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Multiscale Effects of Macroeconomic News on the Dynamic Correlations between Bitcoin and the US Stock Markets

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Abstract

This study investigates how the rhythm of fourteen major US macroeconomic surprises resonates within the bitcoin–stock multiscale dynamic correlations. To do so, we use the Maximum overlap discrete wavelet transform to decompose the daily bitcoin and DJIA return series. The next step in the analysis involves generating the multiscale correlation series from the ADCC-GARCH model. We find that the influence of macro surprises on these correlations unfolds elegantly across distinct economic dimensions and across the market states. That is, most of real-activity indicators such as industrial production, durable goods, and business inventories bind bitcoin more closely to equities in the medium investment horizon during the COVID-19 pandemic, as growth signals ignite synchronized optimism. In contrast, Inflation and policy news (CPI and Fed announcements) amplify this comovement over longer horizons, reflecting shared repricing of risk premia and the chance for other variables to drive the correlations. These results remain the same after replacing the DJIA with the S&P500 and controlling for time-trends, bitcoin volume and the global policy uncertainty. The results bring important implications for both investors and policymakers that bitcoin no longer remains in isolation and its comovmenet with traditional assets must be determined by the macroeconomic surprises and the market state.

Keywords: Macroeconomic surprises; Bitcoin; Stock market; Dynamic Correlation; Wavelet.

JEL: C58, D89, E00, G12, G15.

1. Introduction

Macroeconomic news has been shown to play a significant role in understanding the dynamics and performance of stock markets (Birz and Lott Jr., 2011; Caporale et al., 2016; Ekinci et al., 2019; Hsu et al., 2021), bond markets (Beetsma et al., 2013; Caporale et al., 2018; Consoli et al., 2021; Xing et al., 2024), foreign exchange markets (Evans and Lyons, 2008; Omrane and Savaser, 2016; Cheung et al., 2019; Yamada and Ito, 2022), and commodities markets (Roache and Rossi, 2010; Bakas and Triantafyllou, 2019; Cai et al., 2020; Fernandez-Perez and Lopez, 2023). The theoretical foundation of this importance is primarily described by behavioral finance, which augments the standard model of market efficiency by considering macroeconomic variables as influential factors in asset pricing (Chen et al., 1986; Caporale et al., 2016). Specifically, the efficient market hypothesis suggests that asset prices should reflect all available information and should only react to the arrival of new information which in turn affects expectations about future economic activity (Fama, 1965; 1970). Indeed, investors among other market participants constantly monitor the real-time data flow of news content and make predictions for almost every macroeconomic release, where asset prices tend to move significantly in response to news affecting cash flows, discount rates, and risk premia.

Moreover, cryptocurrencies have emerged as one of the most significant financial innovations of the 21st century. With its increasing popularity along with the wide mainstream media coverage, more than 50 million investors trade different cryptocurrencies on more than 790 trading forums worldwide. As of August 2024, the total market capitalization of cryptocurrencies is estimated at $2.1 trillion, with Bitcoin representing around 55% of crypto dominance.[1] There is now a large

[1] The price of Bitcoin, the most widely recognized crypto, has soared since 2009 climbing from a few cents up to $59,000 by the end August 2024 increasing its total market value to $1.16 trillion (https://coinmarketcap.com/).

body of literature that has examined the predictability and dynamics of the cryptocurrency market, focusing on market efficiency (Urquhart, 2016; Chu et al., 2019; Kakinaka and Umeno, 2022; Okorie et al., 2024), herding behavior (Kaiser and Stockl, 2020; Yarovaya et al., 2021), volatility and long memory behavior (Yi et al., 2018; Katsiampa et al., 2019; Fang et al., 2020; Assaf et al., 2022; Hansen et al., 2024). As pointed out by Corbet et al., (2020), since cryptocurrency markets are relatively new financial markets, they can be highly affected by macroeconomic news since they draw considerable attention from investors as means of information. Therefore, the returns of these highly speculative assets can be influenced by macroeconomic news because of changes in investors' expectations about future economic policy (Corbet et al., 2021). Also, since cryptocurrencies are highly speculative virtual assets, it is assumed that the effect of news announcements on cryptocurrencies may be different from other more efficient and mature markets.[2] Due to possible inefficiency in cryptocurrency markets, they can be quite isolated from traditional assets in terms of shock transmission (Ji et al., 2018; Kurka, 2019) and can possibly demonstrate a weaker response to macroeconomic news announcements as compared to traditional assets and currencies (Vidal-Tomas and Ibanez, 2018; Pyo and Lee, 2020).

The aim of this paper is to investigate the impact of macroeconomic surprises on the dynamic correlation between Bitcoin and the US stock market at various time-scales and across market states (i.e. pre-Covid-19 and post-Coivd-19 periods) In doing so, we emphasis more on the possible role of the Bitcoin market and how it can be a rational market during economic downturns. Doing

[2] For example, Corbet et al. (2020) documented an increase in Bitcoin returns in response to positive unemployment and durable goods announcements. Rognone et al. (2020) found that positive and negative news increase Bitcoin returns, suggesting investor enthusiasm for Bitcoin regardless of the sentiment of the news.

that will also enable us to examine the speed of reaction from traditional-digital asset correlation to the real economic information at the macro level.

This paper is organized as follows. Next section reviews the related literature. Sections 3 and 4 describes the data and methodological approaches. Section 5 describes the empirical results while in Section 6 we perform some robustness checks before summarizing and concluding in Section 7.

2. Literature review

Understanding the correlation dynamics among different asset classes has been a subject of interest for scholars, policy makers and market participants for many years, as it carries important implications for hedging strategies, asset allocation and portfolio management. As the two most fundamental asset classes of investment, the nature of the stock and bond correlation has dominated academic research on cross-asset behavior (see for example, Connolly et al., 2005; Kim and In, 2007; Li and Zou, 2008; Yang et al., 2009; Garcia and Tsafack, 2011; Alsanidis and Christiansen, 2012; Chiang et al., 2015; Asgharian et al., 2016; Skintzi, 2019; Allard et al., 2020; Alomari et al., 2021; Li et al., 2022; Sarwar, 2023). The time-variant stock-bond correlation has mainly been linked to changes in economic fundamentals, market conditions, investor and news sentiments.[3] Further, cryptocurrency research continues to gain sustained interest in the finance literature (Cagli, 2019; Chafeddine and Maouchi, 2019; Celeste et al., 2020; Tiwari et al., 2020; Hardle et al., 2020; Hafner, 2020; Mensi et al., 2021; Sockin et al., 2022; Hackethal et al., 2022; Wang et al., 2022).

[3] It is well-documented that the volatility of different asset classes can vary widely within a business cycle but remain relatively stable over longer horizons. The correlation between stocks and bonds can be persistent with the same sign for extended periods, before eventually reversing. Molenaar et al. (2024) shows that the average correlation between stocks and bonds in the US was 0.35 between 1970 and 1999 and reversed to -0.29 between 2000 and 2023.

One stream of this research focuses on the correlation dynamics between cryptocurrencies and stock markets to uncover the potential diversification benefits. For example, Dyhrberg (2016) employs the generalized autoregressive conditional heteroskedasticity (GARCH) model to show that Bitcoin can be used as a hedge against stock movement in the Financial Times Stock Exchange (FTSE) Index over the period 2010-2015. Klein et al. (2018) use the BEKK-GARCH model to explore the dynamic correlations between Bitcoin, gold, and equity markets (proxied by S&P500 and the MSCI World and MSCI EM50 index). They find an asymmetric response for Bitcoin returns to market shocks between 2011 and 2017 and conclude that Bitcoin does hold hedging properties as compared to gold. Chan et al. (2019) employ Pairwise GARCH models to show that Bitcoin can hedge and diversify risk against the Euro-Stoxx, Nikkei, Shanghai A-Share, S&P 500, and the TSX Index over the period 2010-2017. They document that holding Bitcoin for longer intervals (monthly intervals) provides stronger hedging benefits for investors as compared to shorter intervals (daily and weekly). Tiwari et al. (2019) investigates the time-varying correlations between six cryptocurrencies (Bitcoin, Ripple, Dash, Stellar, Litecoin, Ethereum) and the S&P 500 index using a copula-ADCC-EGARCH model. They report low time-varying correlations between 2015 and 2018 indicating that cryptocurrencies serve as a hedge asset against the risk of S&P 500, with Litecoin being the most effective cryptocurrency. Mokni et al. (2020) employ the DCC-EGARCH model and confirm that Bitcoin is a strong hedge against S&P 500 over the period 2014-2020. They also show that the economic policy uncertainty (EPU) index exerts a negative (positive) impact on the hedging ratio during low (high) uncertainty levels, particularly after the Bitcoin crash of 2017. Mensi et al. (2020) study the co-movements between Bitcoin and the Dow Jones World Stock Market Index, regional Islamic stock markets, and Sukuk markets between 2010 and 2018. Using the cross-wavelet transformation approach, they point out that the benefits

of portfolio diversification with Bitcoin vary across time and frequencies, with the co-movements in the opposite direction being stronger at high frequencies.

Through employing the wavelet coherency approach, Bouri et al. (2020) explore the safe-haven properties of Bitcoin, gold, and commodities against global and country stock market indices between 2010 and 2018. They document weak overall dependence between the assets and stock markets at various time scales, particularly for Bitcoin. Using the same approach, Caferra and Vidal-Tomas (2021) find no evidence of a relationship between cryptocurrencies (Bitcoin and Ethereum) and stock market indices (S&P500 and Euro Stoxx 50) during the first six months of the Covid-19 pandemic, supporting the diversification and hedging properties of cryptocurrencies. Ahmed (2021) examines the sensitivity of stock prices to volatility dynamics of Bitcoin over the period 2012-2019 using the quantile regression framework. Results show that during bear (bull) market regimes, S&P-developed and emerging Broad Market Indices (BMI) respond positively (negatively) to Bitcoin's realized variance, and that downside realized semi-variance has a greater impact on market returns compared to its upside counterpart across both regimes. Goodell and Goutte (2021) employ wavelet coherence and neural network analyses to investigate the role of COVID-19 on the correlation of four cryptocurrencies (Bitcoin, Ethereum, Tether, Litecoin), with seven equity indices (S&P 500, FTSE 100, Euro-Stoxx 50, CBOE VIX, Swiss Index, IBEX 35, DAX, CAC 40). They show that co-movements between cryptocurrencies and equity indices gradually increased as COVID-19 progressed. These co-movements were shown to be either moderately positive or minimal, suggesting cryptocurrencies in general do not provide a diversification benefit during downturns.

Maghyereh and Abdoh (2021) employ a quantile cross-spectral (QS) dependance approach and document a right-tail (high return) dependence between Bitcoin and stock markets between 2011

and 2019, particularly over longer investment horizons. They also document a unidirectional causality from Bitcoin to the MSCI World Index and the US market. Finally, Melki and Nefzi (2022) examine the hedging properties of Bitcoin, Ripple, and Ethereum against the stock, commodity, and foreign exchange markets using a logistic smooth transition regression model (LSTR2). They show that between 2011 and 2020, cryptocurrencies are positively correlated with MSCI World but can be considered safe-haven assets against FX markets, and with Ethereum providing the strongest hedging function for the commodity market during the pandemic.

Our study contributes to existing literature in different ways. Firstly, it becomes the first attempt in the finance literature to examine the impacts of macroeconomic surprises on the dynamic correlations between the Bitcoin and traditional assets. Secondly, this research provides better insights how the stock-bitcoin portfolio diversification benefits may vary across the time-scales following the arrival of the macroeconomic surprises into the markets. Thirdly, our research employs large macro variables that belong to different economic categories. Doing so, is expected to help investors in stock and bitcoin markets in assessing their needs for portfolio rebalancing when different pieces of economic information are taken into consideration. To say it differently, various types of macro information will behave as different solvers for uncertainty and stock-bitcoin portfolio may need continuous rebalancing accordingly. Lastly, this study examines the effects of the macroeconomic surprises at various market states namely the pre- and post-covid-19 periods.

3. Data description

This study employs a set of fourteen macroeconomic news and daily closing prices of the Bitcoin and US stock markets data over the period from August 6, 2010, to June 10, 2023. The former group of data are collected from different US databases namely Bureau of Labor Statistics (BLS),

Bureau of the Census (BC), Federal Reserve Board (FRB), Bureau of Labor Statistics (BLS), Bureau of Economic Analysis (BEA), Bureau of the Census (BC) and Institute of Supply Management (ISM). We collected the closing prices data of the bitcoin from Coinbase database over the sample period of the study while the US closing prices of DJIA 100 index is collected from Datastream. The sole cryptocurrency utilized in our research is Bitcoin since its data is the most easily accessible when compared to other cryptocurrencies. The bitcoin data is accessible every day, including weekends and holidays. We first convert prices to returns by taking the difference between log values in two consecutive days. The data pre-preparation stage then proceeds by leaving only the returns of the bitcoin and stock when they match in specific date with the days of macroeconomic announcement. This matching is also made in Balduzzi et al. (2001) among others for each macroeconomic news at a time. The non-announcement days without macroeconomic news data are excluded from the sample. We use the Eastern Standard time approach for all the macroeconomic variables in the study.

Table 1 shows the descriptive statistics for the variables in sample. The macroeconomic surprise series for a given macroecomic news is calculated for each economic variable *k* using the approach of Balduzzi et al. (2001) such as:

$$u_{k,t} = (Ak,t - Ek,t)/\sigma t \quad (1)$$

Where Ak,t is the monthly actual value obtained from the reporting agency mentioned Table 1, Ek,t the corresponding median expectation as collected from Bloomberg database and σt is the standard deviation of the unexpected component of *k*th economic variable.

Two primary factors lead to the selection of the macroeconomic indicators listed in the table. First, these variables fall into a number of economic categories, including employment (unemployment rate), industrial activity (including the Chicago purchasing manager index (PMI), industrial

production, and business inventory), investment (orders for durable goods), consumption (retail sales and consumer credit), housing (new single-family sales), government trade balance (exports of goods), inflation (CPI, PPI and Fed rate), income (average hourly earnings), and the forward-looking measures (consumer confidence)[4]. Second, there is some missing data in the expected values of other unselected macroeconomic variables, and this is particularly noticeable at the start of the sample period.

4. Methodology

4.1 Wavelet multiscale analysis

This research employs wavelet multiscale decomposition approach to uncover different time-scales of disparity in the dataset. This approach as proved in the finance and economics literature offers a distinctive decomposition of time-series data since it allows for disentangling the different effects of different variables at various consecutive time horizons (Gallegati and Ramsey, 2013; Alomari et al., 2021).

To start, the approach starts by introducing the function $f(t) \in L^2(R)$ into the wavelet analysis to generate a sequence of projections of mother and father wavelets from ϕ and ψ with the scaling and translation such as:

$$\phi_{j,k}(t) = \frac{1}{2^{j/2}} \phi\left(\frac{t-2^j k}{2^j}\right) \quad (1)$$

and

$$\psi_{j,k}(t) = \frac{1}{2^{j/2}} \psi\left(\frac{t-2^j k}{2^j}\right) \quad (2)$$

[4] The same classification is also used by Kurov et al. (2019) thought their study comprises more variables and excludes the COVID-19 period.

Where j and k are the scale and translation indexes respectively. 2^j is the size of the scale or the width of functions $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$, where the larger index j must generate the larger the scale 2^j implying that the function is getting shorter and more spread out. The translation factor $2^j k$ is then matched to 2^j in that as the functions $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ get wider, the corresponding translation steps become larger.

We employ the Maximum Overlap Discrete Wavelet transform (Hereafter, MODWT) in our analysis to decompose both the Bitcoin and US stock market returns. This approach has an advantage over its counterparts such as discrete wavelet analysis since it allows for multiscale analysis without reducing the number of observations in each time scale. In other words, there is no down-sampling at each stage when the decomposition is performed. Therefore, our analysis can ensure that there is redundancy in information at each scale and each scale represents a source of new information that cannot be found in the previous timescale. More specifically, our decomposition approach starts with deploying a pair of mother and father wavelets within a linear combination through a high-pass and low-pass filters. Using the former filter, the return series R_n for the number of observations n can be decomposed into sub-intervals to produce the approximation series A which capture the events that are long in time and infrequently occur with regard to the frequency. On the other hand, other complementing components namely detailed components D_j that are short in time and high in frequency. The overall process to generate both components can be described as follows:

$$V_{i,t} = \phi A_n + \sum_{j=1}^{n} \Psi D_j \tag{3}$$

During the decomposition process we follow Percival and Walden (2000) and deploy the asymmetric Daubechies filter with the length of 8 (Hereafter, D8) since it can capture more hidden

features in such a volatile time series data. Besides, we carefully decide on the number of timescales and 6 scales are found enough to preserve the variance of the Bitcoin and the US market returns series. The time scales are defined as follows: Time-scale 1 characterizes the range [2-4] days, scale 2 reflects the range [4-8] days, time-scale 3 is for [8-16] days, horizon 4= [16-32] days, while horizons 5 and 6 represent the deposition at the ranges of [32-64] and [64-128] days respectively.

Following Maghyereh et al. (2019), the frequency part is categorized into two investment horizons as follows; short-term and intermediate horizons [2–32 days] to represent a period of approximately one month and comprises time scales 1,2, 3 and 4. Longer horizon of [32–128 days] belongs to scales time-horizons 5 and 6.

4.2 The estimation of the decomposed dynamic conditional correlations

Research on dynamic interlinkages between assets usually uses dynamic conditional correlation (DCC) GARCH model of Engle (2002). The model is initially developed to avoid the short-comes of the constant conditional correlation (CCC) model of Bollerslev (1990) by allowing for the correlation pattern to vary and not static over the examination period.[5] An extension to the DCC model is further made by Cappiello et al. (2006) to allow for the asymmetric impact of surprises on the dynamic correlation. Their model is then called ADCC-GARCH to denote the asymmetric dynamic conditional correlation GARCH. Examining the current conditional correlation between several financial time series is a suitable use for this model. Additionally, it incorporates historical conditional volatilities and correlations into the estimating process. Additionally, when compared

[5] A systematic review on the applications of the multivariate GACRH extensions can be found in Silvennoinen and Teräsvirta (2009).

to other multivariate GARCH models, such the copula-based DCC-GARCH model, the ADCC estimators' applicability is comparable to that of less sophisticated univariate GARCH models.

The estimation of the ADCC model works toward extracting the dynamic correlations between two variables in several steps. To begin, the return series from two series (i.e. Bitcoin and US stock price in our case) can be generated given that $r_i \mid \Omega_{t-1,} \sim N(0, H_t)$, where i= 1, 2,...,n, and Ω_{t-1} is the pieces of available information at time *t-1*. The second stage of analysis involves inserting returns into a GARCH model or any of it is univariate extensions. Our research employs the threshold GARCH model of Glosten et al. (1993) since it allows for the asymmetric response from the daily returns to the macroeconomic surprises.

The model is denoted by GJR-GARCH and can be written as follows:

$$h_t^2 = \omega + \sum_{i=1}^{p} \alpha \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \gamma \varepsilon_{t-i}^2 I_{t-i} + \beta h_{t-1}^2 \qquad (4)$$

Where $I_t[\cdot]$ is an indicator with the value of one when the lagged surprise is negative (ε_{t-1}<0) and zero otherwise.

The model assumes that the surprise of negative shock on the volatility as measured by ($\alpha + \gamma$) is economically stronger relative to the positives shock which in turn has to be estimated by α only. The asymmetry in the model this has to be captured by γ, with negative (positive) news having a larger influence on variation when γ>0 (γ<0). Additionally, the lags orders of p and q are basically selected based on the AIC information criteria and set to one for both the stock and the Bitcoin returns estimations. Lastly, the standardized residuals $\varepsilon_{i,t}$ are assumed to be normally and *iid* distributed.[6] Next estimation steps then involve using the extracted conditional

[6] We note that the distribution assumption does not leave a statistical influence on the estimation of the conditional variance equation. Also, using alternative distribution assumption to found to produce qualitatively and quantitatively similar estimation for the correlations from the ADCC model.

volatility,$h_t^{1/2}$ and the error term,$\varepsilon_{i,t}$ before establishing the conditional covariance matrix such as:

$$D_t P_t D_t \tag{5}$$

Where, D_t represents for the ($n \times n$) diagonal matrix of time-varying volatility from Threshold GARCH model on a i^{th} diagonal. $D_t$equals the $diag\{h_t^{1/2}\}$ for the given return series. Moreover, P_t denotes the created conditional correlation matrix from the standardized residuals and can be further described as follows:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{6}$$

Herein, $Q_t^*= \{diag[Q_t]\}^{-1}$ characterizes the diagonal matrix with the main components of Q_t, the conditional covariance matrix of the vector ε_t originates in the i^{th} diagonal amongst the stock and Bitcoin return series. The conditional covariance matrix can be specified by q_{ijt} and the conditional dynamic correlation $\rho_{ij,t}$ characterizes diagonal entries which has to be estimated such as $\rho_{ij,t}= q_{ij,t} /q_{ii,t}^{1/2} q_{jj,t}^{1/2}$.

The estimation the model can proceed by accounting for the expected asymmetry in the effect of the past news shocks on the resulted covariance between the two assets under consideration where:

$$Q_t = (\bar{P} - A'\bar{P}A - B'\bar{P}B - G'\bar{N}G) + A'\varepsilon_{t-1}\varepsilon_{t-1}'A + G'\xi_{t-1}\xi_{t-1}'G + B'Q_{t-1}B \tag{7}$$

In this equation, A, B and G show the parameter matrices and the latter term captures the asymmetric influence as given by, $\xi_{t-1} = I[\varepsilon_t < 0] o\varepsilon_t$. In this step, $I[\cdot]$ is initially considered $k\times 1$ indicator function that has the value 1 if the argument is true and 0 otherwise, while $_o$ represents the element-by-element Hadamard product function. The remaining terms in the equation namely

$\bar{P}$ and $\bar{N}$ are associated with the expectations and are replaced with their sample analogous, such as $\bar{N} = \frac{1}{T}\sum_{t=1}^{T} n_t n_t'$ and the same is true for $\bar{P}$.

The development being reached in equation 7 is then considered by Cappiello et al. (2006) the asymmetric generalized AG-DCC extension of the DCC-GARCH model. This study employs the diagonal version of ADCC model, where the matrices *A*, *B*, and *G* are substituted by their diagonal inputs *a*, *b* and *g* and the model then is described by[7]:

$$Q_t = (i\bar{P}i' - a\bar{P}a' - b\bar{P}b' - g\bar{N}g') + a\varepsilon_{t-1}\varepsilon_{t-1}'a' + g\xi_{t-1}\xi_{t-1}'g' + bQ_{t-1}b' \quad (8)$$

Here *i*is the vector of ones and to get a positive definite value of Q_t for all observations *t*, the coefficient term $(i\bar{P}i' - a\bar{P}a' - b\bar{P}b' - g\bar{N}g')$ must be positive semi definite.

4.3 the Baseline and extended linear regression analyses

Our baseline analysis investigates the influence of each macroeconomic surprise on the subsequent multiscale correlation. An additional lagged correlation on the same timescale of the depended variable is also included in the model to absorb any possible persistence in the correlation such as[8]:

$$\rho SB_{j,t+1} = \alpha_t + \beta 1 U_t + \beta 2 \rho SB_{j,t-1} + e_{t+1} \quad (9)$$

Where $\rho SB_{j,t+1}$ is the one day ahead multiscale dynamic correlation between the stock market return and the Bitcoin returns at scale j. U_t is the macro surprise variable with its observations being matched with the correlation series on the announcement's days only. $\rho SB_{j,t-1}$ is the lagged correlation variable at that same timescale.

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[7] The diagonal version here assumes that the stock –Bitcoin correlation can differ across different stock markets.

[8] We also tried to control for up to five-trading lagged days and the results of our main interest. That is, results of our main interest in terms of the reported significant effects of the macroeconomic surprises in Table 2 remain qualitatively and quantitatively the same.

Following the structure in the macro-news literature across equities (Campbell et al., 2020; Alomari et al., 2021; Duffee, 2023; Metiu, 2025), the second stage of regression analysis involves investigating the time varying effects of macroeconomic surprises on the subsequent multi-scale correlation. In doing so, we use interaction terms along with other predictors as follows:

$$\rho SB_{j,t+1} = \beta 1 D_t + \beta 2(1 - D_t) + \beta 3 D_t U_t + \beta 4(1 - D_t)\, U_t + \beta 5 U^2{}_{j,t} + \beta 6 \rho SB_{j,t-1} + e_{t+1} \quad (10)$$

Where D_t is a dummy variable equals to 1 during the Covid-19 starting from January 19^{th,} 2020, and onwards just immediately when the first case has been diagnosed in the US. Zero dummy is given for the remaining sample period before that date and represents the pre-Covid-19 period. Herein, $D_t U_t$ represents the impact of the surprise during the Covid-19 period and $(1 - D_t)\, U_t$ shows the effect in the pre-pandemic stage. Two more predictors' variables are also used in the analysis namely the squared surprise value and the lagged correlation variable again. Controlling for the squared surprise in the equation also for examining whether the magnitude of the surprise matter in formulating the subsequent correlation series is more than a sign of the surprise. In other words, investors who combine between the stock and Bitcoin in their portfolios might care more about how surprises capture salience whereby large releases may cause excess correlation. Estimating across the effect of surprise across the timescales isolates whether such macro news primarily becomes a significant driver for resulting liquidity from the short-horizon trading or a repricing motive following the long-horizon co-movement. In all these models, we use the HAC/Newey–West standard errors where the lag in the test is decided based on the AIC information criteria. We also use the Wald test in Equation 10 to examine the null hypothesis that there is no statistical difference between the effects of macroeconomic news in the pre- and post-Covid periods (i.e. $\beta 2 = \beta 3$). For the ease of results interpretations, the estimations in equations 9 and 10 are used to represent Models 1 and 2.

5. Empirical results

To begin with, Table 1 reports the main descriptive statistics of the macroeconomic surprises and their associated computed correlation series. Specifically, the mean and the standard deviation are calculated for the variables after matching each macro news data at a time with the correlation series. Herein, we notice that the variables belong to labor market namely the average hourly earnings, and the unemployment rate has the lowest negative mean values while the consumer credit and the export of goods have the largest mean values.

We also observe from the table that correlation series matched with the exports (consumer confidence) has the largest (smallest) mean. Surprisingly, standard deviations of the correlations become the highest (lowest) when the exports (consumer confidence) are considered in the analysis. A rational explanation for this noticeable emphasis on these two variables can be explained by the empirically document finding that export data often accounts for broad changes in global demand and trade policy, producing larger, more erratic joint responses across markets (Narayan et al., 2022). By contrast, consumer-confidence surprises are typically marginal revisions to expectations, generating smaller, more stable responses.

Figures 1 below plots the average of the correlation series again one day before macro announcement, on the announcement (event day) and one day after. It shows these graphical representations over the full sample, pre-covid-19 and post-covid-19 periods. The general observation in the figure shows that the average correlation is time-varying, yet they tend to be the lowest negative in the post-covid period when consumer credit is used. Another possibility for portfolio diversification resulting from the negative correlation is also documented in the post-covid period with the PMI. This negative evidence can again be noticed one day before the export announcement in the post-covid period. More interestingly, both exports and consumer credit are

becoming more able to be directly associated with the largest negative correlations over the full sample period with all events windows.

Next, Figure 2 depicts the distribution of the produced matched correlations with each macro news at six timescales. Noticeably, the average Bitcoin–stock (BTC–DJIA) correlation is low but time-varying, oscillating between weakly positive and negative across short-term and medium-term horizons, which visually confirms the stylized fact that Bitcoin offers limited but unstable diversification potential. This distribution is clearly leptokurtic, indicating fat-tailed behavior and reflecting strong reactions to macroeconomic releases and systemic events. The standard deviations of both correlation and macro-surprise variables are high, remarkably for inflation and industrial-activity surprises, suggesting volatile joint responses across asset classes. The figures further demonstrate that correlation peaks coincide with major U.S. macro announcements, such as CPI and PMI releases, while troughs appear around episodes of monetary tightening or financial stress—visibly during the COVID-19 outbreak—implying that macro news shocks and global uncertainty jointly shape the BTC–stock linkage. More surprisingly, the multiscale estimations in Figure 2 show that the correlations are clearly becoming negative in a time horizon of less than on month (i.e. scale 4: 16-32) days. That is always true without any exception when either of the macro news is used as a main driver of the correlation[9]. However, the most negative correlation evidence is found in the export-based analysis.

[Insert Table 1 about here]

[Insert Figure 1 about here]

[Insert Figure 2 about here]

[9] Using one macro surprise at a time as a single event in the analyses is something previously done in the literature (See, for example, Balduzzi et al. 2001).

Table 5 below reports the estimates of the ADCC GARCH model at six time scales. It can be noticed that all the parameters in all panels are statistically significant. Comparing the estimates across the scales reveals that the value of α (ARCH effect) decreases and β (volatility persistence) increases as we move from scale 1 to scale 3. This pattern suddenly tends to reverse at the intermediate time scale (i.e. scale 4) with about a month of trading. The condition of ($\alpha + \beta < 1$) is met for analysis conducted at all investment horizons. Last, the table also shows that the log likelihood is the highest again at scale 4 confirming that this time horizon is the mid of the multiscaling process.

[Insert Table 2 about here]

Moving to the regression evidence, the baseline findings of model 1 in Table 3 shows that macro surprises have significant and horizon-dependent effects on BTC–stock correlation. In the short-term horizons with scales ranging from 1–3, covering up to 16 days, most real-activity and consumption indicators namely industrial production, PMI, durable goods orders, retail sales, and new-home sales—have positive and significant coefficients. That means favorable macro surprises harmonize optimism and trading behavior between Bitcoin and DJIA stock market and this, in turn is supposed to enhance the comovement in the same direction. Yet, this influence typically reverses at one-month horizon (i.e. scale 4), where coefficients often become negative, suggesting brief portfolio rebalancing and information digestion. This becomes in line with the preliminary documented negative correlation evidence at scale 4 in Figure 2. As we move to longer horizons 5 and 6, all macro variables, including inflation (CPI, PPI), policy rate (Fed funds), and employment measures (unemployment rate, AHE), exert strong positive impacts, implying that shared macro details dominate both markets in the medium-to-long run and systematically minimize diversification benefits.

Considering the adjusted R^2, we observe that the explained variation made by the predictor increases monotonically from around 0.30 in short horizons to above 0.55 at long horizons, evidencing that the explanatory power of macro surprises grows with time, consistent with macro-driven comovement documented by Duffee (2023) in traditional markets. However, this evidence is surprisingly becoming aligned with the less statistical impacts of the macro surprises at the long horizons. PMI here is the only exception since its effect is statistical at the time horizon 5. This overall evidence on the less effects of macro news at the long horizons triggers the need for controlling for other possible drivers of correlations.

Next the regime-specific and nonlinear effects are introduced in Table 4 and Model 2 is then estimated accordingly. We can see that the interaction term $\beta 3$ capturing the Covid-19 period and the squared-surprise term capturing magnitude asymmetry reveals new dynamics. Across most categories—industrial activity, income, consumption, housing, and sentiment—the $\beta 3$ coefficients are negative and significant, showing that reliance on the macroeconomic surprises by investors comprising Bitcoin and DJIA stock investments in their portfolio are weakened during the pandemic. To say it differently, investors considered Bitcoin more as an alternative or speculative asset than a macro-sensitive one. The reverse is however becoming true in the post-covid period, $\beta 4$ coefficients become negative and significant at longer investment horizons, particularly for inflation PMI and PPI while positive and significant at time scale 5 for unemployment and consumer confidence. investment-related news (durable goods, industrial production), signifying that large macro shocks—irrespective of sign—tighten correlation by jointly influencing discount-rate expectations and systemic risk premia. The Wald tests strongly reject equality of coefficients across regimes for most real-sector variables namely, statistically validating that the COVID crisis produced a

structural shift in correlation behavior. Moreover, the Adjusted R^2 rises further (0.58–0.65) once these nonlinear and regime effects are modeled. This, in turn, confirms that state dependence and shock magnitude substantially enhance explanatory precision. Economically, this means that Bitcoin's role as a hedge mainly depends on the timescale and specific macro-economic news arriving the market That is, it provides some short-run protection during extreme uncertainty periods. At the time investors are assumed to use the macroeconomic news as solvers for uncertainty and they will be rebalancing their Bitcoin-stock market portfolio accordingly. This duality mirrors the "time-varying dependence" found by Bouri et al. (2020) and Goodell & Goutte (2021), while challenging earlier findings that portrayed Bitcoin as a stable safe haven (Dyhrberg, 2016).

Finally, the robustness regressions in Table 5, which adds global policy uncertainty (GPU), Bitcoin trading volume, and a time trend, confirm the resilience of these results. Even after controlling for these additional channels, the core macro-news effects remain statistically significant with the same directional patterns: short-term positive comovement followed by mid-term relaxation and strong long-term tightening. The controls marginally raise the Adjusted R^2 by roughly 3–6 percentage points, emphasizing that although uncertainty and liquidity contribute, they do not fully account for the macro-driven co-movement. The Wald tests continue to reject the null of coefficient equality between pre- and post-COVID periods for industrial production, CPI, PPI, retail sales, and consumer confidence, reaffirming that regime-specific dynamics are persistent and statistically robust. Taken all results together, the statistical and graphical evidence converge on a coherent conclusion: macroeconomic surprises, the category they belong to and the prevailing market condition jointly formulate the Bitcoin–stock correlation structure. In calm periods, positive macro surprises cause Bitcoin to behave like a pro-cyclical risky investment, maximizing its

diversification advantage; during crisis regimes, sensitivity declines temporarily, allowing brief hedging benefits; but once large or extreme economic shock hits the markets, the correlation rises again as systemic factors come to the surface. The increasingly higher Adjusted R^2, significant $\beta 3$ and $\beta 4$ coefficients, and some Wald-test rejections across the two coefficients demonstrate both statistical and economic meaning of these findings—showing that Bitcoin's correlation with equities is nonlinear, state-dependent, and partially driven by the macroeconomic information concentration. This thereby makes the Bitcoin investment with various features that combine between those for speculative risk asset and a conditional safe haven investment.

[Insert Table 3 about here]

[Insert Table 4 about here]

6. Robustness Checks

6.1. Accounting for the global policy uncertainty, time trend and the Bitcoin volume

We examine the robustness of our main results by introducing three additional controls into Equation 10. These are namely, the log changes of the global policy uncertainty (Hereafter, GPU) of Davis (2016), a deterministic time trend, and the changes in the Bitcoin trading volume**.** The inclusion of (GPU) is motivated by empirical evidence of Nguyen (2022) where uncertainty at stress time periods is found to drive to stock-bitcoin correlations. Also, that macroeconomic announcements interact with uncertainty regimes, such that observed news effects may partly reflect broader shifts in risk sentiment (Baker et al., 2016). The time trend accounts for slow-moving structural variations in the Bitcoin–Stock nexus, including market evolution, participation by the institutional investors, and continuous updates on the stock market regulations, which could otherwise be confounded with news-driven short-run effects (See, for example, Dyhrberg, 2016).

Lastly, Bitcoin trading volume accounts for fluctuations in the Bictoin liquidity condition. This inclusion is also justified by the documented evidence in the market microstructure that intensified trading increases information absorption and volatility transmission in crypto markets (Baur & Dimpfl, 2018). Henceforth, by including these new predictors, the new model (hereafter, Model 3) can be described as follows:

$$\rho SB_{j,t+1} = \beta 1 D_t + \beta 2(1 - D_t) + \beta 3 D_t U_t + \beta 4(1 - D_t)\, U_t + \beta 5 U^2{}_{j,t} + \beta 6 \rho SB_{j,t-1} + \beta 7 Trend_{\mathrm{t}} + \beta 8 Bvol_{\mathrm{t}} + \beta 9 GPU_{\mathrm{t}} + e_{t+1} \quad (11)$$

Where *GPU* is the changes in the global policy uncertainty, $Bvol$ is the Bitcoin trading volume, and the Trend is the time trend over the full sample period. The model again allows to examine the stability of the previously obtained results from Equation 10 where macroeconomic surprises can still be considered genuine drivers of multiscale Bitcoin–stock nexus.

The results from the above-described analysis are reported in Table 5. Even after controlling these additional channels, the core macro-news effects remain statistically significant with the same directional patterns. The controls marginally maximize the Adjusted R^2 by roughly 3–6 percentage points, indicating that although uncertainty and liquidity contribute, they do not fully account for the macroeconomic-driven correlation. The analysis in this section continues to prove that the Wald test is still rejecting the null hypothesis of coefficient equality between pre- and post-COVID periods for industrial production, CPI, PPI, retail sales, and consumer confidence, reaffirming that regime-specific dynamics are persistent and statistically robust. Taken together, the statistical and graphical evidence converge on a coherent conclusion: macroeconomic surprises, their size, and the prevailing economic regime jointly govern the Bitcoin–stock correlation structure. The increasing pattern in the Adjusted R^2, significant β3 and β4 coefficients, and repeated Wald-test rejections demonstrate both statistical and economic significance of these findings—showing that Bitcoin's correlation with equities is nonlinear, state-dependent, and driven by the intensity of

macroeconomic information, thereby situating it between a speculative risk asset and a conditional safe haven.

Further secondary results also emerge from Table 5 and these can be summarized as follows. First, the squared macro news significantly affects the correlations in either of the first two short term scales in almost all the macro-based regressions. However, the only exception here is for consumer confidence where the impact persists up to the immediate horizons. The rational justification for this can be investors' responses to large positive and large negative surprises are not mirror images of each other only in the short-term horizons. Yet, investors at that time will try to discriminate between the effects of several macroeconomic surprises based on the categories they belong to and timing. The exception of consumer confidence, whose nonlinear influence extends to longer horizons, can be explained by the nature of this indicator. Consumer sentiment represents forward-looking forecasts that impact risk appetite, investment, and consumption decisions over multiple periods. Thus, shocks to confidence persist beyond the initial reaction window, gradually influencing how investors co-move across traditional and digital assets. Such direct evidence on this later argument can be the non-significant effect of fed rate which is one of the late news in the market. Besides, time trends tend to significantly drive the correlation at the long-time horizons in all regressions except those conducted with the average hourly earnings and unemployment rate. The insignificance of the time trend in the average hourly earnings and unemployment rate regressions likely can be attributed to the cyclical patterns in these two macro variables. Bitcoin trading volume variable is also significantly predicting the correlation series at the short-term horizons when either export or consumer credit series is considered in the analysis. Lastly, policy uncertainty coefficients appear only significant at the short and intermediate time scales in the CPI, consumer credit, fed rate, industrial production, PPI and retail sales.

[Insert Table 5 about here]

Overall, the results indicate that the impact of macroeconomic surprises on the Bitcoin–stock correlation is concentrated mainly in the short-term and medium horizons—specifically the first (2-4 days), second and third investment horizons (4–8 and 8–16 days)—rather than in the long horizons. This time-scale dependence suggests that markets require several days after an announcement to absorb new information, adjust expectations, and reprice risk assets. In the very short run (2–4 days), traders react immediately but often in a noise-driven or speculative manner, leading to unclear or inconsistent correlation effects. At longer investment horizons with more a month the impact of individual macro releases tends to fade as other global or structural factors dominate, explaining why coefficients and adjusted R^2 values decrease after the third scale. In essence, the second and third scales capture the core macro–financial transmission channel, when the informational content of surprises is fully digested and risk factors in both markets align—explaining why most of the statistically and economically meaningful effects cluster precisely in this mid-horizon range.

6.2. Alternative stock market index: S&P500 index

In an additional robustness check, a similar baseline analysis was conducted on the effect of macrocosmic news on the dynamic correlation between the S&P500 and Bitcoin returns. Results obtained remain qualitatively and quantitatively the same that the significant impacts of most macroeconomic surprises are centered on in the short and intermediate timescales. However, we documented some differences between the results in the documented analysis here with the DJIA and S&P500. Specifically, the average hourly earnings news in the later regressions are found to bring persistent significant impacts on the correlation up to scale 3. Consumer confidence is significate driving the correlation during the pandemic at scale 3 and not scale 1. Durable goods

are found to leave another significant and negative effect at the shortest timescale both during and outside pandemic periods and not only outside the pandemic. Retail sales lost its significant impact on the third time scale while remaining significant on the first timescale. However, these results were not reported here to save space but are available upon request from the authors.

7. Conclusion and implications

This study examines how macroeconomic news surprises influence the dynamic correlation between bitcoin and U.S. stock market (DJIA) using daily data over a multi-year period encompassing both pre- and post-COVID-19 regimes. The sample includes a comprehensive set of fourteen major U.S. macroeconomic news that reflect the variations in diverse areas of the US economy namely employment, industrial activity, investment, consumption, housing, government trade balance, inflation, income and the forward-looking. To capture the temporal heterogeneity in information assimilation, correlations were decomposed into six wavelet scales using maximum overlap discrete wavelet analysis with the produced scales ranging from 2-day to 128-day horizons. Doing this allowed us to do an in-depth examination of both short-term reactions and long-term structural interlinkage.

The empirical results demonstrate that macroeconomic fundamentals significantly drive the Bitcoin–stock relationship, with predictive power concentrated in the short-term horizons (4–8 and 8–16 days). These scales represent the period during which market participants process new information and rebalance portfolios in response to macroeconomic signals. The results show that bitcoin's comovement with equities is state-dependent and nonlinear—strengthening in response to positive real-sector and inflation surprises but weakening during episodes of uncertainty when coinciding with the COVID-19 pandemic.

During normal market states, favorable macro surprises—including stronger output, higher inventories, and increased retail activity and that in turns maximize the bitcoin–stock correlation by harmonizing investors' risk appetite across different types of assets (i.e. traditional and digital assets). The reverse is, however, true during periods of increased uncertainty where Bitcoin temporarily decouples from equities and partially regains its hedging capacity. However, nonlinear effects of squared macroeconomic surprises reveal that large or extreme shocks eventually re-tighten the link between bitcoin and equities at the short and intermediate timescales the time when investors collectively react to the magnitude of macroeconomic information. This asymmetric pattern proves that bitcoin has an evolving dual role. That is, speculative and a macroeconomic-sensitive asset that adapts dynamically to economic market state.

From a practical perspective, the results indicate that bitcoin's diversification potential is conditional, scale-specific, and transient. Investors seeking risk reduction should be aware that macroeconomic news—particularly within the 4–16-day horizon—can for the time being brings diversification benefits in their stock-bitcoin portfolios by increasing co-movement between crypto and equity markets. Portfolio managers could also exploit this predictable pattern by adjusting exposures before major macro releases or during periods of macro volatility. They can also examine the cross-sectional differences between different categories of economic variables. Policymakers and financial analysts on the other hand, may interpret these findings as evidence of bitcoin's increasing financial integration and macroeconomic responsiveness, suggesting that digital assets are no longer insulated from real-sector forces but have become active participants in global information transmission.

In essence, the results portray a financial system in transition. That is, bitcoin no longer moves in isolation and its comovements with the stock markets are driven by the macroeconomic variations.

of the economy. More specifically, the beauty of this dynamic lies in its macroeconomic asymmetry and market state dependence.

References:

1. Ahmed, W.M., 2021. Stock market reactions to upside and downside volatility of Bitcoin: A quantile analysis. *The North American Journal of Economics and Finance*, *57*, p.101379.
2. Allard, A.F., Iania, L. and Smedts, K., 2020. Stock-bond return correlations: Moving away from "one-frequency-fits-all" by extending the DCC-MIDAS approach. *International Review of Financial Analysis*, *71*, 101557.
3. Alomari, M., Al rababa'a, A.R., El-Nader, G. and Alkhataybeh, A., 2021. Who's behind the wheel? The role of social and media news in driving the stock–bond correlation. *Review of Quantitative Finance and Accounting*, *57*, 959-1007.
4. Asgharian, H., Christiansen, C. and Hou, A.J., 2016. Macro-finance determinants of the long-run stock–bond correlation: The DCC-MIDAS specification. *Journal of Financial Econometrics*, *14*, 617-642.
5. Aslanidis, N. and Christiansen, C., 2012. Smooth transition patterns in the realized stock–bond correlation. *Journal of Empirical Finance*, *19*, 454-464.
6. Assaf, A., Bhandari, A., Charif, H. and Demir, E., 2022. Multivariate long memory structure in the cryptocurrency markets: The impact of COVID-19. *International Review of Financial Analysis 82*, 102132.
7. Bakas, D. and Triantafyllou, A., 2019. Volatility forecasting in commodity markets using macro uncertainty. *Energy Economics*, *81*, 79-94.
8. Balduzzi, P., Elton, E. J., and Green, T. C. 2001. Economic news and bond prices: Evidence from the US Treasury market. Journal of financial and Quantitative analysis, *36*(4), 523-543.
9. Baur, D. G., & Dimpfl, T., 2019. Price discovery in bitcoin spot or futures?. *Journal of Futures Markets*, *39*(7), 803-817.
10. Beetsma, R., Giuliodori, M., De Jong, F. and Widijanto, D., 2013. Spread the news: The impact of news on the European sovereign bond markets during the crisis. *Journal of International Money and Finance*, *34*, 83-101.
11. Birz, G. and Lott Jr, J.R., 2011. The effect of macroeconomic news on stock returns: New evidence from newspaper coverage. *Journal of Banking & Finance*, 35, 2791-2800.
12. Bollerslev T., 1990, Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. *Rev Econ Stat*, *72*(3):498–505.
13. Bouri, E., Shahzad, S.J.H., Roubaud, D., Kristoufek, L. and Lucey, B., 2020. Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, *77*, 156-164.
14. Caferra, R. and Vidal-Tomas, D., 2021. Who raised from the abyss? A comparison between cryptocurrency and stock market dynamics during the COVID-19 pandemic. *Finance Research Letters*, *43*, 101954.
15. Cagli, E.C., 2019. Explosive behavior in the prices of Bitcoin and altcoins. *Finance Research Letters*, *29*, 398-403.
16. Cai, H., Ahmed, S., Jiang, Y. and Liu, X., 2020. The impact of US macroeconomic news announcements on Chinese commodity futures. *Quantitative Finance 20*, 1927-1966.
17. Campbell, J. Y., Pflueger, C., & Viceira, L. M., 2020. Macroeconomic drivers of bond and equity risks. *Journal of Political Economy*, *128*(8), 3148-3185.
18. Caporale, G.M., Spagnolo, F. and Spagnolo, N., 2016. Macro news and stock returns in the Euro area: a VAR-GARCH-in-mean analysis. *International Review of Financial Analysis 45*, 180-188.

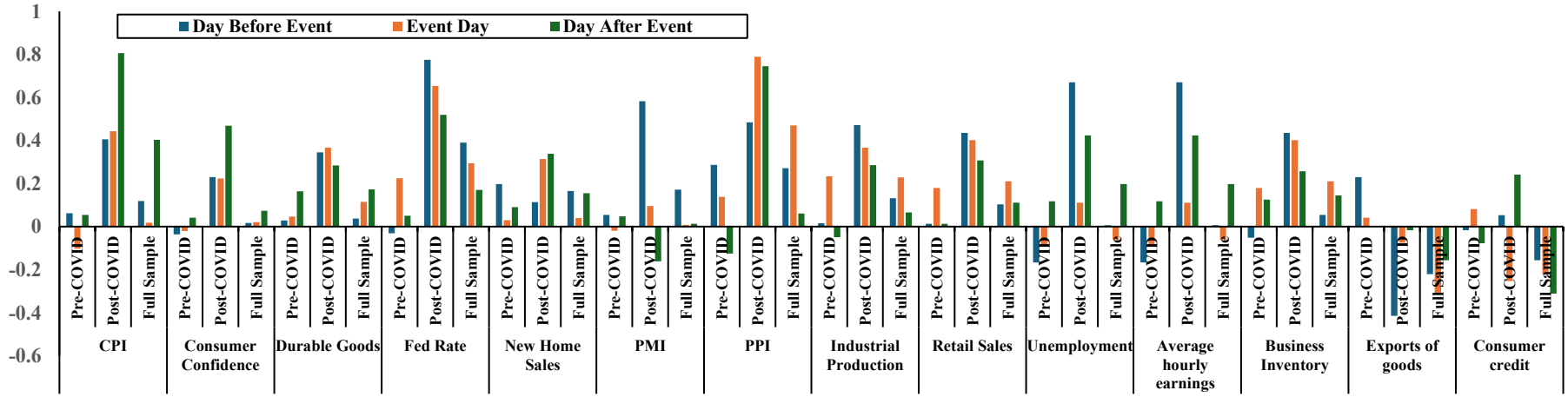
19. Caporale, G.M., Spagnolo, F. and Spagnolo, N., 2018. Macro news and bond yield spreads in the euro area. *The European Journal of Finance*, *24*, 114-134.
20. Cappiello L, Engle RF, Sheppard K., 2006. Asymmetric dynamics in the correlations of global equity and bond returns. *J Financial Econ*, *4*(4):537–572.
21. Celeste, V., Corbet, S. and Gurdgiev, C., 2020. Fractal dynamics and wavelet analysis: Deep volatility and return properties of Bitcoin, Ethereum and Ripple. *The Quarterly Review of Economics and Finance*, *76*, 310-324.
22. Chan, W.H., Le, M. and Wu, Y.W., 2019. Holding Bitcoin longer: The dynamic hedging abilities of Bitcoin. *The Quarterly Review of Economics and Finance*, *71*, 107-113.
23. Charfeddine, L. and Maouchi, Y., 2019. Are shocks on the returns and volatility of cryptocurrencies really persistent? *Finance Research Letters*, *28*, 423-430.
24. Chen, N.F., Roll, R. and Ross, S.A., 1986. Economic forces and the stock market. *Journal of Business*, *59*, 383-403.
25. Cheung, Y.W., Fatum, R. and Yamamoto, Y., 2019. The exchange rate effects of macro news after the global financial crisis. *Journal of International Money and Finance*, *95*, 424-443.
26. Chiang, T.C., Li, J. and Yang, S.Y., 2015. Dynamic stock–bond return correlations and financial market uncertainty. *Review of Quantitative Finance and Accounting*, *45*, 59-88.
27. Chu, J., Zhang, Y. and Chan, S., 2019. The adaptive market hypothesis in the high frequency cryptocurrency market. *International Review of Financial Analysis*, *64*, 221-231.
28. Connolly, R., Stivers, C. and Sun, L., 2005. Stock market uncertainty and the stock-bond return relation. *Journal of Financial and Quantitative Analysis*, *40*, 161-194.
29. Consoli, S., Pezzoli, L.T. and Tosetti, E., 2021. Emotions in macroeconomic news and their impact on the European bond market. *Journal of International Money and Finance*, *118*, 102472.
30. Corbet, S., Larkin, C., Lucey, B.M., Meegan, A. and Yarovaya, L., 2020. The impact of macroeconomic news on bitcoin returns. *The European Journal of Finance 26*, 1396-1416.
31. Davis, S. J., 2016. An index of global economic policy *uncertainty* (No. w22740). *National Bureau of Economic Research*.
32. Duffee, G. R., 2023. Macroeconomic news and stock–bond comovement. *Review of Finance*, *27*(5), 1859-1882.
33. Dyhrberg, A.H., 2016. Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters*, *16*, 139-144.
34. Ekinci, C., Akyildirim, E. and Corbet, S., 2019. Analysing the dynamic influence of US macroeconomic news releases on Turkish stock markets. *Finance Research Letters*, *31*, 155-164.
35. Engle R., 2000, Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional heteroscedasticity models. *J Bus Econ Stat*, *20*(3):339–350.
36. Evans, M.D. and Lyons, R.K., 2008. How is macro news transmitted to exchange rates? *Journal of Financial Economics*, *88*, 26-50.
37. Fama, E.F., 1965. The behavior of stock-market prices. *The Journal of Business*, *38*, 34-105.
38. Fama, E.F., 1970. Efficient capital markets. *The Journal of Finance*, *25*, 83-417.
39. Fang, T., Su, Z. and Yin, L., 2020. Economic fundamentals or investor perceptions? The role of uncertainty in predicting long-term cryptocurrency volatility. *International Review of Financial Analysis 71*, 101566.
40. Fernandez-Perez, A. and Lopez, R., 2023. The effect of macroeconomic news announcements on the implied volatility of commodities: The role of survey releases. *Journal of Futures Markets*, *43*, 1499-1530.

41. Gallegati M, Ramsey JB 2013. Bond vs stock market’s Q: Testing for stability across frequencies and over time. J Empirical Finance 24:138‑150
42. Garcia, R. and Tsafack, G., 2011. Dependence structure and extreme comovements in international equity and bond markets. *Journal of Banking & Finance*, *35*, 1954-1970.
43. Glosten LR, Jagannathan R, Runkle DE., 1993, On the relation between the expected value and the volatility of the nominal excess return on stocks. *J Finance*, *48*(5):1779–1801.
44. Goodell, J.W. and Goutte, S., 2021. Diversifying equity with cryptocurrencies during COVID-19. *International Review of Financial Analysis*, *76*, p.101781.
45. Hackethal, A., Hanspal, T., Lammer, D.M. and Rink, K., 2022. The characteristics and portfolio behavior of bitcoin investors: Evidence from indirect cryptocurrency investments. *Review of Finance*, *26*, 855-898.
46. Hafner, C.M., 2020. Testing for bubbles in cryptocurrencies with time-varying volatility. *Journal of Financial Econometrics*, *18*, 233-249.
47. Hansen, P.R., Kim, C. and Kimbrough, W., 2024. Periodicity in cryptocurrency volatility and liquidity. *Journal of Financial Econometrics*, *22*, 224-251.
48. Hardle, W.K., Harvey, C.R. and Reule, R.C., 2020. Understanding cryptocurrencies. *Journal of Financial Econometrics*, *18*, 181-208.
49. Hsu, Y.J., Lu, Y.C. and Yang, J.J., 2021. News sentiment and stock market volatility. *Review of Quantitative Finance and Accounting*, *57*, 1093-1122.
50. Ji, Q., Bouri, E., Gupta, R. and Roubaud, D., 2018. Network causality structures among Bitcoin and other financial assets: A directed acyclic graph approach. *The Quarterly Review of Economics and Finance 70*, 203-213.
51. Kaiser, L. and Stockl, S., 2020. Cryptocurrencies: Herding and the transfer currency. *Finance Research Letters*, *33*, 101214.
52. Kakinaka, S. and Umeno, K., 2022. Cryptocurrency market efficiency in short-and long-term horizons during COVID-19: An asymmetric multifractal analysis approach. *Finance Research Letters 46*, 102319.
53. Karau, S., 2023. Monetary policy and Bitcoin. *Journal of International Money and Finance*, *137*, 102880.
54. Katsiampa, P., Corbet, S. and Lucey, B., 2019. High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money*, *62*, 35-52.
55. Kim, S. and In, F., 2007. On the relationship between changes in stock prices and bond yields in the G7 countries: Wavelet analysis. *Journal of International Financial Markets, Institutions and Money*, *17*, 167-179.
56. Klein, T., Thu, H.P. and Walther, T., 2018. Bitcoin is not the New Gold–A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105-116.
57. Kurka, J., 2019. Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters 31*, 38-46.
58. Kurov, A., Sancetta, A., Strasser, G., and Wolfe, M. H. 2019. Price drift before US macroeconomic news: Private information about public announcements?. Journal *of Financial and Quantitative Analysis*, *54*(1), 449-479.
59. Li, E.X., Zha, T., Zhang, J. and Zhou, H., 2022. Does fiscal policy matter for stock-bond return correlation? *Journal of Monetary Economics*, *128*, 20-34.

60. Li, X.M. and Zou, L.P., 2008. How do policy and information shocks impact co-movements of China's T-bond and stock markets? *Journal of Banking & Finance*, *32*, 347-359.
61. Lyocsa, S., Molnar, P., Plihal, T. and Siranova, M., 2020. Impact of macroeconomic news, regulation and hacking exchange markets on the volatility of bitcoin. *Journal of Economic Dynamics and Control*, *119*, 103980.
62. Maghyereh, A. and Abdoh, H., 2021. Time–frequency quantile dependence between Bitcoin and global equity markets. *The North American Journal of Economics and Finance*, *56*, 101355.
63. Maghyereh AI, Abdoh H, Awartani B.,2019. Connectedness and hedging between gold and Islamic securities: a new evidence from time-frequency domain approaches. *Pacific-Basin Finance Journal*, 54:13–28.
64. Melki, A. and Nefzi, N., 2022. Tracking safe-haven properties of cryptocurrencies during the COVID-19 pandemic: A smooth transition approach. *Finance Research Letters*, *46*, 102243.
65. Mensi, W., Al-Yahyaee, K.H., Al-Jarrah, I.M.W., Vo, X.V. and Kang, S.H., 2021. Does volatility connectedness across major cryptocurrencies behave the same at different frequencies? A portfolio risk analysis. *International Review of Economics & Finance*, *76*, 96-113.
66. Mensi, W., Rehman, M.U., Maitra, D., Al-Yahyaee, K.H. and Sensoy, A., 2020. Does bitcoin co-move and share risk with Sukuk and world and regional Islamic stock markets? Evidence using a time-frequency approach. *Research in International Business and Finance*, *53*, 101230.
67. Metiu, N., & Prieto, E., 2025. Time-varying stock return correlation, news shocks, and business cycles. *European Economic Review*, *172*, 104916.
68. Mokni, K., Ajmi, A.N., Bouri, E. and Vo, X.V., 2020. Economic policy uncertainty and the Bitcoin-US stock nexus. *Journal of Multinational Financial Management*, *57*, 100656.
69. Molenaar, R., Senechal, E., Swinkels, L. and Wang, Z., 2024. Empirical Evidence on the Stock–Bond Correlation. *Financial Analysts Journal*, 1-20.
70. Narayan, P. K., Rath, B. N., & Syarifuddin, F., 2022. Understanding the role of trade agreements in Indonesia's FDI. *Journal of Asian Economics*, *82*, 101532.
71. Nguyen, K. Q., 2022. The correlation between the stock market and Bitcoin during COVID-19 and other uncertainty periods. *Finance research letters*, *46*, 102284.
72. Okorie, D.I., Bouri, E. and Mazur, M., 2024. NFTs versus conventional cryptocurrencies: A comparative analysis of market efficiency around COVID-19 and the Russia-Ukraine conflict. *The Quarterly Review of Economics and Finance*, *95*, 126-151.
73. Omrane, W.B. and Savaser, T., 2016. The sign switch effect of macroeconomic news in foreign exchange markets. *Journal of International Financial Markets, Institutions and Money*, *45*, 96-114.
74. Percival DB, Walden AT., 2000. Wavelet methods for time series analysis (Cambridge Series in Statistical and Probabilistic Mathematics).
75. Pyo, S. and Lee, J., 2020. Do FOMC and macroeconomic announcements affect Bitcoin prices? *Finance Research Letters 37*, 101386.
76. Roache, S.K. and Rossi, M., 2010. The effects of economic news on commodity prices. *The Quarterly Review of Economics and Finance*, *50*, 377-385.
77. Rognone, L., Hyde, S. and Zhang, S.S., 2020. News sentiment in the cryptocurrency market: An empirical comparison with Forex. *International Review of Financial Analysis 69*, 101462.
78. Sarwar, G., 2023. The determinants of stock–bond return correlations. *Journal of Financial Research*, *46*, 711-732.
79. Silvennoinen A, Terasvirta T., 2009. Multivariate GARCH models Handbook of financial time series.

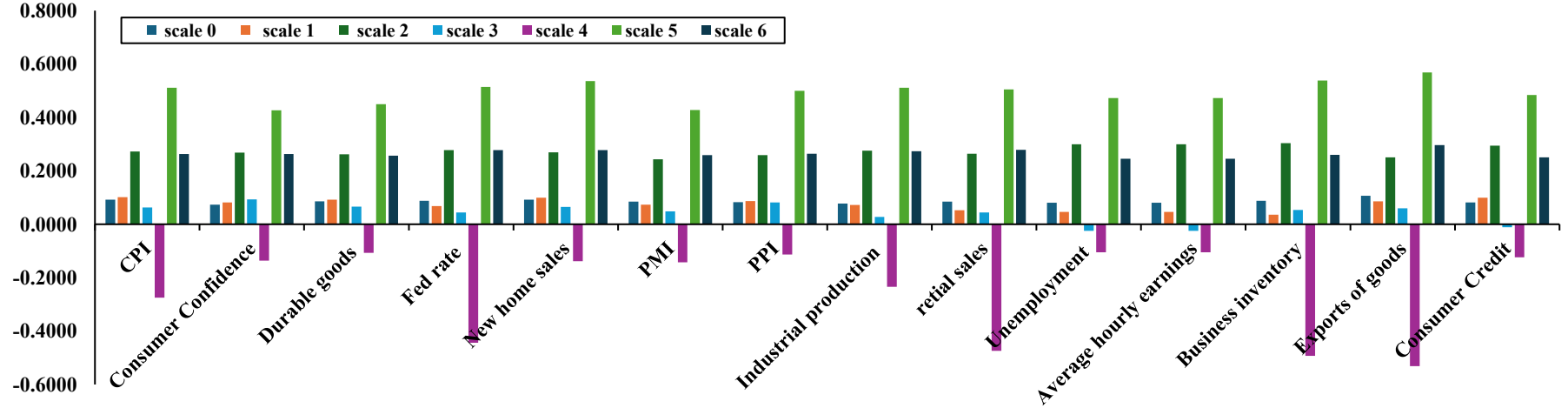
Springer, Berlin, pp 201–229.
80. Skintzi, V.D., 2019. Determinants of stock-bond market comovement in the Eurozone under model uncertainty. *International Review of Financial Analysis*, *61*, 20-28.
81. Sockin, M. and Xiong, W., 2023. A model of cryptocurrencies. *Management Science*, *69*, 6684-6707.
82. Tiwari, A.K., Adewuyi, A.O., Albulescu, C.T. and Wohar, M.E., 2020. Empirical evidence of extreme dependence and contagion risk between main cryptocurrencies. *The North American Journal of Economics and Finance*, *51*, 101083.
83. Tiwari, A.K., Raheem, I.D. and Kang, S.H., 2019. Time-varying dynamic conditional correlation between stock and cryptocurrency markets using the copula-ADCC-EGARCH model. *Physica A: Statistical Mechanics and Its Applications*, *535*, 122295.
84. Urquhart, A., 2016. The inefficiency of Bitcoin. *Economics Letters 148*, 80-82.
85. Vidal-Tomas, D. and Ibanez, A., 2018. Semi-strong efficiency of Bitcoin. *Finance Research Letters 27*, 259-265.
86. Wang, J.N., Lee, Y.H., Liu, H.C. and Lee, M.C., 2022. The determinants of positive feedback trading behaviors in Bitcoin markets. *Finance Research Letters*, *45*, 102120.
87. Xing, B.A., Feunou, B., Nongni-Donfack, M. and Sekkel, R., 2024. US macroeconomic news and low-frequency changes in bond yields in Canada, Sweden and the UK. *Journal of Banking & Finance*, *168*, 107270.
88. Yamada, M. and Ito, T., 2022. Price discovery and liquidity recovery: Forex market reactions to macro announcements. *Journal of International Money and Finance*, *120*, 102502.
89. Yang, J., Zhou, Y. and Wang, Z., 2009. The stock–bond correlation and macroeconomic conditions: One and a half centuries of evidence. *Journal of Banking & Finance*, *33*, 670-680.
90. Yarovaya, L., Matkovskyy, R. and Jalan, A., 2021. The effects of a "black swan" event (COVID-19) on herding behavior in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money*, *75*, 101321.
91. Yi, S., Xu, Z. and Wang, G.J., 2018. Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis 60*, 98-114.

Figure 1. The macroeconomic news and the average DJIA-BTC correlations in full sample and sub-periods



Notes: the average of the correlation between the undecomposed returns series are calculated on the announcement day (Event Day), after the announcement day (day after event) and before the announcement day (day before event). The analysis is repeated for each macro new under consideration and the combined plot is generated after that.

Figure 2. the average DJIA-BTC correlations over the timescales on macro event days



Notes: Timescale 1 represents the range [2-4] days, scale 2 belongs to the range [4-8] days, scale 3 is for [8-16] days, scale 4 is [16-32] days, scale 5= [32-64] days and scale 6= [64-128]. Scale 0 represents the analysis on the original returns' series without decomposition.

Table 1. the Multiscale estimates from the ADCC-GARCH model

Scale	α	β	g	LL
1: [2-4] days	0.2459*** (0.01769)	0.5791*** (0.0276)	0.0373** (0.0161)	20727.32
2: [4-8] days	0.5889*** (0.0137)	0.3560*** (0.0167)	0.0509*** (0.0163)	21626.16
3: [8-16] days	0.7645*** (0.0094)	0.1070*** (0.0114)	0.0057 (0.0274)	5421.962
4: [16-32] days	0.1303*** (0.0000)	0.8549*** (0.0000)	0.2318*** (0.0163)	26225.97
5: [32-64] days	0.1218*** (0.0000)	0.8659*** (0.0000)	0.2332*** (0.0163)	24829.19
6:[64-128] days	0.1344*** (0.0000)	0.8623*** (0.0000)	0.3057*** (0.0192)	47657.48

Notes: α represents the ARCH effect, β proxies for the GARCH effect, asymmetric effect is denoted by g and LL is the log likelihood value. Standard errors are reported between brackets ** and *** denote statistical significance at 5 per cent and 1 per cent, respectively.

Table 2. Summary statistics of the variables in the study

Variable	Mean	Std. Dev.	Source	Start date (D.M.Y)	Obs.	Eastern release time [a]
Avg. hourly earnings	-0.0080 (0.0807)	1.0975 (0.1208)	BLS	6/08/2010	140	8:30
Business inventories	0.0445 (0.0877)	0.8330 (0.1273)	BC	13/08/2010	137	10:00
Consumer confidence	0.0536 (0.0738)	0.9530 (0.0034)	FRB	31/08/2010	142	10:00
Consumer credit	0.1233 (0.0817)	1.0151 (0.1205)	FRB	6/8/2010	141	15:00
CPI	0.0297 (0.0926)	0.8941 (0.1251)	BLS	13/08/2010	141	8:30
Durable goods orders	0.0567 (0.0857)	1.0414 (0.1235)	BC	25/08/2010	141	8:30
Exports of goods	0.1201 (0.1072)	1.0216 (0.1465)	BEA	14/08/2010	95	8:30
Fed rate	0.0381 (0.0874)	0.7757 (0.1293)	FRB	12/08/2010	143	14:00
Industrial production	0.1525 (0.0771)	0.9925 0.1150	FRB	11/08/2010	141	9:15
New homes sales	0.0786 (0.0920)	0.9716 (0.1356)	CB	25/06/2013	108	10:00
PMI	0.1485 (0.0853)	1.0516 (0.1230)	ISM	31/08/2010	142	9:45
PPI	0.0527 (0.0824)	0.8510 (0.1198)	BLS	17/08/2010	142	8:30
Retail sales	0.0426 (0.0852)	1.0689 (0.1237)	BC	13/08/2010	141	8:30
Unemployment	-0.0068 (0.0808)	0.0320 (0.1208)	BLS	06/08/2010	139	8:30

Notes: the associated descriptive statistics for the un-decomposed (original) correlations series are reported between brackets and these are calculated in a sample comprises the announcement days only. Macro data is collected from different sources. These are namely Bureau of Labor Statistics (BLS), Bureau of the Census (BC), Federal Reserve Board (FRB), Bureau of Labor Statistics (BLS), Bureau of Economic Analysis (BEA), Bureau of the Census (BC) and Institute of Supply Management (ISM). PMI denotes the purchasing manager index. [a] denote that all the macro news data are sampled at monthly frequency and released at the Eastern time period.

Table 3. The results from the baseline linear regression model (Model 1)

Variable	Scale (J)	α_t	β1	β2	Adjusted R^2
Avg. hourly earnings	0	0.0132*	-0.0058	0.8753***	0.6905
	1	0.0439	0.0266	0.0370	-0.0057
	2	0.2835***	0.1321***	0.0856	0.0451
	3	-0.0228	0.0153	0.0279	-0.0126
	4	-0.0873**	-0.0114	0.1665*	0.0142
	5	0.4109***	-0.0632	0.1410	0.0149
	6	0.2217***	-0.0604	0.0722	0.0004
Business inventories	0	0.0168***	0.0000	0.8469	0.6639
	1	0.0339	0.0486	0.0438	0.0013
	2	0.2130***	0.1025	0.2900***	0.0816
	3	0.0574	-0.0661	0.1299	0.0102
	4	-0.5246	-0.2382	-0.0019	-0.0135
	5	0.4948***	0.0267	0.0889	-0.0059
	6	0.2536***	-0.0172	0.0022	-0.0146
Consumer confidence	0	0.0158**	0.0021	0.8539***	0.6674
	1	0.0804***	0.0025	0.0048	-0.0145
	2	0.2646***	0.0015	0.0383	-0.0131
	3	0.0903**	0.0379	0.0171	-0.0075
	4	-0.1257***	0.0276	0.0802	-0.0049
	5	0.3356***	0.1234	0.2047	0.0439
	6	0.2597***	0.0419	-0.0105	-0.0100
Consumer credit	0	0.0146**	-0.0004	0.8602***	0.6846
	1	0.0933***	-0.0154	0.1060	-0.0025
	2	0.2659***	-0.0092	0.1215	-0.0004
	3	-0.0094	0.0147	-0.1122	-0.0032
	4	-0.1083	-0.0929	0.0454	-0.0028
	5	0.4017***	0.0782	0.1673*	0.0217
	6	0.2336***	0.0036	0.0416	-0.0129
CPI	0	0.0135**	0.0085	0.8880***	0.7237
	1	0.0989	-0.0464	0.0187	-0.0004
	2	0.2418***	0.0498	0.1239	0.0053
	3	0.0590	0.0223	0.1837***	0.0222
	4	-0.3145*	0.2430	-0.0065	-0.0015
	5	0.4406***	0.0839	0.1478*	0.0211
	6	0.2471***	-0.1281	0.0441	0.0205
Durable goods orders	0	0.0170**	0.0049	0.8383***	0.6465
	1	0.1007***	-0.0568*	-0.0994	0.0188
	2	0.2258***	0.0074	0.1729**	-0.0033
	3	0.0735**	-0.0437	-0.0362	-0.0033
	4	-0.1032***	-0.0330	0.0168	-0.0070
	5	0.3642***	0.0396	0.1792**	0.0218
	6	0.2600***	-0.0044	-0.0336	-0.0134
Exports of goods	0	0.0243**	0.0075	0.8438***	0.6426
	1	0.0796**	-0.0064	0.0576	-0.0183
	2	0.2195***	-0.0065	0.1860	0.0125
	3	0.0569***	0.0709	0.1378*	0.0330
	4	-0.5529	0.1377	-0.0015	0.0330
	5	0.4316***	0.0978	0.2197**	0.0432
	6	0.2672***	-0.0176	0.0813	-0.0141
Fed rate	0	0.0159**	0.0119	0.8631***	0.6683
	1	0.0667***	-0.0193	0.0463	-0.0101
	2	0.2252***	-0.0097	0.1971**	0.0246
	3	0.0432***	0.0259	0.1809	0.0222
	4	-0.4377	-0.2335	0.0069	-0.0132
	5	0.4338***	-0.0698	0.1782**	0.0201
	6	0.2691***	-0.0023	0.0126	-0.0143
Industrial production	0	0.0114**	0.0004	0.8982***	0.7297

	Scale (J)	α_t	β1	β2	Adjusted R^2
Industrial production	1	0.0754**	-0.0576**	0.0713	0.0151
	2	0.2525***	-0.0693	0.1148	0.0136
	3	0.0396	-0.0449	0.1382	0.0127
	4	-0.2155**	-0.1084	0.0302	-0.0061
	5	0.4436***	0.0677	0.1256	0.0092
	6	0.2443***	0.0105	0.0825	-0.0075
New homes sales	0	0.0218**	-0.0034	0.8409***	0.6503
	1	0.1333***	-0.0182	-0.2276**	0.0372
	2	0.1958***	-0.0087	0.2696***	0.0496
	3	0.0765*	-0.0514	-0.0796	-0.0016
	4	-0.1475***	0.0152	-0.0449	-0.0169
	5	0.4625***	-0.0399	0.1662	0.0133
	6	0.2586***	0.0214	0.0710	-0.0125
PMI	0	0.0152**	0.0053	0.8552***	0.6686
	1	0.0806***	-0.0489	0.0435	0.0053
	2	0.2205***	0.1002**	0.0503	0.0185
	3	0.0468	-0.0118	0.0634	-0.0102
	4	-0.1232***	-0.0342	0.0940	0.0009
	5	0.3807***	-0.1251*	0.1554*	0.0350
	6	0.2786***	-0.0795	-0.0441	0.0039
PPI	0	0.0142**	0.0061	0.8654***	0.6904
	1	0.0803**	-0.0092	0.0724	-0.0087
	2	0.2210***	0.0464	0.1457*	0.0098
	3	0.0748	-0.0014	0.1372	0.0040
	4	-0.1064*	0.0355	0.1027	0.0035
	5	0.4212***	0.0758*	0.1591*	0.0229
	6	0.2759***	-0.1641***	-0.0355	0.0349
Retail sales	0	0.0165**	0.0021	0.8433***	0.6602
	1	0.0525*	0.0161	0.0166	-0.0115
	2	0.2246***	-0.0186	0.1525*	0.0107
	3	0.0469	0.0126	0.1050	-0.0026
	4	-0.5203***	0.2134	0.0031	-0.0125
	5	0.4378***	0.0649	0.1385	0.0124
	6	0.2704***	0.0262	0.0060	-0.0126
Unemployment	0	0.0144*	-0.1583	0.8464***	0.6894
	1	0.0261	-2.5210***	0.0399	0.0411
	2	0.2775***	-0.0123	0.1026	-0.0046
	3	-0.0168	0.8726	0.0274	-0.0101
	4	-0.1070***	-2.7537***	0.1603**	0.0621***
	5	0.4138***	0.5462	0.1438	0.0064***
	6	0.2126***	-1.3935	0.0713	-0.0059***

Notes: this table reports the basline linear regression estimates with Newey-West (1987) estimator of the model: $\rho SB_{j,t+1} = \alpha_t + \beta 1 U_t + \beta 2 \rho SB_{j,t-1} + e_{t+1}$

Where $\rho SB_{j,t+1}$ and the $\rho SB_{j,t-1}$ are the lead and the lagged values of the stock-Bitcoin return dynamic correlation at each time-scale j. t-statistics are reported between brackets. Time-scale 1 represents the range [2-4] days, scale 2 belongs to the range [4-8] days, scale 3 is for [8-16] days, scale 4 is [16-32] days, scale 5= [32-64] days and scale 6= [64-128]. Scale 0 represents the analysis on the original returns series without decomposition. days. *, ** and *** denote statistical significance at 10 per cent, 5 per cent and 1 per cent, respectively.

Table 4. the Estimates from the non-linear extended regression Model 2

Variable	Scale (J)	β1	β2	β3	β4	β5	β6	Adjusted R^2
Avg. hourly earnings	1	0.1244***	0.0282	**-0.0792*** **	0.1086	0.0126***	0.0284	0.0533
	2	0.6242***	0.2105***	0.1559***	-0.0541	-0.0051	0.0296	0.0803
	3	0.0361	-0.0400	0.0291	-0.0324	-0.0021	0.0211	-0.0308
	4	-0.0029	-0.1204***	-0.0185	-0.1121	0.0010	0.1517	0.0089
	5	0.6041***	0.3818***	-0.0121	-0.0899***	-0.0092	0.1255	0.0092
	6	0.0422	0.2246***	-0.1744***	-0.2183	0.0198***	0.1122***	0.0346
Business inventories	1	0.2274***	0.0057	0.0609	0.0524*	-0.0186	-0.0070	0.0615
	2	0.4890***	0.1522**	**0.4175*** **	0.0650	0.0168	0.2410***	0.1108
	3	0.2195	0.0165	0.0129	-0.0694	0.0058	0.0902	0.0151
	4	-0.0369	-0.7869	0.2457	-0.3247	0.1692	-0.0065	-0.0317
	5	0.5961***	0.5300***	0.0030	0.0453	-0.0589**	0.0752	-0.0116
	6	0.1744	0.2940***	-0.1300	-0.0013	-0.0220	-0.0078	-0.0295
Consumer confidence	1	0.2524***	0.0924***	**-0.0902** **	0.0360	-0.0454***	-0.0276	0.0432
	2	0.7935***	0.2389***	-0.0239	-0.0049	-0.0528***	-0.0726	0.0995
	3	0.1528	0.1153***	0.0254	0.0193	-0.0362***	0.0440	-0.0020
	4	-0.2555	-0.1017***	0.0561	0.0063	0.0041	0.0644	-0.0108
	5	0.5336***	0.3437***	0.0222	0.1569**	-0.0561**	0.2182**	0.0462
	6	0.2426	0.3006***	-0.0143	0.0525	-0.0306	-0.0221	-0.0193
Consumer credit	1	0.1009	0.0540	0.0105	0.0304	0.0267*	0.0969	0.0251
	2	0.6291***	0.2085***	-0.0270	0.0440	-0.0139	0.0687	0.0291
	3	0.0495	-0.0087	0.0135	-0.0060	-0.0091	-0.1096	-0.0213
	4	-0.0508	-0.1890**	-0.0322	-0.0303	0.0475	0.0317	0.0064
	5	0.4863***	0.3773***	0.1414***	0.0276	0.0169	0.1574**	0.0129
	6	-0.0263	0.2395***	0.0229	0.0571	0.0382*	0.0411	0.0038
CPI	1	0.2702***	0.0675**	-0.1217	-0.0561	0.0046	-0.0030	0.0174
	2	0.5376***	0.2172***	**0.3462*** **	-0.0730	-0.0865***	0.0553	0.0836
	3	0.2272*	0.0257	-0.1283	0.0351	0.0205	0.1700**	0.0229
	4	0.0255	-0.3483*	-0.0322	0.3193	0.0043	-0.0141	-0.0167
	5	0.5378***	0.4023***	0.1157	0.0218	0.0057	0.1435**	0.0101
	6	0.1714	0.3121***	**0.1689**	-0.1244	-0.0957**	0.0455	0.0288
Durable goods orders	1	0.1958***	0.0780**	**0.0533**	-0.0786***	0.0009	-0.1278	0.0296
	2	0.6713***	0.1759***	0.0372	0.0196	-0.0121**	0.0477	0.1196
	3	0.1363	0.0661	-0.0419	-0.0360	-0.0052	-0.0429	-0.0200
	4	-0.0966**	-0.1080***	**-0.1198** **	-0.0243	0.0032	0.0056	-0.0211
	5	0.3937***	0.3020***	0.1585	-0.0494	0.0365***	0.1914***	0.0421
	6	0.1776	0.2681***	0.0169	-0.0218	0.0085	-0.0349	-0.0300
Exports of goods	1	0.1944***	0.0325	-0.0205	-0.0533	0.0031	0.0109	-0.0052
	2	0.4898***	0.0481	-0.1265***	-0.1060	0.0950***	0.0100	0.1811
	3	0.2161	-0.0335	-0.0010	0.1048	0.0354	0.0609	0.0816
	4	-0.1146	-0.7718	-0.0766	0.1948	0.0660	-0.0035	-0.0536
	5	0.3686***	0.4071***	0.1311	0.0021	0.0301	0.2057**	0.0278
	6	0.0453	0.2835***	-0.0507	0.0334	0.0714***	0.0435	0.0150
Fed rate	1	0.1951***	0.0368	-0.0432	-0.0232	0.0048	0.0121	-0.0001
	2	0.5840***	0.1509	-0.1403	-0.0036	0.0253	0.1253	0.0675
	3	0.2700**	-0.0082	0.0816	0.0042	-0.0019	0.1087	0.0521
	4	-0.0498	-0.6394	-0.2407**	-0.2551	0.1490	0.0081	-0.0330
	5	0.6117***	0.4682***	-0.0587	-0.0871	-0.0939**	0.1672	0.0148
	6	0.2421	0.3132***	-0.1241	0.0282	-0.0423	0.0094	-0.0225
Industrial production	1	0.1718*	0.0631*	**-0.0172**	-0.1531***	0.0042	0.0215	0.0460
	2	0.5432***	0.1902***	**-0.1532*** **	0.0204	0.0074	0.0615	0.0561
	3	0.2126***	-0.0073	**-0.1149*** **	0.0784	-0.0015	0.1080	0.0557
	4	-0.1262***	-0.2436	-0.0438	-0.3521	0.0274	0.0264**	-0.0053
	5	0.5919***	0.4084***	**-0.0053**	0.1734**	0.0035	0.1081	0.0086
	6	0.0387	0.2807***	-0.0076	-0.0110	0.0147	0.0651	-0.0085
New homes sales	1	0.2566***	0.0929**	-0.0651	0.0166	-0.0012	-0.2608***	0.0495
	2	0.6891***	0.1692**	-0.0303	0.0792	-0.0819	0.1233**	0.1729
	3	0.0917	0.0607	**-0.2123*** **	0.0353	0.0001	-0.1187*	0.0297

	Scale (J)	β1	β2	β3	β4	β5	β6	Adjusted R^2
New homes sales	4	-0.3157*	-0.1376***	-0.0009	-0.0122	0.0372	-0.0639*	-0.0253
	5	0.5274***	0.4887***	**0.1059**	-0.0824	-0.0420	0.1821*	0.0039
	6	0.0889	0.2577***	0.0539	-0.0438	0.0558	0.0650	-0.0186
PMI	1	0.2243***	0.0493	**-0.1311****	-0.0258	0.0029	0.0221	0.2243
	2	0.7339***	0.2122***	0.1629*	0.0679	-0.0525	-0.0950	0.7339
	3	0.1735	0.0430	**-0.1023****	0.0232	-0.0165	0.0425	0.1735
	4	-0.0562	-0.1280***	-0.0169	-0.0391	-0.0103	0.0816	-0.0562
	5	0.4250	0.3202***	**0.0285**	-0.1997***	0.0447	0.1346	0.4250
	6	0.3161	0.2978***	**-0.2779****	-0.0012	-0.0183	-0.0387	0.3161
PPI	1	0.1793*	0.0704*	0.0160	-0.0253	-0.0137	0.0545	-0.0140
	2	0.5603***	0.1540*	0.0004	0.0255	0.0129	0.0823	0.0483
	3	0.2526*	0.0390	-0.0968	0.0208	0.0048	0.1050	0.0149
	4	-0.0407	-0.1332***	0.0337	0.0255	0.0128	0.1008**	-0.0097
	5	0.3906***	0.3825***	**0.2550****	-0.0054	0.0395	0.1560**	0.0255
	6	0.1980	0.3026***	-0.0923	-0.1816**	-0.0136	-0.0402	0.0206
Retail sales	1	0.2396***	0.0138	0.0345	-0.0838	-0.0047*	-0.0394	0.0345
	2	0.6534***	0.1675***	-0.0200	0.1058	-0.0086	0.0760	0.0703
	3	0.2016	0.0171	**-0.0710****	0.2560	0.0105**	0.0474	0.0403
	4	0.0466	-0.5221	-0.0009	2.7455	-0.0038	0.0059	-0.0085
	5	0.5406***	0.4253***	0.0922	0.0503	-0.0067	0.1308*	-0.0057
	6	0.1030***	0.2908	-0.0001	-0.2009	0.0110*	-0.0068	-0.0060
Unemployment	1	0.0672	0.0051	-0.0634***	-0.0602*	-0.0013*	0.0020	0.0473
	2	0.6728***	0.2065***	-0.0394	-0.0571	-0.0019	0.0189	0.0616
	3	0.0831***	-0.0404***	0.0201	-0.0144	0.0002	0.0135	-0.0238
	4	-0.1376***	-0.1180***	-0.0857	-0.0486	-0.0019	0.1461	0.0639
	5	0.5502***	0.4391***	**0.0106**	0.2251***	0.0003	0.1326	0.0338
	6	0.0308	0.2523	-0.0112	-0.0202***	0.0003	0.0596	-0.0095

Notes: this table reports the non-linear regression estimates with Newey-West (1987) estimator of the model:

$\rho SB_{j,t+1} = \beta 1 D_t + \beta 2(1 - D_t) + \beta 3 D_t U_t + \beta 4(1 - D_t)\, U_t + \beta 5 U^2{}_{j,t} + \beta 6 \rho SB_{j,t-1} + e_{t+1}$

Where $\rho SB_{j,t+1}$ and the $\rho SB_{j,t-1}$ are the lead and the lagged values of the stock-Bitcoin return dynamic correlation at each time-scale j. D_t and $(1 - D_t)$ are the Covid and the non-Covid-19 dummies. β3 and β4 proxy for the effects of the macro surprise during the Covid and non-Covid periods. $U^2{}_{j,t}$ is the squared value of the macroeconomic surprise. β3 coefficient is sometimes made in bold to prove that the null hypothesis on the equality of the effects of macroeconomic surprise across the Covid and non-Covid periods ($\beta 3 = \beta 4$) has been rejected at either 10%, 5% or 1% significance level. For the remaining notations, see notes on Table 3.

Table 5. Controlling for the time trend, Bitcoin trading and global policy uncertainty (Model 3)

Variable	Scale (J)	β1	β2	β3	β4	β5	β6	β7	β8	β9	Adjusted R^2
Avg. hourly earnings	1	0.9429	0.8333	**-0.0907****	0.1018	0.0138***	0.0256	0.0011	-0.0222	-0.3559	0.0546
	2	0.2852	-0.2380	0.1511	-0.0415	-0.0072	0.0072	-0.0024	-0.0517	0.3615	0.0875
	3	-0.8857	-0.8262	0.0397	-0.0269	-0.0027	0.0107	0.0009	0.0255	0.2899	-0.0219
	4	-0.6851	-0.7091	-0.0202	-0.1015	-0.0002	0.1319	0.0005	-0.0251	0.2992	0.0021
	5	1.0469	0.9868	-0.0130	-0.1028	-0.0069	0.1152	0.0036	0.0344	-0.4297	0.0115
	6	0.9945	1.4396	-0.1916	-0.2192	0.0226	0.0380	0.0059	-0.0247	-0.6583	0.0617
Business inventories	1	0.5318	0.2777	0.0541	0.0507	-0.0197	-0.0132	-0.0001	-0.0152	-0.0935	0.0482
	2	0.0874	-0.4769	0.4121*	0.0734	-0.0058	0.1945**	-0.0047***	0.0055	0.4086	0.1136
	3	-0.2779	-0.6053	0.0079	-0.0600	-0.0070	0.0670	-0.0032	-0.0179	0.4025	0.0259
	4	4.8703	3.0333	0.1177	-0.3283	0.0998	-0.0304	-0.0125	-0.2966	-0.8686	-0.0342
	5	1.3026	1.2486	0.0099	0.0413	-0.0521	0.0720	0.0017	0.0443	-0.4552	-0.0183
	6	0.0476	0.4555	-0.1099	-0.0124	0.0015	-0.0313	0.0051**	-0.0030	-0.2017	-0.0108
Consumer confidence	1	0.2989*	-0.0140	-0.0918**	0.0390	-0.0492***	-0.0492	-0.0022*	0.0253	-0.0670	0.0507
	2	0.4787	-0.1662	-0.0246	-0.0012	-0.0558***	-0.0788	-0.0016	0.0131	0.0616	0.0835
	3	-0.0522	-0.0743	0.0278	0.0232	-0.0384***	0.0495	-0.0005	0.0344	0.0958	-0.0112
	4	-0.4577	-0.2851	0.0634	0.0137	-0.0011	0.0561	-0.0015	0.0422**	0.3870	-0.0068
	5	-0.1502	-0.1509	0.0302	0.1585**	-0.0564**	0.2052***	0.0013	0.0436	0.2514	0.0463
	6	0.3535	0.5340	-0.0234	0.0509	-0.0241	-0.0317	0.0030	0.0829	-0.7430	0.0154
Consumer credit	1	0.3388	0.3957	0.0268	0.0341	0.0335***	0.0891	0.0017	-0.0647***	-0.0827	0.0575
	2	-0.8550	-1.2969	0.0178	0.0285	-0.0094	0.0436	-0.0032	-0.0822**	0.9245*	0.0695
	3	-0.9422	-0.8205	0.0252	0.0104	-0.0080	-0.1327	0.0014	-0.0200	0.3685	-0.0202
	4	-1.4780	-1.5801	-0.0498	-0.0182	0.0371	0.0202	-0.0009	0.0880	0.4970	0.0129
	5	0.8279	0.8352	0.1146	0.0483	0.0134	0.1499*	0.0030	0.0554	-0.3878	0.0211
	6	0.7659	1.3380	0.0099	0.0948	0.0422*	-0.0058	0.0063***	-0.0196	-0.6277	0.0376
CPI	1	0.1177	-0.0402	-0.1248	-0.0543	0.0061	-0.0074	0.0005	0.0037	0.0289	-0.0018
	2	-0.0603	-0.4899	**0.3892****	-0.0812	-0.0952**	0.0368	-0.0030	-0.0079	0.4193	0.0771
	3	-1.3781*	-1.5485**	-0.0876	0.0264	0.0183	0.1413	-0.0023	-0.0192	-0.0038**	0.0365
	4	3.3302	2.5212	-0.0580	0.3205	-0.0056	-0.0317	-0.0014	-0.0247	-1.2294	-0.0281
	5	1.0804	1.1249	0.0391	0.0306	0.0232	0.1256	0.0047**	-0.0143	-0.4265	0.0113
	6	0.4842	0.8321	0.0905	-0.1229	-0.0759	0.0158	0.0047***	-0.0292	-0.3086	0.0417
Durable goods orders	1	0.0182	-0.1055	0.0500	**-0.0771*****	0.0005	-0.1309	-0.0003	-0.0081	0.1061	0.0089
	2	0.0284	-0.5511	0.0188	0.0296	-0.0139**	0.0382	-0.0021	-0.0299	0.4410	0.1200
	3	-0.8123	-0.7873	-0.0574	-0.0380	-0.0041	-0.0547	0.0003	-0.0147	0.4084	-0.0290
	4	-0.0085	0.1028	-0.1137**	-0.0343	0.0061	-0.0009	0.0019	0.0343	-0.2073	-0.0028
	5	0.2765	0.5161	**0.1718**	-0.0724	0.0417***	0.1778***	0.0053**	0.0272	-0.2829	0.0637
	6	0.8002	1.1212	0.0433	-0.0395	0.0118	-0.0580	0.0047	0.0231	-0.5519	-0.0083
Exports of goods	1	0.2575	0.2265	-0.0183	-0.0615	-0.0017	-0.0128	0.0034	-0.0255	-0.0855	-0.0154
	2	0.4741	0.0747	-0.0969	-0.0878	0.0881***	-0.0177	0.0005	-0.0880*	0.1609	0.1879
	3	-1.0848	-1.2693	0.0205	0.1071	0.0349	0.0516	-0.0013	-0.0281	0.6260	-0.0290
	4	12.9950	10.0377	-0.0665	0.6130	0.0672	-0.0416	-0.0338	-0.1122	-4.0827	-0.0639

	Scale (J)	β1	β2	β3	β4	β5	β6	β7	β8	β9	Adjusted R^2
	5	-0.7422	-0.4645	0.1157	-0.0588	0.0305	0.1813	0.0047	0.0555	0.2099	0.0300
	6	1.3581	1.9760	-0.0805	-0.0104	0.0636*	-0.0097	0.0124***	-0.0044	-0.9241	0.0546
Fed rate	1	-0.3083	-0.3864	-0.0445	-0.0194	0.0101	0.0036	0.0006	-0.0263	0.2232	-0.0041
	2	0.0987	-0.5067	-0.1541	-0.0206	-0.0102	0.0822	-0.0034	-0.0620	0.1609	0.0913
	3	-1.5395*	-1.8154**	0.0531	0.0017	-0.0225	0.0914	-0.0028	-0.0118	0.9254***	0.0751
	4	10.0633	8.1223	-0.0959	-0.3202	0.0041	-0.0147	-0.0064	-0.0736	-3.6636	-0.0397
	5	0.7875	0.7699	-0.0533	-0.0748	-0.0639	0.1616*	0.0024	0.0360	-0.2728	0.0083
	6	0.7536	1.1018	-0.0936	0.0445	0.0082	-0.0191	0.0055*	-0.0180	-0.4830	-0.0020
Industrial production	1	0.0768	0.0027	**-0.0146**	-0.1501***	0.0038	0.0192	0.0006	-0.0026	-0.0199	0.0258
	2	-0.0560	-0.4196	**-0.1461****	0.0357	0.0076	0.0440	-0.0019	-0.0676	0.6697	0.0738
	3	-0.4490*	-0.6389***	**-0.1321****	0.0845	-0.0041	0.0865	-0.0021	0.0225	0.8001***	0.0790
	4	0.7311	0.5078	-0.0196	-0.3588	0.0317	0.0118	0.0014	-0.0536	-0.8503	-0.0397
	5	0.2809	0.2765	**-0.0058**	0.1786*	0.0006	0.1058	0.0037	0.0466	-0.3768	0.0205
	6	0.0195	0.5474	0.0198	0.0172	0.0120	0.0232	0.0058*	-0.0302	-0.4759	0.0171
New homes sales	1	0.0531	-0.1165	-0.0741	0.0292	-0.0083	-0.2506***	-0.0009	0.0328	0.0822	0.0379
	2	0.4125	0.0477	-0.0128	0.0832	-0.0812**	0.1197	0.0040	-0.0031	-0.2217	0.1588
	3	-0.3657**	-0.1518	-0.2173***	0.0462	0.0086	-0.1496	0.0037	-0.0158	0.2875	0.0448
	4	-0.4612	-0.3706	-0.0352	0.0090	0.0268	-0.0598	-0.0042	0.0511	0.4714	-0.0310
	5	-0.2549	-0.2872	0.0719	-0.0565	-0.0505	0.1829	-0.0028*	0.0480	-0.2728	-0.0100
	6	0.4159	1.0021**	0.1397	-0.0383	0.0593	-0.0253	0.0129***	-0.0291	-1.1562	0.0214
PMI	1	0.1291	-0.1478	0.1303***	-0.0323	0.0053	0.0016	-0.0020	0.0009	0.1490	0.0235
	2	0.1291	-0.1478	0.0303	-0.0323	0.0053	0.0016	-0.0020	0.0009	0.1490	0.1072
	3	0.1999**	0.0678	**-0.0969****	0.0323	-0.0191	0.0455	0.0003	0.0278	-0.1890	-0.0205
	4	-0.2148	-0.2511	-0.0075	-0.0320	-0.0088	0.0843	-0.0007	0.0344	0.2272	-0.0058
	5	-0.1603	-0.0606	**0.0406**	-0.1832***	0.0442	0.1255**	0.0020	0.0339	0.1642	0.0430
	6	0.4006	0.5613	**-0.2779****	0.0199	-0.0268	-0.0616	0.0049	0.0122	-0.7048	0.0466
PPI	1	-0.3186	-0.2714	0.0499	-0.0298	-0.0073	0.0463	0.0007	-0.0178	0.4380	-0.0079
	2	0.2444	-0.2488	0.0754	0.0113	-0.0031	0.0609	-0.0022	-0.0695	0.3786	0.0641
	3	-0.5459*	-0.6648**	-0.0276	0.0100	0.0082	0.0712	-0.0020	-0.0157	0.9548***	0.0376
	4	0.1006	0.0271	0.0096	0.0299	0.0169	0.1020**	0.0009	0.0162	-0.1856	-0.0267
	5	0.1935	0.3163	0.1800*	0.0085	0.0581	0.1593*	0.0030	0.0616	-0.4032	0.0356
	6	0.2230	0.5760	-0.1304	-0.1753**	-0.0012	-0.0765	0.0057*	-0.0228	-0.5984	0.0463
Retail sales	1	0.1168	-0.1560	**0.0440****	-0.1046	-0.0058**	-0.0402	-0.0011	-0.0123	0.1456	0.0244
	2	0.1928	-0.4905	0.0085	0.0242	-0.0132**	0.0271	-0.0042	-0.0268	0.5986	0.0831
	3	-0.3887	-0.5889**	-0.0497**	0.2225	0.0067	0.0284	-0.0026	-0.0012	0.7946**	0.0531
	4	3.6065	1.9493	0.0233	2.5498	0.0023	-0.0203	-0.0044	-0.2392	-3.1310	-0.0108
	5	0.3225	0.3610	0.0584	0.1218	-0.0029	0.1291*	0.0034	0.0486	-0.4592	0.0013
	6	0.0865	0.5817	-0.0048	-0.1580	0.0134**	-0.0476	0.0061**	-0.0319	-0.5359	0.0279
Unemployment	1	0.3127	0.2808	-7.4020	-6.1522	-15.4621	-0.0069	0.0016	-0.0293	-0.3860	0.0565
	2	0.2677	-0.2804	-3.2201	-2.7021	-16.8081	-0.0042	-0.0023	-0.0598	0.4001	0.0736
	3	-0.3337	-0.3320	2.8392	-3.4767	3.3555	-0.0019	0.0008	0.0270	0.3647	-0.0095
	4	-0.1969	-0.0570	-8.6092	-5.6543	-18.4071	0.1344	0.0015	-0.0273	0.0961	0.0598

	Scale (J)	β1	β2	β3	β4	β5	β6	β7	β8	β9	Adjusted R^2
	5	0.4171	0.3879	0.0721	19.6498	0.1848	0.1273	0.0027	0.0418	-0.4918	0.0318
	6	0.0227	0.5556	-2.8175	-5.3871	0.0731	0.0246	0.0060	-0.0319	-0.5001	0.0158

Notes: this table reports the non-linear regression estimates with Newey-West (1987) estimator of the model:
$\rho SB_{j,t+1} = \beta 1 D_t + \beta 2(1 - D_t) + \beta 3 D_t U_t + \beta 4(1 - D_t)\, U_t + \beta 5 U^2{}_{j,t} + \beta 6 \rho SB_{j,t-1} + \beta 7 Trend_t + \beta 8 Bvol_t + \beta 9 GPU_t + e_{t+1}$ Where $\rho SB_{j,t+1}$ and the $\rho SB_{j,t-1}$ are the lead and the lagged values of the stock-Bitcoin return dynamic correlation at each time-scale j. D_t and $(1 - D_t)$ are the Covid and the non-Covid-19 dummies. β3 and β4 proxy for the effects of the macro surprise during the Covid and non-Covid periods. $U^2{}_{j,t}$ is the squared value of the macroeconomic surprise. GPU is the changes in the global policy uncertainty, $Bvol$ is the Bitcoin trading volume, and the Trend is the time trend over the full sample period β3 coefficient is sometimes made in bold to prove that the null hypothesis on the equality of the effects of macroeconomic surprise across the Covid and non-Covid periods ($\beta 3 = \beta 4$) has been rejected at either 10%, 5% or 1% significance level. For the remaining notations, see notes on Table 3.