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Decrypting Bitcoin Prices and Adoption Rates using Google Search

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Abstract

In this paper, I analyze Bitcoin price formation and adoption rates at a global and national level. In determining Bitcoin prices, I consider contemporaneous and lagged values of traditional determinants of currencies, such as inflation and industrial production, and digital currency specific factors, primarily public interest. Using monthly time-series data across five years (2011 – 2016), I find that global public interest in Bitcoin, measured by Google searches for the keyword 'Bitcoin,' has a positive and significant impact on Bitcoin prices. I extend the analysis to a country level by employing a proxy for adoption rates, represented by the number of local Bitcoin client downloads, which is a useful predictor of prices. I examine pooled data across 12 countries to show that searches for 'Bitcoin' can be used to predict adoption rates and, consequently, prices. To the best of my knowledge, this is the first academic article to study Bitcoin usage at a national level. I find that contemporaneous values of traditionally used macroeconomic determinants of currency prices, except inflation, do not have a significant impact on Bitcoin prices.

Keywords: *Bitcoin, Google Trends, Cryptocurrency*

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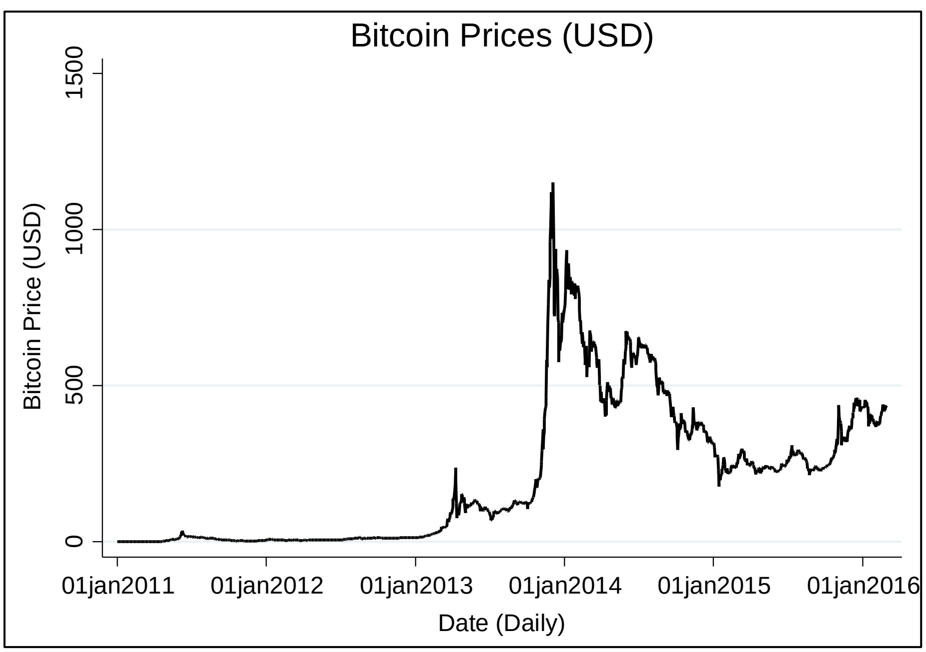
Introduction

The rise of digital currencies, such as Bitcoin, Litecoin, Namecoin, and Ripple, has taken the global payments system by storm. These new currencies are unregulated, created and stored electronically, and typically used by the members of a specific virtual community (Gilpin 2014). Bitcoin, the most widely used of these digital currencies, has over 6.8 million users and continues to grow at an exponential rate. The currency has received extensive public attention due to its large transaction volumes and price volatility. Bitcoin prices have fluctuated from $11 in 2011 to upwards of $400 in 2016. In 2013 alone, prices skyrocketed by over 1700% in the first four months, and later rose to $1100, generating a return of approximately 2900% since the beginning of the year (Kristoufek 2013). Figure 1 depicts daily Bitcoin prices, relative to the USD, from 2011 – 2016.

Figure 1: *Daily Bitcoin Prices (USD) from 2011 – 2016*



Source: blockchain.info/charts

Such extreme price fluctuations are uncharacteristic of traditional currencies such as the dollar and euro whose values can be explained by market forces of supply and demand. I argue that Bitcoin prices are likely to be predicted by factors unique to digital currencies. In this paper, I isolate public interest in Bitcoin as one such factor. I assess whether public interest in Bitcoin, measured by Google searches for the keyword 'Bitcoin,' can determine its prices and transaction volumes globally and regionally. Specifically, I focus on two research questions:

i. Does global public interest in Bitcoin—as measured through Google search volume— affect its price?

ii. Does national level public interest in Bitcoin affect countrywide adoption rates as measured through the number of per capita Bitcoin client downloads?

I find that Google searches for 'Bitcoin' have significant impacts on prices in all estimated models. On a global level, both contemporaneous and lagged search volumes affect Bitcoin prices. These results hold true even when I control for macroeconomic variables such as global levels of inflation, industrial production, unemployment, 3-month Treasury Bill rates, and money supply. I find that inflation is the only contemporaneous macroeconomic variable that has a significant effect on Bitcoin prices. In addition, none of the lagged macroeconomic variables were significant. Bitcoin adoption rates, measured by the number of global Bitcoin client downloads, also impact prices.

In each of the 12 countries, analyzed at pooled and individual levels, Bitcoin searches significantly affect the adoption rates. Country level analysis shows that none of the traditionally used macroeconomic predictors of currencies is statistically significant while determining downloads, and, therefore, prices. I also find that the magnitude of the impact of searches on adoption rates decreases over time in 11 of the 12 countries I analyze.

The paper is divided into five sections. Section 1 provides an overview of the Bitcoin economy. In particular, I describe the currency's roots, its impact on the overall economy, and recent scandals that have raised questions over its legitimacy. In section 2, I summarize relevant previous literature on the subject and highlight gaps in existing research that the paper addresses. Section 3 focuses on the data and methodology. I introduce the variables used, highlight the specific tests I employ, and discuss data limitations that could not be accounted for. Section 4 provides a detailed account of the regression results at a global and country level. In section 5, I discuss my findings, their impacts on monetary policy, and potential avenues for future research.

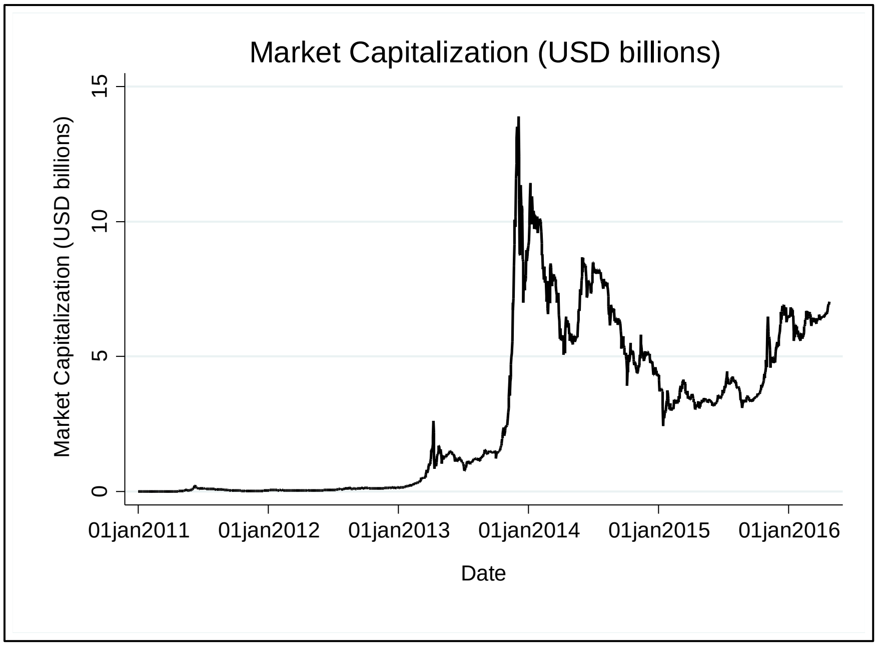
Bitcoin Overview

Bitcoin is a peer-to-peer payment system created with the objective of replacing cash, credit cards and bank wire transfers. The first highly encrypted digital currency, Bitcoin is exclusively electronic (Kristoufek 2013). It relies on an open source software algorithm that uses the global internet network to create Bitcoins and verify its transactions (Ciaian et al. 2015). Unlike ordinary currencies, Bitcoins are not issued by any government, bank, or organization. They are neither backed by any tangible asset nor sanctioned as legal tender. Instead, Bitcoins depend on a highly decentralized and distributed network of users to mint, store, and transfer (Ron and Shamir 2012). Proponents of Bitcoin argue that their high liquidity and low transaction costs simplify the process of making micropayments and instant payments across the internet (Grinberg 2011).

Bitcoin was developed in 2008 - 2009 in the midst of the financial crisis by an unknown group of computer scientists under the pseudonym Satoshi Nakamoto. When Nakamoto published a paper explaining how the currency would work, public trust in the ability of banks and governments to manage the economy was at an all-time low (Wallace 2011). Bitcoin required a lack of faith in the politicians or financiers many held responsible for the global economic downturn. As a result, early adopters included libertarians and technology enthusiasts.

Bitcoin’s adoption rates and transaction volumes have grown exponentially since its inception. As of April 2016, the virtual currency had over 6.8 million active users and a USD transaction volume exceeding $6.5 billion (see figure 2 for USD market capitalization). Established merchants that accept Bitcoin payments include Amazon, Target, IBM, CVS, Dell, PayPal, Tesla, Wikipedia WikiLeaks, Baidu, and Expedia, among others. Bitcoin has slowly seeped into the political sphere too. Larry Summers, the head of the US Department for Treasury under the Clinton administration, stated that he was behind the technology as he wanted to side with the “history of change” (Ross 2015). In April 2015, Kentucky senator Rand Paul became the first US presidential candidate to accept Bitcoin donations. As testament to its growing traction, Bitcoin is now bought and sold with every major currency on hundreds of global Bitcoin exchanges. According to Forbes, venture capital funding in Bitcoin-related businesses exceeded $90 million in 2013 and $300 million in 2014 respectively, and is expected to rise even more sharply in 2016 (Shin 2015).

Figure 2: *Market capitalization (USD billions)*



Source: blockchain.info/charts

To start trading in Bitcoins, users must use a special program, also known as a Bitcoin client. Users can either download the client on their computer that executes the currency's protocol, or create an account on a website that runs the client (Grinberg 2011). The client then saves the user's bitcoins in a file called a wallet which the user must secure and backup. The system resists attacks by creating a distributed peer to peer network over the web (Nakamoto 2008). All transactions are listed on a gigantic public ledger that contains a record of every transaction ever made. The integrity of transactions is maintained through a system of checks conducted by 'miners,' mostly computer scientists who decode problems generated by the Bitcoin system. The transaction is verified and new Bitcoins are created only once they solve the problem. The problem difficulty adjusts based on the number of miners to ensure that Bitcoins are generated at a predetermined rate. Therefore, the Bitcoin algorithm defines, in advance, how currency will be created and at what rate (see Appendix B.4 for changes in Bitcoin mining difficulty over time). Any currency generated by a malicious user that does not follow the rules will be rejected by the network and will be worthless.

Bitcoin's fixed supply and volatile prices make it a fascinating economic case study. Unlike any other currency, Bitcoin has a capped total supply (21 million) based on a computer algorithm that the developers created.[1] As of April 2016, 25 Bitcoins were being mined every 10 minutes, with the total number of Bitcoins in circulation at 15.3 million (Appendix B.3). Because the supply is relatively inelastic due to the capped total, increases in demand due to new users are likely to have a large impact on prices over time. Demand is most likely driven by investors' public interest and return expectations from holding the currency and selling it later. Therefore, we would expect changes in public interest for Bitcoin to influence prices in the same direction.

In the last three years alone, Bitcoin prices have fluctuated between $1150 in late 2013 and $205 in 2015 (figure 1). Such volatility is unusual for traditional currencies, suggesting that there must be factors other than traditional macroeconomic variables that determine prices. While most currency values are driven by the central bank's interest rate announcements and factors such as GDP, inflation, unemployment etc., Bitcoin's supply evolves according to a publicly known algorithm (Kristoufek 2013). Shocks in the Bitcoin market could easily spill over into the broader economy given Bitcoins global

[1] According to Nakamoto's algorithm, Bitcoin supply will reach this limit in 2140, after which miners will be rewarded with a transaction fee, rather than a newly generated Bitcoin.

presence and huge trading volumes. Understanding the primary drivers of Bitcoin prices could help policymakers either regulate the market or prepare for large price fluctuations.

Despite its rising popularity, Bitcoin is at the center of several controversies regarding its legal status. Many point to Bitcoin, an anonymous and unregulated digital currency, as a potential platform for money laundering, tax evasion, illegal drug trade, and child pornography (Grinberg 2011). In November 2015, Ross Ulbricht, the man behind the largest Bitcoin online marketplace, Silk Road, was convicted for enabling approximately $200 million of anonymous drug sales through the website (Bearman 2015). Similarly, in 2014, Mt Gox, the world's largest Bitcoin exchange collapsed into bankruptcy due to security loopholes. The exchange which once handled over 70% of all Bitcoin transactions went bankrupt when hackers stole over $460 million and another $27.4 million disappeared from its Bitcoin accounts (Perez 2015). Numerous countries including China, India, Vietnam, Iceland, and Bangladesh have banned Bitcoin due to its potential for misuse (Smart 2015).

Literature Review

Bitcoin's rising popularity and extreme price volatility have attracted significant scholarly attention (Barber et al. 2012; Kroll et al. 2013; Bouoiyour, Selmi, and Tiwari 2014; Bucholz et al. 2012). Grinberg (2011) explores Bitcoin's viability as a currency and highlight inherent risks of its operations in a 'legal grey area.' Others such as Yermack (2013) question whether Bitcoin is a real currency at all. Because Bitcoin's daily exchange rates exhibit virtually zero correlation with widely used currencies or gold, he claims that it is useless for risk management and exceedingly difficult to hedge.

Yermack concludes that Bitcoin appears to behave more like a speculative investment than a currency.

Moore and Christin (2013) study the risks investors face from Bitcoin exchanges which convert between Bitcoin and regular currency. They examine a track record of 40 exchanges and find that continued operation of an exchange depends on a high transaction volume, which makes the exchange vulnerable to cyber theft. Yelowitz and Wilson (2015) explore the characteristics of Bitcoin users and conclude that those associated with illegal activities are most likely to use the currency.

Previous literature had identified three primary factors that affect Bitcoin prices: (I) Market forces of Bitcoin supply and demand (Buchholz et al. 2012; Bouoiyour and Selmi 2015); (II) Bitcoin's attractiveness to investors (Kristoufek 2013; Bouoiyour and Selmi 2015); and (III) global macro-financial development (van Wijk 2013; Ciaian et al. (2014)). Bucholz et al. (2012) show that supply-demand interaction can be used to determine Bitcoin prices. Bouoiyour and Selmi (2015) argue that Bitcoin is largely detached from macroeconomic fundamentals and behaves as if in a 'speculative bubble.' They conclude that market speculation primarily drives Bitcoin prices.

Few scholars have correlated search engine query volume with prices of digital currencies. According to Kristoufek (2013), standard economic theories, such as future cash-flows, purchasing power parity, and uncovered interest rates, cannot satisfactorily explain Bitcoin price fluctuations. He studies the relationship between Bitcoin prices and related search terms on Google Trends and Wikipedia. He finds a striking positive correlation between Bitcoin price levels and the searched terms as well as a bidirectional dynamic relationship. That is, in addition to search queries influencing Bitcoin prices, prices influence the volume of search queries.

Ciaian et al. (2014) are the first in the literature to study Bitcoin price formation by considering both traditional determinants of currency price, market forces of supply and demand, and digital currency-specific factors such as Bitcoin's attractiveness to investors. They find that the demand-side drivers, including the size of the Bitcoin economy, have strong impacts on price. They suggest that, contrary to previous studies (i.e. van Wijk 2013), global macro-financial developments, including the Dow Jones Index and oil prices, do not significantly affect Bitcoin prices in the long run. They claim that van Wijk's estimates might be biased because he fails to include digital currency specific factors in his model.

Other scholarly work that attempts to predict Bitcoin prices uses social media popularity as a proxy for public interest. Matta et al. (2015) investigate whether public sentiment, as expressed in large-scale collection of daily Twitter posts, can be used to predict prices. Their results show that daily volume of tweets is significantly correlated with future Bitcoin prices. Several works also prove the interdependence between chatter on social media and Bitcoin prices using cross correlation (Constantinides et al. 2009) and linear regression analysis (Bollen et al. 2011; Mittal and Goel 2012). Mai et al. (2015) suggest that more bullish forum posts have a positive effect on Bitcoin returns. In addition, they find that messages on the internet forum have stronger impacts on future Bitcoin market measures at a daily frequency, but microblogs' effects are more significant at an hourly frequency. Garcia et al. (2014) provide evidence that more social media mention increases search volumes, which in turn results in higher social media activity around Bitcoin.

This present paper seeks to fill three key gaps in existing literature. Besides research by Ciaian et al. (2014), there is little or no literature that controls for both global macroeconomic factors and digital currency specific factors while predicting Bitcoin prices. First, I expand existing literature by looking at global factors including Organization for Economic Cooperation and Development (OECD) levels of unemployment, inflation, money supply, and industrial output. I also control for digital currency specific factors, particularly public interest, by using Google Trends data as a proxy. Secondly, researchers have yet to analyze Bitcoin data on a national level. This paper seeks to understand what factors affect countrywide adoption rates, thus in turn providing a link to global level adoption and price. I analyze which countries are more likely to be larger Bitcoin users (normalized by population) by controlling for levels of corruption, industrial production, unemployment, etc. Thirdly, data on Bitcoin is limited to just a few years given the currency's relative nascence. This paper uses the most expansive dataset to date, analyzing Bitcoin prices and trading volumes at a monthly level across a five-year time period from 2011 – 2016.

Data and Methodology

Variable Construction and Specification Tests

I construct the primary dependent variable, *Bitcoin Price*, by using daily data for Bitcoin prices denominated in US dollars. I extract the following monthly data from OECD as proxies for global macroeconomic indicators: Inflation rate (*Inflation)*, harmonized unemployment rate (*Unemployment),* industrial production (*Industrial Production*), and money supply (*M3)*. I also account for the trade weighted USD Index (*TWEXB*) and the value of the 3 month US Treasury Bill (*TB3MS*) to reflect the state of the global economy. Data for the trade weighted USD Index and 3 month Treasury Bill come from the Federal Research Bank of St. Louis. In addition, I include a trend variable to capture changes in Bitcoin prices due to time (*Trend)*. Table I shows summary statistics for all variables used in the global regression. Appendix A contains a comprehensive list of all variables, their definitions, and data sources.

Table I: *Summary statistics for global analysis*

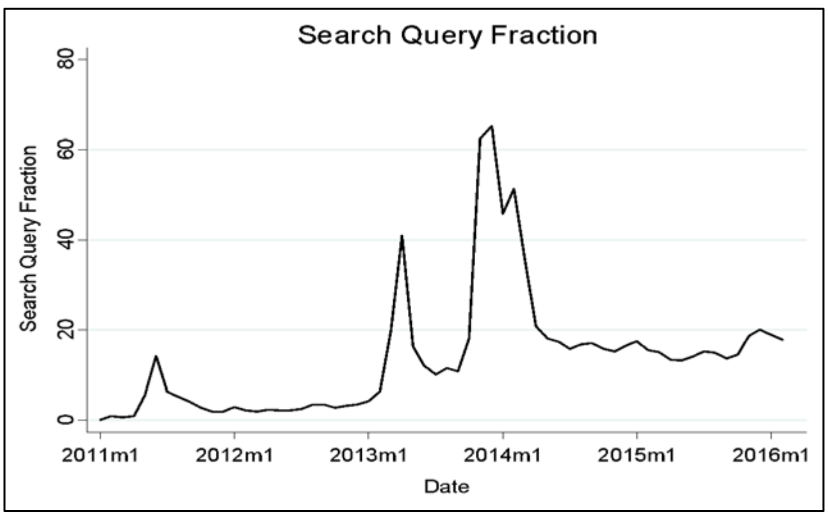
VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Bitcoin Price	62.0	207.0	228.1	0.4	821.1
Search Volume	62.0	13.9	14.0	0.0	65.2
TWEXB	63.0	104.8	8.4	94.7	125.0
Inflation	61.0	1.8	0.8	0.4	3.2
Unemployment	61.0	7.6	0.5	6.5	8.1
TB3MS	62.0	0.1	0.1	0.0	0.3
Industrial Production	60.0	104.9	2.0	101.2	108.5
M3	61.0	118.0	9.4	102.0	134.9
Trend	63.0	32.0	18.3	1.0	63.0
Download	63.0	2,314.1	2,981.5	1.0	12,616

I use Google searches for the keyword 'Bitcoin' as a proxy for public interest.[2] The data are publically available through Google Trends, a feature that illustrates how frequently a term is searched for on Google. Google Trends provides a time series index of search queries about a particular keyword that can be filtered based on location, category (e.g. 'Apple' searches could fall into the category of 'Fruit' or 'Technology'),

[2] Search query frequency is not case sensitive. Various versions of the keyword such as 'Bitcoin,' "BitCoin,' and "bitcoin" are captured in my analysis.

and search type (i.e. whether it was searched through the web, news, images, Google shopping or YouTube).[3] Google calculates this query index, also called query fraction, by comparing the number of web searches performed with a specific term to total number of searches over time. Absolute volumes are not illustrated as the index is normalized on a scale from 0 to 100. Google initially provided the original data on a weekly level which I transformed to monthly estimates to maintain consistency across variables. Figure 3 depicts the query fraction for Bitcoin between January 2011 and March 2016 on a global level.

Figure 3: *Monthly global Google search query fraction for 'Bitcoin' from 2011-2016*



Source: Google Trends

I use the following general regression to capture the impact of search on prices at the global level:[4]

$$Bitcoin\ Price_t \ = \ Search\ Volume_t \ + \ Macro\ Controls_t \ + \ Trend_t + \epsilon_t$$

[3] I look at searches for 'Bitcoin' across the web across all categories from January 2011 – March 2016. The location is either 'worldwide' or one of the 12 countries mentioned below.

[4] Macro controls used were *TWEXB*, *Unemployment*, *Industrial Production*, *M3,* and *Inflation.* I include several variants of the model to test combinations of lagged and contemporaneous values. 'ϵ' denotes the error term.

Obtaining data about country-wide Bitcoin use is more challenging due to the anonymity that the Bitcoin provides. Therefore, I use previously unexplored data about the number of Bitcoin desktop client downloads per country as a proxy for adoption rate. I obtained daily client download data from SourceForge for 96 countries from January 2011 - March 2016.[5] Country level download data was normalized based on population sizes. A Bitcoin desktop client is software that users run on their own computers, as compared to an online client where one's wallet is available on the web. With a desktop client, the wallet is stored as a file on the computer, which means that the wallet is as secure as one's computer. Despite the existence of alternative web and mobile clients, the number of desktop client downloads likely make a good proxy for the number of Bitcoin users.[6] Bitcoin client downloads are highly correlated with Bitcoin usage because desktop clients are known to be more secure than web ones. Assuming that the percentage of users who care about safety and have access to a secure personal computer is uniform across countries, the number of client downloaders will be a similar proportion of the total number of Bitcoin users. In addition, most of the data used in this paper focuses on OECD countries. Users in these developed countries, concerned with privacy, are likey more able to download the client on their personal computers. This is less likely in developing countries where people may not have personal devices and may need to rely on more web based services.

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[5] SourceForge is a web-based service that allows developers to control and manage free and open-source software development. The Bitcoin project on SourceForge tracks the number of Bitcoin client downloads by country and operating system (Mac OSX, Android, Linux, and Windows). I use the sum of all downloads across operating systems per country as the proxy for number of users. Source: https://sourceforge.net/projects/bitcoin/files/stats/map?dates=2013-09-19

[6] It should be noted that the client only needs to be downloaded once per device. Therefore, the proxy actually measures the increase in the number of users in a particular country.

In the second part of my analysis, I test if public interest around Bitcoin affects the number of Bitcoin users per country. I analyze data from 12 countries: USA, UK, Russia, Canada, Sweden, Finland, Estonia, Australia, France, Netherlands, Poland, and Czechia. I chose the 12 abovementioned countries because they are among the top 20 countries with the highest search and download volumes. Their data are also more reliable, as they are provided through OECD databases.

In addition to the macroeconomic indicators previously listed (inflation rate, unemployment, M3, industrial production), I control for national public sector corruption levels (*Corruption)*, country specific exchange rates relative to the USD (Exchange Rate), and percentage of the population with access to the internet (*Internet Access*).[7] The trend variable (*Trend*) measures the number of months elapsed since the beginning of the sample, thus capturing long-term linear trends in download rates; the interaction term (*Search* * *Trend*) will test whether the impact of search volumes on download rates changes over time. Table II shows the summary statistics for each of the variables.

I check for nonstationarity in the data by conducting the Phillips-Perron unit root test. The null hypothesis is that the variable contains a unit root, and the alternative is that the variable was generated by a stationary process (Perron 1989). The unit-root hypothesis could not be rejected for many of the series, implying non-stationarity. Because first differences were found to be universally stationary at the 99% confidence level, I conduct all my analysis on first-differenced variables. In particular, I use the

[7] Corruption Perception Index (*Corruption*) is an index annually reported by Transparency International to measure the perceived level of countrywide public sector corruption. The index ranges from 0 – 100, with 100 being least corrupt. It is likely that countries with less corruption have more Bitcoin users. In such places, users cannot easily access the illegal economy. As a result, they are likely to turn to alternate forms of money such as Bitcoin.

ordinary least square method and account for potential heteroskedasticity by including robust standard errors throughout. For the country level regressions, I create a pooled cross section dataset to find general trends in Bitcoin usage across all 12 countries. This specification is run with country fixed effects in order to eliminate any idiosyncratic variation that may contaminate results. I also run individual country level regressions to highlight country specific exceptions and test variants of the same regression by controlling for first, second, and third lags. The monthly lags of *Search Volumes*, in particular, help account for the dynamic relationship between searches and prices. The results listed only refer to the first lag because most of the longer lags were not significant.

Table II: *Summary statistics for country analysis*

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	732.0	11.8	12.7	0.0	73.0
Inflation	731.0	2.2	2.6	-1.3	16.9
Unemployment	716.0	7.2	2.3	1.0	13.9
Corruption	721.0	71.0	17.7	24.0	94.0
Industrial Production	730.0	105.9	8.7	86.9	135.0
Internet Access	576.0	81.3	10.4	49.0	94.8
M3	365.0	126.3	26.9	95.8	235.9
Exchange Rate (USD)	732.0	2.6	5.5	0.0	25.7
Download per capita	576.0	33.6	45.8	0.6	412.6
Trend	732.0	30.0	17.6	0.0	60.0
Search * Trend	720.0	1.1	282.7	-1,235.0	1,929.5

I use the following general regression to capture the impact of search on downloads per capita at the country level: [8]

[8] Macro controls used were *Unemployment*, *Industrial Production*, *M3*, *Inflation*, *Exchange Rate* (Country currency in USD), *Corruption*, and *Internet Access*. I include several variants of the model to test combinations of lagged and contemporaneous values'ϵ' denotes the error term. I control for country fixed effects throughout.

$$Download\ per\ capita_{it} = Search\,Volume_{it} + Macro\ Controls_{it} + SearchVolume_{it} * Trend_t + Trend_t + FE_i + \epsilon_{it}$$

Data Limitations

There are certain data limitations that I could not account for. It is likely that some of the countrywide client download data may not accurately represent the original country in which the download occurred. In several countries, firms and individuals often outsource Bitcoin management to people abroad to navigate regulatory obstacles. Moreover, in places such as Russia where Bitcoin is officially banned, users rely on a VPN (Virtual Private Network) to access the Bitcoin market through an address that may actually be hosted in the US. The data are likely to show an increase in the number of downloads in the US, rather than in Russia. Even if such re-routed traffic is uncorrelated with other market events, noise in the dependent variable (*Downloads per capita*) will decrease the precision levels of my estimates, while noise in the explanatory variable (*Search Volume*) will attenuate my results. Under most reasonable scenarios, therefore, both my coefficients and standard errors are conservative estimates.

In addition, I could not capture data for all Bitcoin users through the client download and search volume proxies. There are a significant number of users who use non desktop clients on the web or on mobiles. In addition, the Chinese market is considered to be the biggest player in the Bitcoin economy and is likely one of the largest price drivers. Kristoufek (2014) points to this when he claims that the news around Baidu's accepting Bitcoin substantially influenced the dynamic prices. Because Google is yet to enter the Chinese market, search data does not account for any public interest originating in China.

There are also concerns that the OECD database does not provide information about most developing countries. As a result, I could not include countries such as Ghana in my analysis even though they were among the major Google searchers for 'Bitcoin.' Additionally, reverse causality could bias results in the relationship between searches and prices. It is likely that in times of sudden price spikes, as in 2013, news about prices drives search volume rather than the causality going the other way. I control for reverse causality by regressing prices on lagged searches. Lastly, it is important to note that my analysis only accounts for Google search volumes with the keyword 'Bitcoin' as a proxy for public interest. It is possible that public interest is influenced by other keywords, such as 'What is Bitcoin' or 'Bitcoin scandals' which I do not account for.

Results

Global Level Analysis

My findings suggest that, in all estimated models, global public interest in Bitcoin has a statistically significant impact on Bitcoin prices. As seen in Table III (1), Bitcoin search volume and its lagged monthly value are significant at the 99% confidence level and explain almost 56% of the variation in prices. The coefficient on global searches indicates that an increase in 1 search query fraction is expected to increase prices by $4.8. Even when contemporaneous global macroeconomic variables are controlled for (Table III (2)), search volume and its lag continue to remain highly significant and have a positive effect on prices. Note that none of the contemporaneous global macroeconomic variables, except inflation, have a significant impact on prices. In times of high inflation, users are more likely to switch to alternate forms of money as the value of their currency decreases. It is therefore unsurprising that a 1 percent increase in global inflation rates corresponds to a $124 increase in Bitcoin prices. These results partly substantiate van Wijk's research (2013). van Wijk finds that the Dow Jones value, euro-dollar exchange rate, and global oil prices have strong effects on Bitcoin prices. I argue that global inflation rates likely account for these global factors and hence affect prices.

Table III (3) captures the impact of lagged search volume while controlling for other lagged macroeconomic determinants of prices. Yet again, lagged search volume is significant. An additional search query fraction from the previous month is expected to increase prices by $4. Moreover, 40.7% of the changes in prices can be attributed to changes in lagged search volumes and macroeconomic variables, indicating the model's strong predictive power. This time, however, none of the global macroeconomic variables (including inflation) had a significant impact on prices, even at the 90% confidence level. The results from these lagged regressions depart from van Wijk's findings likely because he only accounts for contemporaneous effects of global macroeconomic factors. In the lagged model (Table III (3)), only lagged search volumes had significant coefficients. While no previous researchers have used similar lagged models, my results are broadly substantiated by Kristoufek (2013), Ciaian et al. (2015), and Matta et al. (2015) who find a strong correlation between the public interest in a digital currency and its price.

Table IV highlights the relationship between the number of global Bitcoin client downloads and Bitcoin prices. Using the abovementioned model and replacing searches with download rates, I find that the number of downloads and its lag have a positive and significant impact on prices at the 95% confidence. As seen in Table IV (2), even when contemporaneous global macroeconomic variables are controlled for, an additional 100 downloads, contemporaneously and lagged, increases prices by $1.3 and $1.8 respectively. In Table III (4), the introduction of lagged searches, correlated with lagged downloads, introduces multicollinearity and leads to insignificant results. From a predictive standpoint, however, lagged values of searches, downloads, and macroeconomic variables jointly predict 41% of changes in prices. Note that the model's explanatory power increases from 40.7% (Table III (3)) to 41% (Table IV (4)) due to the addition of client download data. Lagged downloads add approximately .03% explanatory power to a model that would predict prices using lagged data.

Table III: *Impact of global search volumes on Bitcoin prices*

VARIABLES (Monthly)	(1) Search	(2) Macro	(3) Lag Macro
Search Volume	4.808***	5.206***	
	(1.608)	(1.220)	
Lag Search Volume	4.026***	4.046***	4.016***
	(1.092)	(0.847)	(0.903)
TWEXB		2.258	
		(4.943)	
TB3MS		250.991	
		(172.335)	
M3		-8.355	
		(24.701)	
Unemployment		77.579	
		(118.818)	
Industrial Production		9.893	
		(11.836)	
Inflation		124.338***	
		(36.993)	
Trend	0.109	0.193	-0.090
	(0.257)	(0.292)	(0.428)
Lag Inflation			-2.957
			(76.216)
Lag TWEXB			-24.057
			(16.877)
Lag TB3MS			530.380
			(455.821)
Lag M3			13.256
			(31.112)
Lag Unemployment			-431.838
			(307.998)
Lag Industrial Production			1.189
			(12.828)
Constant	0.541	5.585	-0.741
	(6.675)	(15.559)	(17.941)
Observations	60	58	59
R-squared	0.558	0.662	0.407

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

The dependent variable is Bitcoin price in USD. Search Volume is a 0-to-100 index of the share of Google searches for 'Bitcoin.' Column (1) controls only for search volume and the time trend; (2) adds global macroeconomic variables; (3) uses lags rather than contemporaneous values for all controls. Regressions are at the monthly level and all variables are in first differences.

Table IV: *Impact of number of Bitcoin client downloads on Bitcoin prices*

VARIABLES (Monthly)	(1) Download	(2) Macro	(3) L Macro	(4) Search
Global Client Download	0.018**	0.018**		
	(0.009)	(0.008)		
Lag Global Client Download	0.012**	0.013**	0.014***	0.003
	(0.006)	(0.005)	(0.004)	(0.007)
TWEXB		2.994		
		(6.285)		
TB3MS		533.950**		
		(201.494)		
M3		1.725		
		(38.548)		
Unemployment		42.727		
		(215.035)		
Industrial Production		15.876		
		(15.894)		
Inflation		99.380**		
		(46.967)		
Trend	0.183	0.097	-0.196	-0.088
	(0.351)	(0.313)	(0.469)	(0.437)
Lag TWEXB			-24.992	-23.974
			(17.762)	(17.227)
Lag TB3MS			733.910	548.263
			(468.402)	(457.211)
Lag M3			26.418	16.574
			(34.367)	(32.830)
Lag Unemployment			-481.213	-431.294
			(329.329)	(313.899)
Lag Industrial Production			3.363	1.278
			(13.784)	(12.919)
Lag Inflation			-27.558	-4.291
			(80.144)	(76.716)
Lag Search Volume				3.446**
				(1.687)
Constant	1.033	3.732	-4.901	-2.488
	(11.096)	(21.411)	(19.997)	(19.289)
Observations	60	58	59	59
R-squared	0.409	0.508	0.355	0.410

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

Depend variable is Bitcoin price (USD). Column (1) controls for downloads; (2) adds macro variables; (3) uses lags of macro variables (4) adds lag search. Variables are in first differences.

Country Level Analysis

On a country level, I test whether national public interest in Bitcoin affects nationwide Bitcoin adoption rates, measured by the per capita number of client downloads. Table V (1) shows that countrywide search volumes for 'Bitcoin' have positive and significant impacts on the number of downloads. A 1 search query fraction increase is expected to increase the number of downloads by 7.3. Note that even though lagged search volumes are insignificant, they also exhibit a similar tendency to positively affect downloads. The negative coefficient on the interaction term (*Trend * Search Volume*) indicates that search volumes' effect on download rates decreases over time.

It is quite obvious that an increase searches for Bitcoin does not correspond to a greater number of downloads because each device requires only 1 client download. Moreover, as users became more acquainted with the currency, they likely directly access the client download website, completely bypassing Google searches. It is also possible that initial early adopters and curiosity seekers searched for the generic 'Bitcoin' to learn more about the currency. Those who were convinced by its potential downloaded the client, thus creating a strong correlation between search queries and download rates during Bitcoin's early years. As Bitcoin grew in popularity, newer users likely became acquainted with it through other sources such as web articles and word of mouth. I argue that they consequently used more specific searches such as 'Bitcoin client download' or 'Coinbase desktop client' given their preexisting familiarity with Bitcoin.

Consistent with my results from the global analysis, introducing countrywide macroeconomic factors has little effect on the regression outcomes. As seen in Table V (2), none of the macroeconomic variables has a significant impact on per capita downloads at the 95% confidence level. I conclude that search volumes and their lags are the most important factors that determine nationwide Bitcoin adoption rates. They likely capture a large part of the macroeconomic trends, such as internet access per 1000 people, which I control for. The high R^2 values in both countrywide regressions (52% and 54% respectively) indicate that searches and their lags can be useful in predicting future download rates.

The strong correlation between search volumes and per capita downloads is more evident when analyzed on an individual country level. In each of the 12 country specific regressions, search is highly statistically significant with a positive coefficient. The variables also have high explanatory power with an R^2 greater than 59% for every country regression. Table VI captures the effect of search volume and the interaction term (Trend * Search Volume) on download rates. Note that in all countries, except Russia, both variables were highly statistically significant even at the 99% confidence level.[9] In Russia, the effect of search volumes is much lower than that of other countries and the interaction term is insignificant. One reason for this could be strict government control over the Ruble and the legislative ban on Bitcoin. It is likely that Bitcoin users are forced to use virtual private networks through which they appear to be accessing Bitcoin websites through servers abroad. Once again, the introduction of nation specific macroeconomic variables, such as corruption levels, industrial production, exchange rates etc. have insignificant effects on the number of per capita downloads (Table V (2)).

[9] I also calculate the implied average main coefficient to analyze coefficient values at the middle of the month. Results for Russia still remain relatively unchanged.

Table V: *Impact of search volumes on downloads per capita using pooled country-level fixed effects regressions*

VARIABLES	(1) Search	(2) + Macro Controls
Search Volume	7.302***	7.213***
	(2.170)	(2.141)
Lagged Search Volume	0.426*	0.396*
	(0.220)	(0.201)
Trend	-0.062**	-0.056
	(0.027)	(0.031)
Trend * Search Volume	-0.149**	-0.147**
	(0.062)	(0.061)
Inflation		-6.000*
		(3.149)
Industrial Production		-2.236
		(1.854)
Internet Access		-2.026
		(2.314)
Unemployment		-0.226
		(6.813)
Corruption		-3.080*
		(1.691)
Constant	-0.378	-0.294
	(0.554)	(0.595)
Observations	552	552
R-squared	0.521	0.538

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

Column (1) controls for search volumes and time trends; (2) controls for global macroeconomic variables. All variables are in first difference and measured at a country level.

Table VI (a): *Effect of search volume on downloads per capita in individual countries*

VARIABLES	(1) USA	(2) UK	(3) Canada	(4) Russia
Search Volume	8.928***	12.877***	12.943***	0.925***
	(0.669)	(0.822)	(1.250)	(0.239)
Lag Search Volume	0.233	0.378*	0.163	0.312*
	(0.243)	(0.206)	(0.279)	(0.182)
Trend	-0.084	-0.099	-0.163	-0.013
	(0.099)	(0.096)	(0.162)	(0.067)
Trend*Search Volume	-0.222***	-0.323***	-0.324***	0.008
	(0.024)	(0.025)	(0.043)	(0.009)
Constant	-0.650	-0.627	0.063	-0.077
	(1.666)	(1.888)	(2.672)	(1.330)
Observations	46	46	46	46
R-squared	0.882	0.905	0.854	0.768

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

Table VI (b): *Effect of search volume on downloads per capita in individual countries*

VARIABLES	(1) Sweden	(2) Germany	(3) Poland	(4) Czechia
Search Volume	12.043***	7.045***	6.485***	7.992***
	(3.194)	(0.518)	(1.566)	(0.922)
Lag Search Volume	1.207**	-0.361	0.542**	0.404
	(0.513)	(0.297)	(0.233)	(0.414)
Trend	-0.170	-0.085	-0.033	0.145
	(0.295)	(0.136)	(0.130)	(0.251)
Trend*Search Volume	-0.311***	-0.169***	-0.148***	-0.172***
	(0.111)	(0.022)	(0.047)	(0.030)
Constant	0.240	0.499	-0.922	-3.677
	(6.305)	(2.398)	(4.109)	(3.878)
Observations	46	46	46	46
R-squared	0.591	0.870	0.793	0.654

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

Table VI (c): *Effect of search volume on downloads per capita in individual countries*

VARIABLES (Monthly)	(1) Finland	(2) France	(3) Net	(4) Estonia
Search Volume	12.493***	4.295***	40.303***	13.058***
	(1.188)	(0.585)	(6.479)	(3.324)
Lag Search Volume	0.243	0.031	0.225	1.966*
	(0.294)	(0.181)	(0.671)	(1.100)
Trend	-0.110	-0.060	-0.261	-0.089
	(0.144)	(0.056)	(0.213)	(0.443)
Trend*Search Volume	-0.304***	-0.107***	-1.040***	-0.275**
	(0.036)	(0.018)	(0.186)	(0.116)
Constant	-0.444	0.395	-0.872	-1.936
	(3.919)	(1.126)	(4.868)	(7.999)
Observations	46	46	46	46
R-squared	0.894	0.759	0.889	0.586

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

Next steps

Moving forward, my results could be used to create a practical predictive model that forecasts Bitcoin prices. One possible next step is to predict prices at a future time, *t+1*, and then compare them with actual prices. Estimated results from Table III (3) can be used to forecast prices. Based on my initial analysis, the model is expected to have high explanatory power. The large R^2 value indicates the goodness of fit within the sample. I would expect future researchers to simulate an out of sample test to measure the model’s predictive power. They could also add lagged values of downloads in the same regression. While the coefficients might be insignificant due to multicollinearity, the model’s predictive power is likely to increase.

I also lay the foundation for future research that could predict prices at time *t+1* using country specific search volumes at times *t, t-1* etc. It is difficult to find the relationship between country specific searches and Bitcoin prices using a direct regression. The regression of search volumes for multiple countries on prices would suffer from multicollinearity as country searches are correlated with each other. Moreover, regressing prices on searches for a single country would bias results due to omitted variable bias. Even in a purely forecasting model where we are unconcerned with estimating coefficients accurately, there is not enough data to tease out the impact of country-level searches for more than a handful of countries. I solve this problem by introducing the adoption rate variable (downloads) as an intermediary. I solve this problem by introducing the download variable as an intermediary. I demonstrate that prices can be predicted by total client downloads and that client downloads can be predicted by country level search volumes. In the future, it would be fascinating to investigate at the country level the out-of-sample predictive power of searches at time, t, on downloads at $t+1$. We could then use these forecasted downloads across countries to predict prices at time, $t+1$.

Future Bitcoin researchers should also expand their dataset beyond OECD countries. A broader base would allow them to analyze data from developing countries such as India and Ghana that have large Bitcoin search volumes. In addition, they could look at more granular data. My analysis was based on monthly data, but most information about Bitcoin and search volume is available at a daily and weekly level respectively. Lastly, economists should explore the possibility of controlling for longer lags that may be useful in predicting contemporaneous prices. Scholarship on the interplay of Bitcoin prices, adoption rates, and public interest is still limited and has immense potential due to the easily available open source data.

Conclusion

In this paper, I analyze if public interest around Bitcoin impacts Bitcoin prices and countrywide adoption rates. I use Google searches for the keyword ‘Bitcoin’ and number of Bitcoin client downloads as proxies for public interest and adoption rates respectively. Bitcoin prices are measured relative to the USD. On a global level, I find that search volumes and their lags significantly impact prices in all estimated models. The number of client downloads and their lags also affect Bitcoin prices. Except inflation rates, no traditional macroeconomic determinants of currency prices are significant in the contemporaneous variable regression. In the lagged model, all of the macroeconomic determinants are statistically insignificant.

This is the first academic paper that explores countrywide Bitcoin adoption rates. I show that country level search volumes have a significant impact on the number of downloads per capita for that country. The magnitude of search volumes’ impact on download rates decreases each month. The results hold true for 11 of the 12 individual country regressions, indicating the strong correlation between Bitcoin searches and download rates. The only exception was Russia, likely due to misrepresented data.

My conclusions provide a missing link in existing literature that could help economists predict Bitcoin prices and adoption rates. Because lagged values of Google searches significantly affect both prices and countrywide adoption rates, economists can look at the previous month’s global search volume to predict trends in the Bitcoin economy. The same approach can be replicated while analyzing other new and upcoming digital currencies. With such a model, investors in the Bitcoin market can make more educated decisions about when to invest or divest in the currency. Policymakers looking to regulate the currency can make more accurate estimations about the size of the Bitcoin market in their country. Bitcoin is traded with every major global currency, has a total transaction volume exceeding $6.5 billion, and continues to grow as a medium of exchange. A better understanding of Bitcoin price drivers, based on a model such as this one, would allow economists to predict how price shocks could spill over to the broader economy.

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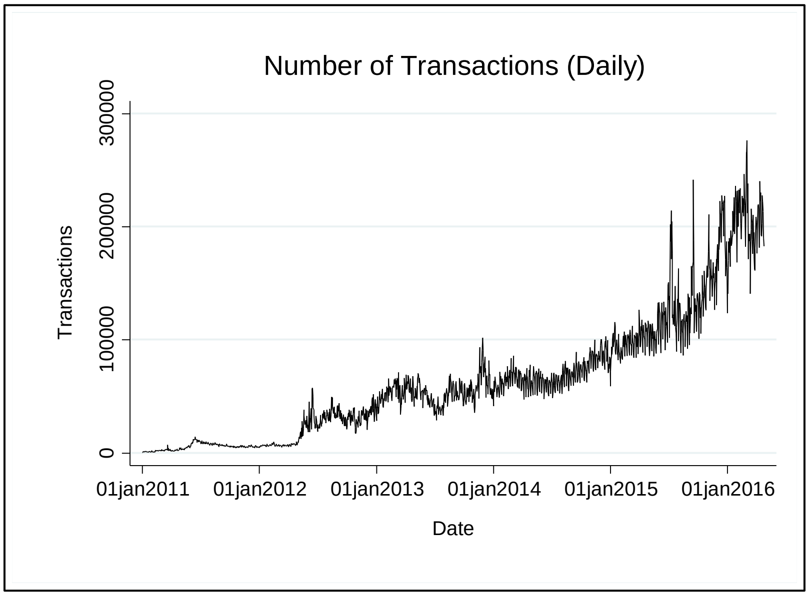
Appendix A: Variable Names, Definitions & Sources

Variable (Aggregated at Monthly Level)	Definition	Data Source	Website
Bitcoin Prices	Bitcoin value measured in USD	Blockchain	https://blockchain.info/charts/market-price
Search Volume	Indexed Google searches for keyword 'Bitcoin'	Google Trends	https://www.google.com/trends/explore#q=bitcoin
Downloads	Number of Bitcoin client downloads across all operating platforms	Source Forge	https://sourceforge.net/projects/bitcoin/files/stats/map?dates=2013-09-19
M3	Seasonally adjusted broad money supply	OECD	https://data.oecd.org/money/broad-money-m3.htm
Inflation	Inflation growth measured by changes in consumer price index	OECD	https://data.oecd.org/price/inflation-cpi.htm
Unemployment	Harmonized Unemployment Rate (% of labor force unemployed)	OECD	https://data.oecd.org/unemp/harmonised-unemployment-rate-hur.htm#indicator-chart
Industrial Production	Output of industrial establishments measured as index based on changes in production volume	OECD	https://data.oecd.org/industry/industrial-production.htm
TWEXB	Trade Weighted USD Index	FRED	https://research.stlouisfed.org/fred2/series/TWEXB
TB3MS	3 – Month T Bill: Secondary Market Rate	FRED	https://research.stlouisfed.org/fred2/series/TB3MS
Corruption	Corruption Perception Index: Measures individuals' perception of public sector corruption	Transparency International	http://www.transparency.org/research/cpi/overview
Exchange Rate	Value of that country's currency in USD	Investing.com	www.research.stlouisfed.org
Population	Number of residents regardless of legal status	World Bank	http://data.worldbank.org/indicator/SP.POP.TOTL
Internet Access	Number of internet users per 100 people	World Bank	http://data.worldbank.org/indicator/IT.NET.USER.P2

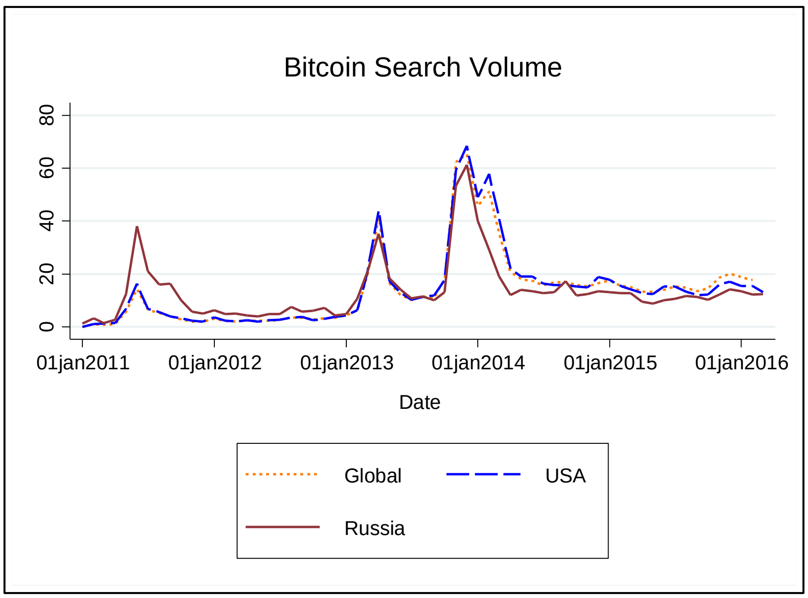
Appendix B: Bitcoin Graphs

B.1: Number of Bitcoin Transactions (Daily)



Source: blockchain.info/charts

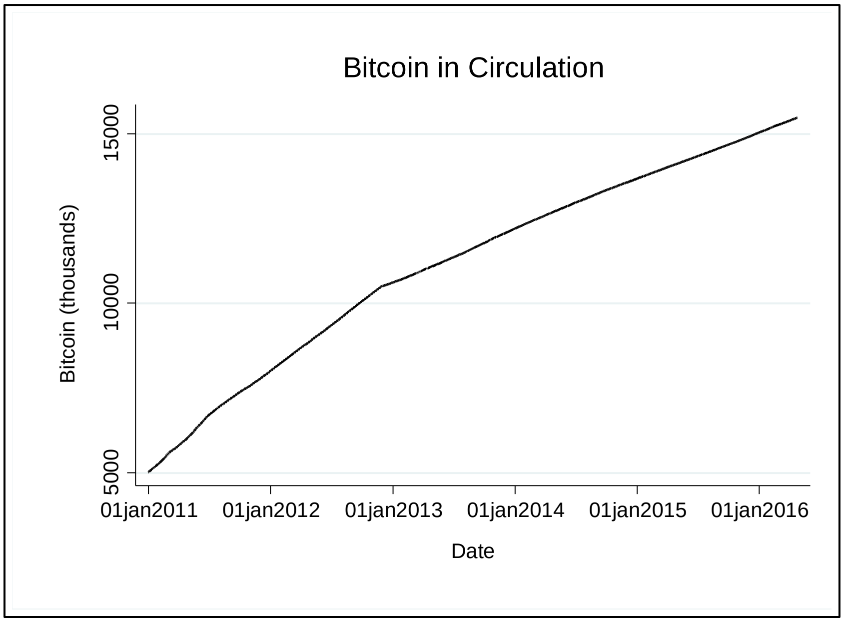
B.2: Monthly Search Volume for 'Bitcoin' in USA, Russia and Globally[10]



Source: Google Trends

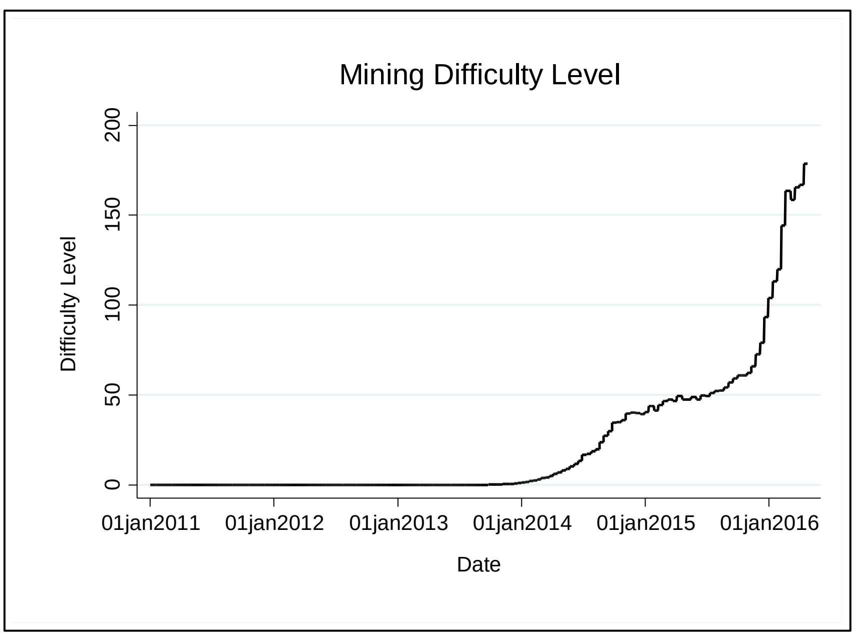
[10] I include only USA, Russia, and global searches as an example to demonstrate the high correlation between and inter-country searches and country-global level searches for 'Bitcoin.'

B.3: Number of Bitcoins in Circulation (Thousands)



Source: blockchain.info/charts

B.4: Mining Difficulty Level[11]



Source: blockchain.info/charts

[11] Mining difficulty adjusts based on a step-wise function. As the number of Bitcoin in circulation has increased over time, so has the mining difficulty.

Appendix C: Country Specific Summary Statistics

C.1: USA Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	14.13	14.77	0	68.40
Inflation	61	1.682	1.079	-0.200	3.868
Unemployment	61	7.130	1.365	4.900	9.100
Corruption	60	73.40	1.639	71	76
Industrial Production	61	108.6	3.998	101.6	114.3
Internet Access	48	80.15	6.736	69.73	87.36
M3	61	124.4	11.98	102.5	144.6
Exchange Rate (USD)	61	1	0	1	1
Download per capita	48	29.78	32.21	1.080	147.4

C.2: UK Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	10.64	10.99	0	55.25
Inflation	61	2.244	1.535	-0.100	5.200
Unemployment	59	7.041	1.086	5.100	8.400
Corruption	60	77.40	2.352	74	81
Industrial Production	61	97.44	1.512	93.87	101.7
Internet Access	48	88.58	2.382	85.38	91.61
M3	61	99.28	1.644	95.85	101.9
Exchange Rate (USD)	61	1.585	0.0594	1.425	1.711
Download per capita	48	29.35	33.90	1.404	159.9

C.3: Canada Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	13.54	15.16	0	65.20
Inflation	61	1.686	0.807	0.409	3.697
Unemployment	61	7.149	0.269	6.600	7.700
Corruption	60	83.20	2.246	81	87
Industrial Production	60	107.3	2.736	102.6	111.8
Internet Access	48	84.73	1.811	83	87.12
M3	61	125.4	14.01	103.7	152.5
Exchange Rate (USD)	61	1.089	0.122	0.945	1.397
Download per capita	48	38.82	44.26	1.189	203.0

C.4: Sweden Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	13.76	13.66	0.400	68.20
Inflation	61	0.718	1.240	-0.626	3.375
Unemployment	61	7.802	0.332	6.800	8.400
Corruption	60	89.20	2.057	87	93
Industrial Production	61	98.04	3.462	92.21	104.8
Internet Access	48	93.31	0.890	92.52	94.78
Exchange Rate (USD)	61	0.144	0.0150	0.115	0.165
Download per capita	48	56.55	59.17	1.891	260.8

C.5: France Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	12.31	13.45	0	73
Inflation	61	1.081	0.851	-0.383	2.515
Unemployment	61	9.982	0.467	9.100	10.60
Corruption	60	70.20	0.755	69	71
Industrial Production	61	101.0	1.521	98.23	105.3
Internet Access	48	81.23	2.173	77.82	83.75
Exchange Rate (USD)	61	1.285	0.111	1.056	1.480
Download per capita	48	10.70	12.85	0.903	50.79

C.6: Poland Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	10.95	10.78	0.200	53.75
Inflation	61	1.553	2.056	-1.287	4.842
Unemployment	61	9.297	1.106	6.900	10.60
Corruption	60	59.20	2.503	55	62
Industrial Production	61	112.1	5.181	102.6	122.5
Internet Access	48	63.43	1.879	61.95	66.60
M3	61	128.2	13.64	104.5	156.1
Exchange Rate (USD)	61	0.308	0.0308	0.245	0.377
Download per capita	48	21.43	25.17	0.605	100.00

C.7: Russia Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	13.43	11.35	1.200	61.20
Inflation	60	8.730	3.798	3.574	16.93
Unemployment	50	1.453	0.318	1.049	2.208
Corruption	60	27.20	1.735	24	29
Industrial Production	61	108.1	2.164	102.7	112.2
Internet Access	48	62.82	8.421	49	70.52
M3	60	166.7	35.65	111.5	235.9
Exchange Rate (USD)	61	0.0277	0.00709	0.0133	0.0365
Download per capita	48	14.06	17.51	0.556	82.35

C.8: Germany Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	11.56	11.67	0	59
Inflation	61	1.332	0.740	-0.283	2.398
Unemployment	61	5.202	0.447	4.300	6.400
Corruption	60	79.40	1.028	78	81
Industrial Production	61	109.4	1.832	105.4	114.1
Internet Access	48	83.49	1.889	81.27	86.19
Exchange Rate (USD)	61	1.285	0.111	1.056	1.480
Download per capita	48	27.26	31.16	1.388	150.9

C.9: Netherlands Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	7.861	11.46	0	65.25
Inflation	61	1.757	0.911	0	3.067
Unemployment	61	6.480	0.975	4.700	7.900
Corruption	60	85.20	2.420	83	89
Industrial Production	61	97.56	3.239	86.90	102.2
Internet Access	48	92.85	0.928	91.42	93.96
Exchange Rate (USD)	61	1.285	0.111	1.056	1.480
Download per capita	48	50.52	70.58	2.188	343.2

C.10: Finland Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	10.67	11.20	0	56
Inflation	61	1.681	1.312	-0.593	3.958
Unemployment	59	8.322	0.615	7.600	9.500
Corruption	61	90.39	1.855	89	94
Industrial Production	61	97.03	3.112	92.30	103.4
Internet Access	48	90.62	1.437	88.71	92.38
Exchange Rate (USD)	61	1.285	0.111	1.056	1.480
Download per capita	48	45.98	45.28	2.093	228.9

C.11: Estonia Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	13.35	14.89	0	70.20
Inflation	61	2.179	2.276	-1.276	5.679
Unemployment	60	8.885	2.237	5.800	13.90
Corruption	60	67	2.551	64	70
Industrial Production	61	125.5	5.196	115.7	135.0
Internet Access	48	79.63	2.887	76.50	84.24
Exchange Rate (USD)	61	1.285	0.111	1.056	1.480
Download per capita	48	53.66	71.98	7.607	412.6

C.12: Czechia Summary Statistics

VARIABLES (Monthly)	(1) N	(2) mean	(3) sd	(4) min	(5) max
Search Volume	61	9.710	10.81	1	53.50
Inflation	61	1.451	1.150	0	3.777
Unemployment	61	6.334	0.806	4.500	7.200
Corruption	60	49.60	3.963	44	56
Industrial Production	60	108.2	4.509	100.7	119.0
Internet Access	48	74.44	3.371	70.49	79.71
M3	61	114.1	9.563	100.6	134.8
Exchange Rate (USD)	61	20.54	2.563	16.28	25.68
Download per capita	48	24.72	32.27	1.855	126.1

Appendix D: Country Specific Regression Showing Impact of Search on Downloads

D.1: USA, UK, Canada, Russia

VARIABLES (Monthly)	(1) USA	(2) UK	(3) Canada	(4) Russia
Search Volume	9.145***	12.936***	12.571***	0.924***
	(0.677)	(1.092)	(1.038)	(0.259)
Lag Search Volume	0.247	0.279**	-0.050	0.186
	(0.218)	(0.128)	(0.168)	(0.135)
M3	-0.694	-8.019	9.590	-2.054
	(2.192)	(6.053)	(10.474)	(1.351)
Corruption	-17.930	0.114	-4.004	-3.889
	(11.339)	(1.198)	(4.909)	(3.516)
Internet Access	2.089	0.700	-8.077	1.265
	(1.785)	(2.521)	(7.718)	(1.086)
Inflation	-1.436	2.300	0.478	-0.344
	(2.847)	(4.136)	(3.296)	(1.279)
Industrial Production	1.329	-0.579	-5.895	-1.333
	(3.501)	(1.052)	(3.731)	(0.797)
Unemployment	-23.296*	16.846	-16.859	-4.529
	(12.117)	(22.708)	(13.586)	(30.379)
Trend * Search Volume	-0.231***	-0.322***	-0.311***	0.011
	(0.022)	(0.033)	(0.033)	(0.012)
Trend	-0.149	-0.014	-0.183	0.004
	(0.103)	(0.095)	(0.184)	(0.066)
Constant	-0.365	-1.590	-5.443	3.214
	(2.400)	(2.521)	(5.826)	(2.331)
Observations	46	46	46	46
R-squared	0.904	0.921	0.890	0.808

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

D.2: Finland, France, Netherlands, Estonia

VARIABLES (Monthly)	(1) Finland	(2) France	(3) Net	(4) Estonia
Search Volume	12.586***	4.430***	40.058***	16.052***
	(1.246)	(0.695)	(7.477)	(3.770)
Lag Search Volume	0.285	0.062	0.227	2.012**
	(0.291)	(0.207)	(0.704)	(0.864)
Corruption	-1.086	2.145	2.717	4.125
	(1.550)	(4.294)	(3.828)	(3.925)
Internet Access	-6.252	-0.508	14.491	-40.355***
	(4.774)	(1.446)	(11.748)	(8.463)
Inflation	1.288	-1.790	-6.707	29.646
	(7.448)	(7.065)	(11.688)	(18.858)
Industrial Production	2.043	0.031	-0.023	-3.356*
	(2.372)	(0.542)	(1.298)	(1.721)
Unemployment	60.903	6.528	-9.593	16.188
	(54.247)	(8.799)	(32.760)	(13.002)
Trend * Search Volume	-0.311***	-0.112***	-1.035***	-0.394***
	(0.039)	(0.024)	(0.215)	(0.111)
Trend	-0.254	-0.057	-0.284	0.009
	(0.233)	(0.071)	(0.229)	(0.346)
Constant	2.637	0.162	-0.151	9.056
	(5.356)	(1.489)	(5.302)	(10.602)
Observations	46	46	46	46
R-squared	0.901	0.765	0.891	0.836

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

D.3: Sweden, Germany, Poland, Czechia

VARIABLES (Monthly)	(1) Sweden	(2) Germany	(3) Poland	(4) Czechia
Search Volume	10.493***	7.036***	6.205***	8.104***
	(2.934)	(0.572)	(1.432)	(0.865)
Lag Search Volume	1.052**	-0.393	0.490*	0.282
	(0.466)	(0.309)	(0.252)	(0.406)
M3			1.668	12.358
			(2.175)	(9.296)
Corruption	-4.216	6.148	-1.274	4.152
	(2.921)	(5.575)	(3.104)	(5.266)
Internet Access	-33.813	5.641	-0.324	-3.390
	(24.029)	(4.589)	(1.806)	(5.510)
Inflation	-18.228	-0.429	-4.078	-15.922
	(16.082)	(12.004)	(4.535)	(11.289)
Industrial Production	0.101	1.338	-1.110	0.053
	(0.823)	(1.203)	(1.462)	(0.603)
Unemployment	2.413	-12.340	-22.358	0.869
	(9.870)	(26.923)	(20.135)	(15.398)
Trend * Search Volume	-0.245**	-0.167***	-0.139***	-0.174***
	(0.095)	(0.028)	(0.043)	(0.028)
Trend	-0.239	-0.099	-0.173	-0.002
	(0.278)	(0.173)	(0.209)	(0.184)
Constant	0.605	-0.114	0.743	-6.485
	(7.037)	(3.332)	(5.829)	(5.205)
Observations	46	46	46	46
R-squared	0.720	0.879	0.808	0.715

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

Appendix E: Explanatory power of lagged searches in predicting downloads

VARIABLES (Monthly)	(1) Search	(2) + Second Lags
First Lag Search Volume	0.332	0.305
	(0.252)	(0.236)
Second Lag Search Volume		-0.114
		(0.229)
First Lag Corruption	-0.629	-1.084
	(1.744)	(1.779)
Second Lag Corruption		1.015
		(1.556)
First Lag Internet Access	-1.882	-1.576
	(1.817)	(1.677)
Second Lag Internet Access		2.019
		(1.204)
First Lag Industrial Production	1.165***	1.825***
	(0.309)	(0.479)
Second Lag Industrial Production		1.816***
		(0.558)
First Lag Inflation	7.098	6.943
	(3.962)	(4.079)
Second Lag Inflation		3.443
		(4.054)
First Lag Unemployment	8.260*	8.172
	(4.513)	(5.002)
Second Lag Unemployment		8.919
		(6.789)
Trend	-0.048	-0.055
	(0.032)	(0.037)
Trend * Search Volume	0.071***	0.071***
	(0.012)	(0.011)
Constant	1.734**	1.862**
	(0.608)	(0.792)
Observations	552	540
R-squared	0.353	0.364
Number of countries	12	12

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

Column (1) shows explanatory power of all first lags; (2) adds second lags.