FROM BEANIE BABIES TO BITCOIN: SPECULATION IN THE DIGITAL ECONOMY?

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**ABSTRACT**

The volatile nature of the price of Bitcoin (BTC), a decentralized cryptocurrency, has incurred a debate about the future of Bitcoin as a speculative investment or as a currency. The inclusion of both speculators and mainstream users in the BTC economy raises the question of whether the value of one coin is driven by speculation or by economic factors like supply and demand. The model in this research aims to analyze the effects of investor sentiment, indicators in the Bitcoin economy, and the effects of political instability and media on its price. Utilizing linear, dynamic, and error-correction models, this paper is able to separate these effects for the years 2012-2013. The results of this study show that the indicators of the price of BTC are consistently significant throughout the years, although with differing magnitudes depending on the time period. The variables representing investor sentiment, political instability, and media return weak or unexpected results. Overall, this research confirms prior results in the literature and sheds new light on the determinants of the Bitcoin economy.

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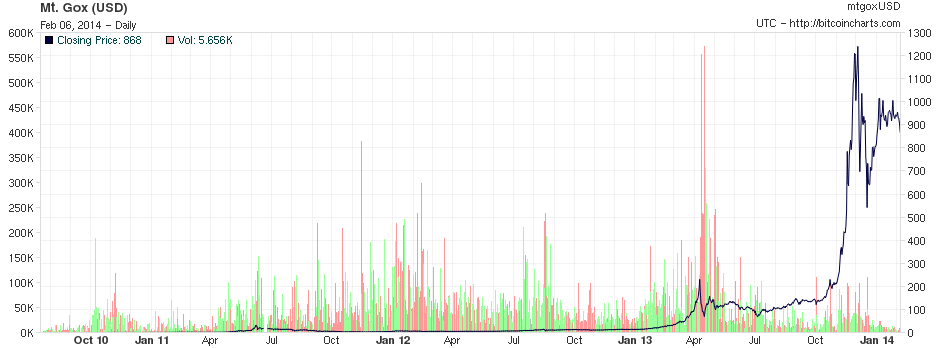
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# Introduction

Bitcoin (BTC), a decentralized, peer-to-peer virtual currency, has gained much praise and controversy in the media as it continues its quest to become the mainstream global cryptocurrency. Currently, Bitcoin is trading at $840 on Mt. Gox, the most popular exchange for buying and selling Bitcoin (bitcoincharts.com). Bitcoin was developed by an anonymous person or group going by the name Satoshi Nakamoto. Nakamoto (2008) discusses how Bitcoin fulfills the need for a trust-based currency that does not require a third-party institution to act as a mediator between two parties. Instead, an electronic cash system can be put in place that uses hash-based proof-of-work and digital signatures to guarantee the value and acceptance of the currency. Bitcoins are generated by miners who expend CPU time and electricity to put them into circulation. Bitcoin is capped at 21 million Bitcoins, and the number of introduced coins into the current supply is decreased by 50% each time a certain amount of BTC has been mined (Kroll, Davey & Felten, 2013, p. 5).

 *Figure 1* Mt. Gox Bitcoin Exchange. Adapted from bitcoincharts.com. This figure illustrates the fluctuations in the price of Bitcoin since its introduction in 2009.

Bitcoin differs from traditional fiat currency for several reasons: it is not backed or governed by a central agency, the use of cryptography makes it anonymous but not untraceable, and it has a predetermined supply cap with gradual introduction of BTC into the market. Traditional characteristics of currency are as a store of value, a medium of exchange, and a unit of account (Yermack 2013). As a new form of currency, the debate focuses on whether Bitcoin exhibits these characteristics or if it functions more as a speculative investment. Ever since its introduction, Bitcoin is known for its wildly fluctuating prices, as shown by the chart of closing prices on the Mt. Gox exchange (*Figure 1*). This research paper aims to develop a model of Bitcoin prices based on economic forces of supply and demand. The model tests the hypotheses that investor sentiment, BTC indicators, media, and political stability are significant determinants of its price.

# Literature Review

Bitcoin as Currency?

While Bitcoin is a cryptocurrency, primarily used as a medium of exchange, others argue that Bitcoin acts more like a speculative investment. Yermack (2013) discusses the characteristics of typical currencies and analyzes how many of those characteristics Bitcoin exhibits. Money is typically defined by its functions as a medium of exchange, a unit of account, and a store of value. Yermack (2013) argues that Bitcoin performs poorly as a unit of account and as a store of value because of its high volatility (p. 2). In addition, Bitcoin’s value is untethered to other currencies, which renders it a poor tool for risk management. Its primary clientele are technology enthusiasts who see the currency taking a prominent role in online commerce, and libertarians who appreciate the decentralized nature of the currency. According to Yermack (2013), the majority of the demand comes from the US and China (p. 6). For Bitcoin to be accepted as currency, its value will have to stabilize. In the meantime, Yermack (2013) argues, the digital currency acts more as a speculative investment rather than a currency, popular among optimistic traders who are motivated by Bitcoin’s ever-rising prices.

Kroll, Davey, and Felten (2013) give more insight into the incentives of miners to introduce new Bitcoin into the supply. In addition to the fixed supply, miners operate under certain rules and incentives to keep the network secure. Consensus is important to maintain stability, and Kroll, Davey and Felten (2013) outline three important types of consensus: Consensus about Rules, Consensus about State, and Consensus that Bitcoins are Valuable. The authors do a further game theoretic analysis to determine why players are incentivized to adhere to these rules and maintain the network. Nakamoto (2008) developed a digital currency as a way to circumvent the middle man in money exchanges because reliance on the intervention of central banks requires trust in institutions. In essence, Bitcoin allows for exchanges without trust, but Kroll, Davey, and Felten (2013) argue that some level of trust and cooperation is required to sustain the currency. Their analysis is key to further discussions regarding Bitcoin regulation and protocol. For the purpose of modeling the price of Bitcoin, Kroll, Davey, and Felten (2013) provide insight into the supply of Bitcoin and the sustainability of this supply over time.

Kristoufek (2013) provides a basis for analyzing the demand of Bitcoin. Utilizing Internet analytics, Kristoufek (2013) is able to model the demand for Bitcoin through search queries. The author emphasizes the importance of investor sentiment as a determinant of the value of the currency. Kristoufek (2013) writes “The demand side of the market is not driven by an expected macroeconomic development of the underlying economy (as there is none); it is driven only by expected profits of holding the currency and selling it later” (p. 1). He echoes Yermack’s sentiment that Bitcoin acts more like a speculative investment rather than a currency. Using Google and Wikipedia data on Bitcoin search queries, Kristoufek finds that the price of Bitcoin is strongly correlated with the search queries of both engines. Thus, speculation and fads dominate Bitcoin price dynamics. Internet queries are an instrumental variable in modeling the price of Bitcoin because of how they proxy demand and investor sentiment and they will be incorporated as variables in this study.

A majority of Bitcoin analysis is covered in the media by journalists, economists, and financial analysts. Together, they form a general picture of Bitcoin’s future. Christopher Matthews (2014) summarizes economists’ sentiments on Bitcoin. Bitcoin’s fails to act as a store of value and disincentivizes merchants to accept the currency at their stores. This in turn may prevent mainstream adoption of the currency. Kashmir Hill (2013) examines the bubbles in Bitcoin caused by increased Chinese buying and media attention. The rapid inflationary effects on price causes analysts to be wary of future market corrections. Evident in Figure 1, the price of Bitcoin has experienced dramatic booms and corrections in April, November, and December 2013.

Woo (2013) released the first financial assessment of Bitcoin. Woo (2013) echoes the sentiment that Bitcoin’s high volatility, driven by speculative activities, hinders its adoption as a mainstream currency. In addition, the author makes some bold assumptions and forecasts about Bitcoin, arguing that the currency’s fair value parallels that of silver and it will reach a market capitalization of $15 billion, with each BTC valued at $1300. To assess whether Bitcoin is entering a bubble, Woo (2014) makes quick calculations under the assumption that it will grow to account for 10% of business-to-consumer (B2C) e-commerce (p. 7). Woo (2014) also analyzes Bitcoin’s parallel to gold and silver as a store of value. Bitcoin is similar to precious metals in its anonymity and use as a hedge against risk, with its value rising during times of uncertainty and lowering in times of stability.

BTC’s Similarity to Gold Models

Like Bitcoin, the volatility of the price of gold is a puzzle to economists and financial analysts alike. Besides its industrial and commercial uses, the value of gold seems to be determined by the cost of mining gold (supply) and the demand for gold as a hedge against risk or as a speculative investment. Unlike Bitcoin, the forces that affect the gold market are known. Abken (1980) writes “The economic and political forces that affect the gold market fall into the following basic categories: (1) extreme political and economic uncertainty, (2) flow supply and demand for gold, (3) inflation, and (4) government auction policy” (p. 6). Bitcoin is similar to gold for reason (2), but may have increasing relevance to reason (1). Efthymiou and Michael (2013) write about the bankruptcy of the Cypriot economy in March 2013, in which the banking system collapsed for two weeks, leaving citizens to rely on ATMs, point-of-sale terminals, and credit cards for their transactions. As the banks stayed closed and imposed further limits on ATM withdrawals, uncertainty and unrest among citizens heightened. According to Efthymiou and Michael (2013), the bank run provided an opportunity for Bitcoin to make its grand debut. They write “Cyprus gained a huge amount of media attention during the fortnight and it was a perfect opportunity for the Bitcoin ATM founders to promote their virtual currency” (p. 24). Thus, the Cypriot banking crisis is an example of a modern period wherein mistrust in traditional banks and currency presented Bitcoin as an alternative medium. In addition, the first dramatic boom and crash in April 2013 in Figure 1 suggests that the Cypriot crisis may have acted as an important catalyst in Bitcoin’s popularity. To determine the significance of this political event, a dummy variable will be incorporated into the model in this research.

When estimating the price of gold, the exchange rate with various countries is an important international benchmark, Sjaastad and Scacciavillani (1996) determine that liberalizing gold and allowing it to float triggered more volatility in the real exchange rate than under the previous regime of Bretton Woods. This comparison proves that volatility is to be expected in liberalized markets, even though it may not be as exaggerated as Bitcoin’s price movements. However, examining various exchange rates may not be productive, as Yermack (2013) argues that Bitcoin’s dollar exchange rate has zero correlation with other currencies. Bitcoin is most popular in the US and China, so it may be of value to analyze Bitcoin’s exchange rate with those countries to determine political and economic forces surrounding the circulation of BTC.

BTC Market Dynamics

Speculation in the price of Bitcoin raises the question of testing for bubbles. Classic bubble literature by Blanchard and Watson (1982), Summers (1986), Schaller and van Norden (2002), and Dezhbakhsh and Demirguc-Kunt (1990) suggest that the best way to test for a bubble is to see how much the price of an asset has deviated from its fundamental value. Gold and Bitcoin both have notoriously difficult-to-determine fundamental values because their values rely on the cost of supply and the demand for them, which fluctuate and are not always known. Thus, gold bubbles are more often attributed to irrationality than to rational deviations from fundamentals. Woo (2013) asserts that Bitcoin’s fair price is similar to that of silver by making rough assumptions on its prevalence in e-commerce. However, the digital currency hovered near the fair price only briefly until it dropped down to around $850. Other assumptions are critical in determining future bubbles in Bitcoin. Blanchard and Watson (1982) state that risk aversion and diffusion of information may affect whether a bubble is rational or irrational (p. 5). They do not write off the effects of crowd psychology and neither does Summers (1986). Summers (1986) acknowledges the psychological forces in the financial market saying “that subjects overreact to new information,” especially when evaluating extraneous events (p. 594). Irrationality may play a role in BTC’s price volatility, but it is inherently difficult to quantify, thus providing an avenue for future research.

Zeira (1999) examines the effects of informational dynamics on the booms and crashes in the stock market. The author argues that informational overshooting “occurs when the market goes through an expansion and the size of an expansion is unknown until it ends” (p. 238). Additionally, informational overshooting results from rapid technological progress and a large entry of new investors (Zeira 1999, p. 238). Arguably, Bitcoin exhibits both these traits, suggesting that informational overshooting is a likely determinant of its price volatility. Kristoufek’s (2013) study on correlating search engine queries is indicative of the value of information in the hands of Bitcoin users. The increase in investors and knowledge gained through search queries may well be driving the booms and crashes of Bitcoin prices.

Exchange Rate Volatility

It is also possible to speculate about Bitcoin’s value through exchange rate volatility, which is how the Bitcoin-US dollar exchange fluctuates over time. Investors profit from short-term holdings of the currency, thus the price may also be determined by exchange rate volatility and its determinants. Rose (1994) discusses whether volatility in exchange rates are determined by macroeconomic phenomena. Typical models include factors such as inflation and money supply, but Rose (1994) argues that “many shocks that drive exchange rates are not macroeconomic in nature” (19). OECD countries have similar macroeconomic volatility while their exchange rate volatilities differ significantly. Rose (1994) outlines the two types of fundamentals that comprise exchange rate volatility: traditional fundamentals and virtual fundamentals. Traditional fundamentals encompass macroeconomic variables, while virtual fundamentals utilize high-frequency asset-market data. Should the model accurately describe reality, then the two fundamentals ought to behave similarly. Rose (1994) finds that this is not the case. While the volatility of virtual fundamentals differ systematically, traditional fundamentals are similar across countries. Rose (1994) eventually concludes that exchange rate volatility may be better explained by microeconomic phenomena, such as noise trading and excessive speculation.

Flood and Rose (1997) examine the effects of fixing versus floating currencies in OECD countries. They share Rose’s (1994) conviction that macroeconomic variables are not critical determinants of exchange rate volatility. Flood and Rose (1997) argue that fixing the exchange rate does not cause volatility to transfer to another part of the economy. Rather, the volatility vanishes, a phenomenon that they prove empirically. By using a simple model, Flood and Rose (1999) demonstrate their argument, emphasizing “macroeconomics is an inessential piece of the exchange rate volatility puzzle” (5). To defend this claim, they cite the same evidence echoed in Rose (1994) and Flood and Rose (1997) - that exchange rate volatility does not match up with macroeconomic volatility. Rather, there is a need to search for possible microeconomic explanations. Currently, the value of one BTC in China is 3,855 yuan, which equals roughly USD634 (bitcoincharts.com). This is similar to the current price of USD631 on BitStamp, an exchange that trades in dollars. This similarity persists despite the news that Bitcoin has been banned for commercial transactions in China (Yang and Lee 2013). In light of the research of Rose (1994), Flood and Rose (1997), and Flood and Rose (1999), macroeconomic variables may not be the best determinant of a digital currency. Rather, BTC’s excessive volatility may be better explained by microeconomic variables such as supply and demand in the BTC market itself or consumer preference as a result of trust.

Researchers like Melvin and Yin (2000) examine the effect of public information on exchange rate volatility and quote frequency in exchange rate markets. Using a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, Melvin and Yin (2000) suggest that “quote frequency and volatility of the mark/dollar and yen/dollar exchange rate are both affected by the rate of public information arrival to the market” (11). Ederington and Lee (1993) also show that news announcements affect exchange markets, although there is some predictability in the time-of-day and day-of-week volatility that stems from scheduled news releases. Ederington and Lee (1993) examine the effect of news released around the opening of the market, and determine that volatility is considerably higher for several hours as the market adjusts prices accordingly. While digital currencies do not operate in a typical market day, the effect of news may have an impact distinct from the effect of search queries (Kristoufek 2013). In addition to the role of public information, private information and noise trading contribute to exchange rate volatility.

Frankel and Froot (1990) describe two types of traders in the exchange market: chartists and fundamentalists. Chartists tend to extrapolate recent trends while fundamentalists rely on long-run equilibrium like purchasing power parity. According to Frankel and Froot (1990), the market shifted toward chartists when fundamentalists failed to predict speculative bubbles in 1981-1985. Trend analysis may be a useful determinant of the price of Bitcoin. Woo (2013) may have a more fundamental approach by assigning a fair value to the currency, but it is also possible that a chartist approach may be more relevant given the excessive volatility of Bitcoin.

In addition to chartists and fundamentalists, financial markets are plagued by noise traders. De Long, Shleifer, Summers, and Waldmann (1990) discuss in-depth the role of noise traders in markets, but several other authors like Melvin and Yin (2000) and Frankel and Froot (1990) also acknowledge the effect of noise in their models. De Long et al. (1990) define noise traders as “irrational noise traders with erroneous stochastic beliefs” who affect prices and earn higher returns (703). According to Friedman (1953) and Fama (1965), noise traders are met by rational arbitrageurs who trade against them and return prices to fundamental values. However, De Long et al. (1990) write “arbitrage does not eliminate the effects of noise because noise itself creates risk,” thereby earning higher returns and continually driving up risk (705). In addition, many traders are passive, multiplying the effect of noise traders when there are only a few sophisticated investors to trade against them. Arguably, Bitcoin is a market largely populated with noise traders. However, because of its anonymous nature, the amount of noise in the market may be difficult to quantify. Overall, some of the determinants of exchange rate volatility may translate to the Bitcoin market.

As the Internet changes the way people interact with each other, Bitcoin may be changing the way payments are made in the digital landscape. While it was originally conceived as a peer-to-peer payment transfer system, its rapid rise in price has made Bitcoin act more like a speculative investment rather than a currency. Several factors may be influencing the price: supply, demand and investor sentiment, economic and political crises, and the effects of media. Additionally, several discussions surround the price of Bitcoin, such as the effect of crowd psychology and irrationality in financial markets. While the literature on Bitcoin is still growing, a model of its price can be informed by previous studies on exchange rates, Google Analytics, and commodity models.

# Methodology

Few scholarly studies have been published that model the price of Bitcoin. This model hopes to shed light on the dramatic fluctuations in the digital currency by incorporating economic variables like supply and the price of substitutes and nonconventional measures like the number of Google queries for Bitcoin. The model is a time-series regression specified as follows:

Where: PBTC = the price of Bitcoin in period t

VIX = the volatility index of the S&P 500

CNY = the volume traded on the Shanghai Stock Exchange (SSE) 380

QUER = a weighted index of the number of BTC queries on Google

SBTC = the total supply of Bitcoin in circulation

VOL = the volatility of the exchange rate

PLTC = the price of Litecoin, a substitute for Bitcoin

DCYP = a dummy variable indicating whether t falls during or after the Cyprus bank run

DNEWS = a dummy variable indicating whether Bitcoin made the news headlines in time t

The signs are hypothesized below:

(+) (+) (+) (+/-) (+) (+) (+)

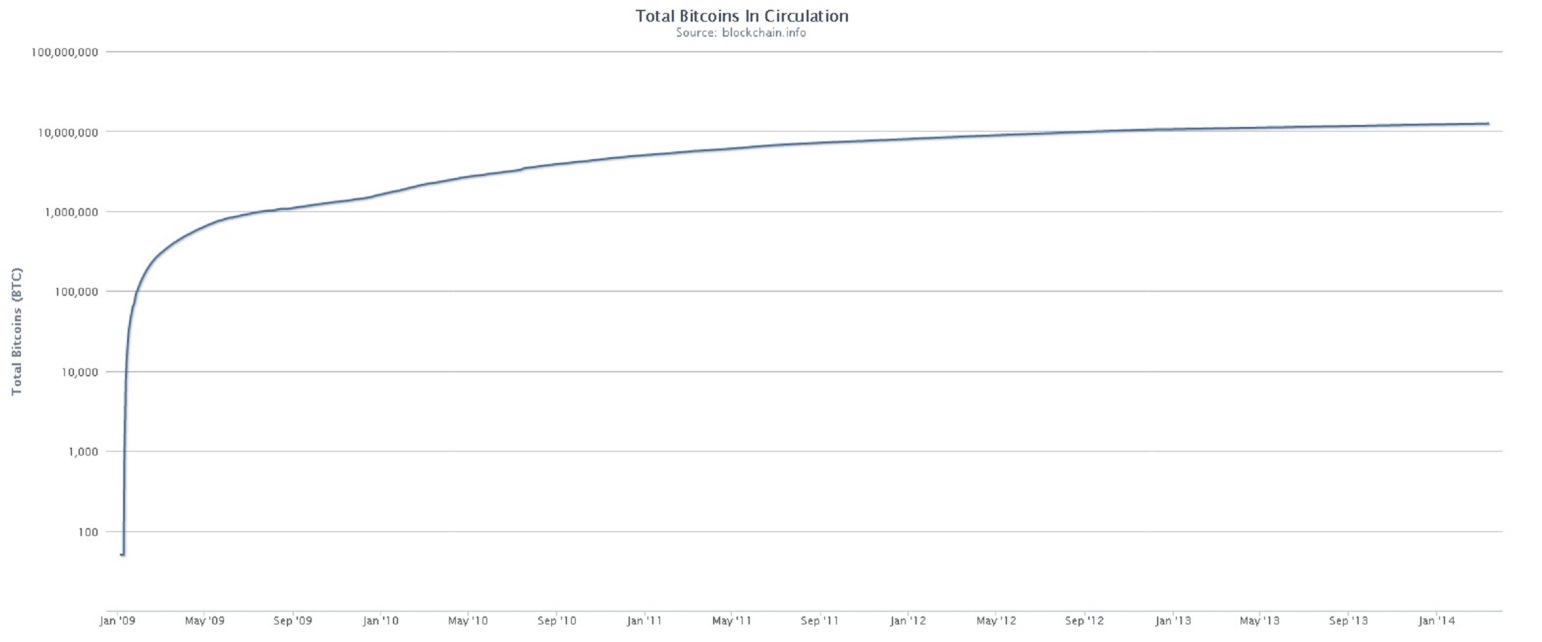
(+)

(1)

Data Sources and Specifications

The data are measured daily for the years 2012 and 2013. Data on the price of Bitcoin (PBTC) can be found on bitcoincharts.com, and refers to the price traded on the Bitstamp exchange. Data on the VIX are found on the Chicago Board Options Exchange (CBOE) Market website (cboe.com), and acts as a measure of investor sentiment in US financial markets. Queries data (QUER) can be found on Google Trends indexed over a certain time period (google.com/trends). Daily data are available in 90-day increments. Beyond the 90 days, Google indexes the data weekly. In light of these facts, the index can be transformed and weighted by multiplying the percentage change in the daily values with the weekly index, creating weighted daily data for the year 2013 (Johansson, 2013).

The supply of Bitcoin (SBTC) follows certain mathematical algorithms such that a) there is a 50% reduction every 4 years and b) the difficulty of mining BTC gets harder with every block mined. The supply of Bitcoin is logarithmic (see Figure 1), evidenced in data and graphs from blockchain.info.



*Figure 1*. Total Bitcoins in circulation. Adapted Total Bitcoins in Circulation, 2014, Retrieved from blockchain.info/charts.

Volatility (VOL) is a measure of the volatility of the BTC/USD exchange rate. The VOL model is the calculated volatility of a one-percent change in the standard deviation of the exchange rate, which can be calculated as follows:

(2)

The price of Litecoin (PLTC), a substitute for Bitcoin, is retrieved from cryptocoincharts.info, and is denoted in US dollars. The volume of stocks traded on the SSE 380 is a measure of market liquidity, which is then used as an indicator of investor sentiment. China holds 8% of all BTC, according to bitcoincharts.com, and the rise in volume traded, holding all others constant, implies a rise in market volatility and risk, thus inducing a rise in the price of Bitcoin as investors either hedge their risk in digital currency or place risky bets on BTC (Baker and Stein 2003, p. 285). Using daily traded volume data on the SSE 380 can indicate whether market liquidity as investor sentiment is significantly correlated with the price of Bitcoin. This data can be found on stockhistoricaldata.com and gives raw values for the total volume traded on day t.

The political and economic events in Cyprus (CYP) are included in the regression as a dummy variable to analyze whether the Cyprus bank run truly acted as a catalyst in Bitcoin’s popularity, which Efythymiou and Michael (2013) argue. The final variable, the number of times Bitcoin was featured on a headline (NEWS) is retrieved from Google trends as well and hopes to measure the effect of media on price volatility, outlined in Ederington and Lee (1993).

Model Specification

Using the data outlined above, the model is a time-series regression, with some variables lagged accordingly. The data is daily, and the price of BTC fluctuates dramatically, so several lags will be tested to determine how quickly information on the Internet and stock market translates into BTC volatility. Additionally, several models will be employed to determine the significance of the different variables during times of volatility, namely by comparing the determinants of volatility in 2012, 2013, and both years together. Kristoufek (2013) tests various forms of the queries and Bitcoin price model, accounting for stationarity and unit root, but not for lags.

Ssekuma (2011) emphasizes the importance of using cointegration in time-series models. Often, time-series variables are nonstationary, but the combination of them is stationary. Thus, the model is determined to be cointegrated. The Pesaran method of cointegration will be used to test whether there is an underlying relationship between the dependent and independent variables (Pesaran, 2001 p. 315). Authors like Narayan and Narayan (2005) employ the Pesaran method of cointegration to test their import demand model and they find that import demand and its determinants have inelastic long-run and short-run relationships. In this study, cointegration is vital in determining which variables, if any, affect Bitcoin in the short and/or long run. The short-run Bitcoin cointegrated model is specified as follows:

(3)

The short-run model is differentiated by the transformation of the independent variables into differenced natural logs and the presence of the error correction variable. The long-run model is determined using the logs of the variables, allowing for the interpretation of the determinants’ elasticities.

(4)

Another short- and long-run model will be employed to determine the significance of the NEWS dummy and the effects of its inclusion into the model. Thus, the short-term error-corrected model without DNEWS is as follows:

And the long-term model without DNEWS is:

(6)

# Results

The first model that was run and then tested was the 2012-2013 linear time-series model, which aimed to understand the effects of the independent variables on the price of Bitcoin over the years in which it was both fairly stable and then extremely volatile. The results of the regression are outlined in Table 1.

Table 1: 2012-2013 Linear Regression Results



As the results of the initial regression reveal, QUER, SBTC, PLTC, VOL, and D1 are highly significant, and the regression has an adjusted R^2 of 0.95, meaning the independent variables account for a very large portion of the price of Bitcoin. Additionally, QUER, SBTC, PLTC, and VOL are of the expected signs. The QUER coefficient means that for every marginal increase in the Google Trends Index, the price of Bitcoin increases by $1.627, all others equal. The SBTC coefficient means that for every new Bitcoin that is increased into circulation, the price rises by $0.000035, all others equal. While this may seem small, the block mining rate is one every ten minutes, which introduces hundreds of individual coins into the market. Thus, when aggregated, the effect of the SBTC coefficient can be quite large. PLTC signifies the effect of the price of a substitute on the price of BTC. Consistent with economic theory, as the price of one Litecoin goes up, the price of Bitcoin increases by $19.11 because of the consequent outward shift in demand, all others constant. VOL is a calculated measure of the price of BTC. The regression results indicate that as the volatility increases, the price increases by $2.45, all other things equal. According to research by Yang and Doong (2004), price volatility indicates a bullish market, in which investors anticipate a rise in prices. Such activity is evident in recent speculative activity with the cryptocurrency sphere. D1, the Cyprus dummy intended to measure the effect of Cyprus bank shutdown on the popularity of Bitcoin, has a negative coefficient, which contradicted the original hypothesis that the Cypriot bank run would have subsequent, positive effects on the price of BTC, indicating a regime change. One possibility for this is omitted variable bias, in which another unknown variable is influencing the effect of D1. Another possibility is that the variable is irrelevant and does not adequately capture the effect of political and economic instability on the price of BTC. A final possibility is that the variable suffers from multicollinearity.

Beyond the unexpected sign of D1 and the insignificance of the VIX, CNY, and D2 variables, the high adjusted R^2 of the initial model may suffer from inflation due to misspecification, multicollinearity, or autocorrelation. To test for these, the Aikaike Information Criterion (AIC), Ramsey Regression Equation Specification Error Test (RESET), and Durbin-Watson tests were conducted. In addition, the Variance Inflation Factors (VIF) were calculated to determine the level of multicollinearity between the variables. A full table of the diagnostics is available in the Appendix.

The AIC measures the quality of the model fit to the data (Studenmund 2010). To interpret the AIC, the model with the minimum AIC value is the better-fitting model. This test does not provide absolute information on the model in the sense that there is no null hypothesis to test. Rather, it determines which model is the best-fitting model relative to other models using the same data.

The RESET test determines whether a linear model is the best way to fit the explanatory variables to the response variable and if there are any omitted variables or specification errors (Studenmund 2010). The null hypothesis for the RESET test is that all of the coefficients are equal to zero. The RESET test statistic for the 2012-2013 model is 88.56, rejecting the null hypothesis and indicating that the specification for the model is not the optimum choice.

The Durbin-Watson tests for serial autocorrelation, which is when the variables from a previous time period affect the dependent variable of the current time period (Studenmund 2010). This problem is especially prevalent in time-series models and may be exacerbated by the model’s use of daily data. The null hypothesis for the Durbin-Watson is that the serial autocorrelation between the variables is zero. The statistic for the 2012-2013 linear model is 0.411, rejecting the null hypothesis and indicating the presence of serial correlation in the model.

In addition to these three tests, the VIFs of the independent variables were calculated to measure the level of multicollinearity between them. The full table is available in the Appendix, but there is no presence of severe multicollinearity between them (VIF >5).

To amend some of the problems indicated by the diagnostic tests, a dynamic model was fit to the 2012-2013 data, the results of which are below:

Table 2: 2012-2013 Dynamic Regression Results

|  |  |  |
| --- | --- | --- |
| Variables | Coefficients | t-statistic |
| (Intercept) | -74.97 . | -1.863 |
| VIX | -0.0449 | -0.257 |
| CNY | 0.000000121 | 0.922 |
| QUER | 0.3151 \*\* | 2.615 |
| SBTC | 0.00000753 . | 1.901 |
| PLTC | 3.096\*\*\* | 5.356 |
| VOL | 0.547\*\*\* | 5.669 |
| D1 | -4.1 | -0.960 |
| D2 | 4.113 | 0.531 |
| PBTC(-1) | 0.8216\*\*\* | 31.815 |
|  |  |  |
| R^2 = 0.986 |  |  |
| Adj. R^2 = 0.985 |  |  |
| D.f. 511 |  |  |
|  |  |  |
| Significance Codes: “\*\*\*” 0, “\*\*” 0.001, “\*” 0.05, “.” 0.1 | | |
|  |  |  |

By fitting the data with a dynamic model, the significance of QUER and SBTC were somewhat reduced and the previous period’s BTC price carried very high significance. Fitting the data to a dynamic model did not change the sign of D1, which remains negative, but it did reduce its significance. The introduction of this lagged variable means that the previous period’s price of Bitcoin positively impacts the current period’s price, namely $0.82 for every increase in the previous BTC price, *ceteris paribus*.

The dynamic model produced mixed results in the diagnostic tests. With an AIC of 6.51, this model is preferred to the linear model’s AIC of 7.6. Both the Durbin-Watson and the RESET tests had p-values of <0.05, rejecting the null hypotheses that there is no serial correlation and that the model is properly specified, but the coefficients were not as large as the results from the linear model. The VIFs showed severe multicollinearity between SBTC, PLTC, and PBTC(-1).

A secondary research question that this paper aims to address is to examine the impact of the independent variables of BTC on two separate years: 2012, when the price volatility was fairly stable, and 2013, when Bitcoin’s popularity skyrocketed and the price experienced unprecedented volatility. The following results tables outline the linear and dynamic results of 2012 and comparing them to the 2013 and overall data.

Table 3: 2012 Linear Model



The 2012 linear model reveals that only BTC supply and the price of Litecoin are significant explanatory variables, resulting in an adjusted R^2 of 0.545, a marked decrease from the 0.95 in the 2012-2013 data. PLTC has a negative sign, which contradicts economic theory of a substitute good. A possible explanation for this is in 2012, those who bought into digital currency bought both Bitcoin and currencies like it because the purchasers were early technological adaptors and were invested in the novelty of the product. In addition, the sign of QUER changed, indicating that the price of BTC actually decreases with an increase in search queries, all others constant. An important note is that the Cyprus dummy, D1 is not applicable in this model because the Cypriot bank run occurred in March 2013. Thus, the 2012 analysis is conducted based on the remaining variables.

A full diagnostic table is available in the Appendix. In this model, the null hypotheses for the Durbin-Watson and the RESET tests are rejected, indicating misspecification and autocorrelation. Severe multicollinearity is not present in the VIFs for the model.

Table 4: 2012 Dynamic Model



The 2012 dynamic model reveals that only the lagged dependent is significant. The QUER sign has become positive once more, but PLTC and VOL remain negative. The R^2 of 0.91 can be attributed mostly to PBTC(-1), indicating that the price of previous periods explains the price of the current period, a result that may be attributed to pure currency speculation.

The AIC of -1.89 is smaller than the linear model’s -0.113 AIC, indicating that this is the superior model. The Durbin-Watson p-value is 0.371, so the null hypothesis that there is no autocorrelation is not rejected. The p-value of the RESET is 0.341, so the null hypothesis that the model is properly specified cannot be rejected. The VIFs do not indicate any multicollinearity. Despite the exaggerated significance of the lagged variable and the non-significance of the other independent variables, the R^2 and the diagnostics indicate that this is a sound model to explain the price of Bitcoin in 2012. Future research must be conducted on the inclusion of omitted variables that may reduce the inflated significance of the lagged dependent variable. This model suggests that the Bitcoin economy in 2012 was influenced by different factors than in 2013 and in the two years combined.

Table 5: 2013 Linear Model



The 2013 linear model attempts to fit the volatile 2013 data to a regression line. The BTC economic indicators like QUER, SBTC, PLTC, and VOL have retained their significance when compared to Table 1. This indicates that the influence of these factors is influential for the majority of 2013, and eclipsed the effects of the determinants in 2012. In addition, CNY has changed signs, which may indicate a shift in investor sentiment in China. As the volatility in the Chinese stock market rises, less Chinese investors speculate in Bitcoin. The same holds true for the VIX, and the negative signs of these two factors may confirm BTC’s function as a speculative investment rather than a currency or as a hedge for investment. Unlike gold, which has historically served as a hedge against financial risk, Bitcoin presents even greater risk in the face of a volatile financial system. Interestingly, D1 is highly significant in 2013, but negative. The original hypothesis regarding the Cypriot bank run is the attention that it shifted towards digital currency would provide a significant, positive effect on BTC. Table 5 shows that this is not the case. One possibility for this unexpected sign is that in the long run, the Cypriot bank run represented such a small portion in the larger picture of Bitcoin price that its effects were insignificant over time. Another possibility is that the Cyprus dummy does not adequately capture political and economic instability and there is an omitted variable that measures daily global instability.

With this model, the p-values of the Durbin-Watson and the RESET tests are highly significant, suggesting autocorrelation and misspecification. The VIFs do not report any severe multicollinearity, but SBTC comes close to it with a VIF of 4.367.

Fitting the 2013 data to a dynamic model produces the results outlined in Table 6 below.

Table 6: 2013 Dynamic Model



Including the lagged dependent in the model produces a highly significant variable, as it did in the 2012 dynamic model. By introducing this variable, the sign of CNY returned to being positive, as expected. However, QUER and D1 lost their significance, which refutes some of the central hypotheses regarding the price of BTC. Comparing the linear and the dynamic model, it appears that volatility and the lagged dependent describe the speculative nature of the currency. The price of Litecoin also holds a high level of significance, a trend evident in the other models.

While the R^2 of this model is higher than the linear version, the Durbin-Watson and RESET tests, while lower in this model, suggests autocorrelation and misspecification. The AIC is lower than the linear model’s, which indicates this is a relatively superior model, but the VIFs are higher, evidence of severe multicollinearity. SBTC, PLTC, and PBTC all have VIFs of above 5. Thus, the DW, RESET, and VIFs diagnose several problems with this model. 2013 may pose a particular challenge for modelling because of the different types of events surrounding BTC. Not only was the Cyprus event striking, but 2013 witnessed multiple global debates and discussions regarding Bitcoin and its inclusion in the world economy.

Utilizing the cointegration model introduced in the methodology, the short-run error-correction model with differenced lags returns the following results, with the differences of the variables taken to create a stationary series.

Table 7: 2012-2013 Cointegrated Short-Run Model



In this model, the insignificant variables in each category are eliminated and the model returns only the most significant lagged variables. In this model, it appears that the most significant variables over all are the 5th lag of the price of Bitcoin, the 4th lag of the Shanghai Stock Exchange, the 3rd lag of the supply of Bitcoin, and the price of Litecoin for several time periods. In this short term model, it appears that the introduction of the error-correction vector has rendered the QUER, VOL, and D1 variables insignificant, a pattern that deviates from the linear and dynamic models of the same time periods. Additionally, the signs of SBTC and the lags of PBTC are unexpected, implying respective negative changes for each unit increase in the independent variable, all others constant. The error-correction coefficient indicates a 0.56% adjustment in the following period, in this case, one day. Using daily data makes the error-correction seem small, but the effects of this is more evident as it compounds over weeks and months.

To diagnose this model, several tests are conducted in addition to the Durbin-Watson and RESET. The Wald test determines the true value of parameters in the data based on the sample estimate, wherein θ denotes a parameter (Fears, Benichou, and Gail 1996). If θ=0, there is no relationship between the parameters. The Breusch-Godfrey test is similar to the Durbin-Watson in that it tests for serial autocorrelation in the residuals, but it provides an even more robust test because it is not limited to nonstochastic regressors, making it especially useful in a cointegrated model (Breusch 1978). A third test, the Jarque-Bera test, tests the normality, kurtosis, and skewness of the model’s fit (Jarque and Bera 1987). The final test is the Augmented Dickey-Fuller test, which determines whether the unit root is zero or nonzero (Ssekuma 2011). If the null hypothesis of unit root equals zero is rejected, then the series is determined to be integrated. A summary of the six tests used in diagnosing the cointegrated model can be found in the appendix, but the most important points of which are discussed in this section.

Firstly, the Wald test rejects the null hypothesis that the relationship parameters are zero, implying the existence of cointegration. The two tests for serial autocorrelation returned mixed results. The Durbin-Watson did not indicate the presence of autocorrelation, but the Breusch-Godfrey did. These may be attributed to the stochastic techniques used in calculating the test statistic. The RESET test suggests there is misspecification. The Jarque-Bera does not the reject the null hypotheses that skewness and kurtosis are zero. Finally, the Augmented Dickey-Fuller test is significant on the 5% level, rejecting the null hypothesis that there is a unit root. Thus, the model is stationary.

The cointegrated model also considers the long-term trends of the Bitcoin price. The table below summarizes the long-term elasticities of the independent variables.

Table 8: 2012-2013 Long-Term Cointegrated Model



The long-term model implies significant results for the research. While VIX and the news dummy are still not significant, all of the other variables are significant and of the expected sign, with the exception of the Cyprus dummy. The adjusted R^2 is also very high, 0.976. In the long run, the supply of Bitcoin is elastic, signifying that there is a major change in the quantity supplied when the currency experiences a large change in the price, all others constant. This is consistent with the fad-like nature of Bitcoin, the incentives of miners to mine more coins and turn a profit, and the low cost of entry into the Bitcoin market. The other variables have positive elasticities of less than 1, indicating that the impact of the other variables are relatively inelastic to the change in BTC price. The long-run investment sentiment variables and economic indicators variables are not as subject to the wild changes evident in the short-run model. For example, over time, a 1% increase in QUER will induce only a 1.11% increase in the price of BTC, all others constant. A similar analysis can be conducted with CNY, PLTC, and VOL. When comparing the short- and the long-term models, an interesting change is the sign of the supply of Bitcoin. In the short run, this may be reflecting movement along the supply curve, which responds to shifts in demand. In the long run, the negative sign may indicate outward shifts in the supply curve itself, which is a reaction to a possible increase in quantity demanded or the result of lower production costs or improved technology.

Throughout the models, the NEWS dummy was insignificant. Removing D2 in the cointegrated model produced the following short-run results:

Table 9: Short-Run Cointegrated Model without D2

 Removing the NEWS dummy slightly diminished the adjusted R^2 and affected the coefficients of the other variables by a slight decimal point, without any noticeable changes to signs, significance, or coefficients. Additionally, there is a similar minimal impact on the diagnostics. The Wald test and Augmented Dickey-Fuller imply there the variables are cointegrated and stationary. The tests for autocorrelation returned the same mixed results are the original short-run error-corrected model, in which the Durbin-Watson hypothesis of zero autocorrelation was not rejected but the Breusch-Godfrey was rejected with a p-value of 0.02. The RESET and Jarque-Bera tests also returned similar results as the original model.

The long-run model without the D2 variable is as follows:

Table 10: Long-Run Cointegrated Model without D2

 The long-run model without the NEWS dummy is also very similar to the original long-run model. The adjusted R^2 is the same and the coefficients are only very slightly different from the results in the first long-run model. The conclusions drawn from the modified model and the consequent diagnostics tests suggest that the inclusion of the NEWS dummy has marginal impact at best and the model does not dramatically suffer with the removal of the dummy. Even though it is an irrelevant variable, the model did not seem to suffer from any diagnostic errors with or without it, but it implies that the NEWS dummy is a poor proxy for media effects on Bitcoin and the variable could be greatly improved.

# Conclusions, Limitations, and Suggestions for Future Research

Bitcoin’s notorious presence in the media raises the question: what are the determinants of the price of Bitcoin? The literature indicates that digital currency currently exists in the realm of speculative investment, and suggests that price is driven not by conventional financial indicators like stock exchange volatility. The variables in the models throughout this paper were informed by the literature review, and the results confirm the general hypotheses that determinants of the price of cryptocurrency like Bitcoin are more likely to be unconventional indicators like queries on Google Trends, and the price of substitutes. Traditional investment measurements were not significant, and dummy variables indicating regime changes and the effects of news returned mixed results. Of the original six models run, the most promising dataset was the combined 2012 and 2013 model, which was then fit to an error-correction model and tested for cointegration. Diagnostic tests suggested that the independent variables were stationary and cointegrated. The short-term and long-term effects of the independent variables were also empirically analyzed, opening up the discussion for improvements on the model.

In the analysis, the NEWS dummy proved to be consistently problematic. This variable was extracted from Google Trends and was a dummy variable indicating whether Bitcoin made the news headlines that day or not. Google Trends only categorized a few days as being “headline days” for BTC, and so the significance of NEWS in all of the models was low. Improvements on the NEWS dummy would be informative to the Bitcoin economy, although a lot of work would first have to go into the definition of Bitcoin news and the evaluation of the effects of different types of media on BTC. After doing so, a full evaluation with the inclusion of the other independent variables can be conducted.

The Cyprus dummy, while positive in the short-run error-correction model, returned an unexpected negative sign in the long-run model. This may have been attributed to the failure of the dummy to capture global political and economic instability beyond the two-week long Cyprus bank run. In light of this, there is an opportunity to investigate the role of Bitcoin as a hedge against political instability, which is driven by the ease it can be transferred across borders.

The price of Litecoin, exceedingly significant in all of the models, may be capturing the effects of omitted variables. While the inclusion of substitute goods is vital to an economic model, the small errors and consequently inflated t-scores suggest there may be omitted variables. Additionally, the removal of the PLTC variable increased the multicollinearity of SBTC, which confirms the need for the inclusion of the PLTC variable and the need for further investigation into the possibility of omitted variables.

The employment of the cointegrated model revealed a more complex interaction between supply, demand, and the price in both the short and long run. The positive sign in the short run seemed to indicate a move along the supply curve as a response to increased shifts in Bitcoin demand. The negative sign in the long run is indicative of shifts in the supply curve. As the quantity supplied shifts outward to meet increased demand, the price diminishes, all others held constant. The use of simultaneous equations would be beneficial in evaluating the interaction between supply and demand. In the same vein, future research could be conducted on the determinants of Bitcoin’s supply and demand separately in order to better understand these shifts.

Overall, the models shed some light on the original research question. The Bitcoin economy continues to puzzle financial analysts and venture capitalists as the price rises and falls dramatically. The question remains whether the mainstream economy will adopt Bitcoin as a viable form of currency, or if it is simply a predecessor to an improved version of cryptocurrency. Nevertheless, employing econometric techniques to such a novel realm of the economy proves fruitful as the Internet continues to evolve and with it, the interaction and behavior of people.

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# Appendix

Appendix 1: 2012-2013 Correlation Matrix



Appendix 2: 2012 Correlation Matrix



Appendix 3: 2013 Correlation Matrix



Appendix 4: 2012-2013 Linear Diagnostics Table

Appendix 5: 2012-2013 Dynamic Diagnostics Table

Appendix 6: 2012 Linear Diagnostics Table

Appendix 7: 2012 Dynamic Diagnostics Table

Appendix 8: 2013 Linear Diagnostics Table

Appendix 9: 2013 Dynamic Diagnostics Table



Appendix 10: 2012-2013 Short-Run Error-Correction Diagnostics



Appendix 11: 2012-2013 Short-Run Error-Correction without D2 Diagnostics



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