



Income-dependent expansion of electricity demand for climate change adaptation in Brazil

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1. Introduction

In the last three decades, the use of energy for space cooling in residential and commercial buildings has been growing faster than any other end use [1]. Rising income and historical climatic conditions have led to a sharp increase in the penetration of cooling appliances in developing economies such as Brazil, growing in the last two decades at a pace of up to 10% per year [2]. In the future, more frequent extreme temperature events, coupled with rising global average temperatures, are expected to scale up the demand for cooling services and, in most cases, the energy necessary to produce them [3,4]. The extent by which lower heating needs may compensate for the increase in cooling needs is heterogeneous across regions, with tropical countries being the areas experiencing the largest increase in total energy demand [5].

On top of the projected timing and intensity of future temperature changes, future cooling demand across economic sectors and regions will evolve based on multiple drivers: socio-economic (population expansion, economic growth, shifts in the sectoral composition of economies); behavioural (the actions of individuals and organizations); and technological (pace of technological development) [4,5,6]. A rapidly growing area of empirical research seeks to understand how these different drivers will affect energy demand (for a review see [7,8,9]). The variation in energy demand associated with heating and cooling needs can be broken down into: i) short-term movements driven by how intensively the current stock of appliances is used (henceforth “intensive margin”) and ii) long-term adjustments driven by agents’ purchase or replacement of appliances, as well as by the pace of technological improvements, such as appliance efficiency (henceforth “extensive margin”). As most of the available empirical studies have estimated the sensitivity of energy demand to weather, based on the intensive margin

[10, 11, 12, 13, 14], one of the key aspects requiring innovation is identification of the adjustments along with the extensive margin [9].

Here, we aim to identify the long-term relationship between electricity demand and weather conditions in Brazil, a rapidly growing tropical economy. We adopt a dynamic econometric model that captures the relationship between weather variations and electricity consumption towards equilibrium, when agents have time to adjust. Furthermore, we test the hypothesis that per capita income modulates the long-term relationship between electricity demand and weather, an effect which is confirmed by studies based on micro-data [15, 16] but not typically captured through macro-level panels [16,17]. We assemble a panel dataset of monthly electricity demand of 27 Brazilian Federal States across four different sectors: residential, commercial, industrial, and rural¹. We couple energy statistics with high resolution weather data, thus enabling us to retain detailed information from the weather distribution and its geographical specificity. We test the adequacy of alternative econometric specifications and thermal discomfort measures as robustness checks. Finally, by building on the estimated response function, we quantify the mid-21st century (2041-2060) amplification of electricity demand due to moderate (RCP² 4.5) and severe (RCP 8.5) warming scenarios [20].

2. Literature Review

The empirical evidence on the impacts of climate change on electricity demand is rapidly expanding. Country-based empirical works have focused both on temperate [11,12,13,21,22] and tropical countries [15,23,24], including Brazil [14,25,26]. Multi-country panel studies have investigated the heterogeneous effect across a broad climatic group of countries, finding that the responses of tropical and temperate groups

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¹ The electricity demand statistics of the rural sector include also the electricity demand of the public sector.

² The Representative Concentration Pathways (RCPs) are a set of four pathways developed for the climate modelling community as a basis for long-term and short-term modelling experiments [17,18]. They include one mitigation scenario leading to a very low forcing level (RCP2.6), two medium stabilization scenarios (RCP4.5/RCP6) and one very high baseline emission scenario (RCP8.5).

differ across sectors and fuels [17,18]. As for Brazil, the magnitude of the projected impacts varies greatly, depending on the study: Schaeffer et al., [25] find that climate change can result in an increase of up to 9% in electricity consumption in the residential sector and up to 19% in the service sector, representing an 8% increase in total electricity consumption by 2030. Lucena et al. [26] point to a lower impact, noting that by 2035 in the worst-case scenario (RCP 8.5), climate change would increase electricity consumption in the residential and service sectors by 6% and 5%, respectively. On the other hand, Trotter et al., [14] find, only a negligible contribution of higher thermal requirements through the end of the century under the RCP 8.5 scenario. Large impacts are projected by the few model-based investigations available. For instance, according to the IEA [1], buildings in Brazil will experience a five-fold increase of cooling demand between 2016 and 2030. Finally, Invidiata and Ghisi [27] focus on three Brazilian cities and find that the decrease in heating needs induced by climate change around 2080 compensates only partially the increase in cooling needs, because the former currently constitutes a small part of buildings' energy demand in the tropical region.

Different empirical frameworks for evaluating the shocks on energy consumption due to varying weather conditions can be found in the literature [9]. Studies that adopt energy statistics aggregated to annual or monthly levels in a panel framework typically capture the elasticities of energy demand employing static models [5, 10, 11, 12, 13, 14, 28, 29, 30]. Static regression models constrain short-term elasticities of the energy response to weather to be stable over time. Yet, weather dependent energy use in the short-term is expected to differ from the long-term response because of the agent's ability to adjust energy-using durable stock over time. Adopting a static econometric model may result in a large underestimation of future energy requirements by failing to account for the rapid increase in energy-intensive durable goods in growing economies, such as Brazil's [9]. Modelling the acquisition of new energy-dependent durables typically necessitates information on stocks of air-cooling appliances. Davis and Gertler [15] and Pavanello et al., [16] are, to the best of our knowledge, the only studies that exploit micro-data on AC ownership for estimating the impacts of climate change on energy demand in tropical countries. Both studies confirm that failing to include the long-term adjustments in the econometric model underestimates the shock of electricity consumption. Because data on the penetration of AC appliances is often not available with the necessary spatiotemporal coverage, a set of empirical studies have adopted statistical workarounds to capture the effects of unobserved extensive margin adjustments. Exploiting billing-level information, Auffhammer [31] proposes a two-step approach based on the estimation of: i) the intensive margin temperature response functions using daily variation in weather and, ii) the variation in the slopes of the dose response functions across space as a function of climate. Another part of the literature relies on a dynamic econometric specification, the Error Correction Model (ECM), that makes it possible to capture the effects of long-term adjustment between the dependent variable and its regressors [17, 18, 32,33]. De Cian and Sue Wing [17] and De Cian et al., [18] adopt an ECM panel with yearly observations and global coverage for demand of three different fuels, finding that the effects of temperature are greater over the long-term than in the short-term. The adjustments captured through the dynamic ECM equation can be considered as a proxy for the extensive margin precisely because, over the long-term, a have time to adopt the set of appliances that maximize their utility. Furthermore, as new appliances and cooling technologies become available, energy efficiency can also be improved, so that the overall impact on energy demand can be mitigated by the improved efficiency. In other words, the ECM model tests the hypothesis that the overall impact of the extensive margin drivers is reflected by the dynamic response of electricity demand to weather shock over the years, without the need to observe appliance penetration rates and their energy efficiency.

Empirical specifications also differ depending on how variability in

weather is accounted for. The literature has generally adopted two different variables: (i) temperature levels, or (ii) Thermal Degree Days. Heating Degree Days (HDDs) measure the number of daily units (usually in °C) that are registered below the thermal comfort threshold, referred to as base temperature, while Cooling Degree Days (CDDs) measure the number of daily units that surpass the thermal comfort threshold (elaborated further in the Methods and Supplementary Information - SI). Changes in HDDs and CDDs have often been adopted in the studies dealing with residential demand of space heating and cooling [14, 34]. Notwithstanding their wide adoption in literature, Thermal Degree Days have the drawback of depending on the threshold values chosen for computing thermal discomfort [9]. On the other hand, direct temperature variations can be represented in the empirical framework, either as the mean temperature [18, 34], or as the exposure to different intervals ("bins") of temperature [11,12,14,17]. In the former, potential non-linear responses of energy consumption can be captured by including higher-order terms, typically the quadratic temperature term. In the latter, a more complex variable is constructed by creating a series of temperature bins covering the full range of possible temperatures and, subsequently, by counting the number of days within each bin in a given period (often years). For the only known comprehensive comparison between the two approaches, we refer readers to Deschenes and Greenstone [11], who find evidence supporting the hypothesis that the standard approach of modelling energy consumption with HDDs and CDDs does not make it possible to capture the non-linear increase in energy consumption at extremely high temperatures.

Though previous studies have investigated the impacts of climate change on Brazilian power demand [14,25,26,27], the estimation of such impacts at finer spatiotemporal scales, while also accounting for the adjustments of appliance penetration over time, is lacking. Furthermore, the empirical works evaluating the sensitivity of energy demand to weather conditions have in general not expanded the analysis beyond the residential and commercial sector [7,9]. While aggregate industrial energy demand is typically considered non-sensitive to weather variations because of the strong composition effects [7], recent empirical investigations show that the energy demand of the industrial as well as the agricultural and transport sectors, could be remarkably affected by climate adaptation [17]. The sectoral disaggregation of electricity demand adopted in this study is therefore an important methodological contribution to the literature. Furthermore, similarly to Deschenes and Greenstone [11], we test the adequacy of alternative weather variables to capture the variation of monthly electricity demand.

3. Methods

3.1. Data

We assemble a panel dataset of monthly observations for the 2004-2017 period, for all 27 Brazilian Federal States, comprising of: (i) per capita electricity consumption disaggregated by sector (residential, commercial, industrial, public and rural); (ii) socio-economic drivers (GDP per capita, sectoral electricity prices) and, (iii) weather variables measuring thermal discomfort (we adopt alternatively monthly temperature bins in the main specification and Degree Days as a robustness check). Electricity consumption is obtained from the Resenha Mensal do Mercado de Energia Elétrica [36], while average monthly electricity prices by the Agência Nacional de Energia Elétrica, ANEEL [37]. State-level monthly GDP and population are calculated by a linear interpolation of the yearly regional GDP available from the Instituto Brasileiro de Geografia e Estatística, IBGE [38]. Hourly near-surface air temperature and relative humidity data (aggregated to daily averages) used for computing the thermal discomfort indices are derived from the ERA5-Land reanalysis data made available by the European Center for Medium Range Weather Forecasting, ECMWF [39], at 0.1° gridded resolution (see SI). Using the input meteorological variables, we

assemble two thermal measurements of CDDs: dry-bulb ($CDDs_{dry}$) and wet-bulb temperatures ($CDDs_{wet}$). $CDDs_{wet}$ make it possible to account for relative humidity, in addition to temperature [40, 16]. Monthly $CDDs_{dry}$ are computed by using a threshold of 24°C, which is the value typically associated with the thermal comfort of tropical countries [41, 16]. $CDDs_{wet}$ by definition are lower in magnitude compared to $CDDs_{dry}$, and equal when $rh=100\%$, i.e., when both dry- and wet-bulb temperature are equal (see Mistry et al. [42] and Pavanello et al. [16], for further details). For this reason, we adopt two alternative thresholds, 18°C and 24°C, for computing monthly $CDDs_{wet}$. HDDs are computed by utilizing the commonly adopted threshold of 18°C, and an alternative threshold of 15°C is used as a robustness check. As an alternative thermal discomfort measure, we adopt the monthly count of days in which the daily mean temperature falls in a set of intervals (henceforth “temperature bins”). Also in this case, we test the adequacy of both dry-bulb and wet-bulb temperature, leading to two alternative measurements of the temperature bins. We adopt the temperature bins to capture the potential non-linear effect of days with extreme temperatures in Brazil, a country where many areas exhibit relatively low variability of daily temperatures [40]. We sort each daily observation into bins with a specific equidistant cut off of 3°C³. Regressions employing bins flexibly trace out piecewise linear splines. The aggregated response is, however, non-linear, broadly representing a parsimonious regression specification with a quadratic term (see Mistry et al. [42] for further details). All meteorological variables are computed at the grid cell level and are subsequently aggregated to the state-level using gridded population data from the Center for International Earth Science Information Network [43].

Concerning projections for future climate change scenarios, changes in weather exposures are assembled utilizing the NASA Earth Exchange Global Daily Downscaled climate Projections (NEX-GDDP) dataset (45)⁴. Our hindcast period, representing the current climate, ranges from 1986-2005⁵, while mid-21st century future climates are drawn from the models’ output for 2041-2060, under both RCP 4.5 and 8.5 scenarios.

3.2. Econometric model

We estimate a dynamic ECM, building on the work by [17, 18, 32, 33]. The statistical tests validating the adequacy of the ECM to our panel data, based on [46, 47], are presented in the SI (see Tables S1-S3). The fixed effect specification described below, makes it possible to check for both the presence of unit-specific unobserved factors which do not change over time⁶, and the time-specific unobserved factors that affect all units equally in each time period. The unit fixed effect in the ECM captures the influence of unobserved time-invariant country-specific factors on the average growth rate of electricity demand, while the time

³ In order to define the bin categories, two possible, commonly employed options are: (i) sorting each observation into a specific equidistant cut off (e.g., 5°C) and (ii) using the percentiles of the daily temperature distributions [12]. Including such extreme temperature exposures by means of a quantile-based analysis would require dividing the distribution range into a large number of intervals.

⁴ NEX-GDDP is a large ensemble of downscaled and biased-corrected 0.25 gridded daily meteorological fields from 21 Global Climate Models (GCMs) that simulate moderate (RCP 4.5, [18]) and vigorous (RCP 8.5, [19]) warming under the Coupled Model Intercomparison, Phase V (CMIP5) climate model exercise (see supplementary material for further details on the 21 GCMs).

⁵ The historical period in the NEX-GDDP GCMs end in 2005, with post-2006 representing years for future projections under the two warming scenarios.

⁶ A set of dummy variables capturing the effect of the economic crisis of 2008-2009 and of 2014-2016 in each Federal State [49] is included as a robustness check, given the drop in power demand experienced during these periods, especially in the industrial sector (see Figure S1 in the Supplementary Material).

fixed effect captures the influence of unobserved unit-invariant time-specific factors on the average growth rate of electricity demand [17, 48]. The equation partitions the influence of the covariates into short-term and long-term effects, captured by the terms in square and curly braces, respectively (Eq. 1a). If the ECM approach is appropriate, then $-1 < \gamma < 0$, while β and η estimate the long-term effect, that of a unit increase in thermal discomfort (h), GDP per capita (gdp) and prices (p) have on y. These long-term effects will be distributed over future time periods according to the rate of error correction γ (Eq. 1b). The specification assumes homogeneous short- and long-term coefficients, as well as the speed of adjustment within the group of 27 Federal States.

$$\Delta y_{i,t} = + \alpha V_i + \theta Z_t + [\delta \Delta gdp_{i,t} + \pi \Delta H_{i,t} + \Delta p_{i,t}] + \gamma \{ y_{i,t-1} - (\eta gdp_{i,t-1} + \beta H_{i,t-1} + p_{i,t-1}) \} + \varepsilon_{i,t} \quad (1a)$$

$$\beta^{long-term} = -(\beta / \gamma); \eta^{long-term} = -(\eta / \gamma) \quad (1b)$$

$$\beta H_{i,t-1} = \sum_{T=Binj}^{Binl} \beta_T T_{i,t-1}^{dry} \vee \sum_{T=Binj}^{Binl} \beta_T T_{i,t-1}^{wet} \vee \beta_{cdd} CDDs_{i,t-1}^{dry} + \beta_{hdd} HDDs_{i,t-1}^{dry} \vee \beta_{cdd} CDDs_{i,t-1}^{wet} + \beta_{hdd} HDDs_{i,t-1}^{dry} \quad (1c)$$

With:

- i: Federal State
- t: month (Jan 2004 to Dec 2017)
- $y_{i,t}$: natural logarithm of per capita monthly electricity consumption
- $H_{i,t}$: the vector containing the thermal discomfort indicators selected in the model, alternatively: set of dry-bulb temperature bins ($T_{i,t-1}^{dry}$), wet-bulb temperature bins ($T_{i,t-1}^{wet}$), dry-bulb CDDs ($CDDs_{i,t}^{dry}$) and HDDs ($HDDs_{i,t}^{dry}$) or wet-bulb CDDs ($CDDs_{i,t}^{wet}$) and HDDs ($HDDs_{i,t}^{dry}$).
- $gdp_{i,t}$: natural logarithm of gdp per capita
- $p_{i,t}$: natural logarithm of electricity prices
- V_i : vector of state-specific dummies
- Z_t : vector of time-specific dummies

ε_i : random errors

In a second model specification (Eq. 2a), we investigate whether the level of income, captured by the monthly GDP per capita, modulates the response of electricity consumption to thermal discomfort in equilibrium. The hypothesis tested here is whether higher levels of per capita GDP amplify the optimal response of electricity consumption to thermal discomfort. This amplification would result from an increase in the optimal level of stock penetration of durables in households characterized by higher average income [45]. Other factors that could affect the aggregate impact of per capita income on the weather response function, include a variation in the propensity to use ACs, and a variation in the tolerance for heat of households. The interaction effect captures the aggregated impact of all possible drivers contributing to identifying the income modulation effect. We test this hypothesis by having the level of GDP per capita interact with the lagged thermal discomfort variables included in the dynamic ECM⁷. The resulting specification is the following:

$$\Delta y_{i,t} = +\alpha V_i + \theta T_t + [\delta \Delta gdp_{i,t} + \pi \Delta H_{i,t} + \tau \Delta p_{i,t}] + \gamma \{ y_{i,t-1} - (\eta gdp_{i,t-1} + \beta H_{i,t-1} + \beta H_{i,t-1} * \eta gdp_{i,t-1} + \tau p_{i,t-1}) \} + \varepsilon_{i,t} \quad (2a)$$

⁷ Interaction terms in ECMs have been adopted, for instance, by Blydes and Kayser [51] and Kono and Montinola [52]. We conduct a Granger causality test [43] and find no evidence to support the hypothesis that monthly variations in thermal discomfort can affect monthly GDP per capita. We rule out the risks of model misspecification due to endogeneity when including the interaction effect between GDP per capita and thermal stress (Eq.2a).

$$\beta^{\text{long-term}} = -[(\beta + \eta \overline{gdp}) / \gamma]; \eta^{\text{long-term}} = -[(\eta + \beta \overline{h}) / \gamma] \quad (2b)$$

With:

$\beta H_{i,t-1}$ as in Eq. 1c and: $i, t, y_{i,t}, h_{i,t}, T_{i,t}, gdp_{i,t}, p_{i,t}, V_i, Z_t$ and ε_i as above.

We estimate Eq. 1a and Eq. 2a for each sector and alternative thermal discomfort variables, using ordinary least squares (OLS) fitting criterion in R statistical software version [50]⁸. The results of the tests on the presence of cross-sectional heterogeneity, serial correlation and multicollinearity among the variables are presented in the SI. Finally, in order to identify which model specification better represents the evolution of electricity over time, we compute multiple performance metrics as described in the SI.

3.3. Projections of electricity demand

In the second stage of the analysis, we combine econometrically estimated long-term elasticities with socioeconomic and climate change scenarios in order to project the future magnitude of sectoral electricity demands around mid-21st century. First, GDP and population projections around the year 2050 drive projections of baseline electricity demand. We use the downscaled shared socioeconomic pathways (SSPs) projections of population and GDP, available for the SSPs 1-3 [55, 56] (see SI). Next, climate change impacts on electricity demand are developed by forcing our fitted empirical response functions with the distributions of the derived thermal discomfort indicators under future climate warming. The plausible future (2041-2060) spread of thermal discomfort during the baseline historical period (1986-2005) is estimated by utilizing the NEX-GDDP multi-model minimum, maximum and median measurements of the monthly thermal discomfort variables. We use, alternatively, the RCPs 4.5 and 8.5 scenarios, which yield a global average temperature increase, respectively, of 1.5°C and 2°C at around the year 2050. Our climate change impact metric is derived from the computation of the differences in exposure between each GCM's simulated current and future climates, rather than on the direct comparison of simulated future exposures against their observed counterparts, since climate model simulations generally do not reproduce observed high frequency weather extremes and may therefore exhibit biases relative to current climate [57,58,59]. This approach is achieved by adopting the following 'delta' change method [57]:

$$\Psi_{i,h,s,2050} = \left[\frac{\exp\left(\hat{\beta}_s^h * \frac{1}{n} * \sum_{t=1}^n \tilde{h}_{i,t}^{Future}\right)}{\exp\left(\hat{\beta}_s^h * \frac{1}{m} * \sum_{t=1}^m \tilde{h}_{i,t}^{Historical}\right)} - 1 \right] * 100 \quad (3)$$

Ψ represents the change in electricity demand determined by future climate, relative to what is historically computed for each thermal discomfort variable (h) in each Federal State (i), at any given month (t), and for any given sector (s). More details on the delta change method are presented in the SI. The composite effect of socio-demographic and climatic components yields the projected electricity demand. Note that our approach takes into account urbanization dynamics in two ways: implicitly, as future state-level temperature shocks are derived from population-weighted gridded fields, and directly, as we derive total state-level demand by multiplying the projected per capita electricity consumption by the population count, which varies between and within regions across SSPs.

⁸ As explained in Klee and De Boef [53], ECM can be consistently estimated by OLS, as they are a reparameterization of autoregressive distributed lag (ADL) models, which in turn can be consistently estimated by OLS [54].

4. Results

4.1. Income per capita modulates the long-term adjustments to weather shocks

Across all specifications, the ECM coefficients γ, β and η (see Eq. 1a) are statistically significant ($p < 0.05$) and have the expected sign (see the Supplementary Tables S7-S9)⁹. In accordance with part of the literature [7], we find no evidence of a significant relationship between electricity and weather exclusively for the industrial sector. The model based on the temperature bins performs better than the models based on the Degree Days across all sectors (see the Supplementary Results and Supplementary Table S6). This result underscores the importance of allowing for the non-linear impact of temperatures on electricity demand, a characteristic well captured by our specification employing temperature bins. Furthermore, the specification that includes the interaction between per capita GDP and the long-term effect of weather (Eq. 1a) performs better than the specification with no interactions (Eq. 2a). Finally, we find that the model based on dry-bulb temperature bins performs better than the model based on wet-bulb temperature bins (see Supplementary Tables S9-S10). We therefore base our projections of future shocks of electricity demand on the non-linear dry-bulb temperature response function, which allows for the modulating effect of per capita GDP. Figure 1 shows the long-term coefficients ($\beta^{\text{long-term}}$) estimated from Eq. 1b and Eq. 2b¹⁰. Each $\beta^{\text{long-term}}$ element captures the marginal effect of an additional day of exposure within the corresponding interval (e.g., the average effect of one more day in the 24°C-27°C bin, versus the reference comfort level, the bin 18°C-21°C dropped in the regression¹¹). Only intervals >24°C are characterized by a significant interaction coefficient with income (see the Supplementary Tables S7 - S9). The magnitude of the long-term semi-elasticities indicates that electricity consumption tends to increase with higher thermal discomfort. We find a strong non-linear behavior, as the coefficient associated with an increase in the frequency of days with average temperature >30°C is roughly two times larger than the same coefficient of the 27°C-30°C interval, and four times larger than the 24°C-27°C interval (see Figure 1). Furthermore, sectoral differences are non-negligible: residential demand exhibits the highest response, followed by the commercial sector and lastly by the public and rural sector. The level of regional per capita GDP greatly affects the magnitude of the long-term adjustment: the coefficient associated to temperatures >30°C in the highest income decile is almost four times higher than the one in the lowest income decile in the residential sector (a 4% increase in demand versus a 1% increase), and almost three times higher in the commercial sector (a 2.5% increase versus a 0.8% increase), while for the public and rural sectors the difference is negligible. We find no

⁹ We find that results are consistent under different robustness checks, namely the exclusion of the time-fixed effects, the inclusion of the economic crisis dummy variables, and the exclusion of electricity prices. We conduct a further robustness check by changing the omitted reference bin (18°C-21°C or 21°C-24°C): for the residential and public and rural sectors the choice does not affect the value of the significant coefficients, which are always above 24°C, hence we chose as reference interval 21°C-24°C. For the commercial we find a significant coefficient for the bin 21°C-24°C, hence we chose as reference interval 18°C-21°C (see Supplementary Table S8 and S9, comparison between column "2a" and column "2a-alt").

¹⁰ As the standard errors for $\eta^{\text{long-term}}$ and $\beta^{\text{long-term}}$ cannot be taken directly as a ratio the standard errors of β and η , we use the delta method function to derive the correct standard errors and the significance test statistics [65]. The delta method function is used to derive the correct standard errors and the significance test statistics [66]. The interaction with per capita income is computed based on the variance and covariance values of the robust covariance matrix.

¹¹ We test the robustness of the results by dropping alternatively the bins 21°C-24°C and 15°C-18°C, finding no relevant difference in the ECM's results.

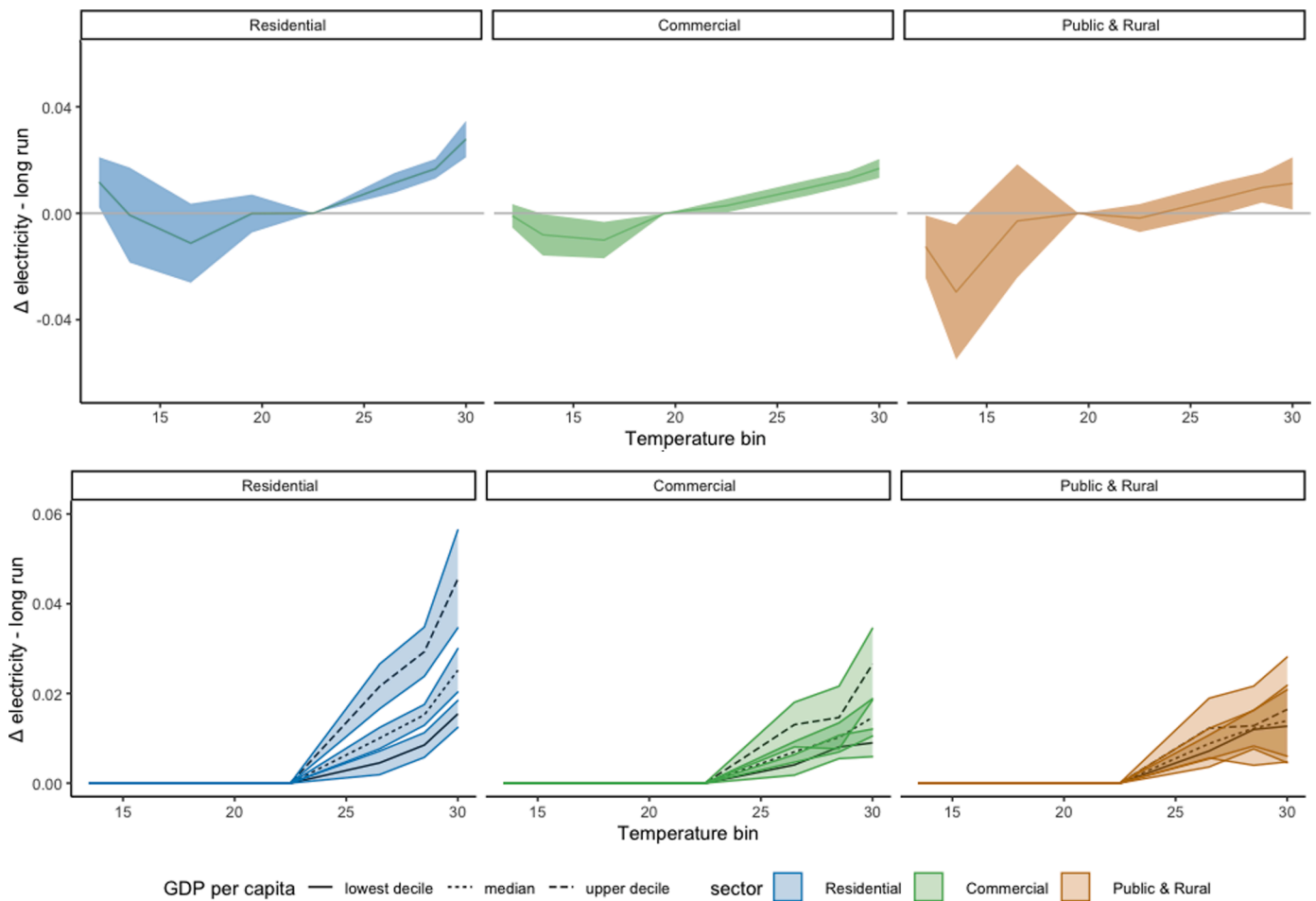


Figure 1. Response of electricity demand to thermal stress. The long-term coefficients of the temperature bins based on the ECM Eq. 1a (Panel a) and Eq. 2a (Panel b) are reported. The 95% confidence intervals (shaded regions) are based on standard errors robust to heteroskedasticity, cross-sectional and auto-correlation. Panel b presents the heterogeneous coefficients based on the interaction with income per capita in different deciles (lower, middle and upper deciles).

evidence of a statistically significant response of power demand to low temperatures, suggesting that heating requirements may be primarily met through other fuels' consumption.

The long-term response is greater than the short-term one by roughly 20%-30%, depending on the specification (see the Supplementary Tables S7-S9). This result validates the distinction between the intensive- and extensive-margin adjustments in our empirical setting, as it confirms that both income and contemporaneous weather shocks exert persistent effects on electricity demand. The error-correction coefficients are uniformly significant, ranging between -0.35 and -0.45 depending on the sector, implying that at each time period, a share of 35%-45% of the remaining gap is corrected. Electricity demand re-equilibrates after a shock so that a full equilibrium is reached within one year across the three sectors. The service sector is characterized by the most rapid response for closing the disequilibrium gap (eight months), suggesting that the propensity of replacement and penetration of energy-using appliances by commercial and public agents under disequilibrium conditions is slightly higher than the propensity of households (12 months).

Turning to the effects of socio-economic growth on the levels of electricity demand captured by the long-term coefficients of per capita GDP, we find that the residential sector's long-term adjustments are 40% higher than those of the commercial, public and rural sectors. Our results are within the range estimated by previous studies [19, 59, 63] (see the Supplementary Table S12). The coefficients associated to the price of electricity are significant but with a counterintuitive, positive sign. An inspection of the time series of prices and GDP per capita suggests that

the two are highly correlated, since the former has been evolving in the wake of increased per capita GDP over the years (see the Supplementary Figure S5). The relationship may further be biased by the imperfection of the market due to the subsidies applied to low-income households [61,62]. We drop electricity prices in our final specification in order to provide unbiased estimates of the GDP per capita coefficient.

4.2. Economic growth amplifies the relative impact of adaptation

The long-term elasticities identified through the ECM model are applied to project the sectoral future electricity demand around mid 21st-century under different socioeconomic and climatic conditions. Baseline future sectoral electricity demand, i.e., demand without climate change, varies greatly depending on the SSP (see Supplementary Table S11): total demand in 2050 is projected to increase from 20% under the SSP 3 to 85% under the SSP 1, with respect to the 2017 level. Per capita electricity consumption grows at a faster pace, respectively between 35% and 110%, depending on the SSP. The residential sector fuels most of the increase, since the demand of households in SSP 1 are more than two times larger than demand in 2017 (from 134 TWh to 164-298 TWh, depending on the SSP).

Climate change exerts an additional influence on electricity demand, deriving from the increase in thermal stress. This shock is driven by a significant shift in the number of days from the mid-temperature bins (24°C-27°C) to the high-temperature bins (27°C-30°C and >30°C), affecting in particular the North, East and Centre-West of Brazil (See supplementary Figure S1). Higher thermal stress triggers a response of

the electricity demand, computed as the ratio of sectoral electricity demand in a future climate relative to the electricity demand under the historical climate (Ψ , see Eq. 3). Figure 2 shows the value of the shock by Federal State and month under the RCP 4.5 (Supplementary Figure S2 presents the total shock for the RCP 8.5). The shocks of all sectors affected (residential, commercial, public and rural, and excluding industrial) are combined into a unique building demand shock. The projections excluding an interaction effect between weather and per capita income point to an increase in the monthly per capita electricity demand of buildings ranging between 10% and 20%, depending on the state and the period of the year (Figure 2, “No income effect panel”). Regional differences in thermal stress exacerbation result in heterogeneous effects across Federal States and seasons, as the percentage increases in total electricity demand are lowest in the South and highest in the North and Centre-West.

Markedly higher adaptation requirements originate when the amplification effect caused by economic growth is taken into account, as per capita monthly electricity demand is projected to increase by up to 30% - 45% in SSP1, 25% - 40% in SSP2 and 20% - 30% in SSP3, depending on the state. In other words, we find that when the rise in thermal stress is combined with the higher sensitivity to weather shocks of a richer economy, the relative increase in electricity demand from adaptation more than doubles in magnitude, with large differences across states and SSPs. The residential and commercial sectors are affected the most, while the combined public and rural sector is characterized by lower shocks due to the lack of a modulating effect of per capita income (Supplementary Figure S3).

4.3. Climate change and population growth fuel large additional electricity requirements

We combine baseline per capita electricity demand with the climate-driven shock and population projections by SSPs to quantify the total

additional electricity required to adapt under the alternative socio-economic and climate projections (Figure 3). Under the RCP 4.5 (RCP 8.5), adaptation increases the electricity demand of Brazilian buildings circa 2050 by up to 20-25% (25%-30%) during summer months, and up to 9%-14% (12%-18%) yearly, depending on the SSPs. This increase corresponds to additional requirements of up to 40-94 TWh (51-117 TWh) per year under the RCP 4.5 (RCP 8.5), up to one third of the total demand of buildings in 2017, equal to 300 TWh (Supplementary Table S13). This result suggests that income has a comparatively more important role than climatic exacerbation in expanding weather-dependent energy requirements. The residential and commercial sectors drive more than 80% of the total increase (Figure 3, panel b). The differences across the possible socio-economic pathways are greater than the differences across RCPs’ and GCMs’ projections. Importantly, the projections allowing for the modulation effect of income per capita results in almost three-times greater energy requirements than the projections excluding this effect (see Supplementary Table S13).

We find a remarkable heterogeneity in the increase of power demand across Federal States (Figure 4). States in the North (Acre, Amapa, Amazonas, Para, Rondonia, Roraima, and Tocantins), and Centre-West (Distrito Federal, Goias, Mato Grosso, Mato Grosso do Sul) experience the highest increases in the per capita yearly demand, with a median value across states ranging from 600 kWh/person to 1200 kWh/person, depending on the SSP and RCP. The highly populous states in the South-West (Espírito Santo, Minas Gerais, Rio de Janeiro, Sao Paulo) account for the largest share of the additional yearly demand, despite the relatively low additional per capita demand. The states of Rio de Janeiro and Sao Paulo in particular experience a remarkable increase in the total electricity requirements due to rising thermal discomfort and population growth, ranging from roughly 9 to 21 TWh in the former, and from 11 to 25 TWh in the latter, depending on the scenario. The amplification of demand is equal to roughly 30%-70% and 13%-30% of the power demand of buildings in 2017 in the two states, respectively.

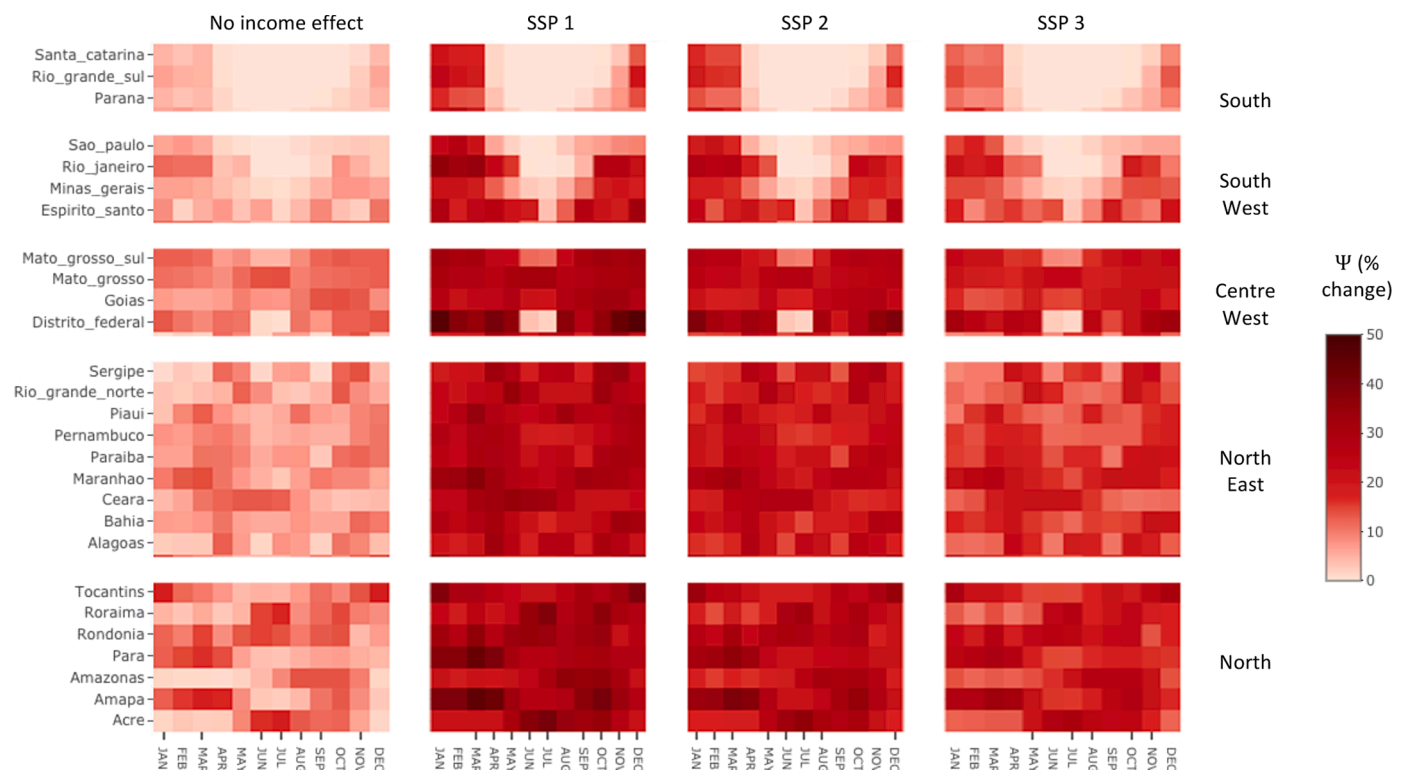


Figure 2. Delta change shock across months and Federal States under the RCP 4.5. Federal States are ordered by regional areas: North: Acre, Amapa, Amazonas, Para, Rondonia, Roraima, and Tocantins; North East: Alagoas, Bahia, Ceara, Maranhao, Paraiba, Pernambuco, Piaui, Rio Grande Norte, Sergipe; Centre-West: Distrito Federal, Goias, Mato Grosso, Mato Grosso do Sul; South: Parana, Rio Grande do Sul, Santa Catarina; South-West: Espírito Santo, Minas Gerais, Rio de Janeiro, Sao Paulo.

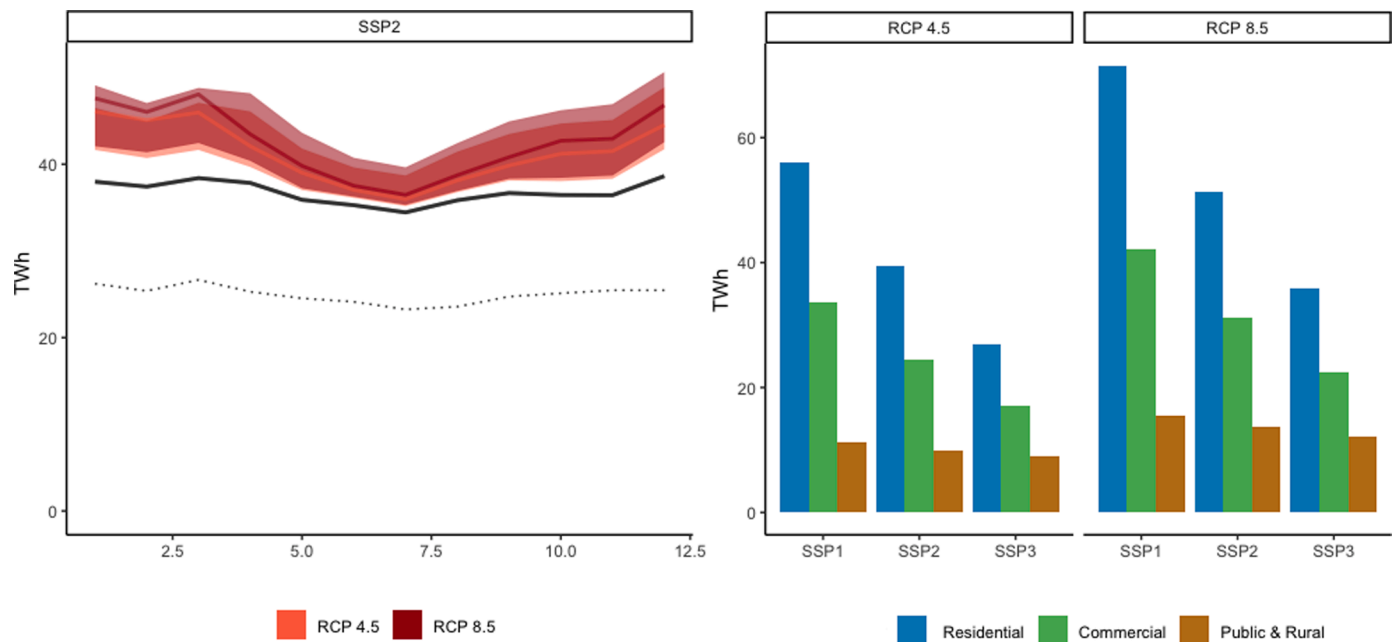


Figure 3. National electricity demand circa 2050. Panel a: Monthly electricity demand (residential, commercial public and rural sectors) in 2017 (dotted line), and in 2050 baseline (black line) and including the climate change amplification (shaded regions), under the SSP 2. Panel b: Additional yearly electricity demand circa 2050 by sector, RCP and SSP. Shaded regions in Panel a depict the GCMs’ projection range (minimum, median and maximum). All projections are based on Eq. 4a and exclude the power demand in the industrial sector.

The possibility of comparing our results with the literature is limited to the small number of studies that directly investigate future power needs in a changing climate, and either focus on Brazil at a country level [14,25,26], or report regionally disaggregated global projections [6,63,64]. The projected additional demand required for climate change adaptation is larger than previous country-level assessments based on static econometric models [14,25,26], while is in line with the results of Integrated Assessment Models [6,63,64], wherein cooling needs are estimated based on bottom-up energy demand models which allow for an increase in the penetration of cooling appliances (see Supplementary Figure S7).

5. Discussion

Our approach provides a novel, empirically grounded method to quantify how socioeconomic developments modulate the response of a population’s power demand for climate change adaptation, on top of the extent to which they scale up climate-independent demand. The dynamic econometric specification makes it possible to investigate the extent to which power demand may evolve in the future depending on the ability of agents to adjust their energy-using durable stock according to different levels of per capita income. The income amplification effect results in thermal adaptation requirements three times larger than in the case where no interaction is included. As a result, we find that income growth has a comparatively more important role than climatic exacerbations in the expansion of electricity demand for cooling. As the amplification of the shock due to per capita income growth can plausibly characterize other world areas, expanding this analysis to other rapidly growing tropical economies would be of great importance. This aspect is underscored by recent micro-level evidence on the determinants of future air-conditioning adoption in tropical economies [16]. Pavanello et al., [16], focusing on Brazil, India, Indonesia, and Mexico, find that these countries have a vast unmet demand for air-conditioning, and that appliance ownership is highly uneven across income deciles. Their results in line with our study, indicate that a household’s ability to adapt to climate change through the use of energy is linked to its socio-economic condition.

Benefits of early mitigation, expressed by the reduction in the additional electricity required to adapt under the RCP 4.5 with respect to the RCP 8.5, are non-negligible. In the pathway characterized by the largest GDP per capita and population growth among the three SSPs evaluated (SSP 1), the avoided increase in electricity demand associated with early mitigation totals 24 TWh per year, equal to one-fourth of the electricity demand of Brazil’s buildings in 2017. The benefits of early mitigation are lower under the SSP 2 (middle-of-the road) and SSP 3 (regional rivalry) pathways, respectively 17 TWh and 12 TWh per year. The difference derives from the smaller GDP and population growth projected under these pathways. Our projections therefore provide quantification of a trade-off between economic growth and sectoral adaptation costs. It is important to underscore that the long-term adjustment effects captured empirically though the error correction model are based on the business-as-usual practices over the last decades. Therefore, our projections depend on the assumption that the historical evolution of the extensive margin, including appliances’ diffusion and energy efficiency, can be an appropriate measure of the evolution of the extensive margin in the future. The adoption of energy efficient appliances at a rate higher than the historical one, let alone breakthrough technological changes, can reduce the large adaptation needs projected under the “sustainability” storyline of SSP 1. The future adoption of energy efficient appliances will be a key modulating factor because currently the average efficiency of ACs sold in Brazil is well below the efficiency of the best-performing models on the market [1]. In addition to appliance efficiency, consumer energy-saving behavior will affect the intensity of appliance use, contributing to modulate the energy consumption necessary for adapting to climate change. The purchase of a more efficient appliance may for instance increase the propensity of households to use it (i.e., would increase the intensive short-term margin shock), resulting in a rebound effect.

The adoption of more stringent energy policies can contribute to reducing the increase in energy needs for adaptation: energy standards can foster the adoption of efficient appliances, while the reduction of energy consumption subsidies would contribute to passing on to households correct market signals and reducing unnecessary electricity use. Furthermore, currently untapped alternative adaptation measures

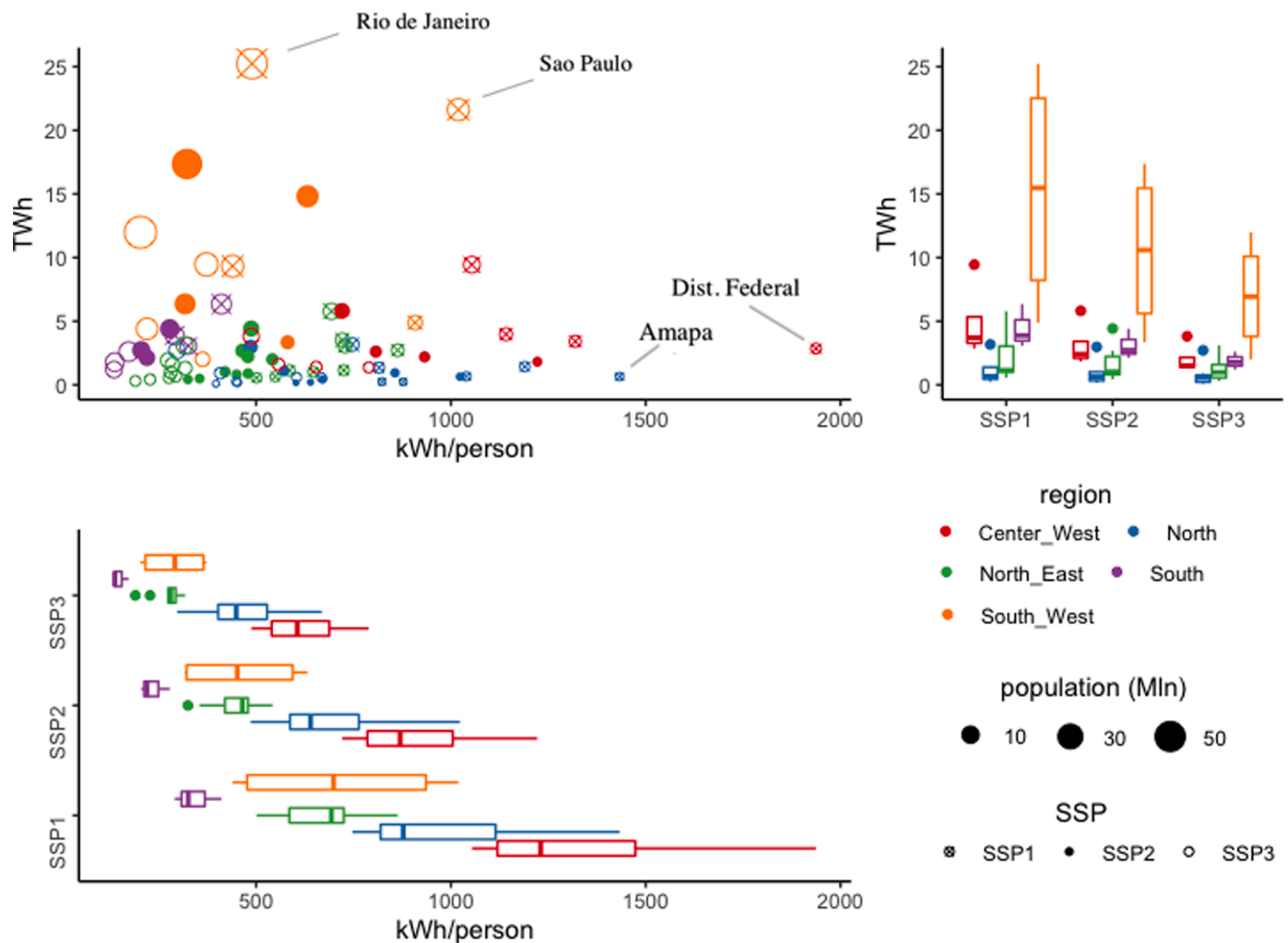


Figure 4. Additional yearly electricity demand circa 2050 by Federal State and region in RCP 4.5: increase of electricity demand per capita (kWh/person) and total (TWh). The shape of the points represents the different SSPs, the size represents the population in each state and the colour the regional classification. Boxplots represent the variables' variability within each regional group, by SSP. Values are computed based on the GCMs' ensemble median.

may be deployed in buildings through the mid 21st-century. Invidiata and Ghisi [27] for instance, find that applying a combination of passive design strategies can neutralize the increases in the thermal discomfort hours and the cooling energy usage of Brazil's residential buildings due to the effects of climate change. A decarbonized energy mix will limit GHG emissions associated with the additional electricity demand required for adaptation, making it possible to avoid a risky, vicious, and positive feedback between the economy and the climate [66]. Although Brazil's power generation mix has a relatively low carbon intensity due to its high share of hydropower, model-based projections of the decarbonization efforts of Brazil's energy system by mid-century suggest that in the scenarios unconstrained by climate policies carbon intensity may substantially rise as a result of a growing penetration of gas- and coal-fired generation [67,68]. The interaction between adaptation and mitigation policies is therefore an important area for future research [69].

6. Conclusions

In this study we investigate how climate change will shape the mid-century electricity demand of a large tropical country, Brazil, by adopting a dynamic econometric model based on sub-national data. In doing so we are contributing to the empirical literature, as previous studies have failed to unambiguously identify the role of climate change

on Brazil's power demand by using spatio-temporally aggregated data [17] or static empirical specifications [14,25,26]. The estimation of reduced-form responses of electricity demand to thermal discomfort makes it possible to identify long-term effects of climatic and socio-economic drivers on electricity consumption in the residential, commercial, public and rural sectors, while we find that industrial consumption is insensitive to the occurrence of extreme temperatures. By testing the adequacy of alternative model specifications and of alternative weather variables, we find that thermal stress affects Brazil's electricity demand: i) non linearly, and ii) by an extent dependent on the per capita income level of its states. The amplification effect on thermal discomfort from socio-economic dynamics considerably increases the projected impact of climate change (by as much as three times that of the model excluding the modulation effect of per capita income).

Our results call for a new set of integrated evaluations of demand shocks and supply side-vulnerabilities due to climate change, an approach rarely adopted [8]. Several new lines of research can broaden the identification of adaptation impacts on the energy sector. First, our quantification of the additional electricity demand is a sector shock that precedes any market adjustment. Mechanisms internal to the power market such as price signals and rebound effects could result in different market-based ex-post demand shocks. Second, implications of climate change adaptation should consider the corresponding supply-side effects of an increase in the frequency of extreme temperatures: energy system

models have projected a reduction of up to 50-70 TWh per year of hydropower (around 10% of future total hydropower capacity) due to climate change adaptation by 2050 [70]. Furthermore, the surge in the use of air-conditioners can increase not only overall power needs but also the peak demand, affecting in turn the requirements for generation capacity and distribution systems, thus placing further stress on the power system. The lack of a high-frequency power market in Brazil has constrained our analysis to an evaluation of monthly-level total demand fluctuations. As we focus only on electricity demand, our work disregards the future variation in the energy demand of fuels such as gas and oil, that can be used by households to heat their homes in the winter. Nevertheless, the available evidence suggests that consumption of fuel for heating purposes constitutes only a small part of buildings' energy demand in Brazil [27]. Finally, the trivial effect of weather shocks on industrial electricity demand, which may derive from the confounding aggregation of heterogeneous industrial processes, points to a need to conduct further assessments with higher sectoral detail.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.egycc.2022.100071](https://doi.org/10.1016/j.egycc.2022.100071).

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