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Regional Estimates of Residential Electricity Demand in Brazil#

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ABSTRACT

Understanding consumers' short- and long-run response to electricity prices is essential for efficient market regulations, supplier planning decisions, and evaluation of policies for the economic development of the country. This work estimates the determinants of residential electricity demand for Brazil and for each of its five geographic regions, North, Northeast, Midwest, Southeast and South in a cointegration setup. The demand model accounts for the electricity prices, personal income, production and price of appliances, and climatic conditions, all of which show pronounced regional disparities. The data confirm that price and income elasticities are inelastic, both in the short- and long-run. Regional disaggregation yields the insight that price elasticities are insignificant in the North, Southeast and South, both in the short- and long-run. For the country as a whole, the short-term price effect is insignificant as well. This novel result casts doubt on recently implemented and future price-based policy measures that are necessary to reduce electricity consumption in a system that is frequently close to its maximum capacity. Brazil's dependency on increasingly scarce rainfall and the rising electricity demand due to income increases require effective responses, however.

Keywords: Electricity Demand, Price Elasticities, VECM, Brazilian Regions
JEL Classifications: C22, C54, D12, Q41

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1. INTRODUCTION

Blackouts and electricity shortage are recurrent problems all over Brazil. On the one hand, the country's electricity supply relies to a great extent on hydro-power generation and naturally suffers when rainfall is lacking. On the other hand, ineffective management system and insufficient investment are problems that could be mitigated by policy makers (De Lima and Bacchi, 2019). According to these authors, the economic cost of electricity rationing is estimated at 3% of GDP per year, even without taking the individual welfare losses and lower economic growth potential into account (Payne, 2010). Because the Brazilian electricity market is heavily regulated and (public and private) investors regularly compete via public tenders, the essence of the problem seems to be that forecast of electricity supply and demand do not match.

The objective of the present research is to provide more accurate estimates for the long- and short-run effects of determinants for the residential electricity demand in Brazil. To this end, we use monthly data from January 2003 to June 2015 and apply the Vector Error Correction Model (VECM). The VECM is then extended to a variance decomposition and a Granger causality analysis that shed more light on the relation between electricity demand and its determinants. The selected period is characterized by a relatively uniform expansion of the Brazilian economy. Since 2015 until the present day, Brazil suffered several unfavorable shocks that prevent the economy from getting back on its previous growth path. Over this period demand decreased markedly, even for relatively important services such as internet and telecommunication (Silva et al., 2020). We exclude the recent period deliberately in order to avoid structural break issues and to derive estimates that are representative for a uniform and more favorable scenario to which the economy hopefully will return soon.

The main distinction of our paper is to present novel estimates for each of the five geographic regions, North, Northeast, Midwest, Southeast and South. As hypothesized, our estimates present substantial heterogeneity across the regions which are related to the disperse distribution of income, market size, productive capacity, rainfall, among others. To the best of our knowledge, there is only one study from Brazil that presents demand estimations by geographic region. Martins et al. (2021), however, use different data, a different estimation technique and come to conclusions that are distinct but complementary to ours. Other recent studies from Brazil, are either also based on GMM estimations that apply lagged values as internal instruments (de Assis Cabral et al., 2020, de Abreu Pereira Uhr et al., 2017) or focus on forecasting electricity demand via an ARIMA model (De Lima and Bacchi, 2019). Our approach addresses endogeneity through the Granger causality analysis, where we observe in several cases that the link between income, electricity prices and demand is indeed bidirectional. Another distinction of the present paper is that the VECM allows us to provide both short- and long-run effects and that we can quantify their relative order in the variance decomposition.

The present paper confirms that price and income elasticities are inelastic, both in the short-and long-run. However, regional disaggregation yields the insight that price elasticities are insignificant in the North, Southeast and South, both in the short- and long-run. For the country as a whole, the short-term price effect is insignificant as well. This novel result casts doubt on recently implemented and future price-based policy measures that are necessary to direct electricity consumption according to the disposable supply. Our variance decomposition confirms that in all but one of the regions, income has a much larger predictive power than electricity prices. Only in the Midwest and Southeast where large parts of Brazil's manufacturing production is located, do we observe that the production of apparatuses and machines is the most important determinant for electricity demand.

Comparison of the present approach with studies from other countries shows that there are also surprisingly few attempts that pay attention to within-country differences. Silva et al. (2018) is a notable exception who also highlight that calculating elasticities at the national level may be misleading given the substantial variation in climate, culture, social and economic conditions. In their case, the divergence between rural and urban regions in Portugal is analyzed. Similar to our results, Mikayilov et al. (2020) find substantial regional heterogeneity in the price elasticity estimates in Saudi Arabia, with one of the regions also being completely price-insensitive. Arguably, researchers should be aware that aggregate estimates at the national may omit important insights due to regional heterogeneity.

Not only is Brazil known for its large and persistent regional inequality (Ehrl and Monasterio, 2019), but the electricity sector also presents some unique features that differ across space. Although the system is highly regulated by the Brazilian Electricity Regulatory Agency (ANEEL), tariffs must reflect the cost of electricity generation, transmission and distribution (de Abreu Pereira Uhr et al., 2019). Distribution costs obviously differ due to the continental dimension of the country, poor infrastructure quality and the need to transmit electricity through the interconnected system SIN (*Sistema Interligado Nacional)*. The composition of electricity sources also contributes to tariff differences. While the cheapest and most important component (61.9%) of the electricity generation is hydropower, other sources that are less dependent on local natural characteristics like natural gas (13.7%), biomass (8.2%), petroleum derivatives (4.4%), or coal and derivatives (3.3%) are more expensive[1].

Having accurate estimates for price and income elasticities of demand is relevant for the electric power sector where actors make long-run decisions. For the market regulator ANEEL, forecasts of future demand and adequate tariffs are essential for the design of auctions, which help to increase allocative efficiency. For utilities, demand projections are equally important because the companies are obliged to submit their forecasts to the ANEEL and inaccuracies above 3% lead to fines (de Assis Cabral et al., 2020). Finally, policymakers should carefully consider how regional differences in income, tariffs, consumption patterns and climatic conditions affect the demand for electricity in order to direct investments that foster the economic development of the country, guarantee fair tariffs and avoid costly electricity shortages. Therefore, estimating income and price elasticities in the short-and long-term can help generators, distributors and regulators make wise decisions about public policies for the electricity sector.

The residential segment deserves attention, since it is the second largest in terms of demand and it is subject to price fluctuations. According to Villareal and Moreira (2016), electricity consumption in Brazil is still small compared to developed countries, leaving much room for future growth. The economic theory associated with the behavior of this type of consumer suggests that demand is generally more elastic to prices in the long term in relation to the short-run (Topel and Rosen, 1998, Athukorala and Wilson, 2010). Residential consumers face resistances from some factors, such as replacement of durable goods and consumption habits that can take years to respond completely to price changes. Besides the four endogenous variables, namely, income, tariff, price and production of domestic appliances, the present demand model also accounts for differences in temperature and rainfall.

The remainder of the paper is structured as follows. Section 2 discusses previous related studies from Brazil and other countries. Section 3 presents the details of the econometric estimation, the demand model and the underlying database. Section 4 contains the estimation results, and the last section derives the associated conclusions and policy recommendations.

2. RELATED STUDIES

Various studies have examined residential energy demand functions using cointegration techniques to estimate short-and long-run elasticities. The results and implications of these studies depend on the econometric methods applied, the frequency of the data, the development stage of a country or region and the type of variables

1 This composition is for the year 2015. Source: National Energy Balance (BEN) for 2016, base year 2015.

considered. Generally, they are based on aggregated variables of price and income along with some additional factors, such as climate or urbanization. In an interesting contribution, Miller and Alberini (2016) compare how different approaches regarding data aggregation, variable definitions, use of instrumental variables and fixed effects influence the price elasticity of residential electricity demand. Relying on annual data from US states, the authors find that, although estimates are somewhat affected by the modeling choice, the price elasticities are inelastic, within a range of −0.2–−0.8. We agree with their conclusion that analysis and policy makers should calculate different scenarios based on different elasticity values, while carefully weighting the source of data and the underlying econometric technique.

Similar studies from other countries include Athukorala and Wilson (2010) who investigate the short-term dynamics and the long-run equilibrium relations between residential electricity demand and its determinants in Sri Lanka. Using annual data for the 1960-2007 period, they demonstrate that a long-run relation exists and find a long-run price elasticity of −0.62. De Vita et al. (2006) use data for the Namibian economy from 1980 to 2002 and the autoregressive distributed lag (ARDL) bounds testing approach to cointegration to estimate the long-run energy demand elasticities. With inclusion of some exogenous variables such as temperature, they find a long-run price elasticity of −0.34. Galindo (2005) estimate the demand for electricity in Mexico for different types of consumption in the 1965-2001 period. He obtains a small long-term price elasticity, of around −0.2. Narayan and Smyth (2005) estimate the long- and short-run elasticities of residential demand in Australia. The results show a long-term price elasticity of −0.54 and short-term elasticity of −0.26. Beenstock, et al. (1999) focus on Israel using two dynamic models with cointegration restrictions and also obtain long-run price elasticities of about −0.2. Kamerschen and Porter (2004) investigate the electricity demand for the residential and industrial classes in the United States in the period from 1973 to 1998. Using a simultaneous equations model, they find a long-run elasticity between −0.85 and −0.94 for the residential sector. In sum, the range of those price elasticity fits well with our findings and with the meta-study by Labandeira et al. (2017) which report a short-term price elasticity of –0.20 and –0.51 in the long-term for the electricity market. Other energy goods such as natural gas, gasoline or heating oil yield quite similar results.

Martins et al. (2021) seems to be the only study besides ours that estimates electricity demand functions for the five geographic regions in Brazil. Their approach and findings differ from and complement the present one. In contrast to our estimation strategy, the authors use annual data by federal state and apply a system GMM estimator where one or two period lagged variables are used as instruments for prices and income. The main difference regarding our results is that Martins et al. (2021) report significant and considerably larger absolute values for price elasticities. For the Midwest region, the price elasticity is even below −1, suggesting that consumers' demand is elastic. The range of income elasticities (0.29–1.63) is also larger than in the present case. The results from de Abreu Pereira Uhr et al. (2017) seem to confirm that those large long-term elasticities are specific for the system GMM estimation technique which relies on the assumption that demand shocks are not serially correlated such that lagged values for prices and other variables serve as valid instruments.

Other noteworthy studies from Brazil include Achão and Schaeffer (2009) who acknowledge the potential importance of regional characteristics. Yet when controlling for region fixed effects in their aggregate demand model, the authors find that these factors seem to have a small impact of residential electricity use. Villareal and Moreira (2016) rely on linear regression models and a more extensive horizon (1985–2013). The derived price and income elasticities have a magnitude of about 0.2, which leads Villareal and Moreira (2016: 258) to conclude that "[a] lthough the elasticity of residential electricity consumption with respect to tariff is not high […] it is sufficient to control the electricity demand in residences." Our results suggest that their conclusion is valid only in the short-run, and not within all of Brazil's regions. Both Schmidt and Lima (2004) and Irffi *et al*. (2009) also report inelastic price and income elasticities from aggregate Brazilian data that covers three to four decades. Different to these studies and to our approach, de Abreu Pereira Uhr et al. (2019) have access to a confidential household-level survey (POF). Nevertheless, the derived price and income elasticities range from −0.46 to −0.56, and from 0.20 to 0.32, respectively, and are thus comparable to the ones we obtain for Brazil as a whole.

3. METHODOLOGY

3.1. Demand Model

Residential demand for electricity is driven by the individual needs of household members, whose level of consumption depends on variables such as electricity price, income and other exogenous factors (Al-Bajjali and Shamayleh, 2018, Du et al., 2015). In the present context, we propose the following model to describe the residential electricity demand in the Marshallian tradition:

$$d_t = kp_t^{\alpha} \tilde{y}_t^{\theta} e_t^{\gamma} l_t^{\delta} \exp(u_t), k>0, \alpha<0, \theta>0, \delta<0, \gamma>0 \quad (1)$$

where the expected sign of the variables is indicated in the above equation and their definitions are as follows:
d_t: is the electricity consumption at time t;
p_t: is the price of electricity at time t;
$\tilde{y}_t$: is the average household income at time t;
e_t: is the index of production of machines and apparatuses at time t;
l_t: is the price of electrical appliances at time t; and
u_t: is the disturbance term at time t.

In order to avoid heterocedasticity problems it is common to transform the demand model in neperian logarithmic form (Gujarati, 1995). Taking the logarithm of equation (1), yields a linear demand equation:

$$D_t^i = K^i + \alpha^i P_t^i + \theta^i Y_t^i + \gamma^i E_t^i + \delta^i L_t^i + u_t \quad (2)$$

Note that the capital letter variables are defined as logarithmic values, for example *D* = *log* (*g*) Moreover, the index is added to indicate that the variables, in the aggregate model, are specific for month and for each of the five regions of the country: North, Northeast, Midwest, Southeast and South. Finally, the demand equation (2) will also be estimated separately for each region *i*.

3.2. Econometric Model

Some caution needs to be taken to estimate the long-run relationship with non-stationary time-series data. The appropriate procedure for non-stationary variables is to transform the series in first differences before any estimation is done. The major problem in this case, however, is that low frequencies are eliminated from the data, leaving the model only capable of explaining short-term relationships. Since energy prices and real income are indeed found to be non-stationary processes, the econometric modeling of electricity demand can be successful through cointegration analysis with error correction, as frequently done in the literature (Al-Bajjali and Shamayleh, 2018, Labandeira et al., 2017).

Consider a Gaussian vector autoregression of finite order P, VAR(p):

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + \varepsilon_t \tag{3}$$

where y_t is a vector of n first-order integrated I(1) and endogenous variables, $\phi_i = 1,\ldots, p$ are matrices of dimension n × n and $\varepsilon_t \sim$ Normal $(0,\Omega)$, $E(\varepsilon_t) = 0$, $E(\varepsilon_t\varepsilon_\tau) = \{\Omega,\ if\ t = \tau$ and $0_{n\times n}$, if $t \neq \tau\}$; where Ω is not singular. The model in equation (3) can be written equivalently as:

$$\Pi(L)\, y_t = \varepsilon_t \tag{4}$$

where $\Pi(L) = I_n - \sum_{i=1}^{p} \phi_i L^i$ is a polynomial matrix in *L*, and *L* represents the lag operator. Furthermore, $\Pi(1) = I_n - \sum_{i=1}^{p} \phi_i$ when $L = 1$.

The demand can be represented by a VAR(p) model with $n = 5$ stacked variables in the vector $y_t = [D_t\ P_t\ Y_t\ E_t\ L_t]'$. Considering the polynomial transformation $\Pi(L) = \Pi(1)L + \Pi^*(L)\Delta$ in the VAR(p) model given by equation (4), where $\Delta \equiv (1-L)$, we can rewrite it as:

$$\Delta y_t = -\Pi(1)\, y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + \varepsilon_t \tag{5}$$

Equation (5) is known as the vector error correction model (VECM) or error correction model (ECM). The parameters of the first-difference variables represent the short-term components, whereas the parameters of the variable in level (y_{t-1}) denote the long-run coefficients.

3.2.1. Long-run restrictions (cointegration)

The following hypotheses are assumed:

Assumption 1: The (n × n) matrix $\Pi(\cdot)$ satisfies:

1. *rank* $(\Pi(1)) = r$, $0 < r < n$ such that $\Pi(1)$ can be expressed as $\Pi(1) = -\alpha\beta'$, where α and β are (n × r) matrices with full column rank r.
2. The characteristic equation $|\Pi(1)| = 0$ has $n-r$ roots equal to 1 and all others are outside the unit circle.

Assumption 1 implies that y_t is cointegrated with order (1, 1). The elements of are the adjustment coefficients and the columns of β span the cointegration space. Decomposing the polynomial matrix $\Pi(L) = \Pi(1)L + \Pi(L)\Delta$, where $\Delta = (1-L)$ is the difference operator, a vector error correction model (VECM) is obtained:

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{j=1}^{p-1} \Gamma_j \Delta y_{t-j} + X_t'\varphi + \varepsilon_t \tag{6}$$

where $\beta' = -\Pi(1)$, $\Gamma_j = \sum_{s=j+1}^{p} \phi_s\ (j = 1,\ldots, p-1)$ and $\Gamma_0 = I_n$. If we add the exogenous variables X_t to equation (5) our final VECM can be expressed as equations (6), where is a vector of $m \times 1$ dimension.

In this study we use three exogenous variables: precipitation (precip), temperature (temp) and a dummy variable to capture the effect of the subprime crises in 2008. The vector X_t is thus defined as $X_t' = [precip_t, temp_t, dummy]'$. We can then obtain the long-run elasticity from the long-run relationships $\beta' y_{t-1}$ by estimation of the ECM. Normalizing the cointegration vector in D_t^i and considering a constant in the cointegration vector, we can denote the deviations from long-run equilibrium for each region *i* as:

$$\beta^{i\,\prime} y_{t-1}^i = \left(K^i, -1, \alpha^i, \theta^i, \gamma^i, \delta^i\right) \cdot \left[1, D_{t-1}^i, P_{t-1}^i, Y_{t-1}^i, E_{t-1}^i, L_{t-1}^i\right]'$$

$$= -u_{t-1}^i$$

$$D_{t-1}^i = K_i + \alpha^i P_{t-1}^i + \theta^i Y_{t-1}^i + \gamma^i E_{t-1}^i + \delta^i L_{t-1}^i + u_{t-1}^i \tag{7}$$

Where $u_{(t-1)}^i$ represent the deviations from the long-run equilibrium.

3.3. Database

The series of average residential consumption (D_t), in MWh, and the electricity tariff (P_t), in R\$[2], were obtained from the National Electric Energy Agency (ANEEL). The index of appliance production (E_t) was obtained from the Brazilian Institute of Geography and Statistics (IBGE). For the price of appliances at time (L_t), we use the segment for non-durable consumer goods from the Wholesale Price Index (IPA-DI), also computed by the (IBGE), as a proxy. The average household income (Y_t) was also obtained from the IBGE, based on the Monthly Employment Survey (PME). The average rainfall series stems from the company Della Coletta Bioenergia. Finally, the mean temperature series was obtained from the National Institute of Meteorology (INMET). All of these series have monthly and regional variation. Variables in monetary terms are transformed to real values by means of the IGP Inflation index calculated on a monthly basis by the Brazilian Institute of Economics (IBRE) of the Getulio Vargas Foundation (FGV).

2 Brazil's currency is the Real (R\$). Over the study period of this paper, the exchange rate with the dollar fluctuated in an interval between approximately R\$1.56/US\$ and R\$ 3.97/US\$, with a rough average of R\$ 2.28/US\$.

Figure 1 shows the evolution of aggregate residential electricity demand in the five regions. It can be seen that electricity consumption was steadily increasing in all regions from 2003 until 2014. Apparently due to the economic downturn, consumers in the South and Southeast reduced their electricity demand from 2014 onwards, similar to what was observed for internet accesses (Silva et al., 2020). Figure 1 also illustrates how income inequality across regions affect electricity consumption. Although the Southeast is the most populated region, covering the states of Espírito Santo, Minas Gerais, Rio de Janeiro and São Paulo, its consumption level is overproportionally larger than those in the other states due to the high wealth of its residents. Aggregate electricity consumption in the wealthy South was only gradually overtaken by the poorest region Northeast, despite having about twice the South's population (Almeida et al., 2021). Similarly, the North accommodates more inhabitants than the Midwest, but due to the much higher per capita income, the latter region presents a higher aggregate electricity consumption throughout the observation period.

Figure 2 presents how average electricity prices evolved over time in the five regions. Despite a co-movement of the curves, there is clearly variation across regions over time. While in 2003, prices were highest in the Southeast and lowest in the Northeast, the relative ranking among the regions has been revered several times since. As regulated in Decree-Law 8,631, electricity tariffs must reflect the regions' size, average income, tax level, among others (de Abreu Pereira Uhr et al., 2019, Martins et al., 2021). Moreover, the calculation of the tariff by the ANEEL considers regional differences in the cost of electricity generation, transmission and distribution. Finally, residential electricity prices are also affected by the type of phase connection and whether the household is eligible for receiving a subsidy. Note also that the price of electricity increased over the entire period under analysis. As a consequence of the rainfall shortage in 2014 and the low water reservoir levels, consumers had to carry the extra costs of the additional electricity supply from other sources (de Abreu Pereira Uhr et al., 2019).

Figure 1: Residential consumption by region

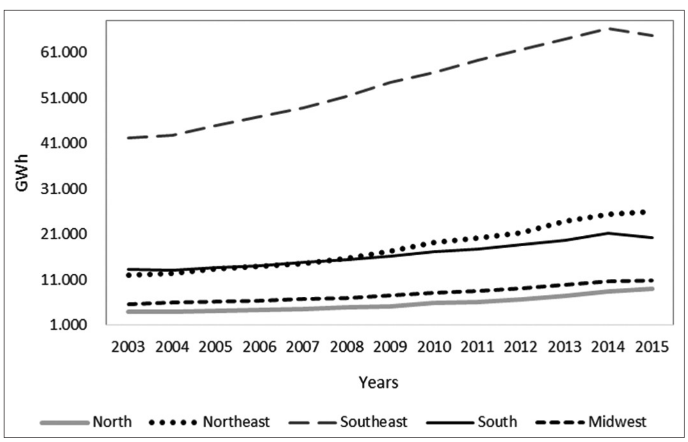
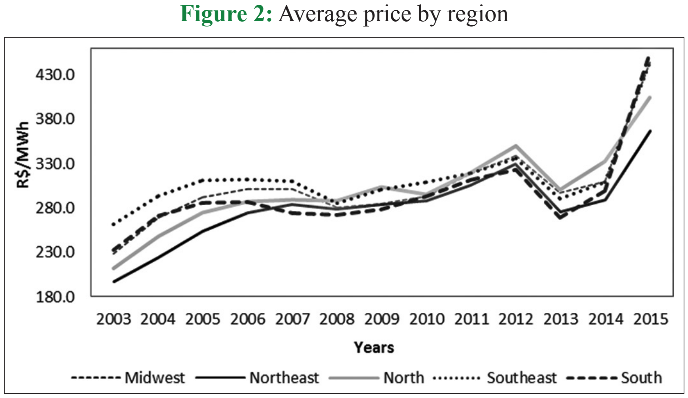


Figure 2: Average price by region



4. EMPIRICAL ANALYSIS

4.1 Unit Root Tests

According to equation (3), the vector y_t that comprises the endogenous variables is defined as of n first-order integrated I(1). In the first step of our empirical analysis, we perform the augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root tests, whose results are reported in Table 1. Recall that the null hypothesis of the KPSS test is the exact opposite of the ADF and PP tests (non-stationarity of the series), so that contrary results are expected regarding their significance values. In general, those tests suggest the presence of unit roots in the series D_t, P_t, Y_t, E_t and L_t in our Brazilian data and for all the geographical regions. Therefore, the variables that compose the vector $y_t = [D_t\ P_t\ Y_t\ E_t\ L_t]'$, have the property $y_t \sim$ I(1). Hence, the first condition for the application of the VEC model is satisfied. For the exogenous variables, the unit root test shows that the pluviosity is stationary, but the temperature series has a unit root. We incorporate this information in the VECM estimation.

The next step is to test the existence of a long-run relation of these variables. For this purpose, we identified the order of lags of the VAR(p) model according to the Akaike (AIC), Schwarz (SC) and Hannan-Quinn (HQ) information criteria. In most cases the criteria indicate the lag order $p = 2$. More specifically the AIC and SC set $p = 2$ for Midwest, Northeast, North and Southeast. The HQ suggests $p = 2$ for South and finally the SC and HQ criteria also indicate $p = 2$ for Brazil.

4.2. Cointegration test

Because the final aim of this research is to identify short-as well as long-term elasticities of electricity demand, we need to verify the existence of a cointegration relationship between the variables proposed in our model. Cointegration implies that the time series follow a balanced relationship in the long-term because they share similar underlying stochastic trends (De Lima and Bacchi, 2019). Following Johansen (1998) and Johansen and Juselius (1990), the λ-trace and λ-max eigenvalue cointegration test statistics are presented in Table 2. As usual, the parameter r determines the number of cointegration vectors.

The results of the λ-trace test reveal the existence of one cointegration vector, both for the entire country and for each region. Except in one case, the max-eigenvalue test confirms the λ-trace results at the 0.01 level. This observation is line with previous studies on electricity demand from Brazil (Viana and Silva, 2014, Villareal and Moreira, 2016). The findings of one cointegration vector is then incorporated into the VECM in order

Table 1: Unit root tests

Country/Regions	Variable	ADF-Test[1]	PP-Test[2]	KPSS[3]	Results
		t-Statistic	*t-Statistic*	*t-Statistic*	
Brazil	Dt	−0.283366	−0.16768	1.4489***	I (1)
	ΔD_t	−13.8070***	−23.130***	0.206578	I (0)
	Pt	−1.011893	−0.712269	1.1438***	I (1)
	ΔP_t	−7.79288***	−7.8022***	0.131914	I (0)
	Y_t	0.780551	1.0196	1.46287***	I (1)
	ΔY_t	−15.7161***	−16.0852***	0.27783	I (0)
	E_t	−2.09288	−2.3852	0.95219***	I (1)
	ΔE_t	−17.11935***	−17.6734***	0.3609*	I (0)
	Lt	−0.465221	−0.6151	1.4512***	I (1)
	ΔL_t	−4.60181***	−6.3585**	0.03501	I (0)
	temp	−0.19180	−5.12662***	0.26285**	I (0)
	pluv	−9.38116***	−5.53986***	0.037924	I (0)
Midwest	Dt	−0.221984	−0.376029	1.4467***	I (1)
	ΔD_t	−20.6643***	−41.5189***	0.173531	I (0)
	Pt	−1.156677	−0.571908	1.0219***	I (1)
	ΔP_t	−1.743119	−9.1296***	0.156279	I (0)
	Y_t	−1.289182	−1.046779	1.4533***	I (1)
	ΔY_t	−10.716***	−11.1492***	0.283606	I (0)
	E_t	−2.092881	−2.385222	0.9521***	I (1)
	ΔE_t	−17.119***	−17.6734***	0.3609*	I (0)
	Lt	−2.220953	−2.598134	0.216496	I (1)
	ΔL_t	−4.1289***	−9.7043***	0.270579	I (0)
	temp	−0.485849	−4.2594***	0.5239**	I (1)
	pluv	−1.306967	−6.6704***	0.266243	I (0)
Northeast	Dt	0.106283	0.375199	1.4564***	I (1)
	ΔD_t	−14.7278***	−34.569***	0.203046	I (0)
	Pt	−1.156677	−1.758533	1.2044***	I (1)
	ΔP_t	−9.13492***	−9.7096***	0.102687	I (0)
	Y_t	−1.28918	−1.035838	1.4509***	I (1)
	ΔY_t	−10.7160***	−11.348***	0.221431	I (0)
	E_t	−2.092881	−2.385222	0.9521***	I (1)
	ΔE_t	−17.119***	−17.673***	0.3609*	I (0)
	Lt	−2.22095	−0.615127	1.4512***	I (1)
	ΔL_t	−4.12895***	−6.3585***	0.03501	I (0)
	temp	−4.0715***	−4.2599***	0.71939**	I (0)
	pluv	−8.9690***	−5.7508***	0.071833	I (0)
North	Dt	0.668523	0.240273	1.4229***	I (1)
	ΔD_t	−14.378***	−28.017***	0.175849	I (0)
	Pt	−1.217447	−1.359972	1.2783***	I (1)
	ΔP_t	−11.816***	−11.864***	0.043654	I (0)
	Y_t	−0.209433	−0.280502	1.4435***	I (1)
	ΔY_t	−11.089***	−11.725***	0.245237	I (0)
	E_t	−2.092881	−2.385222	0.9521***	I (1)
	ΔE_t	−17.119***	−17.673***	0.3609*	I (0)
	Lt	−0.465221	−0.615127	1.4512***	I (1)
	ΔL_t	−4.6018***	−6.3585***	0.03501	I (0)
	temp	−3.4390**	−3.1703**	0.6964**	I (0)
	pluv	−10.187***	−5.3085***	0.02591	I (0)
Southeast	Dt	−1.171672	−1.079485	1.4448***	I (1)
	ΔD_t	−7.5473***	−23.953***	0.50**	I (0)
	Pt	−0.855372	−0.471412	0.5658**	I (1)
	ΔP_t	−7.9481***	−7.8822***	0.197068	I (0)
	Y_t	−0.298963	−0.332812	1.4427***	I (1)
	ΔY_t	−10.734***	−10.922***	0.192341	I (0)
	E_t	−2.092881	−2.385222	0.9521***	I (1)
	ΔE_t	−17.119***	−17.673***	0.3609*	I (0)
	Lt	−0.465221	−0.615127	1.4512***	I (1)
	ΔL_t	−4.6018***	−6.3585***	0.03501	I (0)
	temp	0.312465	−5.3056***	0.4024*	I (0)
	pluv	−1.709639	−7.3468***	0.139226	I (0)

(Contd...)

Table 1: ***(Continued)***

Country/Regions	Variable	ADF-Test[(1)] t-Statistic	PP-Test[(2)] t-Statistic	KPSS[(3)] t-Statistic	Results
South	Dt	−0.227947	−0.454918	1.4233***	I (1)
	ΔD_t	−9.2326***	−23.338***	0.240044	I (0)
	Pt	−0.388389	−0.059028	0.8265***	I (1)
	ΔP_t	−8.1160***	−8.0613***	0.204795	I (0)
	Y_t	−0.576321	−0.538058	1.449***	I (1)
	ΔY_t	−10.761***	−11.174***	0.203469	I (0)
	E_t	−2.092881	−2.385222	0.9521***	I (1)
	ΔE_t	−17.119***	−17.673***	0.3609*	I (0)
	Lt	−0.465221	−0.615127	1.4512***	I (1)
	ΔL_t	−4.6018***	−6.3585***	0.03501	I (0)
	temp	0.44147	−5.1266***	0.26284	I (0)
	pluv	−10.179***	−10.174***	0.26241	I (0)

The definition of the existence or not of unit root in the series is based on at least two of the unit root tests in column (3) to (5). The null hypothesis of the ADF and PP tests is the non-stationarity of the series while the KPSS tests the stationarity of the series. The last column indicates the results, where I (0) means that a series is stationary and I (1) means that a series has a unit root. We chose the constant as the deterministic component. Significance levels of 0.01, 0.05 and 0.10 are represented by ***, ** and *, respectively. Δ indicates the first difference of these variables. (1) ADF test is based on the Schwartz criteria. The critical points are−3.47487 (1%), −2.88099 (5%) and−2.57722 (10%). (2) PP test is based on Bartlett kernel and Newey-West Bandwidth. The critical points are−3.47487 (1%), −2.88099 (5%) and−2.57721 (10%). (3) KPSS tests rely on Bartlett kernel and Newey-West Bandwidth. The critical points are 0.7390 (1%), 0.4630 (5%) and 0.3470 (10%)

Table 2: Cointegration test

Country/ Regions	Hypothesized Number of r	Eigenvalue	λ Trace	λ Max
Brazil	$r = 0$	0.323605	105.73***	57.86471***
	$r \leq 1$	0.165413	47.86*	26.76113*
	$r \leq 2$	0.11265	21.10382	17.68827
	$r \leq 3$	0.022798	3.415548	3.413101
	$r \leq 4$	1.65E-05	0.002447	0.002447
Regions				
Midwest	$r = 0$	0.442392	121.3015***	86.4467***
	$r \leq 1$	0.146237	34.8548	23.39912
	$r \leq 2$	0.042447	11.45568	6.419415
	$r \leq 3$	0.024529	5.036266	3.675614
	$r \leq 4$	0.009151	1.360652	1.360652
Northeast	$r = 0$	0.1745	70.69379**	28.38885
	$r \leq 1$	0.1422	42.30494	22.69544
	$r \leq 2$	0.0964	19.6095	14.99735
	$r \leq 3$	0.0282	4.61215	4.235661
	$r \leq 4$	0.0025	0.376488	0.376488
North	$r = 0$	0.2340	73.18525**	39.46083***
	$r \leq 1$	0.1158	33.72443	18.2207
	$r \leq 2$	0.0760	15.50372	11.69802
	$r \leq 3$	0.0245	3.805709	3.666174
	$r \leq 4$	0.0009	0.139535	0.139535
Southeast	$r = 0$	0.2607	75.57758**	44.71065***
	$r \leq 1$	0.1243	30.86693	19.63781
	$r \leq 2$	0.0663	11.22912	10.15887
	$r \leq 3$	0.0072	1.070248	1.067718
	$r \leq 4$	0.0000	0.00253	0.00253
South	$r = 0$	0.3652	101.581***	67.25136***
	$r \leq 1$	0.1272	34.32966	20.1311
	$r \leq 2$	0.0757	14.19856	11.65133
	$r \leq 3$	0.0171	2.54723	2.545408
	$r \leq 4$	0.0000	0.001822	0.001822

*, ** and *** denote rejection of the null hypothesis at the 0.1, 0.05 and 0.01 level, respectively. The null hypothesis states that there is/are no more than r cointegrating equations

to correctly account for the long-term dynamics of electricity demand.

4.3. Results of the short-and long-run elasticities

Table 3 presents the estimated short-and long-run determinants of electricity demand in Brazil considering monthly data from 2003 to 2015. Recall that these coefficients stem from six different estimations, one for the entire sample and one estimation for each of the five geographical regions. The impact of the exogenous variables temperature and rainfall can only be interpreted as short-term effects whereas the coefficient β of the autoregressive term in the VECM allows us to derive the long-term effects from

Table 3: Estimations of short-and long-run elasticities

Country		P_t	Y_t	E_t	L_t	$Temp_t$	$Pluv_t$
Brazil	Long-run	−0.122***	0.701***	0.0319*	-0.0776		
		(0.025)	(0.039)	(0.019)	(0.055)		
	Short-run	0.045	0.312*	-0.079***	-0.028	-0.002**	0.043
		(0.071)	(0.161)	(0.027)	(0.173)	(0.001)	(0.033)
Regions							
Midwest	Long-run	−0.086***	0.705***	−0.214***	0.641***		
		(0.026)	(0.010)	(0.023)	(0.061)		
	Short-run	−0.138*	0.952***	−0.173***	−0.838*	0.001	−0.016
		(0.074)	(0.267)	(0.039)	(0.433)	(0.001)	(0.029)
Northeast	Long-run	−0.323***	0.447***	0.065	0.767***		
		(0.104)	(0.126)	(0.087)	(0.179)		
	Short-run	−0.231**	0.205	−0.099**	0.211	−0.004***	−0.000
		(0.092)	(0.205)	(0.040)	(0.263)	(0.001)	(0.000)
North	Long-run	0.039	0.628***	0.072	0.268*		
		(0.107)	(0.105)	(0.074)	(0.151)		
	Short-run	−0.083	0.258	−0.007	0.346	0.004*	0.031
		(0.097)	(0.298)	(0.048)	(0.294)	(0.002)	(0.029)
Southeast	Long-run	−0.041	0.380***	0.185***	0.178**		
		(0.049)	(0.059)	(0.036)	(0.079)		
	Short-run	0.002	0.002	−0.078**	0.279	−0.002*	0.049*
		(0.081)	(0.199)	(0.037)	(0.223)	(0.001)	(0.027)
South	Long-run	−0.057	0.486***	0.047	0.098		
		(0.038)	(0.053)	(0.034)	(0.074)		
	Short-run	−0.121	0.474*	−0.051	0.327	−0.000	−0.020
		(0.089)	(0.266)	(0.041)	(0.250)	(0.001)	(0.038)

The table shows the estimate of the short- and long-run elasticities derived from the VECM in equations (6) and (7) where $\beta^{i\,\prime} y^{i}_{t-1} = \left(K^{i}, -1, \alpha^{i}, \theta^{i}, \gamma^{i}, \delta^{i}\right)\left[1, D^{i}_{t}, P^{i}_{t}, Y^{i}_{t}, E^{i}_{t}, L^{i}_{t}\right]$, for each region i and year t

the short-term estimates according to equations (6) and (7). For Brazil as a whole, we find that the long-run price elasticity is statistically significant at the 1% level and equal to −0.12, whereas the short-term effect is insignificantly different from zero. The short-and long-term income elasticities are significant and equal to 0.31 and 0.70, respectively. Thus, the electricity demand is inelastic in relation to price and income. This general result holds for the disaggregated estimations as well and it is in accordance with the meta-analysis by Labandeira et al. (2017) and findings from the US (Woo et al. 2018).

The production of machines and apparatuses (E_t) seems to positively affect electricity demand in the long term, as expected. Its short-term effect, however, is slightly negative and thus counterintuitive. At least the price of electrical appliances (L_t) shows the expected negative sign but is insignificant no matter the horizon of the analysis. The precipitation level also does not seem to affect electricity consumption at the national level while lower temperatures apparently increase electricity use in Brazil. Separate estimations of our demand model reveal some interesting heterogeneities across regions. The results in the lower part of Table 3 provide the following insights. Only in the Southeast, where the average monthly rainfall (120 mm) is below the national average (139 mm), a significant positive effect is observed. Regarding temperature, the regional disparities are even more pronounced. Higher temperatures increase electricity use in the hot, humid North where the Amazon rainforest is located. Conversely, the relatively dry and moderate climate in the Southeast seems to foster electricity use when temperatures are lower. The same applies to the Northeast.

The most striking result concerns the price elasticities. In three regions, the North, Southeast and South, our estimations yield insignificant, i.e., highly inelastic short-and long-term price elasticities. On the one hand, the lack of price sensitivity in the North may be related to the social program "Luz para Todos" (Light for Everyone) that provides free energy installation and use until 50kV for eligible rural households since 2003.[3] In this region, 683 thousand out of a total of 5.4 million households made use of the program in 2020 according to the responsible public energy supplier company Eletrobras.[4] On the other hand, the South and Southeast are the most developed regions, where GDP per capita is more than 250% higher than in the Northeast (Almeida et al., 2021). The amount on the electricity bill is thus less relevant in the household budget which may explain consumers' price insensitivity. In line with that interpretation, consumers in the poorest region, the Northeast, present a short-term (−0.23) and long-term (−0.32) price elasticity whose magnitude is above the national average.

The most relevant determinant of electricity demand in Brazil seems to be income. All five regions present positive and statistically significant long-term elasticities at the 1% level. Short-term income elasticities also have a positive sign throughout but are only significant in two of the five regions. The sensitivity of demand to variations in income can be explained by the need to operate devices incorporated in people's lifestyle that goes beyond what is captured by the domestic appliances. Richer households enjoy larger homes, more air condition,

3 https://www.gov.br/mme/pt-br/canais_atendimento/ouvidoria/perguntas-frequentes/programa-luz-para-todos

4 https://eletrobras.com/pt/Paginas/Luz-para-Todos.aspx

swimming pools, and other electricity intensive amenities. The range of 0.70–0.38% for the long-term income elasticities confirm previous findings. For example, De Lima and Bacchi (2019) estimate the relation between GDP and electricity demand with monthly data from 2004 to 2018. In line with the present estimates of personal income, the authors report an elasticity of 0.47%. Therefore, the relation between income and residential energy demand seems robust due to the economic stability, continuous growth, an increased minimum wage, as well as cash transfer programs to the poorest households (Bolsa Família) during the period of observation. Specifically, even over a four-decade period (1973-2011), energy consumption growth (5.8% per year average) exceeds GDP growth (3.4%) by far (De Lima and Bacchi, 2019). Despite the recent economic crises, the forecast for the next 10 years is a growth rate at 3.1% per year and that the total electricity use exceeds economic growth by 44% (EPE, 2021).

The production of electronic appliances at the regional level may not be a very accurate proxy for its use and consumption because the largest part of the domestic appliances as well as other manufactured goods is concentrated in the state of São Paulo in the Southeast. In fact, only in this region, the expected negative long-term relation between appliances production and electricity consumption is observed. In contrast, the price of electrical appliances is a much better predictor for electricity demand. In line with our previous interpretations, we observe that changes in appliance prices provoke less or no reaction in electricity demand in the richer regions South and Southeast. Yet, the Northeast and Midwest show elasticities of considerably high magnitude. The

Table 4: VECM granger causality/block exogeneity wald tests

Country	Dependent variables	Independent variables					
		ΔD	ΔP	ΔY	ΔE	ΔL	ECT
	ΔD	-	0.401	3.735*	8.434***	0.027	12.508**
Brazil	ΔP	1.712	-	2.950*	0.219	0.046	7.981*
	ΔY	0.256	1.073	-	0.342	0.032	1.970
	ΔE	3.339*	5.644**	0.000	-	1.104	9.655**
	ΔL	1.690	0.001	2.589	0.739	-	7.961*
Regions		ΔDt	ΔPt	ΔY_t	ΔE_t	ΔLt	ECT
	ΔD	-	3.407*	12.736***	19.729***	3.756*	42.986***
	ΔP	8.337***	-	0.322	0.449	0.649	8.689*
Midwest	ΔY	4.479**	0.072	-	2.733*	4.967**	12.73**
	ΔE	0.019	5.435**	1.264	-	0.477	8.080*
	ΔL	0.543	0.068	0.015	0.472	-	0.935
	ΔD	-	6.237**	1.003	5.919**	0.643	16.380***
	ΔP	4.207**	-	0.042	0.057	0.005	4.384
Northeast	ΔY	0.430	0.398	-	1.380	0.856	3.531
	ΔE	7.847***	5.487**	1.294	-	0.381	14.129***
	ΔL	0.176	2.161	0.126	0.928	-	3.314
	ΔD	-	0.742	0.745	0.023	1.383	2.767
	ΔP	14.603***	-	6.809***	1.220	1.733	20.804***
North	ΔY	0.307	0.405	-	0.017	5.749**	6.897
	ΔE	5.084**	0.169	0.155	-	0.511	5.762
	ΔL	4.134**	2.186	0.348	0.011	-	7.231
	ΔD	-	0.030	0.000	4.405**	1.555	6.950
	ΔP	11.796***	-	0.908	1.732	1.281	13.847***
Southeast	ΔY	0.256	0.045	-	1.896	1.572	4.519
	ΔE	8.358***	8.023***	2.885*	-	0.070	16.758***
	ΔL	5.736**	0.161	0.073	0.304	-	7.343
	ΔD	-	1.843	3.195*	1.595	1.701	9.151*
	ΔP	2.346	-	0.033	1.555	0.687	4.503
South	ΔY	1.270	0.310	-	0.305	2.881*	5.469
	ΔE	1.011	1.819	0.071	-	0.035	3.523
	ΔL	3.520*	0.155	0.134	1.120	-	5.160

***, **, * denote significance at 1%, 5%, and 10% level, respectively. Values represent Wald Chi-square-statistics. All the variables in are in first differences denoted by Δ. The error correction term ECT is derived by normalizing the cointegration vector on D_t

fact that we observe positive elasticities in this case may either suggest that our proxy variable price of non-durable consumer goods absorbs rather the general effect of rising prices and the business cycle than the specific effect of electricity consuming domestic appliances. Another possibility is that lower prices induce consumers to substitute their old energy inefficient appliances like freezers with new energy-saving ones, thus leading to less electricity use.

4.4. Complementary Robustness Analyses

In order to check robustness of our analysis, we provide a VECM Granger causality test that informs about the direction of the causality, complementing the results presented in Table 3. Finally, we decompose the variance of residential energy demand stemming from either random shocks or from the contribution of each explanatory variable in our model.

Table 4 reports the Granger causality results based on the VECM that was identified by the information criteria. For Brazil as a whole, there is an evidence of a unidirectional Granger causality effect running from the average household income (Y) and from the production of machines and apparatuses (E) to residential demand for electricity (D) in the short-run. The significant ECT indicates that these causal relations are valid in the long-run as well, confirming our previous interpretations.

The Granger causality results for the regions also corroborate those from the short-run elasticities regarding residential electricity demand. For the Midwest region, we identify a bidirectional Granger causality between the electricity tariff, per capita income and the residential energy demand. The stock and price of appliances have a unidirectional Granger causal impact on electricity demand. For the Midwest regions these effects hold in the short- as well as in the long-run. Similar results are found for the Northeast region, where the Granger causalities between electricity price, apparatuses production and electricity demand are bidirectional. Again, the error correction terms indicate that the effects are valid in both the short-and long-run.

In line with the previous results from Table 3, there is no significant Granger causality from tariffs, income or appliances on electricity demand in the North and Southeast region in the short-run. A novel insight is that the electricity demand itself has a Granger causal effect on the price and production of appliances and electricity prices, independent of the time horizon. In case of appliances prices, the VECM Granger causality analysis is particularly interesting because we observed a significant relation between that variable and energy demand from Table 3. Based on Table 4, however, we see that this relation is rather inverse, that is, appliances have a significant Granger causal effect on electricity demand in three states, whereas the only in one state shows an effect of L on D. Finally, there is evidence for unidirectional Granger causality of income on residential electricity demand for the South region in the short- and long-run.

Table 5 shows the result for the variance decomposition error in forecasting, over 12 months, which can be attributed to its own random innovations and those of the other explanatory variables

Table 5: Variance decomposition of electricity demand

Country	S.E.	D	P	Y	E	L
Brazil						
4	0.0208	69.89	8.66	14.73	6.18	0.53
8	0.0255	49.62	16.71	27.78	4.50	1.39
12	0.0294	39.42	20.74	34.31	3.64	1.89
Regions						
Midwest						
4	0.0279	72.36	1.8616	4.2140	11.6599	9.9065
8	0.0332	51.92	4.3103	7.7461	24.4533	11.5736
12	0.0380	40.05	5.8671	10.3172	31.8127	11.9557
Northeast						
4	0.0316	93.17	1.7749	0.4291	4.1548	0.4668
8	0.0376	79.97	8.2917	1.8232	4.5891	5.3296
12	0.0441	64.26	16.7078	3.0853	4.5206	11.4264
North						
4	0.0349	98.09	0.5247	0.4052	0.4080	0.5637
8	0.0379	94.27	0.9168	2.8273	1.4049	0.5800
12	0.0395	87.21	1.5392	7.6562	2.9216	0.6767
Southeast						
4	0.0270	80.56	0.7887	2.4274	15.7907	0.4332
8	0.0315	61.43	3.0189	7.2574	27.9345	0.3566
12	0.0358	47.86	4.9982	10.8438	35.9707	0.3222
South						
4	0.0279	93.71	0.8499	1.8961	2.8276	0.7135
8	0.0299	83.72	1.5930	10.1080	3.8914	0.6873
12	0.0328	74.56	2.4172	17.7421	4.4200	0.8627

The values in the third column represent the standard error (S.E.) of electricity demand after 4, 8 or 12 month (column 2) for Brazil or its regions (column 1). Columns 4 to 8 indicate the percentage share that is explained by each of the variables in our VECM, being demand shocks (D), electricity price (P), per capita income (Y), production of apparatuses (E) and price of appliances (L). The sum of the values in columns 4 to 8 is equal to 100%

in our VECM. Note that in the first period, by definition, the variation is entirely attributed to the proper shocks on electricity demand. Over the following periods, the contribution of the explanatory variables tends to increase. Still, even after a period of 12 month, the own demand shocks represent the single largest component according to the variance decomposition. In the case of residential consumption for Brazil, the part of own shocks over the 12 periods is equal to 39.42%. Electricity prices and income, however, also explain considerable shares equal to 20.7% and 34.3%, respectively. The combined variance that is attributable to price and production of appliances is only as large as 5.5%. Thus, we observed that although electricity tariffs and residential income are not only significant factors for the electricity demand in the long-run, their contribution is economically important when the country as a whole is considered.

Regional disaggregation once again offers further insights. Electricity tariffs only have a comparably large effect on demand in the Midwest and particularly in the Northeast region. For the other three regions the share of prices in the variance decomposition remains below 5%. Income is the first or second largest component in the demand composition for the North, South and Southeast regions. However, in line with our previous interpretations, income adds little in absolute terms to the explanation of electricity demand in the poorest regions, the Northeast and North. Interestingly, in the Midwest and Southeast, where most of the apparatuses production is located, this variable has an extraordinarily large effect on electricity demand, being above 32% over the 12-month period. It is also striking that while for the Midwest region, 60% of the variance is explained by our VECM, this share is as low as 13% in the North of Brazil where the huge Amazonas rainforest is located.

5. CONCLUSION AND POLICY IMPLICATIONS

The present paper is the first to provide short-and long-run elasticities of residential energy demand for Brazil as a whole and for each of the five geographic regions, North, Northeast, Midwest, Southeast and South, using a database with monthly frequency and a Vector Error Correction Model. We extend this model and also provide a Granger causality analysis and quantify the relative size of the demand components.

Among the explanatory variables in our model, we observe that personal income as well as the price level of non-durable goods (including domestic appliances) have the most significant effect on electricity demand in Brazil. As expected, the data clearly indicates that future increases in household income will raise the demand for electricity. Notwithstanding, for all variables, the estimates vary considerably across the geographic regions, providing additional insights for the regionally operating companies and policy makers.

Our main contribution is to challenge conventional wisdom about price elasticities in Brazil. Particularly, we find that the North and the two richest regions (South and Southeast) are not sensitive to price changes, neither in the short-or long-term. This novel result casts doubt on the effectiveness of recent price-based policy measures that aim to reduce energy consumption, such as "tariff flags" that increase the energy tariff when water shortage leads to the addition of more costly geothermic plants. More effective policy measures may be related to stimulate the purchase of energy efficient electrical appliances, education and awareness of energy saving measures as suggested by Lin and Zhu (2020). The fact that the Brazilian states are continually converging towards each other in terms of social and economic conditions (Almeida et al., 2021), at least until the middle of the second decade of the 21st century when the Brazilian economy was still on a promising growth path, indicates that residential energy consumption may even become less sensitive to tariff changes in the future. Our results also demonstrate the need for further research using alternative models but, most importantly, without aggregating across regions or federal states.

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