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Electricity demand in the iron ore industry: Evidence from Brazil

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Abstract

Electricity planning is a key strategic business in the mining industry. Thus, this paper assesses the electricity demand in the Brazilian iron ore industry with an emphasis on electricity prices and the production value chain to address the sector-specific behavioral patterns, using daily data from December 2018 to April 2020. By employing impulse response functions and variance decomposition analysis, the paper shows that electricity demand is primarily determined by internal factors of the ore production rather than exogenous variables, such as the electricity price and weather conditions. Moreover, short and long-run electricity price elasticities are computed, providing further insights into the dynamics of the sector, and indicating that price is inelastic with similar values for both time frames. This suggests from an energy policy perspective that any price movements (taxes) are bound to have a fairly limited effect as they may cause financial turmoil given the long-term characteristic of delivery contracts in the sector.

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1 Introduction

The industrial sector accounts for about one-third of the world's final energy demand, with the mining sector being one of the most energy-intensive industries, which makes electricity planning a key strategic business priority as it affects productivity, financial performance, and safety, especially when the sector faces an increasingly competitive global business environment. Thus, increased energy management in this area will remain critical to businesses in matters of attaining a stable supply, cost control, and meeting the standard quality requirements for finished products (OECD, 2015; Calvo et al., 2016; Palacios et al., 2019).

Despite extensive empirical studies investigating residential electricity demand, the literature on industry-level is scarce (Labandeira et al., 2017). The vast majority of these studies are built on aggregate demand models that are useful in formulating macroeconomic policies, normally based on panel data (Otsuka, 2015; Cialani and Mortazavi, 2018; Sharimakin et al., 2018) and time-series approaches (Inglesi-Lotz and Blignaut, 2011; Arisoy and Ozturk, 2014), but fail to capture the potentially more diverse energy consumption behavior of disaggregated sectors of the economy. Indeed, electricity loads for all horizons, that is, in the short, medium and long terms, are highly variable in nature on both macroeconomic and sectoral levels, highlighting the need to use data at the lowest level of aggregation possible (Henriksson et al., 2014; Bernstein and Madlener, 2015). Hence, the detailed information and understanding required for formulating specific energy-related policies can be provided.

In addition to the investigation of electricity demand functions, several studies simultaneously discuss the importance of the price elasticities in the industrial sector. Cialani and Mortazavi (2018), based on panel data for 29 European countries, indicate that the electricity demand is price inelastic for both short- and long-run horizon. Similarly, Otsuka (2015) analyzing the Japanese industrial sector, argues that price elasticity is not a key determinant of electricity demand functions whereas production factors are. Inglesi-Lotz and Blignaut (2011) also employ a panel framework to examine the South African economic sector's electricity demand responses to electricity prices and verify that agriculture, transport, and mining are not affected by price variations. Similarly, Bernstein and Madlener (2015) estimate sub-sector-specific electricity demand elasticities with regard to German industry by employing single-equation error correction models based on a log-linear demand function. Their results suggest that the short-run price elasticities range from -0.20 to -0.83 and are significant only in the non-metallic and transport equipment sectors. Moreover, the sizes of the short-run elasticities are in accordance with the corresponding long-run elasticity in a sector.

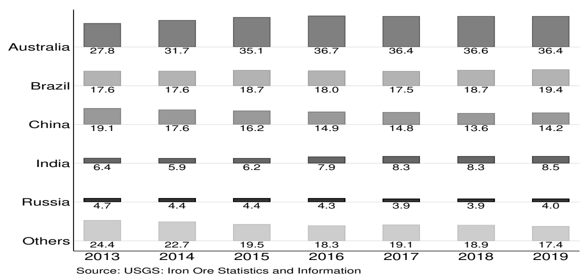
Business strategies and policy efforts aiming to increase energy efficiency in industrial sectors should be built on an in-depth understanding of energy demand behavior. Thus, this research takes advantage of a unique data set that permits the inference of the electricity demand at the firm level in the Brazilian mining industry, with special emphasis on the impact of spot electricity prices and on the production value chain, to assess industry-specific behavioral patterns, whereas the majority of studies use aggregate data. In this sense, this paper's contributions are twofold. First, to trace the dynamic behavior of the electricity demand on the basis of a multivariate VAR framework, impulse response functions and variance decomposition analysis are computed, indicating that the electricity price impulse has no major impacts whereas the sub-stages of the iron ore value chain, wet route processing (production), and the pipeline transport system are the most relevant to the electricity demand and production stability. Second, short- and long-run price elasticities are estimated using the auto-regressive model with distributed lags (ARDL), and the results indicate that the price is inelastic with similar values in both time frames, implying from an energy policy perspective that electricity price increases (taxes) are not a good instrument for discouraging the electricity demand in the Brazilian mining sector as they would cause financial imbalances and negatively affect long-term contracts' profitability.

2 The Brazilian iron ore industry

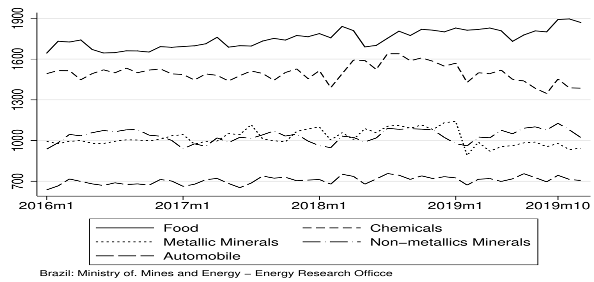
The global production of iron ore is concentrated in a few countries, of which Australia and Brazil are the largest producers, making 930 and 480 million metric tons, respectively, in 2019. Indeed, from 2013 to 2019, these two countries combined increased their global production share, from 45% to 55%, as shown in Figure 1a. Despite being the world's leading iron ore-consuming country, China's usable ore production has decreased by 5% due to the low-grade of its ore, which makes it expensive to process and increases domestic prices compared with foreign ones, even when considering overseas freight costs. Thus, China's iron ore imports are expected to increase, particularly from countries with high-grade ores, such as Brazil and Australia (USGS, 2020).

From 2013 to 2019, Brazil's iron ore exports represented, on average, 84% of the country's mineral production, although this rate has reached its lowest value, 70%, in the last year due to the major VALE dam rupture in the state of Minas Gerais (Brazil, 2020). Despite the accident, which reduced VALE's export levels by 20% between 2018 and 2019, the company remains the main Brazilian exporter, with more than 80% of the total foreign trade share (Figure 1c). The second largest ore producer in Brazil is Anglo American, exporting nearly 25 million tons in 2019 and representing 7% of the total exports. From 2013 to 2017 the firm consistently expanded its market share, but in 2018, two pipeline leaks forced Anglo to stop operations at its mine site for eight months, resuming then in November of the same year. As for Samarco and MMX, the former stalled its operation in November 2015 at its highest level of production due to the Fundão dam collapse and has been struggling to obtain all the required licenses to restart mining since then and the latter, it has filed for bankruptcy in 2015 and has ceased its operations.

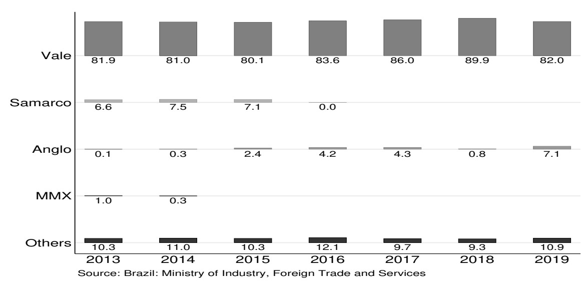
Figure 1: Brazil: Iron ore industry dashboard



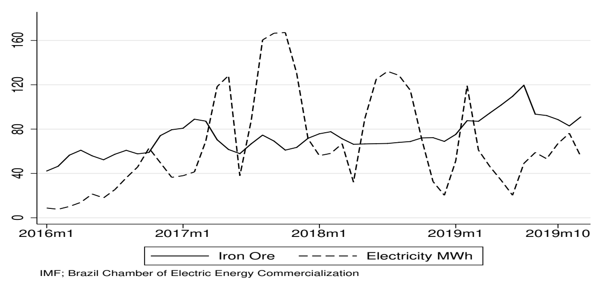
(a) Iron ore production share by major producing countries (%)



(b) Brazil: Electricity consumption by industry (GWh)



(c) Brazil: Iron ore exports by firms (%)



(d) Iron Ore 62% Fe ($/ton) & Electricity Prices (US$)/Mwh

Industrial production in Brazil relies significantly on electricity for processing raw materials and refining and shaping material goods. It is therefore crucial to assess this input demand properly, making companies less vulnerable to turmoil on the electricity open market. Regarding the mining industry, the four-year historical trend indicates that it accounts for roughly 10% of the total electricity consumed in the manufacturing sector, averaging 1.019 million MWh monthly, as displayed in Figure 1b (Brazil-EPE, 2020). Furthermore, it is clear from Figure 1d, that the electricity spot prices (Brazil-CCEE, 2020) for the industrial sector have a higher variance than the ore prices, mostly associated with rainfall shortages and government regulation; however, it presents a lower average price, US$55.71, compare to US$70.86 of the rock. On practical matters, it has cash flow implications that may increase the firm financial risk level as the demand side does not seem to be sensitive to variations in the wholesale price of electricity in the short term. In this context, this highlights the need to propose a model that takes into account the characteristics of the mineral's production process at the firm level and thereby reduces the need to trade electricity on the free market and keep the production costs as stable as possible. This is the contribution that this paper aims to make.

3 Data and Methodology

This paper takes advantage of a unique daily data set from an iron ore processing plant in Brazil with a slurry pipeline; it combines the electricity demand, production process, a measure of climatic conditions, such as temperature, and electricity prices for a specific market (Southeast) in the Brazilian energy system from December 23, 2019 to April 12, 2020. This data set has two advantages with respect to existing industrial sub-sector data sources: first, it minimizes the risk of measurement errors as the data are very accurate and based on actual readings of the production process; and, second, the use of the sectoral electricity price is an advantage over the use of the aggregate national price as a proxy (Bernstein and Madlener, 2015; Cialani and Mortazavi, 2018), allowing research to extend the understanding of the demand side of the electricity market and thereby facilitating efforts to improve efficiency energy planning.

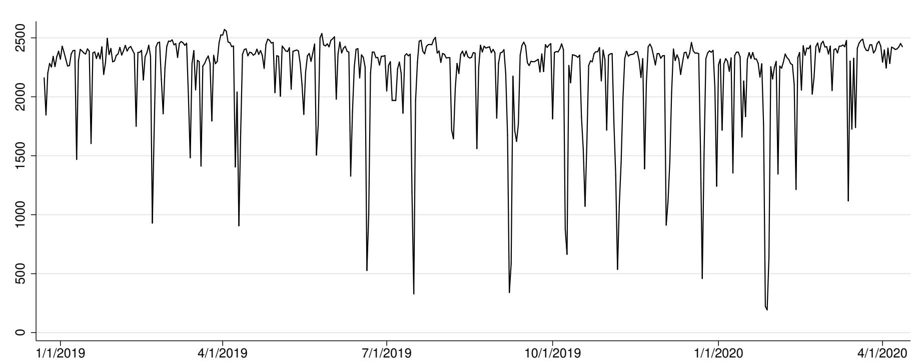
The iron ore production value chain involves extraction, blasting, crushing, grinding, processing (wet route production), and transportation to the ports for exporting and local consumption; among these, the electricity requirements of grinding and processing account for more than 50% of the total energy consumed in open pit mines (Jeswiet and Szekeres, 2016). In particular, the amount of rock produced in each stage could present a minimum of 0 tons (t); that is, on a specific date when the sub-stage operation was shut down, normally related to maintenance requirements. As for the transportation pipeline system, it operates continuously, that is, up to 24 hours daily. Table 1 presents the summary statistics of the variables.

Table 1: Descriptive statistics

Variables	**Description**	**Unit**	**Mean**	**S.D.**	**Min**	**Max**
ED	Electricity demand	MWh	2207.11	398.15	193	2571
EP	Electricity price	US$	56.01	31.22	7.41	138.30
temp	Average temperature at site	$^{\circ}$C	22.63	2.82	12.38	29.22
crush	Primary crushing	t	117490.20	35434.97	0.00	178101.70
grind	Grinding feed	t	117926.11	31770.12	0.00	158883.70
wet	Wet route production	t	58626.21	17310	0.00	84211.44
pipe	Pipeline hours of operation	h	23.79	1.69	0.05	24.00

The average daily electricity demand during the time frame considered was 2200 MWh, and Figure 2 reveals no cycle trend as the electricity load curves are similar on different days of the week – see Figure 5 in the Appendix. In addition, the series show large, sudden level shifts, mainly due to maintenance procedures, which normally take place on weekdays. Therefore, when they happen in the crushing and grinding stages, the electricity demand reduces to 1000–1700 MWh daily, whereas, when there is an operational stop in the pipeline, drastic power reduction takes place due to a ripple effect throughout the entire production process. Furthermore, since March 2020, the global economy has been experiencing an economic slowdown as a result of the COVID-19 pandemic. However, a visual inspection of the electricity demand time series suggests that the effects on mining operations have been minimal to date when compared with other economic sectors, such as transportation and the textile industry, mainly due to the high level of digitalization and industrial automation in the sector and increased storage areas that help to mitigate this risk.

Figure 2: Daily Electricity Demand (MWh)



Therefore, the microeconomic framework underlying the econometric specification of the mining industry electricity demand follows Lin and Ouyang (2014), Bernstein and Madlener (2015) and Cialani and Mortazavi (2018) and uses the Cobb-Douglas demand function, $ED_t = A(EP_t^{\beta_1})(temp_t^{\beta_2})(X_{n,t}^{\beta_n})$, in which X_n denotes the sub-stages of the production value chain. A logarithmic transformation of this demand function yields:

$$\ln ED_t = \beta_0 + \beta_1 \ln EP_t + \beta_2 \ln temp_t + \beta_3 \ln crush_t + \beta_4 \ln grin_t + \beta_5 \ln wet_t + \beta_6 \ln pipe_t + \varepsilon_t, \tag{1}$$

where $\beta_1, ..., \beta_n$ are the industrial sub-sector demand elasticities, which can be useful for ex-ante evaluation of the impact of the pricing policy on the demand-side management of electricity. Then, to check for stationarity behavior in each transformed time series, the Augmented Dickey-Fuller (ADF) test is conducted. The results are summarized in Table 4 (in Appendix), which shows that, in general, the ADF statistics are smaller than the 1% critical value, except for the price indicator. Thus, the test performed on its first difference demonstrates that the time series is stationary at the 1% significance level.

Assuming this stationary characteristics, to evaluate the dynamic behavior of the electricity demand at the firm level, this paper specifies a multivariate VAR framework as follows (Enders, 2008):

$$y_t = \nu + A_1 y_{t-1} + \ldots + A_\rho y_{t-\rho} + \varepsilon_t, \tag{2}$$

where y_t is a vector of jointly determined endogenous variables, ν is a $k \times 1$ vector of constants, $y_{t-i}, i = 1, \ldots, \rho$ is specified as a linear combination of past observations of the same variables, and $A_i, i = 1, \ldots, \rho$ are a $K \times K$ matrix of parameters, interpreted as the sensitivity of a predictor to the lag of another variable, hence, generating impulse-response functions (IRFs). In addition, $\varepsilon_t \sim N(0, \Sigma_\varepsilon)$ is conditional on past values and initial conditions, which are useful for variance decomposition analysis (VDA).

Formally, the VAR approach is used for model evaluation and prediction. In this sense, an IRF indicates how long, and to what extent, a shock u_j (an external change in any input) to one endogenous variable may affect on the independent variable. In this paper, it indicates how the electricity demand reacts to an unanticipated change in any other endogenous variable. VDA is a statistical method to uncovered structural changes, defined as a change in variable y at time t that could not have been forecast between $t-1$ and t; that is, it quantifies the importance of each shock in explaining the variation in each of the variables in the system. Thus, the VAR approach is highly flexible in terms of identifying important dynamic relationships among the electricity demand data set. Simultaneously, it can capture the temporal autocorrelation in a specific variable and allows dynamic cross-correlation between different predictors. That is, the estimation of the parameters is performed by imposing as restrictions the structure of the production process, the choice of the relevant set of variables, and the maximum number of lags involved in the relationships between them.

Furthermore, assuming Equation 1 and the results displayed in Table 4, this paper uses the autoregressive distributed lag error correction approach (ARDL) to estimate short- and long-run electricity elasticities in the mining industry as it overcomes the restriction in traditional cointegration approaches that all the variables must be integrated of the same order (Pesaran et al., 2001; Kripfganz and Schneider, 2016). From an operational perspective, the first step is to investigate the existence of a long-run linkage among the variables by the bounds $F - test$, and, if this is the case, then the short-run and long-run elasticities can be computed. A general ARDL model with an ordinary least squares (OLS) estimation technique is specified as:

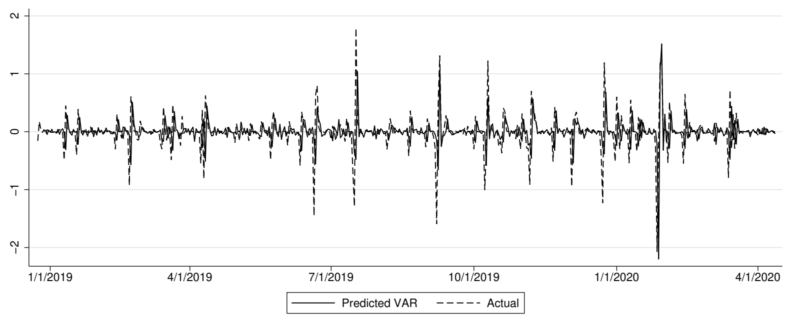
$$\Delta y_t = c_0 + c_1 t - \alpha\left(y_{t-1} - \theta \mathbf{x_{t-1}}\right) + \sum_{i=1}^{\rho-1} \phi_{yi} \Delta y_{t-i} + \sum_{i=1}^{\rho-1} \beta'_{xi} \Delta \mathbf{x}_{t-i} + u_t, \tag{3}$$

where $\alpha = 1 - \sum_{j=1}^{\rho} \phi_i$ is the speed of adjustment from convergence to equilibrium, $\theta = \frac{\sum_{\mathbf{i=0}}^{\mathbf{q}} \beta_{\mathbf{j}}}{\alpha}$ are the long-run coefficients, β are the short-run multipliers, ρ lags of y_t and q lags of k variables $x_{j,t}$ for $j = 1, ..., k$. are selected by the Akaike information criterion (AIC). Thus, if α is statistically significant and presents a negative sign for the coefficient, any long-run disequilibrium among the dependent variables and k independent variables will converge back to the long-term equilibrium association.

4 Empirical analysis

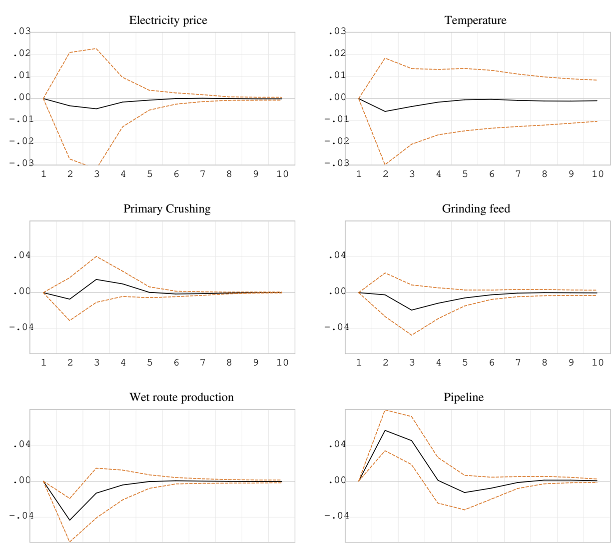
To trace the dynamic behavior of the electricity demand in response to one-time innovations in the variables listed in Table 1, this paper performs an impulse response and variance decomposition analysis on the basis of a VAR specification. First, the optimal choice of lag length is set at $\rho = 4$ as defined by the AIC methodology; onetheless, a number of diagnostic tests are computed on the orthogonalized VAR residuals to test for autocorrelation (Lagrange multiplier test: the p-value at lag 1 (0.28) is greater than the 5% level) and normality (Jarque-Beta statistic: for all variables $p = 0.00$), suggesting that the K disturbances in the VAR are normally distribute. Figure 3 displays the fitted values for the electricity demand of the VAR model over the actual data, indicating considerable adherence of the model to the data.

Figure 3: (Log) Differenced Daily Electricity demand (actual) and Predicted VAR Model



Further, to explore the IRF analysis, the VAR model needs to be tested for stability. From Figure 6a (in Appendix), it can be seen that the absolute values of all the unit roots are inside the unit circle; that is, the specification meets the stability conditions. Hence, these results indicate the VAR approach's capacity to be used as a technical instrument for predicting and assessing the electricity demand. Figure 4 displays the cumulative responses in the electricity demand due to impulses in the other control variables. In general, the figure indicates that the shocks appear to be transitory and the system approaches the equilibrium relatively fast, which is a typical characteristic of technologically consolidated mining processes.

Figure 4: Response to Cholesky One S.D. Innovations



The results of this exercise are twofold. Firstly, the electricity price impulse has no major significance as it has stabilized around the zero level from the beginning, reinforcing the evidence that the industrial electricity demand has been highly inelastic (Bernstein and Madlener, 2015; Cialani and Mortazavi, 2018). A peculiar situation of the iron ore industry in Brazil corroborates the idea that, due to the high quality of the ore grade and economies of scale, the processing and refining require less costly technology and use less energy when compared with other world top producers (China and Russia), which is a crucial determinant of its competitiveness. Moreover, the main energy source is hydropower, so that, whatever its price, it will be acquired to meet the contract agreements. Thus, this productive context causes the electricity price to have minimum effects on its demand.

Secondly, for the production value chain, all the variables present transitory effects as they are all integrated of order 0. Given that, convergence to the equilibrium occurs after approximately five to seven days, depending on the stage-specific speed of adjustment. Specifically, in the primary crushing, a set of techniques aims to reduce, through external and sometimes internal mechanical action, a solid of a certain size into fragments of a size small enough to be taken into the next stages of production. It can be noticed that it has little effect on the energy demand. Similarly, at the grinding feed stage, despite a small negative effect due to buffer storage piles that ensure regularity in the production process, mitigating the probability of ore outages , the electricity demand shifts back to its smooth pattern after no more than three days. As for wet route production (processing) and continuous pipeline operations, the IRF approach corroborates the perspective that they are the most relevant equipment to electricity consumption and production stability. That is, depending on the quality and size of the ore that feeds the wet route processing stage, the electricity demand tends to drop if it is operating below its maximum capacity level. Once that level is reached, the electricity demand tends to stabilize again, which can take up to 7 days. The impulse induced by the ore transport equipment generates the biggest short-term fluctuation in the electricity demand due to a ripple effect in the production process. It rises at the first moment to compensate for any higher level of production or the necessity to maintain shipment deadlines at the port, quickly returning to the standard electricity demand level.

From the variance decomposition results presented in Table 2, the fluctuation in the electricity demand from 0 to 7.75% can be explained by pipeline operation noise, although the need for continuous improvement in maintenance requirements tends to reduce this share. The innovations in the production sub-stages of crushing, grinding, and wet route production combined account for nearly 10% of the variation in the energy demand in the long run, indicating that the actual technology level contributes to a small part of it, once the designed nameplate production capacity of the plant is achieved, although reducing the level of ore grade variation and electricity efficiency through the improvement of facilities' usage is still a key factor in reducing the energy costs. As for the price innovation, the results corroborate the IRF evidence, suggesting that its long-term influence on the electricity demand is minimal. Thus, the empirical analysis shows that electricity demand movements are conditioned more by internal factors of the ore value chain than by exogenous variables, such as the electricity price and weather conditions.

Table 2: Variance Decomposition Analysis: $\ln(ED)$

Period (days)	ED	EP	Temp	Crush	Grind	Wet Route	Pipe
1	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	88.2259	0.0119	1.0379	1.0580	2.0063	3.0906	5.5694
3	83.5160	0.0338	1.0496	1.2832	3.4016	3.1688	7.5471
4	82.2729	0.0364	1.0522	1.3814	3.5482	4.1725	7.5293
5	82.0858	0.0369	1.0524	1.3808	3.5843	4.1731	7.6847
6	82.0204	0.0368	1.0525	1.3827	3.5901	4.1737	7.7437
7	82.0162	0.0368	1.0532	1.3840	3.5904	4.1737	7.7458
8	82.0134	0.0368	1.0544	1.3841	3.5904	4.1737	7.7472
9	82.0105	0.0369	1.0558	1.3841	3.5904	4.1737	7.7487
10	82.0092	0.0369	1.0568	1.3841	3.5905	4.1737	7.7487
15	82.0060	0.0369	1.0598	1.3841	3.5908	4.1737	7.7487
20	82.0045	0.0369	1.0613	1.3841	3.5909	4.1737	7.7487
30	82.0036	0.0369	1.0622	1.3841	3.5910	4.1737	7.7488

Econometric analyses of the price elasticity at the industrial sub-sector level of the electricity demand are scarce. Therefore, by employing an ARDL framework, short-run and long-run price elasticities are estimated to gain a better understanding of the relationship between them over time. As the first step of the ARDL technique, the long-run relationship of the underlying variables is detected through a bounds-testing procedure based on the joint $F-statistic$ (Kripfganz and Schneider, 2016) —– the calculated F-value is 25.02, above the upper bound at the 5% significance level of 3.63. Then, Equation 3 is estimated to obtain the elasticities. Table 3 presents the results.

Table 3: Brazilian iron ore industry: Price elasticities

	Elasticities		**Speed of adjustment**
	Short-Run	**Long-Run**	α
Ln(EP)	-0.0203**	-0.0312**	-0.6541***
	(0.009)	(0.011)	(0.055)

Note: Standard deviations are in parentheses. ** → p < .05.; *** → p < .01

The findings are economically reasonable in terms of both sign and magnitude with respect to the industrial sector (Bernstein and Madlener, 2015; Labandeira et al., 2017), and the values for the short-run and long-run elasticities are only slightly different, indicating that the relationship between the two variables remains practically stable over time. In addition, the ARDL framework measures the speed of adjustment (α) at which the electricity demand restores the equilibrium path, and the results imply that about 65.4% (statistically significant at the 1% level) of any movements into disequilibrium are corrected within one day; that is, short-term movements of the electricity demand in the mining industry, due to the price and sub-stages' production-level variations, are rapidly reduced. Further, stability diagnostics for the coefficients of the estimated ARDL model are tested by applying the cumulative sum of recursive residuals (CUSUM). The results in Figure 6b (in the Appendix) show that all the parameters are stable over time, suggesting that there are no structural breaks over the sample period.

These results have implications for both public policies and business planning. Following Inglesi-Lotz and Blignaut (2011) and Henriksson et al. (2014), from an energy policy perspective, the results indicate that price increases (taxes) are bound to have a fairly limited effect; that is, the increases may have to be unfeasibly large to have substantial effects and may generate severe financial and cash flow impacts. This situation stems from the fact that the main energy source is hydropower, which makes a firm extremely dependent on this input to fulfill its long-term constructs. In this context, the Brazilian mining sector should be encouraged to engage in a process of cogeneration of renewable energy sources due to their ecological, economic, political, and social advantages; consequently, their electricity demand from the national supplier will tend to drop. Thus, an energy policy must prioritize incentives for the development of these renewable energy projects, whether through favorable credit lines, greater legal security for companies, or royalty payments, mainly because these projects face high initial costs and longer payback times.

5 Conclusion

Reliable energy sources are essential to the iron ore mining industry. However, despite the fundamental importance of energy, the day-to-day focus on meeting operational targets at a mine often means that energy is not used efficiently. Thus, this paper adopts a VAR model to analyze the electricity demand dynamics in the Brazilian mining industry, with special emphasis on electricity prices and the production value chain, using a daily data set from an iron ore plant based on a log-linear demand function. The results indicate that the electricity demand movements are mostly conditioned by internal factors related to the production process rather than exogenous variables, such as the electricity price and weather conditions. Moreover, short-run and long-run price elasticities are calculated through an ARDL model, and the values obtained confirm the presence of price inelasticity that is persistent over time in this industrial sector.

These results are important for providing realistic baseline assessments for future evaluations of energy policies as the empirical evidence suggests that a stimulus through electricity prices has a limited effect on the mining industry and that other instruments should be considered, such as the promotion of co-generation projects. Future research should consider collecting data from other plants globally to enable a detailed comparison with the results achieved in this research.

References

Arisoy, I. and I. Ozturk (2014). Estimating industrial and residential electricity demand in turkey: A time varying parameter approach. *Energy 66*, 959–964.

Bernstein, R. and R. Madlener (2015). Short-and long-run electricity demand elasticities at the subsectoral level: A cointegration analysis for german manufacturing industries. *Energy Economics 48*, 178–187.

Brazil (2020). Iron ore reports. *Ministry of Industry, Foreign Trade and Services*.

Brazil-CCEE (2020). PLD spot price. *Brazil Chamber of Electric Energy Commercialization*.

Brazil-EPE (2020). Statistical yearbook of electricity. *Ministry of. Mines and Energy − Energy Research Officce*.

Calvo, G., G. Mudd, A. Valero, and A. Valero (2016). Decreasing ore grades in global metallic mining: A theoretical issue or a global reality? *Resources 5*(4), 36.

Cialani, C. and R. Mortazavi (2018). Household and industrial electricity demand in europe. *Energy policy 122*, 592–600.

Enders, W. (2008). *Applied econometric time series*. John Wiley & Sons.

Henriksson, E., P. Söderholm, and L. Wårell (2014). Industrial electricity demand and energy efficiency policy: the case of the swedish mining industry. *Energy Efficiency 7*(3), 477–491.

Inglesi-Lotz, R. and J. N. Blignaut (2011). Estimating the price elasticity of demand for electricity by sector in south africa. *South African Journal of Economic and Management Sciences 14*(4), 449–465.

Jeswiet, J. and A. Szekeres (2016). Energy consumption in mining comminution. *Procedia CIRP 48*, 140–145.

Kripfganz, S. and D. C. Schneider (2016). ardl: Stata module to estimate autoregressive distributed lag models. In *Stata Conference, Chicago*.

Labandeira, X., J. M. Labeaga, and X. López-Otero (2017). A meta-analysis on the price elasticity of energy demand. *Energy Policy 102*, 549–568.

Lin, B. and X. Ouyang (2014). Electricity demand and conservation potential in the chinese nonmetallic mineral products industry. *Energy Policy 68*, 243–253.

OECD (2015). Energy efficiency in the steel sector: why it works well, but not always. *OECD Steel Committee*.

Otsuka, A. (2015). Demand for industrial and commercial electricity: evidence from japan. *Journal of Economic Structures 4*(1), 9.

Palacios, J.-L., I. Fernandes, A. Abadias, A. Valero, A. Valero, and M. A. Reuter (2019). Avoided energy cost of producing minerals: The case of iron ore. *Energy Reports 5*, 364–374.

Pesaran, M. H., Y. Shin, and R. J. Smith (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics 16*(3), 289–326.

Sharimakin, A., A. J. Glass, D. S. Saal, and K. Glass (2018). Dynamic multilevel modelling of industrial energy demand in europe. *Energy Economics 74*, 120–130.

USGS (2020). Iron ore statistics and information. *National Minerals Information Center*.

Appendix

Figure 5: Weekdays electricity Demand (MWh)

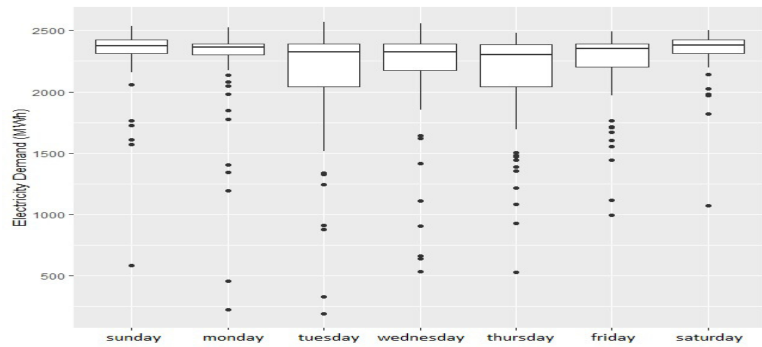
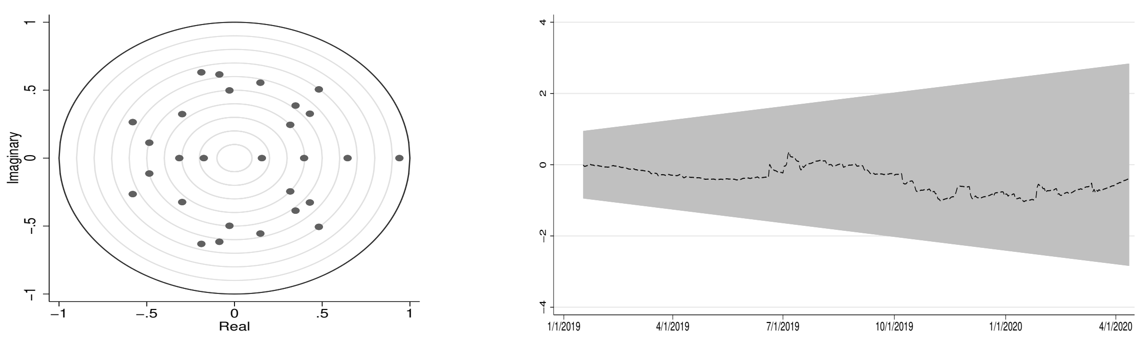


Table 4: Augmented Dickey-Fuller test for unit root

	ADF Statistics	1% Critical Value	5% Critical Value	p-value
ln(ED)	-12.847 (1)	-3.442	-2.871	0.000
Ln(EP)	-1.987 (1)	-3.442	-2.871	0.292
D(ln(EP))	-19.499 (1)	-3.442	-2.871	0.000
ln(Temp)	-4.218 (1)	-3.442	-2.871	0.001
ln(crush)	-14.052 (1)	-3.442	-2.871	0.000
ln(grind)	-14.137 (1)	-3.442	-2.871	0.000
ln(wet)	-14.241 (1)	-3.442	-2.871	0.000
ln(pipe)	-15.199 (1)	-3.442	-2.871	0.000

Note: Lag lengths are in parenthesis. Experiments with more lags in the augmented regression yield the same conclusion. Test specification includes both intercept and trend.

Figure 6: Post estimation tests



(a) Stability test of VAR model

(b) ARDL:Cumulative Sum of Recursive Residuals (CUSUM)