Relation between Searches for Bitcoin and Searches for the Characteristics of Bitcoin Users in Canada

by Manavi Garg

(300025042)

Major Paper presented to the

Department of Economics of the University of Ottawa

in partial fulfilment of the requirements of the M.A. Degree

Supervisor: Professor Francesca Rondina

ECO 6999

Ottawa, Ontario
March 2019

Abstract

Bitcoin has recently gained wide attention in the news and across different social media platforms. With this increasing interest in the cryptocurrency, there have been several purposes for which Bitcoin has been used by people from different backgrounds. This paper uses Google Trends to analyse the relation between search interest in Bitcoin and the users of the currency. The users of Bitcoin were grouped into four categories and data were obtained for the period 2015 – 2017, for seven Canadian provinces. After conducting the initial analysis to examine the relation, I further include data on Bitcoin prices, unemployment rate and a placebo clientele group to study the sensitivity of the results due to the inclusion of additional variables. Overall, the paper finds no evidence of a robust relation between search interest in Bitcoin and its users in Canada.

Table of Contents

List of Tables and Figures

Tables

Figures

1 Introduction

Bitcoin was introduced in 2008 by Satoshi Nakamoto as the world's first decentralised digital currency[1] which became functional in 2009. Nakamoto (2008) gives a description of bitcoin and how it is used. The currency was built as an electronic payment system which essentially involved transactions between individuals based on trust. The ownership of bitcoins is crypted through digital signatures ensuring privacy. Furthermore, Bitcoin can also be stored in digital wallets which comprises Web Services, Local Applications and USB Drivers. The currency is secured by private/public keys with the possibility of also printing the currency. In addition to the privacy provided whilst using Bitcoins, Bitcoin cannot be frozen in a way a bank can freeze money. Payments can be made without relying on a third party, such as a bank, and transactions are made secure through online cryptographic algorithms.

More recently, Bitcoin has gained wide popularity across the world, with Bitcoin prices reaching as high as $(USD)20,000. The currency is highly volatile mostly because it is still a relatively new currency, sometimes accompanied by illiquid markets (Bitcoin.org, n.d). With the cryptocurrency actively making the news, it has gained the attention of a number of users from different backgrounds using the currency for various purposes. Furthermore, in the age of cryptocurrencies, social media plays a key role in increasing awareness and informing people of the various changes taking place. Thus, my paper explores the relation between the number of searches for the characteristics of the users of Bitcoin and searches for Bitcoin.

The methodology used to carry out the analysis in my paper is based on the paper by Yelowitz and Wilson (2015). Yelowitz and Wilson (2015) look at the correlation between the number of

[1] Note that the terms cryptocurrency and currency for Bitcoin have been used interchangeably throughout the paper.

searches of Bitcoin and searches for the characteristics of the users of Bitcoin in the United States (US). They define the user categories into four groups - Libertarians, Computer Science, Illegal Activity and Speculative Investors and use Google Trends (GT) data to conduct their analyses. My paper examines a similar relation, however, the analyses is conducted for Canada over a time period different than the time period examined in Yelowitz and Wilson (2015). There has been an increase in research carried out to study various topics surrounding Bitcoin. However, there is an existing gap in the literature focussing on the use of Bitcoin in Canada. My paper aims to fill in this gap and contributes to the existing literature by exploring the characteristics of Bitcoin users in Canada and their relationship with Bitcoin search interest on Google.

The paper is structured as follows. Section 2 discusses the literature surrounding the topic, Section 3 explains the data used for conducting the analysis with Section 4 specifying the econometric models used for the analyses. Results are discussed in Section 5 and Section 6 carries out robustness checks to examine the sensitivity of the results. Finally, Section 7 concludes the paper.

2 Literature Review

Bitcoin has recently gained significant popularity. Bohme et al. (2015) report that since 2009 (until 2015), over 62.5 million transactions have been carried out using Bitcoin between 109 million accounts. This was equivalent to approximately $(USD)50 million as the value of transactions at market exchange rates as of March 2015, with the daily transaction volume being 200,000 Bitcoins, totalling $(USD)3.5 billion as the market value of Bitcoins in circulation (Bohme et al., 2015; Blockchain.info, 2015). With this increasing popularity, it is important to

consider the reasons behind this rising interest in the cryptocurrency. Three characteristics listed for an ideal cryptocurrency are:

- The deregulation of a cryptocurrency where no authority can control the use of the currency and the reasons for which it is used
- Ease of access to the currency such that it can be simply used across borders and exchanged without any limitations to locations, and
- The currency should be "apolitical", so as to not favour a specific system or group of people, (Bitcoin Magazine, n.d.).

Overall, Bitcoin generally encompasses all of the characteristics listed above. In my opinion, one of the reasons Bitcoin has appealed to a wider audience as compared to other cryptocurrencies is because it comprises the characteristics of an ideal currency as mentioned. The following literature delves further into some of the characteristics mentioned above and builds a foundation to the hypothesis being analysed in my paper.

One of the key characteristics of Bitcoin is that it is an unregulated and decentralised currency. Payments using Bitcoin can be made over the internet without any control from a central authority. Before Bitcoin was introduced, online transactions could not be made without the involvement of a third party as a trusted intermediary so that the verification of transactions could take place, (Nian and Chuen, 2015; Brito and Castillo, 2013). Bitcoin has been described as "an unbacked, unregulated form of virtual currency that allows for transactions that are faster, cheaper, and more anonymous than any other existing schemes" (Turpin, 2014, p.339). Douma (2016) identifies that the rise in interest towards Bitcoin, which is an unregulated currency, is due to the fact that, as a result of the financial crisis of 2008 people have increasingly lost trust in the government and central banks.

Due to this mistrust, people are finding alternative ways to make money and overcome "government intervention and regulation", (Douma, 2016). "Electronic currencies, on the other hand, would answer to market forces, rather than the policies of the national government and the various special interests they represent" (Douma, 2016, p.16; Plassaras, 2013, p.390). Douma (2016, p.16; Plassaras, 2013, p.392) also further gives an example of a prediction made by the European Central Bank in 2012 – "a 2012 study from the European Central Bank suggests that use of digital currencies like Bitcoin is only expected to grow in the near future. Recent financial crisis in both Spain and Cyprus have caused Bitcoin prices to spike as worried citizens exchange their government-backed euros for Bitcoins". Thus, based on the literature it is evident that people have an increased interest in Bitcoin due to limited or no intervention by the government or a central bank.

The Internal Revenue Service (IRS) in the United States (US) has linked the use of Bitcoin to concerns such as tax evasion, money laundering and buying and selling contraband. A website called the Silk Road was an anonymous online marketplace started in February 2011. The payments made between the buyers and sellers on this website were made anonymous through the use of Bitcoin, in addition to the anonymity of communication between two parties through a hidden network. Christin (2012) compares Silk Road to Craigslist, eBay or the Amazon Marketplace with the difference being that Silk Road ensures the anonymity of the transactions and the parties involved. This marketplace was largely used for buying illegal drugs across different countries, with a large number of users originating from Germany and the Netherlands (Douma, 2016).

The anonymity of transactions and ease of exchanging the currency across borders made Bitcoin an appealing currency to be used as a part of the Silk Road website payments. Christin (2012)

uses a 29-day moving average for 2012 as the sliding window to calculate the number of transactions and Bitcoin traded, finding that "approximately 1,335,580 BTC[2] were exchanged on Silk Road", and about "29,553,384 BTC were traded in Bitcoin exchanges over the same period" (Christin, 2012, p.19). A comparison of these two numbers showed that transactions that occurred on Silk Road accounted for 4.5% of all transactions across Bitcoin exchanges. The Silk Road gained wide attention of the US regulatory authorities for all the illegal activities taking place on the website which resulted in the US Federal Bureau of Investigation (FBI) shutting down the website in 2013 and arresting its founder. In addition to the founder's arrest, the FBI found that over one million users were registered on the website, who used approximately USD $1.2 billion worth of Bitcoins at the time (Ponsford, 2015).

The literature provides evidence of people using Bitcoin for illegal activity. However, in addition to using Bitcoin for illegal transactions, the volatile currency has allowed individuals to make thousands of dollars by holding Bitcoin as a stock. Investors began to look for alternative ways to make money after the financial crisis. Furthermore, the launch of the Winklevoss Bitcoin Trust – a Bitcoin exchange traded fund by the renowned American internet entrepreneurs Cameron and Tyler Winklevoss, made Bitcoin a "credible investment vehicle" (Briere et. al, 2015; Balchunas, 2013; Massoudi and Alloway, 2013). Some of the key factors that make Bitcoin an appealing investment include that the markets are accessible over the weekends, there is no central bank intervention as there is for other traditional currencies and that Bitcoin depends entirely on the supply and demand forces in the market. Moreover, Bitcoin also has high diversification benefits due to low correlations with the traditional assets and financial instruments (Briere et. al, 2015).

[2] BTC here refers to the number of Bitcoins traded.

Bitcoin has been recognised as highly volatile. Although, investments in Bitcoin led to people losing money, it also allowed some investors to make extremely large gains (more than double their money) in a short period of time. Coin Desk (2017)[3] reports that, Bitcoin prices went from around USD $930 in 2016 to an all-time high of approximately USD $20,000 towards the end of 2017. However, shortly after this all-time high, the prices tumbled down to below USD $11,000. The currency has experienced a decrease as high as 30% within short periods of time. Although the currency has been observed to be very volatile, the rewards from investing have been especially high.

In addition to all the characteristics of Bitcoin and its uses, one of the major characteristics of the cryptocurrency is that it is a virtual currency and based on a blockchain platform that has been programmed using algorithms. "Bitcoin's rules were designed by engineers with no apparent influence from lawyers or regulators" (Bohme et. al, 2015, p. 213). Mining cryptocurrency is "process of synchronising transactions in a network of computers" (Bhaskar and Chuen, 2015, p.45). Computer science programmers are highly interested in the advanced technology behind Bitcoin, and the possibility of mining the currency. These uses allow programmers to earn high profits. Profits earned through mining are a function of the cost of mining, which increases over time, and price of the cryptocurrency which fluctuates frequently (Bhaskar and Chuen, 2015).

Bitcoin evidently has various uses and factors that appeal to a wide audience for various purposes. Following this evidence, it is reasonable to understand that users of Bitcoin can fall under different categories, with each user group having distinct characteristics. With multiple uses of Bitcoin, my paper has narrowed the user categories into four groups based on the uses of Bitcoin discussed above. Thus, the number of searches of the characteristics of four user groups

[3] The article by Coin Desk was written on Dec 30, 2017, and thus the price of $930 is from a year before the time of writing this article.

– Libertarians, Illegal Activity, Speculative Investors and Computer Science are analysed in correlation with the number of searches of Bitcoin in the following sections. These user groups are the same categories as defined in Yelowitz and Wilson (2015).

Glaser et. al (2014) use data from 2011 to 2013 and visitor statistics from a Wikipedia article on Bitcoin to analyse the user's intentions of changing from a domestic currency to a digital currency such as Bitcoin. The paper finds that new users of Bitcoin largely use it for investment purposes rather than for payment to buy goods and services. Bohr and Bashir (2014) carry out empirical analyses to identify who uses bitcoin. They find statistical significance that users interested in using Bitcoin for illegal activity had about 25% - 45% more Bitcoins than those who did not use it for illegal activity. A study carried out by Bashir et al. (2016) finds evidence that political views of individuals do indeed contribute to the adoption of Bitcoin, such that "Libertarian ideology was the only consistent factor for both attitudes and experience with the virtual currency" (Bashir et al. 2016, p.362). These papers discuss evidence found in the literature that support for these user groups largely influencing the use of Bitcoin.

The focus of my paper is on users in Canada. The research I conducted enabled me to only find limited literature on the use of Bitcoin in Canada. For instance, research shows that about 64% of Canadians have heard of Bitcoin with only 2.9% owning Bitcoin, (Henry et al., 2018). The survey used to gather information in Henry et al. (2018), found that about 6% of Bitcoin users in Canada did not trust their banks, the government or the Canadian dollar. Furthermore, data also showed that 12% of Bitcoin owners held Bitcoin for investment purposes, with the Canada Revenue Agency also recognising Bitcoin as taxable. Therefore, from the literature, it can be observed that the use of Bitcoin is limited in Canada. Although, Filipi (2014) specifies that Bitcoin-ATMs are being installed in Canada, US and Berlin, "their overall functionality,

acceptance and use remain extremely limited in Canada and elsewhere" (Fung et al., 2015, p.3). As these are the only papers for user of Bitcoin in Canada that I am aware of, my paper contributes to the literature by providing more information on the relation between search interest in Bitcoin and its users in Canada.

3 Data

Data in my paper are obtained for the time period January 2015 – December 2017 for seven Canadian provinces. Data are analysed on seven Canadian provinces as data for some of the search terms were not available for all provinces. As a result, the provinces for which data on all search terms were not available were not included in the final data set. The provinces included in my paper are – Alberta, British Columbia, Manitoba, Nova Scotia, Ontario, Quebec and Saskatchewan.

Yelowitz and Wilson (2015) define four categories as the main users of Bitcoin, so, using the same methodology as Yelowitz and Wilson (2015), I define the same user categories in my paper. Data for searches on Bitcoin and each user group is obtained from Google Trends (GT). Additionally, data on Bitcoin prices and unemployment rate are also included in the dataset. These are discussed in more detail below.

3.1 Google Trends

GT provides data on topics and search terms trending worldwide. The homepage of the website displays topics that are trending on Google Search, Google News or YouTube. The stories that are trending are determined through Google's Knowledge Graph technology, which essentially collects information from the three platforms mentioned to identify which stories are trending on

these platforms. This tool is used for various purposes including academia, marketing and research and analysis.

GT allows the comparison of different topics based in any region, time period and categories such as Business & Industrial, Arts & Entertainment etc. Additionally, GT has features such as searching for topics and terms in different languages which also allows comparing the results for the same terms in different languages.

A search for a term on GT shows the "term's popularity over time in (nearly) real time" (Google News Initiative Lesson 4, n.d., p.3). The data is not completely in real-time as Google's technology is constantly improving and updating the results. The data that users obtain through these searches indicates how many times that term has been searched within a particular region compared to the total number of searches done on google in that region within the time period being examined. This data that users obtain goes through a re-scaling process by GT which results in the final data that users can see. GT scales data on its own scale between 0 – 100 such that a value of 100 or close to a 100 is assigned to the region with the highest number of searches. The graphs that show the final data on GT do not represent the total number of searches in absolute terms, rather, they show scaled data. A specific data point calculated thus represents its relative popularity to all the other searches for a particular term on GT.

For instance, a google search on Bitcoin for Canada from January 2015 – December 2017 results in the data as in Figure 1. The search in Figure 1 was carried out on February 23, 2019 at 5:31 p.m.

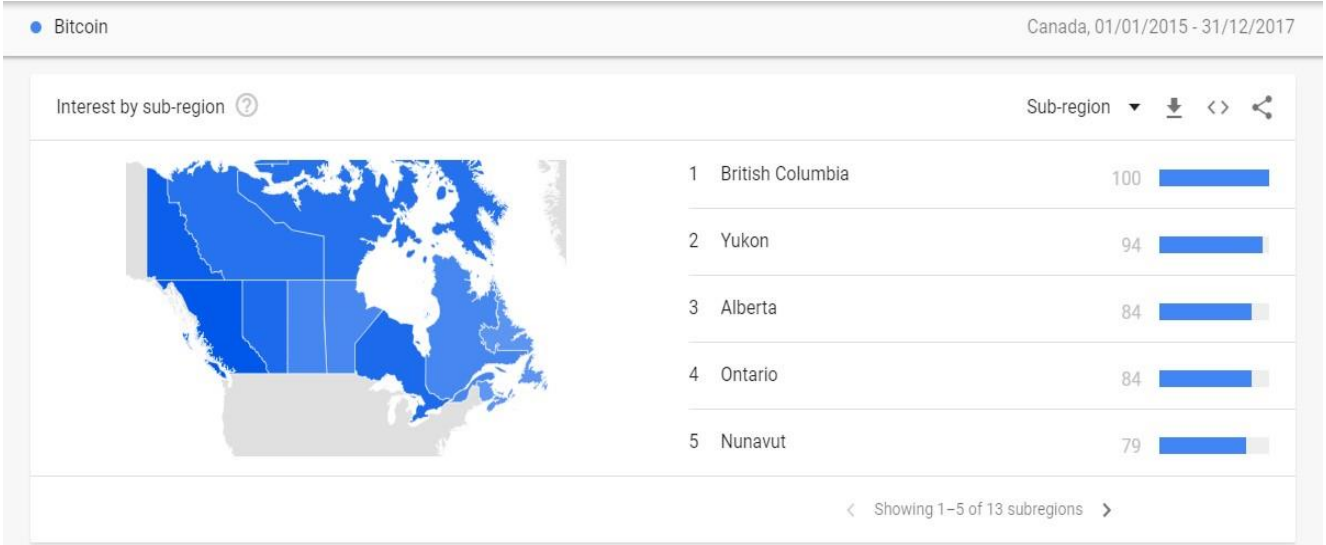

Figure 1 Bitcoin Searches in Canada

Source: Google Trends

Given the data in Figure 1, it can be seen that British Columbia has the highest search volume of Bitcoin in Canada. Alberta has a value of 84, which means that the search volume in Alberta is 84% of the highest search volume, which is British Columbia in this case. It is also intriguing to observe that provinces with a lower population rank higher in terms of the search volume than some of the provinces with a relatively larger population, such as Yukon is ranked higher than Alberta in Figure 1. This is because GT normalises data such that out of all provinces, Yukon had the second highest percentage of searches for Bitcoin out of all the other searches that took place in Yukon within the specified time period. "If we had looked at raw data rather than normalized values, we would've seen larger states (provinces) with higher populations rise to the top of the ranks" (Medium Google News Lab, 2016). An important issue to note with data from GT is that the search volume values change mostly every time the web page is refreshed, even if the same restrictions are applied to the search. The overall final sample in my paper, however, is not affected. This is because GT provides data on search terms using random samples that are

generally representative of the term being searched. Although refreshing of the webpage does not report the exact data, the change in the data is negligible such that it does not affect the overall sampling. GT also assigns a value of 0 to searches that are mostly negligible.

If a graph, which is obtained when a search is carried out on google trends, shows a downward line, it implies that the popularity of that search term is diminishing compared to other search terms on google and "not necessarily that the total number of searches for that term is decreasing" (Google News Initiative Lesson 4, n.d., p.3).

GT only analyses popular search terms and excludes certain data from the search results displayed. For example, searches which are made only by a small number of people that are near zero for a fixed time period are excluded. Furthermore, if repeated searches are made by the same user over a short time period then those searches are eliminated for a better accuracy of results.

GT allows searches to be made in two ways – by entering a search term or a topic. Search terms provide data on the exact term or query that has been entered whereas topic will return data on the overall interest and information related to that query. My paper includes data only on search terms for all variables, data for which have been obtained from GT, and not topics to ensure consistency.

Therefore, as can be seen, GT is a highly user-friendly way to filter search results and carry out analyses as required. Although there are other search engines and internet platforms such as Wikipedia, Twitter and Facebook available to conduct a similar analysis, GT was chosen as the platform to analyse the hypothesis based upon the ease of access to data and its popularity to determine real time results.

3.2 Data on Search Terms

Data on search terms in this paper is collected from GT for the time-period January 2015 – December 2017 for seven Canadian provinces. GT is used to collect data on the search term – Bitcoin and searches for the four user categories - Computer Science, Illegal Activity, Libertarians and Speculative Investors. As previously mentioned, GT allows searches to be made either for topics or search terms. Yelowitz and Wilson (2015) use search terms to obtain data for all variables except for Bitcoin and Computer Science for which they use topics – "Currency" and "Discipline" respectively. However, the data in my paper, for all variables, is based on search terms instead of topics to ensure consistency. Yelowitz and Wilson (2015) use proxy search terms for the user groups – Illegal Activity, Libertarians and Speculative Investors. Similarly, I use the same proxy search terms as Yelowitz and Wilson (2015) for the three user groups, such that, for Illegal Activity the search term 'Silk Road' is typed into GT to obtain data. The search term 'Free Market' is used for Libertarians and 'Make Money' is used for Speculative Investors. To obtain data from GT for Bitcoin and the user group Computer Science, the search terms 'Bitcoin' and 'Computer Science' were used respectively.

Once the data for each search term of each province was obtained from GT, using the methodology of Yelowitz and Wilson (2015), I calculated monthly averages of the data for each search term. After the monthly averages were calculated, the province-series for each search term was scaled relative to the most popular province. This means, if the monthly average for Bitcoin data, obtained from GT, in January 2015 for Ontario was 2 and the search volume of Bitcoin in Ontario from 2015 – 2017 was 84 (see Figure 1), then the scaling for Bitcoin in January 2015 results in a value of 1.68 i.e. 2*0.84. The interpretation of the data after scaling is such that search volume at each data point is relative to highest volume of searches for that

province within the sample period. The search volume at each data point is also relative to the province with the highest volume of searches.

After I calculated the monthly averages and scaled the data, I standardised the scaled data for all variables based on the methodology used by Yelowitz and Wilson (2015). Yelowitz and Wilson (2015) follow a normalisation methodology used by Stephens-Davidowitz (2014), where data for each search term in the full sample are standardised to their own z-scores. Following the same methodology, the data for all the search terms (Bitcoin and the four user groups) in my paper are standardised to their respective z-scores. The standardisation of the search terms helps in interpreting the estimates in regression analysis.

If standardisation of data to z-scores had not been carried out, then the coefficient estimates that are obtained through regression analyses would not capture the unit of measurement. This would make it difficult to interpret the results as the data for each search term would not have been comparable and would have been different across provinces. Therefore, standardisation of data of search terms to their z-scores is important. Furthermore, each province-month observation is weighted by the province population in 2015. The addition of weights in the model allows to mitigate variation in data based on difference in sizes of provinces. The year 2015 is chosen as the base year for weights so that the estimates obtained do not vary due to population in different years.

The final sample size in my paper includes 252 observations for seven provinces over the time-period January 2015 to December 2017. The reason behind choosing this particular time period is that Bitcoin reached the peak of popularity then and therefore, it is interesting to study the relation between the search interest of Bitcoin and its users for this time period.

3.3 Additional Data

Following the methodology used by Yelowitz and Wilson (2015), data on Bitcoin prices and unemployment rate are also included in the regression model.

Data on Bitcoin prices (BTC) is taken from CoinMarketCap.com. All market data available on CoinMarketCap (CMC) is updated to the minute, with the exchanges listed on the website being contacted every minute for the latest data. The prices of the cryptocurrencies on CMC are calculated as the volume weighted average of market pair prices for that cryptocurrency. CMC defines market pair as the "trade between one cryptocurrency and another, for example, the trading pair: BTC/ETH[4]" (CoinMarketCap.com, n.d.). As data on Bitcoin prices was available on a daily basis from CMC, monthly averages were calculated. CMC gives data on opening and closing prices of BTC and monthly averages of the closing price of BTC were calculated.

Data on unemployment rate was obtained from Statistics Canada, where monthly unemployment rates by province for the years 2015 -2017 were collected. Table 14-10-0287-01 Labour Force Characteristics, monthly, seasonally adjusted for 2015 – 2017 was used to collect the data on unemployment rate. Furthermore, weights are also included in the model and were based on the population estimates for the seven provinces included in the sample, the data for which was also obtained from Statistics Canada. Particularly, Table 17-10-0009-01 Population estimates, quarterly was used to collect population estimates for the seven provinces for the year 2015. The weights used in the regressions are such that $\sigma_{j,t}^2 = \frac{\sigma^2}{\overline{P_{j,2015}}}$, where $\overline{P_{j,2015}}$ are the weights and $\sigma_{j,t}^2$ is the variance of the error term for province *j* and time *t*. The software Stata, used to perform the regressions in my paper, internally computes σ^2 and also rescales the weights such that "the

[4] BTC refers to Bitcoin prices and ETH is the price of the cryptocurrency Ethereum.

observations (in the sample) represent averages and the weights are the number of elements that give rise to the average" (Stata 10 Help for Weight, n.d.). So, $\overline{P_{j,2015}} = \frac{\Sigma_{j,2015} P_{j,2015}}{N}$, where N is the number of observations in the data set and $P_{j,2015}$ is the population of province j in 2015. This allows to correct for heteroskedasticity that may arise due to difference in size of provinces, as discussed by Solon et al. (2015).

3.4 Summary Statistics

As the sample in the paper is a panel dataset, Table 2 presents the summary statistics in three groups – overall, between and within. Table 2 shows that, overall there are 252 observations for each variable. The between category shows the variation in statistics between or across the 7 provinces that are taken into account. And, the within category indicates the statistics within each variable across time of 36 months i.e. January 2015 to December 2017. The summary statistics for all the search terms – Bitcoin, Computer Science, Illegal Activity, Libertarians and Speculative Investors show, overall, a mean of zero and a standard deviation of one. This is because, following the methodology used by Yelowitz and Wilson (2015), all search terms were standardised to their z-score.

Table 2 provides interesting information. For instance, for Bitcoin, the value of the standard deviation under the between group is less than the standard deviation under within, whereas for the user groups standard deviation under the between group is higher than standard deviation under within. This is because Bitcoin is a volatile currency that experiences high variation across time and could result in a higher variation in the searches for this currency, thus, leading to a higher standard deviation under the within group which looks at variation across time. On the

other hand, for the user groups, higher variation is expected across provinces as the number of searches for each individual category do not vary as much over time.

4 Econometric Model

The analysis for the econometric models in my paper is carried out using the Ordinary Least Squares (OLS) regression methodology for a panel dataset. The specification that is used for analysis is:

$$BITCOIN_{jt} = \beta_0 + \beta_1 X_{jt} + \delta_j + \delta_t + \varepsilon_{jt} \qquad (1)$$

where $BITCOIN_{jt}$ is the search interest in Bitcoin in province *j* and month *t*. This is the dependent variable of the model. X_{jt} is the number of searches for each of the characteristics of Bitcoin users in province *j* and month *t*. δ_j and δ_t are province and time fixed effects. Fixed effects help control for variation that arises due to unobservable factors over time and across provinces in the sample. More specifically, the provincial fixed effects take into account time-invariant provincial level differences in searches whereas the time fixed effects consider the changes that occur over time which are common to all provinces. The impact of including fixed effects in the model will be discussed in more detail in the following section based on the results obtained.

The regression equation specified in (1) analyses a correlation and not a causal relation between number of searches for the characteristics of the users of Bitcoin and searches for Bitcoin. This equation is simply measuring if there is any statistically significant relation between the number of searches for Bitcoin and searches for the characteristics of Bitcoin users, whilst taking into account province and time fixed effects. It is evident from the literature review in section 2 that

each of the four user categories is related, to some extent, with the use of Bitcoin. So, the equation in (1) is examining the partial correlation between the number of searches for the characteristics of each user group, which is defined by X_{jt}, and the number of searches of Bitcoin, defined by the variable $BITCOIN_{jt}$, in Canada. Thus, the objective behind the regression equation is to identify the extent to which X_{jt} relates to $BITCOIN_{jt}$. By analysing the value of β_1, the paper is investigating to conclude whether or not the two variables are significantly related and the extent to which the two variables are associated with each other but the value of β_1 does not give information on whether one variable was the cause of the other.

It should also be noted that standard errors are corrected for two-way clustering at the province and time levels, following the methodology used by Yelowitz and Wilson (2015). Panel datasets generally have correlated errors within each panel unit, such that "each panel unit or individual can be considered as a cluster" (Baum et al., 2010, p.10). For a simple cross-sectional dataset robust standard errors correct for heteroskedasticity. However, in my paper, as there is a panel dataset with observations across time and provinces, there is variation across two different dimensions. And therefore, a two-way clustering of standard errors coupled with time and province fixed effects allows to control for this variation arising from unobservable factors.

The model in equation (1) represents the main model analysed throughout the paper. However, more variables are subsequently added into the model, as a part of robustness checks, to identify any additional changes that might occur in the relation between the search interest in the user categories and searches on Bitcoin. The additional variables result in the following two models:

$$BITCOIN_{jt} = \beta_0 + \beta_1 X_{jt} + \beta_2 X_{jt}(Y_t / 100) + \beta_3 Y_t + \delta_j + \delta_t + \varepsilon_{jt} \qquad (2)$$

$$BITCOIN_{jt} = \beta_0 + \beta_1 X_{jt} + \beta_2 X_{jt}(Y_t / 100) + \beta_3 Y_t + \beta_4 Z_{jt} + \delta_j + \delta_t + \varepsilon_{jt} \qquad (3)$$

where, in model (2) and (3), Y_t is the average monthly Bitcoin price. In model (3), Z_{jt} is the unemployment rate across the different provinces *j* and month *t*. Bitcoin prices are included as a regressor and as an interaction with the searches on user categories. The prices are added separately as a regressor in the model because it is common knowledge that since Bitcoin is a cryptocurrency, it is bound to be affected by its prices and therefore, the search interest in Bitcoin is also expected to be affected by prices. The interaction term between prices and the search interest in user groups is also included in the model as it allows me to examine more than just the direct relation between $BITCOIN_{jt}$ and X_{jt}. The inclusion of the interaction terms allows me to take into account the possibility that the searches of user groups can change depending on the prices of Bitcoin and therefore, impact the relation between $BITCOIN_{jt}$ and X_{jt}.

Unemployment rate is also added as a regressor in the model as it is capturing the business cycle effects that are different across provinces. For instance, due to some economic event during the given time period and business cycle, it is possible that the effect of that event was more in British Columbia compared to Ontario. Including a time trend or a time fixed effect does not capture these differences and the unemployment rate is able to capture such a difference which could be related to the number of searches for Bitcoin. Moreover, there is also a possibility that when the unemployment rate is high, people are more interested in earning money through other means and therefore might related to an increase in the number of searches on Bitcoin.

Before introducing Bitcoin prices and the unemployment rate, I perform an additional exercise in which I include a placebo clientele group in the model. The placebo clientele group is added to capture spurious effects, if there are any.

5 Results[5]

The analysis starts by looking at a simple OLS regression of the model in equation 1 without including any province or time fixed effects. From column (1) of Table 3 it can be seen that the estimates on the Computer Science and Speculative Investors group are statistically significant at the 5% significance level. This means that an increase in the number of searches for Computer Science is positively related with a 0.17 standard deviation (SD) increase in number of searches for Bitcoin whereas an increase in the number of searches for the Speculative Investors user group is negatively related with the number of Bitcoin searches. Column (2) of Table 3 includes province fixed effects. However, the estimates on all the search interest groups are statistically insignificant, except that for Computer Science, where the coefficient is statistically significant at 10% level. Adding fixed effects at a provincial level allows to control for any unobservable factors that might cause differences in searches across provinces. Furthermore, as variables are not only being observed across provinces but also over time, it is important to control for unobservable factors or changes that occur over time and are common to all provinces. Therefore, it is also important to control for these unobservable factors that are not time-invariant.

The third model includes both province fixed effects and a time trend in column (3) of Table 3, similar to the methodology used by Yelowitz and Wilson (2015). A time trend assumes a

[5] It is important to keep in mind the problem of few clusters while understanding the results of the analysis carried out in my paper. (See Appendix B for more information on this issue).

constant trend across the time period under analysis. This means that the unobservable factors that might affect search interest in Bitcoin are not occurring in a particular year and instead are assumed to exist generally across the time period under analysis. Including a time trend also reduces the number of parameters to be estimated compared to a model with time fixed effects as there is only one-time trend variable that is included in the model.

It is observed that the time trend is statistically significant at the 5% significance level which means that searches for Bitcoin increased over time. Moreover, the province fixed effects were also found to be statistically significant at the 5% significance level.

It is interesting to note the economic significance behind these results. The time period under analysis in the paper is when Bitcoin prices were reaching their peak. Overall, the time period from 2015 – 2017 was lucrative in terms investing in Bitcoin with the popularity of the cryptocurrency also increasing, which could have potentially influenced the number of searches for Bitcoin during this time period. And adding a time trend to the model shows that the increase in number of searches over time is indeed statistically significant. Moreover, differences across provinces also plays a significant role in the relation with number of Bitcoin searches. A potential reason could be that some provinces have a higher number of people with more awareness about Bitcoin than others. So, it means that both province fixed effects and time trend are significantly capture factors that are related to Bitcoin searches.

The model in column (3) includes a time trend, the benefits of which have been discussed above. However, an important limitation of including a time trend is that it does not account for seasonality and any changes that occur in a particular year as it assumes a constant trend over time. It is important to remember that Bitcoin prices are very volatile. This means that the volume of searches on Bitcoin can also be very seasonal and are influenced by various factors

that change over time. Only including a time trend in the model does not take into account the variation in these factors. The solution for this is including time fixed effects instead.

Thus, the model in column (4) includes both province and time fixed effects. By including time fixed effects, the model is now able to take into account seasonal and more volatile variation that may occur due to some potential unobservable factors. The coefficients on all user groups, however, are statistically insignificant.

Column (5) of Table 3 now includes a placebo clientele group which is added to the model. The placebo clientele chosen is such that it is in no way related to the original variables in the model. Yelowitz and Wilson (2015) chose searches on the American singer Miley Cyrus in their paper. To conduct a similar experiment for Canadian provinces, I included data on search interest of a Canadian singer – Drake, in my paper.

As mentioned, placebo clientele group allows to examine whether the relation between the searches for the placebo group and searches for Bitcoin is significant and capture spurious effects, if there are any. As expected, Column (5) of Table 3 shows that the relation between the searches for the placebo group and searches for Bitcoin is insignificant, so no spurious effects are being captured. Moreover, adding the placebo clientele group into the model does not change the relation between the search interests in user groups and search interest in Bitcoin.

Overall, from the results in Table 3, there is no evidence of a strong correlation between the number of searches for the characteristics of Bitcoin users and number of searches for Bitcoin for all seven Canadian provinces analysed over the time period 2015 – 2017.

6 Robustness Checks

The models analysed so far only consider the direct relation between the search interests in user groups and search interest in Bitcoin. An additional search term Drake was added as a placebo clientele to see whether any spurious effects exist and examine the relation between the search interest in the placebo clientele group and search interest in Bitcoin. Overall, Section 5 shows that there is no strong evidence of a significant relation between the search interest in the characteristics of Bitcoin users and searches for Bitcoin.

It is also important to consider that the user groups itself can be influenced by other factors. For instance, the user category Speculative Investors for whom the search term "Make Money" was used on Google Trends to obtain data, could be influenced by the Bitcoin prices which has a further impact on number of searches of Bitcoin. As Bitcoin is a cryptocurrency, its prices play an important role in determining the relation between searches for the users of the currency and the searches made for Bitcoin. If prices are not accounted for in the analysis, then there would exist a gap in terms of examining the users' motivation to search for Bitcoin, as Bitcoin is ultimately a currency.

Based on the discussion in Section 4 about including prices, using equation (2) from Section 4, a regression was carried out with prices as a regressor and prices interacting with the user groups. An important issue to note here is that of collinearity. Bitcoin prices have been found to change over time. As the model being analysed includes time fixed effects, in addition to province fixed effects, the impact of prices on Bitcoin searches (the dependent variable) is already being captured by the time fixed effects. Including Bitcoin prices as a regressor in the model with time fixed effects therefore leads to the problem of collinearity. Thus, the variable for Bitcoin prices (

Y_t) as a regressor is dropped from the model to avoid collinearity. Column (6) of Table 4 shows the estimates on the interaction between number of searches for each user group and Bitcoin prices. The interaction terms can be interpreted as, for example, Libertarians are more interested in searching for Bitcoin when the prices are high as compared to lower Bitcoin prices. A change in the coefficients of the user category search interests is observed such that the coefficient on Libertarians changes from 0.03 in column (4) of Table 3 to 0.02 in column (6) of Table 4. However, the results in column (6) are statistically insignificant and do not indicate a strong relation between the interaction terms and search interest in Bitcoin.

Column (7) includes an additional interaction between the placebo clientele Drake and the Bitcoin price. This interaction term is statistically insignificant implying that there is no significant relation between the interaction of the placebo clientele with Bitcoin prices and searches for Bitcoin.

Another factor considered by Yelowitz and Wilson (2015) that may be related with the search interest in Bitcoin is the unemployment rate. For example, when the unemployment rate is high then there might be more illegal activity carried out using Bitcoin or earn money using Bitcoin. Thus, using equation (3) from Section 4, Column (8) of Table 4 shows the estimates obtained when provincial level monthly unemployment rate is included in the model. This column shows that on adding the unemployment rate in the model, the relation between searches for the characteristics of Bitcoin users and searches for Bitcoin remains statistically insignificant. The unemployment rate itself is positively related to the search interest in bitcoin, however, this relation is not statistically significant.

The model in Column (9) of Table 4 includes both the placebo clientele group and the unemployment rate. No change in the statistical significance of the estimates is observed upon adding both the placebo clientele and the unemployment rate. Lastly, the model in Column (10) of Table 4 includes all search interest groups, the placebo clientele, unemployment rate and the interaction between the search groups and Bitcoin prices, whilst including both provincial and time fixed effects. In this final model, it can be seen that the coefficients on all variables remain statistically insignificant. This allows the paper to conclude that there is no strong relation between the number of searches for the characteristics of the users of Bitcoin and searches for Bitcoin across all seven Canadian provinces for the time period 2015 – 2017, regardless of the additional variables that were added as a part of the robustness checks.

This is fairly in line with the results Yelowitz and Wilson (2015) obtain in their paper. They find a positive association between Bitcoin interest and those who are interested in computer programming and illegal activity, whilst also obtaining limited evidence for a Libertarian motive driving up Bitcoin interest. The results they obtained are for the US for the time period January 2011 to July 2013. On the other hand, my paper follows the methodology used by Yelowitz and Wilson (2015) to conduct a similar analysis for provinces in Canada, for the time period January 2015 – December 2017.

Comparing the results between the two papers firstly shows that, overall, there is no robust evidence of the association between search interests in each user category and search interest in Bitcoin in Canada, whereas, in the US evidence was found for a positive association between a few user categories and Bitcoin. Some important factors to consider are that, for example, financial markets in the US are larger and more influential at a global scale than Canada. This can lead to a larger number of people from the US interested in Bitcoin for various purposes such

as to invest money, to buy goods and services and more recently, even to pay tuition fee at limited schools and universities in the US. In Canada, compared to the US, financial markets are not as influential at a global scale. Another factor to consider is that the time periods analysed in the two papers are different. The time period considered in my paper is when Bitcoin became very popular all around the world and was at its peak towards the end of 2017, whereas in Yelowitz and Wilson (2015), the time period analysed is when people were slowly becoming more aware of Bitcoin. This could be one of the reasons why Yelowitz and Wilson (2015) have some significant results as when people were becoming slowly aware, more searches would have been carried out on GT to look up what Bitcoin is. On the other hand, when Bitcoin was already popular and the prices were reaching their peak between 2015 – 2017, people could have been more interested in obtaining information on Bitcoin from other sources such as, the financial markets news channels. And this is reflected in the results as there is no significant relation between searches carried out on GT on Bitcoin and the characteristics of Bitcoin users, in Canada.

In my paper, the effects of any unobservable factors are considered by including fixed effects in the model. For example, factors that change over time maybe taken into account through time fixed effects and those that vary across provinces are controlled through province fixed effects. Endogeneity could, however, exist in my model due to potential omitted variables. For instance, technology is constantly improving which facilitates users to access the internet more readily over time. This could have an impact on the search interest in Bitcoin. Another factor that could impact the relation between search interest in Bitcoin and searches for user categories is that there are several other cryptocurrencies that are emerging. For instance, if the price of another cryptocurrency such as Ethereum, rises, investors might be drawn towards it and therefore

searches for Bitcoin might instead decrease. Although the literature showed that for the some of the user categories discussed in my paper, Bitcoin was a top choice of cryptocurrency, it is possible that some user groups prefer other currencies. This could further influence the search interest in Bitcoin. Further research could be carried out considering some of these additional factors in the model.

7 Conclusion

The analysis in this paper investigates the correlation between number of searches for Bitcoin and searches for the characteristics of the users of the cryptocurrency, across seven Canadian provinces for the time-period 2015 – 2017. The four user categories included are – Libertarians, Computer Science, Illegal Activity and Speculative Investors. These groups are some of the main users of Bitcoin, which has been supported through the literature surrounding the topic. Data on searches for Bitcoin and the user groups was obtained using Google Trends.

An initial analysis shows that there is no robust evidence of a relation between the search interest in each of the user categories and search interest in Bitcoin. Further examination of this correlation was conducted by including additional variables such as a placebo clientele group, prices of Bitcoin and the unemployment rate. These additional variables did not change the initial result obtained, thus concluding that there is no statistically significant correlation between the number of searches of Bitcoin and searches for terms that define the main users of Bitcoin.

References

Balchunas, E. (2013). "Diamonds and Kazakhs and Bitcoins, Oh My: An ETF Parade", *Bloomberg*, Retrieved from https://www.bloomberg.com/news/articles/2013-07-12/diamonds-and-kazakhsand-bitcoins-oh-my-an-etf-parade

Bashir, M., Strickland, B., & Bohr, J. (2016). "What Motivates People to Use Bitcoin?", *International Conference on Social Informatics, SocInfo 2016,* 347-367

Baum, C. F., Nichols, A., and Schaffer, M. E. (2010). "Evaluating One-Way and Two-Way Cluster-Robust Covariance Matrix Estimates.", *Presentation Made for the 16th UK Stata User Group Meeting*

Bhaskar, N. D., & Chuen, D. L. K. (2015). "Bitcoin Mining Technology." *Handbook of Digital Currency, Academic Press,* 45-65

Bitcoin.org (n.d.). "Some Things You Need to Know", Retrieved from https://bitcoin.org/en/you-need-to-know, Access date: March 14, 2019

Bitcoin Magazine (n.d.). "What Makes Bitcoin Valuable?" *Guides, Bitcoin Magazine,* Retrieved from https://bitcoinmagazine.com/guides/what-makes-bitcoin-valuable/ , Access date: March 14, 2019

Blockchain.info (2015). "Bitcoin Charts", Retrieved from https://www.blockchain.com/charts/

Böhme, R., Christin, N., Edelman, B., and Moore, T. (2015). "Bitcoin: Economics, Technology, and Governance." *Journal of Economic Perspectives*, *29*(2), 213-238

Bohr, J., & Bashir, M. (2014). "Who Uses Bitcoin? An Exploration of the Bitcoin Community.", *Twelfth Annual International Conference on Privacy, Security and Trust*, 94-101

Briere, M., Oosterlinck, K., and Szafarz, A. (2015). "Virtual Currency, Tangible return: Portfolio Diversification with Bitcoin." *Journal of Asset Management*, 16(6), 365-373

Brito, J., Castillo, A. (2013). "Bitcoin: A Primer for Policymakers", *Mercatus Center, George Mason University*

Cameron, A. C., and Miller, D. L. (2015). "A Practitioner's Guide to Cluster-Robust Inference", *Journal of Human Resources*, 50(2), 317-372

Christin, N. (2012). "Traveling the Silk Road: A Measurement Analysis of a Large Anonymous Online Marketplace." In *Proceedings of the 22nd International Conference on World Wide Web*, ACM, 213-224

Coin Market Cap (n.d.). "Methodology", *Coinmarketcap.com*, Access date: February 1, 2019

Correia, S. (2016). "A Feasible Estimator for Linear Models with Multi-Way Fixed Effects", *Duke University Preliminary Version*

De Filippi, P. (2014). "Bitcoin: A Regulatory Nightmare to a Libertarian Dream.", *Internet Policy Review*, 3(2)

Douma, S. (2016). "Bitcoin: The Pros and Cons of Regulation", *Leiden University*, Master's thesis

Fung, B., Huynh, K. P., and Stuber, G. (2015). "The Use of Cash in Canada.", *Bank of Canada Review*, 45-56

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., and Siering, M. (2014). "Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions.", *Twenty Second European Conference on Information Systems, Tel Aviv*

Google News Initiative (n.d.). "Google Trends Lessons: See What's Trending Across Google Search, Google News and YouTube", *Google News Initiative*, Access date: January 25, 2019

Google News Initiative (n.d.). "Google Trends Lessons: Understanding the Data", *Google News Initiative*, Access date: January 25, 2019

Google Trends (n.d.). “About Google Trends”, *Trends Help*, Access date: January 11, 2019

Henry, C. S., Huynh, K. P., and Nicholls, G. (2018). “Bitcoin awareness and usage in Canada.”, *Journal of Digital Banking*, 2(4), 311-337

Higgins, S. - CoinDesk. (2017). “From $900 to $20,000: Bitcoin's Historic 2017 Price Run Revisited”, *CoinDesk*, Retrieved from https://www.coindesk.com/900-20000-bitcoins-historic-2017-price-run-revisited

Massoudi, A. and Alloway, T. (2013). “Bitcoin ETF Plan Struggles to Find Support”, *The Financial Times*, Retrieved from https://www.ft.com/content/1e187c88-eda2-11e2-8d7c-00144feabdc0

Nakamoto, S. (2008). “Bitcoin: A Peer-to-Peer Electronic Cash System”

Nian, L. P., and Chuen, D. L. K. (2015). "Introduction to Bitcoin." *Handbook of Digital Currency*, *Academic Press*, 5-30

Plassaras, N. A. (2013). “Regulating Digital Currencies: Bringing Bitcoin Within the Reach of IMF. *Chicago Journal of International Law*, 14(1), 377 – 407

Ponsford, M. P. (2015). “A Comparative Analysis of Bitcoin and Other Decentralised Virtual Currencies: Legal Regulation in the People's Republic of China, Canada, and the United States.”, *Hong Kong Journal of Legal Studies*, 9, 29 – 50

Rogers, S. – Medium Google News Lab. (2016). “What is Google Trends Data - and What Does it Mean?”, *Medium Google News Lab*, Retrieved from https://medium.com/google-news-lab/what-is-google-trends-data-and-what-does-it-mean-b48f07342ee8

Roodman, D. M., MacKinnon, J. G., Nielsen, M. Ø., and Webb, M. (2018). "Fast and Wild: Bootstrap Inference in Stata Using Boottest", *Queen's Economics Department Working Paper*, (No. 1406)

Solon, G., Haider, S. J., and Wooldridge, J. M. (2015). "What Are We Weighting For?", *Journal of Human resources*, 50(2), 301-316

Stata 10 Help for Weight (n.d.). "Stata 10 Help for Weight", Retrieved from https://www.stata.com/help10.cgi?weight , Access date: March 24, 2019

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

Turpin, J. B. (2014). "Bitcoin: The Economic Case for a Global, Virtual Currency Operating in an Unexplored Legal Framework." *Indiana. Journal of Global Legal Studies*, 21, 335 -368

Yelowitz, A., & Wilson, M. (2015). "Characteristics of Bitcoin Users: An Analysis of Google Search Data.", *Applied Economics Letters*, 22(13), 1030-1036

Appendix A

Table 1: Description of the Data

Variables	**Description**	**Frequency and Sample Period**	**Source**
Bitcoin	Searches for Bitcoin on Google Trends standardised to its z-score	Monthly, 2015 - 2017	Google Trends
X: Computer Science Libertarians Illegal Activity Speculative Investors	Searches for each user group on Google Trends, standardised to their respective z-scores	Monthly, 2015 - 2017	Google Trends
BTC (Bitcoin Price)	Price for the currency Bitcoin computed using monthly averages	Monthly, 2015 - 2017	Coin Market Cap
Drake (Placebo Clientele)	Searches for the Canadian singer Drake on Google Trends, standardised to its z-score	Monthly, 2015 - 2017	Google Trends
Unemployment Rate	Unemployment rate for 7 Canadian provinces	Monthly, 2015 - 2017	Statistics Canada Table 14-10-0287-01

Table 2: Summary Statistics

Variables		Mean	Standard Deviation	Min	Max	Observations
Bitcoin	overall	3.17e-09	1.000	-0.438	7.479	N = 252
	between		0.131	-0.173	0.208	n = 7
	within		0.993	-0.569	7.271	T = 36
Computer Science	overall	-1.47e-08	1.000	-1.466	2.963	N = 252
	between		0.943	-0.893	1.456	n = 7
	within		0.483	-1.709	1.703	T = 36
Illegal Activity	overall	-6.35e-09	1.000	-1.066	4.658	N = 252
	between		0.974	-0.685	1.853	n = 7
	within		0.428	-1.239	2.804	T = 36
Libertarians	overall	9.92e-09	1.000	-1.465	2.450	N = 252
	between		0.995	-0.995	1.208	n = 7
	within		0.385	-1.203	1.341	T = 36
Speculative Investors	overall	8.73e-09	1.000	-2.142	1.983	N = 252
	between		1.016	-1.801	1.186	n = 7
	within		0.335	-0.879	0.883	T = 36

Table 3: Regression Results

Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Computer Science	0.170**	0.193*	-0.142	0.120	0.115
	(0.052)	(0.096)	(0.149)	(0.094)	(0.088)
Illegal Activity	0.127	0.154	0.459	0.039	0.039
	(0.069)	(0.148)	(0.281)	(0.033)	(0.034)
Libertarians	-0.011	0.144	0.025	0.029	0.031
	(0.031)	(0.105)	(0.161)	(0.029)	(0.034)
Speculative Investors	-0.088**	0.234	0.912	-0.080	-0.081
	(0.026)	(0.387)	(0.509)	(0.091)	(0.092)
Time Trend			0.067**		
			(0.025)		
Drake					-0.024
					(0.050)
Constant	0.006	-0.139	-2.670*	0.006	0.014
	(0.165)	(0.090)	(1.138)	(0.048)	(0.034)
Province Fixed Effects	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	Yes	Yes
Observations	252	252	252	252	252
R-squared	0.019	0.033	0.381	0.9629	0.9629

Notes: All regressions are weighted and estimated using OLS. Robust standard errors, corrected for two-way clustering, are in parentheses. The dependent variable is search interest in Bitcoin (*BITCOIN)*. The statistical significance levels are: * is 10% significance level, ** is 5% significance level, *** is 1% significance level.

Table 4: Robustness Analysis Regression Results

Explanatory Variables	(6)	(7)	(8)	(9)	(10)
Computer Science	0.140	0.139	0.118	0.113	0.136
	(0.106)	(0.105)	(0.091)	(0.086)	(0.101)
Computer Science x BTC	-0.001	-0.001			-0.001
	(0.001)	(0.001)			(0.001)
Illegal Activity	0.043	0.044	0.038	0.037	0.042
	(0.034)	(0.037)	(0.037)	(0.039)	(0.043)
Illegal Activity x BTC	-8.90e-05	-0.0004			-0.0004
	(0.001)	(0.001)			(0.001)
Libertarians	0.019	0.021	0.032	0.034	0.024
	(0.037)	(0.044)	(0.034)	(0.0387)	(0.052)
Libertarians x BTC	0.001	0.001			0.001
	(0.001)	(0.001)			(0.001)
Speculative Investors	-0.075	-0.0803	-0.080	-0.080	-0.078
	(0.090)	(0.094)	(0.091)	(0.093)	(0.0971)
Speculative Investors x BTC	-0.001	3.07e-06			-6.45e-05
	(0.001)	(0.00102)			(0.001)
Drake		-0.025		-0.024	-0.026
		(0.051)		(0.051)	(0.051)
Drake x BTC		-0.001			-0.001
		(0.001)			(0.001)
Unemployment			0.011	0.011	0.011
			(0.039)	(0.039)	(0.046)
Province Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
Constant	0.003	0.009	-0.064	-0.059	-0.060
	(0.051)	(0.041)	(0.273)	(0.263)	(0.323)
Observations	252	252	252	252	252
R-squared	0.9631	0.9632	0.9629	0.963	0.9632

Notes: All regressions are weighted and estimated using OLS. Robust standard errors, corrected for two-way clustering, are in parentheses. The dependent variable is search interest in Bitcoin ($BITCOIN_{jt}$). The statistical significance levels are: * is 10% significance level, ** is 5% significance level, *** is 1% significance level.

Appendix B

Cameron and Miller (2015) suggest that, although there is no set rule as to the number of clusters that is considered ideal to have the standard errors robust to two-way clustering, generally "more is better". However, as the clustering of standard errors in my paper is carried out at the province and time level and there are only 7 provinces and 36 months, the number of clusters is relatively small. It is impossible to increase the number of clusters in the data set being used and, in any case, the total number of provinces in Canada is evidently small, problems such as possible over-rejection of hypothesis tests may arise with such data. (Cameron and Miller, 2015).

Roodman et al. (2018) propose using a new method of conducting a wild bootstrap which is shown to be more robust to small numbers of clusters than other methods. In my paper, the clustering of standard errors has been carried out using the estimator proposed by Correia (2016). Roodman et al. (2018) suggest that their method for two-way or multi-way clustering can be used with the estimator from Corriea (2016), but only with one-way fixed effects. So, in the software Stata, Roodman et. al (2018) "boottest" command does not work with models estimated using Corriea (2016) "reghdfe" command if they include more than one set of fixed effects. The models in my paper, include two-way fixed effects, and thus, as the Roodman et. al (2018) method cannot be used with more than one fixed effect yet, the problem of too few clusters remains. Standard errors in all the models have been corrected for two-way clustering at the province and time levels using Corriea (2016) method, but the interpretation of the results is affected by the problems discussed.

Attempts were made to see if the method suggested by Roodman et. al (2018) could work after changing the specification of the models in the estimation command. For instance, one set of

fixed effects was treated as group of explanatory variables such that one regression included time fixed effects as explanatory variables and another regression included province fixed effects as explanatory variables. No change in the estimates of the coefficients of the user group variables was observed in either of these regressions. However, two problems arose – firstly, the standard errors estimated, whilst running the regressions using the method by Corriea (2016) and using the bootstrapping method of Roodman et. al (2018), changed depending on which fixed effects were included as explanatory variables in the model. Second, the t-statistics produced by the bootstrapping method changed depending on which set of fixed effects were included in the model.

It is clear that there is more research that can be conducted with regards to this issue, however, it is beyond the scope of my paper. This problem brings up opportunities for further research where the number of clusters could be increased by perhaps changing the time period and increasing the number of months.