Bitcoin Mining Activity and Volatility Dynamics in the Power Market ⋆

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Abstract

Utilizing a measure of the Bitcoin network's daily electricity load, we document a significant volatility effect of Bitcoin mining activity in three prominent electricity markets in the U.S. The volatility effect is found to be increasing over time, particularly with the widespread lockdowns enforced due to the COVID-19 pandemic. The findings provide novel insight to the non-virtual side of mining and trading of cryptocurrencies and underscore the need for establishing mechanisms to prevent possible destabilizing effects of this growing industry, both from a power consumption and carbon emissions perspective.

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1. Introduction

The digital gold rush into cryptocurrencies has led to an unprecedented growth in the market value, trading and mining of these assets, driving total market capitalization in cryptocurrencies from around one billion USD in early 2013 to close to two trillion USD in September 2021.[1] Not surprisingly, cryptocurrencies, Bitcoin (BTC) in particular, have also attracted increasing attention from academics who examined these assets from various perspectives including their portfolio diversification and hedging benefits for conventional investment portfolios (Bouri et al. (2017); Shahzad et al. (2019); Smales (2019)), return and volatility dynamics (Aalborg et al. (2019)); price efficiency (Urquhart (2016)), return/volatility transmissions with other asset classes (Bouri et al. (2018)), and liquidity patterns (Scharnowski (2021)), among others. The fast growth in the mining and financial trading of these assets, however, has been accompanied with a large carbon footprint fueled by the vast energy consumption due to mining activity. In fact, according to the Bitcoin Electricity Consumption Index project maintained by the Digital Assets Programme (DAP) Team at the Centre for Alternative Finance at the University of Cambridge, as of September 2021, bitcoin mining now consumes around half as much electricity as the U.K., surpassing the total annual electricity consumption of countries like Sweden, Ukraine and Australia. Against this background, the goal of this paper is to present novel perspective to the carbon footprint of bitcoin mining by examining, for the first time in the literature, the effect of mining activity on the price and volatility dynamics in three prominent U.S. power markets.

Thanks to the liberalization of the power market towards a competitive setting over the past several decades, today, electricity can be traded as any other commodity at market driven rates. However, unlike other commodities, several features of electricity distinguish it from other tradable commodities, which in turn lead to extreme price volatility and unanticipated spikes in prices. Demand-driven volatility factors in this market are largely due to the price inelastic and weather or business cycle dependent nature for electricity demand while, on the supply side, since electricity cannot be stored, consumption has to be balanced with production due to lack of an inventory planning option (Weron and Misiorek (2008)). From an investment planning perspective, price uncertainty and extreme volatility in the electricity market is not only a major operating risk for utility companies, but also crucial for the real economy as electricity price forecasts have become a fundamental input for corporate decisions (Bunn (2004); Eydeland and Wolyniec (2002)).In fact, recent studies show that industrial electricity usage growth rate carries predictive ability over stock returns up to one year (Da et al. (2017))) where the predictive power of industrial electricity usage is explained by an "industry effect" that is transmitted via the volatility channel (Bonato et al. (2018)). Not surprisingly, there is a growing literature on the predictability of daily electricity prices with a particular focus on the price behavior in the day-ahead spot market.[2] Surprisingly, however, despite the large number of works on the predictability of electricity prices, the literature has not yet examined the effect of the growing energy consumption needed to mine and maintain Bitcoin on the price dynamics and volatility in electricity prices.

Utilizing daily spot price data for three prominent U.S. power markets, namely Northern Illinois hub (NI), Western Hub (West) and New England hub (NE), and the Cambridge Bitcoin Electricity Consumption Index, developed by the Centre for Alternative Finance at the University of Cambridge, as a measure of the Bitcoin network's daily electricity load, we document a significant volatility effect of bitcoin mining activity in the electricity market. While our tests suggest insignificant price effects, we observe significant forecasting gains over the volatility patterns in electricity prices due to Bitcoin mining activity. Further extending the test to a time-varying setting, we find that the impact of the Bitcoin consumption index on electricity market volatility is increasing over time in parallel with the unprecedented growth in the mining and trading of these assets. The rising trend in the volatility effect of Bitcoin mining activity indeed corresponds to the COVID-19 pandemic period during which an increase in trading volume and volatility in Bitcoin futures is documented, driven by an increase in the belief dispersion due to the pandemic related

[1] https://coinmarketcap.com.

[2] See Weron (2014) for a detailed review of this literature.

market uncertainty (Guzmán et al. (2021), Park (2022)). The findings provide novel insight to the non-virtual side of mining and trading of cryptocurrencies and underscore the need for establishing mechanisms to prevent possible destabilizing effects of this growing industry, both from a power consumption and carbon emissions perspective. The remainder of the paper is organized as follows. Section 2 describes the data and the time-varying Regression+ GARCHX in volatility model utilized in our tests. Section 3 presents the empirical findings and Section 4 concludes with further discussion.

2. Impact of BTC energy consumption on mean and volatility of electricity pricing

2.1. Data

In this exposition, we choose our response variable to be the electricity pricing returns in three different prominent U.S. markets, namely Northern Illinois hub (NI), Western Hub (West) and New England hub (NE). Daily spot price data over the period Dec. 19, 2017- June 18, 2021 is obtained from Commodity Systems Inc. and the Cambridge Bitcoin Electricity Consumption Index is used to measure the Bitcoin network's daily electricity load.[3]. Because the exact electricity consumption value cannot be determined, a hypothetical range consisting of a lower bound, upper bound and best-guess estimate is computed where the lower (upper) bound is based on the assumption that all miners always use the most (least) energy-efficient equipment available on the market. The best-guess estimate is based on the more realistic assumption that miners use a basket of profitable hardware rather than a single model. Understandably, the sample period is governed by the availability of the Bitcoin consumption index series.

2.2. Method for Time-varying estimation

Let y_t stand for the return on the t-th day on a particular electricity market. We wish to regress the mean and variance of y_t on three different bitcoin consumption index series (BCI henceforth) available, i.e. max , min and guess based on the upper/lower bounds and the best-guess estimate, respectively. This yields 9 different scenarios given 3 choices each for the response and the covariate. Considering that our sample period covers the COVID-19 pandemic and the evidence that associates pandemic lockdowns with increasing trading activity in cryptocurrencies including Bitcoin (e.g. Guzmán et al. (2021), Park (2022)), we utilize the following time-varying Regression+ GARCHX in volatility model (see Francq et al. (2019); Sucarrat (2021)) formulated as

$$y_t \sim N(\mu_0(t/n) + \mu_1(t/n)X_t, \sigma_t^2) \text{ with } \sigma_t^2 = \alpha_0(t/n) + \alpha_1(t/n)y_{t-1}^2 + \beta_1(t/n)\sigma_{t-1}^2 + \gamma(t/n)|X_t|, \tag{2.1}$$

where X_t stands for the covariate used at time-stamp t. Note that the log-returns of the covariates are employed in the model in order to make them stationary.

For a suitable choice of kernel K and bandwidth $b_n \in [0, 1]$ we use, for the parameter estimation of θ.

$$\hat{\theta}_{b_n}(t) = \operatorname*{argmin}_{\theta \in \Theta} \sum_{i=1}^{n} K((t - i/n)/b_n)\ell(y_i, X_i, \theta) \qquad t \in [0, 1]. \tag{2.2}$$

where $\ell(\cdot)$ is the corresponding negative log-likelihood or quasi log-likelihood for estimating the GARCH parameters. In particular, we use the rectangular kernel here for the choice of K so as to be able to use the standard `lm` and `garchx` routine. Moreover, as we describe later, forecasting future observations even in a time-varying model requires a stationary in-sample estimation so we wanted to remain consistent throughout. Note that, under some mild smoothness conditions, the final implications should not differ too much for using a specific kernel as discussed in Karmakar et al. (2021). This reduces the estimation at time-point t with the parameters assuming there is a stationary model for time-stamps $\max\{1, t - nb_n\}$ to $\min\{n, t + nb_n\}$.

[3]For further details, see: `https://cbeci.org/`.

3. Empirical findings

Towards estimating $\theta(\cdot) = (\mu_0(\cdot), \mu_1(\cdot))'$ in the context of (2.1), we choose the following Gaussian log-likelihood:

$$\ell(y_i, X_i, \theta) = (y_i - \mu_0 - \mu_1 X_i)^2.$$

Our results are robust even when we implemented a GARCH(1,1) error specification instead of the rather simplistic homoscedastic likelihood as above. We plot the pointwise confidence band for all the cases in Figure 1. In each of these cases, one can see the horizontal line of nullity passing through the confidence bands for both coefficients, establishing the insignificance of the covariate in regressing electricity pricing returns. Thus, we observe largely insignificant effects of the BTC energy consumption indices on the mean of electricity returns.

In the light of insignificant mean effects, we proceed with simply modeling price volatility using the `garchx` R package. In the context of the time-varying model in (2.1), we choose the following likelihood function to estimate $\theta'(\cdot) = (\alpha_0(\cdot), \alpha_1(\cdot), \beta_1(\cdot), \gamma(\cdot))'$,

$$\ell(y_i, X_i, \theta') = -\frac{1}{2}\log(\sigma^2) + y_i^2/\sigma^2 \text{ with } \sigma^2 = \alpha_0 + \alpha_1 y_{i-1}^2 + \beta_1 \sigma_{i-1}^2 + \gamma |X_i|.$$

We present the time-constant estimates, the estimated four coefficients (as function of time) and their lower intervals based on one-sided confidence intervals in Figures 2, 3 and 4. These confidence intervals are constructed based on $\hat{\theta} - 1.645 se(\hat{\theta})$ following the pointwise central limit theory from Karmakar et al. (2021) for a time-varying specification. Further detail on the method to compute these estimates is provided in Francq et al. (2019). It is well-known in the GARCH literature that for GARCH(1,1) models, the ARCH and GARCH effects are small and large, respectively. Our confidence bands show that the volatility effects and the covariate effects were significant in most of the time-spectrum when it was estimated to be positive.[4]

Towards gauging the behavior of these estimates over time, it is clear that except for the NE market, the effect of covariates are generally increasing from the second half of 2020 until the end of the sample, indicating the increasing impact of covariates over time. Thus, while the findings point to the presence of a volatility effect of Bitcoin mining activity in the electricity market, we also find that the effect is indeed increasing over time, particularly starting with the second half of 2020. The rising pattern in the volatility effect, particularly during the period when the pandemic has become more widespread with lockdowns enforced globally, is in line with the evidence in several recent studies including Guzmán et al. (2021) and Park (2022) that investors became active participants during the COVID-19 pandemic period and traded more bitcoins on days with low mobility associated with lockdown mandates. While Park (2022) suggests that the increase in trading volume and volatility in BTC futures is induced by the increase in belief dispersion due to the pandemic related market uncertainty, Divakaruni and Zimmerman (2021) show that the wealth shock induced by the U.S. government's economic impact payment program in 2020 has led to a significant increase in Bitcoin buy trades, particularly among individuals without families and at exchanges catering to nonprofessional investors. Nevertheless, it is interesting that the volatility effect on the electricity market due to the Bitcoin consumption index becomes particularly significant during the pandemic period that is associated with herding behavior in global financial markets (Bouri et al. (2021)) and increased trading activity in cryptocurrencies. Further extending the analysis to a forecasting context, additional tests corroborate the importance of the choice of covariates by providing evidence that the inclusion of the Bitcoin consumption index provides significant forecasting gains as well. These gains are viewed through the lens of CW tests, the statistical hypothesis tests from Clark and West (2007) adapted for log-returns variance. In particular, given that both the intercept and slope for the covariates are found to be insignificant in Section 2, we simply use y_t^2 as our target forecast and the fitted variance from two models, $\hat{\sigma}_t^2$ and $\hat{\sigma}_{t0}^2$ (without covariate) as the two competing forecasts.

[4] Based on the suggestions of an anonymous referee, we also estimated asymmetric GARCH models, and consistent with the symmetric version of the same, we found that our basic findings are qualitatively similar, i.e., the predictors fail to have any statistically significant effect on electricity returns, but increases its volatility in a statistically signficant fashion. Complete details of these results are available upon request from the authors.

Table 1 presents the forecasting gains for n_{ahead} days based on the full model that includes the bitcoin indexes and the benchmark model that does not include the covariates. Note that m is our in-sample length, in other words, we choose an in-sample of $y_{t-m+1}, \cdots, y_t$ to fit a stationary GARCHX using the `garchx` package in R. This allows us to use the `predict` routine to obtain predictions for n_{ahead} steps. As was discussed in Karmakar et al. (2021), a time-varying forecast remains difficult to be properly defined given the popular in-fill asymptotics culture in the time-varying literature and a stationary fit for the last m observations along with rolling this window provides the best possible time-varying estimation. The choice for n_{ahead} was made to predict the one-day, one-week and one-month ahead forecasts. For brevity, we present in Table 1 the results for $m = 200$ only, but when we extend the analysis to other values of m such as 400 or 600, we obtain similar results. We also report in the table the ratio of MSPE (Mean-square prediction errors) for the two models. We observe that most of the p-values are small and the MSPE values for the augmented model that includes the Bitcoin consumption index are generally smaller in most cases and almost similar in few cases. This ascertains the predictive information captured by the Bitcoin consumption index over the subsequent volatility patterns in the electricity market. Considering that the literature on the predictability of daily electricity prices generally focuses on the price behavior in the day-ahead spot market (Weron (2014)), our finding present a novel opening on the predictive role of Bitcoin mining proxies to improve the accuracy of electricity forecasting models.

4. Conclusion

Utilizing the Bitcoin Electricity Consumption Index, developed by by the Digital Assets Programme Team at the Centre for Alternative Finance at the University of Cambridge, we document a significant volatility effect of Bitcoin mining activity in three prominent electricity markets in the U.S. While the results do not yield a significant impact on mean electricity returns, we observe an increasing volatility effect in electricity spot prices, particularly starting with the global lockdowns enforced due to the COVID-19 pandemic. The rising pattern in the volatility effect, particularly during the period when the pandemic has become more widespread with lockdowns enforced globally, is in line with the evidence in recent studies including Guzmán et al. (2021) and Park (2022) that investors became active participants in the cryptocurrency market during the COVID-19 pandemic period and the evidence of herding behavior in global financial markets driven by the pandemic induced market uncertainty (Bouri et al. (2021)). Nevertheless, the evidence of significant forecasting gains due to Bitcoin mining activity presents an opening to better model and monitor price fluctuations in the power market with significant hedging and investment planning implications. In future research, it will be interesting to employ alternative dynamic models including the full-fledged flexible kernel-based time-varying fit or the Bayesian time-varying GARCH estimation technique proposed in Karmakar and Roy (2021) in order to check the robustness of the volatility effect observed. Nevertheless, the findings provide novel insight to the non-virtual side of mining and trading of cryptocurrencies and underscore the need for establishing mechanisms to prevent possible destabilizing effects of this growing industry, both from a power consumption and carbon emissions perspective.

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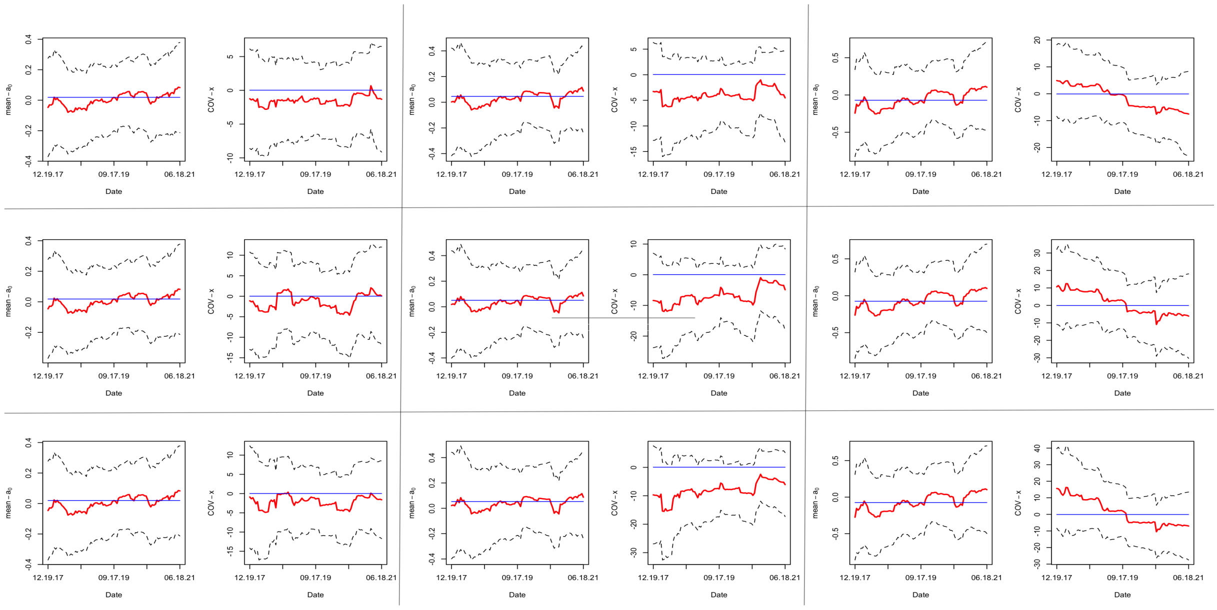

Fig. 1: Time-varying regression coefficients with pointwise confidence bands. The rows stand for the covariates Max, Min and Guess BCI, while the column stands for the responses for NI, West and NE electricity spot markets. Each image has the horizontal line of zero passing through the 95% pointwise bands.

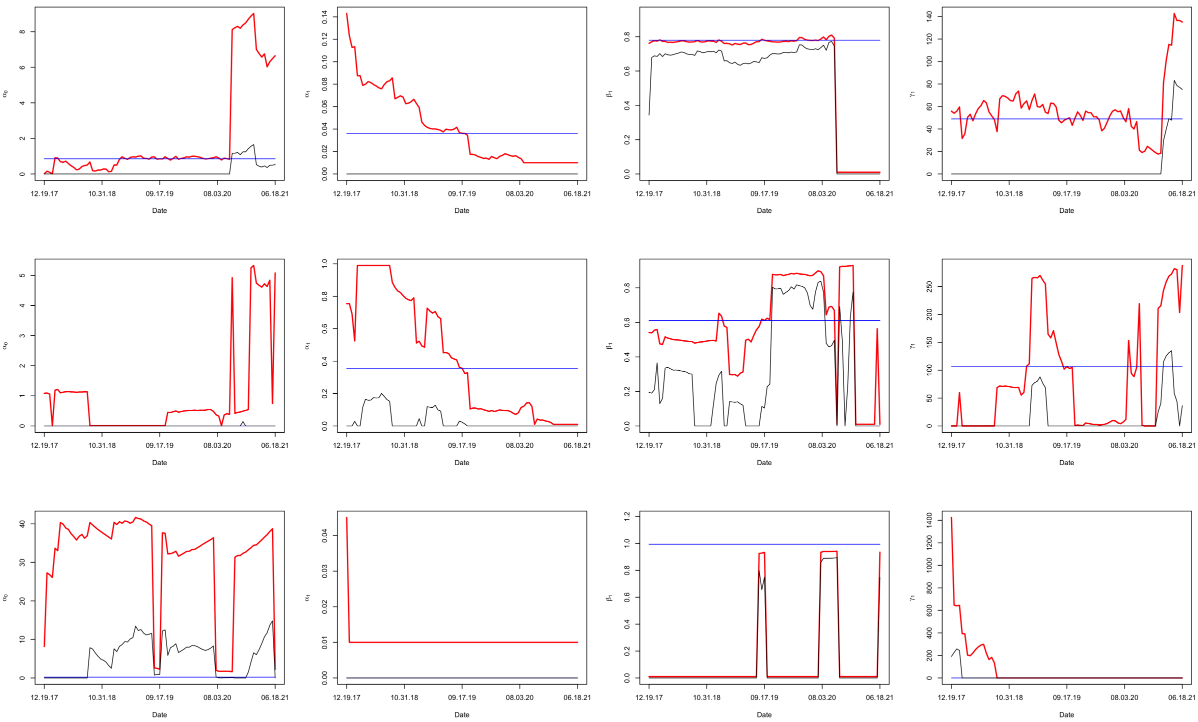

Fig. 2: Time-varying garchx plot for Max BCI. The rows stand for the responses for NI, West and NE electricity spot markets. The black curve represents the lower endpoint of one-sided pointwise 95% confidence band. The blue line stands for the time-constant estimate.

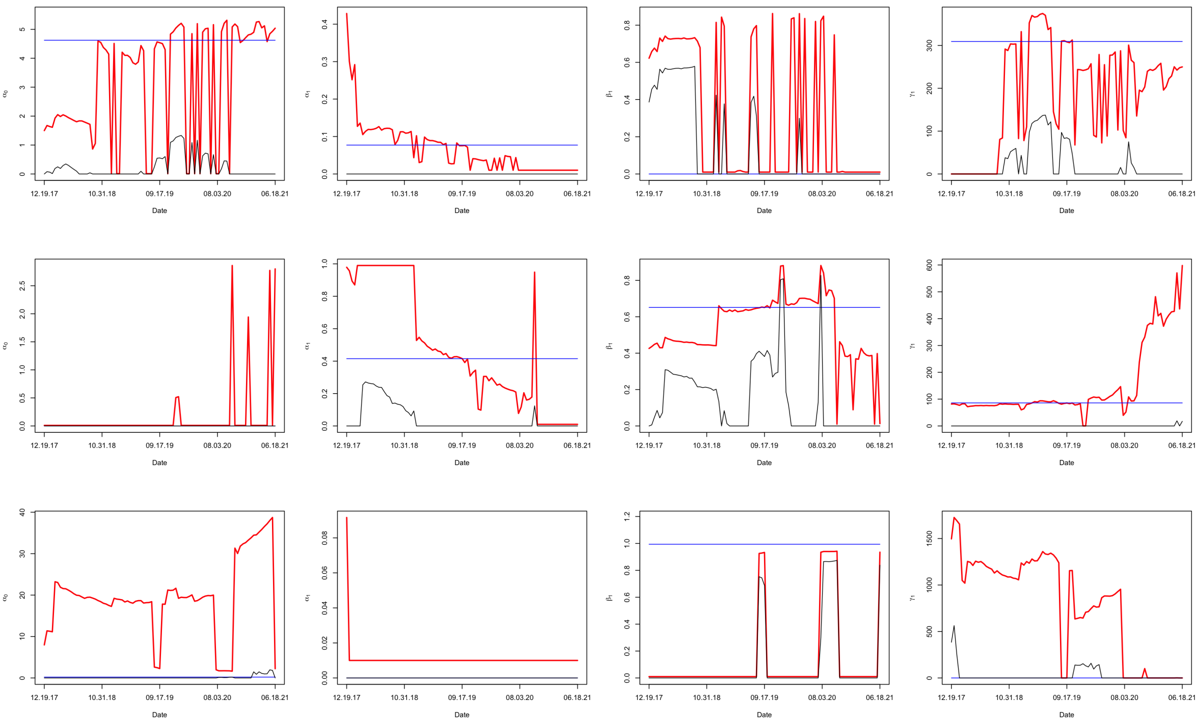

Fig. 3: Time-varying garchx plot for Min BCI. The rows stand for the responses for NI, West and NE electricity spot markets. The black curve represents the lower endpoint of one-sided pointwise 95% confidence band. The blue line stands for the time-constant estimate.

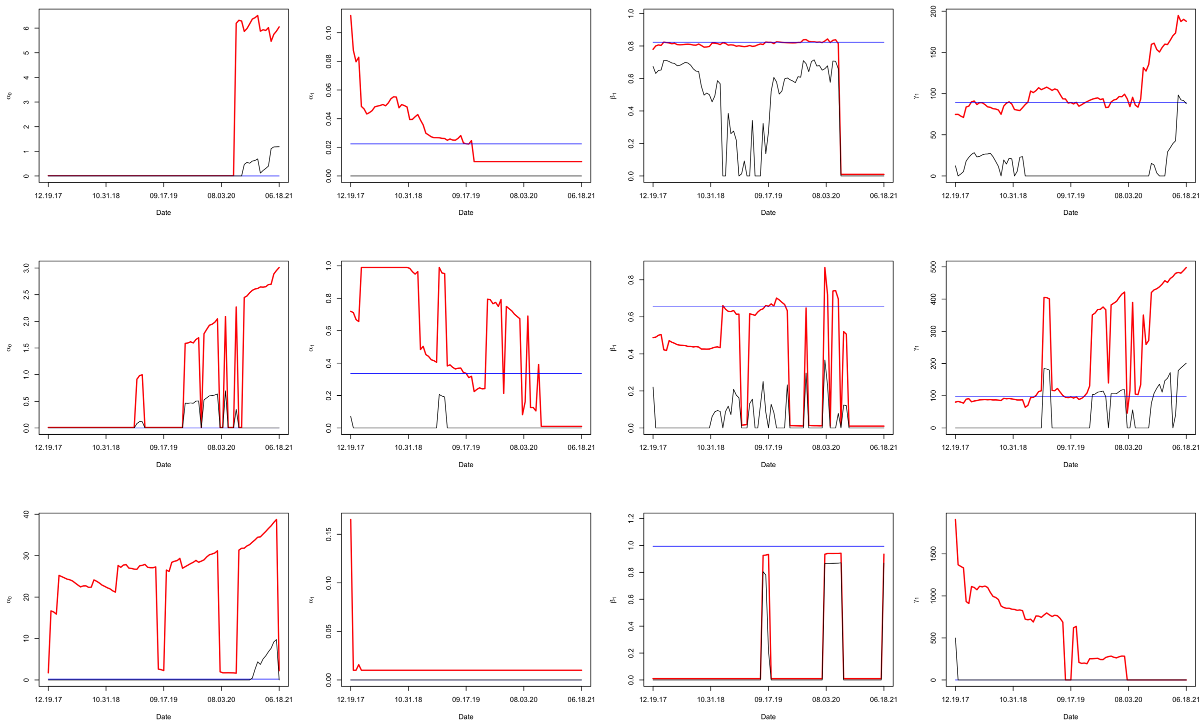

Fig. 4: Time-varying garchx plot for Guess BCI. The rows stand for the responses for NI, West and NE electricity spot markets. The black curve represents the lower endpoint of one-sided pointwise 95% confidence band. The blue line stands for the time-constant estimate.

Table 1: Forecasting gain results for $m = 200$. $MSPE_1$ and $MSPE_2$ stand for the models without the covariates and the full model respectively. P-values correspond to the CW test. $MSPE_1/MSPE_2 > 1$ signifies the BTC covariates provide forecasting gains.

	$n_{ahead} = 1$		$n_{ahead} = 5$		$n_{ahead} = 20$	
Data	pvalue	$MSPE_1/MSPE_2$	pvalue	$MSPE_1/MSPE_2$	pvalue	$MSPE_1/MSPE_2$
Max NI	0.099	0.99683	0.065	1.28024	0.816	0.04007
Max West	0.024	1.03230	0.077	3.22436	0.155	10.77268
Max NE	0.738	0.99288	0.839	0.40212	0.109	0.86348
Min NI	0.181	0.99818	0.147	9.57209	0.078	4.58211
Min West	0.040	1.03682	0.202	0.97545	0.157	165.1649
Min NE	0.714	0.99094	0.082	2.54933	0.149	25.55265
Guess NI	0.029	1.07761	0.055	1.63147	0.141	16.22775
Guess West	0.051	1.05985	0.475	0.17272	0.352	0.01990
Guess NE	0.157	1.25996	0.063	7.91852	0.156	63.98823