.014
		(0.007)			(0.013)
Addresses			-0.036*		-0.065*
			(0.02)		(0.035)
Google searches				-0.0004	0.001
				(0.007)	(0.0075)
Observations	61	61	61	61	61
R^2	0.002	0.0007	0.0205	0.0001	0.034

In model 15.1, 15.3 and 15.4 none of the variables are significant.. In model 15.3 and 15.5 unique Bitcoin addresses is significant at 10% level. Model 15.5 have a R^2 of 0.034. In both model 15.3 and 15.5 unique Bitcoin addresses has a negative explanatory effect on the abnormal returns for Visa. The variables Bitcoin returns, Bitcoin transaction volume and Bitcoin google searches aren't significant in any of the models.

Unique Bitcoin addresses was also the only significant variable at a weekly level. In our monthly model unique Bitcoin addresses was significant both in model 15.3 and 15.5. In our weekly model the variable was only significant in model 8.5.

7.3 MasterCard

Next we investigate whether abnormal returns for Mastercard can be explained by various Bitcoin variables. In this model our dependent variable is the monthly abnormal returns for Mastercard. Our model can be shown in model (11):

$$ARMastercard_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (16)$$

The independent variables in this model are the monthly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from model (16) are presented in Table (15).

Table 15: Monthly multiple regression results for Mastercard. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is monthly data from February 2013 – February 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table..*

Dependent variable: MasterCard monthly abnormal log returns					
Model	(16.1)	(16.2)	(16.3)	(16.4)	(16.5)
Intercept	0.011**	0.011**	0.013**	0.009	0.01
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Bitcoin returns	0.004				0.01
	(0.011)				(0.019)
Volume		-0.002			0.01
		(0.01)			(0.016)
Addresses			-0.041		-0.08**
			(0.032)		(0.04)
Google searches				0.003	0.004
				(0.006)	(0.007)
Observations	61	61	61	61	61
R^2	0.0015	0.001	0.026	0.004	0.056

In model 16.1, 16.2, 16.3 and 16.4 none of the variables are significant. In model 16.5 the variable unique Bitcoin addresses is significant at 5%. The R^2 of model 16.5 is 0.056. Bitcoin unique addresses has a negative explanatory effect on the abnormal returns for MasterCard. Bitcoin returns, Bitcoin transaction volume and Bitcoin google searches aren't significant in any of our models.

In our weekly model for MasterCard Bitcoin transaction volume was significant at 10% in model 9.5 which included all the variables. Unique Bitcoin addresses was significant at 5% in both model 9.3 and 9.5 at a weekly level.

7.4 Western Union

Next we investigate whether abnormal returns for Western Union can be explained by various Bitcoin variables. In this model our dependent variable is the weekly abnormal returns for Western Uniom. Our model can be shown in equation (17):

$$ARWesternUnion_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (17)$$

The independent variables in this model are the monthly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (17) are presented in Table (16).

Table 16: Monthly multiple regression results for Western Union. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is monthly data from February 2013 – February 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: Western Union monthly abnormal log returns

Model	17.1	17.2	17.3	17.4	17.5
Intercept	0.002	0.001	0.001	0.003	0.003
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Bitcoin returns	-0.035**				-0.02
	(0.015)				(0.02)
Volume		-0.025**			-0.008
		(0.012)			(0.022)
Addresses			-0.07*		-0.025
			(0.04)		(0.05)
Google searches				-0.008	-0.001
				0.008	(0.009)
Observations	61	61	61	61	61
R^2	0.06	0.06	0.05	0.014	0.08

The variables Bitcoin returns, Bitcoin transaction volume and unique Bitcoin addresses are significant in the univarite regressions at 5%, 5% and 10% level respectively. All of the variables have a negatively relationship with the abnormal returns for Western Union. In the multivariate regression none of the variables are significant. The variable Bitcoin google searches isn't significant in any of our models

In our weekly regressions for Western Union Bitcoin transaction volume and unique Bitcoin addresses weren't significant and Bitcoin google searches was significant at 10%.

7.5 American Express

Next we investigate whether abnormal returns for American Express can be explained by various Bitcoin variables. In this model our dependent variable is the monthly abnormal returns for American Express. Our model can be shown in equation (18):

$$ARAmericanExpress_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (18)$$

The independent variables in this model are the monthly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (18) are presented in Table (17).

Table 17: Monthly multiple regression results for American Express. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is monthly data from February 2013 – February 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: American Express monthly abnormal log returns

Model	18.1	18.2	18.3	18.4	18.5
Intercept	-0.003	-0.0001	-0.0001	-0.007	-0.007
	(0.007)	(0.006)	(0.007)	(0.008)	(0.008)
Bitcoin returns	0.023				0.035
	(0.015)				(0.025)
Volume		-0.003			-0.019
		(0.012)			(0.028)
Addresses			-0.01		-0.02
			(0.03)		(0.06)
Google searches				0.012	0.01
				(0.008)	(0.008)
Observations	61	61	61	61	61
R^2	0.02	0.001	0.001	0.03	0.07

In our models with the monthly abnormal returns for American Express as the dependent variable none of the independent variables are significant in any of our models. This indcates that the Bitcoin variables doesn't have any explanatory effect on the monthly abnormal returns of Amercian Express.

In our weekly model for American Express Bitcoin google searches is significant at 10% in model 11.4, but the model can only explain 0.1% of the variation in the abnormal returns of American Express.

7.6 PayPal

Next we investigate whether abnormal returns for PayPal can be explained by various Bitcoin variables. In this model our dependent variable is the weekly abnormal returns for PayPal. Our model can be shown in equation (19):

$$ARPayPal_t = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (19)$$

The independent variables in this model are the monthly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (19) are presented in Table (18).

Table 18: Monthly multiple regression results for PayPal. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is monthly data from August 2015 – February 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: PayPal monthly abnormal log returns					
Model	19.1	19.2	19.3	19.4	19.5
Intercept	0.007	0.013	0.014	0.004	0.001
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Bitcoin returns	0.056				0.054
	(0.05)				(0.06)
Volume		0.008			0.005
		(0.02)			(0.03)
Addresses			0.007		-0.04
			(0.06)		(0.11)
Google searches				0.018	0.011
				(0.023)	(0.016)
Observations	31	31	31	31	31
R^2	0.04	0.003	0.0003	0.03	0.06

In our monthly model with the monthly PayPal abnormal returns as the dependent variable none of the independent variables are significant in any of our models. This indcates that the Bitcoin variables doesn't have any explanatory effect on the monthly abnormal returns of PayPal. In our weekly model for PayPal unique Bitcoin addresses was significant at 10% in our multivariate model.

7.7 Financial sector

Next we investigate whether returns for the iShares US Financials ETF can be explained by various Bitcoin variables. In this model our dependent variable is the monthly returns for iShares US Financials ETF. Our model can be shown in equation (20):

$$FinancialSectorReturns = B_0 + B_1 BitcoinReturns_t + B_2 TransactionVolume_t + B_3 Addresses_t + B_4 GoogleSearches_t + \varepsilon_t \qquad (20)$$

The independent variables in this model are the monthly data for Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches. The results from equation (20) is presented in Table (19).

Table 19: Monthly multiple regression results for the Dow Jones U.S. financial sector. Various variable inclusions tested. Standard errors are reported in parantheses. One, two and three stars indicates significance at 10%, 5% and 1% respectively. The sample period is monthly data from February 2013 – February 2018. The $\boldsymbol{R^2}$ *of the model is stated at the bottom of the table.*

Dependent variable: iShares US Financials ETF monthly abnormal log returns					
Model	20.1	20.2	20.3	20.4	20.5
Intercept	0.002	0.002	0.002	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bitcoin returns	0.001				0.0004
	(0.004)				(0.007)
Volume		0.002			0.006
		(0.004)			(0.01)
Addresses			-0.005		-0.02
			(0.01)		(0.02)
Google searches				0.0004	0.0003
				(0.003)	(0.003)
Observations	61	61	61	61	61
R^2	0.001	0.003	0.002	0.0003	0.015

None of the variables in this model are significant in any of our models. This indicates that the Bitcoin variables doesn't have any explanatory effect on the monthly returns of the financial sector. In our weekly model unique Bitcoin addresses was significant at 5% level in model 13.3 and at 1% level in model 13.5.

8. CONCLUSION

In this thesis we study whether Bitcoin returns, Bitcoin transaction volume, unique Bitcoin addresses and Bitcoin google searches can explain abnormal returns of traditional payment companies and the financial sector. We find that the relationship between Bitcoin and payment systems is weak. However, unique Bitcoin addresses have a negatively relationship with the abnormal returns for most of the payment companies and the financial sector at a weekly level. However, only a small part of the variation in the abnormal returns of payment companies and the financial sector can be explained by the various variables related to Bitcoin. This indicates that investors that typically invests in these companies doesn't see Bitcoin as a serious competitor or as an alternative payment system.

We tested the robustness of our models by estimating the same models using monthly data. The results were mostly the same using weekly and monthly frequency with a few exceptions. At a monthly level none of the Bitcoin variables had any relationship with the abnormal returns for American Express and PayPal or the financial sector.

Our study indicates that unique Bitcoin addresses, which is significant in most of the models, can explain a small part of the variation in the abnormal returns for payment companies. This can indicate that the number of unique addresses catches the non-speculative side of Bitcoin. However, most of the variation in the abnormal returns are left unexplained by our models. Bitcoin returns, Bitcoin transaction volume and Bitcoin google searches don't explain any of the variation in the abnormal returns for payment companies, even though there are some differences across companies. These variables looks to be driven by speculative behaviour from investors rather than from its use as an payment system. It is also very interesting when you compare the market capitalization, number of transactions and transaction volume of Visa and MasterCard with Bitcoin. This is another indication of the big speculative side of Bitcoin. The speculative side can inhibit Bitcoin to operate as a currency or payment system. Unique Bitcoin addresses is also negatively related with the abnormal returns of the financial sector at a weekly level.

It will be interesting to see whether Bitcoin will be a fully good alternative as a payment system and more widely accepted across the world in the future. For this to happen it will be important that the Bitcoin price stabilizes and Bitcoin needs to be accepted as a means of payment.

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