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Does natural gas volatility affect Bitcoin volatility? Evidence from the HAR-RV model

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ABSTRACT
While volatility spillover is a vital research area in financial economics (due to its importance for risk valuation and portfolio diversification strategies), the volatility linkage between Bitcoin and electricity/energy markets has not received adequate attention. As the Bitcoin mining cost comes mainly from electricity (which is highly dependent on natural gas), we hypothesize that natural gas is a non-trivial Bitcoin price volatility driver and aim to test if this is the case. Specifically, we employ a widely used model called the HAR-RV model to assess volatility spillover across Bitcoin and natural gas using high-frequency data. We find a spillover effect from natural gas to Bitcoin, and the positive (negative) component of natural gas volatility stabilizes (destabilizes) Bitcoin volatility. The spillover effect is further examined and confirmed using an out-of-sample approach.

KEYWORDS
Bitcoin; volatility; realized volatility; HAR; energy commodities

JEL CLASSIFICATION
C5; C32; Q4

I. Introduction

Identifying the source(s) of volatility (or risk) of investments is a longstanding topic for investors and policy-makers. Arguably, this is particularly the case for Bitcoin, as Bitcoin is known to be an extremely speculative investment instrument (Baek and Elbeck 2015). For investors to formulate risk valuation and portfolio diversification strategies and for policy-makers to categorize, supervise and regulate Bitcoin, it is imperative that the volatility behaviour of Bitcoin, and, especially, what drives Bitcoin volatility, be examined.

It is a well-known fact that Bitcoin is a big electricity 'eater' for its computer labour-intensive mining activity Kristoufek (2020). As argued in Garcia and Schweitzer (2015), in theory, the lower-boundary of Bitcoin's fundamental value depends on the electricity cost of mining. Thus, Bitcoin price changes (or its variations) should be a function of changes (or variations) in the electricity cost of mining, and this, in turn, provides a fundamental link between the volatilities of these two markets. The literature focuses on how Bitcoin is related to other types of cryptocurrencies, conventional financial assets and/or commodities in terms of return spillover. Papers that examine high-moment (e.g. volatility) spillover between Bitcoin and electricity and that use high-frequency data are scant.[1]

The purpose of this study is to examine the role of electricity cost variability in explaining the volatility of Bitcoin, using high-frequency data. To this end, we employ the heterogeneous autoregressive realized volatility/variance (HAR-RV) model introduced by Corsi (2009). Recent studies have shown the superior performance of the HAR-RV model in forecasting volatility (see, e.g. Gong and Lin 2017; Wen, Gong, and Cai 2016). In addition, it captures the long memory dynamics of volatility estimated on high-frequency price data (Andersen, Bollerslev, and Diebold 2007; Jayawardena et al. 2016) and often outperforms many popular models, including GARCH-type models (Andersen et al. 2006)[2]

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[1]See Section II Literature Review for details.
[2]Katsiampa (2017) compares six GARCH-type models for estimating volatility for Bitcoin returns, and finds that the AR-CGARCH model fits their data well. However, Charles and Darné (2019) replicate the study and find no concrete evidence for these six GARCH-type models..

This study uses the returns volatility of natural gas as a proxy for the risk associated with electricity, as natural gas is a major source of electricity[3] As Bitcoin mining is spread across the globe, no single electricity price can represent this cost. Due to lack of high-frequency data and of market depth of electricity futures during the sample period, we use natural gas as a proxy of electricity market. According to Energy Information Administration (EIA), natural gas is the cleanest burning and fastest growing fossil fuel, accounting for almost one-third of total energy demand growth through the last decade, and more than any other fuel.

In general, our analysis shows a significant volatility spillover effect from natural gas to Bitcoin, and the effect is dependent on both the sign of the shocks and their time variations. Moreover, additional test shows that adding the (realized price) volatility of natural gas to our empirical model improves its out-of-sample forecasting power, confirming the importance of natural gas volatility in determining the volatility of Bitcoin.

In terms of contribution, first and foremost, this study examines the volatility linkage between Bitcoin and natural gas markets using high-frequency data, an issue that has received inadequate attention in the literature, despite the fact that this effect is highly relevant to risk valuation and portfolio diversification strategies (Garcia and Tsafack 2017)[4] In particular, our finding helps Bitcoin miners make their strategic capital investment decisions on mining technology. Second, this study adds to an emerging line of research that explores interlinkages across the bitcoin and energy markets by showing that these two markets are connected through the volatility channel. Third, this paper also shows how Bitcoin volatility is associated with shocks arising from the positive and negative uncertainties of the natural gas price: a proxy for the electricity price.

The remainder of this paper is organized as follows: Section II reviews relevant literature, Section III outlines the data and methodology, Section IV discusses the empirical results, and Section IV concludes.

II. Literature review

The literature on spillover effects of Bitcoin is large and focuses predominately on Bitcoin's relationship with other cryptocurrencies (Katsiampa 2017); Kumar et al. 2022) [5] and conventional assets, such as stocks, bonds, currencies, commodities (Al-Yahyaee et al. 2019), or a combination of them (see, e.g. Bouri et al. (2018, 2018), Urom et al. (2020), Gkillas et al. (2022)).[6] Only a handful of papers are concerned with the relationship between Bitcoin and energy markets and their focus is on return spillovers or spillover from volatility to return. For example, Ciaian, Rajcaniova, and Kancs (2016) show a significant effect of oil price on Bitcoin price, but Baur, Dimpfl, and Kuck (2018) find that oil has no impact on Bitcoin returns[7] Moreover, as shown in Bouri et al. (2017), Bitcoin and the general commodity index are negatively correlated up to 2013, and the relationship turns positive thereafter. Ji et al. (2019) examine the return spillover among various commodities (including energy) and leading cryptocurrencies (including Bitcoin) and find evidence that cryptocurrencies are generally integrated within these commodity markets.

Two papers are related to our paper. Yuen et al. (2022) examine the static and dynamic spillover effects between Bitcoin and energy consumption using daily data of Cambridge Bitcoin electricity consumption index (BTCE) and Bitcoin energy consumption index (BTCC). They find that 'energy consumption and the Bitcoin market are strong risk-related' (p.9). Afjal and Sajeev (2022) use Granger causality and the DCC-MGARCH model to examine the return spillover between cryptocurrencies and four energy markets. They fnd a low and weak correlation between them. Our paper

[3]Worldwide, natural gas is the second main source for electricity generation and coal is the first. However, due to a thin trading issue of coal futures, we are unable to incorporate coal in the analysis..

[4]There is a small literature on the role of Bitcoin in risk valuation and portfolio diversification. See, e.g. (Guesmi et al. 0000), Jin et al. (2019) and Khelifa, Guesmi, and Urom (2021). The presence of return spillover between energy markets and the bitcoin market has been recognized recently in the literature (Ciaian, Rajcaniova, and Kancs 2016; Symitsi and Chalvatzis 2018)..

[5]See Kyriazi (2019) for a survey and the references therein.

[6]The literature on Bitcoin and commodities is growing, and its focus is mainly on Gold (e.g. Baur, Dimpfl, and Kuck (2018) and Shahzad *et al*. (2022)). See Bouri et al. (2017) and the references therein for this line of literature.

[7]See also Symitsi and Chalvatzis (2018)..

differs from them in the following ways. First, we use high-frequency (5 min) data. Second, we measure volatility in terms of realized volatility (RV). Third, we employ HAR-RV model that can account for microstructure effects commonly observed in high-frequency data.

III. Data and methodology

Following Liu, Patton, and Sheppard (2015), two high-frequency price series (Bitcoin and natural gas) with 5-min intervals from September 2011 to May 2022 are used for volatility computation. The Bitcoin data are from one of the largest exchanges: Bitstamp (obtained from Bitcoincharts.com and https://www.CryptoDataDownload.com). For natural gas, we use the futures prices of the Henry Hub Natural Gas traded on NYMEX[8], extracted from Thomson Reuters Tick History database. We follow Clements and Todorova (2016) and use trading volumes of futures contracts with different maturities to select the most liquid one for volatility estimation, in order to ensure that highly liquid contracts for natural gas are employed. To compute the daily realized variance (RV), we follow Andersen and Bollerslev (1998) and compute it as

$$RV_t = \ln\left(\sum\nolimits_{j=1}^{k} r_{t,j}^2\right) \tag{1}$$

where $r_{t,j} = \ln(p_{t,j}) - \ln(p_{t,j-1})$ is the return for interval j within day t.

RV is selected as it overcomes the issue of modelling risk including the microstructure effect (Bouri et al. 2021; Ma et al. 2017), unlike other volatility estimation techniques.

We also follow Barndorff-Neilsen, Kinnebrouk, and Shephard (2010) to decompose RV into two semi-variance measures, where the positive variations capture positive shocks from a market upturn, and the negative variations capture negative shocks from a market downturn. By using these measures, we can examine whether the volatility linkage between Bitcoin and natural gas is direction-specific. This will shed light on the spillover mechanism in terms of volatility sign and direction, which is important for Bitcoin investors. Specifically, the decomposed RVs for day t are given as

$$\begin{aligned} RV_t^+ &= \ln\left(\sum\nolimits_{j=1}^{k} r_{t,j}^2 I\{r_{t,j} > 0\}\right) \\ RV_t^- &= \ln\left(\sum\nolimits_{j=1}^{k} r_{t,j}^2 I\{r_{t,j} < 0\}\right) \end{aligned} \tag{2}$$

where I is the indicator function.

To proceed with the analysis, the following HAR-RV models are considered:

$$\begin{aligned} RV_{t+1,Coin} = \beta_0 &+ \sum\nolimits_{i\in(d,w,m)} \beta^i_{Coin} RV^i_{t,Coin} \\ &+ \sum\nolimits_{i\in(d,w,m)} \beta^i_{Gas} RV^i_{t,Gas} + \varepsilon_t \end{aligned} \tag{3a}$$

$$\begin{aligned} RV_{t+1,Coin} = \beta_0 &+ \sum\nolimits_{i\in(d,w,m)} \beta^{+,i}_{Coin} RV^{+,i}_{t,Coin} \\ &+ \sum\nolimits_{i\in(d,w,m)} \beta^{+,i}_{Gas} RV^{+,i}_{t,Gas} \\ &+ \sum\nolimits_{i\in(d,w,m)} \beta^{-,i}_{Coin} RV^{-,i}_{t,Coin} \\ &+ \sum\nolimits_{i\in(d,w,m)} \beta^{-,i}_{Gas} RV^{-,i}_{t,Gas} + \varepsilon_t \end{aligned} \tag{3b}$$

where the superscript i (d, w and m) indicates that the measures are the daily, weekly (7-day) and monthly (30-day) averages. *Coin* indicates Bitcoin and *Gas* indicates natural gas.

Bariviera (2017) finds that the Bitcoin market appears to have become informationally efficient in recent years only, i.e. in the latter half of our sample period. This implies that Bitcoin prices may have been less sensitive to the arrival of new information from the related commodity market during the first half of the sample period, while they became more sensitive in the latter half. In other words, the relationship between the volatility of Bitcoin and natural gas may be time varying. To check for this possibility, we estimate Equation (3b) with a four-year rolling window.

IV. Empirical results

In-sample examination

Basic analysis

The full-sample results using Equation (3a) are given in Table 1. Column 2 (3) of Table 1 shows the results when the volatility measures of natural

[8]Data from the Henry Hub is employed because it is one of the key natural gas contracts in the international commodity market (Mazighi 2005). In particular, the Bloomberg Commodity Index (previously known as Dow Jones-UBS Commodity Index), the GSCI and the CRB index all use this as the natural gas reference price.

Table 1. Full-sample HAR-RV results.

	Without gas	With gas
Cons	−0.585	−0.748
Std.Err.	0.136	0.216
t-stat.	−4.292	−3.465
Daily RV	0.455***	0.449***
Std.Err.	0.035	0.035
t-stat.	12.930	12.800
Weekly RV	0.336***	0.323***
Std.Err.	0.041	0.041
t-stat.	8.228	7.934
Monthly RV	0.118***	0.139***
Std.Err.	0.030	0.029
t-stat.	3.949	4.770
Daily Gas RV		0.104***
Std.Err.		0.038
t-stat.		2.764
Weekly Gas RV		0.045
Std.Err.		0.073
t-stat.		0.611
Monthly Gas RV		−0.171**
Std.Err.		0.069
t-stat.		−2.472
R^2 Adj.	0.583	0.586

This table presents the result of basic *HAR-RV* analysis. The standard errors are adjusted with the Newey West correction. The explained variable is the one-day ahead realized variance (*RV*) of Bitcoin. Gas indicates natural gas and it is used as a proxy for electricity price. *Daily RV* is the one-day realized variance, *Weekly RV* is the seven-day rolling average realized variance, and *Monthly RV* is the 30-day rolling average realized variance. ***, ** and * indicate the result is significant at the 1%, 5% and 10% level, respectively.

gas (RV_{GAS}) are excluded (included). Column 2 shows that the coefficients of all three lagged volatility measures are highly significant, reflecting the persistence of the Bitcoin volatility. Interestingly, Column 3 reveals that while the one-day lagged RV_{GAS} shows a positive impact, the effect of monthly RV_{GAS} is negative – both are significant (note that the weekly effect is small and insignificant). This result suggests that when long-term (monthly) gas volatility is held fixed, an increase in short-term (daily) gas volatility increases the volatility of Bitcoin. On the other hand, if the increase in gas volatility lasts for a longer period (month), it helps to calm the Bitcoin market. The positive short-term spillover effect can be attributed to the direct linkage between the two markets and the negative long-term effect is most likely due to the dual nature of some Bitcoin miners, who are also Bitcoin investors as explained previously. As mining costs become persistently volatile, swing miners turn to Bitcoin investment, and a denser market often facilitates volatility reduction. The switch in signs obtained for the coefficients of RV_{GAS} may be due to the above-mentioned direction-specific nature of the Bitcoin market response to the change in mining costs.

Table 2. Full-sample HAR-RV results with positive and negative RVs.

Explained variable	*Bitcoin RV*	*Bitcoin RV*$^+$	*Bitcoin RV-*
Cons	−0.229	−0.727***	−0.779***
Std.Err.	0.247	0.240	0.286
t-stat.	−0.926	−3.032	−2.722
Daily Gas RV$^+$	0.003	−0.035	0.019
Std.Err.	0.041	0.050	0.044
t-stat.	0.084	−0.696	0.434
Daily Gas RV-	0.084**	0.068**	0.083**
Std.Err.	0.035	0.032	0.040
t-stat.	2.410	2.143	2.084
Weekly Gas RV$^+$	0.012	−0.020	−0.051
Std.Err.	0.116	0.115	0.125
t-stat.	0.102	−0.173	−0.412
Weekly Gas RV-	0.058	0.116	0.120
Std.Err.	0.103	0.103	0.114
t-stat.	0.563	1.124	1.046
Monthly Gas RV$^+$	−0.319	−0.269	−0.558**
Std.Err.	0.211	0.218	0.248
t-stat.	−1.513	−1.231	−2.253
Monthly Gas RV-	0.146	0.123	0.374
Std.Err.	0.211	0.218	0.232
t-stat.	0.693	0.563	1.611
R^2 Adj.	0.587	0.592	0.529

This table presents the relation between the Bitcoin volatility and decomposed natural gas volatilities. The standard errors are adjusted with the Newey West correction. The dependent variable is the one-day ahead *RV* of Bitcoin indicated in the first row. Gas indicates natural gas and it is used as a proxy for electricity price. *Daily RV* is the one-day realized variance, *Weekly RV* is the seven-day rolling average realized variance, and *Monthly RV* is the 30-day rolling average realized variance. Negative and positive signs next to *RV* indicate the realized variance is estimated from a market downturn and upturn, respectively. For the sake of brevity, only the results of natural gas are displayed. ***, ** and * indicate the result is significant at the 1%, 5% and 10% levels, respectively.

We report the full-sample estimation results of Equation. (3b) as the Bitcoin RV column in Table 2. The results show that the one-day lagged RV^-_{GAS} is positive and significant, implying that the short-term downside risk in the price of natural gas amplifies the overall returns variability of Bitcoin. This is consistent with the view that reduction in the electricity cost leads to an increase in Bitcoin miners and, thereby, attenuates Bitcoin in exchange trading and destabilizes the market. By contrast, neither the weekly/monthly average RV^+_{GAS} nor RV^-_{GAS} shows a significant relationship. This is also consistent with Afjal and Sajeev's (2022) finding that there is a weak relationship between Bitcoin and energy markets.

Time-varying relationship

Table 3 shows that the lead-lag association between the RV of Bitcoin and the decomposed RVs of natural gas is time-varying. For daily RVs of natural gas, the negative component displays a significant positive effect in many of the early

Table 3. Subsample HAR-RV results with positive and negative RVs (sub-sampling).

Years	2011–2014	2012–2015	2013–2016	2014–2017	2015–2018	2016–2019	2017–2020	2018–2021	2019–2022
Cons	−0.645	−0.171	−0.216	−0.381	0.101	−0.228	−0.122	−0.228	−0.448
Std.Err.	0.599	0.493	0.492	0.464	0.402	0.443	0.365	0.342	0.350
t-stat.	−1.077	−0.347	−0.439	−0.821	0.252	−0.515	−0.335	−0.668	−1.279
Daily Gas RV$^+$	0.003	0.013	0.004	0.013	0.022	0.083	0.112**	0.040	−0.033
Std.Err.	0.082	0.070	0.054	0.048	0.054	0.057	0.057	0.070	0.076
t-stat.	0.038	0.189	0.067	0.282	0.397	1.450	1.971	0.575	−0.435
Daily Gas RV-	0.174**	0.105**	0.075*	0.067*	0.081**	0.011	0.005	−0.016	−0.045
Std.Err.	0.075	0.053	0.044	0.038	0.035	0.038	0.041	0.046	0.058
t-stat.	2.322	1.992	1.694	1.768	2.327	0.281	0.121	−0.353	−0.765
Weekly Gas RV$^+$	−0.152	−0.195	−0.006	0.073	0.128	0.125	0.074	0.038	−0.082
Std.Err.	0.271	0.208	0.171	0.146	0.153	0.165	0.148	0.163	0.173
t-stat.	−0.562	−0.940	−0.038	0.501	0.836	0.758	0.502	0.233	−0.471
Weekly Gas RV-	0.199	0.238	0.018	−0.145	−0.123	−0.073	−0.024	0.046	0.280
Std.Err.	0.250	0.191	0.165	0.142	0.127	0.139	0.137	0.150	0.175
t-stat.	0.797	1.246	0.111	−1.026	−0.975	−0.522	−0.172	0.307	1.603
Monthly Gas RV$^+$	0.194	−0.403	−0.726**	−0.758**	−0.613*	−0.677**	−0.475	−0.216	0.223
Std.Err.	0.434	0.351	0.300	0.342	0.363	0.338	0.328	0.327	0.319
t-stat.	0.446	−1.148	−2.418	−2.220	−1.690	−2.000	−1.448	−0.660	0.699
Monthly Gas RV-	−0.442	0.235	0.604**	0.699**	0.515	0.510	0.300	0.111	−0.369
Std.Err.	0.493	0.359	0.307	0.334	0.345	0.320	0.326	0.309	0.299
t-stat.	−0.896	0.656	1.971	2.094	1.492	1.593	0.921	0.360	−1.233
R^2 Adj.	0.439	0.563	0.692	0.608	0.602	0.591	0.573	0.539	0.534

This table presents the relation between the Bitcoin volatility and decomposed natural gas volatilities by subsampling the sample period. The explained variable is the one-day-ahead *RV* of Bitcoin. The first row indicates which years are used in the analysis. Gas indicates natural gas and it is used as a proxy for electricity price. *Daily RV* is the one-day realized variance, *Weekly RV* is the seven-day rolling average realized variance, and *Monthly RV* is the 30-day rolling average realized variance. Negative and positive signs next to *RV* indicate the realized variance is estimated from a market downturn and upturn, respectively. For the sake of brevity, only the results of natural gas are displayed. ***, ** and * indicate the result is significant at the 1%, 5% and 10% levels, respectively.

periods and the effect becomes weaker over time. In contrast, interestingly, the impact of monthly gas volatility on Bitcoin (both positive and negative) was strong and significant during the subperiods 2013 to 2019. The results for the period prior to 2020, as claimed previously, are likely to reflect the improvement in information efficiency of the Bitcoin market and the switching of miners between mining and investing roles, as argued in the introduction. In contrast, the results for the post-2020 may be linked to the COVID-19 pandemic shock, which we will examine further later in this section.

It is worth noting that this growing importance of long-term information from the natural gas market (prior to the pandemic), represented by its monthly volatility measures (see Figure 1), synchronizes with the expansion in the computer-labour power invested in Bitcoin mining (see Figure 2). More specifically, there has been a sharp increase in the hash rate since 2015. In theory, the association between the two assets should come from a common driving risk factor that relates to electricity price variability. However, a certain fraction of natural gas price volatility caused by 'jump' is unlikely to influence electricity production. The discontinuous component of volatility (i.e. jump) is a phenomenon well explained in the financial literature (see, for example, Chevallier and Sévi (2010), Andersen, Dobrev, and Schaumburg (2012), Nolte and Xu (2015) and Omura et al. (2018)). The discontinuous component is driven by a short-lived shock that does not always have a material impact on other markets because of its idiosyncratic nature. In such a case, the observed shock in the market of one asset is noise to another economically related one. When the market becomes informationally efficient, investors react less against such noise and, rather, respond more towards those persistent shocks that may have a real impact. This also explains why the absolute values of the coefficients obtained for the monthly natural gas variable tend to be larger than those for the daily variable.

Furthermore, our analysis shows that the absolute value of the monthly natural gas coefficient is found to be larger for the positive component. This may have occurred because optimistic investors, who entered the market after observing a sharp rise in price during the latter half of our sample, dominated the Bitcoin market. Regarding the signs of the volatility coefficients, Tables 1 and 2 show that, while the positive component of the monthly *RV* of natural gas stabilizes Bitcoin volatility, the

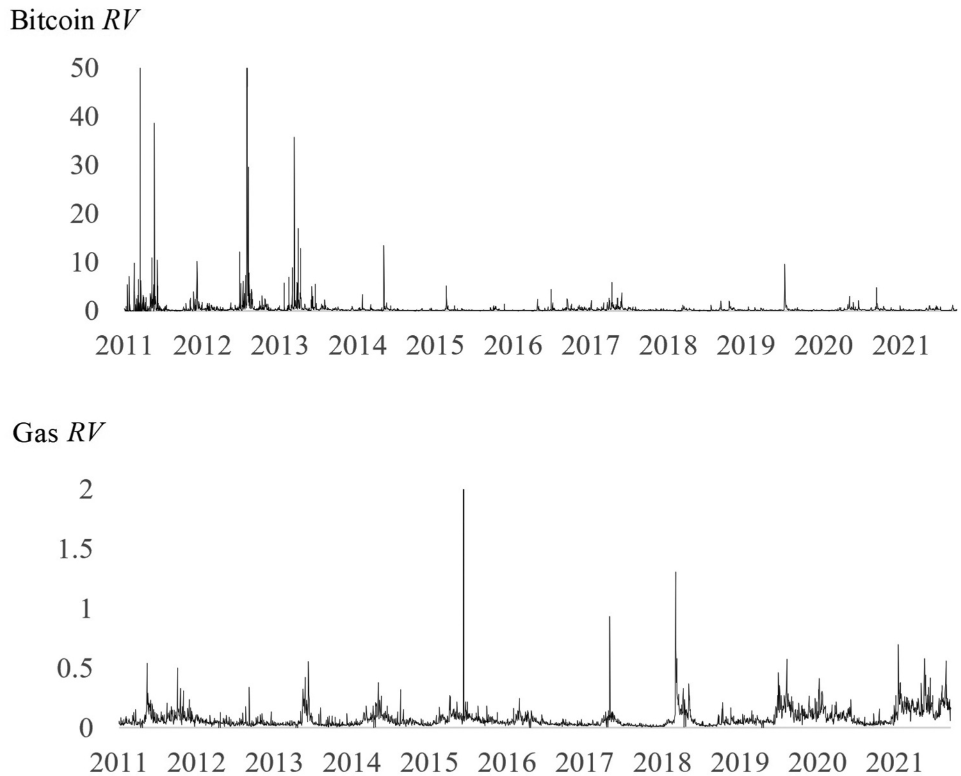

Figure 1. Realized variance of Bitcoin and natural gas (daily). The RV figures are multiplied by 100.

Figure 2. Estimated collective computer-labor power (hash-rate) invested in Bitcoin mining (Million TH/second). Source: Blockchain info.

negative component amplifies it. This is consistent with our speculation that the positive price uncertainty improves the market depth of Bitcoin and, thereby, calms Bitcoin volatility

Therefore, it is meaningful to see whether the relationship that we observed in the earlier sections reflects the association between the positive or the negative component (or both) of the Bitcoin *RV* and the *RV*s of natural gas. Motivated by (Gong and Lin 2017) analysis of the crude oil market, we replace our explained variable with the decomposed *RV*s of Bitcoin, and reanalyse the relationship using Equation (3a) and (3b). This examination provides valuable information to investors and miners on (1) whether the positive and negative components of Bitcoin *RV* are associated differently with the *RV*s of natural gas, and (2) which component of the Bitcoin *RV* has the larger influence over the results obtained in Tables 1 to 3. The results are presented in Tables 4 and 5.

Table 4. HAR results using the RV+ of Bitcoin as an explained variable (sub-sampling).

Years	2011–2014	2012–2015	2013–2016	2014–2017	2015–2018	2016–2019	2017–2020	2018–2021	2019–2022
Cons	−1.002	−0.796*	−1.034**	−1.178***	−0.613	−0.991**	−0.850**	−0.792**	−1.011***
Std.Err.	0.636	0.473	0.491	0.453	0.438	0.497	0.391	0.360	0.377
t-stat.	−1.576	−1.685	−2.109	−2.603	−1.398	−1.995	−2.174	−2.202	−2.684
Daily Gas RV^{+}	−0.102	0.009	−0.003	0.012	0.022	0.073	0.112**	0.045	−0.026
Std.Err.	0.115	0.073	0.054	0.048	0.056	0.055	0.055	0.062	0.068
t-stat.	−0.882	0.123	−0.063	0.258	0.389	1.327	2.050	0.731	−0.387
Daily Gas RV-	0.123*	0.109**	0.073	0.066*	0.082**	0.011	0.004	−0.017	−0.037
Std.Err.	0.064	0.055	0.046	0.039	0.035	0.035	0.039	0.042	0.058
t-stat.	1.918	2.002	1.579	1.707	2.326	0.320	0.103	−0.411	−0.639
Weekly Gas RV^{+}	−0.193	−0.187	0.022	0.106	0.135	0.085	0.005	−0.030	−0.133
Std.Err.	0.275	0.208	0.167	0.132	0.148	0.156	0.144	0.161	0.174
t-stat.	−0.702	−0.897	0.134	0.801	0.914	0.546	0.036	−0.189	−0.763
Weekly Gas RV-	0.305	0.194	−0.026	−0.173	−0.105	−0.020	0.041	0.114	0.303*
Std.Err.	0.261	0.192	0.165	0.135	0.133	0.140	0.137	0.151	0.167
t-stat.	1.170	1.010	−0.158	−1.282	−0.791	−0.143	0.299	0.756	1.815
Monthly Gas RV^{+}	0.068	−0.375	−0.737**	−0.652*	−0.586	−0.634*	−0.363	−0.107	0.390
Std.Err.	0.435	0.369	0.316	0.348	0.365	0.337	0.333	0.343	0.315
t-stat.	0.155	−1.016	−2.335	−1.874	−1.603	−1.884	−1.089	−0.312	1.237
Monthly Gas RV-	−0.217	0.248	0.626*	0.578*	0.455	0.453	0.189	0.001	−0.523*
Std.Err.	0.478	0.378	0.324	0.346	0.352	0.321	0.330	0.327	0.296
t-stat.	−0.455	0.656	1.932	1.674	1.293	1.414	0.574	0.003	−1.766
R^2 Adj.	0.412	0.562	0.699	0.627	0.62	0.609	0.588	0.556	0.559

This table presents the relation between the decomposed Bitcoin volatility and decomposed natural gas volatilities by subsampling the sample period. The explained variable is the one-day-ahead positive *RV* of Bitcoin. The first row indicates which years are used in the analysis. Gas indicates natural gas and it is used as a proxy for electricity price. *Daily RV* is the one-day realized variance, *Weekly RV* is the seven-day rolling average realized variance, and *Monthly RV* is the 30-day rolling average realized variance. Negative and positive signs next to *RV* indicate the realized variance is estimated from a market downturn and upturn, respectively. For the sake of brevity, only the results of natural gas are presented. ***, ** and * indicate the result is significant at the 1%, 5% and 10% level, respectively.

In relation to the time-varying nature of the relationship between Bitcoin and natural gas markets, the results in both Tables 4 and 5 are broadly consistent with the ones in Table 3. As in the analysis of the (undecomposed) Bitcoin *RV*, the results indicate that the association of both positive and negative components with the long-term volatility of natural gas strengthened as the market became more informationally efficient prior to 2020.

We extend the analysis to examine the impact of the shock created by the COVID-19 pandemic during March 2020 to June 2022 and report the results in Table 6. We separate the Covid period into two subperiods (i) March 2020 to May 2021 and (ii) June 2021 to June 2022. Roughly speaking, the first subperiod is with high uncertainty and fear regarding the pandemic when the COVID vaccine is still unavailable, while in the second period the pandemic is ongoing but much alleviated as the vaccine has become relatively available among the world community. We find that the coefficients of the monthly natural gas volatility (both negative and positive) are much larger in magnitude during the Covid period than those in the pre-Covid period (Table 3) and, more interestingly, the sign of the coefficients overturn across the two subperiods. During subperiod (i), the coefficient of monthly Gas RV^{+} (RV-) is positive (negative), implying that the positive (negative) component of the monthly RV of natural gas amplifies (stabilizes) Bitcoin volatility. This is just opposite to the result from pre-Covid and Covid-easing (subperiod (ii)) periods. Understanding how and why the pandemic affects the volatility transmission of energy market to Bitcoin deserves further investigation but is beyond the scope of the paper.

Out-of-sample examination

Forecasting power

We also investigate whether the information contained in the volatility of the natural gas market adds forecasting power to the conventional univariate HAR-RV model. We use Equation (3a) and (3b) to conduct a one-day-ahead out-of-sample analysis for the undecomposed *RV* of Bitcoin. More specifically, we estimate 500-day rolling forecasts for four different HAR models. They are the ones with the *RV* measures of Bitcoin, the *RV* measures of Bitcoin and natural gas, the decomposed *RV* measures of Bitcoin, and the decomposed *RV* measures of Bitcoin and natural gas, respectively. We then first compare the

Table 5. HAR results using RV- of Bitcoin as an explained variable (sub-sampling).

Years	2011–2014	2012–2015	2013–2016	2014–2017	2015–2018	2016–2019	2017–2020	2018–2021	2019–2022
Cons	−0.692	−0.555	−0.808	−0.957**	−0.465	−0.806*	−0.771**	−1.016***	−1.319***
Std.Err.	0.825	0.494	0.497	0.483	0.388	0.421	0.374	0.348	0.352
t-stat.	−0.838	−1.123	−1.627	−1.982	−1.199	−1.915	−2.064	−2.919	−3.750
Daily Gas RV+	0.046	0.026	0.014	0.016	0.026	0.096	0.108*	0.029	−0.051
Std.Err.	0.085	0.068	0.055	0.049	0.055	0.060	0.062	0.080	0.084
t-stat.	0.538	0.386	0.264	0.322	0.462	1.592	1.751	0.364	−0.601
Daily Gas RV-	0.177**	0.094*	0.075*	0.071*	0.073*	0.003	0.000	−0.023	−0.042
Std.Err.	0.088	0.054	0.044	0.039	0.038	0.041	0.043	0.051	0.059
t-stat.	2.016	1.758	1.714	1.808	1.925	0.066	−0.011	−0.453	−0.714
Weekly Gas RV+	−0.359	−0.196	−0.023	0.062	0.125	0.152	0.126	0.075	−0.070
Std.Err.	0.286	0.215	0.175	0.159	0.169	0.189	0.172	0.189	0.191
t-stat.	−1.253	−0.912	−0.132	0.390	0.738	0.803	0.732	0.395	−0.365
Weekly Gas RV-	0.426	0.242	0.049	−0.140	−0.129	−0.102	−0.052	0.025	0.281
Std.Err.	0.312	0.206	0.167	0.150	0.135	0.157	0.159	0.176	0.202
t-stat.	1.365	1.175	0.290	−0.934	−0.957	−0.648	−0.330	0.141	1.390
Monthly Gas RV+	−0.472	−0.584	−0.713**	−0.865**	−0.649*	−0.625*	−0.499	−0.226	0.203
Std.Err.	0.470	0.365	0.297	0.346	0.386	0.365	0.353	0.340	0.335
t-stat.	−1.004	−1.602	−2.406	−2.500	−1.682	−1.710	−1.412	−0.667	0.607
Monthly Gas RV-	0.181	0.444	0.578*	0.817**	0.583	0.469	0.311	0.127	−0.349
Std.Err.	0.507	0.371	0.302	0.335	0.364	0.341	0.347	0.316	0.321
t-stat.	0.358	1.197	1.916	2.436	1.603	1.374	0.898	0.401	−1.087
R^2 Adj.	0.356	0.535	0.677	0.584	0.571	0.561	0.544	0.499	0.486

This table presents the relation between the decomposed Bitcoin volatility and decomposed natural gas volatilities by subsampling the sample period. The first row indicates which years are used in the analysis. The explained variable is the one-day-ahead negative *RV* of Bitcoin. Gas indicates natural gas and it is used as a proxy for electricity price. *Daily RV* is the one-day realized variance, *Weekly RV* is the seven-day rolling average realized variance, and *Monthly RV* is the 30-day rolling average realized variance. Negative and positive signs next to *RV* indicate the realized variance is estimated from a market downturn and upturn, respectively. For the sake of brevity, only the results of natural gas are displayed. ***, ** and * indicate the result is significant at the 1%, 5% and 10% level, respectively.

Table 6. HAR results using RVs of Bitcoin as an explained variable (for the period of post- Covid-19 pandemic shock and post-popularization of the Covid-19 vaccine).

Years	Mar 2020 - May 2021			Jun 2021 - Jun 2022		
Explained variable	*Bitcoin RV*	*Bitcoin* RV^+	*Bitcoin RV-*	*Bitcoin RV*	*Bitcoin* RV^+	*Bitcoin RV-*
Cons	−1.068	−2.006**	−1.655**	−2.969**	−3.556**	−3.773**
Std.Err.	0.822	0.795	0.839	1.492	1.427	1.566
t-stat.	−1.299	−2.524	−1.974	−1.989	−2.493	−2.410
Daily Gas RV+	−0.060	−0.079	−0.065	−0.278**	−0.210*	−0.334**
Std.Err.	0.121	0.117	0.126	0.124	0.118	0.151
t-stat.	−0.492	−0.680	−0.515	−2.247	−1.783	−2.210
Daily Gas RV-	−0.073	−0.069	−0.072	0.024	0.046	0.026
Std.Err.	0.121	0.126	0.128	0.065	0.087	0.058
t-stat.	−0.598	−0.548	−0.565	0.372	0.532	0.448
Weekly Gas RV+	0.108	0.219	0.048	0.502*	0.374	0.568*
Std.Err.	0.404	0.411	0.403	0.302	0.349	0.322
t-stat.	0.266	0.533	0.119	1.661	1.072	1.767
Weekly Gas RV-	−0.166	−0.294	−0.038	0.115	0.176	0.060
Std.Err.	0.365	0.350	0.392	0.311	0.357	0.294
t-stat.	−0.453	−0.839	−0.096	0.372	0.491	0.204
Monthly Gas RV+	1.867**	2.492***	1.303	−2.118**	−2.303**	−1.959**
Std.Err.	0.871	0.942	0.900	0.904	1.025	0.830
t-stat.	2.142	2.644	1.448	−2.343	−2.247	−2.360
Monthly Gas RV-	−1.758**	−2.389***	−1.238	1.642**	1.755*	1.564**
Std.Err.	0.844	0.873	0.892	0.805	0.913	0.732
t-stat.	−2.082	−2.738	−1.389	2.039	1.923	2.137
R^2 Adj.	0.631	0.649	0.592	0.382	0.394	0.317

This table presents the relation between the decomposed Bitcoin volatility and decomposed natural gas volatilities by subsampling the sample period into pre- and post-COVID-19 pandemic shock in 2020, and post-popularization of the COVID-19 vaccine. The popularization of the vaccine is measured by the number of vaccine doses in the world (September 2021 is where the doses reached 3 billion and June 2021 is 1 billion according to https://www.CryptoDataDownload.com). The first row indicates which years are used in the analysis presented in the relevant column, and the second row indicates which one-day-ahead Bitcoin *RV* is used as an explained variable. Gas indicates natural gas and it is used as a proxy for electricity price. *Daily RV* is the one-day realized variance, *Weekly RV* is the seven-day rolling average realized variance, and *Monthly RV* is the 30-day rolling average realized variance. Negative and positive signs next to *RV* indicate the realized variance is estimated from a market downturn and upturn, respectively. For the sake of brevity, only the results of natural gas are displayed. For the sake of brevity, only the results of natural gas are presented. ***, ** and * indicate the result is significant at the 1%, 5% and 10% level, respectively.

Table 7. Out-of-sample one-period ahead forecasting tests.

	RMSE	MSE	MAE
HAR with *RV only*	0.698	0.487	0.515
HAR with *RV of Gas*	0.694	0.481	0.513
HAR with *RV+ and RV-*	0.694	0.481	0.513
HAR with *Gas RV+ and RV-*	0.689	0.475	0.510

This table presents the out-of-sample forecasting test results (a lower value indicates a smaller forecasting error). RMSE is the root mean square error, MSE is the mean square error and MAE is the mean absolute error. The rolling-forecasts are estimated using a window period of 500 days. 'HAR with *RV* only' follows Equation (3a) without the *RV* of natural gas, 'HAR with *Gas RV*' follows Equation (3a), 'HAR with RV^{+} *and RV-*' follows Equation (3b) without the decomposed *RV* of the natural gas, and 'HAR with *Gas* RV^{+} *and RV-*' follows Equation (3b). Natural gas is used as a proxy for electricity price.

root mean square error (RMSE), the mean square error (MSE) and the mean absolute error (MAE) estimated for these four models. The results are presented in Table 7. All three measures support the superiority of the model that includes the decomposed RVs of natural gas as explanatory variables. This further affirms our initial expectation regarding the importance of natural gas in determining the volatility of Bitcoin.

As a robustness check, we conduct the model confidence set (MCS) test of Hansen, Lunde, and Nason (2011) on the out-of-sample forecasts estimated earlier. Following Hansen and Lunde (2005), we employ the following six loss functions and conduct the MCS test separately on these six sets of loss estimates.

$$MSE1 \equiv n^{-1}\sum_{t=1}^{n}(\sigma_t - h_t)^2 \qquad MSE2 \equiv n^{-1}\sum_{t=1}^{n}(\sigma_t^2 - h_t^2)^2$$

$$QLIKE \equiv n^{-1}\sum_{t=1}^{n}\left(log\left(h_t^2\right) + \sigma_t^2 h_t^{-2}\right) \qquad R2LOG \equiv n^{-1}\sum_{t=1}^{n}\left[\log\left(\sigma_t^2 h_t^{-2}\right)\right]^2$$

$$MAE1 \equiv n^{-1}\sum_{t=1}^{n}|\sigma_t - h_t| \qquad MAE2 \equiv n^{-1}\sum_{t=1}^{n}\left|\sigma_t^2 - h_t^2\right|$$

In the equations, σ is the estimated volatility, h is the volatility forecast in the standard deviation form, and n is the number of observations. In the analysis, as the estimated and forecasted RVs are in the log variance form, we invert the logged values and then take the square root of these estimates. In the test, the results are bootstrapped 10,000 times and a confidence level of 0.05 is used.

The results are presented in Table 8. Values from 1 to 4 indicate the rank of the model under a particular loss function; 1 indicates that the model being considered is the best forecasting model among those tested. The analysis requires a sequence of statistical tests developed by Hansen, Lunde, and Nason (2011) to construct a set of superior models. In the analysis, a model that does not satisfy the equal predictive ability test will be eliminated from subsequent tests as an inferior model (Bernardi and Catania 2018). In the table, the sign: '–' indicates eliminated models. The results confirm the superiority of the model with decomposed natural gas RVs. Based on the six loss functions, HAR with Energy RV^{+} and RV- outperforms all other models. This again supports the role of natural gas in demystifying the characteristics of the Bitcoin market

V. Conclusion

As the Bitcoin market is highly speculative, the dynamics of its volatility is of great interest to (and importance for) investors and policy-makers. This paper is the first to analyse the relation between Bitcoin volatility and an economically linked energy commodity (natural gas) volatility relation using the HAR-RV model. By focusing

Table 8. Model confidence set test on the out-of-sample one-period ahead forecasts.

	Loss function					
	MSE1	MSE2	QLIKE	R2LOG	MAE1	MAE2
HAR with *RV only*	4	4	-	-	4	4
HAR with *RV of Gas*	3	2	-	3	3	2
HAR with *RV+ and RV-*	2	3	-	2	2	3
HAR with *GAS RV+ and RV-*	1	1	1	1	1	1

This table presents the result of the model confidence set tests. Each column shows the ranking of the specified HAR model based on the selected loss estimating function (i.e. the value of 1 indicates that the model is the best among four models). MSE1, MSE2, QLIKE, R2LOG, MAE1 and MAE2 indicate which loss function explained in Hansen and Lunde (2005) is used to evaluate the specified volatility forecasting model. '–' indicates that the specified model being eliminated is an inferior model. The test is conducted with 10,000 bootstraps and a confidence level of 0.05. The rolling-forecasts are estimated using a window period of 500 days. 'HAR with *RV* only' follows Equation (3a) without the *RV* of natural gas, 'HAR with *Gas RV*' follows Equation (3a), 'HAR with RV^{+} *and RV-*' follows Equation (3b) without the decomposed *RV* of the natural gas, and 'HAR with *Gas* RV^{+} *and RV-*' follows Equation (3b). Natural gas is used as a proxy for electricity price.

on the information embedded in the volatility of natural gas, we estimate the *RV* as well as the decomposed *RV*s, and then conduct (1) full sample and sub-sample HAR-RV analyses, and (2) out-of-sample forecast analyses. Overall, our results indicate the importance of the information arising from natural gas volatility (a proxy for electricity cost uncertainty) in determining the second moment of Bitcoin price.

More specifically, while the positive component of the natural gas *RV*, especially the monthly average, helps stabilize Bitcoin volatility, the negative component amplifies it. One possible explanation is that when the electricity cost increases, miners who mine Bitcoin as an alternative means of investing directly in Bitcoin would find it more attractive to trade on Bitcoin exchanges directly. This, in turn, would improve the market depth of Bitcoin and thereby improve the depth of Bitcoin exchanges. This then reduces the volatility of Bitcoin.

Furthermore, our study shows that the incorporation of information from natural gas volatility can improve Bitcoin volatility forecasting. These results are also supported by the model confidence set tests we performed on an out-of-sample analysis. The study provides important information for investors, miners and policy-makers on factor(s) affecting the largest cryptocurrency in the world. In particular, our findings shed light on the intrinsic value of Bitcoin from a cost perspective, suggesting that the energy consumed in mining Bitcoin affects the mining cost (and, thus, the value) of Bitcoin. Policy makers may consider regulating the Bitcoin market via energy markets.

We find evidence consistent with the view that mining cost is a non-trivial channel that links the natural gas market with the Bitcoin market. In particular, our results suggest that a hike (decline) in the mining cost may cause a reduction (expansion) in the number of active miners. For those swing miners, technology that improves the efficiency of mining and reduces the electricity cost would motivate them to invest further in mining tools and intensify mining competition. Our evidence helps these miners make their strategic capital investment decisions on mining technology. Our study, therefore, extends discussions on what factors investors should take into consideration when they build a risk model for Bitcoin and/or make their investment decisions.

Our evidence is confined to the linear spillover effect only. Future researchers may explore the nonlinear spillover effect of Bitcoin and use finer time intervals other than 5-minute one to study the spillover effects.

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