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How Presidential Disapproval Affects Bitcoin Returns: A Product of the President

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Abstract

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There has been a growing fascination for decentralized electronic assets, and Bitcoin has emerged as the leader. There have been three different presidents coinciding with the growth of Bitcoin. Since the creation of Bitcoin, each president has faced periods of net disapproval, and these periods have been the norm throughout Obama's, Trump's, and Biden's presidencies. There is currently no existing literature on Presidential ratings as a predictor of Bitcoin, however, there has been research done on the predictors of Bitcoin and Presidential ratings as a predictor of financial markets. I hypothesized that increases in net disapproval ratings are a predictor of increases in the returns of Bitcoin because when people do not trust the government, they are less likely to trust financial institutions and thus more likely to invest in a decentralized asset like Bitcoin. I run OLS regressions with daily, weekly and monthly data to test whether changes in net presidential approval ratings are a predictor of the excess returns of Bitcoin one month later. I add stock market, political, and Cryptocurrency investor sentiment control variables as robustness tests. I find that net presidential disapproval ratings as a predictor of Bitcoin are unique to each president. Under Daily and weekly frequencies, my results show that changes in net disapproval had a nearly no effect, during Biden's presidency, A positive effect during Trump's term, and a negative effect during Obama's regime, on Bitcoin's excess return one month later.

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1. Introduction

In December of 2007, a variety of factors created a perfect storm that led to the global financial crisis. This crisis caused people across the globe to lose trust in the global banking system. As a result of the loss of confidence, on January 3rd, 2009, an unknown man going by the pen-name Satoshi Nakamoto created Bitcoin. Bitcoin was created as a decentralized peer-to-peer payment system, and since then has gained popularity as a store of value (Nakomoto, 2008). Bitcoin is frequently referred to as “digital gold”, as it is a finite asset used as an alternative investment (Naughton, 2015). During the Great Depression, President Herbert Hoover stated, "We have gold because we cannot trust governments". Nearly 90 years later Bitcoin has emerged as a new measure of trust in the government, as it does not require a third party, and this raises the question of whether the asset is truly the 21st century’s version of gold. As of March 2022, the value of Bitcoin has increased by over 120,000% and is about 40% removed from its all-time high. There are more than 12,000 cryptocurrencies, with a global total market value of nearly 2 trillion U.S dollars.

Since the creation of Bitcoin, trust in the American government, measured by presidential approval and disapproval ratings, has been highly volatile, and simultaneously so has the price of Bitcoin. A major shift in the government trust came quickly after the creation of Bitcoin, as President Obama was inaugurated, ending the era of the Bush Administration. President Obama's presidency was marked by many key global events that shifted American citizens' views on the government such as the end of the Iraq war in 2011. As seen in figures one and two disapproval ratings and the price of Bitcoin fluctuated greatly when President Trump's term in office. Soon after

President Trump's, election Bitcoin rallied, skyrocketing to $19,000 in December of 2017. One year later the currency would crash to a price of around $3,000, in December of 2018 and the asset would not break $10,000 until June of 2019. On March 13th, 2020, the day President Trump declared the outbreak of Covid-19 a national emergency, Bitcoin hit a trough of $5,000. In the following months, Bitcoin's price rose rapidly in the tense months preceding the 2020 election and finally rose to its 2017 high of $19,000 on December 4th of 2020 one month after the 2020 presidential election. In the coming month, the price of Bitcoin would more than double, reaching $40,000 on January 8th, two days after the storming of The Capital Building. Over the next two weeks, the price fell 20% before bottoming out on January 22nd two days after President Joe Biden was inaugurated into office. Two months later Bitcoin rose to $60,000 and maintained high price levels until May. From May to June the price would fall by nearly 50%, as Americans began to return to normalcy for the first time since the start of the pandemic.

The main objective of this study is to investigate the relationship between net presidential disapproval ratings and excess Bitcoin returns. As shown in Figures one two and three, and in the preceding paragraph, at first glance Bitcoin, does seem to have a relationship with Presidential ratings. There is no existing literature examining the relationship between presidential ratings and Bitcoin's excess returns, however, Monotone (2022) researched presidential ratings as a predictor of the general stock markets returns and various other academics have researched the predictors of Bitcoin returns (Conlon and McGee, 2020; Nguyen, 2021; Klein et al., 2018).

A secondary goal of this study is to address common questions and research revolving around Bitcoin. One question that is being asked is whether Bitcoin is “digital gold”. Through extensive academic research on this topic, I conclude that Bitcoin is unrelated to Gold (Baur, et al., 2021; Klein, et al., 2018). Many of the papers I examine look at the relationship between the general stock market and Bitcoin (Conlon and McGee, 2020; Nguyen, 2021; Klein et al., 2018). To ensure that this is not the driving factor behind my results I use data, obtained from Bloomberg Terminal, regarding the S&P 500 and the Chicago Boards Volatility Index (VIX), a measure of market volatility that is frequently used in finance to assess investors' fear. Various studies have also pointed out that economic policy uncertainty (EPU) can play a role in predicting Bitcoin’s returns (Nguyen, 2021; Demir et, al 2018; Wang et, al 2022). I include Baker’s (2016) Economic Policy Uncertainty Index to see if my results remain robust when accounting for economic policy uncertainty. Environmental, price, and policy concerns have also been shown to affect Bitcoin’s returns (Wang et al., 2022; Lucey et al., 2021; Gaies et al., 2021). To address these concerns, I control for investor sentiment by including the Index of Environmental Concerns Towards Cryptocurrency as well as the Indexes of Uncertainty towards Cryptocurrency Price and Policy.

To quantify the relationship between net presidential disapproval ratings as a predictor of Bitcoin’s excess returns, I ran OLS regressions, using daily, weekly and monthly data, beginning in January 2014 and ending at the end of December 2021. The initial regressions did not capture any relationship, so I ran more regressions that controlled for presidential, political, financial, and investor sentiment. My findings

show that each president's net disapproval ratings have distinct, but statistically significant effects on Bitcoin's excess returns.

The remainder of this study is organized as follows: Section 2, Literature review, outlines related literature. Section 3, Data, describes how I obtained data. Section 4, Empirical Methodology and Results, explains how I formed my empirical methodology and provides an interpretation of the results from my regression models. Section 5, Conclusion, summarizes the findings, discusses potential issues, and offers advice for future research on this topic Section 6, Appendix, presents all tables and figures referenced in the text. Section 7, Bibliography, cites references used throughout this study.

2. Literature Review

Studies have shown that three main categories affect Bitcoin's price. The first section of my Literature Review examines Bitcoin's relationship with other assets. Research has shown that Bitcoin is strongly correlated with the general stock market, represented by the S&P 500 (Conlon and McGee, 2020; Nguyen, 2021; Klein et al., 2018). This is essential to my research question because it has been shown that presidential approval ratings are a predictor of the stock market (Montone, 2022). The second section of the literature looks at political and policy factors that affect Bitcoin's price. Various academic studies have shown that economic policy uncertainty is a predictor of Bitcoin's price (Nguyen, 2021; Demir et, al 2018; Wang et, al 2022). This is key to my data as it has been shown that presidential approval ratings and economic policy uncertainty are strongly correlated (Olds, 2015). The third section of the

literature looks at how presidential approval ratings are tied to Bitcoin and other assets. The fourth section of the literature review examines the effects of investor sentiment on Bitcoin. Various indexes have been created to measure the effects of investor sentiment on Bitcoin and I will look at how these affect the price. (Wang et al., 2022; Lucey et al., 2021; Gaies et al., 2021).

2.1: Bitcoin's price correlation to other assets

Bitcoin is unique in that it is the first decentralized electronic financial asset traded on public markets. Because Bitcoin is a decentralized asset, it has gained a reputation as digital gold, and this narrative has even been used by wall street legends such as Ray Dalio (Scipioni, 2021). If Bitcoin is a gold-like asset I would expect to see that Bitcoin has an inverse relationship with the general stock market, represented by the S&P 500 because gold is a safe-haven asset that investors flock to during market downturns (Klein et al., 2018). In addition to being thought of as a gold-like asset by many people, it is also thought of as a currency as it was referred to like this in the initial Bitcoin white paper (Nakamoto, 2008). In many ways, Bitcoin does fit the definition of a currency as it is a medium of exchange accepted by people and institutions. Although Bitcoin is used as a medium of exchange, it does not fit the empirical, theoretical and legal definition of money (Kubat, 2015). Kubat (2015) looked at various European, as well as American and Chinese, legal definitions of money and found that Bitcoin cannot easily be considered a currency. This idea of thinking of Bitcoin as a currency can be confusing because it is not regulated by any bank or financial institution and exhibits many different tendencies and correlations than other

currencies (Baur, 2018). I look to further examine Bitcoin's role as a currency and asset by researching its relationship with the dollar and gold, as well as its correlation with other related financial measures.

Although the narrative of Bitcoin being a gold-like asset has gained immense popularity in recent years, studies have pointed out these two assets have near-zero correlation in their returns (Baur, et. al, 2021). If it were true that Bitcoin was a gold-like asset I would expect Bitcoin price changes to be correlated with not only price changes in gold, but also have an inverse relationship with changes in the general stock market. Baur. et, al (2021) used the log of daily and monthly prices for Bitcoin and gold to perform dynamic conditional correlation testing, which is a class of multivariate Ordinary Least Squared (OLS) regressions to obtain their results. The significance of this study is that it shows that the narrative of Bitcoin being digital gold is false. In addition to having no correlation in their returns, Baur (2018) also found in his study on the relationship of Bitcoin with gold and the U.S. dollar, that Bitcoin has fundamentally different returns, volatility, and correlations to these assets (Baur, 2018). Baur (2018) uses the daily prices of Bitcoin, gold, and the U.S. dollar to create a General Autoregressive Condition Heteroskedasticity (GARCH) model to estimate the correlation between these assets. Because gold and the dollar do not have data available on the weekends the authors removed data regarding Bitcoin price changes on the weekends to make the data symmetric. The findings imply that Bitcoin is not a gold-like asset nor is it like modern currency, as Bitcoin has a near-zero correlation with movements of either instrument. If Bitcoin were truly a gold-like asset or a currency I

would expect to have seen strong correlations estimated between the assets by the GARCH model.

A major reason why people believed Bitcoin to be a gold-like asset is that its creation during the great recession gave it a reputation of being a safe-haven asset, like gold. Safe-haven assets exhibit distinctly different patterns than traditional assets as they gain value during market downturns, so if Bitcoin is a safe-haven asset I would expect to see it gain value during periods where the general stock market is suffering. Klein et, al. (2018) looked further into the relationship between Bitcoin and gold as safe-haven assets by researching how the two assets moved during downward markets. The authors use the log of daily prices to create a Baba, Engle, Kraft, and Kroner General Autoregressive Condition Heteroskedasticity (BEKK-GARCH) model that looks at the time-varying correlations of these assets with the S&P 500 (Klein et, al 2018). The BEKK-GARCH model is a multivariate GARCH model that is used to estimate the conditional mean and volatility functions and spillovers of variables in different markets. The GARCH model used by Klein et, al (2018) is like Baur (2018) and the authors also do not include data for Bitcoin on the weekend to make the data symmetric. The authors found that Bitcoin and gold act as opposites during a downward market, as gold tends to gain in value during down markets while Bitcoin loses value (Klein et al., 2018). This study concluded that Bitcoin cannot be considered a safe-haven asset, like gold, because it has a positive relationship with the S&P 500 during downward markets, whereas safe-haven assets, like gold, have an inverse relationship with downward markets.

Bitcoin was initially believed to be a hedge against the U.S. stock market during bear markets meaning that it would gain value during bearish stock market periods, however, research shows that Bitcoin moves in unison with the general stock market during bearish periods (Conlon and McGee, 2020). If Bitcoin is a hedge against the general stock market during bear markets data will reflect that its price would have a negative relationship with a decrease in the value of the S&P 500 during bear markets. Conlon & McGee (2020) sought to answer the question of whether Bitcoin acted as a safe-haven asset for investors during the Covid-19 bear market, by looking at the relationship of the asset with the S&P 500. Conlon & McGee (2020) uses daily price data for Bitcoin and the S&P 500, to create a two momentum Value at Risk (VaR) model to measure the relative downside risk of the assets. The authors create portfolios with and without Bitcoin and calculate VaR by multiplying the standard deviation of these portfolio returns by the standardized distribution and then subtracting this number from the mean. The relative downside risk is defined as the relative change in portfolio risk (VaR). The authors found that Bitcoin was not a safe-haven asset, because adding the asset to portfolios dramatically increased portfolio risk (VaR) because its price moved downwards with the S&P 500 during this time (Conlon & McGee, 2020).

2.2: Bitcoin and Uncertainty

The papers discussed so far have researched Bitcoin's correlation with other assets, but none have investigated its relationship with economic policy uncertainty. Economic policy uncertainty is important to look at when studying Bitcoin's price, as an increase in economic policy uncertainty shows that people are becoming less

confident in centralized financial institutions as it foreshadows declines in investment, employment, and output (Baker, 2016). Baker created the Economic Policy Uncertainty Index by searching through more than 12,000 Newspaper articles for keywords and phrases involving economic policy and creating a measure based on frequency (Baker, 2016). This can have a direct impact on Bitcoin price because Bitcoin is an alternative to centralized financial institutions, as it allows people to execute peer-to-peer payments or store value without going through a financial institution (Nakamoto, 2008). I review various studies such as Nguyen (2021), and Demir et, al. (2018), that review the relationship between Bitcoin and economic policy uncertainty to gain a better understanding of the relationships between the two. In addition to reviewing literature regarding Bitcoin and economic policy uncertainty, I also review papers that examine the relationship between Bitcoin and other political uncertainty variables such as partisan conflict (Chi-Wei, et, al. 2022). There have been various other measures of uncertainty have been created to measure uncertainties regarding Bitcoin. I will also review the literature that focuses on the effects of uncertainty regarding policy towards Bitcoin, crypto environmental concerns, and investor sentiment towards Bitcoin to gain a better understanding of the role that uncertainty plays in Bitcoin pricing.

Nguyen (2021) built off Conlon & McGee (2020) by examining not only how Bitcoin performed in relation to the S&P 500 during Covid-19, but how it performed in other uncertainty periods as well. This study used weekly time series data regarding the prices of the S&P 500 and Bitcoin, from 2016 to 2021 to create a VaR-GARCH model that measured how the risks of the two assets correlated with each other during low, medium, and high uncertainty periods (Nguyen, 2021). This study also uses the

Economic Policy Uncertainty Index from Baker (2016) to control for periods of high and low economic policy uncertainty (Nguyen, 2021). The authors hypothesize that periods of high economic policy would exaggerate the returns of Bitcoin because the Economic Policy Uncertainty Index can be thought of as a measure of confidence in government (Nguyen, 2021). The Economic Policy Uncertainty Index created by Baker (2016) is recurring in the papers used in this literature review, and it was created by looking at more than 12,000 news articles and quantifying the uncertainty in policy that is displayed in these articles (Baker, 2016). The results from Nguyen (2021) showed that during high uncertainty periods like Covid-19, stock market returns positively impacted the returns and risk of Bitcoin. Although it was shown that during periods of high uncertainty Bitcoins returns were affected by the stock market, the authors found that during periods of low and medium uncertainty the stock market did not affect Bitcoin’s returns (Nguyen, 2021). Various other studies have looked at the way economic policy uncertainty affects the returns of assets.

A major finding regarding the effect of economic policy uncertainty on Bitcoin’s price came from Demir et, al. (2018). This paper sought to quantify this relationship by using a VaR model, OLS regressions and Quantile on Quantile regression models (Demir et al., 2018). Demir et, al. (2018) used daily data, spanning from 2010 through 2018, for Bitcoin prices and Baker's (2016) Economic Policy Uncertainty Index to perform these regressions. This paper found that during this time period, increases in economic policy uncertainty were associated with a decrease in the price of Bitcoin, however, during bull markets, the price of Bitcoin would rise when economic policy uncertainty increased (Demir et al., 2018). This replicates the results of

previous findings (Nguyen, 2018) reconfirming that economic policy uncertainty has predictive power over the price of Bitcoin.

Su et al., (2022) investigated the relationship between politics and Bitcoin pricing by researching the effects of United States partisan conflicts on Bitcoin's price. This paper uses Azzimonti's (2014) scale of partisan conflict, which was created by searching through major U.S. newspapers, from 1891 to 2013. The data range for this paper spans from July 2010 to February 2020 and uses monthly data on Bitcoin prices and partisan conflict to run a boot-strap Granger Causality test (Su, et al 2022). The results found that during periods of high partisan conflict Bitcoin prices tend to rise (Su, et al 2022). This supports the need for research into the effects of presidential approval ratings on the price of Bitcoin, as shifts in partisan conflict are associated with shifts in presidential approval ratings (Klein, 2009).

Many of the papers I have discussed have investigated how economic policy uncertainty affects the stock market and Bitcoin returns, however, few have discussed Bitcoin policy uncertainty, which may also have a predictive role in Bitcoin pricing. Lucey et al., (2021) used 729 million different news articles from the LexisNexis database, spanning from 2013 to February 2021, to develop a cryptocurrency uncertainty index. This index combines data regarding crypto policy uncertainty and crypto price uncertainty to capture uncertainty regarding Crypto prices (Lucey et al., 2021). The URCY Price and Policy Indexes were created in the same way that Baker (2016) created his Economic Policy Uncertainty Index, as the creators searched hundreds of millions of articles on the LexisNexis database for keywords regarding Bitcoin price and policy and then created daily aggregate scores for uncertainty on these

topics. A key benefit to this methodology is that the LexisNexis database does not only use mainstream sources of media, so the index captures a much broader range of media which is good because Bitcoin is deeply rooted in non-mainstream media sources. The authors were able to find that the price of Bitcoin and the URCY policy and price indexes are highly correlated by running a Johannsen test to see if the variables are cointegrated and a Structural Vector Correction model to explore how shocks to these indexes affect Bitcoin.

Recently environmental concerns towards Bitcoin have played a role in affecting consumer sentiment towards the asset. Wang et al., (2022) created another cryptocurrency sentiment index, this one being an index of cryptocurrency environmental attention (ICEA). This index was created by searching more than 778 million articles from the LexisNexis database, spanning from 2014 to 2021 (Wang, et al., 2022). The authors performed an OLS regression and found that ICEA was found to have a significantly positive relationship with the UCRY Policy and Price indexes, the volatility index (VIX), Brent crude oil (BCO), and Bitcoin, and a significantly negative relationship with the global economic policy uncertainty (Wang, et al., 2022).

Another index that is used to measure sentiment regarding Bitcoin is the Bitcoin misery index (BMI), which is a sentiment index that measures Bitcoin owners' happiness with the asset on a scale of 0-100. One study used this index to measure its effects on Bitcoin price, by using monthly data regarding Bitcoins price from August 2011 to July 2020 (Gaies et al., 2021). In addition to the BMI and Bitcoin prices, the author also used the VIX and the 10-year Interest Rates to run an Autoregressive Distributed Lag test. The results found that an optimistic shock to BMI increases

Bitcoin returns while a pessimistic shock decrease returns, however, positive shocks had a larger impact than negative shocks in the short run, while Bitcoin returns are more sensitive to pessimistic shocks in the long run (Gaies et al., 2021). The authors also found that the 10-year Nominal Interest rates and the global volatility of US stock markets (the VIX) have negative effects on Bitcoin returns (Gaies et al., 2021). This shows that Bitcoin investor sentiment is also influenced by the VIX, which negates Bitcoins' value as a safe haven even further.

Another way that academics have investigated the effects that Bitcoin sentiment has on its price is through social media. Shen et al., (2018) investigated this relationship by examining tweets involving Bitcoin, spanning from September 2014 to August 2018. Through a Vector-Autoregressive model, the authors were able to conclude that there was no relationship between Tweets involving Bitcoin and its price, however, Tweets did have a strong correlation with the volume and volatility of Bitcoin (Shen et al., 2018). Guegen and Renault (2021) used multivariate regressions along with Granger Causality Test to examine the relationship between bullish and bearish tweets regarding Bitcoin on its returns. The authors found that there is a relationship between investor sentiment and Bitcoin returns but only for frequencies up to 15 minutes (Guegan and Renualt, 2021). This study also notes that the magnitude of this relationship is so small that it would be impossible for a trader to use it to make profits and that there is no relationship between investor sentiment from tweets and Bitcoin returns at frequency levels above 15 minutes the authors found (Guegan and Renualt, 2021).

2.3: Bitcoin and Presidential Approval Ratings

Presidential approval ratings are polls that measure the percentage of American citizens who approve or disapprove of the President. The relationship between presidential approval ratings and Bitcoin has yet to be explored in academic research, and this relationship is the backbone of this study. Presidential approval ratings are the ultimate measure of trust in the U.S. government, so I hypothesize that decreases in presidential approval ratings will lead to an increase in the price of Bitcoin because people will want to stray from third party transactions and stores of value when they do not trust the government and Bitcoin offers them this opportunity. To support this hypothesis, I review literature that looks at the relationship between presidential approval ratings and assets that Bitcoin has relationships with.

Montone (2022) looked further into the predictive power of economic policy uncertainty by using it to estimate the relationship between presidential approval ratings and stock market returns. Montone (2022) uses Gallup's nationwide polls to measure disapproval ratings, and the aggregate returns of all stocks traded on NYSE, Amex, and NASDAQ to measure market returns, the Index of Economic Policy Uncertainty from Baker et al., (2016), and consumer sentiment data from the University of Michigan to measure investor sentiment. Monotone (2022) uses these variables to run OLS regressions and finds that when net disapproval is greater than net approval a 1% increase in net disapproval is associated with a 0.11% decrease in excess stock returns over the following month, however, when net approval ratings are greater than disapproval ratings the results have nearly no effect. The author also finds the losses the stock market receives during periods of presidential disapproval are exaggerated when

these periods are coupled with high economic policy uncertainty, low consumer sentiment, and when the president is republican (Montone, 2022). I believe that this study is important because there has not been much research into the relationship between Bitcoin and presidential approval ratings, and this can be used as a framework for modeling their relationship.

Presidential approval ratings have other correlations with the general stock market as displayed by Gupta (2021). Gupta (2021) looked at the power of presidential approval ratings as a predictor of S&P 500 returns and volatility. The study uses the natural log of monthly S&P 500 returns from July 1941 to April 2018 and the natural log of Gallup presidential approval surveys to perform a multivariate Generalized Autoregressive Conditional Heteroscedasticity (DCC-MGARCH) model (Gupta, 2021). In line with findings from Monotone (2022), the authors found that presidential approval ratings can be used as a predictor of S&P 500 returns, as they have a positive relationship (Gupta, 2021). In addition to having a relationship with S&P 500 returns, it was also found that presidential approval ratings are a strong predictor of market volatility, except during the bullish periods of the late 1980s and early 1990s (Gupta, 2021). A shortcoming of this study is that the VIX could not be used as a measure of market volatility because the index was only created in 1993.

2.4: Summary of Literature review

The reasoning behind my hypothesis stems from the question of what impacts the price of Bitcoin. People have suggested that Bitcoin and gold are correlated, however existing literature sees no relationship between the two (Baur, et al., 2021). In

addition to these assets having uncorrelated returns, the narrative that Bitcoin is a safe-haven asset like gold during bear markets has also been found to be false, as gold prices have typically risen while Bitcoin has fallen during bear markets (Klein et al., 2018). It has also been shown that a factor that leads to bear markets is times in which presidential disapproval ratings are high (Montone, 2022). During these times stocks tend to follow and the effects are exaggerated by policy uncertainty and low consumer sentiment (Montone, 2022). It has also been pointed out that during bear markets, which have been shown to arise during periods of presidential disapproval, Bitcoin returns tend to correlate with the S&P 500 (Conlon & McGee, 2020). This leads to the question of how presidential disapproval ratings affect the returns of Bitcoin.

3. Data

Each series of data consist of 13 variables, spanning from the beginning of January 2014 to the end of December 2021. The data begins in January 2014 and ends in December 2021 because the UCRY Price and Policy indexes, as well as the ICEA, did not have data before or after this time span. This data only includes observations on dates when the U.S. Stock market is open during this time span. As a result of this, there are 1,974 daily observations presented in Table 1, 412 weekly observations, presented in Table 2, and 95 weekly observations, presented in Table 3. Unless otherwise noted, all financial variables were obtained through a Bloomberg terminal, spanning from January 1st, 2014, to December 31st, 2021, and Stata was used for data manipulation and analysis. Data from days on which the stock market was not open were not used in the analysis. The dependent variable for this study is the excess return of Bitcoin,

Exc_rtn. In order to create this variable, I downloaded the daily closing prices of Bitcoin, *BTC_close*. My next step to obtaining the excess return of Bitcoin was to obtain the daily, weekly, and monthly natural logs of Bitcoin's price, *ln_BTC_close,*

Equation 1: $ln\_BTC\_close = ln(BTC\_close(t))$

The reasoning behind using the natural log of the price of Bitcoin is that over the time series Bitcoin prices range from hundreds to tens of thousands of U.S. dollars, so I needed to standardize this skewed distribution because many of the other variables are only measured on scales of 0-100 and are not in U.S. dollars. Once, I created the *ln_BTC_close* variable I needed to subtract the risk-free rate measured as the 10-year treasury yield, *Ten_close*, from *ln_BTC_close* to obtain the Bitcoin's excess returns. After obtaining data for the 10-year treasury yields, *Ten_close*, I had to divide this number by the frequency I was measuring. For example, I had to divide *Ten_close* by 364 for the daily data, 52 for the weekly data, and 12 for the monthly data to obtain the adjusted 10-year treasury yield, *TenC.* I then subtracted the adjusted 10-year treasury yield from the natural log of the price of Bitcoin to obtain Bitcoin's excess return for all the observations.

Equation 2: $Daily\ TenC(t) = Ten\_close/364$

Equation 3: $Weekly\ \ TenC(t) = Ten\_close/52$

Equation 4: $Monthly\ TenC(t) = Ten\_close/12$

Equation 5: $Exc\_rtn(t) = ln\_BTC\_close(t) - TenC(t)$

My independent variable of interest is net presidential disapproval, *Net_dis*. To create this variable, I obtained daily presidential approval, *APRV_open*, and presidential disapproval ratings, *DIS_open*. The data for this variable was collected by Real Clear Politics, by creating an aggregate percentage of daily net disapproval and approval ratings for presidents by looking at various presidential approval rating polls and taking the average across these polls. I chose to use the Real Clear Politics data because they are the only database that has an accessible set of daily data regarding presidential approval ratings on the Bloomberg terminal. I downloaded Real Clear Politics presidential approval and disapproval ratings for Biden and Trump directly off a Bloomberg terminal. The Bloomberg terminal did not have downloadable data for President Obama's presidency however, I was able to manually enter this data in as it is available online. Once I collected acquired data for approval and disapproval ratings I created a net disapproval variable, *Net_dis*. This variable was created by uploading by subtracting the presidential approval variable from the presidential disapproval variable.

Equation 6: $Net\_dis(t) = DIS\_open - APRV\_open$

Presidential disapproval and approval data were not converted to their natural log because it would be unnecessary as the approval and disapproval ratings are already measured in percentages and on scales of 100. In addition to having a moving net disapproval variable, I also created a net disapproval dummy variable, *Net_dis_d.* This variable is equal to one if net disapproval is positive and 0 if otherwise.

Equation 7: $Net\_dis\_d(t) = 1$ if $Net\_dis > 0$

Equation 8: $Net\_dis\_d(t) = 0$ if otherwise

To research the differential effects of each president on the relationship between excess Bitcoin returns and presidential approval ratings I created presidential control variables. I created presidential dummy variables for Biden and Trump that are set equal to one when they are in office and set equal to zero when they are not.

Equation 9: $Trump\_d(t) = 1$ if President = Trump

Equation 10: $Trump\_d(t) = 0$ if President *does not* = Trump

Equation 11: $Biden\_d(t) = 1$ if President = Biden

Equation 12: $Biden\_d(t) = 0$ if President *does not* = Biden

In addition to creating presidential dummy variables for Biden and Trump I also created interaction terms for the president, to examine differential effects in their presidency. These variables were created by multiplying the presidential dummy variables by the net disapproval variable.

Equation 13: $Trump\_dis(t) = Trump\_d(t) * Net\_dis$

Equation 14: $Biden\_dis(t) = Biden\_d(t) * Net\_dis$

In addition to presidential variables, I also plan to control for changes in the general stock market to see if the relationship between presidential approval and Bitcoin remains robust when these factors are included. To control for changes in the general stock market and its volatility, I obtained data regarding the Chicago Board Options Exchange's CBOE Volatility Index, defined as *VIX_close*, and S&P 500, defined as *SP_close*. I converted these variables to the natural logs of the S&P 500, *ln_SP*, and the VIX, defined as *ln_VIX_close* to ensure that they were standardized with the other variables.

Equation 15: $ln\_SP(t) = ln(SP\_close(t))$

Equation 16: $ln\_VIX\_close(t) = ln(VIX\_close(t))$

It has also been found that economic policy uncertainty is a key predictor of the price of Bitcoin. To capture the effects of economic policy uncertainty I use the natural log of Baker's (2016) Economic Policy Uncertainty Index, *ln_EPU*, to measure this. To create this variable, I downloaded the values of Baker's economic policy uncertainty index, *EPU_open*, and converted these values to their natural log to create the natural log of the economic policy uncertainty variable, *ln_EPU*.

Equation 16: $ln\_EPU(t) = ln(EPU\_open(t))$

Indexes such as The UCRY price, UCRY policy, and ICEA indexes have been created to measure the effects of investor sentiment on Bitcoin. I will use data for these

variables to see if the relationship between presidential disapproval and Bitcoin's excess return is robust after their inclusion, as Wang et al. (2022) has suggested in his findings that these indexes can play a key role as predictors of Bitcoins returns. The UCRY policy index is used to measure fear regarding policies affecting cryptocurrencies and the URCY price index measures uncertainty regarding the price of cryptocurrencies. The ICEA is used to measure environmental concerns towards cryptocurrencies. I was able to download this data set directly from a google data set created by the authors of these indexes (Wang et al., 2022; Lucey et al., 2021). The data was initially presented in frequencies covering spans of one to two weeks, so I converted the values to daily frequencies by stretching the weekly frequency value across each day that it covered. The UCRY policy variable, *UCRYPolicy*, UCRY Price variable, *UCRYPrice*, and ICEA variable, *ICEA* were then converted to their natural logs to obtain variables ln_Price, ln_Policy, and ln_ICEA.

Equation 17: $LnPrice(t) = ln(UCRY\_price(t))$

Equation 18: $LnPolicy(t) = ln(UCRY\_policy(t))$

Equation 19: $LnICEA(t) = ln(ICEA(t))$

4: Empirical Methodology and Results:

To test my hypothesis that increases in, net presidential disapproval led to higher excess returns in the price of Bitcoin. The models used for this empirical regression are all OLS regressions. I use a total of 6 models to test my hypothesis, every new model includes additional variables as a robustness test. The dependent variable in all these

regressions is Bitcoin's excess return, pushed forward one month in order to see the role of the independent variables as predictors of Bitcoin's excess return one month prior. I Run all 6 models using daily, weekly, and monthly data. Table 4 presents the results of the regressions ran with daily data, table 5 presents the results ran with weekly data, and table 6 presents the results ran with monthly data.

Model 1:

$$Y_{(t+1)}Exc\_rtn = \beta 0 + \beta 1\ Net\_dis + \epsilon_i$$

For model one there was one independent variable, net presidential disapproval. I expected that the coefficient on this variable has a positive coefficient because I hypothesized that an increase in net presidential disapproval would lead to an increase in the excess returns of Bitcoin. The reason why I hypothesize this is because increases in net presidential disapproval show that fewer people are trusting the government, and if people do not trust the government, they are less likely to trust financial institutions and thus more likely to invest in a decentralized asset like Bitcoin. When Model one was run with daily observations, the results came back as insignificant.

Model 2:

$$Y_{(t+1)}Exc\_rtn = \beta 0 + \beta 1\ Net\_dis + \beta 2\ Net\_dis\_d + \epsilon_i$$

In the second model, I added the net disapproval dummy variable to see if the results from model one would become robust during periods of net disapproval. I

expected that the estimated sign on this coefficient would also be positive as it is reflecting changes in Bitcoin excess returns during periods of net disapproval. Under daily frequencies, the net presidential disapproval dummy variable came in as insignificant at the 10% level for Model 2. The interpretation of this estimated coefficient tells us that during times of presidential disapproval a 1% increase in presidential disapproval is associated with a 0.447% decrease in the natural log of Bitcoins' excess returns.

Model 3:

$$Y_{(t+1)}Exc\_rtn = \beta 0 + \beta 1\ Net\_dis + \beta 2\ Net\_dis\_d + \beta 3\ Trump\_dis + \beta 4\ Trump\_d + \beta 5 Biden\_dis + \beta 6\ Biden\_d + \epsilon_i$$

In the third model, I include presidential control variables for Biden and Trump to test for effects that are unique to each president. These control variables included both the presidential disapproval interaction terms and the presidential dummy variables. I hypothesized that these variables would also have positive coefficients as they are measuring whether the effect of disapproval during the Biden and Trump presidencies is the same as during Obama's presidency. I would also expect that the Trump variables would have an even more positive coefficient as his presidency was paired with higher disapproval and more controversy.

For daily frequencies, when the presidential control variables are included all the variables become significant at the 99% level, except for the Trump dummy variable which is significant at the 95% level. This tells us that the relationship between net

presidential disapproval and the price of Bitcoin is reliant on the presidential control variables. Although all the variables in this equation are significant, this model shows that only during Trump's presidency did net disapproval have the negative effect on the excess returns of Bitcoin that I hypothesized. During Biden's term, the relationship was significant however the coefficient was nearly zero telling us that changes in Biden's net disapproval had a strong relationship but not much effect on Bitcoin's excess returns. Changes in net presidential disapproval during Obama's presidency were shown to have a significant effect on the excess returns of Bitcoin, however, the results show that the effect of increases in Net disapproval led to decreases in the price of Bitcoin during Obama's Presidency.

There are various possible reasons why Bitcoin's relationship is unique to each president. During Obama's presidency, it is shown that an increase in disapproval led to decreases in the excess returns of Bitcoin, however, the opposite relationship occurred during Trump's presidency. A reason why this may be is that Trump and Obama represent opposite sides of the political spectrum. Because increases in disapproval ratings led investors to shy away from Bitcoin during Obama's presidency and move towards investment during Trump's presidency, this may show that Bitcoin investors trusted Obama more than the average American, while they trusted Trump less. An area of future research could be to see how liberals' or conservatives' approval of the president relates to Bitcoin's excess returns, as it is likely that those who disapproved of Obama leaned right and those who disproved of Trump leaned left. Based on my results I would hypothesize that increases in presidential disapproval from the left would lead to increases in Bitcoin's excess returns and increases in disapproval from the right

would lead to decreases in the returns of Bitcoin. Another potential explanation could be the extent and sources of dissatisfaction during these two presidents' terms. For example, although Obama did have periods of Net disapproval during his presidency, he was not impeached twice like Trump was. The length of the data series could also play a factor in the differences between the president's results, as Trump was the only president who had data obtained for the entirety of his presidency.

Model 4:

$$Y_{(t+1)}Exc\_rtn = \beta 0 + \beta 1\ Net\_dis + \beta 2\ Net\_dis\_d + \beta 3\ Trump\_dis + \beta 4\ Trump\_d + \beta 5 Biden\_dis + \beta 6\ Biden\_d + \beta 7\ ln\_SP + \beta 8\ ln\_VIX\_close + \epsilon_i$$

For the fourth model, I included the stock market control variables. I included these variables to see if the results from model three would remain robust with their inclusion. The inclusion of these variables helps to address the concern that general changes in the stock market are leading to the changes in Bitcoin’s return. The stock market control variables that I included were the natural log of the S&P 500 and VIX. I hypothesized that the natural log of the S&P 500 variable would have a positive coefficient because various papers showed that Bitcoin and the S&P 500 had a positive relationship (Conlon and McGee, 2020; Nguyen, 2021; Klein et al., 2018). I expect that the natural log of the VIX would have a negative coefficient because Gaies et al., (2021) showed that the VIX had a negative relationship with Bitcoin’s returns.

The fourth model for daily frequencies included the stock market control variables and the results from Model 3 remained robust with the inclusion of these

variables. The same story that was told for Model 3 is displayed in Model 4 as an increase in net disapproval led to increases in the excess returns of Bitcoin during Trump's presidency, nearly no change during Biden's presidency, and a negative effect during Obama's Presidency. While an increase in the natural log of the S&P 500 was shown to have a negative relationship with the excess returns of Bitcoin, at the 10 % level. Increases in the VIX were shown to have a positive relationship with the excess returns of Bitcoin at the 95% level. The natural log of the VIX and S&P 500 had the opposite sign on their coefficients than I was expecting and there are many reasons why this may be, such as that the excess returns of Bitcoin are lagged one month forward. A reason why this one-month forward lag on the dependent variable causes the VIX to have a positive coefficient is that it shows that volatility in the stock market can cause more people to fear the stock market and thus invest in Bitcoin which causes Bitcoin to have higher excess returns.

Model 5:

$$Y_{(t+1)}Exc\_rtn = \beta 0 + \beta 1\ Net\_dis + \beta 2\ Net\_dis\_d + \beta 3\ Trump\_dis + \beta 4\ Trump\_d +$$

$$\beta 5 Biden\_dis + \beta 6\ Biden\_d + \beta 7\ ln\_SP + \beta 8\ ln\_VIX\_close + \beta 9\ ln\_EPU + \epsilon_i$$

The fifth model that I estimate included the natural log of Baker's (2016) economic policy uncertainty index. I hypothesized that this variable would have a positive relationship as various academic studies have shown that economic policy uncertainty is a predictor of Bitcoin's returns and many of these papers used the index

created by Baker (2016) as their measure of economic policy uncertainty (Nguyen, 2021; Demir et al., 2018; Wang et al., 2022).

The fifth model for daily frequencies included the natural log of economic policy uncertainty. When this variable was included most of the results mentioned in models three and four remained robust, except the estimated coefficient for the natural log of the VIX became insignificant. The economic policy uncertainty variable was also shown to have a positive relationship with the excess returns of Bitcoin, at the 99% level, which is in line with previous findings.

Model 6:

$$Y_{(t+1)}Exc\_rtn = \beta 0 + \beta 1\ Net\_dis + \beta 2\ Net\_dis\_d + \beta 3\ Trump\_dis + \beta 4\ Trump\_d + \beta 5 Biden\_dis + \beta 6\ Biden\_d + \beta 7\ ln\_SP + \beta 8\ ln\_VIX\_close + \beta 9\ ln\_EPU + \beta 10\ ln\_Policy + \beta 11 ln\_Price + \beta 12\ ln\_ICEA + \epsilon_i$$

For my sixth and final model, I included Bitcoin investor sentiment variables to examine their effects on the relationship between changes in net presidential disapproval and changes in the excess return of Bitcoin. These control variables included the natural log of the ICEA and UCRY Price and Policy indexes. I expected that these variables would have negative relationships with the excess returns of Bitcoin because it shows consumer sentiment toward crypto is lower and previous literature has shown this (Wang et al., 2022; Lucey et al., 2021). The final model ran for daily frequencies includes cryptocurrency investor sentiment variables.

The results from models three, four, and five remained robust with the inclusion of the natural log of the ICEA and UCRY Price and Policy variables, except for the natural log of the S&P 500 which became insignificant. These variables were insignificant except for the natural log of ICEA which showed to have a very negative relationship with the excess returns of Bitcoin, at the 99% level.

The results for the weekly frequencies showed much of the same story as the daily frequencies. All variables in the first two models were insignificant, however, when the presidential control variables were included in the third model all the variables except for the dummy variables were robust and repeated the findings that there was a near-zero coefficient during Biden's presidency, during Trump's presidency increases in disapproval led to increased excess returns and the opposite during Obama's presidency. The inclusion of the stock market control variables did not change the robustness of the relationships examined in model three, and the only difference examined from the daily frequencies, which has not already been mentioned, was that neither the natural log of the S&P 500 nor VIX were significant. The results mentioned in model 4 remained robust with the inclusion of Economic Policy in model 5, and the economic policy uncertainty variable was shown to have a positive relationship with the excess returns of Bitcoin as it did in the daily frequencies. Model 6 for the weekly frequencies only caused the Biden interaction and dummy variable to become more robust, and these crypto sentiment variables showed the same relationship as they had for the daily frequencies. Overall, the results for the weekly frequencies helped to validate the results from the daily frequencies as many of the variables told the same story while remaining robust.

The results from the regressions ran with the monthly data did not validate the results obtained from the regressions ran with daily and weekly frequencies, as the only variables that remained robust across the regressions were the Trump interaction term and ICEA variables. A reason why this may have occurred is the lack of observations used for monthly frequencies as it is only measuring the variables once a month.

4. Conclusion

In this paper, I test whether net presidential disapproval ratings can be used to predict excess returns of Bitcoin one month later, across daily, weekly, and monthly observations spanning from January 1st, 2014, to December 31st, 2021. To estimate this relationship, I use an OLS regression that includes various presidential, stock market, policy, and Cryptocurrency sentiment control variables. Overall, my findings show that net presidential approval ratings are a predictor of Bitcoin's excess return one month later, however, the relationship that it has with Bitcoin's returns is dependent on and unique to each president.

Regressions ran with daily frequencies showed that there is a statistically significant relationship between each president's net presidential disapproval ratings and Bitcoin's excess returns. The results showed that during Obama's presidency there was a negative correlation, during Trump's presidency a positive correlation, and during Biden's presidency a near-zero effect. The results for the weekly frequencies helped to validify the results from the daily frequencies as nearly all the variables remained robust and told the same story. When rerunning the regression model with monthly data the results from the daily and weekly models did not remain robust, other than net

disapproval was still shown to have a positive relationship with Bitcoin's excess returns one month later during Trump's presidency.

The results show that my hypothesis is not proven, because my three models show that increases in net presidential disapproval ratings only lead to an increase in the excess returns of Bitcoin during Trump's presidency. There are a variety of factors that can be the reason why my models did prove my hypothesis. I believe that because data regarding the price of Bitcoin and cryptocurrency investor sentiment was unavailable, before 2014, my results regarding Obama's presidency may be inadequate as they only captured data for the final two years of his eight-year regime. This same problem is also relevant to my data regarding President Biden's Presidency, as I only was able to obtain data, for all the variables, through 2021 which only represents one year of his presidency. Trump was the only president for whom I had a full data set for the entirety of their presidency and my models showed that he was the only president whose results supported my hypothesis.

My hypothesis may be proven in future research if the authors are able to obtain data for all the variables that I included in my models, spanning from the inception of Bitcoin to when they run their regressions. Another factor that may have caused my hypothesis to not be empirically supported is that Bitcoin is a relatively new asset. Many people have little to no understanding of what Bitcoin is, a decentralized peer-to-peer payment system, so when it becomes common knowledge of what Bitcoin is people may begin investing in Bitcoin as an alternative to financial institutions and there may be more data to support my hypothesis. All in all, at this time investors

should not use presidential approval ratings as a buy or sell signal for Bitcoin, as there is not sufficient evidence to support doing so.

6: Appendix

Figure one (Log of Bitcoin Price During Trump's Presidency)

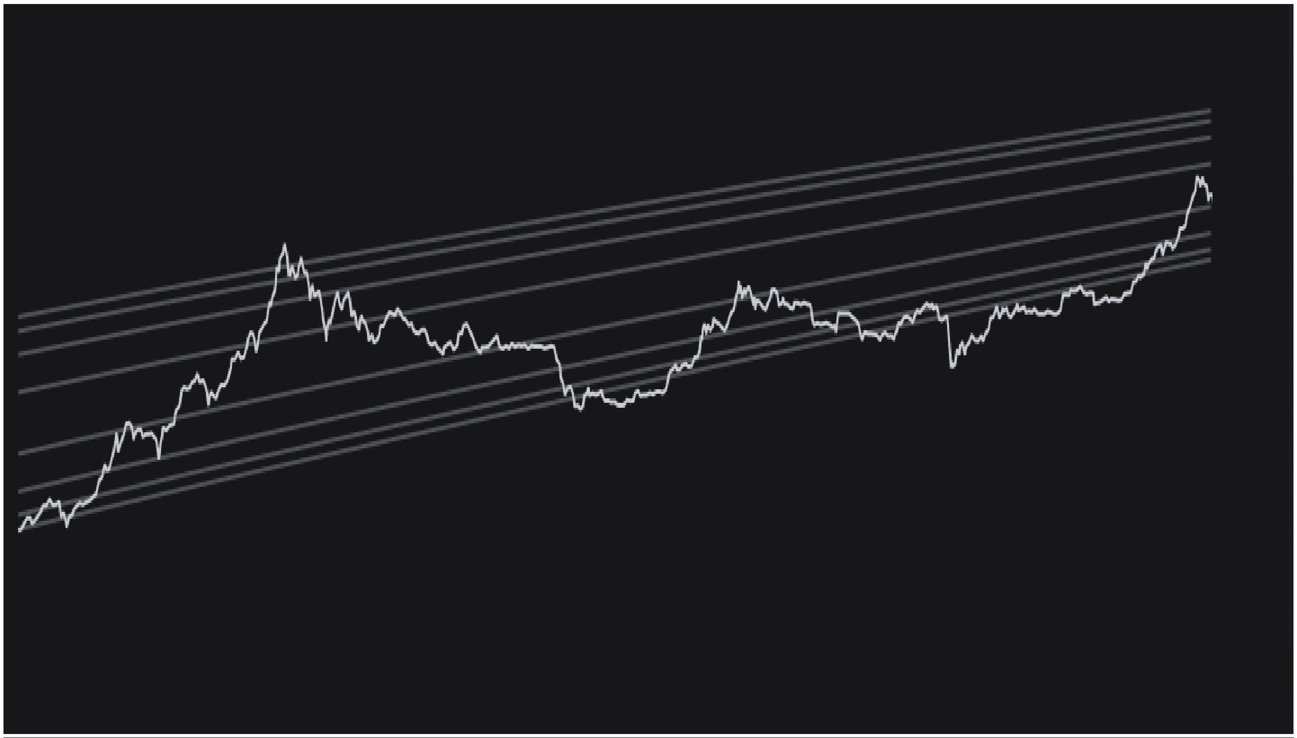

Figure Two (Trumps Disapproval vs Approval rating)

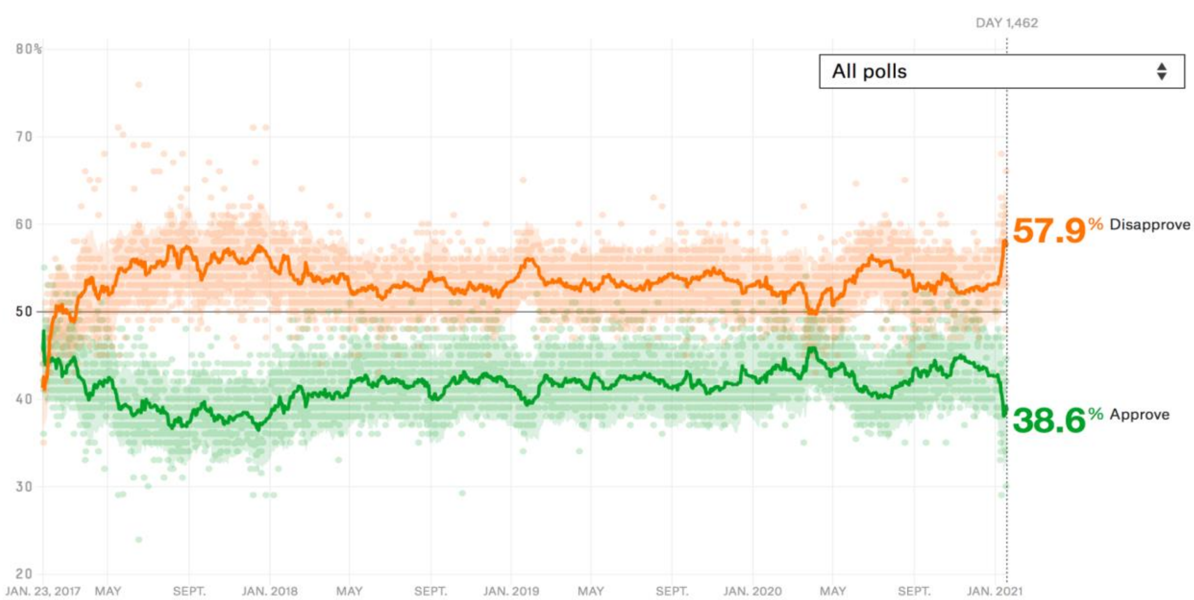

Figure Three: ***Natural log of Bitcoin returns vs. Presidential Disapproval Rating***

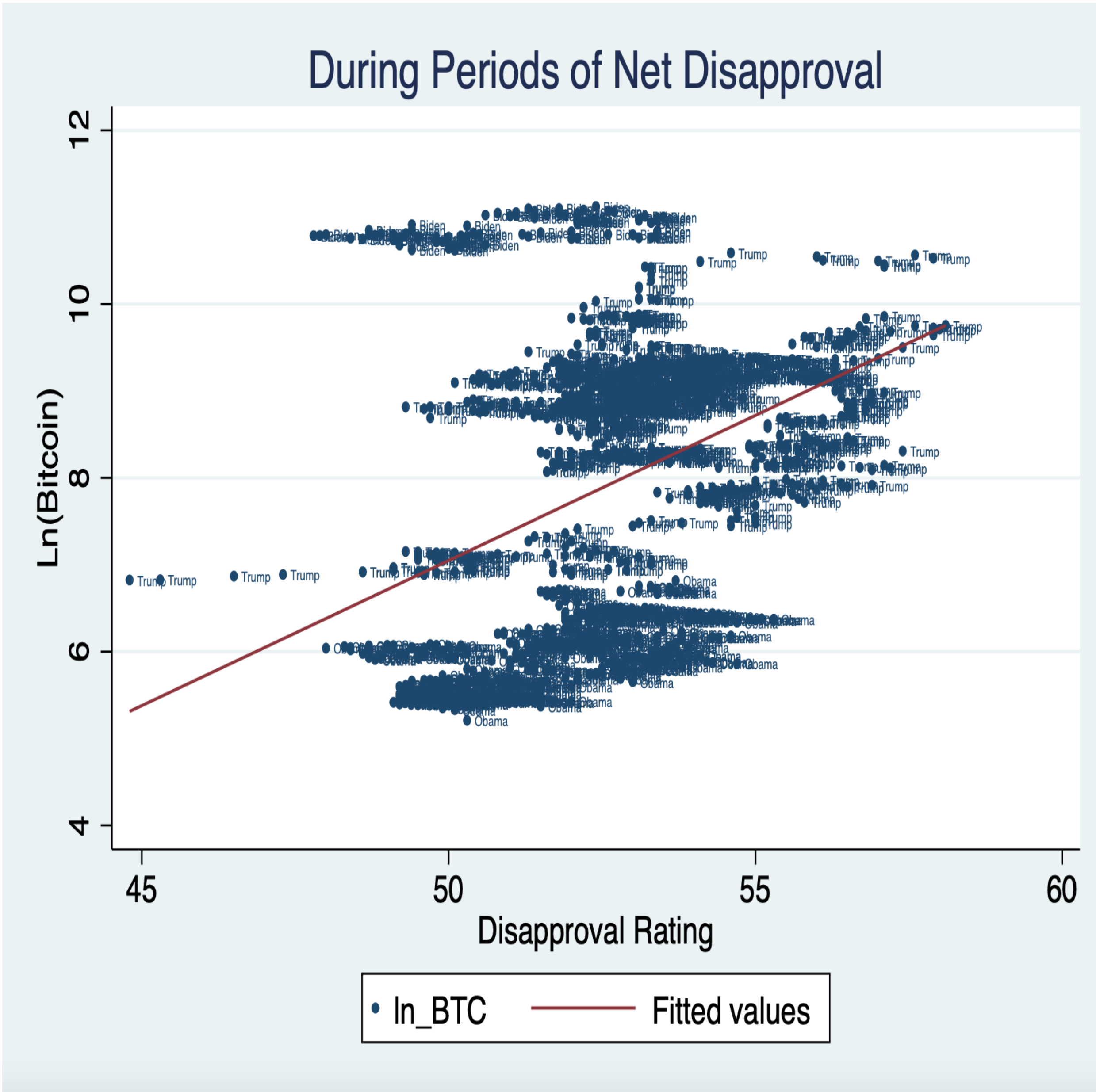

Table 1: *Summary Statistics for Daily Observations*

Variable	Obs	Mean	Std. Dev.	Min	Max
net_dis	1,974	6.26388	7.782376	-20.3	21.1
net_dis_d	1,974	.816616	.3870791	0	1
biden_d	1,974	.1084093	.3109754	0	1
trump_d	1,974	.5050659	.500101	0	1
ln_VIX_close	1,974	2.793246	.3355339	2.198335	4.415099
ln_SP	1,974	7.863881	.2498285	7.463833	8.457868
ln_EPU	1,974	4.493678	.6558473	1.199965	6.694141
ln_Policy	1,974	4.607913	.0142498	4.595364	4.684514
ln_Price	1,974	4.608102	.0148481	4.595428	4.692978
ln_ICEA	1,974	4.609948	.0198417	4.599143	4.718478
exc_rtn	1,974	.0415839	.2283625	-.8062258	1.039823
biden_dis	1,974	-.5993921	3.518557	-20.3	12.2
trump_dis	1,974	5.37153	5.915863	-4.3	21.1

Table 2: *Summary Statistics for Weekly Observations*

Variable	Obs	Mean	Std. Dev.	Min	Max
net_dis	412	6.327427	7.760653	-20.3	20.4
net_dis_d	412	.8179612	.3863457	0	1
biden_d	412	.1067961	.3092294	0	1
trump_d	412	.5072816	.5005548	0	1
ln_VIX_close	412	2.774082	.3349598	2.21266	4.19026
ln_SP	412	7.864619	.2504288	7.485823	8.454884
ln_EPU	412	4.836761	.6423078	1.398717	6.758211
ln_Policy	412	4.60793	.0142753	4.595364	4.684514
ln_Price	412	4.608126	.0148676	4.595428	4.692978
ln_ICEA	412	4.609951	.0197732	4.599143	4.718478
exc_rtn	412	.0400636	.2244994	-.702961	.9148607
biden_dis	412	-.5854369	3.506009	-20.3	12.1
trump_dis	412	5.385437	5.891912	0	20.4

Table 3: *Summary Statistics for Monthly Observations*

Variable	Obs	Mean	Std. Dev.	Min	Max
net_dis	95	6.007368	7.855033	-20.3	18.1
net_dis_d	95	.8210526	.3853417	0	1
biden_d	95	.1157895	.3216698	0	1
trump_d	95	.5052632	.5026247	0	1
ln_VIX_close	95	2.810113	.3392641	2.260721	4.049696
ln_SP	95	7.858452	.2469796	7.485873	8.436117
ln_EPU	95	4.583202	.6255091	3.37827	6.322906
ln_Policy	95	4.608772	.013777	4.595364	4.665172
ln_Price	95	4.60849	.0136443	4.595428	4.662013
ln_ICEA	95	4.609602	.0181019	4.599214	4.67105
exc_rtn	95	.0461351	.2163365	-.4362631	.5427008
biden_dis	95	-.6515789	3.801032	-20.3	10.1
trump_dis	95	5.268421	5.791176	0	18.1

Table 4: *Regression Results for Daily Observations*

Dependent Variable: BTC Excess Return (Daily)

VARIABLES	(1) model1	(2) model2	(3) model3	(4) model4	(5) model5	(6) model6
net_dis	-0.000368	0.00154	-0.0158***	-0.0159***	-0.0153***	-0.0127***
	(0.000661)	(0.00129)	(0.00220)	(0.00223)	(0.00222)	(0.00217)
net_dis_d		-0.0447*	0.0996***	0.0901***	0.0917***	0.0578*
		(0.0258)	(0.0318)	(0.0321)	(0.0320)	(0.0312)
trump_dis			0.0202***	0.0209***	0.0208***	0.0207***
			(0.00286)	(0.00290)	(0.00288)	(0.00285)
trump_d			-0.0653**	-0.0371	-0.0546	-0.0434
			(0.0279)	(0.0358)	(0.0358)	(0.0352)
biden_dis			0.00879***	0.0101***	0.00996***	0.0117***
			(0.00205)	(0.00215)	(0.00214)	(0.00209)
biden_d			-0.0520***	0.0229	0.0258	0.430***
			(0.0201)	(0.0482)	(0.0479)	(0.0621)
ln_SP				-0.108*	-0.134**	-0.0432
				(0.0593)	(0.0592)	(0.0591)
ln_VIX_close				0.0333**	-0.00807	-0.0109
				(0.0168)	(0.0189)	(0.0187)
ln_EPU					0.0467***	0.0327***
					(0.0101)	(0.00996)
ln_Policy						2.810
						(2.323)
ln_Price						0.176
						(2.314)
ln_ICEA						-9.044***
						(0.843)
Constant	0.0439***	0.0684***	-0.00529	0.736*	0.850*	28.10***
	(0.00660)	(0.0157)	(0.0182)	(0.445)	(0.444)	(3.835)
Observations	1,974	1,974	1,974	1,974	1,974	1,974
R-squared	0.000	0.002	0.064	0.067	0.077	0.131

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: *Regression Results for Weekly Observations*

Dependent Variable: BTC Excess Returns (Weekly)						
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	model1	model2	model3	model4	model5	model6
net_dis	-0.000100	0.00193	-0.0144***	-0.0143***	-0.0135***	-0.0113**
	(0.00143)	(0.00281)	(0.00489)	(0.00494)	(0.00492)	(0.00486)
net_dis_d		-0.0473	0.0945	0.0824	0.0860	0.0585
		(0.0565)	(0.0721)	(0.0729)	(0.0725)	(0.0715)
trump_dis			0.0197***	0.0205***	0.0198***	0.0197***
			(0.00648)	(0.00656)	(0.00653)	(0.00656)
trump_d			-0.0724	-0.0489	-0.0582	-0.0500
			(0.0635)	(0.0801)	(0.0797)	(0.0796)
biden_dis			0.00785*	0.00905*	0.00851*	0.00972**
			(0.00445)	(0.00466)	(0.00464)	(0.00457)
biden_d			-0.0490	0.0182	0.0405	0.389***
			(0.0437)	(0.103)	(0.103)	(0.135)
ln_SP				-0.0986	-0.150	-0.0614
				(0.126)	(0.127)	(0.130)
ln_VIX_close				0.0386	-0.00512	-0.0130
				(0.0361)	(0.0406)	(0.0404)
ln_EPU					0.0525**	0.0420*
					(0.0229)	(0.0226)
ln_Policy						6.301
						(5.061)
ln_Price						-3.549
						(5.070)
ln_ICEA						-7.895***
						(1.922)
Constant	0.0407***	0.0666*	-0.00568	0.649	0.917	23.98***
	(0.0143)	(0.0340)	(0.0405)	(0.948)	(0.951)	(8.383)
Observations	412	412	412	412	412	412
R-squared	0.000	0.002	0.058	0.062	0.074	0.117

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: *Regression Results for Monthly Observations*

Dependent Variable: BTC Excess Returns (Monthly)

VARIABLES	(1) model1	(2) model2	(3) model3	(4) model4	(5) model5	(6) model6
net_dis	0.00119	0.00809	-0.00892	-0.00827	-0.00652	-0.00115
	(0.00285)	(0.00550)	(0.00990)	(0.0102)	(0.0102)	(0.0100)
net_dis_d		-0.164	0.0179	0.00111	-0.0195	-0.0841
		(0.112)	(0.142)	(0.145)	(0.145)	(0.142)
trump_dis			0.0276**	0.0288**	0.0293**	0.0268**
			(0.0133)	(0.0137)	(0.0136)	(0.0134)
trump_d			-0.167	-0.157	-0.205	-0.179
			(0.127)	(0.171)	(0.174)	(0.169)
biden_dis			0.00900	0.0100	0.00966	0.0147
			(0.00871)	(0.00935)	(0.00930)	(0.00936)
biden_d			0.0246	0.0731	0.0630	0.640**
			(0.0862)	(0.221)	(0.220)	(0.317)
ln_SP				-0.0770	-0.110	0.0839
				(0.278)	(0.278)	(0.282)
ln_VIX_close				0.0531	0.00551	-0.00883
				(0.0746)	(0.0819)	(0.0799)
ln_EPU					0.0704	0.0299
					(0.0514)	(0.0516)
ln_Policy						11.87
						(10.82)
ln_Price						-5.229
						(11.76)
ln_ICEA						-15.87***
						(5.579)
Constant	0.0390	0.132*	0.0268	0.477	0.573	41.81*
	(0.0281)	(0.0696)	(0.0828)	(2.095)	(2.085)	(21.45)
Observations	95	95	95	95	95	95
R-squared	0.002	0.025	0.088	0.094	0.114	0.201

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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