The Covid Shock, the Rise of DeFi and Bitcoin's Increasing Market Risk

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Abstract

Our paper employs the CAPM (Capital Asset Pricing Model), the Carhart Four Factor model, and the Fama-French Five Factor model to determine whether the models that investment managers typically rely on for measuring the risk associated with investing in a traditional asset may also act as measure of risk for an investment in Bitcoin. Using a rolling 250-day window and daily returns for 2014-2021, our analysis provides estimates of Bitcoin's beta over time. We find that prior to the COVID-19 lockdown, the pricing model factors were rarely significant. After the onset of the lockdown, however, the market factor increased sharply and remained statistically significant through the end of our analysis period in December 2021. We also investigate Bitcoin's beta over time and scale using wavelet analysis. The results support our previous estimates of significant market betas by finding high coherence between Bitcoin and the market portfolio after the onset of the lockdown at every scale. Prior to 2020, the wavelet analysis also finds that there was a systematic relationship between Bitcoin and the market portfolio for longer (high scale) horizons, while the relationship was sporadic for short horizons. We also study the relationship between Bitcoin's beta and the macro-economy. We do not find that macroeconomic fundamentals explain Bitcoin's beta. We explain that Bitcoin's lack of scalability in times of crisis and its growing use in Defi applications on the Ethereum blockchain led to significant increases in its market risk. From the standpoint of traditional investments, we find that a Bitcoin investment after March 2020 is similar to that of a risky tech stock.

Keywords: Blockchain, Bitcoin, DeFi

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1 Introduction

The Capital Asset Pricing Model (CAPM), the Fama-French-Carhart Four Factor Model, and the Fama-French Five Factor Model are familiar asset pricing models that are part of the toolkit investment managers use to determine the risk properties of traditional assets. Our analysis employs these models to find rolling window estimates using daily returns of Bitcoin's beta over the period 2014-2021.

We benefited from helpful comments on an earlier draft of this paper, presented at the New York State Economics Association Conference, Oct. 2022.

The models produce estimates of significant market risk coinciding with the onset of the COVID-19 lockdown. Our estimates associate March 2020 with a dramatic change in Bitcoin's return/risk dynamics that continued throughout 2021. Our explanation is that the Covid panic of March 2020 was a period of high market volatility as investors sold off risky assets. The large scale liquidity needs induced by the pandemic shock created selling pressure that spilled over to Bitcoin. In the absence of any formal relationship with a liquidity provider of last resort, the liquidity needs of Bitcoin investors were not met by a Central bank. This along with Bitcoins fixed money supply rule resulted in an inadequate supply of Bitcoin for investors to hold during the risk off selling at the start of the pandemic. Investors' liquidity needs were more cheaply met with traditional securities such as short-term government bonds. During the panic, Bitcoin's failure to operate as a safe or uncorrelated asset with the market became obvious.

Another change that occurred was the growth of Defi (decentralized finance) with applications on the Ethereum blockchain for the wrapped version of Bitcoin.The use of wrapped bitcoin for loans and collateral on the Ethereum blockchain generated volatility with a significant non-diversifiable component. The total value locked in Defi on the Ethereum blockchain went from approximately 1 billion in May 2020 to 90 billion by Dec. 2021. Some examples of the expanding scope for bitcoin's services in Defi include depositing bitcoin as collateral for loans, exchanging it for its Wrapped version that could be traded on the Ethereum blockchain, and using Bitcoin to take out loans where the proceeds were used to buy a stablecoin that is deposited in a yield farm.footnote needed We view the expanding scope of bitcoin activities as creating an increased risk from fraud, scams, and theft, while introducing credit risk, and increasing custody risks. These changes led to greater aggregate risk for Bitcoin investors.

We also investigate whether Bitcoin's increase in non-diversifiable risk could be explained by macroeconomic fundamentals including uncertainty, and where network effects are measured by the growth in Bitcoin addresses. We find through the application of two state space models that it does not. We conclude that the expanding scope of Bitcoin's activities on to different blockchains increased its non-diversifiable risk while its lack of scalability became obvious once a wide scale safe haven was needed.

Our paper differs from others that consider Bitcoin's risk and return properties in several ways. While Liu et al. (2022) apply the techniques of standard asset pricing models to the universe of crypto assets and find three factors of importance for explaining the cross-section of returns, they do not consider crypto along with other assets. We estimate Bitcoin's risk when Bitcoin is one piece of a larger traditional portfolio of different types of assets. Another way it differs is by applying wavelet methodology to estimate scale betas and comparing them with estimates from standard models.

Our contributions are as follows: 1) We find that the value premise that Bitcoin acts a safe haven does not stand up to the liquidity stresses of the Covid shock. 2) The expansion of Bitcoin uses to other blockchains is viewed as a source of aggregate risk that is employed to explain bitcoin's increase in market risk after the Covid shock of March 2020. 3) We support estimates of significant betas found from the one factor four factor and five-factor models with wavelet methodology 4) We employ two state-space models and find that macroeconomic fundamentals do not explain the increase in Bitcoin's non-diversifiable risk.

In the next section we begin with a review of background literature on Bitcoin's risk and return characteristics in a portfolio context, its use as a safe haven, and summarize research on the risks of Defi. In section 3, we summarize the key findings from the voluminous research literature on the statistical properties of Bitcoin returns. In section 4, we consider the historical performance of Bitcoin and create a market portfolio that consists of bonds, gold, and eleven equity sectors. In section 5, we estimate Bitcoin's beta for CAPM one-factor model, the Fama-French-Carhart four-factor and

According to Arcane Research, the amount of Bitcoin locked on the Ethereum blockchain has increased to 189,000 BTC in 2021 https://cointelegraph.com/learn/a-beginners-guide-to-understanding-wrapped-tokens-and-wrapped-bitcoin.

source: Statistica

https://www.fsb.org/2023/02/the-financial-stability-risks-of-decentralized-finance.

the Fama-French five-factor model. We also provide a wavelet analysis of the relationship between Bitcoin returns and the larger market. In section 6, we consider whether the change in Bitcoin's beta over time can be explained by macroeconomic fundamentals. The last section contains concluding comments.

2 Background Literature

The topic of Bitcoin's returns and risk over different time periods has received considerable research attention. Huang et al (2021) include the pre and post Covid-19 time period to examine diversification benefits of crytpocurrencies. They define categories or classes of cryptocurrencies based on the properties of the blockchain such as the specific consensus protocol that is used to validate transactions. The expected utility of a mean-variance investor is examined. They find Proof of Work consensus tokens such as Bitcoin are beneficial for portfolios independently of an investor's risk aversion. They define the post-Covid-19 pandemic period as an uncertain economic time. A bench market portfolio with equities and bonds is employed and an out of sample analysis performed. However, their paper differs from ours in two major ways. They use a short time period of weekly returns from Nov. 14th, 2020 to Dec. 25th, 2020 to capture the post-Covid time period. The classes of cryptocurrencies they construct effectively eliminates the correlated risk of using Bitcoin across blockchains that serves as a source of aggregate risk in our analysis. Brauneis & Mestel (2019) use daily market data from 01/01/2015 to 12/31/2017 to examine whether there are diversification benefits from holding a portfolio of cryptocurrencies. The employ the mean-variance framework of Markowitz, for long only portfolios. The performance of cryptocurrency portfolios are examined out of sample. They conclude that a portfolio of cryptocurrencies provides diversification benefits. However, their portfolios did not include traditional assets and their time period did not extend to Covid-19. Kajtazi & Moro (2019) examine the role of Bitcoin in well diversified portfolios. Three different geographically defined and well-diversified portfolios in the U.S., Europe, and China are examined in the time period 2013-2016. The find Bitcoin's high returns compensate for its high volatility to generate improvements in portfolio performance. The time period is pre-Covid and misses the launch of Defi with the associated opportunities for expanding Bitcoin's scope across blockchains. Liu et al.(2022) explain the cross-section of cryptocurrency returns and find three factors, market, size, and momentum are important. They consider crptocurrencies with a market value greater than one million dollars for the period, 2014-2018. Their focus is on the cryptocurrency universe to find similarities with empirical asset pricing model results for traditional equities and identify nine factors that create long-short trading strategies with excess returns. They end their analysis prior to the Covid shock and do not consider a broader portfolio context that includes traditional assets to estimate the risk characteristics of crypto assets.

Conlon et al. (2020) examines the role of Bitcoin as a safe haven during the Covid-19 bear market. They address the question of whether adding Bitcoin to a portfolio helped weather the Covid storm. Their comparison is to a portfolio of only equities. They find holding a portfolio comprised of the S&P 500 equities performs better with less downside risk than the same portfolio with Bitcoin added to it. Their data are daily prices from July 2010-March 2020. While similar to our finding that Bitcoin did not serve as a safe haven during March 2020, their research does not extend to consider an increase in beta risk after the pandemic panic of March 2020. Smales et al. (2018) discuss other issues that make Bitcoin ill-suited to serve as a safe haven asset such as its volatility, less liquidity, and transactions costs. This research cautions against viewing Bitcoin as a safe haven prior to the Covid-19 pandemic.

An issue affecting the security of investments in Bitcoin that plays an important role is our analysis is the risk of hacks, fraud, and illicit activities that increase with Bitcoin's expanding scope of applications across different blockchains. Chen et al. (2018) propose an approach for detecting Ponzi schemes on the Ethereum blockchain. Based on their approach, they estimate that more than 400 Ponzi schemes are running on the Ethereum blockchain. Badawi et al. (2020) apply stringent criteria to a sample of 1,221 articles and carefully review 66 that satisfy their criteria. They find that high yield investment programs as well as pump and dump schemes using cryptocurrencies have been used to steal millions of dollars, halt services and harm productivity. Chen et al. (2020) examine phishing attacks on the blockchain that are directed at cryptocurrencies. They cite a Chain-analysis report that since 2017 more than 50% of revenue from cyber-crime came from phishing scams. They focus on the Ethereum blockchain and offer technical approaches that can warn users of scams. Bartoletti et al. (2021) discuss the role of AMMs (automated market makers) in processing billions of dollars in daily transactions in the Defi space. Attacks using AMMs, particularly where a miner front runs a transaction and extracts value are common. The authors introduce a solution to obtain optimal MEV (Miner Extractable Value). They do not offer a solution to the risks MEV poses to less experienced users. Weintraub et al. (2022) discuss the rise of Defi and the associated problem of malicious behavior that takes the form of front running and MEV on the Ethereum network. Qin et al. discuss the rise of opportunistic trades in Defi (2022). Their focus is on BEV (Blockchain Extractable Value). Their paper quantifies BEV from various sources, such as sandwich attacks, liquidations, and arbitrage. They find the presence of a BEV relayer increases security risks on Defi platforms. Heimback et al (2022) creates a SoK (Systematization of Knowledge) regarding attacks that stem from the reordering of transactions. They find such attacks are prevalent in Defi applications with no solution that does not involve trading-off a beneficial feature of the blockchain.

Qin et al (2021a) introduce a classification scheme that develops firmer boundaries between centralized and decentralized finance. Greater custody risks in Defi are noted. They point out the potential for a bank run in DeFi where assets are returned to users but at a penalty exchange rate. They discuss mixer services and their rewards to users. The rewards incentivize contributions to mixer servers that help money laundering. Qin et al. (2021b) investigates flash loans. The dangers of flash loans are explored. They point our that wash trades that artificially inflate the trading volume of an asset to generate momentum are easier to achieve with flash loans since the proceeds of the flash loans can reduce the cost of holding and using real assets to create fake accounts. Calderli (2021) researches wrapped tokens and finds as of September 2021 that 270,000 BTC are used in DeFi as wrapped tokens. Eighty percent of wrapped tokens are wrapped Bitcoin. Wrapped Bitcoin requires trust over the custodians and results in different security standards. Ferroni (2022) addresses the question of how interconnected are cryptocurrencies and finds high correlation among crytpocurrencies for the period Jan. 1, 2018 to May 10, 2021. Bitcoin is one of the most interconnected in terms of spill over effects. The Financial Stability Report finds that DeFi amplifies the risks found in traditional finance such as liquidity and maturity mismatches. In summary, there is much evidence that blockchains have correlated risks for which diversification is not a remedy.

3 Examining the Data

Our paper's focus is on Bitcoin as an investment where its risk is estimated by beta, a measure of the sensitivity of Bitcoin's returns to market movements. We construct a broadly based market portfolio as a value weighted average of the returns on equities, bonds, and gold. All returns are reported as excess of the one month risk free rate. The specific assets included in the market portfolio are 12 equity sector portfolios, bonds, and gold. Our analysis uses daily data from January 2, 2013 to Dec. 31, 2021. The daily closing price of Bitcoin in US-dollars is from Glassnode. Bond returns are from the Bloomberg Barclays Aggregate Index which includes corporate bonds, Treasuries, residential mortgage backed securities (pass-throughs), asset backed securities, and commercial mortgage backed securities. Gold prices for the daily close of the London Bullion Market are also from the FRED database. The equity portfolio is from the Kenneth French data library. It consists of the returns for all stocks traded on the NYSE, NASDAQ, and AMEX.

Calculations with Bitcoin added to market portfolio are available from the authors. There are no differences in the estimates of significant betas.

The one month risk free rate is from the Kenneth French data library. A more detailed explanation of the construction of the market portfolio is discussed in the Appendix.

https://glassnode.com/

https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

1 BitCoin, Daily prices from Glassnode
2 Gold, Gold Fixing Price 10:30 A.M. (London time) in London Bullion Market
3 Bonds, Bloomberg Barclays Aggregate Bond Index
4 Equity, Kenneth French Data Library includes all NYSE, AMEX, and NASDAQ firms
5 Mkt, Market portfolio value weighted index comprised of equities, bonds, BitCoin and Gold. See Appendix for details.

Table 1: Data Series Used in the Analysis

The price of bitcoin rose dramatically during the sample period. It was $13.17 on Jan 02, 2013, and peaked for the time period at $57,589 on Nov.8, 2021, and ended 2021 at $46,329. Most of the growth occurred after its price reached $10,620 on October 1, 2020. (See Figure 1.) The period that followed coincided with a dramatic increase in the amount of activity in Decentralized Finance (Defi). (See Figure 2.)

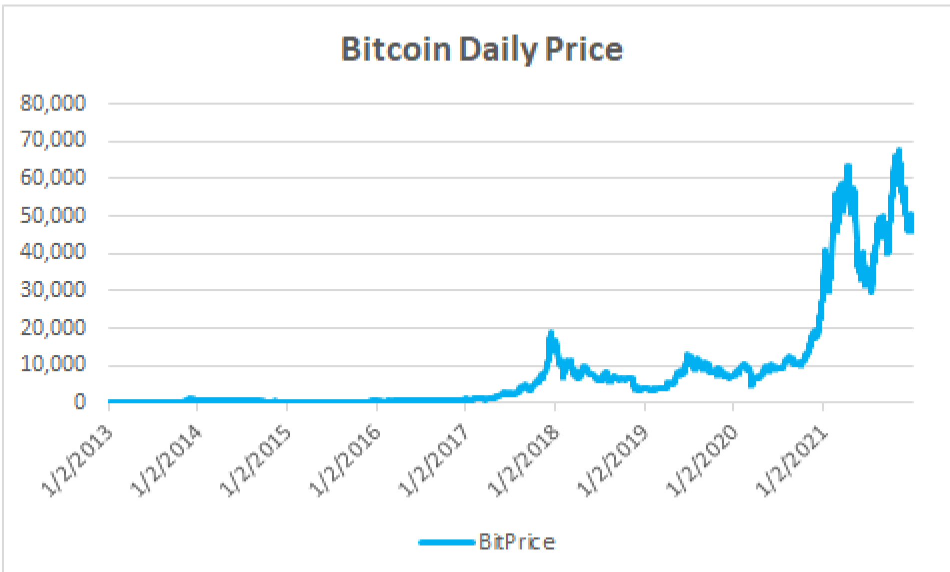

Figure 1: Bitcoin Daily Prices, Jan.02,2013-Dec.31,2021

Table 2 provides summary statistics for all of the assets. Returns are reported in excess of the risk free rate. The risk free rate is the Ibbotson 1 month rate from the K. French website. Bitcoin stands out as having the highest average daily return (0.41%), the highest standard deviation (4.92%), and the largest single day decrease and increase. Skewness is negative for the returns of all assets, and kurtosis is positive. Bitcoin skewness is not the most negative, nor is its kurtosis the most positive among the assets.

	Mean	Std Dev	Skewness	Excess Kurtosis	Min.	Max.
Bit (Bitcoin)	0.0041	0.0492	-0.0825	13.66	-0.4927	0.4047
Mkt (Market Portfolio)	0.0004	0.0062	-0.7262	15.34	-0.0600	0.0524
Equity (Equity Aggregate)	0.0006	0.0107	-0.7739	19.04	-0.1200	0.0934
Bonds (Bond Aggregate)	0.0001	0.0021	-0.7444	7.04	-0.0207	0.0103
Gold	0.0001	0.0094	-0.5943	6.85	-0.0907	0.0509

Table 2: Summary Statistics for Daily Asset Excess Returns, Number of observations = 2,267

All returns are calculated as simple returns.

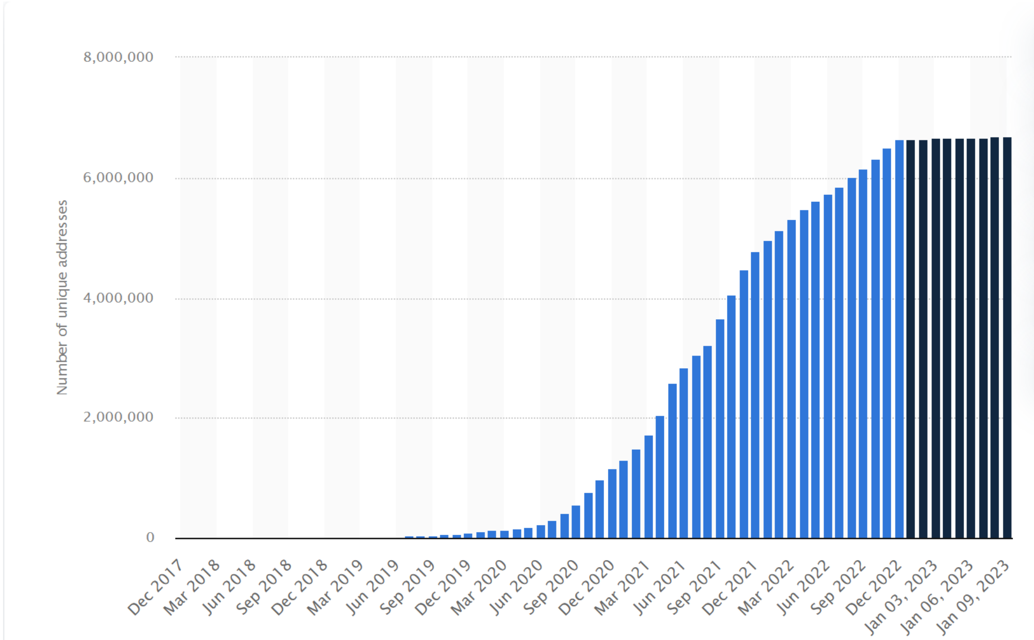

Figure 2: Unique Addresses that bought or sold a decentralized finance asset worldwide. Source: Statistica

4 Examining Bitcoin's Beta over Time

A rolling 250 day window is used to estimate the single factor market model, the Fama-French-Carhart four factor model, and the Fama-French five factor model. A rolling window approach was chosen over a more sophisticated time varying parameter model in order to capture the real time changes that an investor experiences. The results are summarized in Figures 3 to 5. Each chart displays daily parameter estimates (solid line, left-hand side axis) and t-statistics (gray dashed line, right-hand side axis) for the sample period.

The single factor beta (Figure 3, right-side) varies quite a bit over time. For most of the estimation period prior to the Covid shock the estimates of beta were not significantly different from zero. Although Bitcoin's price appreciated, especially during 2017, it was weakly connected to the overall market. The only significant beta estimate in the pre-Covid period is found in 2018 when spiked at 3, and the t-statistic remained at about 2. This is a year associated with increasing scrutiny of Initial Coin Offerings (ICO's) by the SEC following enforcement activity in 2017. This suggests that increasing regulatory scrutiny is very risky for Bitcoin as an investment. The increase in regulatory risk, growing security concerns, and weakening of the hype and speculation surrounding cryptocurrencies lead to a major price correction for Bitcoin. By the end of 2018, Bitcoin had lost 80% of it value.

The beta story changed dramatically beginning in 2020 where we estimate significant betas ranging from 1.5 to 2.7. This period of large and statistically significant estimates of beta coincides with the announcement of a worldwide pandemic, and the rapid rise of decentralized finance (DeFi). The expansion of Bitcoin to uses on other blockchains began with the introduction of wrapped Bitcoin in 2019, an ERC20 token that could be traded on the Ethereum blockchain. In May 2020, automated market makers were introduced that created additional use cases for Bitcoin to serve as collateral for stablecoins. The explosive growth of DeFI in the 2020 -2021 period is seen in Figure 2.

The single factor model intercept (Figure 3, left chart) was significant and positive in 2014, 2018, and 2020. In the context of a standard financial asset the meaning of a positive intercept would

The red dashed line indicates a t-statistic of +/-2.0

indicate pure alpha (i.e. return without risk). That is unlikely the case for a non-traditional asset such as Bitcoin where the three years associated with a positive intercept had events that increased risks. The Mt. Gox hack in 2014 cast doubt on Bitcoin's security and called attention to its use for illicit purposes. The SEC crack down on ICOs was in 2018, and 2020 is the year of the Covid lockdown, and also the expansion of Bitcoin's services to other blockchains. Our hypothesis is that the returns captured by the intercept for those three years compensate for additional risk that our models did not identify as a source of aggregate risk. The difficulty of aggregating the risk of providing services across blockchains into standard asset pricing models is also evident by the weak explanatory power, with R-square (not displayed) reaching a maximum of 11 percent in 2021. Further research is needed to better capture sources of aggregate risk for Bitcoin when critical events occur.

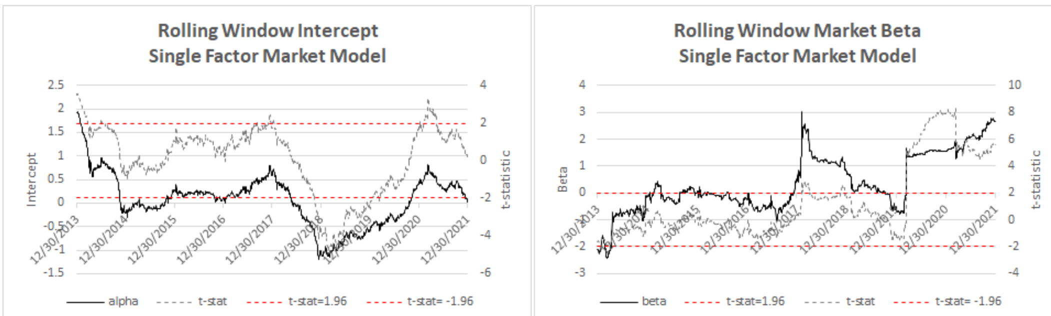

Figure 3: Single Factor Model, Rolling Window Beta of Bitcoin

The four and five factor models tell a similar story. Figure 4 shows the parameter estimates and t-statistics for the Fama-French-Carhart four factor model. The market beta and intercepts display the same pattern as the single factor model. The momentum factor is generally insignificant. The value (book-to-market) factor is a significant, but small negative value in the latter part of 2020. The firm size factor is statistically significant for about 15 months starting in March 2020 but the magnitude is small, averaging about 0.008. Figure 5 shows the parameter estimates and t-statistics for the Fama-French five factor model. As expected, the market beta and intercept are similar to the single factor model. The coefficient estimate for the size factor is similar to the four factor model until 2021 when it basically drops to zero. The value factor in the five factor model is similar to that of the four factor model. The parameter estimate for the CMA factor is only significant from March 2019-July 2019 during which time it averaged -0.02. The CMA factor is calculated as the average return on portfolios of firms that invest conservatively minus the average return of firms that invest aggressively. The sign on the profitability factor flips at various points throughout the sample period, but it is not statistically significant until 2021 when it turns negative. Fama and French define the profitability factor as the average return on the two robust operating profitability portfolios less the average return on the two weak operating profitability portfolios,

$$\text{Profit factor} = 1/2(\text{Small Robust} + \text{Big Robust}) - 1/2(\text{Small Weak} + \text{Big Weak}). \tag{1}$$

where robust and weak refer to profitability.

The profit factor is designed to capture the possibility that companies reporting higher future earnings have higher returns. The significant negative sign when the model is applied to bitcoin as well as our other results showing significant value and size factors after March 2020 tell the same story. The risk dynamics of Bitcoin for investors changed after the Covid liquidity shock of March 2020. Bitcoin began to share similar characteristics of other asset classes, in this case, equities. Although Bitcoin is not a firm, one way to understand albeit small but still significant results after March 2020 is that investors make sense of what is happening with Bitcoin as an investment in light of what is happening with traditional investments such as equities.

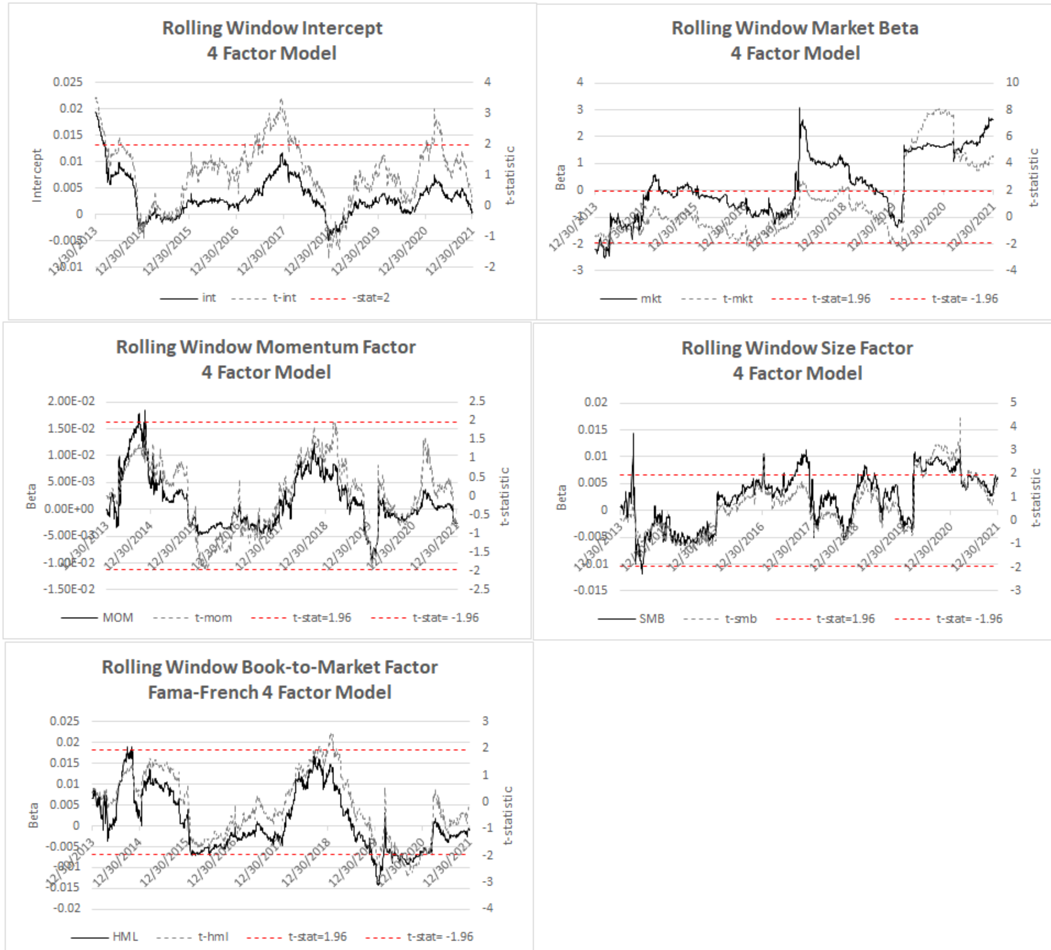

Figure 4: Four Factor Model, Rolling Window Beta of Bitcoin

4.1 Examining Bitcoin's Beta over Time and Scale

Wavelet analysis provides a set of techniques for examining the behavior of a time series across both time and scale. It enables our analysis to separate the dynamics of the data over different time horizons. Wavelet analysis is particularly relevant since it captures multi-scale features. This matters since capturing the interrelationship between markets is more finely tuned to discovery when scales, which may behave differently, are introduced. Research has found that betas change over time scale. There is also research that finds as the scale increases the relationship between portfolio return and risk is stronger. In this section we explore whether the weak market connection for Bitcoin found prior to the pandemic and the fairly strong connection after 2020 is supported by wavelet analysis. We also investigate whether the beta risk of bitcoin changes with scale. We use both the continuous and discrete wavelet transform to examine the relationship between bitcoin returns and the market portfolio.

Wavelet coherence measures the co-movement of two time series across time and scale. It is similar to a correlation coefficient and can be interpreted as a correlation that is localized in time-scale space. Figure 6 contains the coherence for bitcoin and the market portfolio. The vertical axis measures the

See Percival and Walden for a comprehensive discussion on Wavelet Analysis.
This chart was created using the Matlab Wavelet Toolbox

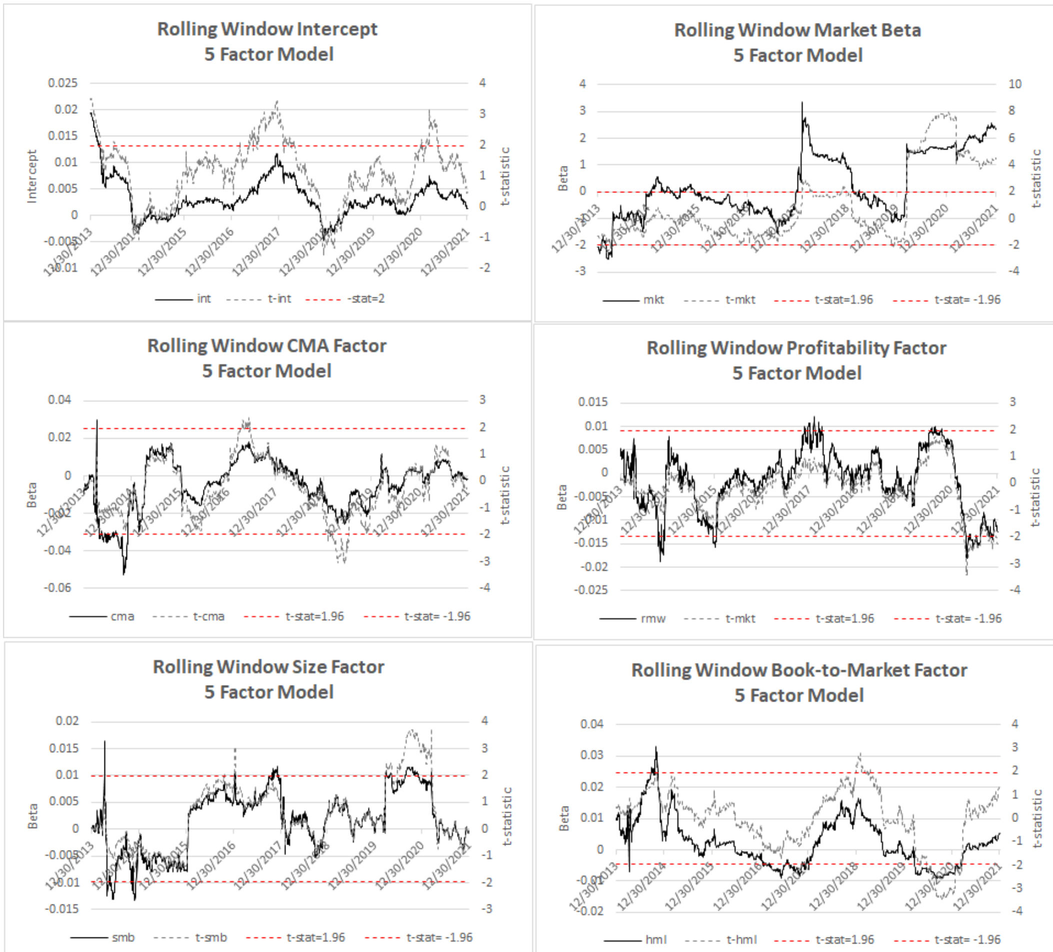

Figure 5: Five Factor Model, Rolling Window Beta of Bitcoin

scale in days, and the horizon axis is time in days. Red areas indicate that the coherence is high. In areas when the coherence exceeds 0.7, the plot contains phase arrows which indicate the phase lag of the market portfolio with respect to bitcoin. Arrows pointing right indicate the two series are in phase, while arrows pointing left indicate that the market portfolio lags bitcoin by a half-cycle. The area outside of the dotted white line or the cone of influence, is typically disregarded as there is not enough information for the wavelet to properly describe that area. Figure 6 shows that at high frequencies there is sporadically high coherence over the sample period. The picture changes in 2020 when there is a significant area of coherence (circled in white) for the entire year at a scale of 64 to 128 days. This supports the previous finding that the market beta became statistically significant in 2020. The findings of pre-pandemic weak coherence between Bitcoin and the market at low frequencies and sporadic high coherence at high frequencies suggest that whatever sporadic high coherence was present is not strong enough to generate estimates of significant betas in the absence of scale. Our earlier estimates of high beta risk in 2018 is evident in high coherence at low frequency for 2018. Suggesting that significant beta estimates based on the standard market model translate into findings of high coherence at low frequency. Wavelet coherence also provides some insight into the relationship between the investment horizon and the market beta. That is, longer investment horizons had greater coherence during a period of market stress that elicited policy responses. In 2021 the coherence reveals sporadic high coherence at high frequencies with periods of high coherence at low frequencies.

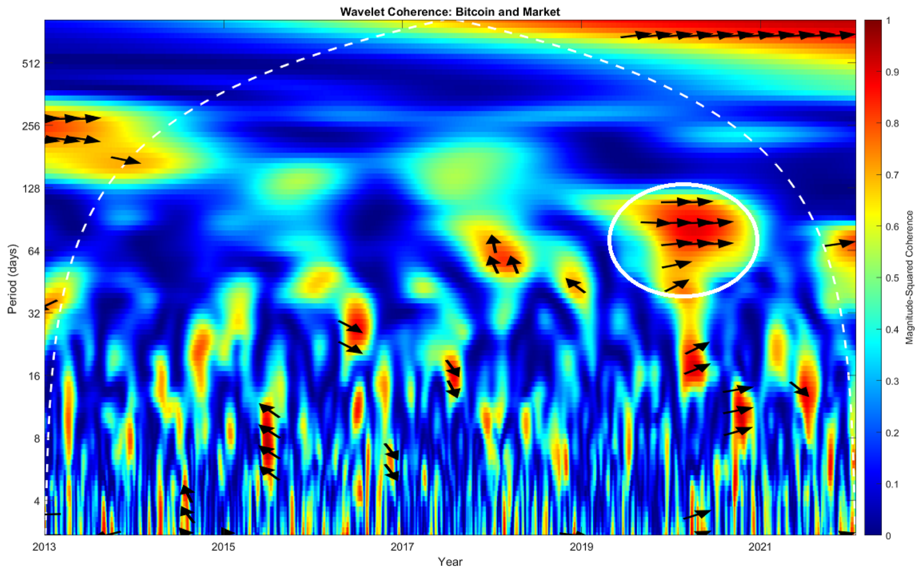

Figure 6: Wavelet Coherence: Bitcoin and the Market Portfolio

A more formal analysis of the relationship between Bitcoin and the market portfolio is found by employing the discrete wavelet transform (DWT), which is essentially a critical sampling of J scales from the continuous wavelet transform (CWT). The DWT can be used to estimate the CAPM at different scales. Applying the DWT to a time series x(t) results in a time series of length k of smooth coefficients at the maximal scale J, and J time series of detailed coefficients each of length k. If there are 6 scales, the frequency of the first scale is associated with the interval [1/4,1/2], and the frequency of scale 6 is associated with the interval [1/128, 1/64].

A time series x(t) can be represented in decomposed form, as follows:

$$x(t) = a_J + d_J + d_{J-1} + ... + d_1 \tag{2}$$

The discrete wavelet transform decomposes a time series into orthogonal signal components at different scales. a_j is a smooth signal, and each d_j is a signal of higher detail.

In the case of daily data decomposing the series into seven scales (d1-d7) corresponds to 2-4, 4-8, 8-16, 16-32, 32-64, 64-128, and 128-256 days. D1 is the shortest scale (highest frequency) component and D7 is the longest scale (lowest frequency) component. The smooth component (a7) captures the trend of the original series.

Bitcoin and Mkt returns were decomposed into 7 levels. Figure 7 shows the actual returns for bitcoin, the 7 detail levels (d1-d7), and the smooth level (S7). The plots show the series with a period boundary filler. The regression analysis does not use the filler.

The scale level estimates of bitcoin's beta are compared to the standard market model (labeled "All") in Table 3. The standard estimate of the beta for bitcoin over the entire sample period is 0.909 while the scale betas range from 0.613 to 2.66. All of the betas are statistically different from zero. The first 4 scales (through 16 days) have betas that are all less than one. The scale beta jumps appreciably from scale 5 to 6, The adjusted R-square is noticeably higher for scale 6. The jump in beta suggests that Bitcoin's relationship with the larger market is most sensitive at longer horizons.

The data allows for 8 levels, but the 8th has 310 observations so we did not include it in the analysis.

The discrete wavelet transform was done using the Waveslim package in R. The chart was done using the Matlab Wavelet toolbox

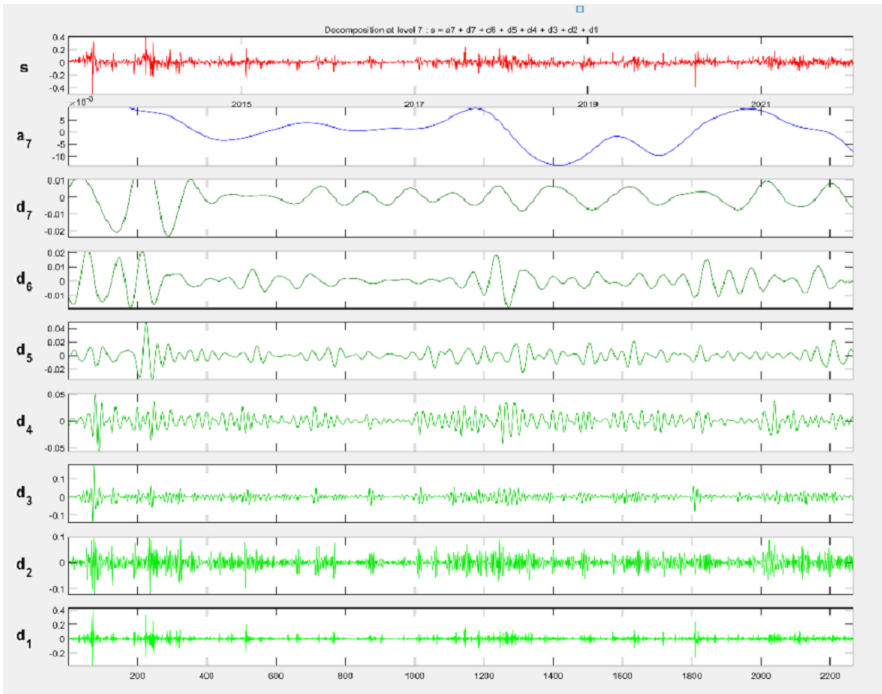

Figure 7: Bitcoin Returns - Discrete Wavelet Transform

scale	**beta**	**t-Stat**	**R-Sq**	**Nobs**
All	0.909	5.47	0.0126	2265
d1	0.941	5.94	0.0150	2258
d2	0.650	3.68	0.0055	2244
d3	0.613	3.60	0.0054	2216
d4	0.958	5.30	0.0124	2160
d5	1.027	6.35	0.0188	2048
d6	2.662	17.30	0.1405	1824
d7	0.828	4.27	0.0124	1376

Table 3: Scale Betas for Bitcoin

The rolling window analysis in the previous section showed that the beta was only statistically different from zero for the last two years of the sample (2020 and 2021). Figure 8 contains rolling window betas for scales d1 to d6. The results are similar to those in Table 3. Prior to 2020 beta for scales d1-d4 betas tend to be insignificant except in mid-2018. Scale 5 has a much longer stretch of significance prior to 2020, and scale d6 is significant for almost the entire period from 2014 to 2020. After the onset of the pandemic in March 2020 the beta at each scale is statistically significant. Again offering evidence that the rapid growth of defi created opportunities for bitcoin that were a source of aggregate risk reflected in beta estimates.

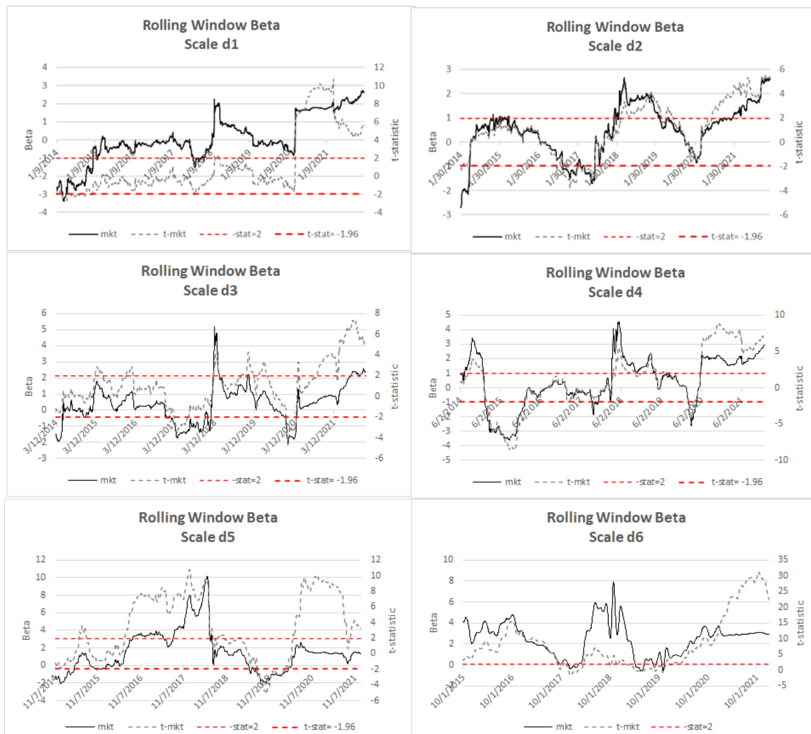

Figure 8: Bitcoin Beta - Scales d1 to d6

The wavelet analysis indicates that there has always been a systematic relationship between bitcoin and the market portfolio at an horizon of 64 to 128 days. For short horizons (less than 64 days), the connection between bitcoin and financial markets is weak, and sporadic.

5 The Factors Driving Bitcoin's Beta Through Time

Since March 2020 the market has basically priced bitcoin as a high-risk tech-like asset. Our explanation is that the rapid growth of Defi is associated with increasing uses for Bitcoin across blockchains that resulted in correlated risk that became a source of aggregate risk. In this section, we consider two model specifications to evaluate whether changes in bitcoin's beta are explained by macroeconomic fundamentals.

5.1 Model One: Time Varying Parameters with Shrinkage

First we apply the model of Cadonna, et. al. (2019) to a set of asset returns, macroeconomic variables, and news based measures of uncertainty. The specification is a state space model with time varying parameters and shrinkage. This model estimates time varying parameters with shrinkage. Here we provide a basic outline of the model. Interested readers are referred to Frühwirth-Schnatter and Wagner (2010), Bitto and Frühwirth-Schnatter (2019), and Cadonna et al. (2019). A state space model where the state equation follows a random walk is defined as follows:,

$$\beta_t = \beta_{t-1} + w_t \quad w_t \sim N(0, \Omega_t^2) \tag{3}$$

$$y_t = x_t\beta_t + v_t \quad v_t \sim N(0, \sigma_t^2) \tag{4}$$

where $b_t \sim (dx1)$, $\Omega_t \sim dxd$, $y_t \sim (1x1)$, $x_t \sim (1xd)$, and $\sigma_t^2 \sim (1x1)$

Using the non-centered parameterization introduced by Frühwirth-Schnatter and Wagner (2010) the model can be re-written as:

$$\tilde{\beta_t} = \tilde{\beta}_{t-1} + \tilde{w_t} \quad w_t \sim N(0, I_d) \tag{5}$$

$$y_t = x_t\beta + Diag(\sqrt{\theta_1}, \ldots, \sqrt{\theta_d})\tilde{\beta}_t + v_t \quad v_t \sim N(0, \sigma_t^2) \tag{6}$$

Where $I_d \sim (dxd)$ identity matrix. This reparameterization, which is equivalent to the original specification, places all of the model parameters in the measure equation and splits the state variable into time invariant and time varying components. The time varying component, which follows a random walk, is scaled by its standard deviation, $\sqrt{\theta}$. The advantage of this approach is that it can automatically reduce time varying coefficients to invariant coefficients. If the variance of $\tilde{\beta_{jt}} = 0$, the coefficient will be static, and possibly zero. This specification helps prevent over fitting. The model specifies a Normal-Gamma-Gamma prior for elements in the state vector β:

$$\beta_j|\tau_j \quad \sim N(0, \tau_j^2) \tag{7}$$

$$\tau_j^2|\alpha^\tau, \lambda_j^2 \sim G\left(a^\tau, \frac{\alpha^\tau\lambda_j^2}{2}\right) \tag{8}$$

$$\lambda_j^2|c^\tau, \lambda_B^2 \sim G\left(c^\tau, \frac{c^\tau}{\lambda_B^2}\right) \tag{9}$$

The prior for θ has a hierarchical triple gamma which is a very a general specification encompassing many types of the existing priors such as the horseshoe, and lasso.

$$\theta_j|\xi_j^2 \quad \sim G\left(\frac{1}{2}, \frac{1}{\xi_j^2}\right) \tag{10}$$

$$\xi_j^2|\alpha^\xi, \kappa_j^2 \sim G\left(a^\xi, \frac{\alpha^\xi\kappa_j^2}{2}\right) \tag{11}$$

$$\kappa_j^2|c^\xi, \kappa_B^2 \sim G\left(c^\xi, \frac{c^\xi}{\kappa_B^2}\right) \tag{12}$$

The triple gamma prior places a large mass (for θ) at zero, effectively challenging the data to prove otherwise. . In addition to the state space specification, heteroskedasticity is estimated as a latent volatility model with the log volatility, h_t following an AR(1) process:

$$h_y \sim N(\mu + \phi(h_{t-1} - \mu), \sigma_\eta^2) \tag{13}$$

Model estimation was done using the R package, "shrinkTVP", Package: shrinkTVP,"Efficient Bayesian Inference for Time-Varying Parameter Models with Shrinkage",Version: 2.0.2,Peter Knaus, Angela Bitto-Nemling, Sylvia Frühwirth-Schnatter

See Cadonna, et. al., 2019 for additional details

See page 8 of Cadonna, 2019 for a list of the priors related to the triple gamma

The list of explanatory variables used in the analysis is shown in Table 4. The choice of variables is designed to test whether the change in bitcoin's beta over time is related to economic activity, or uncertainty. Bitcoin addresses were included to capture although imperfectly the growth of the network.

addr	Bitcoin addresses (daily change)
ted	TED spread
gold	Daily return of gold
oil	Daily return of Oil
vix	Volatility of the S&P 500
baa10y	Seasoned corporate bond yield less 10 yr treasury yield
gvix	Volatility of gold
t210	10 yr Treasury yield less 2 year Treasury yield
QQQ	Daily return on NASDAQ Tech Stocks
TEU	Twitter-based uncertainty index
diseaseun	Infectious Disease Equity Market Volatility Tracker
gtrends	Index of Google searches for 'crypto'

Table 4: Variables used to Evaluate Beta Drivers

Estimates of β_j and θ are shown in Tables 5 and 6. The remaining parameter estimates are presented in Appendix A. The model was estimated using 50,000 iterations, with a burn-in of 10,000, and thinning equal to five. The large number of observations made a larger simulation prohibitively costly. The results indicate that only a small subset of the variables are significantly different from zero. The only variables with a significant time invariant parameters are the intercept and t210. Variables with significant time variation include the intercept, baa10y, and t210. Time plots of the parameters are shown in Figure 9 The light and darker blue areas represent the 95% and 80% credible intervals. The coefficient on the spread between seasoned corporate bond yields and the 10 year CMT has a significant positive peak in early 2020. The actual spread increased by 200 bps from late February through mid-March as the demand for Treasuries increased and the demand for corporate bonds decreased. The 2-10 Treasury spread (t210) shows quite a bit of variation over the sample period, but is really only significantly different from zero when it increases in early 2020. This was a time when equities were selling off due to the pandemic. The demand for liquidity was high as investors sold stocks and purchased short duration Treasuries.

In summary, our measures of equity returns, market volatility, and economic uncertainty fail to explain the increase in bitcoin's beta after the onset of the pandemic. However, the beta was temporarily driven up by the flight to safety in early 2020 again offering evidence that in times of stress bitcoin is not a safe or uncorrelated asset. The change in bitcoin addresses over time appears to have had no impact on the beta.

All variables have been standardized.

"Measuring Economic Policy Uncertainty" by Scott Baker, Nicholas Bloom and Steven J. Davis at www.PolicyUncertainty.com.

param	**mean**	**sd**	**median**	**HPD 2.50%**	**HPD 97.50%**	**ESS**
beta_mean_Intercept	-1.005	0.246	-1.006	-1.530	-0.548	142
beta_mean_addr	0.000	0.000	0.000	0.000	0.000	319
beta_mean_baa10y	0.003	0.051	0.000	-0.102	0.081	168
beta_mean_ted	0.000	0.001	0.000	0.000	0.000	389
beta_mean_gold	0.000	0.000	0.000	0.000	0.000	35
beta_mean_oil	0.000	0.000	0.000	0.000	0.000	26
beta_mean_vix	0.000	0.002	0.000	-0.003	0.003	547
beta_mean_gvix	0.000	0.003	0.000	-0.003	0.005	354
beta_mean_t210	-0.814	0.192	-0.812	-1.182	-0.426	158
beta_mean_QQQ	0.000	0.001	0.000	-0.001	0.001	6
beta_mean_TEU	0.000	0.000	0.000	0.000	0.000	348
beta_mean_diseaseun	0.000	0.000	0.000	0.000	0.000	103
beta_mean_gtrends	0.000	0.003	0.000	-0.004	0.003	483

Table 5: Mean State Parameters

	mean	**sd**	**median**	**HPD 2.50%**	**HPD 97.50%**	**ESS**
abs(theta_sr_Intercept)	0.021	0.001	0.021	0.019	0.023	416
abs(theta_sr_addr)	0.000	0.000	0.000	0.000	0.000	12
abs(theta_sr_baa10y)	0.012	0.002	0.012	0.008	0.016	165
abs(theta_sr_ted)	0.000	0.000	0.000	0.000	0.001	6
abs(theta_sr_gold)	0.000	0.000	0.000	0.000	0.000	29
abs(theta_sr_oil)	0.000	0.000	0.000	0.000	0.000	59
abs(theta_sr_vix)	0.001	0.001	0.001	0.000	0.003	9
abs(theta_sr_gvix)	0.001	0.000	0.001	0.000	0.001	21
abs(theta_sr_t210)	0.044	0.002	0.044	0.039	0.048	369
abs(theta_sr_QQQ)	0.000	0.000	0.000	0.000	0.000	11
abs(theta_sr_TEU)	0.000	0.000	0.000	0.000	0.000	67
abs(theta_sr_diseaseun)	0.000	0.000	0.000	0.000	0.000	13
abs(theta_sr_gtrends)	0.001	0.001	0.000	0.000	0.002	13

Table 6: Scale Parameters, θ_j

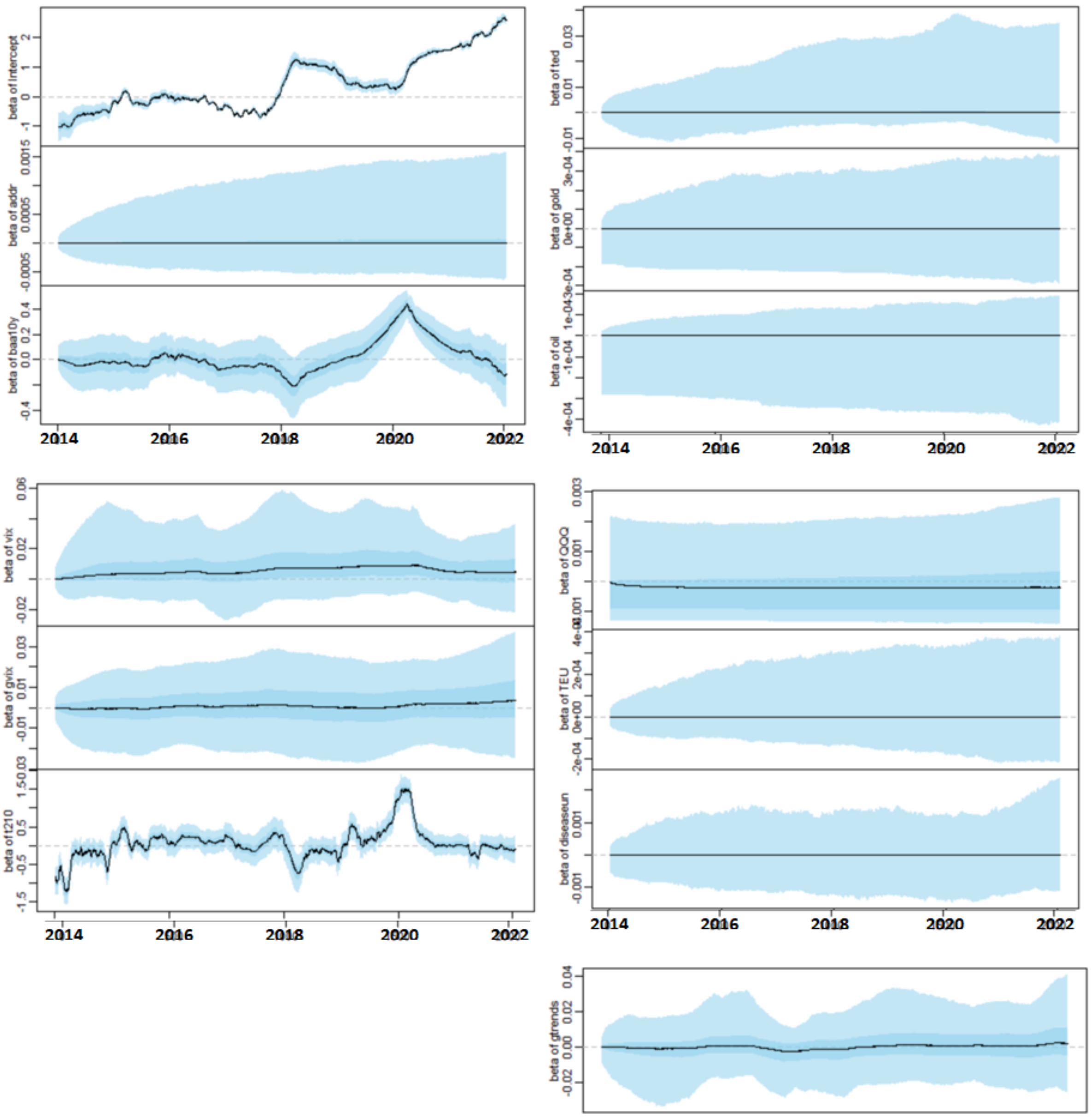

Figure 9: Parameters for Model One

5.2 Model Two - The State Vector as a System

In this section we consider a slightly different approach for modeling the determinants of bitcoin's beta. Following Andersen et.al.(2005) we include macroeconomic fundamentals in a dynamic state space model by augmenting the state vector as a system. The system consists of bitcoin's unobserved "true" beta along with a set of macroeconomic variables.The measurement variable in this model is the estimated beta. The specification is as follows:

$$\hat{\beta}_t = FX_t + v_t \tag{14}$$
$$X_t = GX_{t-1} + w_t \tag{15}$$
$$X_t^T = [\beta_t, X_{1,t}, X_{2,t}] \tag{16}$$
$$F = [1, 0, 0] \tag{17}$$
$$v_t \sim N(0, \sigma^2_{v_t}) \tag{18}$$
$$w_t \sim N(0, R) \tag{19}$$

where $\hat{\beta}_t$ is the rolling window estimate of daily beta, and x_t consists of the latent 'true' value of beta and a set of macroeconomic variables. The shortcoming of this specification is that the estimated coefficients on the state equation are fixed over time. On the other hand, G is not constrained to be one as it is in Model One so it allows for the possibility that the state equation does not follow a random walk. Based on the results from the shrinkage model, we estimated this model using only two economic factors: baa-10 year spread, and the 2-10 year yield spread.

The state equation is specified as a 3 equation system. This specification allows the macroeconomic fundamentals to impact beta contemporaneously through the cross correlation of residuals, and with a lag via the first state equation.

$$\beta_t = \gamma_{10} + \gamma_{11}\beta_{t-1} + \gamma_{12} baa10y_{t-1} + \gamma_{13} t210_{t-1} + w_{1t} \tag{20}$$
$$baa10y_t = \gamma_{20} + \gamma_{22} baa10y_{t-1} + w_{2t} \tag{21}$$
$$t210_t = \gamma_{30} + \gamma_{31} t210_{t-1} + w_{3t} \tag{22}$$
$$\tag{23}$$

At time t the matrix of explanatory variables is (3x8) block diagonal:

$$X_{t-1} = \begin{pmatrix} 1 & \beta_{t-1} & baa10y_{t-1} & t210_{t-1} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & baa10y_{t-1} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & t210_{t-1} \end{pmatrix}$$

$$vec(G^T) = \begin{pmatrix} \gamma_{10} & \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{20} & \gamma_{21} & \gamma_{30} & \gamma_{31} \end{pmatrix}$$

$$R = \begin{bmatrix} \sigma^2_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma^2_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma^2_{33} \end{bmatrix} \tag{24}$$

Prior Distributions of Parameters:

$$G \sim N[(\underline{\mu}, \underline{V}] \tag{25}$$
$$R^{-1} \sim W(\underline{R}, \underline{\nu}) \tag{26}$$
$$\underline{\sigma^2_v} \sim G(\underline{\alpha}, \underline{\beta}) \tag{27}$$

The model could be generalized to allow for $G(t)$

Conditional Posterior Distributions of Parameters:

$$\bar{\sigma_v^2}|\beta_t, G, R = G(\bar{\alpha}, \bar{\beta}) \tag{28}$$

$$\bar{\alpha} = \alpha_0 + T, \tag{29}$$

$$\bar{\beta} = \underline{\beta} + (\hat{\beta}_t - Fx_t)(\hat{\beta}_t - Fx_t)^T \tag{30}$$

$$G|\beta, R, \sigma_v^2 \sim N(\bar{G}, \bar{V}) \tag{31}$$

$$\bar{V} = (\underline{V}^{-1} + X_{t-1}^T(R^{-1} \otimes I_T)X_{t-1})^{-1} \tag{32}$$

$$d = (X_{t-1}^T(R^{-1} \otimes I_T)X_t + \underline{V}^{-1}\underline{\mu}) \tag{33}$$

$$\bar{G} = d\bar{V} \tag{34}$$

$$R^{-1}|\beta, \sigma_v^2, G \sim W(\bar{R}, \bar{\nu}) \tag{35}$$

$$\bar{\nu} = \underline{\nu} + T \tag{36}$$

$$\bar{R} = \underline{R} + \Sigma_{t=1}^T(X_t - vec(G^T)X_{t-1})(X_t - vec(G^T)X_{t-1})^T \tag{37}$$

$$\text{(Note that } \bar{R} \text{ is stacked by time)} \tag{38}$$

The model was estimated using a Bayesian algorithm. The state variables were estimated with Kalman filter and the Carter-Kohn backward sampling algorithm (FFBS). The model parameters (G, σ_{vt}^2 and Q) were updated after each FFBS sweep by applying the Gibbs sampling algorithm. The model was run for 2000 sweeps and the first 500 was treated as burn-in. Volatility in the measurement equation was estimated using the same latent stochastic volatility specification used for Model One. The volatility model was simulated 10,000 times each FFBS sweep and burn-in was set at 1,000.

Parameter estimates for the transition matrix, G are shown in Table 7. The estimation period covers 3/13/2020 to 12/31/2021 which is the time when these $baa10y$ and $t210y$ were significant for Model One. The results indicate that γ_{11}, the coefficient on β_{t-1} is very close to one, which supports the drift specification for β in Model One. The coefficients for $baa10y_{t-1}$ (γ_{12}) and $t210t - 1$ (γ_{13}) are significant and have opposite signs.

The covariance estimates, σ_{21} and σ_{31} are both small and positive indicating that a positive shock to either spread will have a small positive contemporaneous impact on β_t. These results suggest that the random walk specification for the state equation, as assumed in Model One, is appropriate. Posterior distributions and trace plots for the G matrix are show in Figure 10. The smoothness of the distributions, and the lack of any pattern in the trace plots is indicative of model convergence.

beta_t	intercept (γ_{10})	lag beta (γ_{11})	lag baa10y (γ_{12})	lag t210y (γ_{13})
Mean	0.0034	0.9972	-0.0025	0.0010
Std. Error	1.88E-06	1.91E-06	2.25E-06	2.19E-06
baa10y_t	intercept (γ_{20})	lag baa10y (γ_{21})		
Mean	-0.0003	0.9985		
Std. Error	7.78E-06	1.56E-05		
t210_t	intercept (γ_{30})	lag t210y (γ_{31})		
Mean	-0.0007	0.9970		
Std. Error	8.67E-06	1.69E-05		

Table 7: Posterior Estimates of G Matrix

Stochastic volatility was estimated using the R package "Stochvol",Efficient Bayesian Inference for Stochastic Volatility (SV)

	σ_{12}	σ_{13}
Mean	1934	1624
Std. Error	43	36
Correlation	0.0081	0.0146

Table 8: Covariance Estimates

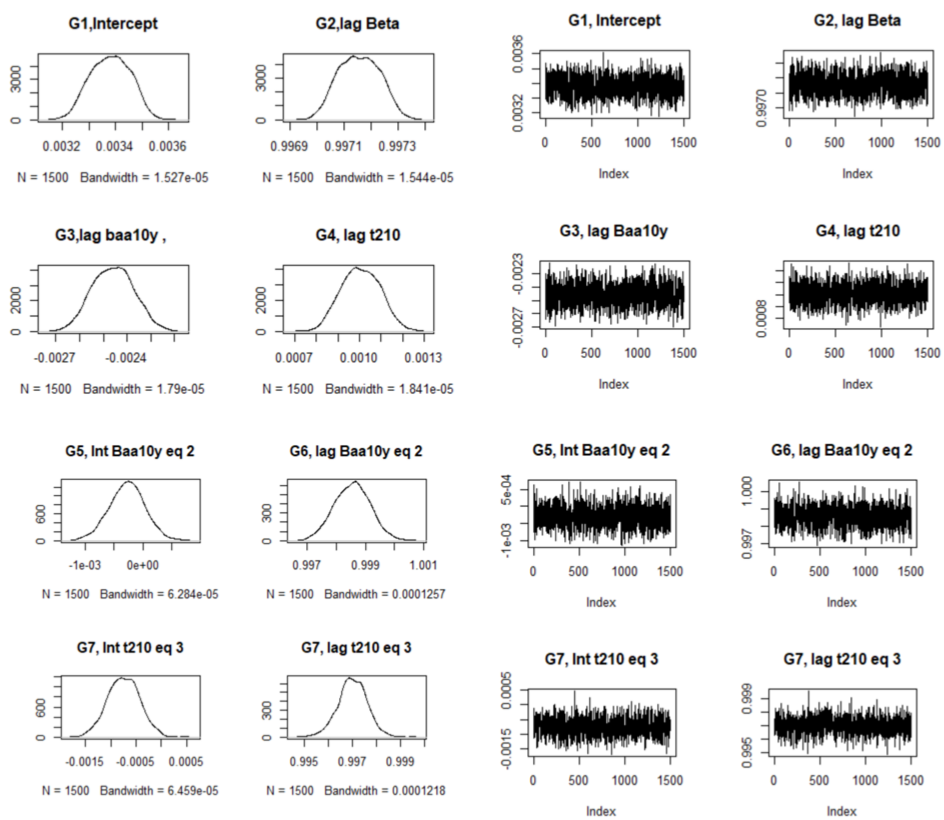

Figure 10: Post Burn-in Densities and Trace Plots for G Matrix

6 Concluding Comments

Our paper investigates Bitcoin's risk dynamics employing familiar asset pricing models. In our account, the Covid shock and the rise of DeFi transformed Bitcoin into a high risk investment with market risk estimates similar to those of risky tech stocks. We argue that the pandemic induced liquidity crunch put to a test whether Bitcoin had the scale to serve as an uncorrelated asset where investors park their funds during times of stress. Based on our findings this use case failed. In the David (Bitcoin) versus Goliath(Treasuries) framework, Golaith won. However, we argue that the Covid liquidity shock of March 2020 gave investors the opportunity to reconsider Bitcoin's value proposition. Investors gave Bitcoin a thumbs down as a safe asset uncorrelated with the larger market. However, they gave it a thumbs up as a high beta investment offering exposure to a high growth sector of DeFi applications on various blockchains. We offer estimates of beta after the Covid shock that are consistent with the existence of correlated risk from the expansion of Bitcoin services across different blockchains. We argue that such correlated risk is a source of non-diversifiable risk and as a consequence Bitcoin began to take on the appearance of a risky tech stock.

Bitcoin's increasing correlation with the broader market of traditional assets and the resulting significant estimates of beta offer evidence that Bitcoin is on solid ground for attracting the interest of investment managers. Significant beta estimates of risk can serve to anchor investors expectations regarding expected returns that without such measures would be adrift in a sea of possibilities. However, the positive and significant intercepts in 2014, 2018, and 2020 suggest that even within the familiar framework of the CAPM and Fama/French models there are warning signs of challenges for aggregating all the relevant risk factors for Bitcoin into traditional models. Since all three alpha estimates are associated with major events it is far from clear that they represent risk factors that will hold in the future. Our main conclusion remains intact. Applying traditional Asset Pricing models to Bitcoin results in significant risk measures after the Covid panic of March 2020. The estimates based on familiar models that are used to measure the risk of traditional assets may lower the psychological barriers many investors face because of Bitcoin's complexity. This along with more suitable offerings for professional investors should hasten the adoption of Bitcoin as an investment.

The promise of suitable crypto offerings for institutional investors such as an ETFs based on the spot price of Bitcoin is one example of innovative products that are on the horizon.

Amnous, Saifedean, The Bitcoin Standard: The Decentralized Alternative to Central Banking, 2018, John Wiley & Sons, Inc, Hoboken, New Jersey.

Andersen, Torben G., et al. “A Framework for Exploring the Macroeconomic Determinants of Systematic Risk.” The American Economic Review, vol. 95, no. 2, 2005, pp. 398–404. JSTOR, www.jstor.org/stable/4132855. Accessed 18 July 2021.

Ando, Tomohiro and Arnold Zellner, ”Hierarchical Bayesian Analysis of the Seemingly Unrelated Regression and Simultaneous Equations Models Using a Combination of Direct Monte Carlo and Importance Sampling”, Bayesian Analysis (2010),5 No.1 pp.65-96. Techniques

Badawi, Emad and Guy-Vincent Jourdan. “Cryptocurrencies Emerging Threats and Defensive Mechanisms: A Systematic Literature Review.” IEEE Access 8 (2020): 200021-200037.

Bartoletti, Massimo, James Hsin-yu Chiang and Alberto Lluch-Lafuente. “Maximizing Extractable Value from Automated Market Makers.” ArXiv abs/2106.01870 (2021):

Bitto, Angela and Sylvia Frühwirth-Schnatter, ”Achieving shrinkage in a time-varying parameter model framework”,Journal of Econometrics, Volume 210, Issue 1,2019,Pages 75-97.

Brauneis, Alexander, and Roland Mestel. ”Cryptocurrency-portfolios in a mean-variance framework.” Finance Research Letters 28 (2019): 259-264.

Cadonna, Annalisa et al. “Triple the Gamma—A Unifying Shrinkage Prior for Variance and Variable Selection in Sparse State Space and TVP Models.” arXiv: Econometrics (2019): n. pag.

Caldarelli, Giulio. “Wrapping trust for interoperability. A study of wrapped tokens.” Inf. 13 (2022): 6.

Carapella, Francesca, Edward Dumas, Jacob Gerszten, Nathan Swem, and Larry Wall(2022). Decentralized Finance (DeFi): Transformative Potential & Associated Risks,”Finance and Economics Discussion Series 2022-057. Washington: Board of Governors of theFederal Reserve System, https://doi.org/10.17016/FED

Chan, J. C. C. (2017). ”The Stochastic Volatility in Mean Model with Time-Varying Parameters: An Application to Inflation Modeling”, Journal of Business and Economic Statistics, 35(1), 17-28.

Chen, Weili, Zibin Zheng, Jiahui Cui, Edith C.-H. Ngai, Peilin Zheng and Yuren Zhou. “Detecting Ponzi Schemes on Ethereum: Towards Healthier Blockchain Technology.” Proceedings of the 2018 World Wide Web Conference (2018): n. pag.

Chen, Weili, Xiongfeng Guo, Zhiguang Chen, Zibin Zheng and Yutong Lu. “Phishing Scam Detection on Ethereum: Towards Financial Security for Blockchain Ecosystem.” IJCAI (2020).

Conlon T, McGee R. Safe haven or risky hazard? Bitcoin during the Covid-19 bear market. Financ Res Lett. 2020 Jul;35:101607. doi: 10.1016/j.frl.2020.101607. Epub 2020 May 24. PMID: 32550843; PMCID: PMC7246008.

Elton, Edwin J., Martin J. Gruber and André de Souza. “Target Risk Funds.” Mutual Funds (2015).

Fama, Eugene F. and French, Kenneth R., A Five-Factor Asset Pricing Model Journal of Financial Economics,Volume 116, Issue 1,2015, Pages 1-22,ISSN 0304-405X, https://doi.org/10.1016/j.jfineco.2014.10.010.

Federal Reserve Board ”Economic Well-Being of U.S. Households in 2021.” Federal Reserve Board Research Report, May 2022.

Ferroni, Filippo (2022) Federal Reerve Bank of Chicago, Essays on Issues, March 2022, No. 466, https://doi.org/10.21033/cfl-2022-466.

Financial Stability Risks of Decentralized Finance https://ww.fsb.org/2032/02/the-finanical-stability-risks-of-decentralized-finance.

Frühwirth-Schnatter, Sylvia, Helga Wagner, Stochastic model specification search for Gaussian and partial non-Gaussian state space models,Journal of Econometrics, Volume 154, Issue 1,2010,Pages 85-100.

Harvey, Campbell, Tardc Abou Zeid, Teun Draaisma, Martin Luk, Hnery Neville, Andre Rzym, and Otto Van Hemert. ”An investor’s guide to crypto” Journal of Portfolio Management, forthcoming, Nov. 2022.

Heimbach, Lioba and Roger Wattenhofer. “SoK: Preventing Transaction Reordering Manipulations in Decentralized Finance.” ArXiv abs/2203.11520 (2022).

Huang, Xinyu and Han, Weihao and Newton, David and Platanakis, Emmanouil and Stafylas, Dimitrios and Sutcliffe, Charles M., The Diversification Benefits of Cryptocurrency Asset Categories and Estimation Risk: Pre and Post COVID-19 (January 16, 2022). The European Journal of Finance, Forthcoming, Available at SSRN: https://ssrn.com/abstract=3894874 or http://dx.doi.org/10.2139/ssrn.3894874

Kajtazi, Anton and Moro, Andrea, The Role of Bitcoin in Well Diversified Portfolios: A Comparative Global Study (October 5, 2018). Available at SSRN: https://ssrn.com/abstract=3261266 or http://dx.doi.org/10.2139/ssrn.3261266

Koopman, Siem Jan and Charles S Bos, "State Space Models With a Common Stochastic Variance" Journal of Business & Economic Statistics, Vol. 220, No.3, pp. 346-357, 2004.

Li, Zhenghui, Hao Dong, Christos Floros, Athanasios Charemis and Pierre Failler. "Re-examining Bitcoin Volatility: A CAViaR-based Approach." Emerging Markets Finance and Trade 58 (2021): 1320 - 1338.

Liu, Yukun, Aleh Tsyvinski, Xi Wu, Common Risk Factors in Cryptocurrency, Journal of Finance, Volume 77, issue 2, April 2022, pages 1133-1177.

Park, Andreas, A 2022 Primer for Crypto-Trading (June 28, 2022). Available at SSRN: https://ssrn.com/abstract=414 or http://dx.doi.org/10.2139/ssrn.4148717

Percival, D., & Walden, A. (2000). Wavelet Methods for Time Series Analysis (Cambridge Series in Statistical and Probabilistic Mathematics). Cambridge: Cambridge University Press. doi:10.1017/CBO9780511841040

Platanakis, Emmanouil, and Andrew Urquhart. "Should investors include bitcoin in their portfolios? A portfolio theory approach." The British accounting review 52, no. 4 (2020): 100837.

Qin, Kaihua, Liyi Zhou, Benjamin Livshits and Arthur Gervais. "Attacking the DeFi Ecosystem with Flash Loans for Fun and Profit." Financial Cryptography (2021).

Qin, Kaihua, Liyi Zhou, Yaroslav Afonin, Ludovico Lazzaretti and Arthur Gervais. "CeFi vs. DeFi - Comparing Centralized to Decentralized Finance." ArXiv abs/2106.08157 (2021).

Qin, Kaihua, Liyi Zhou and Arthur Gervais. "Quantifying Blockchain Extractable Value: How dark is the forest?" 2022 IEEE Symposium on Security and Privacy (SP) (2022): 198-214.

R. S. Bucy and P. D. Joseph, "Filtering for Stochastic Processing with Applications to Guidance." Providence, RI: AMS Chelsea Publishing, 2nd ed., 2005.

Package: fPortfolio Title: Rmetrics - Portfolio Selection and Optimization Date: 2017-11-12 Version: 3042.83.1 Author: Diethelm Wuertz [aut], Tobias Setz [cre], Yohan Chalabi [ctb], William Chen [ctb]

Shiller, Robert. 2019. Narrative economics: How Stories Go Viral & Drive Major Economic Events. Princeton University Press, Princeton, N.J.)

Smales, Lee A., Bitcoin as a Safe Haven: Is It Even Worth Considering? (June 28, 2018). Finance Research Letters, Vol. 30, 2019, Available at SSRN: https://ssrn.com/abstract=3204237 or http://dx.doi.org/10.2139/ssrn.3204237

Package: stochvol Title: Efficient Bayesian Inference for Stochastic Volatility (SV) Models Version: 3.2.0 Authors@R: c(person("Darjus", "Hosszejni", role = c("aut", "cre"), email = "darjus.hosszejni@wu.ac.at", comment = c(ORCID = "0000-0002-3803-691X")), person("Gregor", "Kastner", role = c("aut"), email = "gregor.kastner@aau.at", comment = c(ORCID = "0000-0002-8237-8271")))

Weintraub, Ben, Christof Ferreira Torres, Cristina Nita-Rotaru and Radu State. "A Flash(bot) in the Pan: Measuring Maximal Extractable Value in Private Pools." ArXiv abs/2206.04185 (2022): n. pag.

Wharton Research Data Services. "WRDS" wrds.wharton.upenn.edu, accessed 2021-07-08.

7 Appendix

7.1 Creating the Market Portfolio

The market portfolio is a value weighted average of simple daily returns for the following asset classes:

- Equity: The CRSP portfolio of all equities for NYSE, NASDAQ and AMEX. Returns are from the Kenneth French website, and the market value is from WRDS. The estimated market value as of Dec. 2021 is $45T.

- Bonds: Bloomberg Barclays U.S. Aggregate Bond Index - measures the investment grade U.S. taxable bond market including, Treasuries, corporate bonds, MBS, ABS, CMBS. Estimated market value as of Dec 2021 $25.5T.

- Gold: The Gold Fixing Price 3:00 P.M. (London time) in London Bullion Market, based in U.S. Dollar from the FRED database. The quantity is the total known ETF holdings of gold.from Bloomberg (ETFGTOTL). The Dec. 2021 market value is $203B.

Table 9 shows the weights for start and end dates of the analysis.

	Jan-13	**Dec-21**
Equity	53.05%	66.3%
Bonds	46.56%	34.4%
Gold	0.39%	0.26%

Table 9: Portfolio Weights by Asset Class

7.2 Model Parameters

The remaining model parameters are in Tables 10 to 14

	mean	**sd**	**median**	**HPD 2.50%**	**HPD 97.50%**	**ESS**
tau2_Intercept	0.121	0.336	0.008	0.000	0.637	1776
tau2_addr	0.000	0.002	0.000	0.000	0.000	8000
tau2_baa10y	0.004	0.043	0.000	0.000	0.002	2608
tau2_ted	0.000	0.016	0.000	0.000	0.000	8000
tau2_gold	0.000	0.001	0.000	0.000	0.000	5400
tau2_oil	0.000	0.000	0.000	0.000	0.000	3395
tau2_vix	0.000	0.018	0.000	0.000	0.000	4452
tau2_gvix	0.000	0.013	0.000	0.000	0.000	4086
tau2_t210	0.113	0.310	0.006	0.000	0.617	1482
tau2_QQQ	0.001	0.029	0.000	0.000	0.000	2510
tau2_TEU	0.000	0.002	0.000	0.000	0.000	8000
tau2_diseaseun	0.000	0.003	0.000	0.000	0.000	8000
tau2_gtrends	0.001	0.028	0.000	0.000	0.000	1931

Table 10: Parameters for TVP Model with Shrinkage

	mean	sd	median	HPD 2.50%	HPD 97.50%	ESS
xi2_Intercept	0.115	0.305	0.006	0.000	0.638	897
xi2_addr	0.000	0.008	0.000	0.000	0.000	2295
xi2_baa10y	0.078	0.248	0.002	0.000	0.421	1283
xi2_ted	0.005	0.065	0.000	0.000	0.002	1012
xi2_gold	0.000	0.001	0.000	0.000	0.000	8000
xi2_oil	0.000	0.001	0.000	0.000	0.000	8000
xi2_vix	0.014	0.105	0.000	0.000	0.033	2722
xi2_gvix	0.012	0.081	0.000	0.000	0.032	2042
xi2_t210	0.159	0.375	0.015	0.000	0.824	1165
xi2_QQQ	0.000	0.008	0.000	0.000	0.000	3962
xi2_TEU	0.000	0.005	0.000	0.000	0.000	8000
xi2_diseaseun	0.000	0.010	0.000	0.000	0.000	2092
xi2_gtrends	0.012	0.095	0.000	0.000	0.033	1551

Table 11: Parameters for TVP Model with Shrinkage

	mean	sd	median	HPD 2.50%	HPD 97.50%	ESS
lambda2_Intercept	0.280	0.513	0.068	0.000	1.280	3978
lambda2_addr	0.395	0.630	0.142	0.000	1.622	7343
lambda2_baa10y	0.391	0.613	0.143	0.000	1.592	7137
lambda2_ted	0.397	0.625	0.147	0.000	1.641	7270
lambda2_gold	0.389	0.615	0.143	0.000	1.636	7585
lambda2_oil	0.400	0.625	0.148	0.000	1.633	7114
lambda2_vix	0.402	0.638	0.142	0.000	1.690	7383
lambda2_gvix	0.408	0.657	0.142	0.000	1.710	7248
lambda2_t210	0.288	0.515	0.077	0.000	1.320	4636
lambda2_QQQ	0.400	0.662	0.136	0.000	1.676	7442
lambda2_TEU	0.409	0.653	0.143	0.000	1.710	7393
lambda2_diseaseun	0.404	0.632	0.150	0.000	1.648	7190
lambda2_gtrends	0.391	0.635	0.138	0.000	1.638	7510

Table 12: Parameters for TVP Model with Shrinkage

	mean	sd	median	HPD 2.50%	HPD 97.50%	ESS
kappa2_Intercept	0.309	0.551	0.085	0.000	1.379	4343
kappa2_addr	0.426	0.658	0.161	0.000	1.752	7047
kappa2_baa10y	0.338	0.562	0.105	0.000	1.481	4906
kappa2_ted	0.424	0.656	0.162	0.000	1.793	6640
kappa2_gold	0.415	0.648	0.155	0.000	1.706	7405
kappa2_oil	0.435	0.659	0.166	0.000	1.761	7409
kappa2_vix	0.411	0.638	0.156	0.000	1.687	7596
kappa2_gvix	0.410	0.643	0.156	0.000	1.694	7577
kappa2_t210	0.267	0.517	0.060	0.000	1.250	2935
kappa2_QQQ	0.408	0.635	0.154	0.000	1.674	7168
kappa2_TEU	0.415	0.636	0.164	0.000	1.723	8117
kappa2_diseaseun	0.430	0.673	0.158	0.000	1.801	7550
kappa2_gtrends	0.406	0.640	0.144	0.000	1.741	8000

Table 13: Parameters for TVP Model with Shrinkage

	mean	**sd**	**median**	**HPD 2.50%**	**HPD 97.50%**	**ESS**
a_xi	0.053	0.026	0.047	0.017	0.106	63
c_xi	0.372	0.072	0.382	0.226	0.486	2156
a_tau	0.024	0.015	0.021	0.006	0.054	24
c_tau	0.377	0.07	0.387	0.241	0.491	2855
kappa2_B	340224.5	6321014.002	1231.542	0	257438.6	1697
lambda2_B	1252.425	27448.787	2.951	0	478.92	1589
sv_mu	-1.001	0.975	-0.985	-3.078	0.858	26
sv_phi	0.994	0.002	0.994	0.989	0.999	172

Table 14: Parameters for TVP Model with Shrinkage