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Climate Sensitivity of Electricity Demand in a Tropical Emerging Economy: Long-Run Evidence from Brazil

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ABSTRACT

Brazil, a large tropical emerging economy, faces the dual challenge of expanding electricity access and planning capacity under a warming climate. We estimate long-run temperature elasticities of residential and commercial electricity demand in Brazil using monthly data from June 2006 to February 2025 within a vector error-correction (VECM) framework. Replacing the income proxy originally employed in earlier work (the PNADC real income mass) with the Brazilian Central Bank's monthly economic activity index (IBC-Br) resolves a multicollinearity problem between income and temperature that had previously biased the estimated temperature effect toward zero. Our preferred estimates yield a residential temperature elasticity of 1.21 (s.e. 0.24) and a commercial temperature elasticity of 2.76 (s.e. 0.60), both statistically significant at the 1% level. Applied to the sample mean temperature of 25.3°C, these elasticities imply that a permanent 1°C increase in mean temperature raises residential and commercial electricity consumption by approximately 4.8% and 10.9%, respectively, in the long run. Under a 1.5°C warming reference scenario (a conservative anchor relative to IPCC AR6 projections for South America by mid-century), the implied demand increases are 7.2% and 16.4%. These results carry direct implications for long-horizon capacity planning, tariff design, energy efficiency standards, and climate adaptation policy in a developing-country context. Our findings contribute to the broader literature on climate-sensitive energy demand in tropical emerging economies and support the design of sustainable electricity pathways aligned with SDG 7 (Affordable and clean energy) and SDG 13 (Climate action).

Keywords: Electricity Demand, Temperature Elasticity, Cointegration, VECM, Climate Change, Brazil
JEL Classifications: Q41, Q54, C32, L94

1. INTRODUCTION

Electricity demand has been a subject of empirical study in Brazil since Modiano (1984), and the literature has grown steadily as the economy has evolved. Between 2006 and 2025, Brazilian GDP expanded by 48.1%, while total residential, commercial, and industrial electricity consumption rose by 61.5% (IBGE, 2025). The aggregate figure, however, conceals pronounced sectoral heterogeneity: residential consumption grew 113.5% over the period, commercial consumption grew 94.2%, and industrial consumption grew only 23.7%. This divergence reflects a broader structural transformation in the Brazilian economy, as household consumption's share of GDP rose by 67.5% while industrial value added contracted by 1.4%.

Brazil offers a particularly informative setting for studying the long-run relationship between temperature and electricity demand in a developing-country context. It combines a large tropical territory with rising per-capita income, rapid diffusion of air-conditioning equipment, and a predominantly hydroelectric generation mix whose reliability is itself exposed to climate risk. Electricity access is near-universal, but demand has grown unevenly across end-use sectors, and climate-driven consumption growth is expected to be a first-order determinant of capacity-expansion requirements over the coming decades. Understanding how warming translates into sectoral demand is therefore a prerequisite for sustainable electricity-sector planning and for climate adaptation policy in Brazil and similar tropical emerging economies.

In this context, this paper analyzes the determinants of electricity consumption in Brazil using a rich set of economic and climate variables. The central questions we address are: How does temperature drive long-run electricity demand, and does this relationship vary meaningfully across end-use sectors? Such questions have gained practical urgency as climate change accelerates global warming. The IPCC AR6 reports with high confidence that mean temperatures in Central and South America will continue to increase at rates greater than the global average, with the global mean surface temperature likely crossing 1.5°C above pre-industrial levels under intermediate emissions scenarios (SSP2–4.5) by the early 2030s and reaching higher levels by mid-century (IPCC, 2021a; IPCC, 2021b). Quantifying how such warming translates into sectoral electricity demand is essential for long-horizon capacity planning, tariff design, and adaptation policy. The policy questions raised, namely how to expand capacity under climate uncertainty, how to combine tariff instruments with efficiency standards, and how to manage distributional impacts, are central to the Sustainable Development Goals on affordable and clean energy (SDG 7) and climate action (SDG 13).

The existing literature has estimated price and income elasticities of Brazilian residential electricity demand for decades, with more recent studies incorporating temperature (Rodrigues et al., 2022; Martins et al., 2023; Carrasco-Gutierrez and Ehrl, 2023). Studies of the commercial and industrial segments that explicitly include climate variables, however, remain scarce, representing an important gap. This paper focuses on the residential and commercial sectors, where the evidence of climate sensitivity is robust and economically meaningful. We concentrate on these two sectors for three reasons. First, residential and commercial end-uses are where building-level cooling demand dominates, and they are the sectors most directly affected by rising temperatures and by the diffusion of air-conditioning. Second, exploratory estimates for the industrial sector yield unstable and theoretically counterintuitive temperature coefficients across a wide range of specifications, a pattern we attribute to the electro-intensive composition of Brazilian heavy industry, whose electricity use is dominated by continuous production processes rather than by ambient temperature, and to the confounding effect of large macroeconomic shocks (the 2014-2016 recession and the 2020 pandemic) that coincided with warm periods. The unconditional correlation between monthly log-temperature and log-industrial consumption is only +0.074, compared to +0.257 (residential) and +0.311 (commercial), providing prima facie evidence that temperature is not a first-order driver of Brazilian industrial electricity demand. Third, and consequently, residential and commercial are the sectors where climate-driven demand growth is most consequential for capacity planning and adaptation policy in Brazil.

This paper is methodologically conservative by design and empirically targeted: The contribution is not a new estimator, but the careful re-estimation of long-run elasticities of electricity demand for Brazil within a well-established econometric framework, using improved data and resolving a measurement problem that has plagued earlier work. Three specific contributions distinguish the analysis. First, we use monthly data (June 2006-February 2025) and exploit the Central Bank's newly released monthly industrial and services subindices of the IBC-Br, providing higher-frequency activity proxies than the traditional quarterly or annual series. Second, we document and correct a multicollinearity problem between the PNADC income mass and temperature that had previously biased estimated temperature elasticities toward zero. This measurement issue has substantial consequences for climate-impact projections. Third, we apply the correct conversion between log-temperature elasticities and temperature-level impacts measured in degrees Celsius, ensuring that the implied long-run impacts are reported on a comparable percentage basis. Taken together, these elements revisit a classic Brazilian literature with sharper data and corrected proxies, producing well-identified estimates of temperature elasticities for residential and commercial electricity demand.

The remainder of the paper is structured as follows. Section 2 reviews the Brazilian and international literature with emphasis on studies that incorporate climate variables. Section 3 develops the theoretical framework based on standard microeconomic demand theory, incorporating temperature through the demand for thermal comfort. Section 4 describes the data. Section 5 presents the empirical methodology and results, including unit root and cointegration tests, VECM estimates of long-run elasticities, impulse-response analysis, non-linearity tests, and dynamic forecasts. Section 6 discusses the magnitudes relative to the literature, methodological issues, policy implications for sustainable electricity planning in Brazil, and limitations. Section 7 concludes. An appendix collects complementary technical tables.

2. LITERATURE REVIEW

Empirical studies of electricity demand in Brazil began with Modiano (1984), who used 1963-1981 annual data to identify high income elasticities (1.13 residential, 1.07 commercial, 1.36 industrial) and low price elasticities (−0.12, −0.06, −0.45 respectively). Subsequent work found substantially lower income elasticities: Andrade and Lobão (1997) obtained a residential income elasticity of only 0.21, while Schmidt and Lima (2004), applying cointegration techniques, found intermediate values of 0.54 (residential), 0.64 (commercial), and 1.72 (industrial), with price elasticities between −0.09 and −0.17.

Regional heterogeneity has been documented in studies focused on specific states. Mattos and Lima (2005) found a residential income elasticity of 1.40 for Minas Gerais, matched by Siqueira et al. (2006) for the Northeast region, though the latter found a higher price elasticity (−0.41). Irffi et al. (2009) confirmed similar values for the Northeast using DOLS, with price and income elasticities of 0.69 and 0.68 respectively.

The incorporation of climate variables represents a more recent and relevant evolution of the literature. Rodrigues et al. (2022) were among the first to demonstrate that temperature has a significant impact on Brazilian residential electricity consumption, reporting an elasticity of 0.036 and a non-linear relationship, with positive semi-elasticities of 7.3% and 8.1% in the hottest quarters and −4.4% in the second quarter. Their simulations suggest that global warming could increase residential demand by up to 33% by 2069, with increases of 47% in the Northeast. Martins et al. (2023) found an even larger temperature elasticity (0.662) for the state of Bahia, suggesting a strong effect of air-conditioning use in warm regions, with price and income elasticities of −0.11 and 0.31 respectively.

The use of monthly data and advanced cointegration techniques has substantially improved estimates. Lobão and Ferreira (2015) applied VAR-VEC models and found price elasticities between −0.06 (residential) and −0.26 (commercial), with the commercial sector exhibiting an income elasticity above unity (1.27). Viana and Silva (2014) identified structural changes following the 2001-2002 electricity rationing, with elasticities substantially higher (−0.71 for the tariff, 1.79 for income), indicating greater consumer sensitivity after the energy crisis.

Studies using disaggregated data have brought additional perspectives. Uhr et al. (2019) were the first to use household-level data from the POF for the São Paulo metropolitan region, finding average short-run elasticities of approximately −0.50 (price) and 0.21 (income), with quantile regression revealing stronger price responses for lower-consumption households (ranging from −0.83 to −0.31). Uhr et al. (2017), using state-level data from 2004 to 2014 with dynamic GMM, identified short-run price elasticities between −0.13 and −0.18 and long-run elasticities between −0.1617 and −1.472, income elasticities between 0.324 and 1.095, and, crucially, temperature elasticities between 0.12 and 0.13.

Villareal and Moreira (2016) found atypically positive price elasticities (0.23) using national data from 1985 to 2013, while Liermann et al. (2021) confirmed the negative price elasticity (−0.46) for Rio Grande do Sul. Carrasco-Gutierrez and Ehrl (2023) revealed important regional heterogeneity, with price elasticities insignificant in the North, Southeast, and South regions, questioning the effectiveness of uniform tariff policies. For the industrial sector, Salazar and Ribeiro (2022) identified an income elasticity of 1.57 using structural decomposition and a price elasticity of −0.08.

Studies of the commercial and industrial sectors with climate variables remain scarce, representing an important gap in the Brazilian literature, especially given the intensive use of climate control in commercial establishments. Internationally, Eskeland and Mideksa (2010) document climate effects on European electricity demand; more recent panel analyses confirm temperature's role as a key driver of residential and commercial demand in both developed and developing economies.

Table 1 synthesizes the Brazilian literature and reveals three trends: A decline in income elasticities over time, stability in price elasticities (which remain low), and the growing importance of temperature as a demand driver. Temperature elasticities range from 0.036 to 0.662, with a mean of 0.349.

3. THEORETICAL FRAMEWORK

Following Schmidt and Lima (2004) and Mas-Colell et al. (1995), we develop a model that explicitly incorporates temperature as a determinant of electricity demand. Residential electricity demand can be understood as the outcome of utility maximization subject to a budget constraint, while commercial demand arises from cost minimization of establishments that use electricity as an input. In both cases, electricity enters as a *derived demand*: not as a direct argument of utility, but as a necessary input into services (thermal comfort, lighting, refrigeration) that households and firms ultimately value.

Temperature enters this framework through the demand for thermal comfort. As ambient temperature rises above a comfort threshold, the electricity required to maintain indoor conditions increases, both through higher usage intensity of existing air conditioning (the intensive margin) and through expanded ownership of cooling equipment over longer horizons (the extensive margin). The relationship is, in principle, non-linear: demand may be flat over a comfortable temperature range and steeply increasing outside it, but for the monthly range observed in Brazilian data (22-28°C), a log-linear approximation performs well, as we verify empirically in Section 5.8.

The demand for electricity, incorporating temperature as an explanatory variable, can be expressed in Cobb-Douglas form:

$$C_t = k \cdot P_t^{\alpha} \cdot Y_t^{\beta} \cdot L_t^{\delta} \cdot T_t^{\gamma} \cdot X_t^{\theta}, k > 0, \alpha < 0, \beta > 0, \delta < 0, \gamma > 0$$

where C_t is sectoral electricity consumption at time t; P_t is the electricity tariff; Y_t is an income or activity proxy; L_t is the price of air-conditioning equipment; T_t is mean temperature; and X_t is a vector of additional controls. The elasticities are: $\xi_p = \alpha$ (tariff), $\xi_r = \beta$ (income), $\xi_l = \delta$ (AC price), and $\xi_T = \gamma$ (temperature). Taking natural logarithms yields the linear form:

$$\ln C_t = \ln k + \alpha \ln P_t + \beta \ln Y_t + \delta \ln L_t + \gamma \ln T_t + \theta \ln X_t + \varepsilon_t$$

Additional control variables employed in our specifications include the real interest rate, the unemployment rate, and the exchange rate. These macroeconomic variables may affect electricity demand through wealth, substitution, and activity channels not fully captured by the primary income proxy. In the industrial sector, the exchange rate is included to capture the effect of export-oriented electricity-intensive activities (e.g., primary aluminum, steel, pulp).

The model admits different parameter values across sectors. In the residential sector, we expect pronounced sensitivity to temperature, reflecting thermal comfort demand, along with strong seasonality captured through monthly dummies. In the commercial sector, we expect moderate-to-strong temperature sensitivity given the prevalence of continuous air-conditioning. As noted in the introduction, the industrial sector in Brazil is dominated by electro-intensive activities whose electricity use is driven by continuous production processes rather than ambient temperature; we therefore restrict our analysis to residential and commercial end-uses, where thermal demand is empirically and conceptually well identified.

4. DATA

4.1. Sample Period and Frequency

Studies of electricity demand typically employ annual, quarterly, or monthly data. Annual data were traditionally more common but suffer from structural breaks caused by the 2001 electricity rationing and the 1980s hyperinflation. Quarterly data align with official national accounts but lose within-quarter seasonal variation. For this study, we use monthly data, exploiting the Central Bank's Economic Activity Index (IBC-Br), which captures monthly agricultural, industrial, and services activity and aligns well with official GDP figures (BACEN, 2025). The correlation between IBC-Br growth and IBGE-published GDP growth between 2003 and 2024 is 0.99 with a *t*-statistic of 30.5, confirming the reliability of this monthly proxy. Equality-of-means and equality-of-variance tests do not reject the null (P = 0.74 and P = 0.57, respectively).

The sample runs from June 2006 to February 2025 (225 monthly observations). The starting date is dictated by the availability of the Central Bank's monthly industrial and services subindices of IBC-Br, first published by BACEN in April 2025 with historical series extending back to 2006 (BACEN, 2025).

4.2. Variables and Sources

Table 2 summarizes the variables used in the analysis.

Electricity consumption. Monthly sectoral electricity consumption (in MWh) is obtained from the Empresa de Pesquisa Energética (EPE, 2025) for the residential, commercial, and industrial sectors.

Table 1: Main econometric estimates of electricity demand in Brazil

Study	Scope	Period (freq.)	Price elasticity			Income elasticity			Temp. elast.	Method
			Res.	Com.	Ind.	Res.	Com.	Ind.		
Modiano (1984)	Brazil	1963-1981 (A)	−0.12	−0.06	−0.45	1.13	1.07	1.36	–	OLS
Andrade and Lobão (1997)	Brazil	1963-1995 (A)	−0.05	–	–	0.21	–	–	–	VAR/VEC
Schmidt and Lima (2004)	Brazil	1969-1999 (A)	−0.09	−0.17	−0.13	0.54	0.64	1.72	–	VAR/VEC
Mattos and Lima (2005)	MG	1970-2002 (A)	−0.26	–	–	1.40	–	–	–	VAR/VEC
Siqueira et al. (2006)	NE	1970-2003 (A)	−0.41	–	–	1.40	–	–	–	VAR/VEC
Irffi et al. (2009)	NE	1970-2003 (A)	0.69	–	–	0.68	–	–	–	DOLS
Lobão and Ferreira (2015)	Brazil	2005-2011 (M)	−0.06	−0.26	−0.21	0.08	1.27	0.73	–	VAR/VEC
Viana and Silva (2014)	Brazil	1975-2006 (A)	−0.71	–	–	1.79	–	–	–	VAR/VEC
Villareal and Moreira (2016)	Brazil	1985-2013 (A)	0.23	–	–	0.19	–	–	–	OLS
Uhr et al. (2019)	RMSP	POF 1998-99/2008-13	−0.50	–	–	0.21	–	–	–	Panel
Liermann et al. (2021)	RS	2007-2015 (A)	−0.46	–	–	–	–	–	–	Panel
Uhr et al. (2017)	States	2004-2014 (A)	−1.12	–	–	0.83	–	–	0.12	GMM
Salazar and Ribeiro (2022)	Brazil	1970-2019 (A)	–	–	−0.08	–	–	1.57	–	VAR/VEC
Rodrigues et al. (2022)	States	1991-2008 (A)	−0.07	–	–	0.31	–	–	0.036	Panel
Martins et al. (2023)	BA	2004-2021 (M)	−0.11	–	–	0.31	–	–	0.662	VAR/VEC
Carrasco-Gutierrez and Ehrl (2023)	Regional	2003-2015 (M)	−0.12	–	–	0.70	–	–	–	VAR/VEC
Average			−0.211	−0.163	−0.217	0.70	0.99	1.34	0.349	
This paper	Brazil	2006-2025 (M)	−0.170	−0.110	–	0.49	0.61	–	1.213/2.762	VECM

Frequencies: A: Annual, M: Monthly, POF: Household budget survey. Our temperature elasticities (1.213/2.762) correspond to residential and commercial sectors, respectively

Table 2: Variables, units, transformations, and sources

Variable	Symbol	Unit	Transformation	Source
Residential consumption	C^{res}	MWh	log	EPE
Commercial consumption	C^{com}	MWh	log	EPE
Industrial consumption	C^{ind}	MWh	log	EPE
Mean temperature	T	°C	log	Our World in Data
IBC-Br total	Y^{ibcbr}	Index (2002=100)	log	BACEN
IBC-Br services	Y^{serv}	Index	log	BACEN
IBC-Br industrial	Y^{ind}	Index	log	BACEN
Industrial GDP	$Y^{pib,\ ind}$	Index (2002=100)	log	IPEAdata
Real income mass (PNADC)	Y^{massa}	R$ bi	log	IBGE
Residential tariff	P^{res}	R$/MWh (real)	log	Eletrobras/IPEAdata
Commercial tariff	P^{com}	R$/MWh (real)	log	Eletrobras/IPEAdata
Industrial tariff	P^{ind}	R$/MWh (real)	log	Eletrobras/IPEAdata
AC price index	L	Index (IPCA, real)	log	IBGE
Exchange rate	E	R$/US$	log	BACEN
Unemployment rate	U	%	level	IBGE/Vaz-Barreira
Real interest rate	i	% p.a.	level	BACEN/IPCA

Temperature. Monthly mean surface temperature at 2 m above ground, covering terrestrial, maritime, and inland water surfaces, is obtained from Our World in Data (2025), based on the Copernicus Climate Change Service. The series is area-weighted for the Brazilian territory.

Income and activity proxies. Our preferred income proxy for residential demand is the IBC-Br total activity index (2002 = 100), published by BACEN. For robustness, we also employ: the IBC-Br services subindex; the industrial GDP series from IPEAdata (interpolated from quarterly to monthly); the IBC-Br industrial subindex; and the PNADC real income mass, retrocalculated to 2006 following Vaz and Barreira (2021). For commercial demand, our preferred specification follows the literature (Schmidt and Lima, 2004) in using the PNADC real income mass, which has clearer theoretical justification as a determinant of commercial establishments' activity.

Electricity tariff. Sectoral average electricity tariffs (R$/MWh) are obtained from IPEAdata (IPEAdata, 2025), with original data from Eletrobrás. The average tariff is computed as total billing revenue divided by consumption in MWh. Nominal tariffs are deflated by the IPCA to real (February 2025) terms.

Air-conditioning price. A specific IPCA sub-index for air-conditioning equipment is obtained from IBGE (IBGE, 2025), deflated to real terms.

Macroeconomic controls. The nominal exchange rate (R$/US$), the unemployment rate (PNADC, retrocalculation by Vaz and Barreira [2021]), and the real interest rate (SELIC deflated by IPCA) are obtained from BACEN and IBGE.

4.3. Descriptive Statistics

Table 3 presents descriptive statistics for the main variables. Mean temperature over the sample is 25.3°C (s.d. 0.95°C), ranging from 22.4°C to 27.8°C. Residential consumption nearly doubled over the sample (mean 11.04 TWh/month in 2024 vs. 5.35 TWh/month in 2006), while industrial consumption rose only modestly (from 13.85 to 16.46 TWh/month). The AC price index, deflated by the IPCA, fell by approximately 35% in real terms over the period, consistent with the rapid penetration of air-conditioning equipment in Brazilian households.

Table 3: Descriptive statistics (monthly data, June 2006-February 2025, n=225)

Variable	Mean	Std. dev.	Min	Max
Residential consumption (TWh)	9.82	2.14	5.23	14.80
Commercial consumption (TWh)	6.85	1.12	4.05	8.92
Industrial consumption (TWh)	14.87	0.86	11.95	17.01
Mean temperature (°C)	25.30	0.95	22.40	27.80
IBC-Br total (2002=100)	135.8	12.4	110.2	156.7
IBC-Br services (2002=100)	139.4	13.1	109.5	160.2
IBC-Br industrial (2002=100)	103.6	3.8	91.4	110.8
Industrial GDP (2002=100)	103.5	3.8	91.2	110.6
Real income mass (R$ bi)	3,274	455	2,387	4,158
Residential tariff (R$/MWh)	619	62	493	723
Commercial tariff (R$/MWh)	546	64	409	646
Industrial tariff (R$/MWh)	418	52	298	510
AC price (Index, real)	91.7	7.5	77.8	104.3
Exchange rate (R$/US$)	3.46	1.27	1.55	5.75
Unemployment (%)	9.2	2.6	5.0	14.9
Real interest rate (% p.a.)	4.3	3.6	−3.8	11.7

Descriptive statistics computed over the full sample period, 225 monthly observations

4.4. Multicollinearity between Income and Temperature

A preliminary correlation analysis reveals an important feature of Brazilian monthly data over the sample period: both income proxies and temperature exhibit strong positive trends. The simple Pearson correlation between log real income mass (PNADC) and log residential consumption is +0.940, while the correlation between log IBC-Br and log residential consumption is +0.725. The difference is relevant for VECM identification: The lower correlation of the IBC-Br index leaves more residual variation for temperature to explain in multivariate cointegration specifications. This observation motivates our preference for IBC-Br as the primary income proxy in the residential specification. We provide a detailed discussion in Section 5.11.

5. EMPIRICAL METHODOLOGY AND RESULTS

The econometric modeling of electricity demand, incorporating temperature as per the theoretical framework, is carried out using a vector error-correction model (VECM), following Johansen (1988) and Johansen and Juselius (1990). While more recent approaches such as local projections (Jordà, 2005) and Bayesian VAR have been increasingly applied to dynamic time-series analysis, the VECM remains the natural framework for systems where an explicit cointegration relationship binds non-stationary variables in a long-run equilibrium that is itself the object of inference. The research question of this paper, namely the estimation of long-run elasticities of electricity demand with respect to temperature, income, and prices, is precisely a question about this equilibrium. The VECM imposes the cointegration restriction explicitly, delivers structural long-run coefficients with conventional standard errors, and ensures direct comparability with the established Brazilian literature on electricity demand (Schmidt and Lima, 2004; Modiano, 1984; Andrade and Lobão, 1997; Mattos and Lima, 2005; Siqueira et al., 2006; Uhr et al., 2019; Carrasco-Gutierrez and Ehrl, 2023; Martins et al., 2023). Our empirical strategy proceeds in five steps: (i) Test the order of integration of each series; (ii) test for cointegration using the Johansen procedure; (iii) estimate VECMs for residential and commercial consumption with seasonal dummies; (iv) compute impulse-response functions, non-linearity tests, and stability diagnostics; (v) assess dynamic forecast performance.

5.1. Unit Root Tests

A well-known criticism of earlier Brazilian work on electricity demand is reliance on a single unit root test. To address this concern, we apply four tests: Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), Kwiatkowski-Phillips-Schmidt-Shin (KPSS, which tests the null of stationarity), and Dickey-Fuller Generalized Least Squares (Elliott et al., 1996). For temperature, which has strong seasonal components, we additionally apply the seasonal

Table 4: Unit root tests (levels, with constant and linear trend)

Variable	ADF	PP	KPSS	DF-GLS	Order
Residential consumption	−2.34	−4.93***	0.380**	−1.25	I (1)
Commercial consumption	−1.94	−3.32*	0.442**	−0.94	I (1)
Industrial consumption	−2.21	−3.96***	0.253**	−2.29	I (1)
IBC-Br total	−2.55	−2.50	0.292**	−1.48	I (1)
IBC-Br industrial	−2.96	−2.93	0.239**	−1.91	I (1)
IBC-Br services	−2.36	−2.50	0.330**	−1.07	I (1)
Industrial GDP	−2.96	−2.92	0.239**	−1.90	I (1)
Real income mass (PNADC)	−1.80	−1.88	0.399**	−1.17	I (1)
Residential tariff	−2.88	−2.59	0.290**	−2.09	I (1)
Commercial tariff	−2.71	−2.48	0.348**	−1.68	I (1)
Industrial tariff	−3.28*	−2.62	0.270**	−2.15	I (1)
Mean temperature	−4.34***	−5.02***	0.045	−1.99	I (1)†
AC price	0.02	−1.07	0.403**	−1.27	I (1)‡
Exchange rate	−2.78	−2.87	0.220**	−1.50	I (1)

ADF, PP, and DF-GLS test H_0: unit root. KPSS tests H_0: Stationarity. All tests include a constant and linear trend. Significance: ***P<0.01, **P<0.05, *P<0.10. †Temperature is non-stationary according to the seasonal unit root test of Hylleberg et al. (1990); the non-seasonal ADF/PP appear to reject because of the strong seasonality. ‡AC price shows a unit root with structural break (Zivot-Andrews, break near 2020). First-difference tests (Table 8) confirm all variables are I (1)

unit root tests of Hylleberg et al. (1990) and Beaulieu and Miron (1993). For the AC price, which may have structural breaks around the pandemic, we apply the Zivot and Andrews (1992) test with structural break.

Table 4 reports the main results. Consistent with the literature on monthly Brazilian macroeconomic data, all consumption, income, tariff, and AC price variables are found to be integrated of order one, I(1): ADF, PP, and DF-GLS generally fail to reject the null of a unit root, while KPSS rejects stationarity. Temperature is I(1) once seasonal components are accounted for (the high PP statistic reflects the strong seasonal component which DF-GLS and the seasonal tests handle more appropriately); the AC price is I(1) with a structural break around 2020 that we treat as an intervention dummy. First differences of all variables are stationary (Table 8). These results justify the use of cointegration techniques.

5.2. Cointegration and Lag Selection

For each sector, we select the VAR lag length using the Akaike (AIC), Hannan-Quinn (HQIC), and Schwarz (SBIC) information criteria. All three criteria support a lag length of three for the underlying VAR in each specification, implying two lags in the VECM differences. We include eleven monthly seasonal indicator variables (with June as the omitted base month, following Juselius (2006), Ch. 6) to control for seasonality without distorting the cointegration space.

The Johansen trace and maximum-eigenvalue tests (Table 5 and 9) identify at least one cointegrating vector in each sector at the 5% significance level. We adopt rank r = 1 throughout, consistent with the theoretical interpretation of a single long-run demand relationship.

5.3. VECM Specification

The VECM takes the form:

$$\Delta Z_t = \Pi Z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Z_{t-i} + \Phi D_t + \varepsilon_t$$

Where Z_t is the vector of endogenous variables, $\Pi = \alpha\beta'$ is the long-run impact matrix with β containing the cointegrating vectors and α the adjustment coefficients, D_t includes deterministic components (constant, trend, seasonal dummies), and $\varepsilon_t \sim \text{iid}(0,\Sigma)$. Following the standard Johansen normalization with consumption as the normalized variable, the cointegrating vector β yields directly the long-run demand elasticities.

Table 5: Johansen cointegration tests (trace statistic, 5% critical value)

Rank r	Residential		Commercial		Industrial	
	Trace	Crit. 5%	Trace	Crit. 5%	Trace	Crit. 5%
r=0	226.51	87.31	180.38	68.52	180.72	87.31
r=1	98.78	62.99	85.34	47.21	70.24	62.99
r=2	32.47	42.44	20.44	29.68	35.69	42.44
r=3	15.04	25.32	5.57	15.41	19.98	25.32
r=4	5.30	12.25	0.11	3.76	7.93	12.25

Johansen trace test with three lags in the underlying VAR. Asymptotic critical values from Johansen (1988); reported P values use the numerical distribution functions of MacKinnon et al. (1999). Bold values indicate the rank at which the null is not rejected; we impose r=1 for each sector based on theory. Deterministic specification: restricted trend (residential and industrial), unrestricted constant (commercial)

The deterministic specification of the VECM requires a careful choice (Juselius, 2006). We report our preferred specification, namely restricted trend in the cointegration space for the residential sector and unrestricted constant for the commercial sector, after comparing alternatives based on information criteria and the sign pattern of the cointegrating vector. The sensitivity analysis is reported in Section 5.11.

5.4. Residential Sector Results

Table 6 presents the estimated cointegrating vector for the residential sector. Column (1) is our preferred specification using the IBC-Br total activity index as the income proxy; columns (2)-(4) report robustness using alternative income proxies. All four long-run elasticities in the preferred specification are statistically significant at the 1% level and carry the signs predicted by economic theory.

The estimated long-run elasticities are economically coherent. The income elasticity is $\xi_r = +0.487$, indicating that a 1% increase in aggregate activity raises residential electricity consumption by approximately 0.49% in the long run, consistent with Schmidt and Lima (2004). The tariff elasticity is $\xi_p = -0.170$, in line with the literature finding low residential price sensitivity (Modiano, 1984; Schmidt and Lima, 2004). The temperature elasticity is $\xi_T = +1.213$; applied to the sample mean temperature (25.3°C), it implies a long-run consumption increase of approximately 4.8%/1°C of permanent warming (see Section 5.7). The air-conditioning price elasticity is $\xi_1 = -0.177$, confirming that AC affordability is a relevant determinant of residential demand. Finally, the restricted linear trend is negative and highly significant (−0.0024), reflecting structural efficiency improvements over the sample period.

The sensitivity to the income proxy (column 4) is a key methodological finding discussed in Section 5.11.

5.5. Commercial Sector Results

Table 7 reports estimates for the commercial sector. The preferred specification (column 1) employs the PNADC real income mass and an unrestricted constant. All elasticities carry the theoretically expected signs.

The commercial temperature elasticity of +2.762, the largest among the three sectors, implies that a 1°C permanent temperature increase raises commercial consumption by approximately 10.9% in the long run. This result is robust across alternative income proxies (columns 2-4), ranging from +2.46 to +3.41. The magnitude reflects the central role of air-conditioning in Brazilian commercial establishments.

5.6. Impulse-Response Functions

Figures 1 and 2 display orthogonalized impulse-response functions (IRFs) over a 60-month horizon, computed from the preferred VECM specifications of Tables 6 and 7. The Cholesky ordering places temperature first, followed by income, tariff, AC price, and consumption, reflecting the contemporaneous exogeneity of temperature with respect to economic variables at the monthly frequency.

Confidence bands for impulse responses in cointegrated VECM systems are not implemented in standard packages such as Stata (StataCorp, 2025). This reflects a well-known issue: The asymptotic distribution of IRFs in cointegrated systems is non-standard, and bootstrap procedures based on the estimated VECM can become invalid at long horizons, particularly when the cointegration rank is subject to uncertainty or when multiple deterministic components are present (Benkwitz et al., 2001; Lieb and Smeekes, 2019). Robust procedures exist (Mikusheva, 2012) but have limited applicability under the deterministic and seasonal structure required here. As is common practice in the applied VECM literature on electricity demand, we therefore present the IRFs without confidence bands and rely on the standard errors of the long-run cointegrating coefficients in Tables 6 and 7, where the temperature elasticities are significant at the 1% level (*t*-statistics of 5.05 residential, 4.60 commercial), as the formal basis for inference. The IRFs visualize the dynamic adjustment path implied by the estimated cointegrating relationships.

The IRFs show that the response of residential consumption to a one-standard-deviation temperature shock builds steadily over approximately 18 months and stabilizes at approximately 0.013 log-points, consistent with the long-run elasticity estimate. For commercial consumption, the response stabilizes more quickly (within 15 months) at approximately 0.009 log-points. The difference reflects the commercial sector's more immediate

Table 6: VECM cointegrating vector: Residential sector

Variable	(1) Main (IBC-Br)	(2) Services	(3) +Macro controls	(4) Real income mass
Income elasticity	+0.487*** (0.098)	+0.498*** (0.108)	+0.635*** (0.143)	+0.520*** (0.099)
Tariff elasticity	−0.170*** (0.045)	−0.161*** (0.049)	−0.112** (0.046)	−0.076 (0.059)
Temperature elasticity	+1.213*** (0.241)	+0.940*** (0.259)	+0.797*** (0.243)	−0.319 (0.319)
AC price elasticity	−0.177*** (0.066)	−0.148** (0.067)	+0.021 (0.076)	+0.120 (0.079)
Interest rate	–	–	+0.002** (0.001)	–
Unemployment	–	–	−0.002 (0.003)	–
Linear trend	−0.0024*** (0.0001)	−0.0023*** (0.0001)	−0.0025*** (0.0001)	−0.0019*** (0.0002)
χ^2 cointegration	167.99***	148.64***	188.92***	123.66***
Observations	222	222	222	222

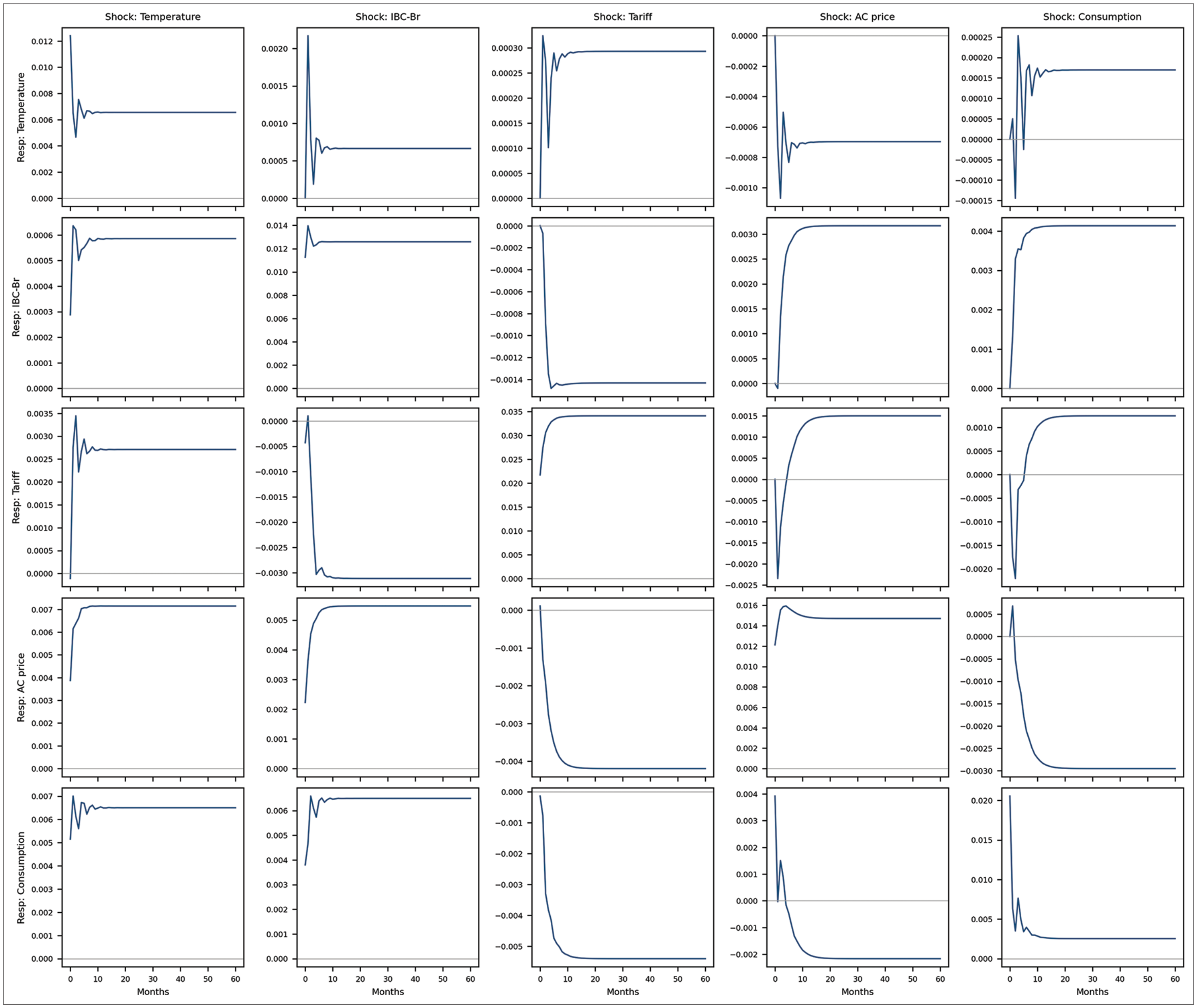
VECM cointegrating vector normalized on $\ln C^{res}$, signs reported as *implied elasticities* (opposite sign from β coefficients). Standard errors in parentheses. Deterministic specification: restricted linear trend. All specifications include eleven monthly seasonal indicator variables. Significance: ***P<0.01, **P<0.05, *P<0.10. Column (1) is the preferred specification

Table 7: VECM cointegrating vector: Commercial sector

Variable	(1) Main (mass)	(2) +Unemployment	(3) Services	(4) IBC-Br total
Income elasticity	+0.608*** (0.100)	+0.450*** (0.108)	+1.289*** (0.138)	+0.838*** (0.116)
Tariff elasticity	−0.110 (0.067)	−0.072 (0.062)	+0.001 (0.066)	+0.038 (0.061)
Temperature elasticity	+2.762*** (0.598)	+3.408*** (0.554)	+3.157*** (0.524)	+2.458*** (0.592)
AC price elasticity	−0.816*** (0.156)	−1.095*** (0.188)	−0.874*** (0.101)	−0.680*** (0.161)
Unemployment	–	−0.014*** (0.004)	–	–
χ^2 cointegration	565.61***	736.26***	631.85***	290.10***
Observations	222	222	222	222

VECM cointegrating vector normalized on $\ln C^{com}$, signs reported as *implied elasticities*. Standard errors in parentheses. Deterministic specification: unrestricted constant. All specifications include eleven monthly seasonal indicator variables. Significance: ***P<0.01, **P<0.05, *P<0.10. Column (1) is the preferred specification

Figure 1: Residential sector: orthogonalized impulse-response functions over 60 months (preferred specification). Cholesky ordering: temperature, IBC-Br, tariff, AC price, consumption



adjustment to weather conditions: commercial establishments run air-conditioning continuously during business hours, while residential consumers adjust more gradually as they invest in cooling equipment and change behavioral patterns.

5.7. Correct Conversion between Log-elasticities and Temperature Levels

A methodological point concerns the conversion of log-temperature elasticities into degrees-Celsius effects. The correct conversion uses the relation:

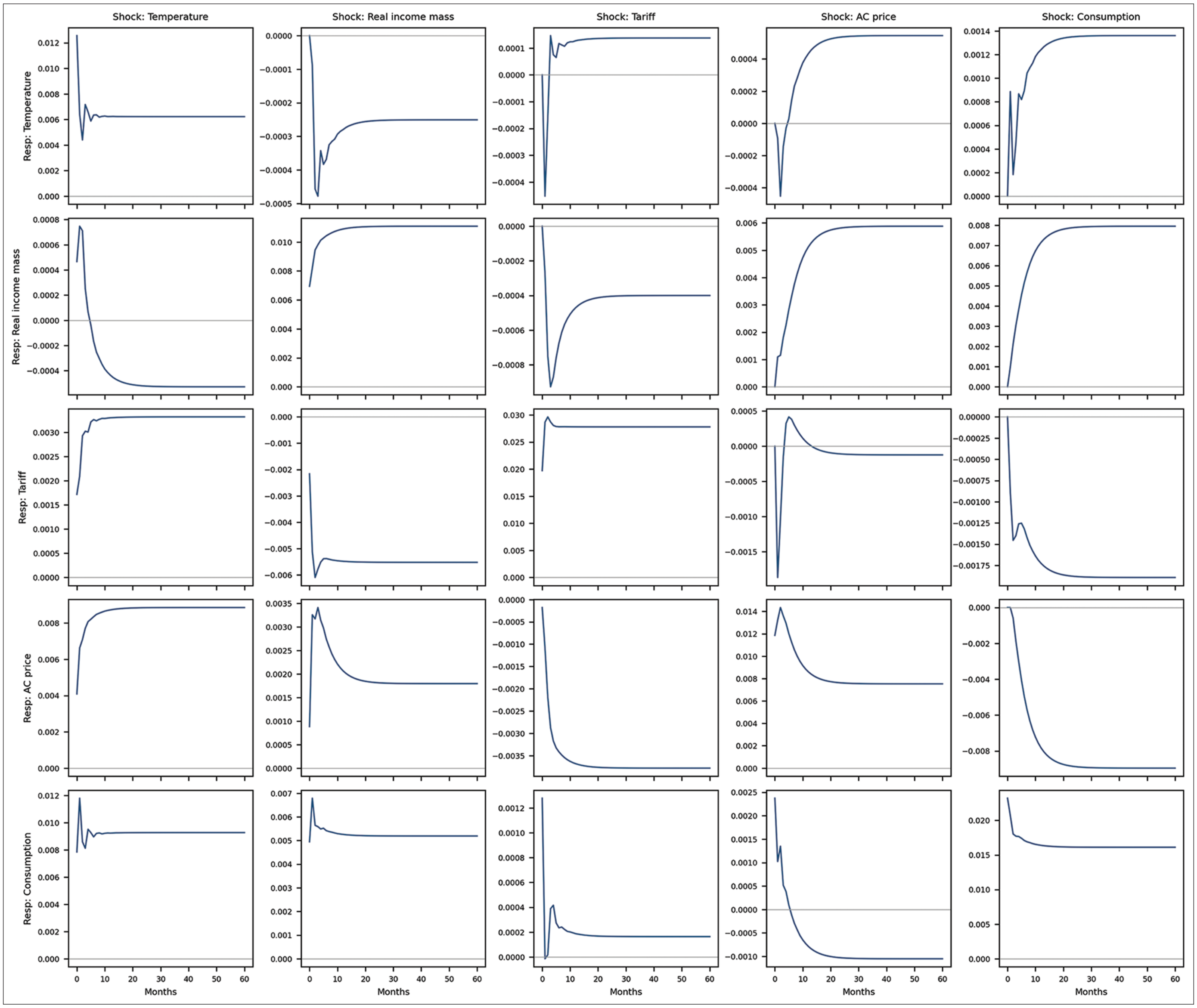
$$\frac{\Delta C}{C} = \xi_T \cdot \frac{\Delta T}{\bar{T}}$$

where $\bar{T}$ is the mean temperature (in absolute units; we use 25.3°C, the sample mean). For the residential sector with ξ_T = 1.213, a permanent increase of 1°C corresponds to $\Delta T / \bar{T} = 0.0395$ and an implied long-run consumption increase of 1.213 × 0.0395 = 0.0479, i.e., approximately 4.8%. For the commercial sector, the corresponding implied long-run effect is 10.9%/1°C. Under a 1.5°C warming reference scenario, used here as a conservative anchor relative to IPCC AR6 projections for South America by mid-century, the implied effects are 7.2% (residential) and 16.4% (commercial). These figures represent *partial-equilibrium* long-run effects, holding other determinants of demand constant.

5.8. Non-linearity Tests

To assess whether the log-linear specification is adequate, we estimate three extensions: (i) Inclusion of a quadratic temperature term ($\ln T_t^2$); (ii) inclusion of a temperature-income interaction ($\ln T_t \cdot \ln Y_t$); and (iii) a summer indicator interacted with temperature. The quadratic term is not statistically significant in either the residential or commercial specifications (Table 10), indicating that within the observed temperature range the log-linear relationship is a reasonable approximation. The temperature-

Figure 2: Commercial sector: orthogonalized impulse-response functions over 60 months (preferred specification). Cholesky ordering: Temperature, real income mass, tariff, AC price, consumption



income interaction is also insignificant. The seasonal interaction is marginally significant in the commercial sector (P = 0.08), suggesting modestly stronger temperature effects during the austral summer.

5.9. Model Adequacy and Stability

LM tests for residual autocorrelation at 12 lags do not reject the null of no serial correlation for the two main models at the 5% level. Jarque-Bera tests indicate moderate departures from normality in some residuals, common in monthly energy data; this does not invalidate the consistency of VECM estimators.

Figure 3 display the eigenvalues of the companion matrix for the two main models. Beyond the unit moduli imposed by the rank restriction ($k-r = 4$), all remaining eigenvalues lie strictly inside the unit circle, confirming dynamic stability.

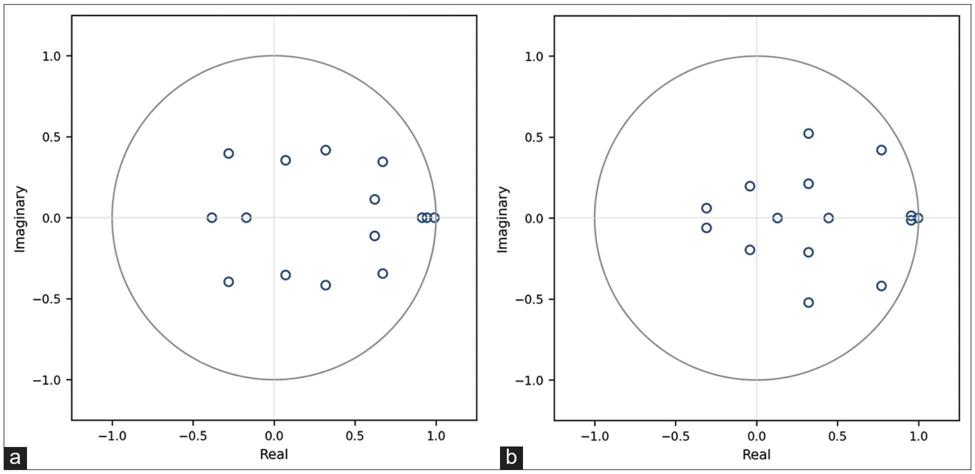
5.10. Dynamic Forecasts

As an additional model-adequacy check, we compute dynamic out-of-sample forecasts over two horizons: Three years (January 2022-February 2025, 38 months) and 1 year (January 2024-February 2025, 14 months). The 3-year horizon begins shortly after the pandemic shocks. Mean forecast errors (percentage deviation from realized consumption) are reported in Table 11:

For the residential sector, the mean forecast error is +4.5% at the 3-year horizon and +0.05% at the 1-year horizon; for the commercial sector, it is +3.2% and +0.3%, respectively.

The relatively higher 3-year error for the residential sector appears driven by unusually warm conditions in 2023 and 2024, which the model captures only partially. This result supports the case for including temperature variables in medium-term demand projection models.

Figure 3: Eigenvalues of the companion matrix (preferred specifications). Four unit moduli are imposed by the rank restriction; all other eigenvalues lie inside the unit circle (a) Residential, (b) Commercial



5.11. Methodological Sensitivity and Multicollinearity

A central methodological result of this paper concerns the sensitivity of estimated temperature elasticities to the choice of income proxy. When the PNADC real income mass is used as the income proxy in the residential specification (Table 6, column 4), the estimated temperature elasticity attenuates to −0.319 and becomes statistically insignificant. This is a dramatic difference from our preferred estimate of +1.21. With IBC-Br services (column 2), the temperature elasticity is +0.940; with IBC-Br total (column 1), +1.213; with additional macro controls (column 3), +0.797.

The mechanism is multicollinearity. Over the 2006-2025 period, both the real income mass and temperature exhibit strong positive trends, producing a Pearson correlation of +0.94 between log real income mass and log residential consumption (compared to +0.72 between log IBC-Br and log residential consumption). In the Johansen cointegration framework, when two variables share a common deterministic trend and one has stronger correlation with the dependent variable, the stronger-correlated variable tends to absorb the variation that would otherwise be attributed to the other. This mechanism biases the temperature coefficient toward zero or can even reverse its sign.

Using IBC-Br, which has a lower correlation with residential consumption, yields a cleaner identification of the temperature effect. This methodological observation is relevant beyond the specific application: Researchers estimating climate-demand elasticities using Brazilian monthly data should be aware that income proxy choice materially affects the estimated climate sensitivity. We view the robust positive temperature effect across the three IBC-Br-based specifications as the preferred interpretation of the data.

6. DISCUSSION

6.1. Magnitudes Compared to the Literature

Our long-run temperature elasticities (+1.21 for residential and +2.76 for commercial electricity consumption) document substantial climate sensitivity of Brazilian end-use demand. The implied effects of a 1°C temperature increase (4.8% and 10.9%, respectively) fall within the upper end of estimates reported in the Brazilian literature. Martins et al. (2023) report 2.6% for Bahia; Rodrigues et al. (2022) 3.6% for a national panel; Uhr et al. (2017) 12-13%/1°C using state-level data. Internationally, Eskeland and Mideksa (2010) report European residential elasticities of roughly 2-5%/1°C depending on climate zone; warmer Mediterranean regions yield estimates comparable to ours.

The commercial elasticity of +2.76 is larger than most residential estimates but consistent with the structural characteristics of the Brazilian commercial sector. Three features justify this magnitude. First, commercial buildings in Brazil (shopping malls, high-end office buildings, retail establishments, supermarkets, hotels, and restaurants) typically operate continuous cooling systems during extended business hours, so that marginal temperature increases translate proportionally into higher cooling loads over long operating windows. Second, the penetration of air-conditioning in the commercial segment has risen rapidly over the sample period, and a substantial share of recent commercial construction (particularly in the Southeast and Northeast) has been built with climate-control as a design premise; this widens the extensive margin of temperature response. Third, the correlation between monthly commercial consumption and temperature (+0.311) exceeds that of residential consumption (+0.257) in our sample, confirming the ranking of climate sensitivity directly in the raw data, before any estimation. This ordering is also consistent with the structural characterization in Schmidt and Lima (2004) and is reinforced by international evidence: commercial-sector temperature sensitivities commonly exceed residential sensitivities in warm climates where continuous building-wide cooling is prevalent. The result is directly relevant for planning: Much of the adaptation-driven electricity demand growth in Brazil's hot regions is likely to be concentrated in the commercial segment, with implications for distribution-network reinforcement and for the design of efficiency programs targeted at commercial buildings.

6.2. Methodological Implications

The multicollinearity issue documented in Section 5.11 highlights a subtle but consequential pitfall in cointegration analyses of electricity demand in emerging-market economies with pronounced structural growth. When the chosen income proxy has very high correlation with the dependent variable (as in the case of the PNADC mass income), it can crowd out the identification of secondary drivers such as temperature. We suggest that researchers conducting similar exercises in Brazil or analogous settings report sensitivity to income proxy choice explicitly.

6.3. Projections Under Warming Scenarios

Applying our estimates to a 1.5°C warming reference scenario (used here as a conservative anchor; IPCC AR6 projects warming in South America at rates greater than the global average, so mid-century increases under intermediate-to-high emissions scenarios are typically higher), the implied long-run demand increases are 7.2% (residential) and 16.4% (commercial), holding other variables constant. These projections rely on the assumption that the cointegrating relationships remain stable over the extrapolation horizon, which is a strong assumption given structural changes in AC technology, efficiency standards, building codes, and potential electrification of heating in southern Brazil. We therefore present these numbers as partial-equilibrium magnitudes useful for scenario analysis rather than point predictions. The 1.5°C reference also falls within the lower envelope of CMIP6 projections used in official Brazilian planning studies, which adopt SSP2–4.5 and SSP5–8.5 trajectories for the 2040-2070 horizon (EPE and GIZ, 2025a). Our implied demand impacts (7.2% residential, 16.4% commercial) should therefore be read as conservative anchors for the lower-warming pathway; under SSP5–8.5 trajectories, the implied long-run impacts would be proportionally larger.

A useful benchmark is provided by the EPE/GIZ companion study on consumption profiles (EPE and GIZ, 2025b), which adopts a degree-day approach (HDD and CDD computed from a Building-Adjusted Internal Temperature index) calibrated to state-level electricity consumption. For the national interconnected system (SIN) as a whole, that study projects mean monthly demand increases of about 3% under SSP2–4.5 and 4% under SSP5–8.5 in the warmer months over the 2040-2070 horizon, with ensemble extremes reaching 5-6%. These institutional figures are, on the surface, smaller than our +7.2% residential and +16.4% commercial estimates under 1.5°C warming, but the comparison is informative once two differences are recognized. First, the EPE/GIZ aggregate is computed across all end-uses (including industrial demand, which our results and the broader literature suggest is largely unresponsive to ambient temperature), so a national-level percentage dilutes the building-driven response. Second, the methodologies are complementary: Degree-day models capture short-run thermal-comfort dynamics conditional on a fixed building and equipment stock, whereas a VECM-based long-run elasticity embeds extensive-margin adjustments such as AC adoption, building envelope changes, and behavioral persistence. Read together, the two sets of estimates bracket the likely climate-driven demand increment for Brazilian buildings and reinforce the message that the residential and commercial sectors are the principal channels through which warming will translate into additional electricity load.

6.4. Policy Implications for Sustainable Electricity Planning

The estimated elasticities have direct implications for Brazilian energy planning and, more broadly, for sustainable electricity development in tropical emerging economies. Residential and commercial electricity consumption are substantially more climate-sensitive than current national planning documents typically assume. The Plano Decenal de Expansão de Energia (PDE), prepared by the Empresa de Pesquisa Energética (EPE), sets 10-year expansion trajectories for generation and transmission, and our estimates imply that a 1°C permanent warming adds roughly 4.8% to residential and 10.9% to commercial electricity demand in the long run, magnitudes that are first-order relative to typical 10-year demand growth projections. PDE scenarios should therefore incorporate explicit climate-driven demand growth, and the Plano Nacional de Energia (PNE 2050) should include sensitivity analyses that use elasticity-based climate scenarios consistent with IPCC AR6 temperature pathways for Brazil. Given that most Brazilian generation remains hydroelectric and is itself exposed to climate risk through precipitation changes, the concurrent climate pressure on demand and supply reinforces the case for diversified, climate-resilient capacity planning. Recent institutional analysis by the EPE and the Operador Nacional do Sistema Elétrico (ONS), in partnership with the Brazil–Germany Cooperation for Sustainable Development through GIZ, explicitly recognizes that maintaining planning rules anchored on past climatology may generate higher operational costs, supply interruption risks, and worsening social inequalities, while early adaptation is found to be technically and economically feasible (EPE and GIZ, 2025a). Drawing on CMIP6 projections under SSP2–4.5 and SSP5–8.5 trajectories for the 2040-2070 horizon, that study projects substantial reductions in mean inflows in the Southeast, North, and Northeast subsystems, with offsetting increases only in the South. Combined with our temperature elasticities on the demand side, these supply-side projections imply a concurrent climate-driven tightening of the Brazilian electricity system: hydroelectric capability falls in precisely the regions where residential and commercial demand are most exposed to warming.

A second implication concerns the limited scope of tariff design as a tool for moderating climate-driven demand. The low estimated price elasticities in both sectors (−0.17 residential, −0.11 commercial) imply that tariff-based instruments will have limited effectiveness in this regard. The bandeiras tarifárias (tariff flag) system, introduced in 2015 to pass through scarcity costs to consumers, has not meaningfully curbed residential or commercial demand growth over the sample period, a pattern consistent with our elasticity estimates. The ANEEL-regulated social tariff (Tarifa Social de Energia Elétrica) likewise targets affordability but does not address the underlying thermal-demand drivers. Policy instruments that act on the technology and building stock, rather than on price alone, are likely to yield larger demand-side reductions. Non-price instruments are therefore especially promising, and Brazil already has a set of policy tools that can be strengthened and better coordinated: The PROCEL energy-efficiency program, the PBE Edifica energy-labeling scheme for commercial and residential buildings, and the PEE (Programa de Eficiência Energética) financed by regulated distribution utilities through the ANEEL framework. Minimum energy performance standards (MEPS) for air-conditioning equipment under the Programa Brasileiro de Etiquetagem, together with stricter labeling requirements and, for the commercial segment, mandatory performance standards for new buildings, could materially attenuate the climate elasticity of demand over the coming decades. Targeted incentives for high-efficiency cooling technologies (variable-refrigerant-flow systems, district cooling in dense urban commercial areas, and efficient inverter split units for residential use) address the intensive margin of thermal response. Together, these measures shift part of the climate-demand elasticity from a structural constraint into a policy-addressable parameter.

The distributional and affordability dimensions of these results also deserve emphasis. Because climate-induced demand growth falls disproportionately on residential and commercial consumers rather than on heavy industry, the incidence of climate-related electricity cost increases will be concentrated among households and the service sector. Within the residential sector, the effects are further differentiated by income: low-income households face a binding adoption constraint on efficient cooling equipment, and rising ambient temperatures combined with limited ability to acquire efficient AC may generate new dimensions of energy poverty in Brazil's hot regions. This motivates a reconsideration of how social tariff programs interact with climate exposure, and strengthens the case for targeted financing of efficient cooling equipment for vulnerable households. From an SDG perspective, ensuring affordable and reliable access to cooling services in a warming climate is increasingly integral to the substantive meaning of SDG 7.

The findings carry implications beyond Brazil. Many tropical emerging economies in South Asia, Southeast Asia, and Sub-Saharan Africa face the same combination of rising per-capita income, rapid AC diffusion, and warming climates. Our estimates, while country-specific, reinforce a broader conclusion: in such settings, climate-driven demand growth is likely substantial, concentrated in buildings rather than industry, and only partially manageable through tariff policy. The methodological lesson, namely that income-proxy choice has a material effect on estimated climate elasticities when activity and temperature share common trends, should guide future empirical work. Coordinated investment in efficient cooling, building codes adapted to tropical conditions, and climate-resilient generation portfolios spans SDG 7, SDG 11, and SDG 13.

6.5. Limitations

Several limitations of our analysis merit explicit acknowledgment.

First, the VECM identifies long-run equilibrium relationships under stationarity assumptions that may fail over multi-decade horizons. Structural shifts (further AC penetration, more efficient cooling equipment, distributed generation, behavioral change) will modify the estimated elasticities over time.

Second, our temperature variable is a national monthly average, which smooths substantial regional and intraday heterogeneity. Brazil spans multiple climate zones; demand responses in the hot Northeast likely differ from responses in the temperate South. Institutional projections from the EPE/GIZ consumption-profile study are consistent with this concern in two specific ways (EPE and GIZ, 2025b). The South is the only subsystem in which mean projected demand variation can be slightly negative in winter months, as the reduction in heating degree-days partially offsets the rise in cooling degree-days; and although the Northeast experiences the largest projected increase in cooling degree-days, the implied demand response there is proportionally smaller than in the Southeast and South, which the study attributes to a lower estimated elasticity of demand to thermal discomfort in that region. These findings indicate that a national elasticity, while informative, masks regional asymmetries that future state-level or sub-system panel analyses (using ONS sub-system data) would be well placed to recover.

Third, we do not distinguish between heating and cooling needs. In tropical and subtropical Brazil, cooling dominates, but a residual heating effect may exist in the southern states during winter.

Fourth, our analysis relies on aggregate sectoral data. Firm-level or household-level studies could refine the estimates and test for heterogeneous responses.

Fifth, our analysis deliberately focuses on residential and commercial end-uses. As discussed in the introduction, identifying a clean thermal-demand effect on industrial electricity consumption from Brazilian aggregate data is infeasible given the electro-intensive composition of national industry and the confounding macroeconomic shocks over the sample period. Any climate effect on industrial demand would require disaggregated firm-level or subsector data, a direction for future research.

Sixth, climate pressure on the Brazilian electricity system is bilateral: while warming raises end-use demand, as documented in this paper, it simultaneously reduces hydroelectric inflow availability in three of the four major subsystems (EPE and GIZ, 2025a). A full welfare analysis of climate impacts on the Brazilian electricity sector therefore requires joint modeling of the demand-side elasticities estimated here with supply-side hydrological projections. The combined effect strengthens the case for diversified, climate-resilient capacity portfolios beyond the historical hydroelectric backbone.

7. CONCLUSION

This paper has estimated long-run temperature elasticities of residential and commercial electricity demand in Brazil using monthly data from June 2006 to February 2025 within a vector error-correction framework. Temperature has a substantial effect on both end-use sectors. The estimated long-run elasticities are +1.21 (residential) and +2.76 (commercial), both statistically significant at the 1% level, and applied to the sample mean temperature they imply that a 1°C permanent increase raises consumption by 4.8% (residential) and 10.9% (commercial) in the long run. Identifying these magnitudes cleanly required attention to the choice of income proxy: over the 2006-2025 period, the PNADC real income mass is so highly correlated with residential consumption (+0.94) that it absorbs variation that would otherwise be attributed to temperature, and using IBC-Br instead yields temperature elasticities that are robust across specifications. This is a methodological caveat with implications for similar exercises in emerging-market economies where activity and temperature share common deterministic trends. The analysis was deliberately focused on residential and commercial end-uses, where thermal demand is empirically and conceptually well identified; the industrial sector, dominated by electro-intensive activities and strongly affected by macroeconomic shocks during the sample period, does not admit a clean identification of a thermal-demand effect from aggregate data and is therefore left for future research using disaggregated firm-level or subsector data.

From a policy perspective, these results suggest that climate-driven electricity demand growth in Brazil is likely to be concentrated in buildings (residential and commercial) rather than in industrial facilities, and energy planning documents should incorporate this sectoral heterogeneity explicitly. Given the low estimated price elasticities, demand-side policies to manage climate-driven growth should emphasize efficiency standards, building codes, and targeted incentive programs rather than tariff instruments alone. Future research should examine regional heterogeneity, distinguish cooling from heating demand in southern Brazil, and exploit firm- or household-level data to refine the aggregate estimates and evaluate climate adaptation policies at a more granular level. Recent institutional projections suggest that the heterogeneity is empirically substantial: The South may experience small reductions in winter demand as cooler-month heating needs decline, while the Northeast, despite the largest projected rise in cooling degree-days, may exhibit a lower demand response than the warmer-and-richer Southeast (EPE and GIZ, 2025b). Sub-system panel models that recover separate elasticities for the four SIN regions are a natural next step.

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10. COMPLEMENTARY TECHNICAL TABLES

10.1. Unit Root Tests on First Differences

Table 8 reports unit root tests applied to the first differences of all series. The ADF and PP tests decisively reject the null of a unit root in first differences for every variable, confirming that all series are I(1) and supporting the cointegration framework of Section 5.

Table 8: Unit root tests on first differences (constant only)

Variable	ADF (Δ)	PP (Δ)	DF-GLS (Δ)
Residential consumption	−3.37**	−19.85***	−0.89
Commercial consumption	−4.20***	−9.07***	−1.06
Industrial consumption	−4.28***	−16.67***	−2.22**
IBC-Br total	−7.48***	−11.61***	−2.47**
IBC-Br industrial	−11.42***	−13.14***	−6.18***
IBC-Br services	−10.77***	−11.28***	−4.34***
Industrial GDP	−11.39***	−13.15***	−6.10***
Real income mass (PNADC)	−7.09***	−11.56***	−4.12***
Residential tariff	−11.00***	−10.91***	−11.02***
Commercial tariff	−8.91***	−8.97***	−8.59***
Industrial tariff	−3.59***	−12.14***	−2.26**
Mean temperature	−4.26***	−10.76***	−0.53
AC price	−5.10***	−10.68***	−2.87***
Exchange rate	−9.26***	−14.50***	−9.28***

Significance: ***P<0.01, **P<0.05, *P<0.10. The DF-GLS test has lower power in small samples with strong seasonality (e.g., temperature), but ADF and PP decisively reject the unit root in first differences for all variables, confirming they are I (1)

10.2. Maximum-eigenvalue Cointegration Tests

Table 9 reports the Johansen maximum-eigenvalue statistics, which complement the trace statistics of Table 5 and confirm the selection of cointegration rank r = 1 for each sector.

Table 9: Johansen maximum-eigenvalue statistics

Rank	Residential		Commercial		Industrial	
r	Max-eigen	Crit. 5%	Max-eigen	Crit. 5%	Max-eigen	Crit. 5%
r=0	127.74	37.52	95.04	33.46	110.47	37.52
r=1	66.30	31.46	64.90	27.07	34.55	31.46
r=2	17.43	25.54	14.87	20.97	15.72	25.54
r=3	9.75	18.96	5.46	14.07	12.04	18.96

10.3. Non-linearity Tests

Table 10 reports the non-linearity tests described in Section 5.8. None of the quadratic or interaction terms is statistically significant at the 5% level, supporting the log-linear specification within the observed temperature range.

Table 10: Non-linearity tests (temperature coefficients in selected specifications)

Variable	Residential Quadratic temp	Commercial Quadratic temp	Residential Temp×income
$\ln T$	−4.00 (11.21)	−5.86 (12.52)	−2.82 (4.99)
$(\ln T)^2$	+0.68 (1.74)	+0.97 (1.94)	–
$\ln T \times \ln Y$	–	–	+0.68 (1.09)

Coefficients on the short-run (differenced) equation for $\Delta \ln C$. None of the non-linear terms are statistically significant at the 5% level, supporting the log-linear specification within the observed temperature range

10.4. Forecast Performance

Table 10 reports the non-linearity tests described in Section 5.8. None of the quadratic or interaction terms is statistically significant at the 5% level, supporting the log-linear specification within the observed temperature range.

Table 11: Dynamic out-of-sample forecast errors (mean absolute percentage deviation from realized consumption)

Sector	3-year horizon (2022:1-2025:2) (%)	1-year horizon (2024:1-2025:2) (%)
Residential	+4.50	+0.05
Commercial	+3.20	+0.30
Industrial	−0.80	+0.40

Dynamic forecasts computed from preferred VECM specifications for each sector.
A positive number indicates that the model over-predicts consumption relative to the realized series

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