University of Pretoria
Department of Economics Working Paper Series

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Working Paper: 2022-39
September 2022

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On the pricing effects of bitcoin mining in the fossil fuel market: The case of coal

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August 30, 2022

Abstract

This paper examines the effect of crypto-currency mining activities on fossil fuel price dynamics, focusing on the coal market. Specifically, we utilise static and time-varying Granger causality tests to explore the causal linkages between Bitcoin electricity consumption and coal prices captured by the Argus/McCloskey's Coal Price Index for coal imported into northwest Europe. The results unsurprisingly reveal a time-varying causal link from the coal price to Bitcoin mining activities' electricity consumption. That is, the coal price is a constraint on mining activities. Surprisingly the evidence in the opposite direction is stronger, suggesting that electricity consumption from Bitcoin mining activities impacts the coal price. This interplay suggests that electricity consumption from Bitcoin mining activities may be larger than current estimates.

Keywords: Time-varying Granger causality, Crypo-currency market, Commodity Markets, Coal price

JEL Codes: C12, C32, C58, G14, Q02

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1 Introduction

Despite the climate agenda to reduce fossil fuel usage, coal remains a key energy source for many economies (Chang et al., 2017). BP's latest Statistical Review of World Energy estimates that coal was the dominant fuel for power generation in 2021, with its share increasing to 36%, up from 35.1% in 2020, while China and India accounted for over 70% of the growth in coal demand in 2021. In China alone, the country generated 70% of its electricity from coal-fired power stations in 2017, consuming 50% of global coal production (Li et al., 2019). Brendow (2004) suggests that coal is an important energy source to meet global energy demand and will continue to expand for economic and social development. Therefore, understanding coal price dynamics is highly important as it has a downstream effect on economic growth driven by the inflationary effects of rising coal prices, particularly in the case of economies like China, whose energy structure is dominated by coal (Guo et al., 2016a). In this paper, we explore coal price dynamics from a novel perspective by examining the role of crypto-currency mining activities on fossil fuel prices, particularly coal. Given the unprecedented rush into the so-called digital gold over the last decade, examining the link between mining activities and fossil fuel prices is highly important from a policy-making and environmental perspective.

In the literature, price dynamics in the coal market have been related to various driving factors including the output value of the industry, gross domestic product and retail price index (Ding et al., 2010), oil demand and supply shocks (Zamani, 2016), economic downturn and excessive production (Guo et al., 2016b), coal production and imports (Zhu and Wang, 2017), production costs and economic growth (Ikenberry, 2018), environmental regulations and falling natural gas prices (Coglianese et al., 2020), while Jiang et al. (2020) highlight the interconnection between coal and new energy prices. Lin and Li (2015) suggest the presence of a slow transition in the coal market wherein the increasing use of other sources will continue to limit the use of fossil fuels such as coal due to technical difficulties and comparatively high costs. Generally, two factors are argued to affect the coal price. These are coal market fundamental factors associated with supply and demand and other coal market-specific factors that relate to speculation and spillover effects (Guo et al., 2016a). Expanding on these factors, Chen (2014) found that other energy prices can have a price through effect leading to fluctuations in the coal price. Furthermore, Liu et al. (2013) quantified a long-term relationship between the coal price and electricity prices, although this relationship can be non-linear (Joëts and Mignon, 2012), as is the case in our particular study. At a macroeconomic level, indirectly or via coal consumption, Wang and Li (2016) established a strong correlation between the coal price and economic growth. Unsurprisingly, several studies focusing on China (for example, Yu-zhao et al., 2009; Hao et al., 2015) demonstrated that coal consumption is predictive of coal prices, which is a key factor in some coal-intensive markets such as China.

More recently, examining the period between 1970 and 2020, Khan et al. (2021) identify three bubble periods for global coal prices. The authors argue that the first bubble was largely driven by oil price shocks and supply concerns, while robust global growth and rising freight rates contributed to the second

bubble. Similarly, the third bubble was found to be related to growing demand from emerging economies and a rise in oil prices. However, none of those mentioned above studies has explored the impact of the recent rush toward cryptocurrency investments and the remarkable rise in energy consumption associated with mining activities. In a recent study, Karmakar et al. (2021) note that 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. In contrast, Khan et al. (2021) find that electricity consumption positively impacts coal price bubbles. Therefore, the main goal of this study is to explore the role of Bitcoin mining as a factor that might explain coal price fluctuations.

In recent years, Bitcoin and other cryptocurrencies have gained relevance with investors as an asset class offering profits that cannot be obtained in traditional investment alternatives. The rise in the trading of these assets naturally led to a boom in mining activity, a highly energy-intensive process, thus putting tremendous pressure on electricity consumption. Bitcoin miners run server farms that produce a unique hash key or a "proof of work" to confirm transactions and introduce new bitcoins on the network. The "proof of work" is computationally intensive, draining large amounts of power from the electric grid as a higher hash rate increases the probability of success for a specific miner who then gains a commission. In emerging economies such as China and Russia, where Bitcoin mining has been concentrated, mining activities can have serious implications for the coal price as these economies heavily rely on coal-fired power stations to generate electricity. This, in turn, can have downstream effects on the real economy as energy costs constitute a significant portion of production costs in most emerging economies. The idea that Bitcoin mining activities can affect other markets is not new. There is a growing literature on the electricity consumption of Bitcoin mining and its carbon footprint (Stoll et al., 2019; Küfeoğlu and Özkuran, 2019; Sedlmeir et al., 2020; De Vries, 2018). The latest estimates suggest that the peak electricity consumption of the bitcoin network is in the region of 2.55 GW based on 2.6 quintillion hashes per second and is estimated to reach around 8 GW in the future (De Vries, 2018). In 2018, this was equivalent to 45 TWh per year, and carbon emissions of between 22 to 22.9 $MtCO_2$ (Stoll et al., 2019). However, others, such as Sedlmeir et al. (2020), argue that these estimates depend on the equipment used to process transactions. Therefore, these numbers may be subject to changes as technology improves. Nevertheless, the emerging literature shows that Bitcoin mining and trading activity have a real non-virtual side which can potentially be disruptive to other industries (Karmakar et al., 2021).

Regarding the possible link between crypto-currency mining activity and coal price, the literature is virtually non-existent. However, a limited number of works have established a link between coal and stock prices. For example, Oberndorfer (2009) found that coal price fluctuations affected the stock price of European utility companies. Likewise, Aruna and Acharya (2021) found a similar link in India, where coal price shocks led to asymmetric shocks to stock returns and inflation. A relevant paper by Li et al. (2022) found extreme risk transmission between Bitcoin and crude oil returns, that is, evidence of causality between shocks to Bitcoin and crude oil price returns. Separately, cryptocurrencies have

been examined in various studies in the literature via various methodologies, most commonly using time-varying approaches (for example, Li et al., 2022; Karmakar et al., 2021). In our case, we explore the causal links between mining activities and coal prices via time-varying Granger causality (Engle, 2002, Lu et al. (2014)) tests for both instantaneous and bi-directional causality. Indeed, our results reveal a causal relationship between the coal price and Bitcoin mining activity. The causal link, however, is found to be stronger in the opposite direction, i.e. from mining-driven electricity consumption to the coal price. Thus, our results confirm another non-virtual side effect of cryptocurrencies, suggesting that electricity consumption from Bitcoin mining impacted the coal price. These results confirm that Bitcoin mining has environmental side effects and can be classified as a 'dirty' investment.

The remainder of the paper is organised as follows. In Section 2, we describe the procedure for the time-varying Granger causality tests and the data. Section 3 presents the empirical findings and Section 4 concludes with a discussion of policy implications and suggestions for future research.

2 Methodology and Data

2.1 Methodology

In line with Lu et al. (2014), we consider two stationary time series Y_t and X_t. Given $Z_t(j) = \left(\frac{X_t}{Y_t}\right)$ where j represents the lag order used in the dynamic correlation coefficient, the DCC-MGARCH model is defined as follows (Engle, 2002),

$$\begin{aligned} Z_t(j)|I_{t-1} &\sim N(0, D_{t,j}R_{t,j}D_{t,j}) \\ D^2_{t,j} &= \text{diag}\{\omega_{i,j}\} + \text{diag}\{\kappa_{i,j}\} \text{ o } Z_t(j)Z_t^{'}(j) + \text{diag}\{\lambda_{i,j}\} \text{ o } D^2_{t-1,j} \\ u_{t,j} &= D^{-1}_{t-1,j}Z_t(j) \\ Q_{t,j} &= S \text{ o } (\iota\iota^{'} - A - B) + Au_{t-1,j}u^{'}_{t-1,j} + BQ_{t-1,j} \\ R_{t,j} &= \text{diag}\{Q_{t,j}\}^{-1}Q_{t,j}\text{diag}\{Q_{t,j}\}^{-1} \end{aligned} \tag{1}$$

For the widely used DCC-MGARCH(1,1) model, the dynamic correlation estimator with lag j is,

$$\begin{aligned} \rho_{pq,t}(j) = \overline{\rho_{pq}}(j) + \alpha_j(u_{p,t-1}u_{q,t-1-j} - \overline{\rho_{pq}}(j)) + \beta_j(\rho_{pq,t-1}(j) - \overline{\rho_{pq}}(j)) \\ r_{pq,t}(j)\frac{\rho_{pq}(j)}{\sqrt{\rho_{11,t}}\rho_{22,t}(j)} \end{aligned} \tag{2}$$

where p,q =1,2.

Based on the choice of a positve interger M, and a kernel function $k(x)$, the unidirectional DCC-MGARCH Hong test for Y_t to X_t is denoted as $H_{1,t}(k)$,

$$H_{1,t}(k) = \frac{T\sum_{j=1}^{T-1} k^2\left(\frac{j}{M}\right) r_{12,t}^2(j) \; - \; C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{3}$$

where

$$C_{1T}(k) = \sum_{j=1}^{T-1}\left(1-\frac{j}{T}\right)k^2\left(\frac{j}{M}\right)$$
$$D_{1T}(k) = \sum_{j=1}^{T-1}\left(1-\frac{j}{T}\right)\left(1-\frac{j+1}{T}\right)k^4\left(\frac{j}{M}\right)$$

The bidirectional DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{2,t}(k)$,

$$H_{2,t}(k) = \frac{T\sum_{j=2-T}^{T-2} k^2\left(\frac{j}{M}\right) r_{12,t}^2(j) \; - \; C_{2T}(k)}{\sqrt{2D_{2T}(k)}} \tag{4}$$

where

$$C_{2T}(k) = \sum_{j=1-T}^{T-1}\left(1-\frac{|j|}{T}\right)k^2\left(\frac{j}{M}\right)$$
$$D_{2T}(k) = \sum_{j=1-T}^{T-1}\left(1-\frac{|j|}{T}\right)\left(1-\frac{|j|+1}{T}\right)k^4\left(\frac{j}{M}\right)$$

The instantaneous DCC-MGARCH Hong test from Y_t to X_t is denoted as $H_{3,t}(k)$,

$$H_{3,t}(k) = \frac{T\sum_{j=0}^{T-2} k^2\left(\frac{j+1}{M}\right) r_{12,t}^2(j) \; - \; C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{5}$$

where $C_{1T}(k)$ and $D_{1T}(k)$ are estimated in $H_{1,t}(k)$.

It is not efficient to estimate all lagged dynamic correlations in DCC-MGARCH and as highlighted by Hong (2001) a suitable kernel function can address this shortcoming. The choice of non-uniform kernels and M has little impact on the size of the DCC-MGARCH Hong tests. The Bartlett kernel is defined as follows,

$$k(z) = \begin{cases} 1-|z|, & \text{if } |z|<1 \\ 0, & \text{if } |z|>1 \end{cases}$$

when $j \geq M$, the Bartlett kernel $k\left(\frac{j}{M}\right) = 0$. The Bartlett kernel is kernel is typically used in empirical studies (Lu et al., 2014).

2.2 Data

The main data sources used to capture bitcoin mining activity are the Cambridge Bitcoin Electricity Consumption Index (CBECI)[1], and the Digiconomist Bitcoin Energy Consumption Index (DBECI)[2]. The CBECI is based on the work of Bevand (2017), and the CBECI model comprises daily miner fees, electricity costs, mining equipment efficiency, and others that drive its evolution. Since the actual electricity consumption value cannot be determined, the CBECI provides a hypothetical range of electrical consumption estimates, comprising a lower bound (Min index) and upper bound (Max index).[3] A realistic estimate is then calculated within this range (Guess index). The CBECI, therefore, comprises three sub-indexes. In concrete terms, the Min estimate is based on the minimum theoretical electricity expenditure, assuming miners use the most energy-efficient equipment. The Max estimate captures the opposite case, where miners use the least energy-efficient equipment. Therefore, the Guess index represents a realistic compromise between these two. In contrast, the DBECI is a top-down index based on the estimated Bitcoin mining revenue. The DBECI utilises Bitcoin miner revenues from transactions to come up with an estimate for energy consumption (see De Vries, 2018). The DBECI estimates actual energy consumption (Estimated index) and minimum energy consumption (Minimum index) based on the assumption that Bitcoin miners spend 60 per cent of revenue on operational costs such that for every five cents (US) spent on operational costs, Bitcoin miners consume one kilowatt-hour of electricity. In our main analysis, we prefer the CBECI as it represents one of the few available bottom-up real-time (updated every 24 hours) Bitcoin electricity consumption estimates.[4] Therefore, we conduct our main analysis using the CBECI and then use the DBECI as an alternative to check the robustness of our findings. Both the CBECI and DBECI series are in terawatt-hours per year.

Regarding the coal price series, we use the Argus-McCloskey API2 coal futures traded on NYMEX (in USD per ton), sourced from the *Global Financial Database*. The Argus/McCloskey's Coal Price Index is a popular benchmark used globally by coal traders, and API 2 refers to the industry standard reference price for coal imported into northwest Europe. Therefore, the analysis is conducted on five indexes—three for the CBECI and two from the DBECI and the Coal Price. Based on data availability, the sample period covers July 2014 through July 2021, including 1843 daily observations. In Figures A.1 and H.1.1 in the Appendix, we present the time series plots for the bitcoin indexes and daily coal price returns in level, log, and log-differenced terms and Table B.1 presents the descriptive statistics. Jarque-Bera tests presented in Table B.1 fail to confirm normality for the Coal Price, Min, Max, and Guess series, while

[1]Sourced from `https://ccaf.io/cbeci/index`
[2]Sourced from `https://digiconomist.net/bitcoin-energy-consumption/`
[3]The exact composition of the equipment used by miners cannot be determined as mining activities often occur behind closed doors.
[4]See University of Cambridge (2021) for a comparison of the different indexes.

the kurtosis statistics, which are less than three, and the negative skewness values for all series provide support for non-normality implied by the Jarque-Bera test. These initial observations are also confirmed for the DBECI data (Estimated and Minimum) in Table H.2.1. It must be noted, however, that due to data availability limitations, the sample size is truncated to 1152 daily observations between February 2017 and July 2021. The augmented Dickey-fuller and Phillips-Perron tests, presented in Tables C.1 and H.3.1, also confirm that the data are non-stationary in log terms. Therefore, we utilise the stationary log-differenced series in our subsequent analysis. Finally, a visual inspection of the log-differenced series in Figures A.1 and H.1.1 reveals outliers and volatility clustering, which are common features of non-linear series.

3 Empirical Results

We begin our analysis with several preliminary checks, including the static Granger causality (Granger, 1980) test between the Coal Price and the CBECI indexes. As shown in Table D.1, the static tests do not reveal any presence of causality for all the CBECI indexes. The lack of causality using the static test is also observed for the Coal Price and the DBECI indexes (see Table H.4.1). The lack of causality via static tests is not unexpected given the non-linear features observed for all time series employed in the analysis. The static Granger causality test is based on several vector auto-regressions (VAR) between the Coal Price and all other variables. The selected VAR lag for each model is the maximum lag based on the Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQ), Schwarz Criterion (SC), and the Final Prediction Error (FPE) Criterion.[5] Thus, the static Granger causality test yields no evidence of causal links between the Coal Price and Bitcoin mining electricity consumption.

The rejection of causality via the static specification coupled with the descriptive statistics that suggest non-linearity in the data suggests that the inferences obtained from static Granger causality tests may not accurately assess the causal relationships. For this reason, we next test for structural breaks in the data using the Bai and Perron (2003) test. Employing the same VAR models from the static Granger causality test, the Bai and Perron (2003) test indicates evidence of structural breaks in all variables (see Tables E.1 and H.5.1). To further confirm non-linearity in the data series, we conducted the Brock et al. (1996) test for residual serial dependence (or non-linearity). As shown in Tables F.1 and H.6.1, the Brock et al. (1996)test for residual serial dependence provides further support for the evidence of nonlinearity. Therefore, we conclude that the time-varying version of the Granger causality test, as proposed by Lu et al. (2014), is an appropriate methodology to capture the time variation and possible structural breaks in the causal relationships.

Figures G.1 to G.3 show the results of the time-varying Granger causality tests for the Max, Min and Guess series, respectively. Given the energy-intensive nature of Bitcoin mining, one can expect, in

[5]Implemented using the VAR select function from the R 'var' package (see Pfaff and Stigler, 2021). The same method and lags are used in the subsequent time-varying Granger causality tests.

general, unidirectional causal effects, that is, causality in the direction of the Coal Price from the various Bitcoin energy usage indexes. Considering that the Coal Price is a constraint on Bitcoin mining activities, greater electricity usage via mining activity would pressure the demand for coal to generate electricity, hence the price of coal. Indeed, Panels A and C in Figures G.1 to G.3 confirm this expectation. We find significant causal effects of bitcoin mining on the price of coal. Interestingly, however, we also observe in Panels B and D significant causal effects from coal price to the bitcoin mining series. This result is also not unexpected, given that electricity costs play an important role in the computation of the CBECI. Indirectly, significant causality observed in Panels B and D in Figures G.1 to G.3 confirm that Bitcoin mining is indeed dependent on "dirty" energy such that the price of coal serves as a significant driver of mining activity. This finding is in line with Rauchs et al. (2017), who noted that most Bitcoin mining activity was in China, where market regulators generally impose less strict environmental standards than developed economies. The finding of causal effects in Panels B and D is also in line with the recent evidence by Khan et al. (2021) that coal consumption is negatively explained by price dynamics, implying that crypto miners adjust their consumption patterns based on price fluctuations in their energy costs.

Although our findings indicate bidirectional causal interactions between bitcoin mining activities and the price of coal, as indicated in Panel E in Figures G.1 to G.3, interestingly, the evidence for causality in the direction of the coal price in Panels A and C is found to be generally stronger than in Panels B and D. This suggests that electricity consumption from Bitcoin mining activities are significant enough to impact the Coal Price, indicating that energy usage in Bitcoin mining activities may be higher than current estimates (De Vries, 2018). Thus, our findings indicate that while coal prices serve as a determinant of Bitcoin mining activities, at the same time, Bitcoin miners also have a significant impact on the coal price. Statistically, this is confirmed in Panel E in Figures G.1 to G.3, indicating significant bi-directional causal effects. This finding provides valuable insight for market regulators as the evidence of causality in the direction of mining activity could be used to design a pricing mechanism to mitigate the possible negative effects of miners' energy usage on the overall economy. Considering that energy demand from Bitcoin mining activities is sensitive to the price of coal, which in turn, drivers the energy costs of power generation, policymakers can help alleviate the demand pressures exerted by crypto miners via creative pricing mechanisms that will limit the pricing effects of mining activities. Finally, these inferences are further confirmed by the DBECI results for the Minimum series presented in Figure H.7.2 although the findings for the Estimate series in H.7.1 indicate no significant causality between the Coal Price and electricity consumption form Bitcoin mining activities.

4 Conclusion

An increasing number of studies in the literature highlight the role of cryptocurrencies as a dirty asset that contributes to energy consumption and climate change. While most studies focus on the effect of mining activity on the power market, its effect on fossil fuel prices is relatively neglected. Given that coal

remains the dominant fuel for power generation and crypto mining is a highly energy-intensive process, this paper examines the link between Bitcoin mining activities and fossil fuel prices, with a special focus on coal. Specifically, we employ static and time-varying Granger causality tests to explore the causal links between coal prices and Bitcoin mining activities. Our analysis focuses on two Bitcoin electricity consumption indexes (CBECI and DBECI), with the former offering one of the few real-time bottom-up indexes available. The results unsurprisingly reveal significant time-varying causal links between the Coal Price and electricity consumption from Bitcoin mining activities. In addition, we report significant causality from the Coal Price to electricity consumption from Bitcoin mining activities, implying that the Coal Price is a constraint on Bitcoin mining activities. However, the evidence in the opposite direction is found to be even stronger, suggesting that electricity consumption from Bitcoin mining activities is also significant enough to impact the Coal Price. This interplay suggests that electricity consumption from Bitcoin mining activities may be larger than the current estimates, a view that is also confirmed in the literature (for example, De Vries (2018)).

These results were partially confirmed by the DBECI results that are based on miners' revenues to estimate electricity consumption. Although our results indicate that the findings are highly sensitive to the accuracy of the Bitcoin electricity usage indexes employed, the findings establish a strong bi-directional link between mining activity and the price of coal. Our results have significant policy-making implications in that the evidence of significant causal effects of coal prices on mining activity can be used to devise creative pricing mechanisms to mitigate the negative effect of intense energy needs of miners on the overall economy. Perhaps, one implication would be the creation of a laddered pricing mechanism wherein price adjustments are made within certain consumption brackets. Another strategy would be to impose a dirt energy tax on miners who exceed a certain level of consumption. Considering that coal price serves as a determinant of mining activity, as implied by our tests, policymakers could utilize this information to influence consumption patterns by miners. Another important policy implication of our findings is that Bitcoin mining activities must be a part of climate change policies to mitigate its growing negative impact. Nevertheless, it would be interesting in future studies to extend our analysis to quantify the impact of mining activity on price patterns in the coal market and examine possible hedging strategies to mitigate the possible negative effects of price fluctuations.

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Appendices

A Data

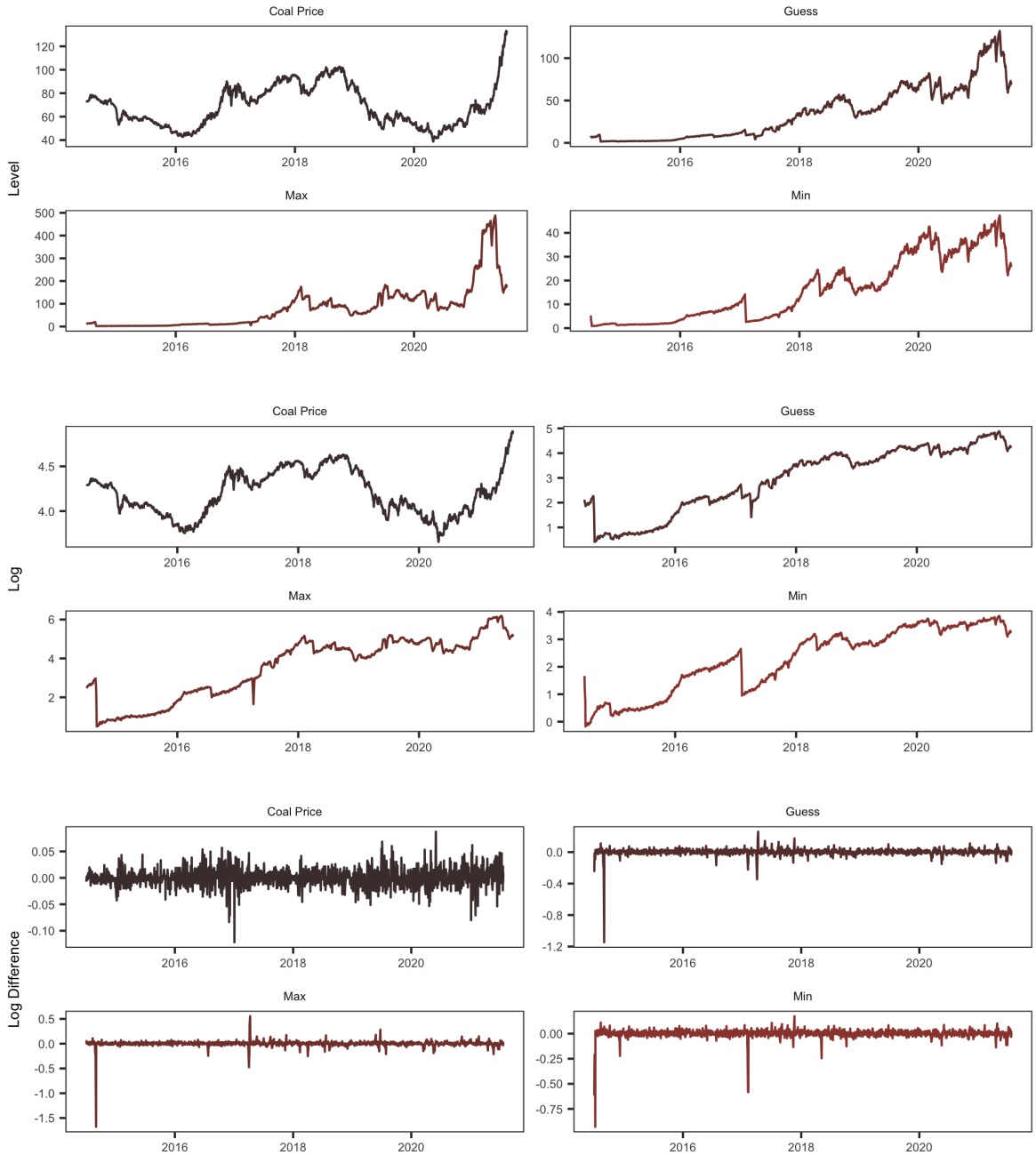

Figure A.1: Data

B Descriptive Statistics

Table B.1: Summary Statistics

	Coal Price	Max	Min	Guess
Observations	1843	1843	1843	1843
Mean	4.20	3.51	2.26	2.93
Standard Deviation	0.25	1.56	1.16	1.31
Skewness	0.13	-0.42	-0.42	-0.46
Kurtosis	-0.89	-1.15	-1.19	-1.13
Jarque Bera Test	65.52*	153.41*	162.00*	162.65*

Note: Coal Price, Max, Min, and Guess are in log form. * indicates that the null of normality is rejected at a 1 per cent level of significance.

C Stationarity Tests

Table C.1: Stationary Tests

Variable	Test	Test Statistic	P value	Significance
Coal Price	Augmented Dickey-Fuller Test	0.2	0.99	not significant
Coal Price Differenced	Augmented Dickey-Fuller Test	-11.3	0.01	significant
GUESS	Augmented Dickey-Fuller Test	-3.0	0.17	not significant
GUESS Differenced	Augmented Dickey-Fuller Test	-12.6	0.01	significant
MAX	Augmented Dickey-Fuller Test	-3.0	0.15	not significant
MAX Differenced	Augmented Dickey-Fuller Test	-12.5	0.01	significant
MIN	Augmented Dickey-Fuller Test	-2.8	0.24	not significant
MIN Differenced	Augmented Dickey-Fuller Test	-11.9	0.01	significant
Coal Price	Phillips-Perron Unit Root Test	1.2	0.99	not significant
Coal Price Differenced	Phillips-Perron Unit Root Test	-1694.0	0.01	significant
GUESS	Phillips-Perron Unit Root Test	-19.9	0.07	not significant
GUESS Differenced	Phillips-Perron Unit Root Test	-1429.1	0.01	significant
MAX	Phillips-Perron Unit Root Test	-16.2	0.20	not significant
MAX Differenced	Phillips-Perron Unit Root Test	-1273.3	0.01	significant
MIN	Phillips-Perron Unit Root Test	-23.2	0.04	significant
MIN Differenced	Phillips-Perron Unit Root Test	-1109.8	0.01	significant

Note: Coal Price, Max, Min, and Guess are in log form. Significance based on a 5 per cent level of significance, indicating stationarity.

D Linear Granger Causality Results

Table D.1: Linear Granger Causality Tests Using Granger (1980)

Direction	F-statistic	P-value	Significance
Coal Price to Max	0.41	0.84	not significant
Max to Coal Price	0.30	0.91	not significant
Coal Price to Min	0.51	0.88	not significant
Min to Coal Price	0.91	0.52	not significant
Coal Price to Guess	0.35	0.88	not significant
Guess to Coal Price	0.43	0.83	not significant

Note: Coal Price, Max, Min, and Guess are in log differenced form. The tests for Max, Min and Guess are implemented based on a VAR(5), VAR(10) and VAR(5) specification, respectively. Significance based on a 5 per cent level of significance, indicating Granger causality.

E Structual Break Test

Table E.1: Estimated Break Points Using Bai and Perron (2003)

Coal Price	Max	Min	Guess
2015-11-30	2016-03-08	2015-12-25	2016-03-08
2016-12-22	2017-04-03	2017-01-25	2017-04-03
2018-01-22	2018-05-09	2018-04-03	2018-04-25
2019-03-11	2019-06-06	2019-04-22	2019-06-07
2020-04-21	2020-06-26	2020-05-08	2020-06-26

Note: Coal Price, Max, Min, and Guess are in log differenced form. The tests for Max, Min and Guess are implemented based on a VAR(5), VAR(10) and VAR(5) specification, respectively.

F Non-Linearity Tests

Table F.1: Residual Serial Dependence Tests Using Brock et al. (1996)

Dimension	Coal Price	Min	Max	Guess
2	0.01*	0.01*	0.03*	0.02*
3	0.01*	0.03*	0.05*	0.03*
4	0.02*	0.04*	0.06*	0.05*
5	0.03*	0.05*	0.09*	0.06*
6	0.03*	0.06*	0.10*	0.07*

Note: Coal Price, Max, Min, and Guess are in log differenced form. The tests for Max, Min and Guess are implemented using the residuals from a VAR(5), VAR(10) and VAR(5) specification, respectively. * indicates rejection of the null hypothesis of independence.

G Time-varying Granger causality results

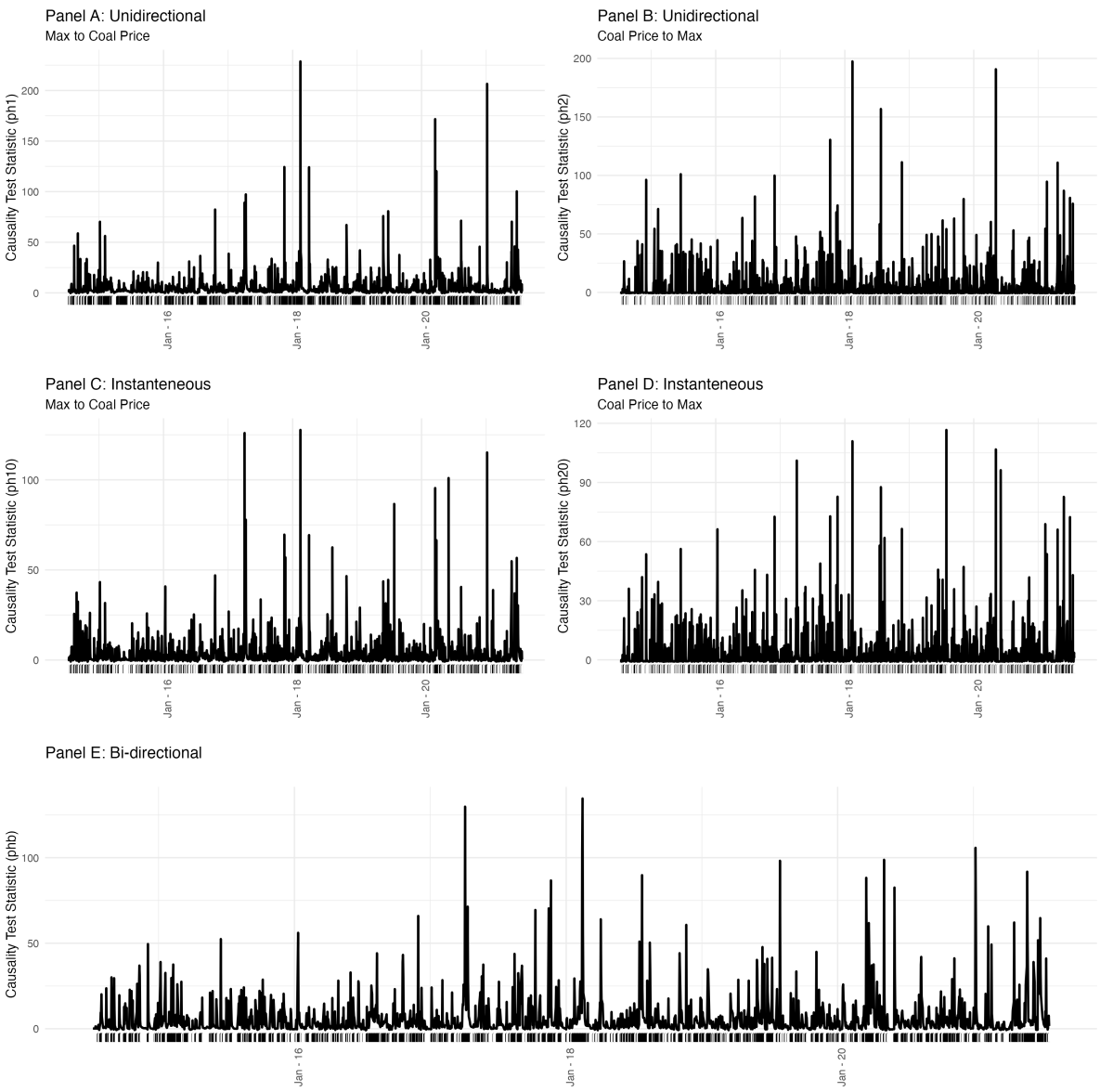

Figure G.1: Time-varying Granger Causality: Coal Price and Max. Note: ph1, 2, 10, 20, and b are p-values at 5 per cent level of significance from the Hong test statistics. Significance is indicated by the shaded region in the 'bar' plot at the bottom of each panel.

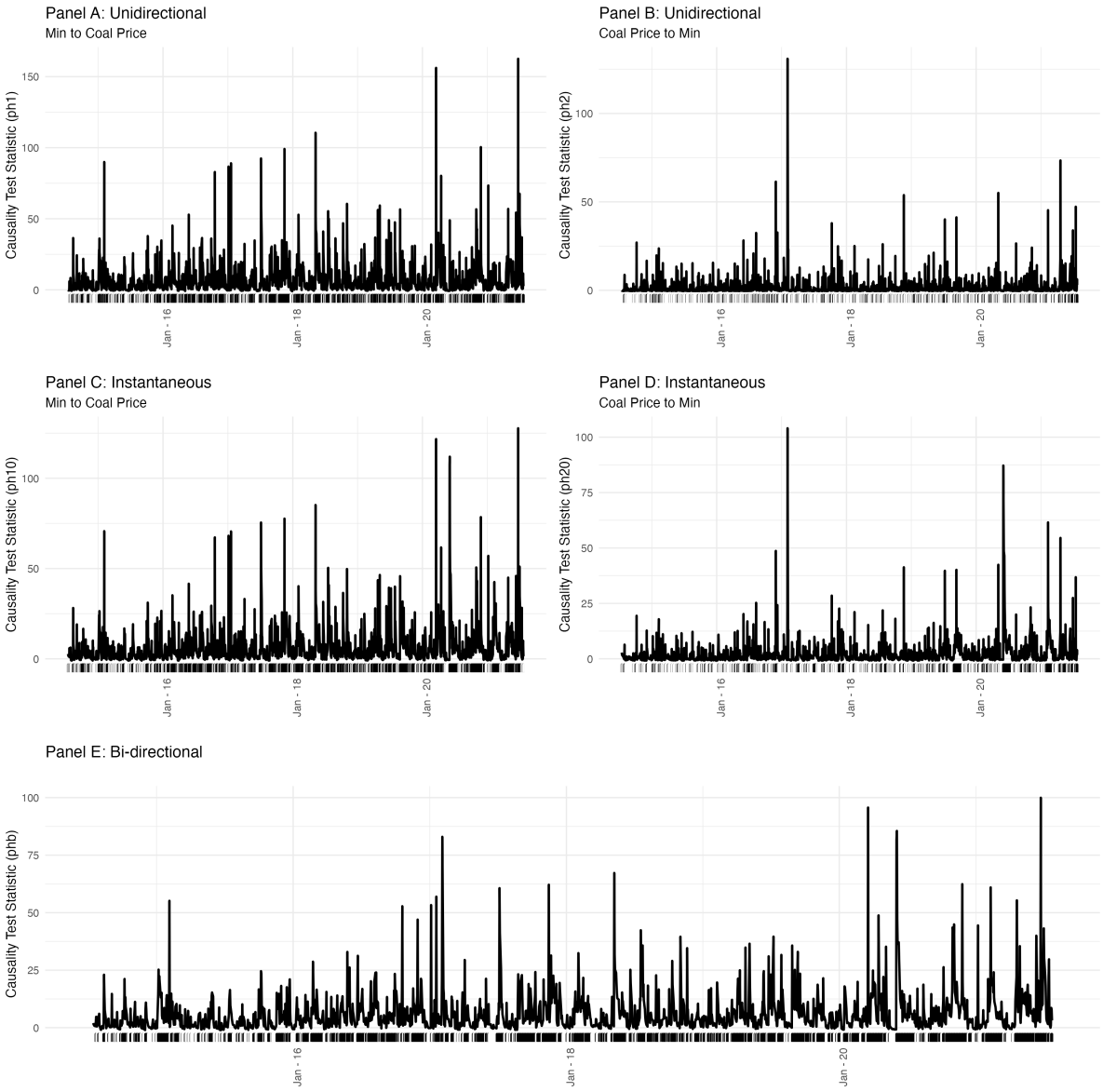

Figure G.2: Time-varying Granger Causality: Coal Price and Min. Note: ph1, 2, 10, 20, and b are p-values at 5 per cent level of significance from the Hong test statistics. Significance is indicated by the shaded region in the 'bar' plot at the bottom of each panel.

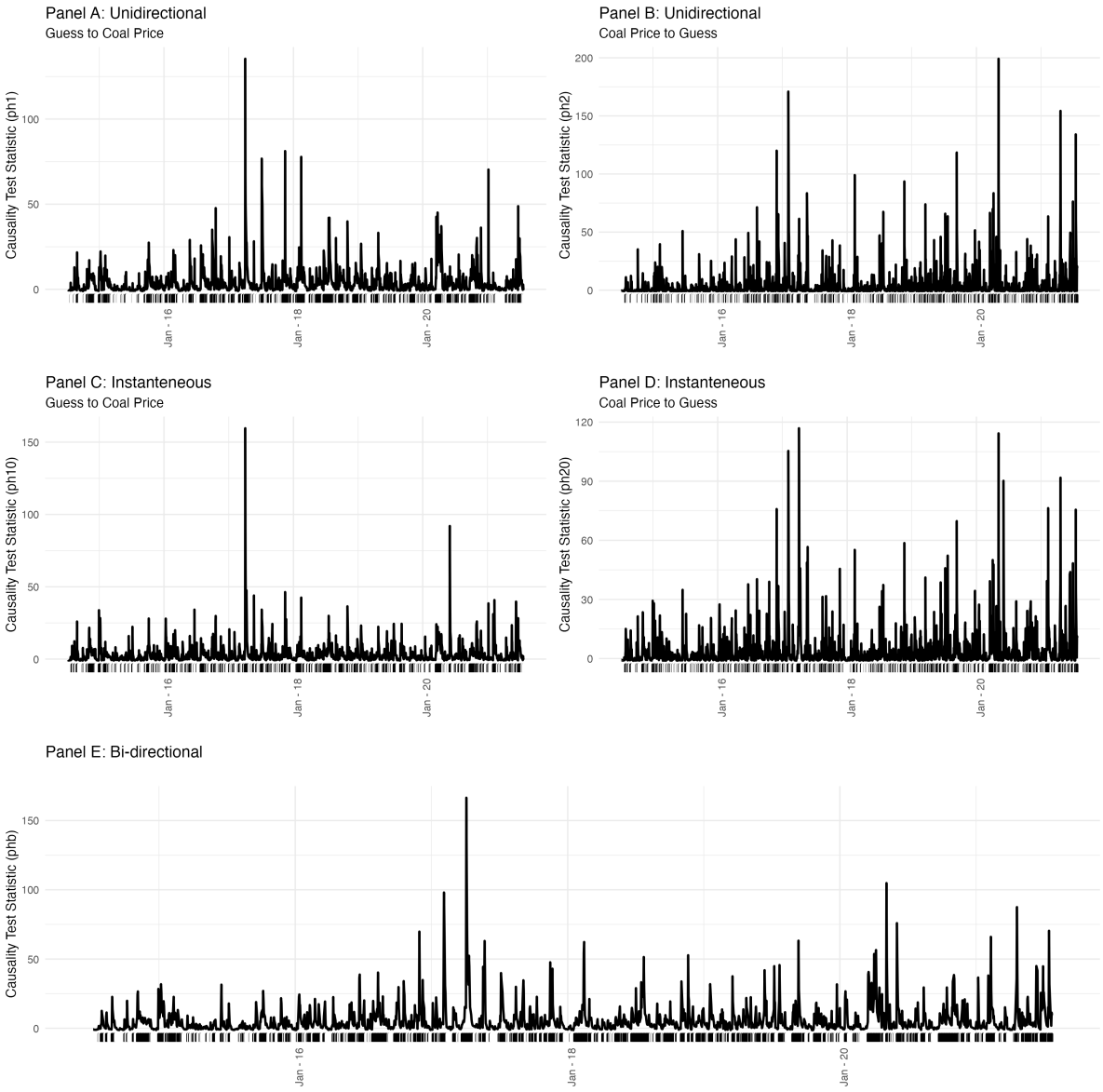

Figure G.3: Time-varying Granger Causality: Coal Price and Guess. Note: ph1, 2, 10, 20, and b are p-values at 5 per cent level of significance from the Hong test statistics. Significance is indicated by the shaded region in the 'bar' plot at the bottom of each panel.

H Robustness Checks–DBECI series

H.1 Data

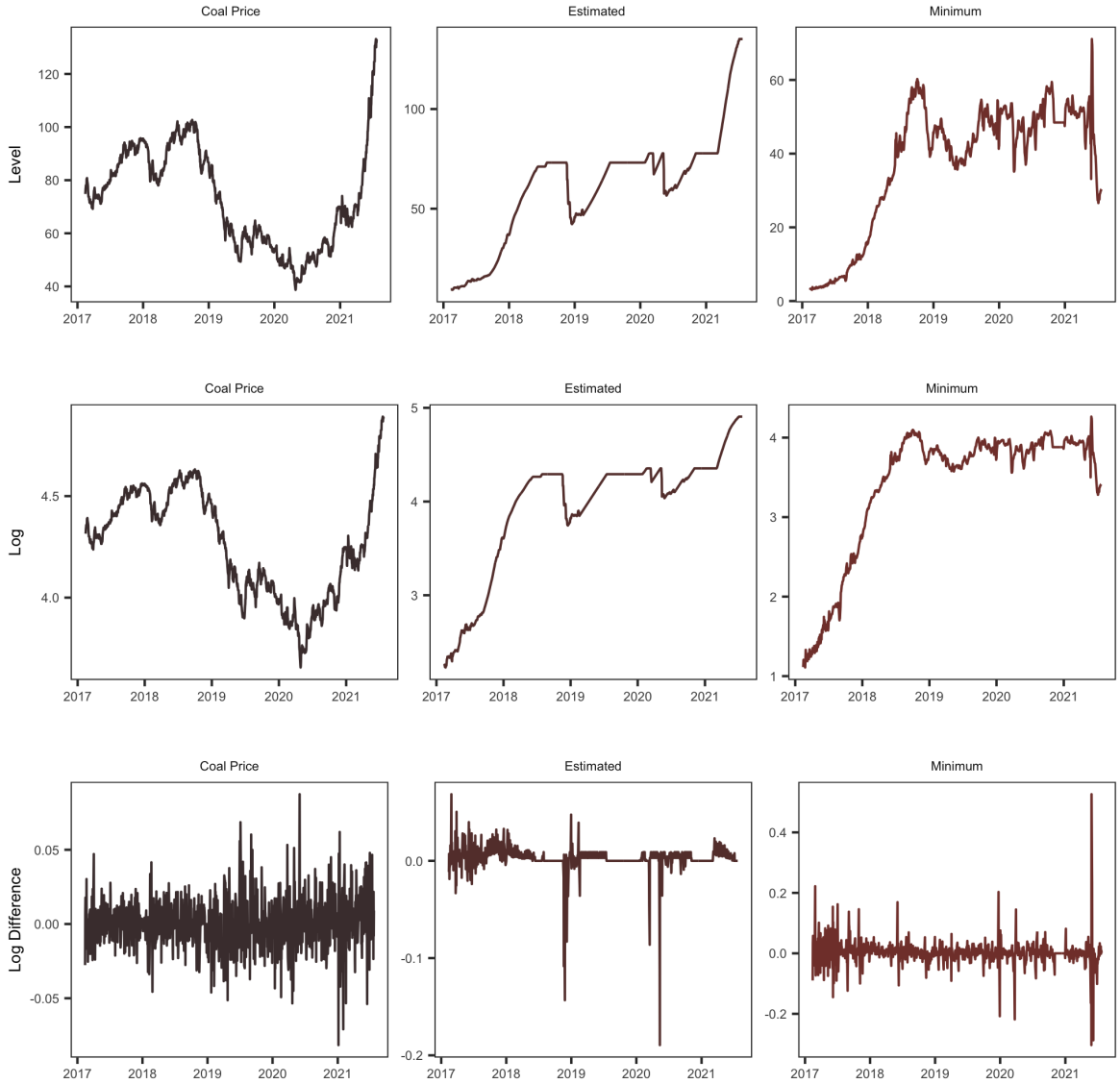

Figure H.1.1: Data

H.2 Descriptive Statistics

Table H.2.1: Summary Statistics

	Coal Price	Estimated	Minimum
Observations	1159	1159	1159
Mean	4.26	3.95	3.40
Standard Deviation	0.26	0.64	0.83
Skewness	-0.11	-1.30	-1.52
Kurtosis	-0.96	0.67	0.89
Jarque Bera Test	33.91*	9.81*	161.41*

Note: Coal Price, Max, Min, and Guess are in log form. * indicates that the null of normality is rejected at a 1 per cent level of significance.

H.3 Stationarity Tests

Table H.3.1: Stationary Tests

Variable	Test	Test Statistic	P value	Significance
Coal Price	Augmented Dickey-Fuller Test	0.20	0.99	not significant
Coal Price Differenced	Augmented Dickey-Fuller Test	-11.28	0.01	significant
Estimated	Augmented Dickey-Fuller Test	-1.33	0.86	not significant
Estimated Differenced	Augmented Dickey-Fuller Test	-7.18	0.01	significant
Minimum	Augmented Dickey-Fuller Test	-0.65	0.97	not significant
Minimum Differenced	Augmented Dickey-Fuller Test	-12.13	0.01	significant
Coal Price	Phillips-Perron Unit Root Test	1.22	0.99	not significant
Coal Price Differenced	Phillips-Perron Unit Root Test	-1693.96	0.01	significant
Estimated	Phillips-Perron Unit Root Test	-0.50	0.99	not significant
Estimated Differenced	Phillips-Perron Unit Root Test	-813.23	0.01	significant
Minimum	Phillips-Perron Unit Root Test	-6.68	0.74	not significant
Minimum Differenced	Phillips-Perron Unit Root Test	-999.00	0.01	significant

Note: Coal Price, Estimated, and Minimum are in log form. Significance based on a 5 per cent level of significance, indicating stationarity.

H.4 Granger Causality Results

Table H.4.1: Linear Granger Causality: Granger (1980) Test

Direction	F-statistic	P-value	Significance
Coal Price to Estimated	0.73	0.68	not significant
Estimated to Coal Price	0.90	0.52	not significant
Coal Price to Minimum	0.75	0.63	not significant
Minimum to Coal Price	0.94	0.48	not significant

Note: Coal Price, Estimated, and Minimum are in log differenced form. The tests for the Estimated and Minimum series are implemented based on a VAR(9) and VAR(7) specification, respectively. Significance based on a 5 per cent level of significance, indicating Granger causality.

H.5 Structural Breaks

Table H.5.1: Estimated Break Points: Bai and Perron (2003) Test

Coal Price	Estimated	Minimum
2017-11-27	2018-01-01	2017-10-13
2018-08-29	2018-11-13	2018-08-23
2019-04-26	2019-07-11	2019-04-22
2019-12-25	2020-03-16	2019-12-24
2020-11-05	2020-11-12	2020-10-22

Note: Coal Price, Estimated, and Minimum are in log differenced form. The tests for the Estimated and Minimum series are implemented based on a VAR(9) and VAR(7) specification, respectively.

H.6 Non-Linearity Tests

Table H.6.1: Residual Serial Dependence Tests: Brock et al. (1996)

Dimension	Coal Price	Estimated	Minimum
2	0.01*	0.00*	0.02*
3	0.01*	0.01*	0.03*
4	0.02*	0.01*	0.04*
5	0.03*	0.02*	0.06*
6	0.03*	0.02*	0.07*

Note: Coal Price, Estimated, and Minimum are in log differenced form. The tests for the Estimated and Minimum series are implemented based on residuals from a VAR(9) and VAR(7) specification, respectively. * indicates rejection of the null hypothesis for independence.

H.7 Time-varying Granger causality results

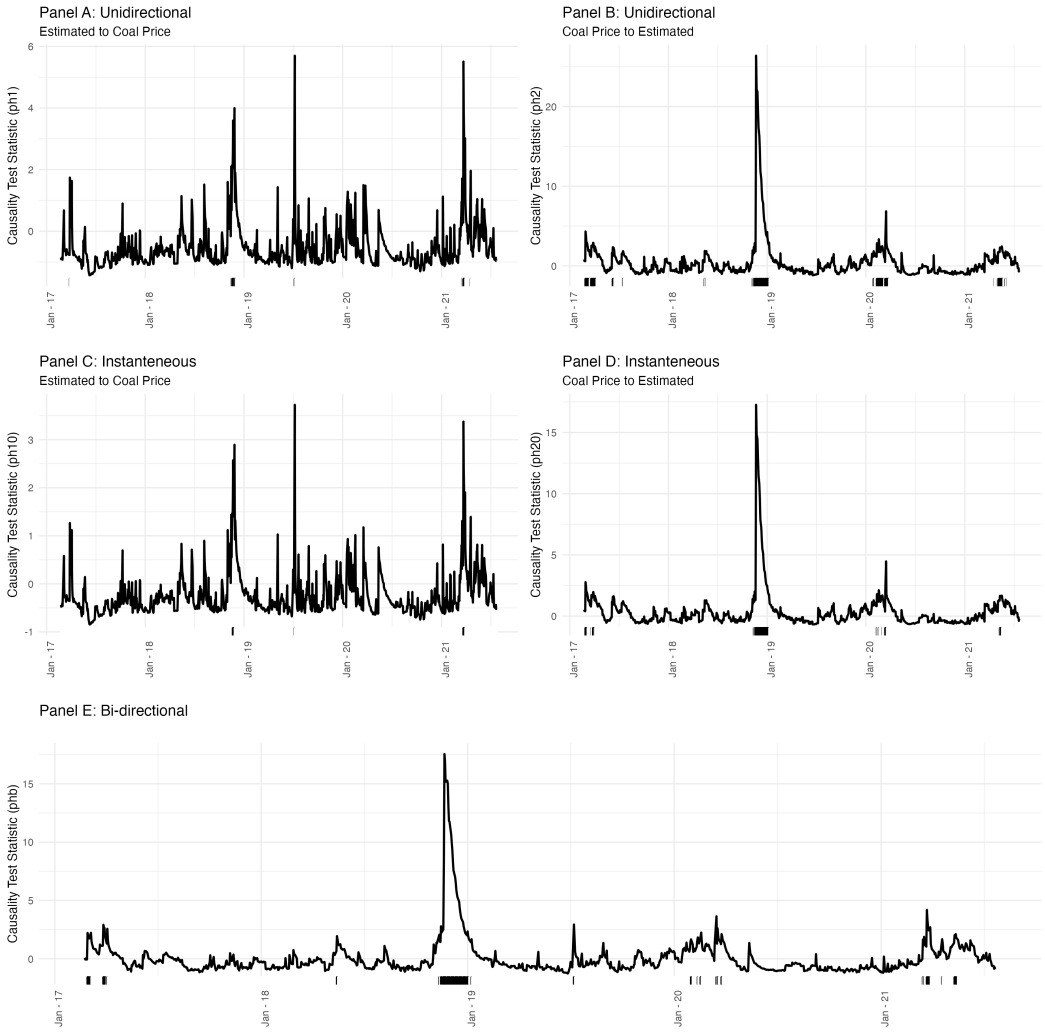

Figure H.7.1: Time-varying Granger Causality: Coal Price and Estimated. Note: ph1, 2, 10, 20, and b are p-values at 5 per cent level of significance from the Hong test statistics. Significance is indicated by the shaded region in the 'bar' plot at the bottom of each panel.

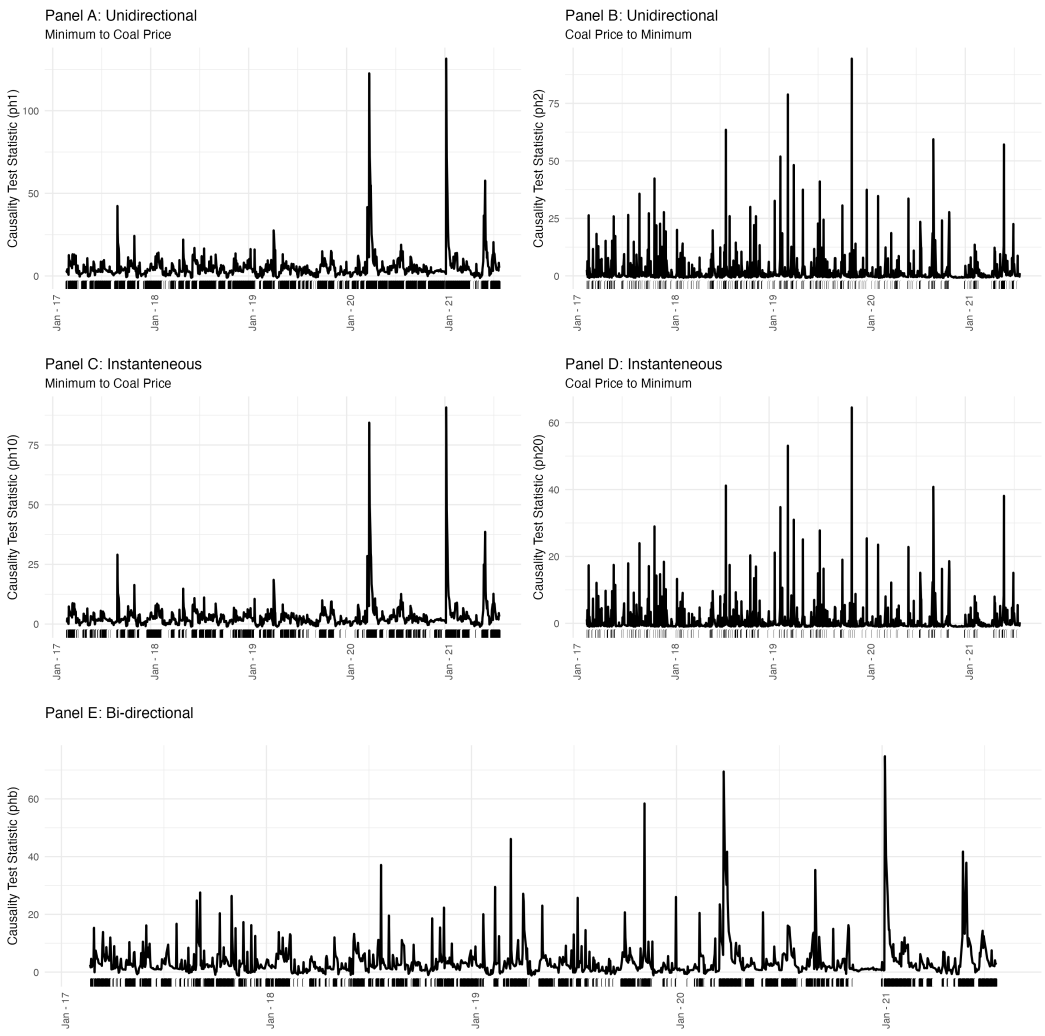

Figure H.7.2: Time-varying Granger Causality: Coal Price and Minimum. Note: ph1, 2, 10, 20, and b are p-values at 5 per cent level of significance from the Hong test statistics. Significance is indicated by the shaded region in the 'bar' plot at the bottom of each panel.