THE COVID SHOCK, THE RISE OF DEFI, AND BITCOIN'S INCREASING MARKET RISK

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ABSTRACT

This paper aims to determine whether Bitcoin's market risk increased in response to the COVID-19 shock. Our analysis employs familiar asset pricing models used by investment managers. Our main result is that Bitcoin's market risk increased after the lockdown in March 2020. Wavelet analysis that captures both time and scale changes is introduced, and risk estimates that allow for both time and scale changes are provided, consistent with our main finding. From the standpoint of traditional investments, we find that the market risk of a Bitcoin investment after March 2020 is similar to that of a risky tech stock.

KEYWORDS

Blockchain, Bitcoin, DeFi, Ethereum, Wrapped Bitcoin, CAPM, Fama/French

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 from 2014-2021. 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 throughout 2021. We explain 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. Without 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 Bitcoin's 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 apparent.

Another change was the growth of Defi (decentralized finance) with applications on the Ethereum blockchain for the wrapped version of Bitcoin. Using 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. We view the expanding

Bibhu Dash et al: NLPAI, IOTBC -2024
pp. 107-124, 2024. IJCI – 2024 DOI:10.5121/ijci.2024.130208

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 the growth in Bitcoin addresses measures network effects. We find through applying a state space model that it does not. We conclude that the expanding scope of Bitcoin's activities on different blockchains increased its non-diversifiable risk. At the same time, 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. [19] 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 as a safe - haven does not stand up to the liquidity stresses of the Covid shock. 2) The expansion of Bitcoin's use 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-19 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 a state-space model 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. Section 3 summarizes the key findings from the voluminous research literature on the statistical properties of Bitcoin's 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. Section 5 estimates Bitcoin's beta for the CAPM one-factor model, the Fama-French-Carhart four-factor and the Fama-French five-factor model. We also provide a wavelet analysis of the relationship between Bitcoin returns and the larger market. Section 6 considers whether macroeconomic fundamentals can explain the change in Bitcoin's beta over time. The last section contains concluding comments.

2. BACKGROUND LITERATURE

The topic of Bitcoin's returns and risks over different periods has received considerable research attention. Huang et al. [16] include the pre- and post-Covid-19 periods to examine cryptocurrencies' diversification benefits. They define categories or classes of cryptocurrencies based on the properties of the blockchain, such as the specific consensus protocol 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 is performed. However, their paper differs from ours in two major ways. They use weekly returns from Nov. 14th, 2020, to Dec. 25th, 2020, to capture the post-Covid period. The classes of cryptocurrency they construct effectively eliminate the correlated risk of using Bitcoin across blockchains that serve as a source of aggregate risk in our analysis. Brauneis and Mestel [5] 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. They employ Markowitz's mean-variance framework for long-only portfolios. The performance of cryptocurrency portfolios is 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 and Moro [17] 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. They find Bitcoin's high returns compensate for its high volatility to generate improvements in portfolio performance. The period is pre-Covid and misses the launch of Defi with the associated opportunities for expanding Bitcoin's scope across blockchains. Liu et al. [19] explain the cross-section of cryptocurrency returns and find three factors, market, size, and momentum are important. They consider cryptocurrencies with a market value greater than one million dollars for 2014- 2018. They focus on the cryptocurrency universe to find similarities with empirical asset pricing model results for traditional equities. They also identify nine factors that create long-short trading strategies with excess returns. They ended their analysis before the Covid shock and did not consider a broader portfolio context that included traditional assets to estimate the risk characteristics of crypto assets. Conlon et al. [11] examine the role of Bitcoin as a safe haven during the Covid-19 bear market. They address 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 to 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. [25] discuss other issues that make Bitcoin ill-suited to serve as a safe haven asset, such as its volatility, less liquidity, and transaction costs. This research cautions against viewing Bitcoin as a safe haven before the Covid-19 pandemic.

An issue affecting the security of investments in Bitcoin that plays an important role in 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. [9] 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 and pump-and-dump schemes using cryptocurrencies have been used to steal millions of dollars, halt services, and harm productivity. Chen et al. [10] examine phishing attacks on the blockchain directed at cryptocurrencies. They cite a Chainalysis report that since 2017, more than 50% of revenue from cybercrime has come from phishing scams. They focus on the Ethereum blockchain and offer technical approaches that can warn users of scams. Bartoletti et al. [3] 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. Weintraub et al. [30] 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. [24] discuss the rise of opportunistic trades in Defi.

Qin et al [23] 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 at a penalty exchange rate. They discuss mixer services and their rewards to users. The rewards incentivize contributions to mixer servers that help with money laundering. Qin et al. [22] investigate the dangers of flash loans. Caldarelli [7] researched wrapped tokens and found that as of September 2021, 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 [13] addresses how interconnected cryptocurrencies are and finds a high correlation among cryptocurrencies from Jan. 1, 2018, to May 10, 2021. Bitcoin is one of the most interconnected in terms of spillover 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 focuses on Bitcoin as an investment where its risk is estimated by beta, which measures the sensitivity of Bitcoin's returns to market movements. We construct a broadly based market portfolio as a value-weighted average of equities, bonds, and gold returns. 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 NYSE, NASDAQ, and AMEX stocks.

Table 1: Data Series Used in the Analysis

Bitcoin	Daily prices from Glassnode
Gold	Gold Fixing Price 10:30 A.M. (London time) in London Bullion Market
Bonds	Bloomberg Barclays Aggregate Bond Index
Equity	Kenneth French Data Library includes all NYSE, AMEX, and NASDAQ firms
Mkt	Market portfolio value-weighted index comprised of equities, bonds, and gold

The price of Bitcoin rose dramatically during the sample period. It was $13.17 on Jan 02, 2013, and peaked for the 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. (Figure 1.) The period that followed coincided with a dramatic increase in the amount of activity in Decentralized Finance (Defi). (Figure 2.)

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 has 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. All returns are calculated as simple returns.

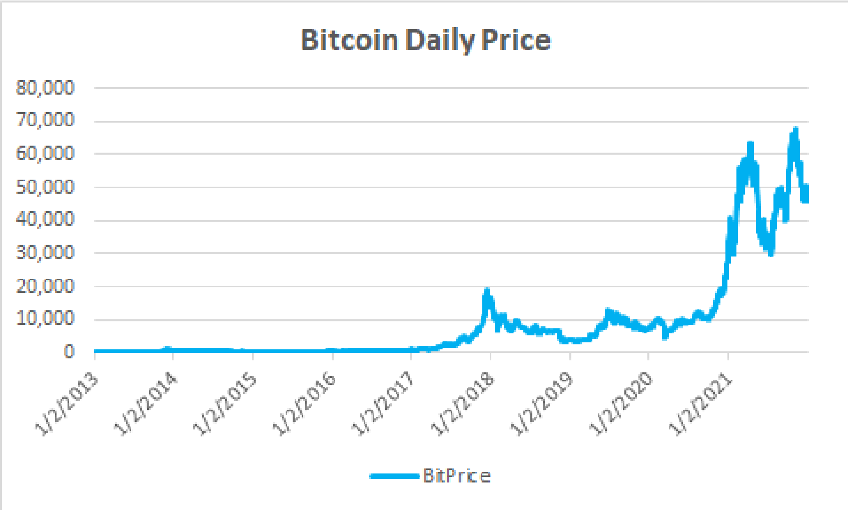

Figure 1: Bitcoin Daily Prices, Jan.02,2013-Dec.31,2021

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

	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

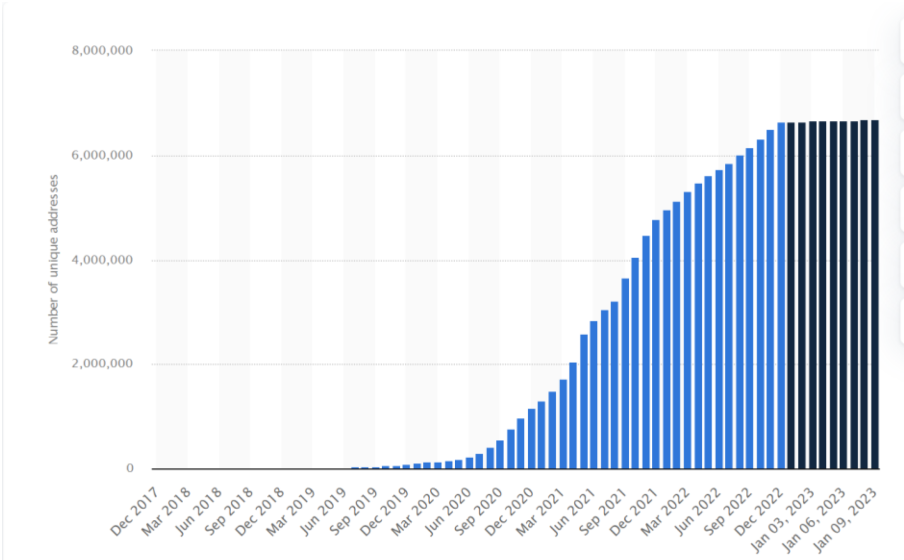

Figure 2: Unique Addresses that bought or sold a decentralized finance asset worldwide. Source: Statistica

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 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 (grey dashed line, right-hand side axis) for the sample period.

The single factor beta (Figure 3, right-side) varies considerably over time. The beta estimates were not significantly different from zero for most of the estimation period before the COVID-19 shock. 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 was found in 2018 when it spiked at 3, and the t-statistic remained at about 2. This year is associated with increasing scrutiny of Initial Coin Offerings (ICOs) by the SEC following enforcement activity in 2017. This suggests that increasing regulatory scrutiny is risky for Bitcoin as an investment. The increased 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 its 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 beta estimates coincides with the announcement of a worldwide pandemic and the rapid rise of decentralized finance (DeFi). The expansion of Bitcoin to use 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, creating 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 indicate pure alpha (i.e., return without risk). This is unlikely to be 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 crackdown on ICOs was in 2018, and 2020 is the year of the Covid lockdown and the expansion of Bitcoin's services to other blockchains. We hypothesize that the returns captured by the intercept for those three years compensate for the additional risk traditional asset pricing models do 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.

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.

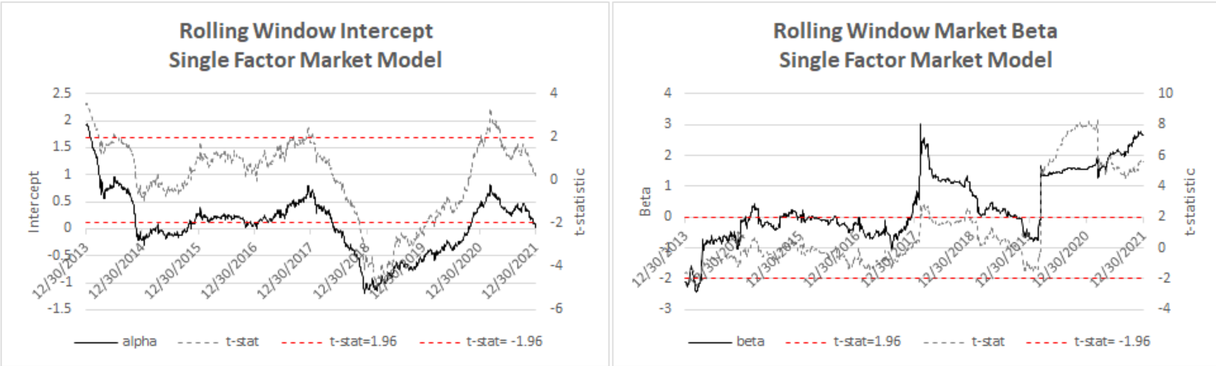

Figure 3: Single Factor Model, Rolling Window Beta of Bitcoin

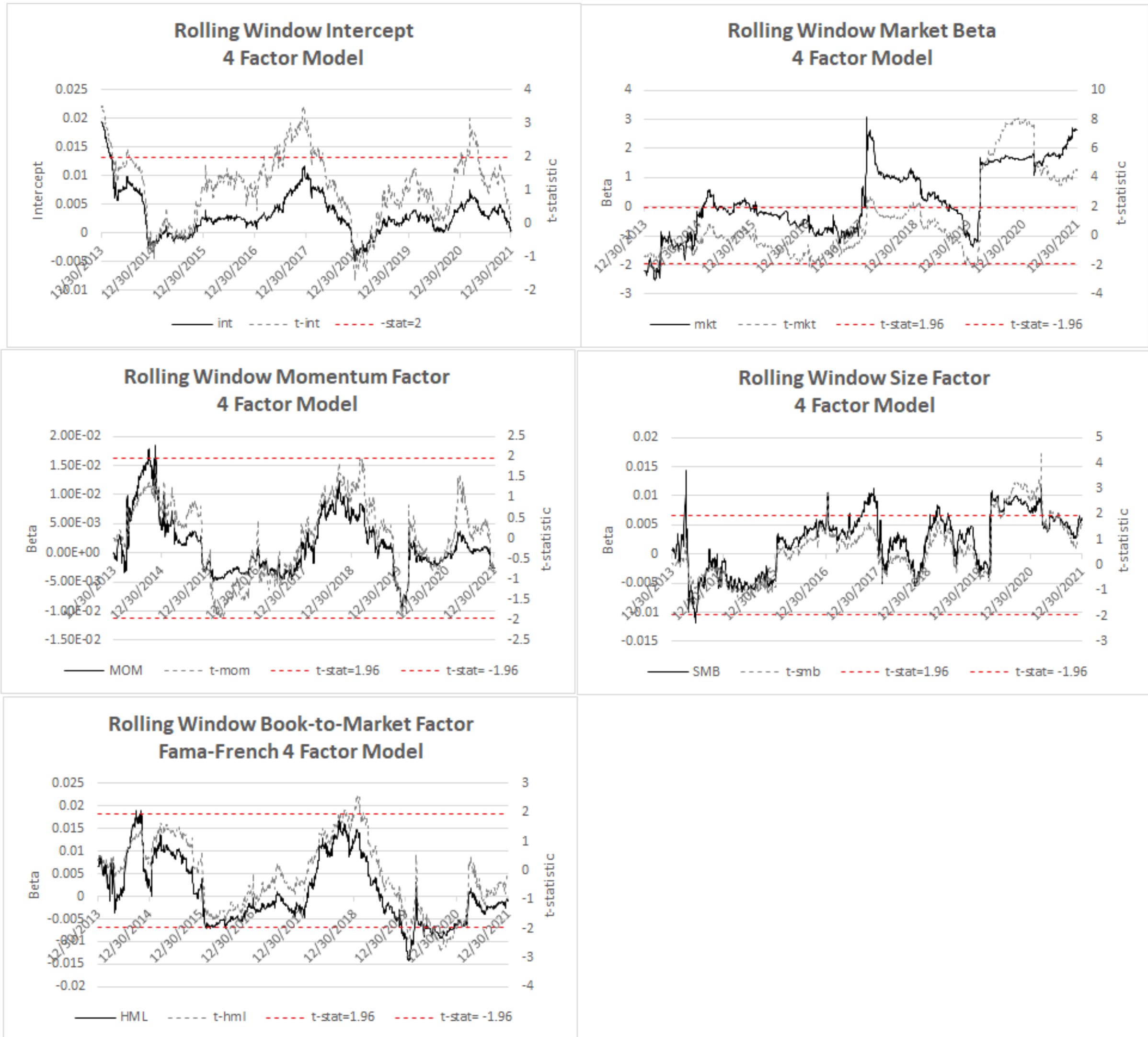

Figure 4: Four Factor Model, Rolling Window Beta of Bitcoin

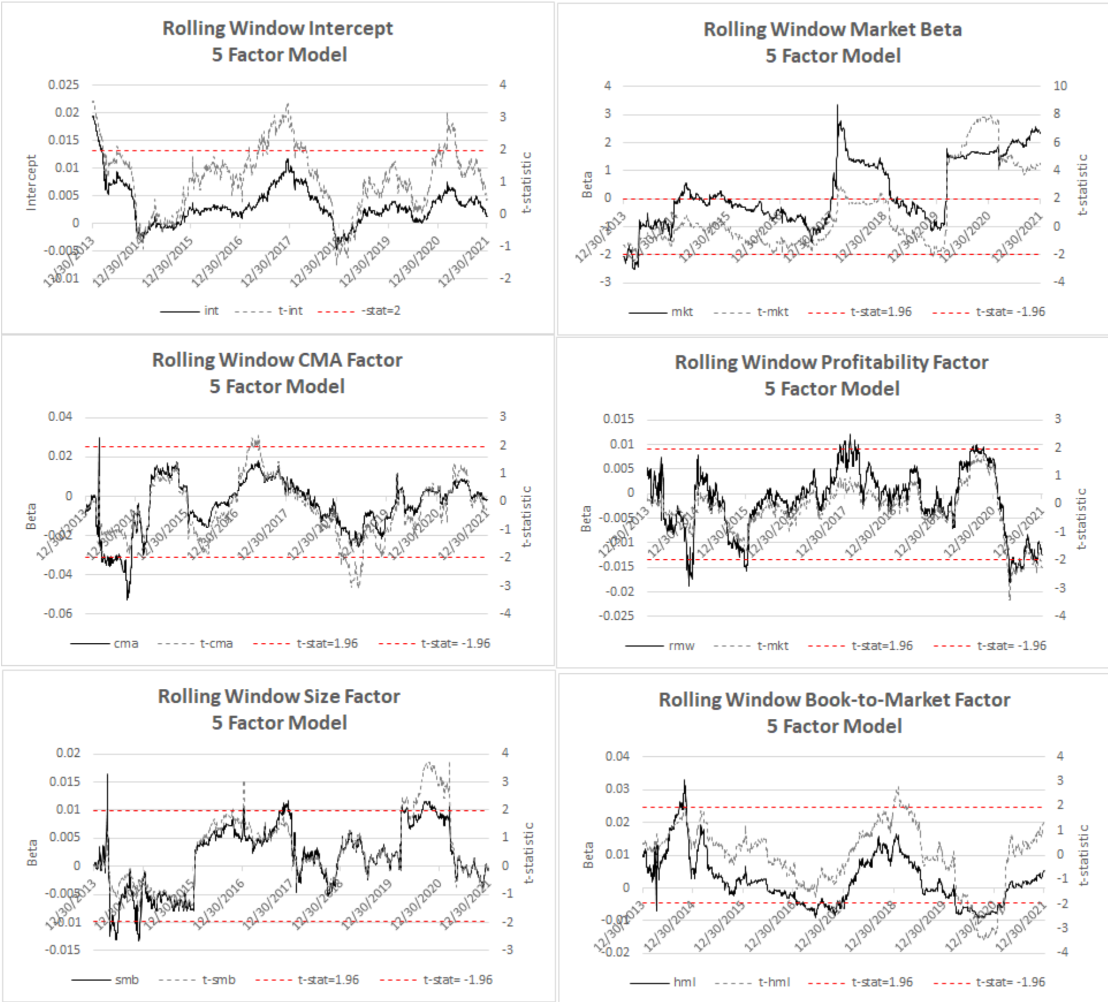

Figure 5: Five Factor Model, Rolling Window Beta of Bitcoin

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 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 to July 2019, when 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,

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

where robust and weak refer to profitability.

The profit factor captures the possibility that companies reporting higher future earnings have higher returns. The significant negative sign when the model is applied to bitcoin, and 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-19 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.

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 data dynamics 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. Research also finds that the relationship between portfolio return and risk is stronger as the scale increases. In this section, we explore whether the weak market

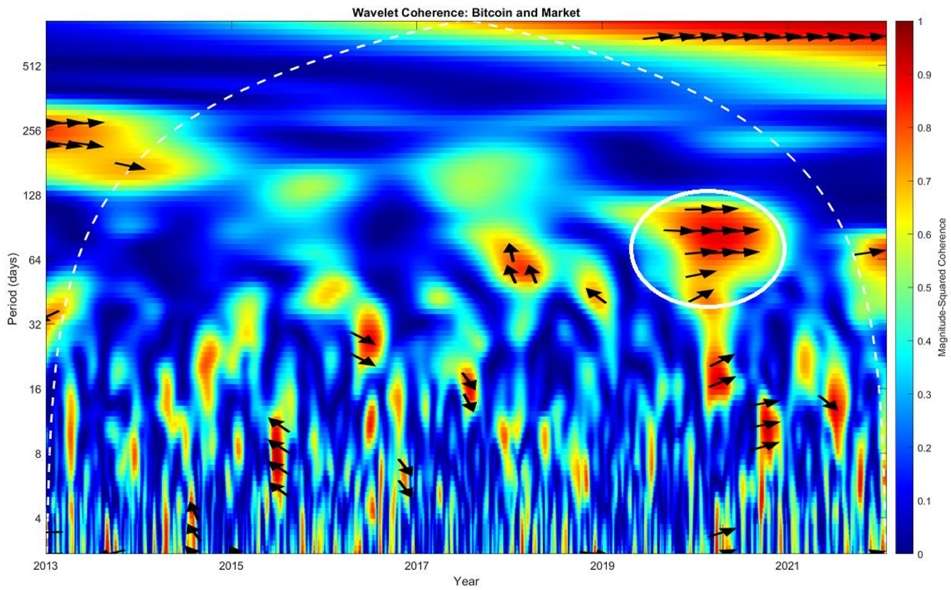

Figure 6: Wavelet Coherence: Bitcoin and the Market Portfolio

connection for Bitcoin found before 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 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 localized in time-scale space. Figure 6 contains the coherence for Bitcoin and the market portfolio. The vertical axis measures the scale in days, and the horizon axis is the time in days. Red areas indicate that the coherence is high. In areas where the coherence exceeds 0.7, the plot contains phase arrows that indicate the phase lag of the market portfolio for 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 the dotted white line, or the cone of influence, is typically disregarded as there is insufficient information for the wavelet to describe that area properly. 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 are 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 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 revealed sporadic high coherence at high frequencies with periods of high coherence at low frequencies.

A more formal analysis of the relationship between Bitcoin and the market portfolio is found by employing the discrete wavelet transform (DWT), 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. We are applying the DWT to a time series x(t), which 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:

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

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 greater detail.

Daily data decomposes the series into seven scales (d1-d7) corresponding 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 beta estimate 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 a scale of 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 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. Before 2020 beta for scales, d1-d4 betas tend to be insignificant except in mid-2018. Scale 5 has a much longer stretch of significance before 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, this offers evidence that the rapid growth of defi created opportunities for Bitcoin that were a source of aggregate risk reflected in beta estimates.

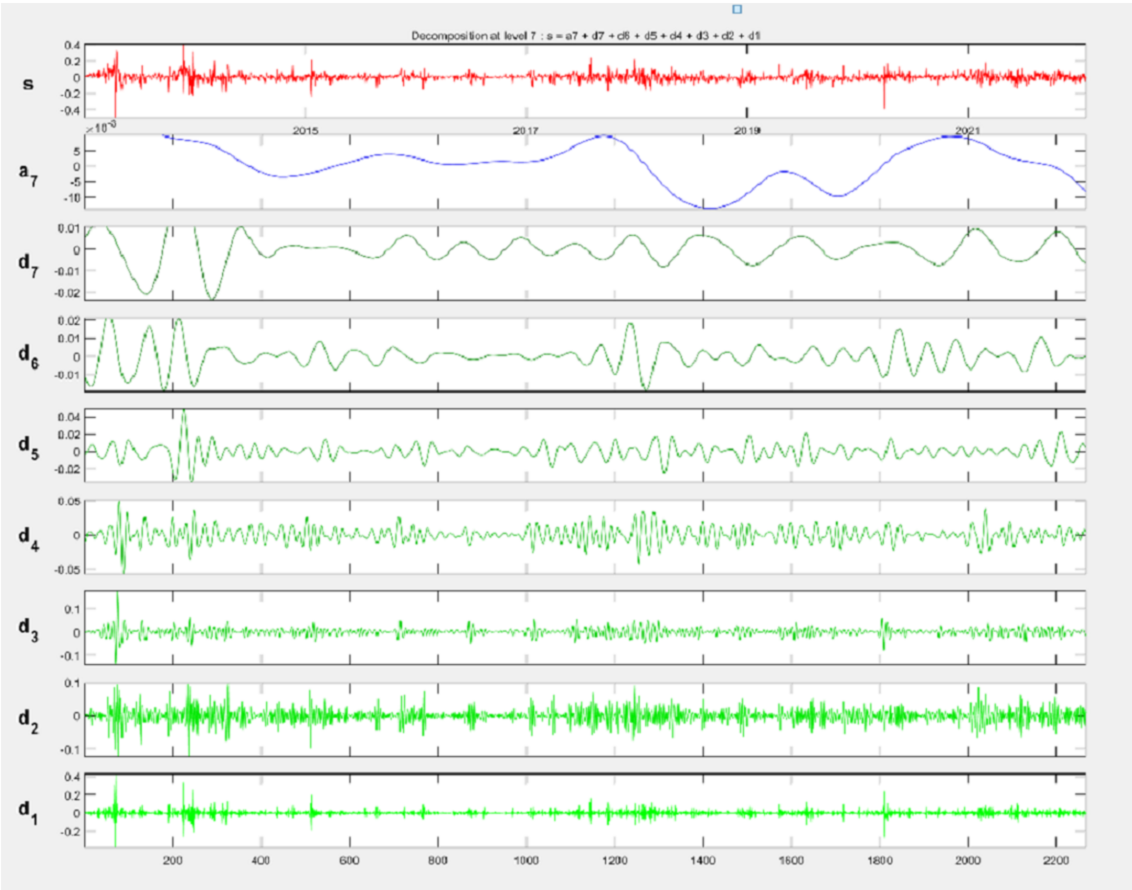

Figure 7: Bitcoin Returns - Discrete Wavelet Transform

Table 3: Scale Betas for Bitcoin

Scale	Beta	t-Stat	R-Sq	Nobs
All	0.909	5.47	0.0126	2265
d1	0.941	5.94	0.015	2258
d2	0.65	3.68	0.0055	2244
d3	0.613	3.6	0.0054	2216
d4	0.958	5.3	0.0124	2160
d5	1.027	6.35	0.0188	2048
d6	2.662	17.3	0.1405	1824
d6	0.828	4.27	0.0124	1376

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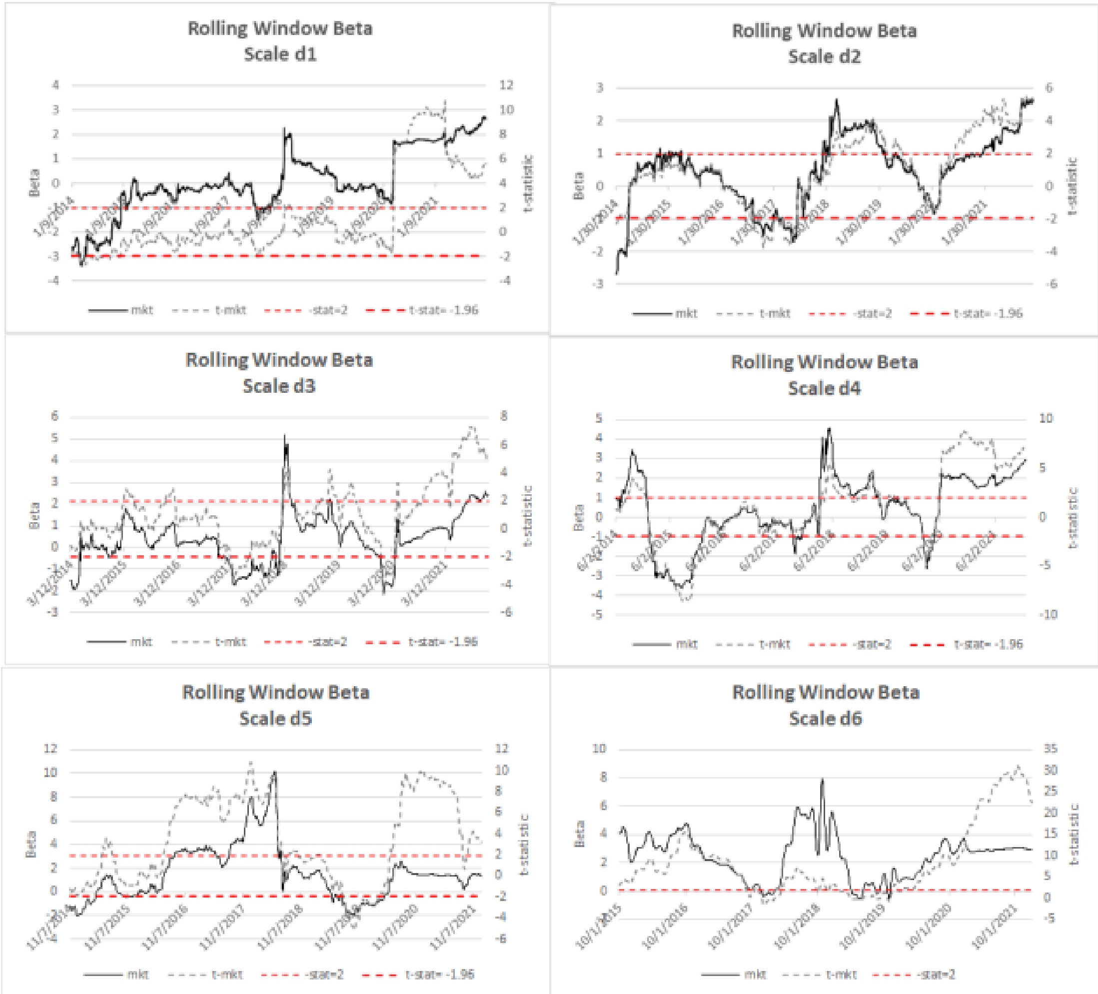

Figure 8: Bitcoin Beta - Scales d1 to d6

Scale 5 has a much longer stretch of significance before 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 was statistically significant. Again, this offers evidence that the rapid growth of defi created opportunities for Bitcoin that were a source of aggregate risk reflected in beta estimates.

The wavelet analysis indicates that there has always been a systematic relationship between Bitcoin and the market portfolio at a 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 priced Bitcoin as a high-risk tech-like asset. We explain 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 one model specification to evaluate whether macroeconomic fundamentals explain changes in Bitcoin's beta.

We apply the model of Cadonna et al. [6] 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 [15], Bitto and Frühwirth-Schnatter [4], and Cadonna et al. [5]. 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 equation (3) is the state equation and (4) is the measurement equation. The variance-covariance matrix of the state equation is diagonal with elements q_i.

Using the non-centered parameterization introduced by Frühwirth-Schnatter and Wagner [15] 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~(dxd) identity matrix. This reparameterization, equivalent to the original specification, places all the model parameters in the measure equation and splits the state vector into fixed and time-varying components. The time-varying component follows a random walk and is scaled by its standard deviation. In instances where the variance of the time-varying component, $\tilde{\beta}_{jt} = 0$, the coefficient will be fixed and may be zero. The purpose of this specification is to aid in the prevention of overfitting.

The model specifies a hierarchical Normal-Gamma-Gamma prior for elements in the state vector β. The prior of each element of the state vector has a unique variance t^2_j. The variance of t_j^2 shares a common variance, c^t/l^2_B. This specification allows for shrinkage of the non-time-varying component of the state equation.

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

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

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

The prior for *q* has a hierarchical triple gamma, a general specification encompassing many different types of existing priors, including the lasso and horseshoe. See Section 2.4 of Cadonna et al. [6] for a thorough discussion of the priors encompassed by this specification.

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

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

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

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 stochastic volatility model with the log volatility, h_t following an AR(1) process:

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

Where m is the long-term mean, and f is the rate of reversion to the mean.
Model estimation was done using the R package, “shrinkTVP” [28]. 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 relates to economic variables or uncertainty. Bitcoin addresses were included to capture network growth.

Table 4: Variables Used to Evaluate Beta Drivers

Name	Description
addr	Bitcoin addresses (daily change)
ted	TED spread
gold	Daily return of gold
oil	Daily return of oil
vix	Volatility of the S
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'

Estimates of β_j and θ are shown in Tables 5 and 6, respectively. The model was estimated using 50,000 iterations, with a burn-in of 10,000 and thinning of 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 significant time-invariant parameters

Table 5: State Parameters

Variable	**Mean**	**SD**	**Median**	**2.50%**	**97.50%**	**ESS**
Intercept	-1.005	0.246	-1.006	-1.530	-0.548	142
addr	0.000	0.000	0.000	0.000	0.000	319
baa10y	0.003	0.051	0.000	-0.102	0.081	168
ted	0.000	0.001	0.000	0.000	0.000	389
gold	0.000	0.000	0.000	0.000	0.000	35
oil	0.000	0.000	0.000	0.000	0.000	26
vix	0.000	0.002	0.000	-0.003	0.003	547
gvix	0.000	0.003	0.000	-0.003	0.005	354
t210	-0.814	0.192	-0.812	-1.182	-0.426	158
QQQ	0.000	0.001	0.000	-0.001	0.001	6
TEU	0.000	0.000	0.000	0.000	0.000	348
diseaseun	0.000	0.000	0.000	0.000	0.000	103
gtrends	0.000	0.003	0.000	-0.004	0.003	483

are the intercept and t210. Variables with significant time variation include the intercept, baa10y, and t210. Time plots of the parameters are shown in Figures 9 and 10. 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 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 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.

Table 6: Scale Parameters, θ_j

Variable	Mean	SD	Median	2.50%	97.50%	ESS
abs(Intercept)	0.021	0.001	0.021	0.019	0.023	416
abs(addr)	0.000	0.000	0.000	0.000	0.000	12
abs(baa10y)	0.012	0.002	0.012	0.008	0.016	165
abs(ted)	0.000	0.000	0.000	0.000	0.001	6
abs(gold)	0.000	0.000	0.000	0.000	0.000	29
abs(oil)	0.000	0.000	0.000	0.000	0.000	59
abs(vix)	0.001	0.001	0.001	0.000	0.003	9
abs(gvix)	0.001	0.000	0.001	0.000	0.001	21
abs(t210)	0.044	0.002	0.044	0.039	0.048	369
abs(QQQ)	0.000	0.000	0.000	0.000	0.000	11
abs(TEU)	0.000	0.000	0.000	0.000	0.000	67
abs(diseaseun)	0.000	0.000	0.000	0.000	0.000	13
abs(gtrends)	0.001	0.001	0.000	0.000	0.002	13

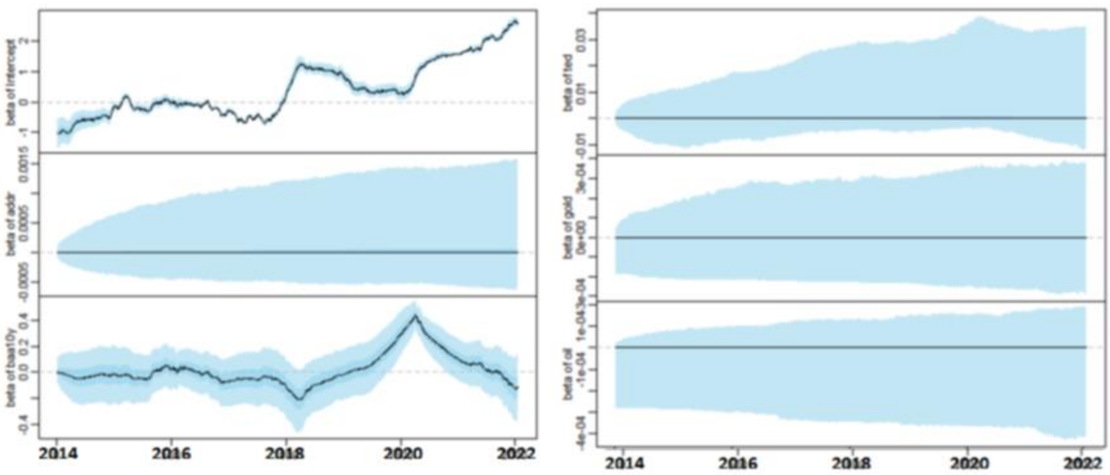

Figure 9: Time series of State Variables

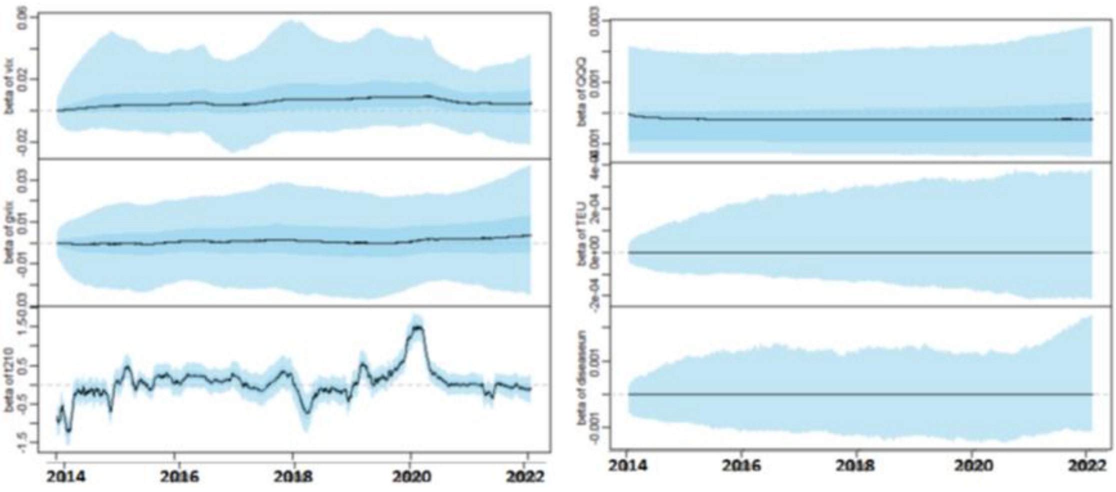

Figure 10: Time series of State Variables

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 Bitcoin is not a safe or uncorrelated asset in times of stress. The change in Bitcoin addresses appears to have had no impact on the beta over time.

6. CONCLUDING COMMENTS

Our paper aimed to discover whether Bitcoin's market risk increased in response to the COVID-19 shock. Based on estimates of Bitcoin's beta, our main result is that its market risk did increase. We offer estimates of beta after the Covid shock that are consistent with the presence 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 consequently, Bitcoin began to look in terms of its Beta risk like that of a risky tech stock. However, the positive and significant intercepts in 2014, 2018, and 2020 suggest that the familiar framework of the CAPM and Fama/French models may not be up to the job of aggregating all the relevant risk factors for Bitcoin that investors care about. However, traditional asset pricing models remain the only game in town for estimating market risk. Until different models are developed to estimate the market risk of Bitcoin, our main conclusion remains intact. Applying traditional Asset Pricing models to Bitcoin results in significant risk estimates after the Covid panic of March 2020.

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