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ORIGINAL RESEARCH

Cryptocurrency markets, macroeconomic news announcements and energy consumption

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Abstract

Motivated by recent evidence showing that shocks in cryptocurrencies' trade volume increase their energy consumption and carbon footprint, this study seeks to identify the news-based determinants of the volume and number of trades of Bitcoin and Ethereum. Specifically, we investigate how the trading volume and number of trades in Bitcoin and Ethereum react to the release of U.S., German and Japanese macroeconomic news. Using 5-min frequency Bitcoin and Ethereum prices quoted against the US dollar, we find that the volume and number of trades show a significant response to macroeconomic releases. Furthermore, both the volume and number of trades in Bitcoin and Ethereum react to the same U.S. macroeconomic news, such as the Consumer Confidence Index, new home sales, and FOMC rate decisions. Our findings suggest that macroeconomic news can contribute to major cryptocurrencies' increased energy consumption and carbon footprint.

Keywords Energy consumption · Cryptocurrencies · Macroeconomic news · Trading volume · Bitcoin · Ethereum · High-frequency data

1 Introduction

This paper examines whether and how the release of macroeconomic news influences the trading volume and the number of trades in Bitcoin and Ethereum. Since the introduction of Bitcoin in 2008, the cryptocurrency markets continue to experience dramatic growth. As

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of December 1, 2022, we count 534 cryptocurrency exchanges hosting 22,147 cryptocurrencies for a global market capitalization of about $791 billion.[1] The exponential expansion of the cryptocurrency markets has attracted global attention not only from investors around the world, but also from regulators across countries, international media outlets, and academicians working in a wide range of research areas.[2] In the finance field, researchers have examined numerous aspects of cryptocurrency markets with particular emphasis on Bitcoin and its underlying technology, the blockchain.[3]More recently, however, cryptocurrencies have been the subject of much criticism about their carbon footprint putting into question the sustainability aspect of mineable cryptocurrencies such as the popular Bitcoin, Ethereum, and Dogecoin (e.g., De Vries, 2020; Küfeoğlu & Özkuran, 2019; Li et al., 2019; Das & Dutta, 2020; De Vries & Stoll, 2021; Naeem & Karim, 2021; Huynh et al., 2022; Erdogan et al., 2022; De Vries et al., 2022).

The growing demand for mineable cryptocurrencies as a high-return investment led to fierce competition among a large number of miners using energy-intensive mining processes. To increase their profits, miners strive to reduce the cost associated with mining by relying on low-cost and pollution-intensive energy sources such as coal, oil, and gas. For instance, Stoll et al. (2019) argue that the annual energy consumption of Bitcoin mining is estimated at 4.58 TWh, corresponding to a carbon footprint of 22.9 MtCO2eq. According to the Cambridge Centre for Alternative Finance, the Bitcoin network's annual energy consumption in 2019 was estimated to be around 142 terawatt-hours (TWh), which is greater than the annual energy consumption of entire countries such as Sweden, Pakistan, and Argentina.[4] More recently, Jiang et al. (2021) show that, in the absence of government intervention, the power consumption of the Bitcoin industry will reach 296.59 TWh annually by 2024, thus surpassing the total power consumption of Saudi Arabia and Italy and exceeding the carbon emission output of the Czech Republic and Qatar.

Given their substantial energy consumption and carbon footprint, there is a growing stream of literature examining the determinants of energy consumption induced by the mining of major virtual currencies such as Bitcoin (e.g., Huynh et al., 2022; Naeem & Karim, 2021; Erdogan et al., 2022; Sarkodie et al., 2022). Numerous studies have shown that the volume of cryptocurrency mining, hence its power consumption, is driven by its profitability (Badea & Mungiu-Pupazan, 2021; Dittmar & Praktiknjo, 2019; Houy, 2019; Küfeoğlu & Özkuran, 2019; Vranken, 2017). Bitcoin miners realize a profit only when the cost of Bitcoin mining is lower than the price of Bitcoin. Thus, the profitability stemming from the mining of cryptocurrencies depends not only on the cost of electricity per Bitcoin mining but also on the price of Bitcoin (Kristoufek, 2020). As noted by Küfeoğlu and Özkuran (2019), it is challenging to predict the energy consumption of Bitcoin mining as "*Bitcoin prices directly affect mining and hence energy consumption*".

The interconnectedness of Bitcoin prices and Bitcoin mining costs makes it challenging to examine the determinants of energy consumption of Bitcoin mining. In fact, this interconnectedness can explain the documented bidirectional relationship between Bitcoin price and electricity consumption of Bitcoin mining (Erdogan et al., 2022; Huynh et al., 2022).

[1] Source: https://coinmarketcap.com/all/views/all/ (accessed on December 1, 2022).

[2] Goutte, Guesmi, and Saadi (2019, 2020) provide a comprehensive review of the literature.

[3] See, among others, Yermack (2015), Dyhrberg (2016), Urquhart (2016), Nadarajah and Chu (2017), Zhang et al (2018), Al-Yahyaee et al. (2018), Grobys and Sapkota (2019), Philippas et al., (2019), Sun et al. (2020), Corbet et al. (2018), Giudici and Abu-Hashish (2019), Guesmi et al. (2019), Cretarola and Figà-Talamanca (2021), Giudici and Polinesi (2021), Akyildirim et al., (2021) and Ben Omrane et al. (2022).

[4] Country comparisons with Bitcoin's electricity consumption can be found via the website of Cambridge Centre for Alternative Finance: https://ccaf.io/cbnsi/cbeci/comparisons

In a recent study, however, Sarkodie et al. (2022) employed a novel approach involving dynamic ARDL simulations and general-to-specific VAR to overcome the reverse causality problem associated with the interconnectedness of Bitcoin prices and Bitcoin mining costs. The authors show that a 1% increase in Bitcoin trading volume is associated with about a 24% increase in Bitcoin carbon footprint and energy consumption. More relevant to our study, Sarkodie et al. (2022) show that a dynamic shock in Bitcoin trading volume leads to a major increase in Bitcoin energy consumption by 46.54%.

Motivated by the evidence of a causal effect of dynamic shock in Bitcoin trading volume on Bitcoin carbon and energy footprint, the current study seeks to examine the determinants of shocks in the trading of Bitcoin and Ethereum. In particular, we investigate whether the trading volume and the number of trades in Bitcoin and Ethereum react to the release of U.S., German and Japanese macroeconomic news. We focus on Bitcoin and Ethereum because they represent the two most important cryptocurrencies. In fact, together the two cryptocurrencies share about 60% of the global market capitalization of the cryptocurrency markets and have substantial energy and carbon footprint.

To the best of our knowledge, this is the first study examining the link between trading activity in cryptocurrency markets and macroeconomic news announcements. Thus, our work contributes not only to the growing literature on cryptocurrencies but also to the large body of research on the influence of macroeconomic news announcements on the equity market, foreign currency exchange market, and bond markets, among others (e.g., Chen & Gau, 2010; Nowak et al., 2011; Rosa, 2011; Hussain, 2011; Evans, 2011; Dewachter et al., 2014; Chatrath et al., 2014; Ben Omrane & Savaser, 2016, 2017; Huang, 2018; Ayadi et al., 2020). For instance, Evans (2011) shows that macroeconomic news announcements are one of the driving forces behind the documented jumps in the S&P 500, US Treasury Bond and Euro-Dollar foreign exchange futures markets. More recently, Ayadi et al. (2020) show that macroeconomic news announcements influence the probability and magnitude of jumps in exchange rates of several major currencies.

The remainder of the paper is structured as follows. Section 2 outlines our data while Sect. 3 describes our research methodology. Section 4 discusses the empirical results and Sect. 4 concludes the paper.

2 Data

This study makes use of macroeconomic news releases, the number of trades, and the trading volume for Bitcoin and Ethereum. Cryptocurrencies are collected from Bitstamp exchange platform. Bitstamp is a Luxembourg-based cryptocurrency exchange. It enables the exchange of fiat currency, Bitcoin, and other cryptocurrencies and it has been a pillar of the cryptocurrency industry since 2011. Unlike fiat currencies, cryptocurrencies are traded on electronic platforms around the world 24 hours a day, seven days a week. Because of the time differences, we convert local times into Eastern Standard Time (EST); trading days begin at 00:00 EST and end at 23:55 EST. Bitstamp exchange platform has strong fiduciary, security, and compliance controls in place and is licensed in the EU and the US. Data collected includes the number and volume of intraday Bitcoin and Ethereum trades. The study involves seventeen months, from August 1, 2019, to December 31, 2020.

The trade number and volume are calculated as the cumulative number of trades and traded amounts in 5-min intervals. The choice of 5-min intervals is motivated by several studies showing that 5-min intraday data frequency leads to more accurate estimation and less microstructure noise than lower sampling frequencies (e.g., 1-min intervals) and higher sampling frequencies (e.g., 10-min intervals). For instance, studies by Hansen and Lunde (2006), Bandi and Russell (2006), and Liu et al. (2015) show that when using high-frequency data to estimate realized variance, 5-min intervals provide the best estimation results in comparison to lower and higher sampling frequencies.

Figure 1 depicts the annualized Bitcoin power consumption trend, as well as the total daily trades in Bitcoin and Ethereum over our sample period. Although Bitcoin has far more cumulative trades than Ethereum, we can clearly see that a decrease in both Bitcoin and Ethereum cumulative trades is followed by a decrease in power consumption and vice versa. Mining necessitates a substantial amount of computational power, which means that the more mining operations take place, the more power is required to keep the network running. This power consumption is caused by the energy required to run mining hardware, such as ASICs (Application-Specific Integrated Circuits), which are specialized machines designed for Bitcoin mining. As Bitcoin and Ethereum's popularity and demand grow, more people are incentivized to mine for both cryptocurrencies, resulting in a significant increase in power consumption.

Table 1 displays descriptive statistics for Bitcoin and Ethereum cumulative traded amounts and trades per 5-min period. We use the natural logarithm for both trading volume and number of trades to smooth the data and eliminate outliers. With respect to Bitcoin, our sample includes 146,615 observations of trading volume and trades. The average trading volume (trades) is about 11 (42) with a maximum value of 343.35 (299) and a minimum value of 0 (1). Our Ethereum sample is composed of 132,206 observations of trading volume and trades. Its average trading volume (trades) is around 84 (13) with a maximum value of

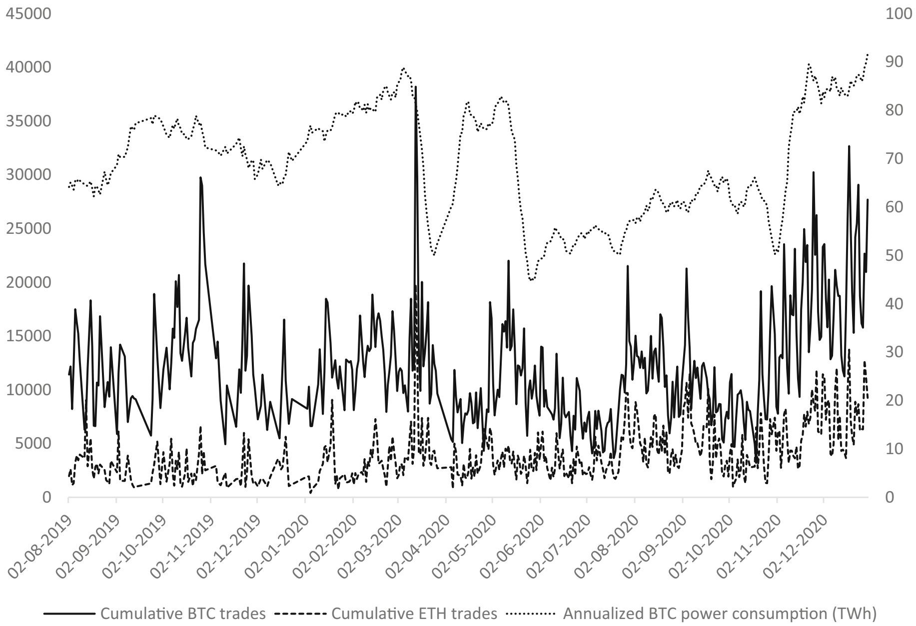

Fig. 1 Annualized Bitcoin power consumption vs. cumulative daily trades in Bitcoin and Ethereum markets. *Note*: This figure depicts the annualized Bitcoin power consumption along with the cumulative daily trades in Bitcoin and Ethereum markets over the sample period August 1, 2019, to December 31, 2020

Table 1 Descriptive statistics

	Bitcoin		Ethereum	
	Volume	Trades	Volume	Trades
Mean	10.84	41.54	83.92	13.15
Median	5.73	35	36.74	8
Maximum	343.35	299	108,88.97	249
Minimum	0.00	1.00	0.00	1.00
Std. Dev	16.02	28.02	150.42	16.14
Skewness	4.53	2.25	9.45	3.62
Kurtosis	36.55	11.51	336.38	24.95
Observations	146,615	146,615	132,206	132,206

The table above displays descriptive statistics about Bitcoin and Ethereum volume and trades from August 2019 to December 2020

10,889 (249) and a minimum value of 0 (1). The trading volume and the number of trades of both cryptocurrencies exhibit high kurtosis, indicating a rejection of the null hypothesis of normality. That said, the kurtosis and skewness of the trading volume as well as the number of trades are much higher for Ethereum in comparison to Bitcoin.

With respect to macroeconomic news announcements, we consider all the major announcements from the U.S., Germany, and Japan. We follow Anderson et al. (2003), Andersen et al. (2007), Ben Omrane and Savaser (2016, 2017), and Ben Omrane et al. (2022) and consider twenty-six, twelve, and ten macroeconomic news announcements related to the U.S., German and Japanese economy, respectively. Table 2 presents the relevant macroeconomic fundamentals used in our study. For instance, in the case of the U.S., we consider announcements related to the country's GDP, unemployment rate, retail sales, industrial production, consumer credit, new home sales, personal consumption, construction spending, trade balance, imports and exports. Our sample period includes a total of 409 U.S. fundamentals news items as well as 207 and 202 German and Japanese news announcements, respectively. The U.S. scheduled news items are announced mainly at 8:30 EST, while the German news releases occur mainly at 2:00 EST and the Japanese news releases at 19:50 EST. The macroeconomic news announcements that occurred at those specific times during the five business days are labelled as scheduled announcements. The remaining announcements are typically unscheduled.

We follow the existing literature and consider U.S. monetary policy indicators consisting of the Federal Reserve Beige Book and the Federal Open Market Committee (FOMC) rate decisions. It is noteworthy that the FOMC rate decisions involved lower and upper bounds of the rate. Since both FOMC rates are announced simultaneously and because the decisions relative to the lower bound rate coincide with the market expectations contrary to the upper rate decisions, our sample includes only the upper bound rate decisions.

3 Methodology

We investigate intraday trading volume and the number of trade responses to macroeconomic news using regression and controlling for intraday seasonality. We begin by calculating

Table 2 Macroeconomic news announcements

US news announcements	Time	Observation	German news announcements	Time	Observation
GDP Advance	8:30	5	GDP	2:00	12
GDP Preliminary	8:30	6	Unemployment Change	3:55	15
GDP Final	8:30	6	Unemployment Claims Rate	3:55	15
Change in Nonfarm Payrolls	8:30	17	Retail Sales MoM	2:00	15
Nonfarm Productivity	8:30	12	Industrial Production SA MoM	2:00	17
Producer Price Index MoM	8:30	17	Trade Balance	2:00	17
Unemployment Rate	8:30	17	Current Account Balance	2:00	17
Retail Sales MoM	8:30	17	GfK Consumer Confidence	2:00	17
Industrial Production MoM	9:15	16	Import Price Index MoM	2:00	16
Personal Income	8:30	17	IFO Business Climate	4:00	17
Consumer Credit	15:00	17	ZEW Survey Current Situation	5:00	16
New Home Sales	10:00	17	Markit/BME Germany Manufacturing	3:30	33
Personal Consumption	8:30	17	Total		207
Factory Orders	10:00	34			
Construction Spending MoM	10:00	17			
Business Inventories	10:00	17			
Monthly Budget Statement	14:00	17			
Trade Balance	8:30	17			
CPI MoM	8:30	17			
Consumer Confidence Index	10:00	17			
ISM Manufacturing	10:00	16			
Housing Starts	8:30	17			
Leading Index	10:00	16			
Capacity Utilization	9:15	16			
FOMC Rate Decision	14:00	16			
Fed Beige Book	14:00	11			

Table 2 (continued)

US news announcements	Time	Observation	German news announcements	Time	Observation
Total		409			

Japanese news announcements	Time	Observation
Tankan	19:50	6
Current Account	19:50	17
GDP	19:50	13
Trade Balance	19:50	33
Retail sales	19:50	17
Producer Price Index	19:50	33
Imports YoY	19:50	16
Exports YoY	19:50	16
Housing Starts YoY	1:00	17
Industrial Production	0:30	34
Total		202

This table displays macroeconomic news from the United States, Germany, and Japan that was released between 00:00 and 15:00 EST

seasonality, specifically the intraday cyclical components of trading volume and trades. As stated above, to smooth the data and exclude outliers we employ the natural logarithm for both trading volume and number of trades. The main components of market activity are transaction volume and the number of trades. As the popularity and demand for Bitcoin and Ethereum grow, more trades and volume are triggered, which would in turn encourage more people to mine for both cryptocurrencies, resulting in a significant increase in power consumption. Thus, trading volume and trade volume would be the best indicators of energy consumption. Figures 2 and 3 depict different patterns for trading volume and trades executed on each day of the week for Bitcoin. A similar observation holds for Ethereum (see Figs. 4 and 5). Because lunchtime on the east coast of North America corresponds to afternoon sessions in Europe, the trading activity would increase due to portfolio rebalancing and position closing initiated at the end of the European trading session. This diurnal pattern is consistent with the major foreign exchange markets. As a result, and in order to properly capture cyclical patterns, we control for specific days of the week in addition to the Flexible Fourier Form:

$$
\begin{aligned}
Tvol_t = \theta_0 + \theta_1 Tvol_{t-1} + \sum_{p=1}^{P}\left(\gamma_{c,p}\mathrm{Cos}\left(\frac{2\pi n}{N}p\right) + \gamma_{s,p}\mathrm{Sin}\left(\frac{2\pi n}{N}p\right)\right) \\
+ \sum\nolimits_{d=1}^{D} DayTvol_t + \sum\nolimits_{j=1}^{J}\sum\nolimits_{k=1}^{K} \delta_{j,k} Pnews_{t,j,k} + u_t, \qquad (1)
\end{aligned}
$$

where $Tvol_t$ is the natural logarithm of the cumulative trading volume over the time interval t and $DayTvol_t$ is the weekly diurnal pattern of trading volume.

To compute the seasonality measure at time t_k of day k, we divide each day into δ time intervals. If we consider that we have J weeks of data, we get $DayTvol_{t_k}$ for each day of the week. Each value represents the average of the J cumulative trading volume at time t_k

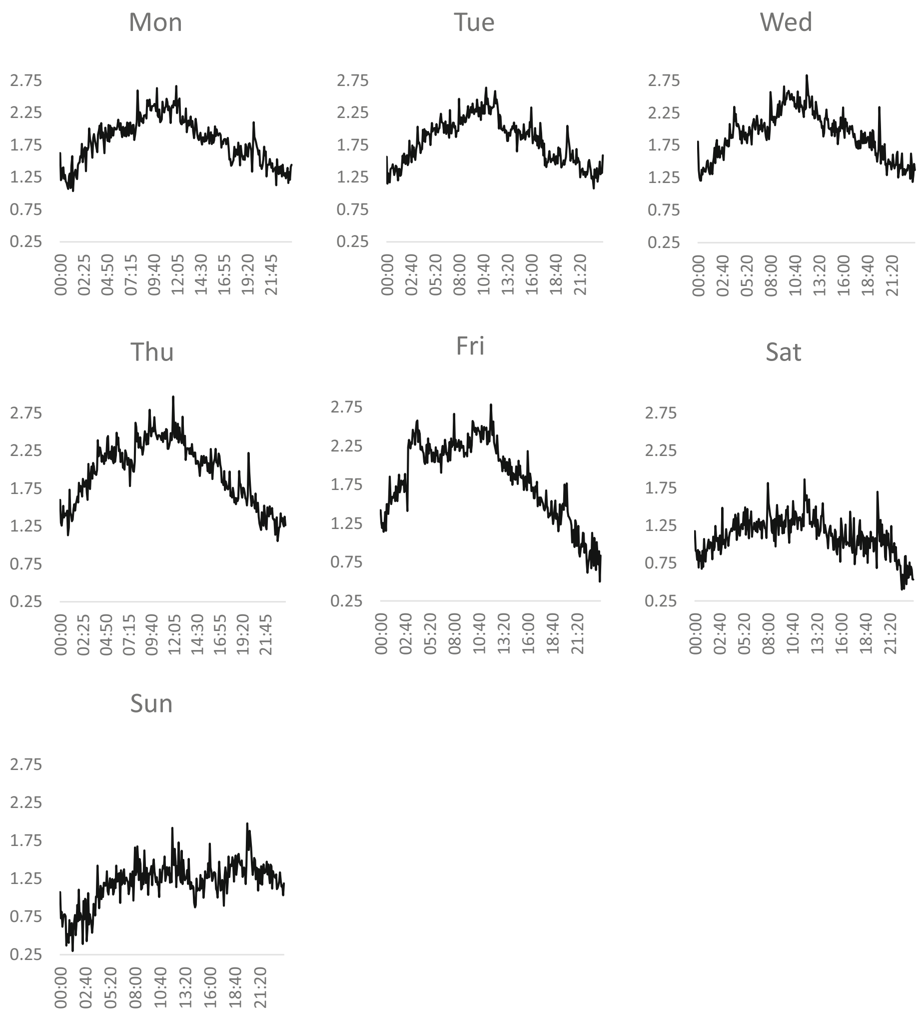

Fig. 2 Bitcoin seasonal log cumulative volume by day-of-the week. *Note*: This figure depicts the natural logarithm of Bitcoin trading volume over the course of a 24-h trading day

of day k ($k = 1$ for Sunday, $k = 7$ for Saturday). Consider the 5-min time frequency and the 24-h trading of the day, and the value of δ is 288 and $DayTvol_{t_k}$ for example on Monday at 00:30 ($k = 2$ and $t_k = 6$) is the average trading volume, *DayTvol*, observed every Monday at 00:30 over the J-week period. Formally:

$$DayTvol_{t_k} = \frac{1}{J} \sum_{j=1}^{J} DayTvol_{f(j,k,t_k)}, \tag{2}$$

and

$$f(j, k, t_k) = \beta(j - 1) + \delta(k - 1) + t_k. \tag{3}$$

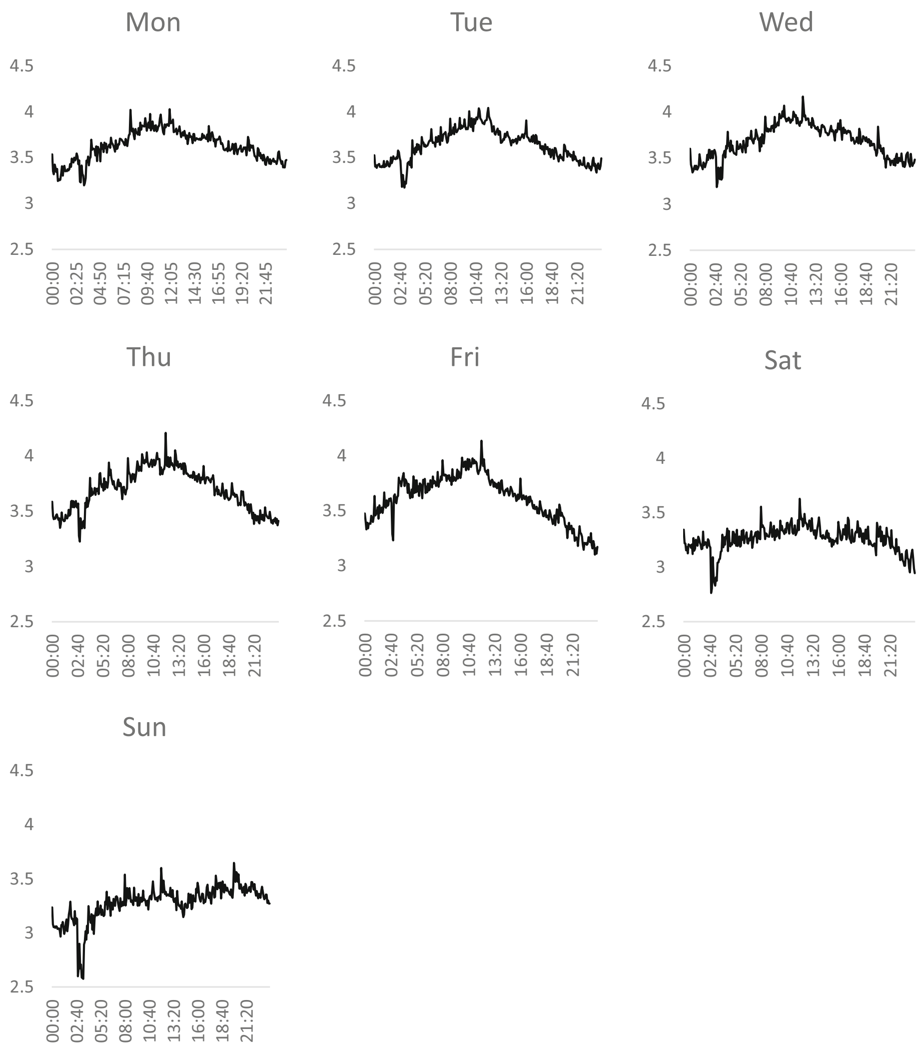

Fig. 3 Bitcoin seasonal log cumulative number of trade by day-of-the week. *Note*: This figure depicts the natural logarithm of the number of Bitcoin trades completed each day during the twenty-four trading hours

β is the total number of time intervals during the week. Using 5-min intervals, t_k= 1, 2…288, $\delta = 288$, and β= 288 × 7 = 2,016. When j varies from 1 to J, the function $f(j, k, t_k)$ varies from 1 to N, where N is the total number of observations in the sample period. Because the number of intervals per day varies from day to day and the day itself must be tracked within the variable, we must consider a function index rather than a single unique time index.

The Flexible Fourier Form order was chosen using the Akaike criterion, with P set to 4. $Pnews_{t,j,k}$ denotes the pure news component of category k related to country J. We focus on the pure news component because previous research has demonstrated the significance of US monetary policy figure effects, where the surprise component is typically muted due to the equality of the forest and actual figures. The main advantage of pure news is that it does

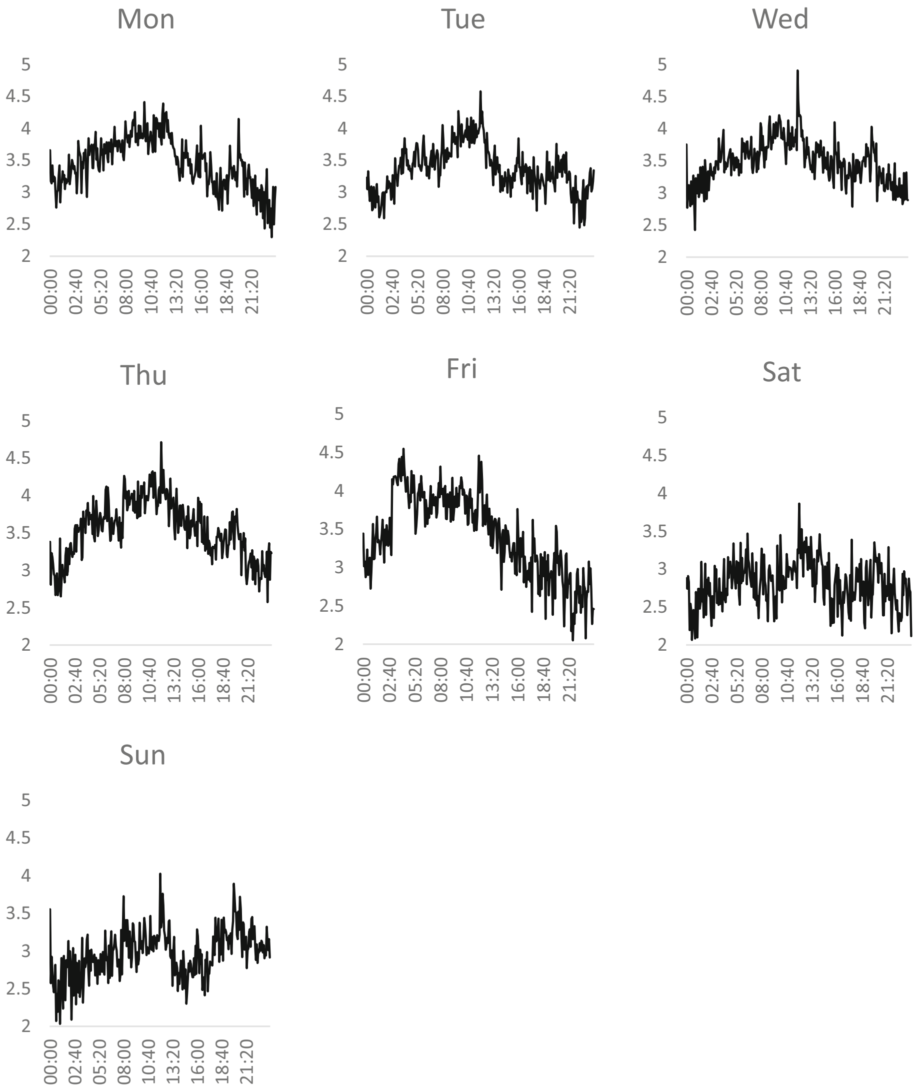

Fig. 4 Ethereum seasonal log cumulative volume by day-of-the week. *Note*: This figure depicts the natural logarithm of Ethereum trading volume over the course of a 24-h trading day

not miss any news releases, even if the actual figure is identical to the forecasted figure. Pure news variables are dummy variables with a value of one at the time of the announcement and a value of zero otherwise.

To ensure consistency, we regress the cumulative number of trades on the pure news announcements and intraday seasonality variables in a second step. Seasonality involves the average cumulative number of trades per time interval t and for every day of the week in the Flexible Fourier Form:

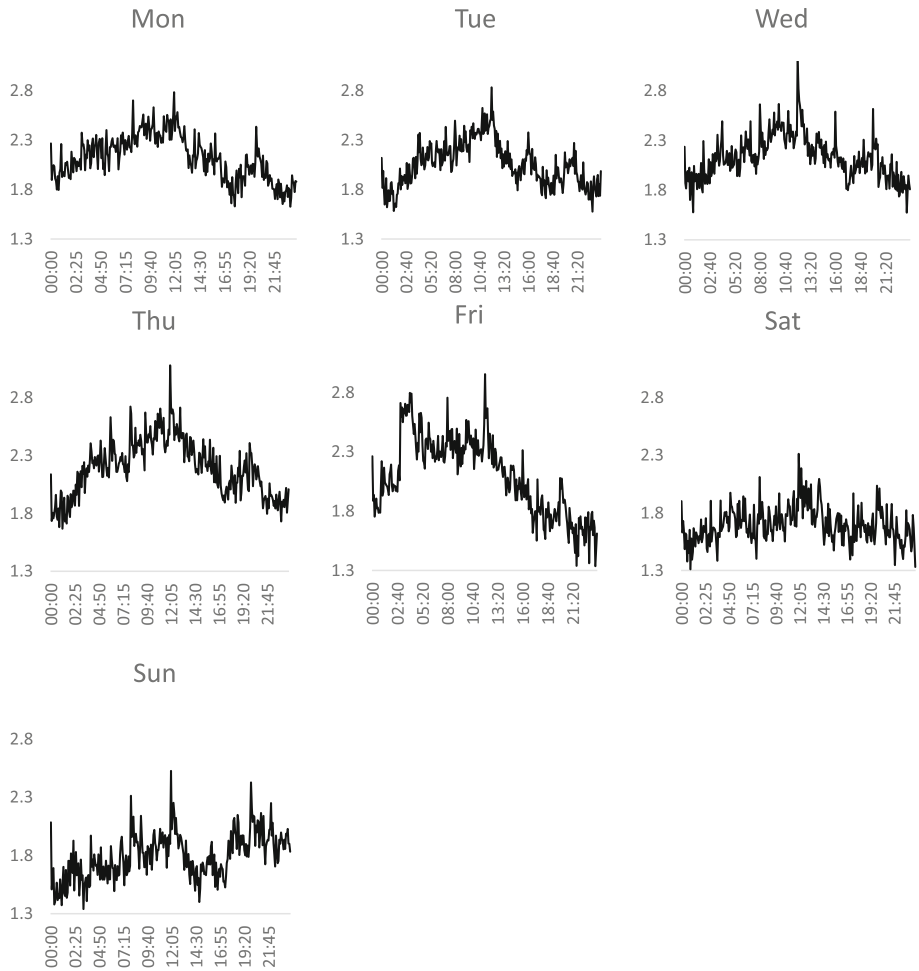

Fig. 5 Ethereum seasonal log cumulative number of trade by day-of-the week. *Note*: This figure depicts the natural logarithm of the number of Ethereum trades completed each day during the twenty-four trading hours

$$
\begin{aligned}
Trades_t =& \theta_0 + \theta_1 Trades_{t-1} + \sum\nolimits_{p=1}^{P}\left(\gamma_{c,p}\mathrm{Cos}\left(\frac{2\pi n}{N}p\right) + \gamma_{s,p}\mathrm{Sin}\left(\frac{2\pi n}{N}p\right)\right)\\
&+ \sum\nolimits_{d=1}^{D} DayTrades_t + \sum\nolimits_{j=1}^{J}\sum\nolimits_{k=1}^{K}\delta_{j,k} Pnews_{t,j,k} + \varepsilon_t,
\end{aligned}
\tag{4}
$$

where $Trades_t$ stands for the natural logarithm for the cumulative number of trades occurred in time interval t and $DayTrades_t$ is the weekly diurnal pattern of the number of trades. It is worth noting that DayTrade's computation is similar to DayTvol's.

4 Empirical results

In this section, we present the result of examining whether and how intraday trading volume and the number of trades of Bitcoin and Ethereum are influenced by the release of macroeconomic news. Table 3 provides the response of Bitcoin and Ethereum to US macroeconomic news and monetary policy announcements after controlling for intraday seasonality. With respect to Bitcoin, both the volume and the number of trades seem to respond to the same type of U.S. macroeconomic news announcements. First, the volume and number of trades are sensitive to the release of news related to changes in payrolls of employees working in the manufacturing, goods and construction firms in the US. Second, both the volume and the number of trades of Bitcoin seem to respond to the announcement of statistics on new home sales in the U.S. The third news announcement to which Bitcoins' volume and the number of trades seem to react to is business inventories. Released by the U.S. Department of Commerce, Business inventories reflect the value of inventories held by manufacturers, retailers, and wholesalers across the country. Business inventories can be used to predict whether goods production will increase or decrease in the future.

Fourth, the coefficients on the volume as well as the number of trades are statistically significant at the 1% level with respect to news announcements related to the consumer confidence indicator (CCI). This suggests that the volume and the number of trades of Bitcoin are sensitive to news reflecting future trends of the U.S. households' consumption and saving. Finally, our results show that the volume and the number of trades of Bitcoin are affected by the Federal Open Market Committee (FOMC) upper-bound rate decisions. The FOMC is the Federal Reserve branch that sets monetary policy in the United States, and their decisions can have far-reaching consequences for the global economy, including the cryptocurrency market. When the FOMC announces a change in interest rates, the value of the US dollar in relation to other currencies as well as the overall health of the economy can be affected. Changes in interest rates can also have an impact on investor sentiment, which can affect cryptocurrency demand. If investors believe interest rates will rise, they may shift their money into more traditional investments such as stocks or bonds, potentially reducing demand for cryptocurrencies. FOMC rate decisions have the greatest impact on the volume and number of trades on both Bitcoin and Ethereum when compared to other macroeconomic news. Although the FOMC's rate decisions are known to have a significant impact on stock and foreign exchange price components such as return, volatility, and jumps, this is the first study to show that FOMC rate decisions affect the volume and number of cryptocurrency trades.

The release of New Home Sales news influences the volume and number of trades in Ethereum, just as it does in Bitcoin. Unlike Bitcoin, however, the release of consumer credit news has a significant impact on the number of Ethereum trades. Changes in Nonfarm payroll affect the volume but not the number of Ethereum trades.

Table 4 presents the response of Bitcoin and Ethereum to German and Japanese macroeconomic news after controlling for intraday seasonality. With respect to Bitcoin, both the volume and the number of trades seem to respond to the same type of German and Japanese macroeconomic news announcements. The volume and the number of trades of Bitcoin are sensitive to four out of twelve German macroeconomic fundamentals: Trade Balance, GfK Consumer Confidence, Import Price Index and IFO Business Climate. Of particular interest, we find the GfK Consumer Confidence Index (CCI) and the IFO Business Climate Index. Prepared by the European Commission (EC), the German Gfk CCI is an indicator of the level of household confidence in economic activity. Carried out by the IFO Institute for Economic Research in Munich, the IFO Business Climate Index is the leading early indicator of

Table 3 US macroeconomic news effects on volume and trades

Announcement	Bitcoin				Ethereum			
	Volume	P.V	Trades	P.V	Volume	P.V	Trades	P.V
US Macroeconomic								
GDP Advanced	0.4474	0.33	0.2360	0.16	– 0.1097	0.88	0.3581	0.32
GDP Preliminary	– 0.0967	0.82	– 0.0693	0.65	0.0168	0.98	0.2067	0.53
GDP Final	0.2911	0.48	0.0130	0.93	0.5411	0.42	0.2588	0.43
Change in Nonfarm Payrolls	**0.2680**	**0.02**	**0.1526**	**0.01**	**0.4821**	**0.04**	0.0126	0.95
Nonfarm Productivity	0.4055	0.17	0.0584	0.59	0.7024	0.15	0.1252	0.61
Producer Price Index MoM	0.1205	0.63	– 0.0529	0.56	– 0.0562	0.89	– 0.0223	0.91
Unemployment Rate	0.1900	0.44	0.0572	0.53	0.2224	0.59	0.0491	0.81
Retail Sales MoM	– 0.0833	0.74	0.0828	0.36	– 0.0510	0.90	0.0705	0.72
Industrial Production	– 0.1322	0.60	0.0197	0.83	0.1945	0.65	0.0767	0.71
Personal Income	0.1268	0.61	0.0503	0.58	0.1702	0.67	0.1698	0.39
Consumer Credit	0.0413	0.87	– 0.0458	0.61	0.0162	0.97	**0.2314**	**0.05**
New Home Sales	**0.3609**	**0.04**	**0.2365**	**0.01**	**0.8391**	**0.03**	**0.4207**	**0.03**
Personal Consumption	0.0940	0.70	0.0232	0.80	0.0102	0.98	0.0763	0.70
Factory Orders	– 0.0537	0.76	– 0.0027	0.97	– 0.1483	0.61	0.0033	0.98
Construction Spending	– 0.0706	0.78	– 0.0287	0.75	– 0.0937	0.82	0.0201	0.92
Business Inventories	**0.5052**	**0.04**	**0.1946**	**0.03**	0.0402	0.92	0.1880	0.34
Monthly Budget St	0.0992	0.69	0.1510	0.11	0.0214	0.96	0.1034	0.60
Trade Balance	– 0.0331	0.89	0.0869	0.34	0.2937	0.46	0.1953	0.32
CPI MoM	0.1319	0.59	0.0767	0.40	0.4392	0.27	0.0816	0.68
Consumer Conf. Index	**– 0.6115**	**0.01**	**– 0.2173**	**0.01**	– 0.3581	0.38	– 0.0660	0.74
ISM Manufacturing	0.0147	0.95	0.0871	0.35	– 0.1597	0.72	0.0736	0.73
Housing Starts	0.1327	0.59	0.0359	0.69	0.0460	0.91	0.0097	0.96

Table 3 (continued)

Announcement	Bitcoin				Ethereum			
	Volume	P.V	Trades	P.V	Volume	P.V	Trades	P.V
Leading Index	0.0052	0.98	0.0621	0.51	0.1277	0.76	0.1244	0.54
Capacity Utilization	− 0.0926	0.72	0.0678	0.47	− 0.1388	0.73	− 0.1725	0.39
FOMC Rate Decisions	**0.5956**	**0.03**	**0.1990**	**0.01**	**1.1150**	**0.03**	**0.5868**	**0.02**
Fed Beige Book	0.3372	0.27	0.1114	0.32	0.6233	0.23	0.2451	0.34
Adjusted R-squared	36.71%		62.95%		22.75%		43.84%	

This table shows the volume and number of trades in Bitcoin and Ethereum in response to US macroeconomic news and monetary policy announcements. Estimated coefficients from Eqs. (1–4) that are statistically significant at 1%, 5%, and 10% levels are highlighted in bold. P.V. stands for *p*-value

the country's economic developments. Out of the four macroeconomic indicators, the news release on Trade Balance is the only one with a negative effect on the volume and the number of trades of Bitcoin.

The volume and the number of trades of Bitcoin are sensitive to the release of three out of ten Japanese macroeconomic news: Tankan, Current Account, and Housing Starts. Short for kigyō tanki keizai kansoku chōsa, Tankan is prepared by the Bank of Japan and it is considered the leading indicator of business confidence in the Japanese economy. A highly regarded measure of economic growth, Housing Starts is the only macroeconomic indicator to positively influence the volume and the number of trades of Bitcoin. As for Ethereum, our results from Table 4 indicate that it is less sensitive to German and Japanese macroeconomic news announcements. In particular, the volume and the number of trades of Ethereum are negatively impacted by news releases on German's GDP and Import Price Index and positively related to the announcement about the status of the Japanese Producer Price Index.

Overall, results from Tables 3 and 4 indicate that, though at different degrees, the trading volume and the number of trades of Bitcoin and Ethereum react to a subset of U.S., German and Japanese macroeconomic news. Given the evidence by Sarkodie et al. (2022) showing that a dynamic shock in Bitcoin trading volume leads to a major increase in Bitcoin energy consumption, our results suggest that macroeconomic news announcements contribute to the cryptocurrency market's energy and carbon footprint.

5 Summary and conclusion

The growing energy consumption and the environmental impacts of mineable cryptocurrencies have attracted major criticism from the advocates of environmental sustainability as well as increasing resections from regulators in some developed and developing countries like Canada and China. This led to a growing stream of literature examining the determinant of energy consumption and carbon emissions induced by the mining process of cryptocurrencies. This study adds to this burgeoning line of inquiry by investigating whether the release of macroeconomic news from the United States, Germany, and Japan affects the trading volume

Table 4 German and Japanese macroeconomic news effects on volume and trades

Announcement	Bitcoin				Ethereum			
	Volume	P.V	Trades	P.V	Volume	P.V	Trades	P.V
German news								
GDP	0.0389	0.89	0.1187	0.27	**0.7287**	**0.07**	**0.4653**	**0.06**
Unemployment Change	0.0313	0.91	– 0.0061	0.95	– 0.0059	0.99	0.0521	0.81
Unemployment Rate	0.0753	0.77	0.0203	0.83	0.1322	0.76	0.0697	0.75
Retail Sales MoM	0.1657	0.53	**0.1542**	**0.09**	– 0.1694	0.71	– 0.0672	0.76
Industrial Production	0.0264	0.91	0.0394	0.67	0.2612	0.54	– 0.0109	0.96
Trade Balance	**– 0.4255**	**0.08**	**– 0.2609**	**0.06**	0.4571	0.28	0.2558	0.22
Current Account Balance	– 0.2389	0.33	– 0.0345	0.70	0.2653	0.53	0.0142	0.95
GfK Consumer Confidence	**0.2096**	**0.06**	**0.1445**	**0.09**	– 0.1018	0.80	0.0646	0.74
Import Price Index MoM	**0.5511**	**0.03**	**0.2986**	**0.00**	**1.0955**	**0.02**	**0.7702**	**0.00**
IFO Business Climate	**0.2947**	**0.00**	**0.1701**	**0.06**	0.1898	0.63	0.2024	0.30
ZEW Survey Current Situation	0.2191	0.39	0.1471	0.55	– 0.3187	0.44	– 0.1935	0.34
Markit/BME	0.1898	0.28	0.0806	0.22	– 0.3618	0.23	0.0324	0.83
Japanese news								
Tankan	**– 0.9284**	**0.03**	**– 0.1903**	**0.06**	– 0.4424	0.55	– 0.4422	0.22
Current Account	**– 0.2546**	**0.06**	**– 0.1974**	**0.03**	– 0.2894	0.48	– 0.0751	0.71
GDP	0.2178	0.44	0.1255	0.23	0.7230	0.13	0.3123	0.18
Trade Balance	– 0.1489	0.40	0.0009	0.99	– 0.3051	0.30	**– 0.2660**	**0.07**
Retail sales	0.0174	0.94	0.0071	0.94	0.2424	0.55	0.1724	0.39
Producer Price Index	– 0.1234	0.49	– 0.0747	0.25	**– 0.5138**	**0.09**	**– 0.1692**	**0.06**
Imports	– 0.0595	0.82	0.0260	0.78	– 0.2584	0.54	– 0.1644	0.43
Exports	– 0.0595	0.82	0.0260	0.78	– 0.2584	0.54	– 0.1644	0.43
Housing Starts	0.3134	0.20	0.1303	0.15	– 0.4106	0.32	0.1115	0.58
Industrial Production	0.2266	0.19	0.0380	0.56	0.2214	0.47	– 0.0266	0.86
Adjusted R-squared	36.71%	62.95%	22.75%	43.84%				

This table shows the volume and number of trades in Bitcoin and Ethereum in response to German and Japanese macroeconomic news and monetary policy announcements. Estimated coefficients from Eqs. (1–4) that are statistically significant at 1%, 5%, and 10% levels are highlighted in bold. P.V. stands for *p*-value and the number of trades in Bitcoin and Ethereum. Our work is driven by recent evidence indicating that shocks in cryptocurrency trade volume increase Bitcoin's energy consumption and carbon footprint, and thus seeks to identify the news-based determinants of Bitcoin's and Ethereum's volume and number of trades.

Using 5-min frequency Bitcoin and Ethereum prices quoted against the US dollar over the 2019–2020 period, we show that the volume and number of trades show a significant response to macroeconomic releases and that Bitcoin is more sensitive to macroeconomic news announcements than Ethereum. Furthermore, both the volume and number of trades in Bitcoin and Ethereum react to the same U.S. macroeconomic news, such as the Consumer Confidence Index, new home sales, and, most importantly, FOMC rate decisions. The release of US monetary policy news consistently affects the trading volume and the number of trades in both cryptocurrencies. The Federal Reserve's interest rate decisions, which affect the broader financial markets, have a positive significant impact on the trading volume of digital assets, causing higher energy consumption. Moreover, the volume and number of Bitcoin and Ethereum trades show a significant response to various German and Japanese macroeconomic news, particularly forward-looking news. Taken together, our findings suggest that macroeconomic news, particularly monetary policy and forward-looking news releases, can contribute to cryptocurrencies' increased energy consumption and carbon footprint.

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Declarations

Conflict of interest The authors have not disclosed any competing interest.

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