REM WORKING PAPER SERIES

Has energy transition impacted the income elasticity of electricity demand? A Portuguese sectoral analysis

Sérgio Cruz

REM Working Paper 0342-2024

September 2024

REM – Research in Economics and Mathematics
Rua Miguel Lúpi 20,
1249-078 Lisboa,
Portugal

ISSN 2184-108X

REM – Research in Economics and Mathematics

Rua Miguel Lupi, 20
1249-078 LISBOA
Portugal

Telephone: +351 - 213 925 912
E-mail: rem@iseg.ulisboa.pt

https://rem.rc.iseg.ulisboa.pt/

https://twitter.com/ResearchRem

https://www.linkedin.com/company/researchrem/

https://www.facebook.com/researchrem/

Has energy transition impacted the income elasticity of electricity demand? A Portuguese sectoral analysis

Sérgio Cruz[1,2]

[1]ISEG - Lisbon School of Economics and Management
[2]ERSE - National Regulatory Authority for Energy Services

Abstract

Discussion on the decoupling between income and energy demand has been surging in the last years with focus on the effects of energy efficiency policies, renewable self-consumption and structural economic changes. On the other hand, electrification and declining of shadow economy may be putting inertia to this decoupling. Using a time-varying parameters framework, this paper provides insights on the decoupling nature between income and electricity demand supplied by the network in Portugal, disaggregated by economic sectors and using regional data between 1995 and 2022. Results suggest a declining, but positive, income elasticity of aggregated electricity demand and in the residential, services and industry sectors. For agriculture there is time invariant decoupling. The results enable to determine the importance of sensitivity analysis for electricity consumption in the context of energy transition, particularly useful for investment decisions in electricity generation and grid planning and development.

Keywords: electricity demand, decoupling, time-varying parameters, sector level data, regional data.*

1. Introduction

Energy prices are a major concern for the European Union (EU), as their escalation not only undermines the global competitiveness of the economy, but also places a financial burden on all sectors of the economy (EuropeanCommission, 2024). Looking ahead, the EU will require large infrastructure investments in electricity generation, transmission and distribution as a large part of its energy consumption shifts to electricity and old generation facilities are decommissioned. In this context, income traditionally emerges as

*I thank João Jalles, Vítor Marques and André Rocha for helpful suggestions and discussions. The usual disclaimer applies, and any remaining errors are the authors' own responsibility. The views expressed herein are those of the authors and not necessarily those of their employers or any other institutions they are affiliated with

an important driver of energy demand and its influence is deeply rooted in the planning of energy networks. In the particular case of electricity networks, income has historically been an important factor to analyze European electricity network planning and investment decisions.

Discussion has been surging about the decoupling between Gross Domestic Product (GDP) and energy/electricity demand (Brockway et al., 2021), and is usually attributed to: i) the growth of the service sector in global economies (Huntington, 2010), ii) the increase in energy efficiency, driven by central planning policies, which can lead to a decrease in the energy intensity of GDP (Kan et al., 2019),(Wu et al., 2018)(Mulder and de Groot, 2004), iii) innovation and grid modernization, a concept closely related to energy efficiency, where new applications allow energy demand to be met with less energy generation,(International Energy Agency (IEA), 2023) iv) the growth of renewable energy generation, self consumption and energy communities (Frieden et al., 2021), (Roberts et al., 2022). On the other hand, it is possible to identify two main forces that can contribute to the inertia of the decoupling behavior of income and electricity demand: i) the electrification of the economy, mainly via the transport sector where the expansion of the electric vehicles market, which, while aiming to reduce dependence on traditional fuel sources, may still exert significant pressure on electricity demand as well as significant impacts on the socio-economic landscape (Liddle et al., 2023), and ii) the decline of the informal economy, as economic activities that take place outside standard income measures become regulated (Sedmíková et al., 2021). (Liddle et al., 2020) literature assessment has concluded that the income/GDP and price elasticities of energy/electricity demand are fairly stable over time, though policy changes, economic crises/recovery/shocks, and economic transitions can cause elasticities changes in certain affected countries.

This paper advances current knowledge by: i) investigating the link between electricity consumption demanded from the network and portuguese economic income proxies, ii) disaggregating the portuguese economy by sectors, iii) using a time-varying panel econometric model (TVP) to assess changes in income elasticity, iv) using regional data (NUTS III). Furthermore, as the research focuses on electricity supplied by networks, the results provide insights, useful particularly in practical frameworks, such as the case of network investments and planning.

Following this initial overview, the paper is structured as follows: the "Literature Review" chapter provides the relevant existing knowledge on the relationship between energy demand and GDP. The "Data and Methods" chapter describes the data utilized, the methods applied and relevant assumptions, transformations, and limitations. Chapter "Main Empirical Results" presents the papers's findings primarily through charts and tables. Chapter "Conclusions" encapsulates the key messages regarding the income-electricity demand nexus, policies recommendations and outlines further research needs. Furthermore, robustness checks can be consulted in the annexes and provides the results of variations in key elements of model.

2. Literature Review

This paper explores the broader theme of decoupling GDP, resource use, and GHG emissions, as identified by (Haberl et al., 2020). Unlike existing literature, this paper distinguishes itself through its focus on grid-supplied electricity demand rather than primary energy consumption. It is detailed by economic sector, uses regional data, and provides implications for DSO and TSO investment plans.

The literature delineates four theories regarding the intricate relationship between GDP and energy/electricity consumption and account for factors such as technological progress, economic structure and energy policies in order to fully assess this relationship:

1. Neoclassical growth theory: This theory is based on the premise that energy, along with labor and capital, is a fundamental driver of economic growth. An important policy implication of this hypothesis is that energy conservation policies could potentially have a negative impact on economic growth. Examples of the application of this theory can be found in (Costa-Campi et al., 2018) and (Schreiner and Madlener, 2022).

2. Energy efficiency hypothesis: This hypothesis suggests that economies tend to become more energy efficient as they progress and technological progress takes place. It assumes that energy consumption is either a small component of real GDP or uncorrelated with income. As a result, a decoupling effect can occur where GDP continues to grow while energy consumption remains relatively stable or even declines. For example, (Cabral et al., 2020) showed that price and income are inelastic for the Brazilian electricity system.

3. Structural Change Theory (or Conservation Hypothesis): According to this theory, an increase in real GDP leads to an increase in energy consumption. This hypothesis implies that energy conservation policies, including initiatives to reduce greenhouse gas emissions, improve efficiency or implement management strategies to curb energy use, would not have a negative impact on real GDP. Changes in the structure of the economy, such as transitions from industrial to service-oriented sectors, may also affect the relationship between GDP and energy consumption. This approach is the most common when assessing the income elasticity of energy/electricity demand. The results of (Csereklyei, 2020), (Liddle et al., 2023), citeCHEN2024e36217 and the broad meta analysis conducted by (Zhu et al., 2018) show that income is a significant driver of electricity consumption, in particular in the long-run.

4. Feedback hypothesis: This hypothesis posits a bidirectional relationship between GDP and energy consumption. (Saldivia et al., 2020) found evidence of bidirectional causality in the medium and long term for most of the 50 states in the United States for the period 1963 to 2017. (Acheampong et al., 2021) found an interdependence between

energy consumption and economic growth for 23 emerging economies. (Abbasi et al., 2021) observed a long-run relationship between energy consumption and income for all sectors considered (residential, commercial, agriculture, industry and total).

The EU Directive 2019/944 (EuropeanParliament, 2019) mandates that electricity distribution system operators (DSOs) create and publish distribution network development plans (DNDPs) to integrate renewable energy, streamline storage development, support transport electrification, and inform users about network extensions. According to the Council of European Energy Regulators (CEER, 2021), factors such as electrification, storage solutions, and distributed energy resources must be considered in these planning processes. In Portugal, Directive (EU) 2019/944 was transposed into Decree-Law 15/2022 (NationalParliament, 2022), requiring both transmission and distribution system operators to provide macroeconomic analyses and long-term forecasts to identify future investment needs. Electricity transmission and distribution are managed by firms under a concession regime due to the natural monopoly characteristics of these services (Priest, 1993). Operators must submit investment plans to the national regulatory authority for evaluation and approval.

Understanding the analytic models used by these firms, especially how they assess the relationship between income and electricity demand, is crucial for evaluating their investment proposals. The Portuguese TSO conducts detailed electricity demand analyses, including comparisons with Spain, focusing on electricity intensity across three main sectors: Industry and Agriculture, Services, and Residential. The TSO uses an augmented Holt-Winters model, incorporating macroeconomic indicators and factors like weather and calendar effects for forecasting (REN, 2021). The main Portuguese DSO (serving 95% of clients) employs a hybrid model (E-Redes, 2022) combining econometric models with neural networks. The model accounts for macroeconomic effects, temperature, calendar effects, consumption inertia, energy efficiency, electric vehicle consumption, and self-consumption. It finds that electricity consumption is sensitive to economic activity and shows variations based on voltage levels and weather conditions. Energy efficiency measures project savings of 0.8% per year from 2021 to 2030, while electric vehicle consumption is projected to increase significantly. Self-consumption renewable generation has been increasing in recent years, but it has not yet reached the levels of early 2000s that was driven by cogeneration. As for the Azores DSO, it uses a combination of autoregressive, linear, and exponential models for forecasting, supplemented by estimates of exogenous factors like tourism and construction. Madeira DSO bases its forecasts on recent data and economic activity, particularly in tourism.

Regarding portuguese analysis conducted outside of the network scope, (Guevara and Domingos, 2017) using an input-output framework that used energy as input, showed a decoupling between GDP and the use of energy due to improvements in the efficiency of the energy sector, end-use energy conversion efficiency and the economic structural transition towards services. Results from (Ribeiro, 2023), while analyzing portuguese residential demand for electricity at the regional, suggested that the main drivers of consumption were electricity prices, human capital, material privation, poverty risk with a negative effect and income as positive effect (income elasticity between 0.17 and 1.27). (Ribeiro, 2023) further advocated for policies based on information campaigns and incentive programs to help fight the climate changes. Another portuguese related paper, conducted by (Sousa et al., 2012), indicated that energy consumption for the portuguese families is positively correlated with an increase in income. On a multisectorial analysis, (Silva et al., 2018)),concluded that rural population electricity consumption is more sensible to changes in the electricity prices compared to the urban population, nonetheless, showed that rural population may be less dependent on electricity, as it can easily substitute more easily with other fuels sources. Furthermore, (Silva et al., 2018) showed that the income elasticity would vary between 0.27 and 0.35.

Regarding the main factors that may change the relationship between energy (and therefore electricity) demand and income are sum up in table 1. Usually, these variables are highly related with the decarbonization targets. Next is presented the literature review which backs up these hypothesis.

Table 1: Summary of factors that may have influence on the relationship between income and energy/electricity demand

Factor	**Energy Efficiency**	**Renewables and Self-consumption**	**Electrification of the Economy**	**Structural Economic Changes**
Hypothesis	EU has taken energy efficiency as one of the cornerstones for the energy transition in order to reduce the energy consumption required to produce the same output. However, literature emphasizes the rebound effect, suggesting that an increase in energy efficiency leads to increased energy consumption due to efficiency gains, which may offset some energy savings.	The rise of decentralized renewable energy impacts the electricity demand supplied by the network, potentially distorting the relationship between income and electricity supply as well as changing the productivity of remaining supplied electricity. This is a new paradigm, though self-consumption has existed for decades in the form of fossil fuel combustion with strict regulation.	The process of increasing electricity's primary energy usage across various economic sectors aims to reduce greenhouse gas emissions, combat climate change, and transition to a more sustainable energy future, may be impacting the income elasticity of electricity demand. Its main drive is the transport sector.	A transition from more industrial to a services-oriented economic activity may alter energy usage for the same income level. Conversely, a declining shadow economy may impede decoupling between income and electricity demand.

Source: Summary based on the literature review.

Global energy scenarios largely predict a fundamental shift where energy consumption decreases while GDP continues to rise, a concept known as absolute decoupling (Brockway et al., 2021). However, historical instances of absolute decoupling are rare, and current literature suggests that income remains a major driver of energy demand. One reason for this persistent correlation is the economy-wide rebound effects from increased energy efficiency, which often exceed conventional assumptions.

Studies have examined the rebound effect, which describes how lower energy costs lead to increased energy use by consumers and producers (Sorrell and Dimitropoulos, 2008). (Berner et al., 2022a) estimated a rebound effect between 78% and 101% in France, Germany, Italy, the UK, and the US over two years. In the industrial sector, (Berner et al., 2022b) found that while energy efficiency improvements at the firm level reduce energy consumption if output is constant, the expansion of output often offsets these savings. On the residential side, (Baležentis et al., 2021) reported a decreasing rebound effect from 2000 to 2015, with notable regional variations; Portugal had smaller rebound effects compared to other regions.

(Brockway et al., 2021) reviewed the magnitude of economy-wide rebound effects and how they are factored into global energy models. Their findings suggest that these effects could diminish more than half of the expected energy savings from improved efficiency. (Rajabi, 2022) concluded that there is no consensus on the rebound effect's magnitude or its implications for environmental policy, after reviewing forty-one years of research.

The EU's "Clean Energy for all Europeans" package aimed to empower end consumers within the energy market, emphasizing the involvement of "active consumers" and promoting both individual and collective renewable energy self-consumption. However, while renewable energy self-consumption may hold the premise for decoupling energy consumption from income and fostering sustainability, it also presents socio-economic challenges. There are concerns across some EU countries that energy communities could exacerbate economic disparities, potentially leading to unfair imbalances and higher system charges for vulnerable groups and non-participating consumers ((Frieden et al., 2021), (Roberts et al., 2022)). (Bielig et al., 2022) conducted a comprehensive literature review on the social impact of energy communities, revealing that while there are benefits, these communities face significant social and economic hurdles. These challenges include shifts in power dynamics and strucutres, ensuring equal access (including diversity and inclusion considerations), fair infrastructure siting, acknowledgment of marginalized groups, and reducing energy poverty. Addressing these complexities is crucial for maximizing the positive impact of energy communities while mitigating potential drawbacks.

(Gryparis et al., 2020) highlight that the rise in electricity demand due to high electric vehicles (EVs) penetration in the EU can significantly reduce GHG emissions if met with renewable energy sources (RES). (Fuinhas et al., 2021) support this view, advocating for policies that utilize battery electric vehicles (BEVs) to combat climate change in the EU. However, socio-economic implications also arise from EV adoption. (Dall-Orsoletta et al., 2022) note that high upfront costs and inadequate charging infrastructure may disproportionately impact impoverished and rural communities, potentially limiting EV ownership and affecting electricity demand across networks.

(Mangipinto et al., 2022) estimate that peak power system demand could increase by 36-51% with a fully electric fleet but suggest that smart charging strategies, supported by strong political backing, could mitigate this impact and optimize energy consumption patterns. (Inci et al., 2024) emphasize the socio-economic benefits, noting that smart grid energy stored in EVs can reduce overall electricity bills through optimized tariff schemes. However, (Lee and Brown, 2021) question the social equity of incentive regimes and the costs of network reinforcement required as EV adoption grows.

The electrification hypothesis posits that replacing fossil fuel-based technologies with electrically powered ones will increase efficiency, reduce energy demand, and impact emissions positively as power generation decarbonizes. This hypothesis suggests that electricity's share in final energy consumption could rise from 20% in 2022 to over 27% by 2030 in the Net Zero Emissions by 2050 (NZE) scenario (IEA, 2023). (Liddle et al., 2023) found that income elasticity for electricity has declined to about 0.3, attributing this to demand saturation for energy services and not to economy-wide efficiency improvements: "Hence, were more energy services to become electrified (e.g., transport), we would expect the GDP elasticity of economy-wide electricity demand to increase".

At the national level, (Felício et al., 2024) and (Martins et al., 2022) examined electrification's role in decarbonizing the Portuguese energy system. They argue that implementing energy policies, such as renewable electricity incentives and conservation measures, can reduce carbon intensity and primary energy consumption relative to GDP. However, they also highlight the significant challenge of fully decarbonizing the Portuguese energy system, which would require electrifying nearly all energy currently imported.

For an european analysis by economic segment it is emphasize the JRC science for policy report ((Triollet et al., 2021)). It reported that the energy consumption in the EU- has been fairly stable between 2000 and 2019, with a decrease in 2020. In terms of energy intensity it drops from 0.14 (toe/thousand of euro) in 2000 to 0.10 in 2020, same trend is observable in the energy consumption per capita. On the residential level, energy consumption has been stable, but as disposable income, population and increase in the floor area of houses increases and cooling and heating degree days are controlled for, it is possible to assess a positive impact of energy efficiency measures in the EU lead to energy savings. The final energy consumption of the tertiary sector increased significantly from 2000 to 2020 (+15.9%), yet energy consumption per employee observed a decrease of -7.2%. Weather and climate conditions, energy prices, remote working, as well as economic and employment growth can be factors affecting energy consumption in the tertiary sector. On the industrial level it was observed a decrease in electricity consumption, accompanied by an increase on the value added to the GDP. The report concluded on the positive impact and effectiveness of policies aimed at promoting energy efficiency in the EU.

As for the argument related to changes in the structure of the economy, several authors have found that the share of industry follows an inverse-U pattern (Schäfer, 2005) which counterbalances the argument in favour of policies towards economic restructuring to service-oriented sectors may lead to energy efficiency improvements. Technical innovations tend to introduce more energy-using appliances to households and energy-saving techniques to industry ((Judson et al., 1999). Furthermore, according to (Csereklyei et al., 2016)) «technological change within industries explains more of the decline in energy intensity globally than does broad structural change». As for informal economy (Canh et al., 2021) showed that a higher shadow economy would induce a higher level and a higher intensity of energy consumption, including a higher renewable energy use.

3. Data and Methods

3.1 Data

For the present analysis it was collected annual data regarding electricity consumption (EC), population (POP), cooling degree days (CDD), heating degree days (HDD), gross value added (GVA), wages per employee (TW), final consumer electricity prices (REP, SEP, AEP, IEP) and gas prices (D1, D2, I2 and I3). Data was gathered with annual frequency between 1995 and 2022 for each municipality, and aggregated to 2013 NUTS III regions(N=644 observations) For the electricity consumption and GVA, data was collected per sector of economy, namely domestic, services, agriculture and industry.

Dependent variable: Electricity consumption per capita – Electricity consumption supplied by the network, at all voltage levels, per capita. Source: Directorate-General for Energy and Geology (DGEG) and National Statistics Institute (INE)

Independent variables:

1. Wages – Gross amount in cash and/or goods, paid to the worker, on a regular basis with respect to the reference period, for time worked or work provided during normal and extraordinary periods. It also includes the payment for compensated but not performed hours (vacations, holidays, and other paid absences). Source: INE

2. GVA Services - Value created by any unit involved in a services productive activity, which corresponds to the balance of the production account, including resources, production, and employment, and intermediate consumption, before the deduction of fixed capital consumption. Source INE

3. GVA Agriculture - Value created by any unit involved in an agriculture productive activity. Source: INE

4. GVA Industry - Value created by any unit involved in an industry productive activity. Source: INE

5. Cooling Degree Days (CDD) – a weather-based technical index designed to describe the need for the cooling energy requirements of buildings. The severity of the heat in a specific time period taking into consideration outdoor temperature and average room

temperature. The calculation of CDD relies on the base temperature, defined as the highest daily mean air temperature not leading to indoor cooling. If $T_m \geq 24°C$ then $CDD = \sum_i (T_{im} - 21°C)$, else $CDD = 0$, where T_{im} is the mean air temperature of day i. Source: Eurostat

6. Heating Degree Days – a weather-based technical index designed to describe the need for the heating energy requirements of buildings. The severity of the cold in a specific time period taking into consideration outdoor temperature and average room temperature. The calculation of HDD relies on the base temperature, defined as the lowest daily mean air temperature not leading to indoor heating. The calculation of CDD relies on the base temperature, defined as the highest daily mean air temperature not leading to indoor cooling. If $T_m \geq 15°C$ then $HDD = \sum_i (18°C - T_{im})$, else $HDD = 0$, where T_{im} is the mean air temperature of day i. Source: Eurostat.

7. Electricity prices - it was considered the final prices reported by DGEG and published by Eurostat. These are divided into household and non-household and then by band of annual consumption. For residential prices it was considered the band of consumption DB (between 1MWh and 2,5MWh of annual consumption) For services prices it was considered the band of consumption DD (between 5MWh and 15MWh of annual consumption). For agriculture it was considered the band of consumption IB (between 20MWh and 500Wh of annual consumption) and a higher voltage level conection. For Industry it was considered the band of consumption IC (between 500MWh and 2000Wh of annual consumption) and a higher voltage level conection. Total demand model used DC band of consumption (proxy of the mean between residential and services prices) and IC band of consumption. Representative bands were chosen according to the reports by National Regulatory Authority for Energy Services(ERSE, 2024). Source:DGEG and Eurostat.

8. Gas prices - it was considered the final prices reported by DGEG and published by Eurostat. These are divided into household and non-household and then by band of annual consumption. For residential prices it was considered the band of consumption D1 (between 0 TJ and 0.02 TJ of annual consumption. For services prices it was considered the band of consumption D2 (annual consumption between 0.02TJ 0.2TJ). For agriculture prices it was considered the band of consumption I2 (between 1TJ and 10TJ of annual consumption). For industry prices it was considered the band of consumption I1 (between 10TJ and 100TJ of annual consumption). Bands of consumption for gas prices are lower in energy compared to electritity prices bands in order to account for the fact that only a partial electricity demand can be met with gas consumption. Total demand model used D2 band of consumption (proxy of the mean between residential and services prices) and I2 band of consumption. Given uncertainties regarding these variables, robustness checks on electricity and gas prices were further conducted in later stages. Source:DGEG and Eurostat. The introduction of natural gas in Portugal was based on objectives of

energy and environmental policy. The use of natural gas, replacing other fuels, allowed for the reduction of atmospheric emissions of the vast majority of pollutants associated with combustion. Investments on the gas network distribution were concentrated between the late 90's through 00's which puts the portuguese gas grid as one of the most recent in europe (ERSE, 2003). Cylinder LPG was more common in the 90's and earlies 00's, therefore, in order to have a full series of prices for gas, LPG and natural gas prices were combined to form a time-series between 1995 and 2022 (by applying LPG prices variation into natural gas prices).

9.Other Variables – Prices variables were deflated using total consumer price index, provided by INE. Population was used mainly to normalize electricity demand and GVA, and refers to a group of people who, regardless of whether they are present or absent in a particular accommodation at the time of observation, have lived at their usual place of residence for a continuous period of at least 12 months prior to the time of observation. Number of supply points was used as an alternative variable for population, without substantial differences on the qualitative results. Normalization per capita was found more common in the literature.

Table 2 shows the main descriptive statistics of the variables collected.

Table 2: Descriptive statistics of variables.

Variables	Minimum	Average	Maximum	Standard Deviation
Services Consumption (MWh)	32,676.9	515,973.7	5,318,604.6	935,703.9
Agriculture Consumption (MWh)	1,586.2	37,114.7	172,806.8	31,441.7
Industry Consumption (MWh)	28,384.996	667,654.660	4,068,066.091	856,297.497
Residential Consumption (MWh)	56,084.237	503,476.140	3,739,831.921	719,204.551
Total Wages (EUR/Emp)	8,080.3	16,262.1	28,486.3	3,491.2
GVA_Services (millions EUR)	455.9	5,371.7	66,114.7	11,397.7
GVA_Agriculture (millions EUR)	44.9	201.5	780.7	123.6
GVA_Industry (millions EUR)	184.8	1,826.5	12,062.7	2,405.8
CDD (Days)	2.3	153.2	585.4	119.1
HDD (Days)	443.6	1,194.9	2,303.9	405.8
Residential Electricity Prices (EUR/MWh)	177.2	217.4	258.5	20.2
Services Electricity Prices (EUR/MWh)	155.2	187.7	229.5	15.9
Agriculture Electricity Prices (EUR/MWh)	142.1	149.9	205.9	22.2
Industry Electricity Prices (EUR/MWh)	116.8	149.9	205.9	22.2
Gas Prices D1 band (EUR/GJ)	17.1	27.1	37.7	5.5
Gas Prices D2 band (EUR/GJ)	15.9	23	31.1	3.8
Gas Prices I2 band (EUR/GJ)	9.4	14.8	31.9	4.5
Gas Prices I3 band (EUR/GJ)	7,3	12,6	30,1	4,4
Population (number of persons)	81,007.0	427,764.4	2,891,663.0	592,601.3

Source: DGEG,ERSE, Eurostat and INE.

Table 3 presents a regional data visualization of key regional variables, highlighting the maximum and minimum values observed along with their corresponding regions and years. In short, Area Metropolitana de Lisboa is the biggest electricity consumer in all 4 sectors, on the other hand Alto Tamega is the region with the lowest demand. Similar pattern can be found for GVA, nevertheless it is possible to see that most minimum values (of electricity consumption and GVA) occur in the beginning of the data set (1995), evidence of a positive trend in the following years.

Table 3: Minimum and Maximum values for the regional data

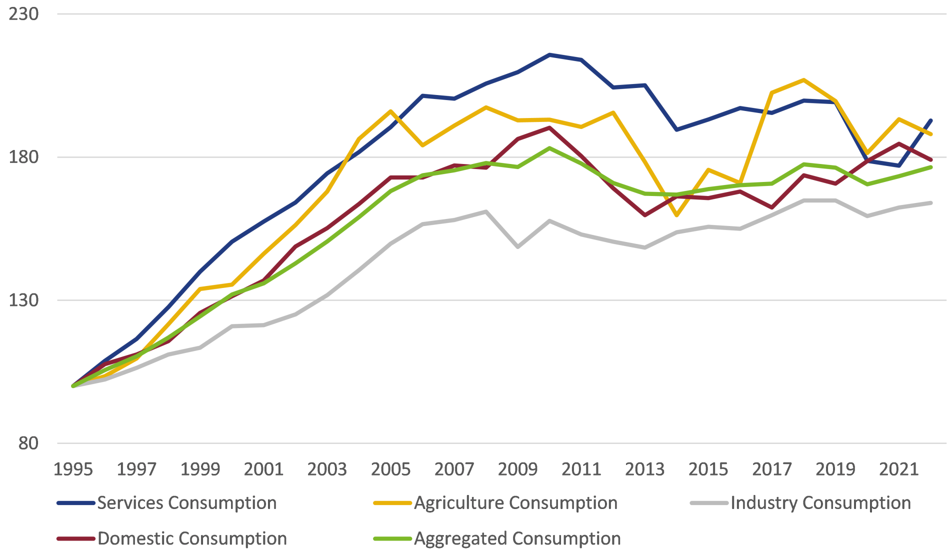
Variable	**Minimum**		**Maximum**	
	Region	**Year**	**Region**	**Year**
SC	Alto Tamega	1995	Area Metropolitana de Lisboa	2010
AC	Alto Tamega	2016	Area Metropolitana de Lisboa	2013
IndC	Alto Tamega	1995	Area Metropolitana de Lisboa	2007
RC	Alto Tamega	1995	Area Metropolitana de Lisboa	2010
TW	Douro	1995	Area Metropolitana de Lisboa	2010
GVA_S	Alto Tamega	1995	Area Metropolitana de Lisboa	2022
GVA_A	Alto Tamega	2022	Leziria do Tejo	1995
GVA_Ind	Alto Tamega	1995	Area Metropolitana de Lisboa	2000
CDD	Oeste	2008	Beira Baixa	2022
HDD	Algarve	1997	Alto Tamega	2004

Source: DGEG, ERSE, Eurostat, INE.
Note: SC: Services electricity consumption; AC: Agriculture electricity consumption; IndC: Industry electricity consumption; RC: Residential electricity consumption; TW: Total wages; GVA_S: Gross value added for services; GVA_A: Gross value added for agriculture; GVA_Ind: Gross value added for industry; CDD: Cooling Degree Days; HDD: Heating Degree Days; REP: Residential electricity prices; SEP: Services electricity prices; IndAEP: Industry and Agriculture electricity prices; GPD2: Gas prices for residential sector; GPD3: Gas prices for services sector; GPI2: Gas prices for agriculture and industry sectors; POP: Population.

Figure 1 shows the evolution of electricity consumption (index 100 in 1995), disaggregated by economic sector. Between 1995 and 2009 was a period characterized by high growth rates, in which services demand had an increase greater 100%, agriculture and residential consumption almost doubled, and industry lagged behind achieving only a 60% increase in consumption in relation to 1995. The period between 2010 and 2016 was characterized by a slow decline in electricity consumption transverse to all segments. This period is coincident with the debt crisis hitting Portugal that induced a cut in the GDP between 2011 and 2013 and a slow GDP growth between 2014 and 2016. A slight increase ever since has been seen in place but still inferior to the increase in the GVA and wages for the same period, which points to a decrease in electricity intensity that may be due to an improvement in electricity efficiency. It should be noted that an increase in consumption, in any sector, does not necessarily signal a sectorial shift towards any sector of activity, but can be rather a sign of energy transition, or a shift towards electricity as a key energy source for the sector.

Figure 2 shows, on a more disaggregated analysis, that GVA of services has been increasing in a faster pace than electricity consumption since 2007, leading to a slightly

Figure 1: Evolution of the Electricity Consumption between 1995 and 2022 - (Index 1995=100)



Source: DGEG.

higher decrease of electricity intensity than residental. For agriculture and industry the relation between income and electricity consumption does not seem to change substantially since 2013. In all sectors, in 2022, the electricity intensity is below the maximum values observed and point to a small decreasing trend.

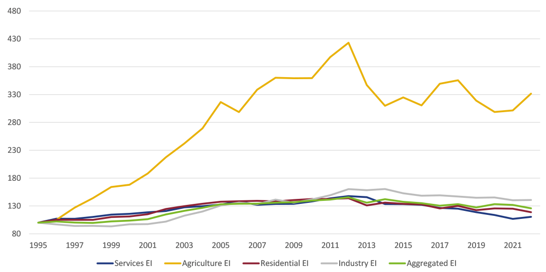
Portugal has experienced a slight decrease in electricity intensity since early 2010's, as shown in Figure 2. This trend can be theoretically attributed to several factors, including both national and european energy efficiency measures, as well as the development of gas networks, which intended to diversify fuels sources and, thus, have partially replaced the demand for more expensive, less cleaner and safe fuels such as bottled LNG and wood. Another hypothetical justification is the recent advances and innovative processes such as distributed energy resources or demand response technologies (e.g. smart meters). On opposite, replacing fossil fuel technologies with electric powered equipment has been on the rise (for example stock of electric vehicles).

The data seems to point to a slight increase in the efficiency of electricity consumption via network supply since the early 10's, as pointed by (ERSE, 2023). Industry and residential are the sectors with greater electricity intensity in absolute terms and thus, have a more theoretical potential to decoupling electricity demand supplied by the grid from income from energy efficiency measures (energy efficient heating and cooling systems in buildings and improvements in insulation), energy communities and self-consumption. Nevertheless, it is the services sector that is registering the biggest decline in relative terms, that may be explained by the digitalization of the sector (Lange et al., 2020) and (Matthess et al., 2023). Agriculture's increase in 90's and 00's is explained by modernization (electricity powered machinery) and fuels diversification where stable and gaseous fuels were abandoned in favor of electricity and investment in renewable capacity (Sharma and Saini, 2020).

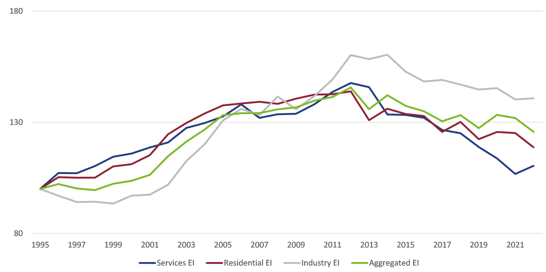
As the main hypothesis for the disconnection between GDP and energy (but also on electricity) demand is attributed to the energy efficiency measures, it is provided a short summary of the recent developments of european energy efficiency policies.

The Energy Efficiency Directive (EED), introduced in 2012, was a cornerstone of the EU's energy policy, setting a target to improve energy efficiency by 20% by 2020 ((EuropeanParliament, 2012)). Member States were required to set national targets to keep primary and final energy consumption below specific thresholds and implement binding measures to achieve these goals.

Figure 2: Evolution of the Electricity Intensity between 1995 and 2022 (1995=100)



(a) Subfigure 2a: Electricity Intensity for all sectors (1995-2022)



(b) Subfigure 2b: Electricity Intensity excluding agriculture (1995-2022)

Over time, the EED underwent significant revisions to align with the EU's evolving climate and energy goals. The 2018 revision, part of the Clean Energy for All Europeans package, raised the energy efficiency target to 32.5% by 2030, with Member States tasked with cutting annual energy consumption by 4.4% until then. National energy and climate plans were developed to outline strategies for achieving these targets.

In 2021, the EU updated the directive to reflect its "energy efficiency first" principle, proposing a 9% reduction in energy consumption by 2030, while addressing energy poverty and public building efficiency. The REPowerEU plan, in response to the Ukraine crisis, further increased this target to 13% ((EuropeanCommission, 2022)).

The most recent revision, enacted in October 2023, mandates a final energy consumption reduction of 11.7% by 2030 ((EuropeanParliament, 2023)), with Member States obligated to achieve cumulative energy savings and focus on public sector energy use and building renovations.

Each revision of the EED has progressively strengthened the EU's energy efficiency efforts, aligning them with broader climate objectives and responding to challenges like energy supply disruptions and energy poverty.

According to the Regulation (EU) 2018/1999 ((EuropeanParliament, 2018b)), at the national level the PNEC (National Energy and Climate Plan, (DGEG, 2023)) is the main instrument of energy policy, that set a target of 35% for energy efficiency by the year 2030. This target is more ambitious than that set by Directive (EU) 2018/2002 ((EuropeanParliament, 2018a)), being established 2.5 percentage points higher than the corresponding one in said Directive.

Overall, the impact of the factors contributing to the decoupling between income and electricity demand seems to outweigh the force of electrification in strengthening this relationship. Nevertheless, it is important to control for other variables, such as gas and electricity prices and weather conditions, in order to avoid omitted variable biases that may lead to inconsistent estimates of the coefficients.

3.2 Methods

This paper aims to test the Structural Change Theory, also known as the Conservation Theory. This theory posits that income serves as the primary macroeconomic driver of electricity consumption (see for example citecosta2018electricity for a summary of the theories). Network operators use income data in their investment plans to justify proposed investments to meet decarbonisation, flexibility procurement, security of supply and linkage with other energy sectors. In addition, national institutions, such as ERSE and DGEG, adopt an approach rooted in conservation theory.

The basis model is a first differences random effects panel model (see Annex A for Hausman test (Hausman, 1978)), in order to make all time series stationary (see Annex B for unit root tests (Levin et al., 2002)). Its math notation consists of:

$$\begin{aligned}\Delta \ln\left(\mathrm{ED}_{i,t}^{s}\right) =&\alpha_i + \hat{\beta}_1 \Delta \ln\left(\mathrm{CDD}_{i,t}\right)\\ &+ \hat{\beta}_2 \Delta \ln\left(\mathrm{HDD}_{i,t}\right) + \hat{\beta}_3 \Delta \ln\left(Y_{i,t}^{s}\right)\\ &+ \hat{\beta}_4 \Delta \ln\left(\mathrm{EP}_{i,t}^{s}\right) + \hat{\beta}_5 \Delta \ln\left(\mathrm{GP}_{i,t}^{s}\right) + u_{i,t}\end{aligned} \tag{1}$$

where the dependent variable is the annual growth rate of per capita electricity consumption provided by the network in sector s in region i and time t. CDD and HDD are cooling and heating degree days and Y is the income proxy for sector s. EP and GP are the electricity and gas prices, respectively.*

It was applied first differences to the panel data, which has the following advantages(Wooldridge, 2010) and (Pesaran, 2015):

- Elimination of time-invariant effects: By differentiating, time-invariant variables, such as individual fixed effects or unobserved heterogeneity, are eliminated. This

*Regional dummy effects were not statistical significant. Time effects were discarded as they may increase the risk of overfitting the model to the data, in particular when the number of parameters is large relative to the sample size. Overfitting can result in poor out-of-sample prediction performance and biased parameter estimates. Additionally, further it will be used a TVP framework, known for its hunger for observations.

can help in isolating the effect of time-varying variables and better understanding the dynamic relationships between variables over time.

- Addressing serial correlation: First differentiating helped in addressing serial correlation, which occurs when error terms in a time series are correlated with each other. This can improve the efficiency of the estimates and the reliability of the statistical inferences drawn from the model.
- Stationarity of all variables: Some variables were not stationary in level (for example Wages), so taking the first difference render them stationary. Thus, it ensures that the statistical properties of the series remain constant over time, making it easier to establish causality between variables.
- Interpretability: Differentiating simplifies the interpretation of coefficients in the model. For instance, after differentiating, coefficients can be interpreted as the marginal effect of a one percent change in the independent variable on the dependent variable, holding other factors constant. As first differentiating is conducted to all variables, the interpretation of the coefficients is equal between variables.

The model of interest will be the time-varying parameter random effects panel model developed by (Casas and Fernández-Casal, 2022) based on (Sun et al., 2009) and (Casas et al., 2021), among others. They proposed a semi-parametric approach, based on kernel regressions, a method that estimates the conditional expectation of a response variable given one or more predictor variables. The kernel function assigns weights to nearby data points, with closer points receiving higher weights. This allows the model to capture local patterns in the data without assuming a specific functional form. Also, the kernel function controls the bandwidth parameter, which is the width of the smoothing window and influences the degree of smoothing applied to the data. Thus, in this model coefficients are allowed to vary over time. Three main advantages can be attributed to time-varying parameter models, namely:

1) Flexibility - TVP models allow parameters to change over time, providing greater flexibility (Casas and Fernández-Casal, 2022) to capture evolving relationships in the data. This flexibility can better account for changes in economic behavior, policy regimes or other structural changes that affect the relationships being modeled. In this analysis, this is useful for understanding how the relationship between income and grid-supplied electricity has changed over the analysis period. Compared to other possible methods, it can allow for gradual transitions and the identification of multiple regimes (and non-recurrent), where the underlying data generating process switches between different states or regimes.

2) Improved forecasting accuracy - by capturing time-varying dynamics TVP models can often provide more accurate forecasts than static parameter models, especially in situations where relationships between variables change over time. This can be particularly

valuable in economic forecasting, where accurate prediction of future trends is essential for decision making. In this context, there is a nice set of TVP-VAR models applied to electricity demand forecasting. (Lindner and Clements, 2020)

3) Time-varying parameter models can generally be robust to cross-sectional dependency and misspecification because they allow parameters to change over time, thereby allowing for different relationships between variables. However, the degree of robustness depends on the specific model and the nature of the cross-sectional dependence(Casas and Fernández-Casal, 2022).

Overall, the advantages of time-varying parameter models lie in their ability to capture the evolving nature of economic relationships, to adapt to changing data patterns and to provide more accurate forecasts and structural insights than static parameter models. In (Sun et al., 2009), the authors proposed a local linear least squares method to estimate a fixed effects varying coefficient panel data model when the number of observations across time is finite. The authors also introduce a data-driven method to automatically find the optimal bandwidth for the proposed FE estimator. The model is further developed by (Casas et al., 2021) and (Casas and Fernández-Casal, 2022) into a R package (TvReg) that allows the estimation of the pooled, fixed and random effects estimator.

Literature on the application of time-varying parameters is extensive, in particular when applied along with vector autoregressive models. (Ozturk and Arisoy, 2016) used a time-varying parameters approach to show that oil demand in Turkey is mainly driven by income while the price elasticity is statistically insignificant, which indicates that oil is a necessity good. (Arisoy and Ozturk, 2014) also used this methodology to prove that the income and price elasticities of industrial and residential electricity demand in Turkey were always lower than unity, result that was not corroborated by (Wang and Mogi, 2017) in Japan, as income elasticity was superior to 1. Also with TVP framework, (Papież et al., 2022) further proved that Dutch TTF and the German NCG were a leading source of shocks to natural gas price and volatility, but with a weakening link.

The area of research in statistics involving the application of kernel smoothing techniques to linear models with time-varying coefficients has become very popular. This combination allows for flexibility and robustness to functional form misspecification of parametric models, but also avoids the "curse of dimensionality", i.e. when many regressors are considered, the rate of convergence of these models decreases with the number of regressors.

Adapted to the research question, the math notation of the TVP model is:

$$\Delta \ln \left(\mathrm{ED}_{i,t}^{s}\right) = \alpha_i + \sum_{j=1}^{5} \beta_{j,t} \Delta \ln \left(X_{j,i,t}\right) + u_{i,t} \tag{2}$$

where:

$$\hat{\beta}_{j,t} = \frac{\sum_i \Delta \ln \left(X_{j,i,t}\right) K\left(\frac{t-t_i}{h}\right) \Delta \ln \left(\mathrm{ED}_{i,t}^s\right)}{\sum_i K\left(\frac{t-t_i}{h}\right)}, \tag{3}$$

where the kernel function K is the gaussian and the bandwidth h is selected by leave one out cross validation:

$$K\left(\frac{t-t_i}{h}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{\left(\frac{t-t_i}{h}\right)^2}{2}} \tag{4}$$

4. Main Empirical Results

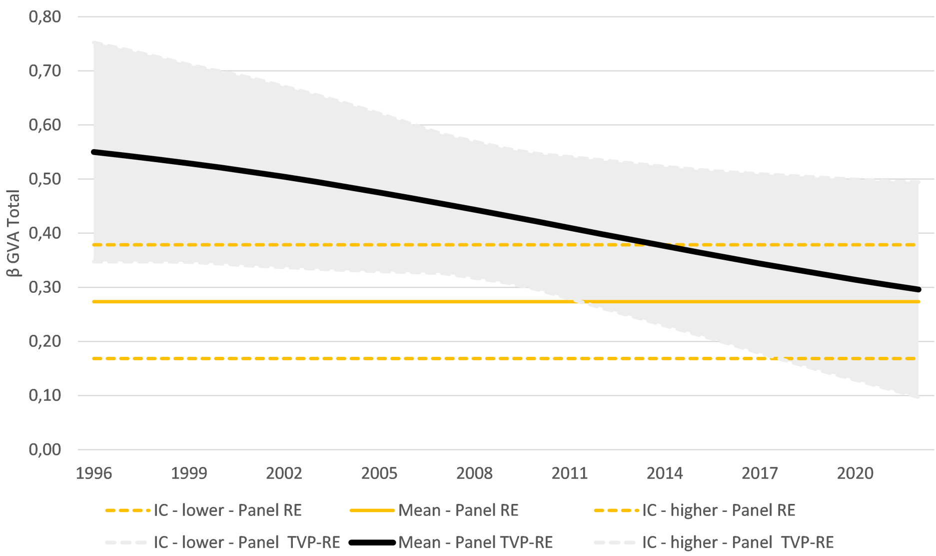
4.1 Aggregated Demand

The initial model considered the total sum of electricity consumption for each sector as the dependent variable. GVAs were also aggregated and included as independent variable. Electricity prices were represented by two bands: one for households and services and another for agriculture and industry. A similar procedure was followed for gas prices.

The results are presented in figure 3, table 4, and annex C and D (the reults show, in addition to the mean of the coefficients, the lower and upper bounds of the confidence intervals at the 95% level) .The inclusion of confidence bands aims to illustrate the intervals for the true parameters. However, this can affect the readability of the time-varying mean of the coefficients, requiring the simultaneous interpretation of both the figure and the table.

In 1996, a 1% increase in aggregated GVA corresponded to a 0.550% increase in total electricity consumption. By 2022, however, the same increase in GVA led to only a 0.296% increase in electricity consumption, suggesting a gradual decline in income elasticity.

Figure 3: TVP-RE coefficient and fixed RE coefficient for total GVA in the total electricity demand model



Notes: Refer to Annex C and D for control variables' coefficients Black line represents the evolution of mean TVP_RE coefficient for the income proxy. Grey lines represent the lower and upper bands at 95% confidence level with 100 runs bootstrapping. Increasing runs did not yield substantial differences. Yellow continuous line represents the estimated coefficient with the fixed coefficients RE model. Dashed yellow lines represent the confidence intervals for the static RE model

Table 4: Panel TVP-RE coefficients for GVA in the total electricity demand model

Year	IC 95% Lower	**Mean**	IC 95% Higher
1996	0.344	**0.550**	0.756
1997	0.343	**0.544**	0.744
1998	0.343	**0.537**	0.730
1999	0.342	**0.529**	0.716
2000	0.340	**0.521**	0.703
2001	0.337	**0.513**	0.689
2002	0.333	**0.504**	0.675
2003	0.329	**0.495**	0.661
2004	0.325	**0.485**	0.645
2005	0.318	**0.475**	0.633
2006	0.309	**0.465**	0.621
2007	0.300	**0.454**	0.609
2008	0.291	**0.443**	0.595
2009	0.286	**0.432**	0.579
2010	0.274	**0.421**	0.568
2011	0.261	**0.410**	0.559
2012	0.248	**0.399**	0.550
2013	0.233	**0.387**	0.541
2014	0.214	**0.376**	0.538
2015	0.198	**0.365**	0.533
2016	0.181	**0.355**	0.528
2017	0.163	**0.344**	0.525
2018	0.146	**0.334**	0.522
2019	0.129	**0.324**	0.519
2020	0.110	**0.314**	0.518
2021	0.092	**0.305**	0.518
2022	0.074	**0.296**	0.517

The first difference random effects model with fixed coefficients estimated the elasticity of GVA at 0.273%, slightly lower than the TVP model.

The income elasticity reported in the literature review ranges from zero or positive but insignificant to slightly above 1 (see, for example, (Zhu et al., 2018). Gross value added coefficients in this paper were slightly lower than expected mean, though well within the interval given by literature.

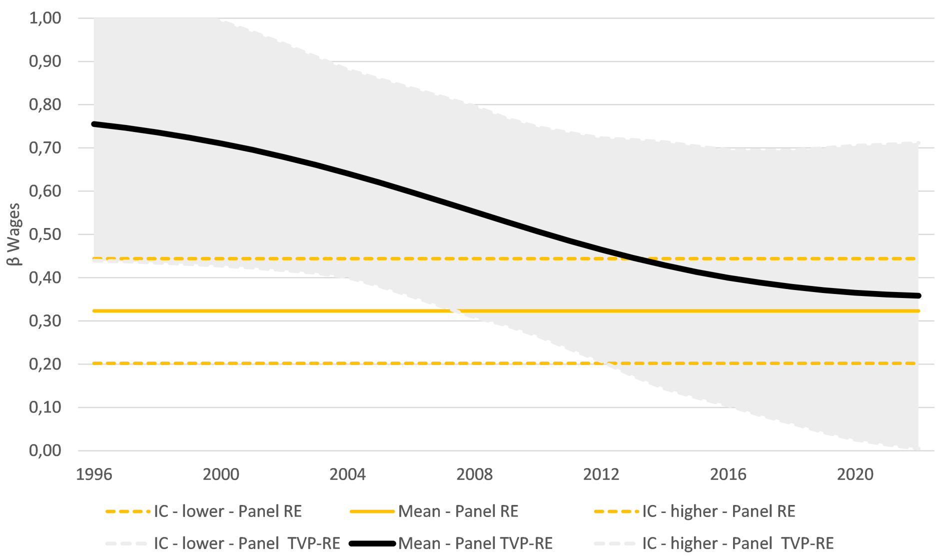
4.2 Residential Demand

For the residential model, refer to figure 4 and table 5. In 1996 an increase in 1% of the wages would lead to an increase of 0.755% in the residential consumption. In 2022 the elasticity dropped to 0.358%.

These values for the coefficients are within the range expected based on the literature review, as findings of (Burke and Csereklyei, 2016), (Chen et al., 2024), (Csereklyei, 2020) or (Sousa et al., 2012) show.

As income rises, households tend to consume more electricity, but the rate of increase in electricity consumption is less than the rate of increase in income. This means that electricity falls within the "normal good" category, as most literature supports. Only a minority of studies would put it either as "luxury good" or completely inelastic.

Figure 4: TVP-RE coefficient and fixed RE coefficient for Wages in the residential's electricity demand model

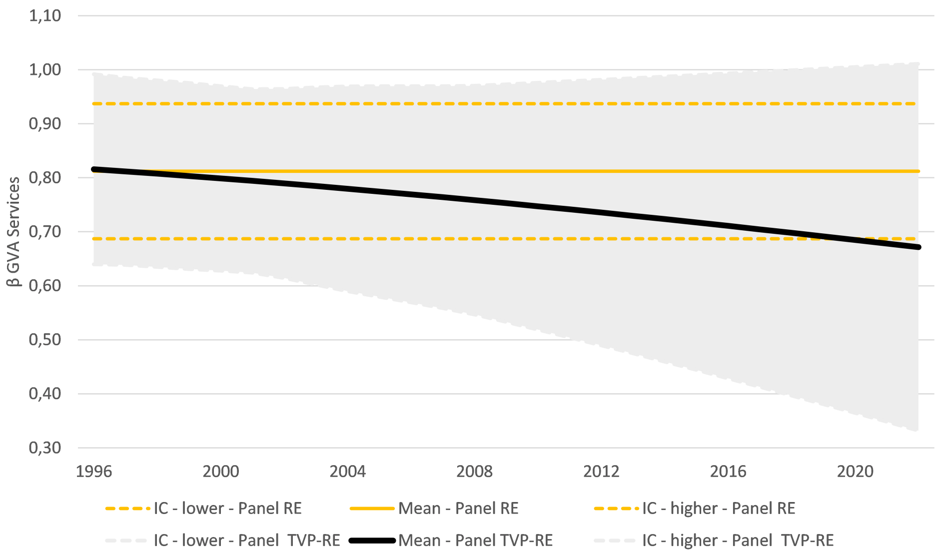


Notes: Refer to Annex E for control variables' coefficients; Black line represents the evolution of mean TVP-RE coefficient for the income proxy. Grey lines represent the lower and upper bands at 95% confidence level with 100 runs bootstrapping. Increasing runs did not yield substantial differences. Yellow continuous line represents the estimated coefficient with the fixed coefficients RE model. Dashed yellow lines represent the confidence intervals for the static RE model

4.3 Services Demand

For the services model, refer to figure 5 and table 5. In 1996, an increase in 1% of the Services GVA would lead to an increase of 0.816% in the electricity consumption. In 2022 the elasticity dropped to 0.671%. Services have the highest income elasticity.

Figure 5: TVP-RE coefficient and fixed RE coefficient for services GVA in the services' electricity demand model



Notes: Refer to Annex F for control variables' coefficients; Black line represents the evolution of mean TVP-RE coefficient for the income proxy. Grey lines represent the lower and upper bands at 95% confidence level with 100 runs bootstrapping. Increasing runs did not yield substantial differences. Yellow continuous line represents the estimated coefficient with the fixed coefficients RE model. Dashed yellow lines represent the confidence intervals for the static RE model

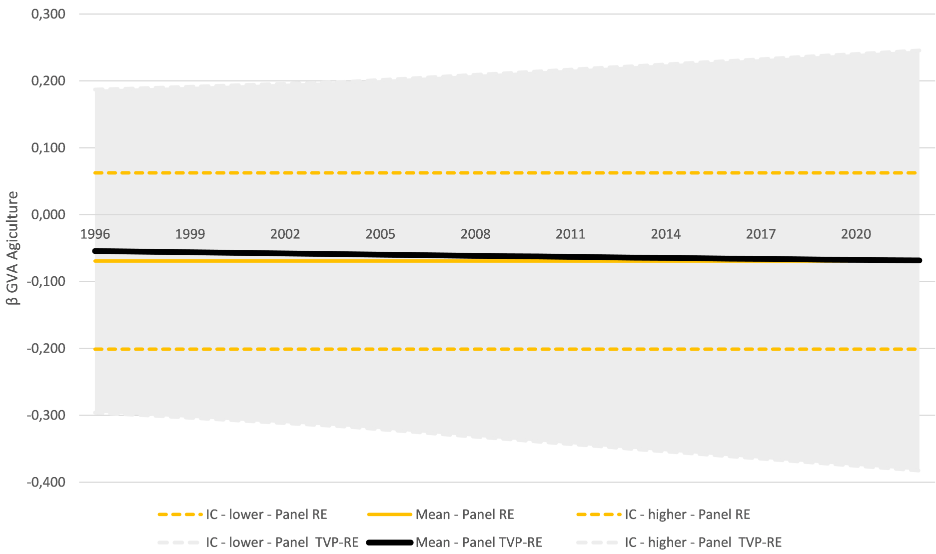
Nonetheless, the true parameter can still be localized in the non-decreasing grey area and within the bands given by the fixed coefficients model.

Energy intensive subsegments of the services sector are prevalent in the portuguese economy, in particular tourism but also healthcare, transportation, real estate and construction services, digital services and telecommunications that may explain the high sensivity of electricity consumption to the services sector.

4.4 Agriculture Demand

For the agriculture, refer to figure 6 and table 5. In 1996 an increase in 1% of the Agriculture GVA would lead to a decrease of 0.054% in the electricity consumption. In 2022 the elasticity dropped to -0.069%. Agriculture and has the lowest income coefficients, with its impact being very small in comparison with the domestic and services segment. As mentioned the modernization of sector, including the adoption of power electricity technologies (for irrigation for example) along with fuels diversification has been increasing substantially the electricity consumption in the sector and, together with an economic shift to other sectors that impact negatively the GVA of the sector, results on insignificant income elasticity.

Figure 6: TVP-RE coefficient and fixed RE coefficient for Agriculture GVA in the agriculture's electricity demand model



Notes: Refer to Annex G for control variables' coefficients: Black line represents the evolution of mean TVP-RE coefficient for the income proxy. Grey lines represent the lower and upper bands at 95% confidence level with 100 runs bootstrapping. Increasing runs did not yield substantial differences. Yellow continuous line represents the estimated coefficient with the fixed coefficients RE model. Dashed yellow lines represent the confidence intervals for the static RE model

Inelastic income elasticity can be found in the literature, though they are not the majority: (Zhu et al., 2018) and (Cabral et al., 2020)

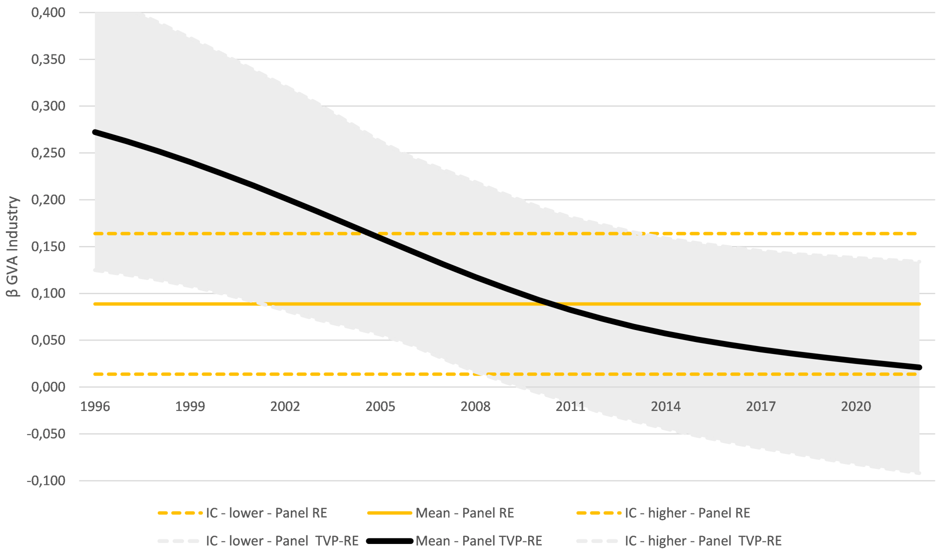
4.5 Industry Demand

For the Industry model, refer to figure 7 and table 5. In 1996 an increase in 1% of the Agriculture and Industry GVA would lead to an increase of 0.272% in the electricity consumption. In 2022 the elasticity dropped to 0.021%. These results follow the findings of (Cabral et al., 2020) closely and inside the range provided by (Zhu et al., 2018) and but they are lower than the findings of (Csereklyei, 2020), (Cialani and Mortazavi, 2018) and (Liddle and Hasanov, 2022)

Comparing the results with those obtained for the services sector, there is no evidence that a shift for a more services sector economy would lead to a weaker relationship between income and electricity demand, as GVA Services elasticity has a higher magnitude and significance than the Agriculture and Industry sector.

In general, the income elasticity for electricity demand tends to be lower in the industrial sector compared to the residential sector. This is because residential electricity

Figure 7: TVP-RE coefficient and fixed RE coefficient for Industry GVA in the industry's electricity demand model



Notes: Refer to Annex H for control variables' coefficients; : Black line represents the evolution of mean TVP-RE coefficient for the income proxy. Grey lines represent the lower and upper bands at 95% confidence level with 100 runs bootstrapping. Increasing runs did not yield substantial differences. Yellow continuous line represents the estimated coefficient with the fixed coefficients RE model. Dashed yellow lines represent the confidence intervals for the static RE model

consumption is often driven by various factors related to household behaviors, lifestyles, and comfort levels, which can be more sensitive to changes in income.However, it's essential to note that the income elasticity may not be directly comparable between sectors due to differences in consumption patterns, technological advancements and specific energy efficiency measures.

In contrast, industrial electricity demand may be influenced more by factors such as technological efficiency and substitution of input factors, rather than be directly linked to changes in income.

Overall, the results seem to point to a common trend the aggregated demand per economic segment: the nexus between income and electricity supplied via power grid is losing magnitude. Residential and Services are the sectors with the biggest decrease, but for agriculture and industry there could be an argument for absolute decoupling.

Robustness checks (presented in Annex I) confirms the robustness of the main findings that income remains a driver of electricity consumption in most situations. Residential and Services sector remain as the sectors with the highest income elasticity but with steep declines since 1996. On the other hand, agriculture and industry electricity consumption supplied by the network have the lowest sensitivity to the income. If policies are targeting the reduction or maintenance of electricity consumption, in particular in times where demand it is met with fossil fuels, then measures that increase the income of agriculture

Table 5: TVP-RE coefficients for total demand and by economic sector

Year	Aggregated GVA	Wages	GVA Services	GVA Agriculture	GVA Industry
1996	0.550	0.755	0.816	-0.054	0.272
1997	0.544	0.746	0.812	-0.055	0.263
1998	0.537	0.736	0.808	-0.056	0.252
1999	0.529	0.724	0.803	-0.056	0.240
2000	0.521	0.711	0.799	-0.057	0.228
2001	0.513	0.696	0.794	-0.057	0.215
2002	0.504	0.679	0.790	-0.058	0.202
2003	0.495	0.661	0.785	-0.059	0.188
2004	0.485	0.641	0.780	-0.059	0.174
2005	0.475	0.620	0.775	-0.060	0.159
2006	0.465	0.598	0.769	-0.060	0.145
2007	0.454	0.575	0.764	-0.061	0.131
2008	0.443	0.552	0.759	-0.061	0.118
2009	0.432	0.529	0.753	-0.062	0.105
2010	0.421	0.507	0.747	-0.063	0.093
2011	0.410	0.485	0.742	-0.063	0.082
2012	0.399	0.465	0.736	-0.064	0.073
2013	0.387	0.446	0.730	-0.064	0.065
2014	0.376	0.429	0.723	-0.065	0.057
2015	0.365	0.413	0.717	-0.065	0.051
2016	0.355	0.400	0.711	-0.066	0.045
2017	0.344	0.389	0.705	-0.066	0.040
2018	0.334	0.379	0.698	-0.067	0.036
2019	0.324	0.371	0.691	-0.067	0.032
2020	0.314	0.365	0.685	-0.068	0.028
2021	0.305	0.361	0.678	-0.068	0.024
2022	0.296	0.358	0.671	-0.069	0.021

and industry are neutral. As the income in the services and residential sector, it should be met with policies that can counterbalance the increase of electricity consumption, such as renewable generation.

A note about the control variables:

1. Cooling Degree Days – Generally, CDD was not statistically significant and had magnitude close to 0. It was kept in the model to assess asymmetrical effects of the temperature in the electricity consumption and because it is theoretically possible that this variable is correlated with electricity consumption and can gain further influence in the future due to the rising of temperatures originated by climate changes(Pablo-Romero et al., 2023).

2. Heating Degree Days – HDD had a positive coefficient in the aggregated demand and services sector. In the residential, agriculture and industry the coefficient was positive, but the intervals of confidence allowed for the true parameter of the model to be negative. Full demand model resulted on a 0.07 coefficient within positive intervals of confidence (For instance, (Csereklyei, 2020) found significant coefficients around 0.01 for temperature). It should be note that regressions without considering income variables yielded higher values for the HDD coefficient. It was the introduction of income variables that affected negatively the magnitude of the coefficient, thus, indicating, that when the temperature is too low, the increase in electricity consumption is correlated and dependent on the income.

3. Final Electricity Prices – Generally, the income elasticity varies between insignificance (aggregated and services demand) and a maximum for the household sector (-0.7). These values are consider within the expected given the previous literature as long-run electricity price elasticity is consider to be in the -0.5 and -1.0 range, but with smaller intervals when measuring short-run effects.

4. Final Gas Prices – Coefficients for gas prices were low on magnitude and statistically insignificant indicating a low substitution effect between electricity demand and gas prices. Future policy directions and environmental considerations, in particular the development of renewable gases, will play an important role on the feasibility and desirability of such substitution.

5. Conclusions and Policies Implications

This study explored the evolution of income elasticity in electricity demand across different economic sectors in Portugal, using regional data and disaggregated sectoral analysis. The findings revealed that income remains a significant factor driving electricity consumption, especially in the residential and services sectors, where elasticity was the highest, followed by the industrial sector. The agricultural sector, however, exhibited signs of full decoupling. Aggregated income elasticity varied between 0.27 and 0.59 over the period studied, highlighting its ongoing importance in shaping electricity demand patterns. These results are critical for developing effective national energy and climate policies, particularly in addressing the rising energy prices that challenge the European Union's global competitiveness and economic stability.

In terms of policy recommendations, increasing investment in renewable energy capacity is essential, although it must be carefully managed to avoid over-investment and the risk of curtailment. Targeted support for sectors with high income elasticity, particularly through promoting self-consumption, could help reduce dependence on the grid. Additionally, as (Liu et al., 2022) suggests, improving institutional quality can help the electricity sector better navigate the challenges posed by the energy transition. Furthermore, incentivizing energy-efficient technologies through subsidies, tax credits, and public awareness campaigns, as highlighted by (Ribeiro, 2023), would help offset declining elasticity while promoting more efficient energy use. A flexible regulatory framework will also be necessary to support energy communities and new technologies, minimizing social and economic impacts during the transition.

Moreover, targeted assistance for low-income households is crucial for ensuring equitable access to energy-efficient solutions. Programs like RePower EU (EuropeanCommission, 2022) provide a model for offering financial support, subsidies for home retrofits, and job training, helping vulnerable populations manage energy costs while contributing to broader sustainability goals. Distribution and transmission system operators should refine their models to better account for potential reductions in income elasticity when forecasting electricity demand, ensuring more accurate planning and investment. Future research should focus on understanding the underlying factors contributing to the observed changes in income elasticity, including energy efficiency measures, self-consumption, electric vehicles, and shifts in the economic structure, to provide deeper insights for policy formulation.

Annex A

Table 6: Hausman Test Results for Fixed and Random Effects Models

Model	Hausman Test Statistic (chi-sq)	p-value
Residental Model	0.30644	0.9975
Services Model	0.54864	0.9902
Agriculture Model	RE and FE generate identical estimates	
Industry Model	RE and FE generate identical estimates	
Aggregated Model	RE and FE generate identical estimates	

Annex B

Table 7: Levin-Lin-Chu Unit-Root Test Results

Variable	z	p-value
RC	-10.048	$<$ 2.2e-16
SC	-11.751	$<$ 2.2e-16
AC	-15.173	$<$ 2.2e-16
IndC	-13.610	$<$ 2.2e-16
TW	-4.2274	1.2e-05
GVA_S	-6.0689	6.4e-10
GVA_A	-16.132	$<$ 2.2e-16
GVA_Ind	-12.425	$<$ 2.2e-16
CDD	-31.345	$<$ 2.2e-16
HDD	-27.674	$<$ 2.2e-16
DB	-14.248	$<$ 2.2e-16
DC	-14.248	$<$ 2.2e-16
DD	-10.248	$<$ 2.2e-16
IB	-15.122	$<$ 2.2e-16
IC	-15.471	$<$ 2.2e-16
D1	-13.241	$<$ 2.2e-16
D2	-13.589	$<$ 2.2e-16
I1	-10.268	$<$ 2.2e-16
I2	-11.308	$<$ 2.2e-16

Annex C

Table 8: Panel TVP-RE coefficients for HDD, DC, and IC in the total electricity demand model

	HDD			**DC**			**IC**		
	IC 95% lower	**Mean**	IC 95% higher	IC 95% lower	**Mean**	IC 95% higher	IC 95% lower	**Mean**	IC 95% higher
1996	0.003	**0.034**	0.065	-0.064	**0.000**	0.000	-0.175	**-0.072**	0.030
1997	0.004	**0.035**	0.065	-0.062	**0.000**	0.000	-0.175	**-0.072**	0.031
1998	0.005	**0.035**	0.066	-0.062	**0.000**	0.000	-0.175	**-0.072**	0.031
1999	0.006	**0.036**	0.067	-0.062	**0.000**	0.000	-0.175	**-0.071**	0.032
2000	0.007	**0.037**	0.067	-0.062	**0.000**	0.000	-0.175	**-0.071**	0.033
2001	0.008	**0.038**	0.068	-0.062	**0.000**	0.000	-0.175	**-0.071**	0.033
2002	0.008	**0.039**	0.070	-0.062	**0.000**	0.000	-0.175	**-0.070**	0.034
2003	0.009	**0.040**	0.071	-0.063	**0.000**	0.000	-0.175	**-0.070**	0.035
2004	0.009	**0.041**	0.073	-0.065	**0.000**	0.000	-0.175	**-0.070**	0.035
2005	0.009	**0.042**	0.075	-0.068	**0.000**	0.000	-0.174	**-0.069**	0.035
2006	0.011	**0.043**	0.076	-0.071	**0.000**	0.000	-0.173	**-0.069**	0.034
2007	0.012	**0.045**	0.078	-0.074	**0.000**	0.000	-0.173	**-0.069**	0.035
2008	0.013	**0.046**	0.079	-0.077	**0.000**	0.000	-0.173	**-0.068**	0.036
2009	0.014	**0.048**	0.081	-0.081	**0.000**	0.000	-0.173	**-0.068**	0.037
2010	0.016	**0.049**	0.082	-0.084	**0.000**	0.000	-0.174	**-0.068**	0.038
2011	0.018	**0.051**	0.083	-0.088	**0.000**	0.000	-0.175	**-0.068**	0.040
2012	0.018	**0.052**	0.086	-0.091	**0.000**	0.000	-0.176	**-0.068**	0.041
2013	0.018	**0.054**	0.090	-0.095	**0.000**	0.000	-0.176	**-0.067**	0.041
2014	0.019	**0.055**	0.092	-0.099	**0.000**	0.000	-0.176	**-0.068**	0.041
2015	0.018	**0.057**	0.096	-0.101	**0.000**	0.000	-0.176	**-0.068**	0.041
2016	0.018	**0.059**	0.099	-0.102	**0.000**	0.000	-0.176	**-0.068**	0.040
2017	0.018	**0.060**	0.102	-0.106	**0.000**	0.000	-0.175	**-0.068**	0.038
2018	0.018	**0.062**	0.105	-0.109	**0.000**	0.000	-0.174	**-0.069**	0.037
2019	0.018	**0.063**	0.108	-0.112	**0.000**	0.000	-0.174	**-0.069**	0.035
2020	0.018	**0.064**	0.111	-0.116	**0.000**	0.000	-0.175	**-0.070**	0.035
2021	0.018	**0.066**	0.114	-0.119	**0.000**	0.000	-0.177	**-0.071**	0.036
2022	0.018	**0.067**	0.116	-0.123	**0.000**	0.000	-0.180	**-0.071**	0.038

Annex D

Table 9: Panel TVP-RE coefficients for D2, I2, and CDD in the total electricity demand model

	D2			I2			CDD		
	IC 95% lower	**Mean**	IC 95% higher	IC 95% lower	**Mean**	IC 95% higher	IC 95% lower	**Mean**	IC 95% higher
1996	-0.039	**0.037**	0.112	-0.040	**0.027**	0.093	-0.001	0.007	0.015
1997	-0.040	**0.037**	0.113	-0.037	**0.028**	0.092	-0.001	0.007	0.015
1998	-0.042	**0.037**	0.115	-0.034	**0.029**	0.091	-0.001	0.007	0.014
1999	-0.043	**0.037**	0.116	-0.031	**0.029**	0.090	-0.001	0.007	0.014
2000	-0.045	**0.036**	0.118	-0.028	**0.030**	0.088	-0.001	0.006	0.014
2001	-0.047	**0.036**	0.118	-0.027	**0.031**	0.089	-0.001	0.006	0.014
2002	-0.049	**0.035**	0.119	-0.027	**0.032**	0.091	-0.001	0.006	0.014
2003	-0.052	**0.034**	0.119	-0.028	**0.033**	0.093	-0.001	0.006	0.013
2004	-0.054	**0.032**	0.119	-0.028	**0.033**	0.094	-0.001	0.006	0.013
2005	-0.058	**0.030**	0.119	-0.029	**0.034**	0.096	-0.001	0.006	0.013
2006	-0.062	**0.028**	0.119	-0.030	**0.034**	0.098	-0.001	0.006	0.012
2007	-0.066	**0.026**	0.118	-0.030	**0.034**	0.099	-0.001	0.005	0.012
2008	-0.069	**0.024**	0.117	-0.031	**0.035**	0.101	-0.001	0.005	0.011
2009	-0.073	**0.021**	0.116	-0.032	**0.035**	0.102	-0.001	0.005	0.011
2010	-0.077	**0.019**	0.114	-0.032	**0.035**	0.103	-0.001	0.005	0.010
2011	-0.081	**0.016**	0.112	-0.033	**0.036**	0.104	-0.001	0.005	0.010
2012	-0.085	**0.013**	0.110	-0.034	**0.036**	0.105	-0.001	0.004	0.010
2013	-0.089	**0.010**	0.108	-0.035	**0.036**	0.107	-0.002	0.004	0.010
2014	-0.092	**0.006**	0.105	-0.035	**0.036**	0.107	-0.002	0.004	0.010
2015	-0.096	**0.003**	0.102	-0.035	**0.036**	0.107	-0.002	0.004	0.010
2016	-0.099	**0.000**	0.100	-0.036	**0.036**	0.108	-0.002	0.003	0.009
2017	-0.103	**-0.003**	0.097	-0.037	**0.036**	0.109	-0.003	0.003	0.009
2018	-0.106	**-0.006**	0.094	-0.040	**0.036**	0.111	-0.003	0.003	0.009
2019	-0.110	**-0.009**	0.092	-0.042	**0.035**	0.113	-0.003	0.003	0.009
2020	-0.114	**-0.012**	0.090	-0.043	**0.035**	0.113	-0.004	0.003	0.009
2021	-0.118	**-0.015**	0.088	-0.045	**0.034**	0.114	-0.004	0.002	0.009
2022	-0.121	**-0.017**	0.086	-0.048	**0.034**	0.115	-0.004	0.002	0.009

Annex E

Table 10: Panel TVP-RE Coefficients for Residential's regression

Year	Wages			CDD			HDD			DB			D2		
	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher
1996	0.440	0.755	1.071	-0.003	0.011	-0.016	-0.034	0.022	0.078	-0.486	-0.259	-0.032	-0.196	-0.038	0.121
1997	0.438	0.746	1.055	-0.003	0.011	-0.016	-0.034	0.023	0.080	-0.491	-0.262	-0.034	-0.199	-0.038	0.123
1998	0.435	0.736	1.037	-0.003	0.011	-0.016	-0.035	0.023	0.082	-0.495	-0.266	-0.037	-0.201	-0.038	0.126
1999	0.432	0.724	1.017	-0.003	0.011	-0.017	-0.036	0.024	0.085	-0.500	-0.270	-0.040	-0.203	-0.038	0.127
2000	0.428	0.711	0.993	-0.003	0.011	-0.017	-0.038	0.025	0.088	-0.505	-0.275	-0.045	-0.203	-0.038	0.127
2001	0.424	0.696	0.968	-0.003	0.011	-0.017	-0.039	0.027	0.092	-0.511	-0.280	-0.050	-0.204	-0.039	0.126
2002	0.417	0.679	0.940	-0.003	0.011	-0.017	-0.040	0.028	0.096	-0.516	-0.286	-0.056	-0.205	-0.040	0.125
2003	0.411	0.661	0.910	-0.003	0.011	-0.018	-0.041	0.029	0.100	-0.520	-0.291	-0.063	-0.210	-0.042	0.126
2004	0.401	0.641	0.881	-0.004	0.011	-0.018	-0.042	0.031	0.104	-0.523	-0.297	-0.072	-0.215	-0.044	0.127
2005	0.381	0.620	0.859	-0.004	0.011	-0.018	-0.043	0.033	0.109	-0.528	-0.303	-0.079	-0.223	-0.046	0.130
2006	0.358	0.598	0.838	-0.004	0.010	-0.019	-0.044	0.036	0.115	-0.532	-0.309	-0.087	-0.233	-0.049	0.134
2007	0.333	0.575	0.818	-0.005	0.010	-0.019	-0.044	0.038	0.120	-0.536	-0.315	-0.094	-0.243	-0.053	0.138
2008	0.308	0.552	0.796	-0.005	0.010	-0.020	-0.043	0.041	0.125	-0.540	-0.320	-0.100	-0.248	-0.056	0.136
2009	0.290	0.529	0.768	-0.005	0.010	-0.020	-0.043	0.044	0.131	-0.545	-0.325	-0.104	-0.255	-0.060	0.136
2010	0.266	0.507	0.748	-0.006	0.009	-0.021	-0.042	0.047	0.137	-0.551	-0.329	-0.107	-0.265	-0.063	0.139
2011	0.236	0.485	0.735	-0.006	0.009	-0.021	-0.041	0.051	0.142	-0.559	-0.332	-0.106	-0.277	-0.066	0.144
2012	0.207	0.465	0.722	-0.007	0.009	-0.022	-0.041	0.054	0.148	-0.563	-0.336	-0.108	-0.286	-0.069	0.148
2013	0.173	0.446	0.718	-0.007	0.009	-0.023	-0.040	0.057	0.155	-0.567	-0.338	-0.110	-0.292	-0.071	0.149
2014	0.144	0.429	0.713	-0.007	0.008	-0.023	-0.039	0.061	0.161	-0.576	-0.341	-0.105	-0.296	-0.073	0.150
2015	0.123	0.413	0.704	-0.008	0.008	-0.023	-0.039	0.064	0.168	-0.589	-0.343	-0.097	-0.300	-0.074	0.152
2016	0.105	0.400	0.695	-0.008	0.008	-0.024	-0.041	0.068	0.177	-0.596	-0.346	-0.095	-0.301	-0.074	0.153
2017	0.083	0.389	0.695	-0.008	0.008	-0.025	-0.042	0.071	0.184	-0.608	-0.349	-0.089	-0.302	-0.073	0.155
2018	0.064	0.379	0.695	-0.009	0.008	-0.025	-0.043	0.075	0.192	-0.624	-0.352	-0.081	-0.302	-0.072	0.157
2019	0.043	0.371	0.700	-0.009	0.008	-0.025	-0.044	0.078	0.199	-0.640	-0.356	-0.072	-0.300	-0.070	0.160
2020	0.026	0.365	0.705	-0.009	0.008	-0.026	-0.044	0.081	0.205	-0.662	-0.362	-0.061	-0.298	-0.068	0.162
2021	0.014	0.361	0.708	-0.009	0.008	-0.026	-0.042	0.084	0.209	-0.684	-0.368	-0.051	-0.297	-0.065	0.167
2022	0.005	0.358	0.711	-0.009	0.008	-0.026	-0.040	0.087	0.213	-0.719	-0.375	-0.030	-0.297	-0.061	0.174

Annex F

Table 11: Panel TVP-RE Coefficients for Services' regression

Year	GVA			CDD			HDD			DD			D3		
	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher
1996	0.640	0.816	0.992	-0.004	0.014	0.032	0.028	0.105	0.182	-0.297	-0.105	0.087	-0.091	0.016	0.123
1997	0.639	0.812	0.985	-0.004	0.014	0.032	0.028	0.105	0.182	-0.296	-0.103	0.089	-0.091	0.016	0.123
1998	0.635	0.808	0.980	-0.004	0.014	0.032	0.029	0.106	0.182	-0.297	-0.101	0.094	-0.092	0.016	0.125
1999	0.631	0.803	0.975	-0.004	0.014	0.032	0.029	0.106	0.182	-0.298	-0.100	0.098	-0.094	0.016	0.126
2000	0.628	0.799	0.969	-0.003	0.015	0.033	0.030	0.106	0.182	-0.298	-0.098	0.103	-0.096	0.016	0.128
2001	0.624	0.794	0.964	-0.003	0.015	0.033	0.031	0.107	0.182	-0.297	-0.095	0.106	-0.098	0.015	0.129
2002	0.614	0.790	0.965	-0.003	0.015	0.033	0.031	0.107	0.183	-0.295	-0.093	0.108	-0.100	0.015	0.130
2003	0.602	0.785	0.967	-0.003	0.015	0.033	0.031	0.107	0.184	-0.294	-0.091	0.112	-0.102	0.015	0.131
2004	0.590	0.780	0.969	-0.003	0.015	0.034	0.031	0.108	0.185	-0.294	-0.089	0.117	-0.104	0.014	0.133
2005	0.580	0.775	0.969	-0.003	0.016	0.034	0.031	0.108	0.185	-0.294	-0.086	0.122	-0.107	0.014	0.134
2006	0.569	0.769	0.970	-0.003	0.016	0.035	0.031	0.108	0.186	-0.294	-0.083	0.128	-0.110	0.013	0.136
2007	0.559	0.764	0.970	-0.003	0.016	0.035	0.031	0.109	0.186	-0.295	-0.081	0.133	-0.113	0.012	0.137
2008	0.547	0.759	0.970	-0.003	0.016	0.035	0.032	0.109	0.186	-0.296	-0.078	0.140	-0.116	0.012	0.139
2009	0.533	0.753	0.973	-0.003	0.017	0.036	0.033	0.110	0.186	-0.300	-0.075	0.151	-0.119	0.011	0.140
2010	0.519	0.747	0.976	-0.002	0.017	0.036	0.034	0.110	0.186	-0.305	-0.071	0.162	-0.122	0.010	0.142
2011	0.504	0.742	0.979	-0.002	0.017	0.036	0.036	0.110	0.185	-0.309	-0.068	0.173	-0.125	0.009	0.143
2012	0.490	0.736	0.981	-0.002	0.017	0.036	0.037	0.111	0.185	-0.314	-0.065	0.185	-0.128	0.008	0.143
2013	0.475	0.730	0.984	-0.002	0.017	0.036	0.037	0.111	0.186	-0.318	-0.061	0.197	-0.131	0.007	0.144
2014	0.460	0.723	0.987	-0.002	0.018	0.037	0.037	0.112	0.187	-0.323	-0.057	0.209	-0.134	0.006	0.145
2015	0.444	0.717	0.990	-0.001	0.018	0.037	0.037	0.112	0.188	-0.328	-0.053	0.222	-0.137	0.004	0.145
2016	0.429	0.711	0.993	-0.001	0.018	0.037	0.037	0.113	0.188	-0.333	-0.049	0.235	-0.140	0.003	0.146
2017	0.413	0.705	0.996	-0.001	0.018	0.037	0.036	0.113	0.190	-0.337	-0.044	0.249	-0.143	0.002	0.146
2018	0.397	0.698	0.999	-0.001	0.018	0.037	0.035	0.114	0.192	-0.342	-0.039	0.263	-0.147	0.000	0.147
2019	0.381	0.691	1.002	0.000	0.018	0.037	0.035	0.114	0.193	-0.347	-0.035	0.278	-0.150	-0.001	0.147
2020	0.365	0.685	1.005	0.000	0.019	0.037	0.036	0.114	0.193	-0.352	-0.030	0.293	-0.153	-0.003	0.147
2021	0.348	0.678	1.008	0.000	0.019	0.038	0.036	0.115	0.194	-0.357	-0.024	0.309	-0.157	-0.005	0.147
2022	0.332	0.671	1.011	0.000	0.019	0.038	0.036	0.115	0.195	-0.363	-0.019	0.325	-0.160	-0.007	0.147

Annex G

Table 12: Panel TVP-RE Coefficients for Agriculture's regression

Year	GVA			CDD			HDD			IB			I2		
	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher
1996	-0.296	-0.054	0.187	-0.033	-0.007	0.019	-0.070	0.050	0.169	-0.516	-0.370	-0.224	-0.207	-0.085	0.037
1997	-0.298	-0.055	0.188	-0.033	-0.007	0.019	-0.071	0.050	0.170	-0.514	-0.368	-0.222	-0.207	-0.085	0.037
1998	-0.301	-0.056	0.190	-0.033	-0.007	0.019	-0.071	0.050	0.171	-0.512	-0.366	-0.220	-0.206	-0.085	0.036
1999	-0.304	-0.056	0.191	-0.034	-0.008	0.018	-0.072	0.050	0.172	-0.511	-0.364	-0.217	-0.206	-0.085	0.036
2000	-0.306	-0.057	0.193	-0.034	-0.008	0.018	-0.072	0.050	0.172	-0.510	-0.362	-0.215	-0.205	-0.085	0.035
2001	-0.309	-0.057	0.194	-0.034	-0.008	0.018	-0.072	0.050	0.173	-0.508	-0.361	-0.214	-0.205	-0.085	0.035
2002	-0.312	-0.058	0.196	-0.034	-0.008	0.018	-0.073	0.051	0.174	-0.505	-0.359	-0.212	-0.205	-0.085	0.034
2003	-0.314	-0.059	0.197	-0.034	-0.008	0.018	-0.073	0.051	0.175	-0.503	-0.357	-0.211	-0.204	-0.085	0.034
2004	-0.317	-0.059	0.199	-0.034	-0.008	0.018	-0.074	0.051	0.175	-0.501	-0.355	-0.209	-0.204	-0.085	0.034
2005	-0.321	-0.060	0.201	-0.034	-0.008	0.017	-0.074	0.051	0.176	-0.498	-0.353	-0.208	-0.204	-0.085	0.034
2006	-0.325	-0.060	0.204	-0.034	-0.009	0.017	-0.074	0.051	0.176	-0.496	-0.351	-0.206	-0.204	-0.085	0.034
2007	-0.328	-0.061	0.207	-0.034	-0.009	0.017	-0.074	0.051	0.176	-0.493	-0.349	-0.206	-0.204	-0.085	0.034
2008	-0.332	-0.061	0.209	-0.035	-0.009	0.017	-0.074	0.052	0.177	-0.489	-0.348	-0.206	-0.203	-0.085	0.034
2009	-0.336	-0.062	0.212	-0.035	-0.009	0.017	-0.074	0.052	0.177	-0.486	-0.346	-0.205	-0.203	-0.085	0.034
2010	-0.339	-0.063	0.214	-0.035	-0.009	0.017	-0.074	0.052	0.178	-0.485	-0.344	-0.203	-0.203	-0.084	0.034
2011	-0.343	-0.063	0.217	-0.035	-0.009	0.016	-0.075	0.052	0.179	-0.483	-0.342	-0.201	-0.203	-0.084	0.034
2012	-0.347	-0.064	0.220	-0.035	-0.009	0.016	-0.075	0.052	0.180	-0.482	-0.340	-0.198	-0.203	-0.084	0.034
2013	-0.350	-0.064	0.222	-0.035	-0.009	0.016	-0.076	0.052	0.180	-0.483	-0.338	-0.194	-0.203	-0.084	0.035
2014	-0.354	-0.065	0.225	-0.035	-0.010	0.016	-0.076	0.053	0.181	-0.483	-0.337	-0.190	-0.203	-0.084	0.035
2015	-0.358	-0.065	0.227	-0.036	-0.010	0.016	-0.077	0.053	0.182	-0.484	-0.335	-0.185	-0.204	-0.084	0.036
2016	-0.361	-0.066	0.230	-0.036	-0.010	0.016	-0.077	0.053	0.183	-0.485	-0.333	-0.181	-0.204	-0.084	0.036
2017	-0.365	-0.066	0.233	-0.036	-0.010	0.016	-0.078	0.053	0.184	-0.486	-0.331	-0.177	-0.204	-0.084	0.037
2018	-0.368	-0.067	0.235	-0.036	-0.010	0.016	-0.078	0.053	0.185	-0.486	-0.329	-0.172	-0.204	-0.083	0.037
2019	-0.372	-0.067	0.238	-0.036	-0.010	0.016	-0.079	0.053	0.186	-0.487	-0.327	-0.168	-0.205	-0.083	0.038
2020	-0.375	-0.068	0.240	-0.036	-0.010	0.015	-0.080	0.053	0.186	-0.488	-0.326	-0.164	-0.205	-0.083	0.039
2021	-0.379	-0.068	0.243	-0.036	-0.011	0.015	-0.080	0.054	0.187	-0.488	-0.324	-0.159	-0.205	-0.083	0.039
2022	-0.383	-0.069	0.246	-0.037	-0.011	0.015	-0.081	0.054	0.188	-0.489	-0.322	-0.155	-0.205	-0.083	0.040

Annex H

Table 13: Panel TVP-RE Coefficients for Industry's regression

Year	GVA			CDD			HDD			IC			I3		
	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher	IC - Lower	Mean	IC - Higher
1996	0.125	0.272	0.420	-0.006	0.008	0.022	-0.038	-0.003	0.031	-0.280	-0.160	-0.040	0.039	0.110	0.182
1997	0.120	0.263	0.405	-0.007	0.007	0.022	-0.037	-0.002	0.034	-0.266	-0.156	-0.046	0.038	0.111	0.185
1998	0.115	0.252	0.389	-0.007	0.007	0.022	-0.037	0.000	0.038	-0.254	-0.152	-0.050	0.036	0.112	0.189
1999	0.108	0.240	0.373	-0.008	0.007	0.022	-0.036	0.003	0.041	-0.242	-0.148	-0.054	0.033	0.113	0.192
2000	0.100	0.228	0.356	-0.008	0.007	0.022	-0.036	0.005	0.046	-0.232	-0.144	-0.056	0.032	0.113	0.193
2001	0.091	0.215	0.339	-0.009	0.006	0.021	-0.037	0.007	0.052	-0.226	-0.140	-0.055	0.032	0.112	0.192
2002	0.082	0.202	0.321	-0.009	0.006	0.021	-0.036	0.010	0.055	-0.220	-0.137	-0.054	0.031	0.110	0.190
2003	0.072	0.188	0.303	-0.010	0.005	0.021	-0.035	0.012	0.059	-0.216	-0.134	-0.052	0.031	0.108	0.185
2004	0.064	0.174	0.283	-0.011	0.005	0.021	-0.035	0.014	0.064	-0.213	-0.131	-0.049	0.028	0.104	0.179
2005	0.056	0.159	0.262	-0.012	0.004	0.020	-0.036	0.017	0.070	-0.209	-0.129	-0.049	0.021	0.098	0.176
2006	0.045	0.145	0.245	-0.012	0.004	0.019	-0.037	0.019	0.076	-0.208	-0.127	-0.046	0.013	0.092	0.171
2007	0.030	0.131	0.232	-0.013	0.003	0.019	-0.037	0.022	0.081	-0.206	-0.126	-0.045	0.009	0.085	0.160
2008	0.016	0.118	0.219	-0.014	0.002	0.018	-0.036	0.025	0.086	-0.205	-0.125	-0.044	0.003	0.076	0.150
2009	0.005	0.105	0.205	-0.014	0.001	0.017	-0.037	0.028	0.092	-0.205	-0.125	-0.045	-0.004	0.068	0.141
2010	-0.006	0.093	0.192	-0.015	0.000	0.015	-0.036	0.031	0.098	-0.205	-0.125	-0.045	-0.011	0.060	0.131
2011	-0.016	0.082	0.181	-0.015	-0.001	0.014	-0.035	0.034	0.103	-0.208	-0.126	-0.043	-0.013	0.053	0.119
2012	-0.027	0.073	0.173	-0.016	-0.002	0.013	-0.034	0.037	0.108	-0.212	-0.127	-0.041	-0.015	0.047	0.109
2013	-0.036	0.065	0.165	-0.017	-0.002	0.012	-0.035	0.040	0.115	-0.218	-0.128	-0.038	-0.015	0.042	0.100
2014	-0.044	0.057	0.159	-0.018	-0.003	0.011	-0.036	0.043	0.121	-0.222	-0.130	-0.038	-0.015	0.039	0.092
2015	-0.052	0.051	0.154	-0.019	-0.004	0.011	-0.034	0.045	0.124	-0.226	-0.132	-0.038	-0.013	0.036	0.085
2016	-0.059	0.045	0.149	-0.020	-0.005	0.010	-0.034	0.047	0.128	-0.230	-0.134	-0.038	-0.010	0.035	0.080
2017	-0.065	0.040	0.145	-0.021	-0.006	0.010	-0.036	0.049	0.134	-0.233	-0.136	-0.039	-0.007	0.034	0.076
2018	-0.071	0.036	0.142	-0.022	-0.006	0.009	-0.036	0.051	0.137	-0.236	-0.138	-0.039	-0.005	0.034	0.074
2019	-0.077	0.032	0.140	-0.023	-0.007	0.009	-0.037	0.052	0.141	-0.239	-0.140	-0.040	-0.005	0.035	0.075
2020	-0.082	0.028	0.138	-0.024	-0.008	0.009	-0.037	0.053	0.144	-0.246	-0.142	-0.037	-0.003	0.036	0.075
2021	-0.087	0.024	0.136	-0.025	-0.008	0.009	-0.037	0.055	0.146	-0.256	-0.143	-0.030	-0.003	0.037	0.077
2022	-0.092	0.021	0.134	-0.026	-0.009	0.009	-0.037	0.056	0.148	-0.268	-0.144	-0.021	-0.002	0.039	0.080

Annex I

Several Robustness checks were performed, in particular:

1. To the bandwidth: In order to control the smoothness of the estimated coefficients over time, it was tested a +- 20% variation in the bandwidth given by the leave one out cross-validation method.

2. To the kernel method of estimation: In order to control for the technique used to estimate the coefficients of the model, it was tested the Triweight and Epanechnikov functions. Kernel methods are non-parametric techniques that smooth the estimation of time-varying parameters by assigning weights to observations based on their proximity to a target time point. These weighted observations are then used to estimate the coefficients at the target time point. The robustness check for these kernel functions are conducted in order to assess the different properties of the methods (sensitivity to outliers,optimal bandwidth, efficiency, variance control and flexibility).

3. To the electricity and gas Prices - Because electricity and gas prices were selected based on the most representative band, there is some underlying uncertainty. Thus, it was tested a lower band for the electricity and gas prices and also higher band for electricity and gas prices.

4. Pooling and Fixed TVP first differences model - An argument can be made that applying first differences to the variables of a model may remove individuals effects to which a pooling model would be more suitable than the random effects model. Furthermore it is presented the model for the within estimator.

Bandwidth

Given a set of observed data points $(x_{i1}, y_{i1}), (x_{i2}, y_{i2}), \ldots, (x_{in}, y_{in})$ for each cross-sectional unit i, where x_{ij} represents the covariates and y_{ij} represents the response variable, and assuming a linear relationship between x and y with time-varying coefficients, the estimator for the coefficients β at time t using the Gaussian kernel method can be represented as:

$$\hat{\beta}_i(t) = \frac{\sum_{j=1}^{n} K\left(\frac{t-t_{ij}}{h}\right) x_{ij} y_{ij}}{\sum_{j=1}^{n} K\left(\frac{t-t_{ij}}{h}\right) x_{ij}^2} \tag{5}$$

where:

- $\hat{\beta}_i(t)$ is the estimated coefficient at time t.
- t represents time, indicating that the coefficients are allowed to vary over time.
- t_i represents the time associated with the i-th data point.

- x_i are the covariates (independent variables) associated with the i-th data point. These covariates could include both time-invariant and time-varying variables.

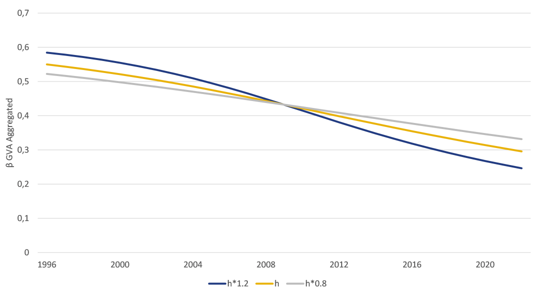
- y_i represents the response variable (dependent variable) associated with the i-th data point.

- $K\left(\frac{t-t_i}{h}\right)$ is the kernel function, where h is the bandwidth parameter.

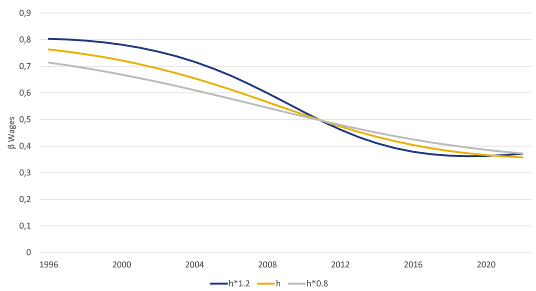
In summary, this formula computes the time-varying coefficient $\hat{\beta}(t)$ by weighting the covariates and response variable based on their proximity to the time point t, with the weights determined by the kernel function K. The estimation process involves summing these weighted values and normalizing by the sum of the weights.

Figure 8, shows the results of the robustness check for the bandwidth.

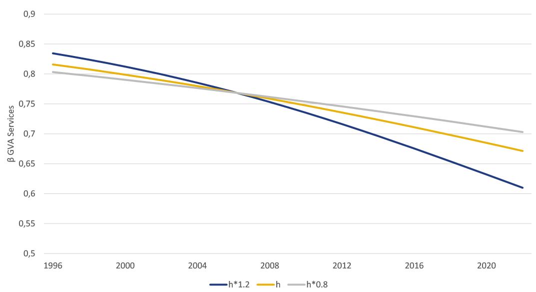
Figure 8: TVP-RE coefficients for bandwidth robustness checks



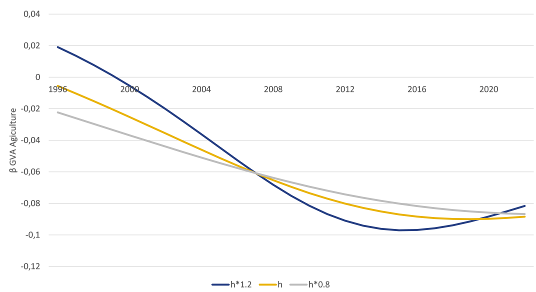
(a) TVP-RE coefficients for Total GVA with bandwidth robustness check



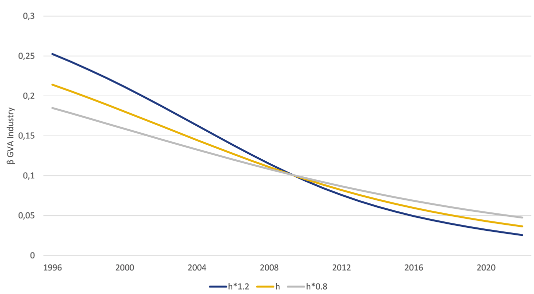
(b) TVP-RE coefficients for Wages with bandwidth robustness check



(c) TVP-RE coefficients for Services GVA with bandwidth robustness check



(d) TVP-RE coefficients for Agriculture GVA with bandwidth robustness check



(e) TVP-RE coefficients for Industry GVA with bandwidth robustness check

Overall, the results qualitatively remained the same in trend and level. Results do not change qualitatively when variation to the bandwidth is applied, though, coefficients are more sensible increases in the bandwidth than to the same % decrease in the bandwidth. This behavior translates to the analysis conducted by economic segment.

Method for kernel estimation

The default kernel function for the basis TVP-RE model is the Gaussian function $K(u)$, defined as:

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} \tag{6}$$

This estimator provides a smooth estimation of the coefficients over time by assigning more weight to the data points closer to the time point t and less weight to the data points farther away. u represents the distance between the data points and the time point t. Adjusting the bandwidth parameter h allows for controlling the smoothness of the estimation.

An alternative to the Gaussian function, there is the Epanechnikov kernel method. The formula for the Epanechnikov kernel function $K(u)$ is given by:

$$K(u) = \begin{cases} \frac{3}{4}(1 - u^2) & \text{for } |u| \leq 1 \\ 0 & \text{for } |u| > 1 \end{cases} \tag{7}$$

Another alternative is the triweight kernel function $K(u)$ which is defined as:

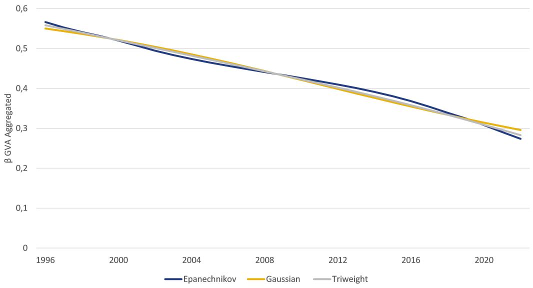
$$K(u) = \begin{cases} \frac{35}{32}(1 - u^2)^3 & \text{for } |u| \leq 1 \\ 0 & \text{for } |u| > 1 \end{cases} \tag{8}$$

The robustness check for these kernel functions are conducted in order to assess the different properties of the methods. Thus, trade-offs between sensitivity to outliers,optimal bandwidth (by minimizing a certain error measure) efficiency, variance control and flexibility (smoothness and shape).

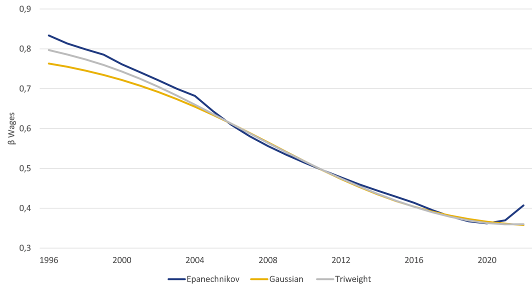
Figure 9 show similar results to the robustness check performed on the bandwidth. There is no substantial changes in the trend or level of the coefficients.

On a more detailed view, the Gaussian and Triweight kernel functions provide very similar quantitative results, and as for the Epanechnikov function slightly deviates from the other two methods. This behavior may be explained by properties of the Epanechnikov kernel shapes, bandwidths, weighting schemes and robustness to outliers.

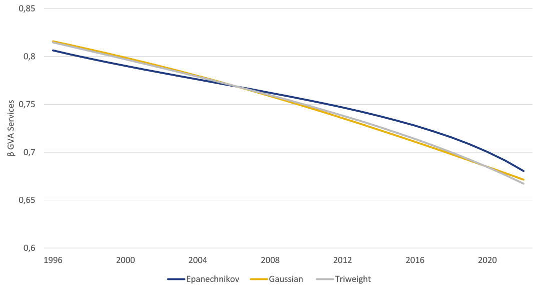
Figure 9: TVP-RE coefficients for kernel function robustness checks



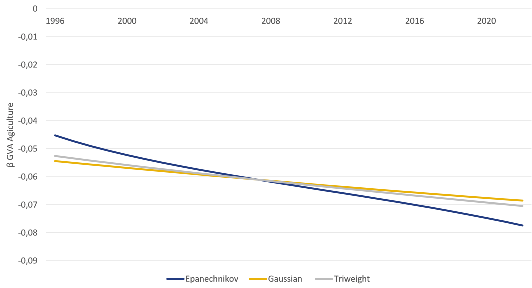
(a) TVP-RE coefficients for Total GVA



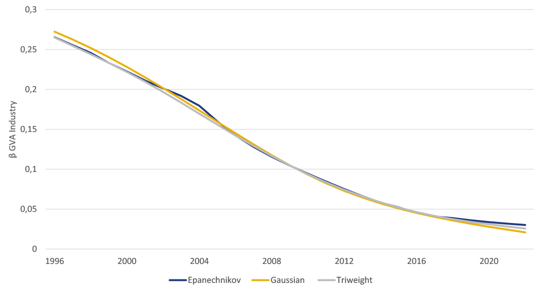
(b) TVP-RE coefficients for Wages



(c) TVP-RE coefficients for Services GVA



(d) TVP-RE coefficients for Agriculture GVA



(e) TVP-RE coefficients for Industry GVA

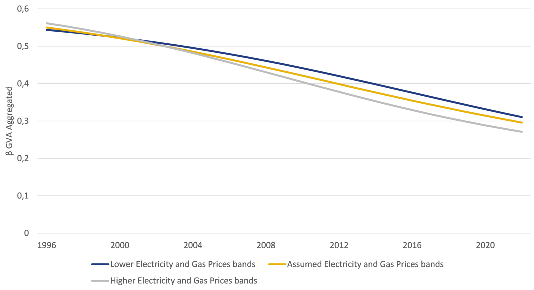
Electricity and Gas Prices

Figure 10 present the outcomes of the robustness assessment conducted to examine the impact of different sets of electricity and gas prices. The approach involved selecting the nearest lower consumption band for electricity and gas prices as the "lower band," and the subsequent higher consumption band for electricity and gas prices as the reference "higher band".

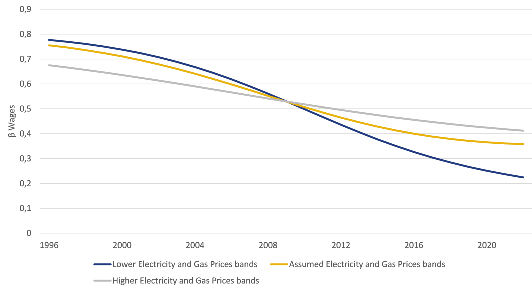
Figure 10 show that income elasticities have some sensitive to the electricity and gas prices considered. This behavior is expected, since electricity and gas prices may vary substantially with the band of consumption. Nevertheless, the trend remains qualitatively the same.

For the aggregated, residential, services and agriculture model the the impact on income elasticity by assuming different bands for electricity consumption is lower than 0,1p.p.. For industry, this result does not hold true for all periods: in 1996 the impact is about 0.15p.p. Nevertheless, it should be highlighted that considering the band ID

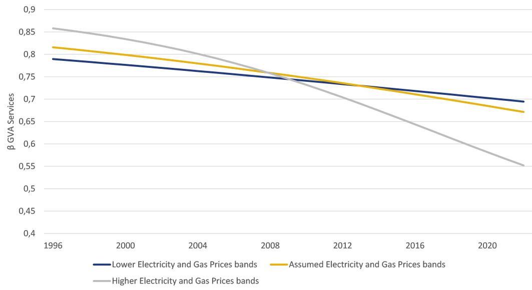
Figure 10: TVP-RE coefficients for electricity and gas prices robustness checks



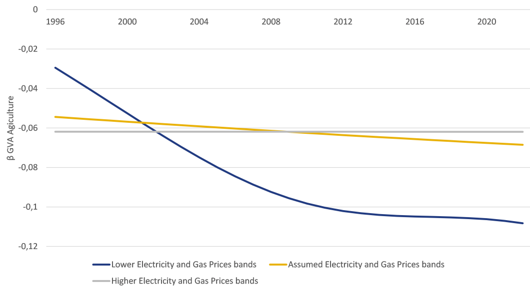
(a) TVP-RE coefficients for Wages with electricity and gas prices robustness checks



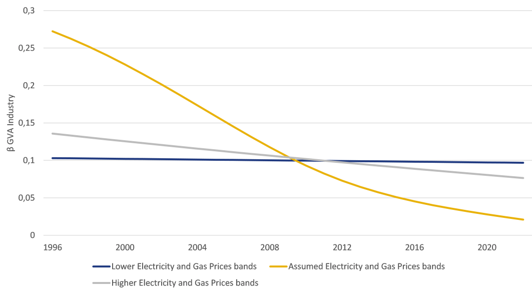
(b) TVP-RE coefficients for Wages with electricity and gas prices robustness checks



(c) TVP-RE coefficients for Services GVA with electricity and gas prices robustness checks



(d) TVP-RE coefficients for Agriculture GVA with electricity and gas prices robustness checks



(e) TVP-RE coefficients for Industry GVA with electricity and gas prices robustness checks

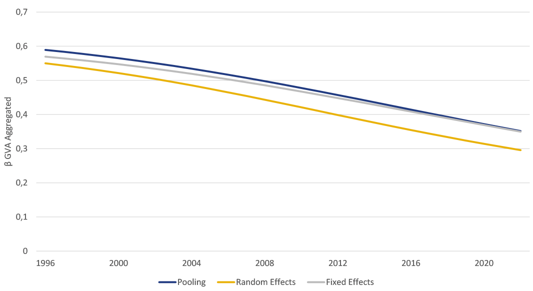
that assumes an annual electricity consumption of 2000MWh and 20000MWh is unrealistic for most portuguese factories. The band IB, though it considers less annual demand per supplying point (20MWh and 500MWh) it falls short to consider medium and large industrial consumers.

Pooling and Fixed Effects

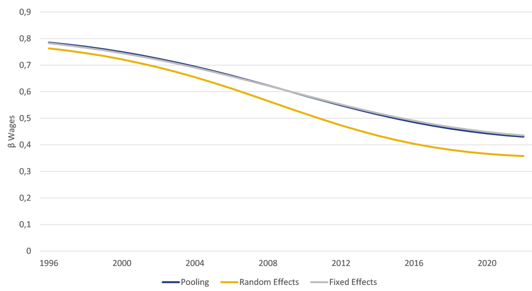
In cases where there is little variation in individual-specific effects across entities or over time (as it may be the case after applying the first differences), pooling can be more efficient than the random effects model. Furthermore it will also be included the fixed effects estimates.

Generally, pooling the data resulted in higher income elasticities in models as a common result shown in (Figure 11. This provides some evidence that the true parameters may be higher in magnitude as well as in significance.

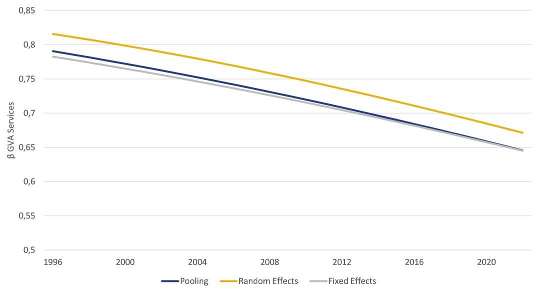
Figure 11: TVP-RE coefficients for pooling, within and random effects estimators



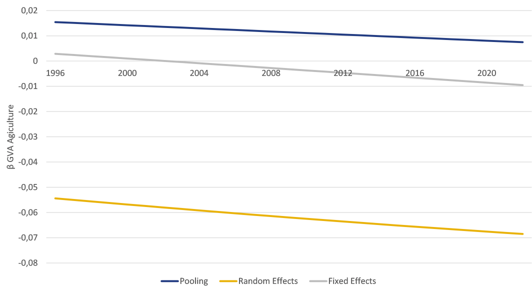
(a) TVP-RE coefficients for pooling, within and random effects estimators



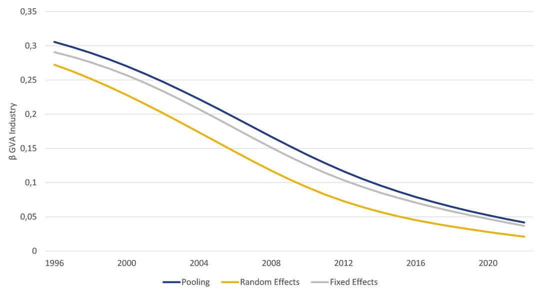
(b) TVP-RE coefficients for pooling, within and random effects estimators



(c) TVP-RE coefficients for pooling, within and random effects estimators



(d) TVP-RE coefficients for pooling, within and random effects estimators



(e) TVP-RE coefficients for Industry GVA pooling, within and random effects estimators

As for the fixed effects, the coefficients estimated are close to the ones estimated by the random effects estimator but with more variation in relation to the random effects estimators. It should be highlighted that the consideration of a pooling or within estimator in the agriculture sector could have yielded a positive income elasticity, but non-significant.

Annex J

On this annex it will be provided the theoretical model applied according to (Casas and Fernández-Casal, 2022). This paper begins by discussing the time-varying coefficientes within the framework of SURE models. SURE models were motivated by the notion that multiple variables might exhibit related variations, as evidenced by the non-diagonal variance-covariance matrix of the system error term. This model (SURE) allows for the exploitation of correlation structures among the error terms of each equation. Consider a scenario where there are N linear regressions with different dependent variables:

$$y_i = X_i^\top \beta_i + u_i \quad i = 1, \ldots, N \tag{9}$$

where $y_i = (y_{i1}, \ldots, y_{iT})^\top$ denotes the values over the recorded time period of the i-th dependent variable. Each equation in (2) may have a different number of exogenous variables, p_i. The regressors for equation i are $X_i = (x_{i1}, \ldots, x_{ip_i})$, from which each element is a vector of dimension $T \times 1$. The constant coefficients of equation i are $\beta_i = (\beta_{i1}, \ldots, \beta_{ip_i})^\top$. The error term $u_i = (u_{i1}, \ldots, u_{iT})$ is a random process such that $\mathbb{E}(u_{it}) = \mathbb{E}(u_{it} \mid x_{it}) = 0$ and $\mathbb{E}(u_{it}u_{ii'tt'}) = \delta_{tt'}\sigma_{ii't}$, where $\delta_{tt'} = 0$ if $t \neq t'$ and 1 if $t = t'$. Stacking the N equations on top of each other, the general system can be written in matrix form:

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{pmatrix} = \begin{pmatrix} X_1 & 0 & \ldots & 0 \\ 0 & X_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & X_N \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_N \end{pmatrix} + \begin{pmatrix} u_1 \\ u_2 \\ \vdots \\ u_N \end{pmatrix} = X\beta + u \tag{10}$$

Extending Model (3) to a model with time-varying coefficients, we obtain the TVSURE whose compact formula at each time t is given by

$$Y_t = X_t\beta(z_t) + U_t \quad i = 1, \ldots, N \quad t = 1, \ldots, T,$$

where $Y_t = (y_{1t} \ldots y_{Nt})^\top$, $X_t = \mathrm{diag}(x_{1t} \ldots x_{Nt})$, and $\beta_{z_t} = \left(\beta_1(z_t)^\top, \ldots, \beta_N(z_t)^\top\right)^\top$ is a vector of order $P = p_1 + p_2 + \ldots + p_N$. The error vector, $U_t = (u_{1t} \ldots u_{Nt})^\top$, has zero mean and covariance matrix $\mathbb{E}(U_t U_t^\top) = \Sigma_t$ with elements $\sigma_{ii'i't}$. The smoothing variable z_t may be t/T or the value of a random variable at time t. System (3) has a total of N different time-varying coefficient linear models (TVLM) with possibly N different bandwidths, b_i. The estimation may be done separately for each equation as if there is no correlation in the error term across equations; i.e., using the estimator Time-Varying Ordinary Least Squares. Two versions of this estimator are implemented by : i) the TVOLS that uses the local constant (lc) kernel method, also known as the Nadaraya-Watson estimator; and ii) the TVOLS which uses the local linear (ll) method. Focusing on the single equation i, and assuming that $\beta_i(\cdot)$ is twice differentiable, an approximation of $\beta_i(zt)$ around z is given by the Taylor rule, $\beta_i(zt) \approx \beta_i(z) + \beta_i^{(1)}(z)(zt - z)$, where $\beta_i^{(1)}(z) = \frac{d\beta_i(z)}{dz}$ is its first derivative. The estimates resolve the following minimization:

$$\left(\hat{\beta}_i(zt), \hat{\beta}_i^{(1)}(zt)\right) = \arg\min_{\theta_0, \theta_1} \sum_{t=1}^{T} \frac{1}{h} \left(y_i - X_i^\top \theta_0 - (zt - z)X_i^\top \theta_1\right)^2 K_{bi}(zt - z)) \tag{11}$$

Roughly, these methodologies fit a set of weighted local regressions with an optimally chosen window size. The size of these windows is given by the bandwidth b_i, and the weights are given by $K_{b_i}(z_t - z) = b_i^{-1} K\left(\frac{z_t - z}{b_i}\right)$, for a kernel function $K(\cdot)$. The local linear estimator general expression is

$$\begin{pmatrix} \hat{\beta}_i(z_t) \\ \hat{\beta}_i^{(1)}(z_t) \end{pmatrix} = \begin{pmatrix} S_{T,0}(z_t) & S_{T,1}^{\top}(z_t) \\ S_{T,1}(z_t) & S_{T,2}(z_t) \end{pmatrix}^{-1} \begin{pmatrix} T_{T,0}(z_t) \\ T_{T,1}(z_t) \end{pmatrix} \tag{12}$$

with

$$\begin{aligned} S_{T,s}(z_t) &= \frac{1}{T} \sum_{i=1}^{T} X_i^{\top} X_i (z_i - z_t)^s K\left(\frac{z_i - z_t}{b_i}\right) \\ T_{T,s}(z_t) &= \frac{1}{T} \sum_{i=1}^{T} X_i^{\top} (z_i - z_t)^s K\left(\frac{z_i - z_t}{b_i}\right) y_i \end{aligned}$$

and $s = 0, 1, 2$. The particular case of the local constant estimator is calculated by $\hat{\beta}_{i,t} = S_{T,0}^{-1}(z_t) T_{T,0}(z_t)$ and it is only necessary that $\beta_i(\cdot)$ has one derivative.

Returning to the balanced panel dataset, we can express panel data models as:

$$y_{it} = \alpha_i + x_{it}^{\top}\beta + u_{it} \quad \Sigma = \begin{pmatrix} \sigma_\nu^2 & \sigma_\alpha^2 & \dots & \sigma_\alpha^2 \\ \sigma_\alpha^2 & \sigma_\nu^2 & \dots & \sigma_\alpha^2 \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_\alpha^2 & \sigma_\alpha^2 & \dots & \sigma_\nu^2 \end{pmatrix}, \quad i = 1, \dots, N,$$

for $t = 1, \dots, T$. The indiosyncratic error is not serially correlated, $E(u_t, u_s) = 0, s \neq t$ with mean zero and a constant variance σ_u^2. The α_i is a random variable with variance σ_α^2. In addition, $\sigma_\nu^2 = \sigma_u^2 + \sigma_\alpha^2$. Some of the three classical estimators of panel data models are explained below.

1. The pooled ordinary least square (POLS) estimator is given by

$$\hat{\beta}_{POLS} = \left(X^{\top}X\right)^{-1} X^{\top}Y$$

where $Y = (y_{11}, \dots, y_{1T}, \dots, y_{N1}, \dots, y_{NT})^{\top}, X$ is defined similar to Y. This estimator ignores the panel structure. It assumes that $E(\alpha_i|X_i) = 0$. It can be proven to be consistent and asymptotically normal under certain conditions. However, it is not efficient and t-, F-, z- and Wald-tests based on its standard errors are not valid.

2. The random effects (RE) estimator corrects for this inefficiency by considering the estimation of Σ from the POLS estimation residuals,

$$\hat{\beta}_{RE} = \left(X^{\top}\hat{\Sigma}^{-1}X\right)^{-1} X^{\top}\hat{\Sigma}^{-1}Y.$$

3. The fixed effects (FE) or within estimator that considers that $E(\alpha_i|X_i) \neq 0$,

$$\hat{\beta}_{FE} = \left(\ddot{X}^\top \bar{X}\right)^{-1} \ddot{X}^\top \ddot{Y}$$

The variables elements are demeaned over time and therefore all time-independent variables, including α_i disappear after the transformation: $\ddot{y}_{it} = y_{it} - \bar{y}_i, \ddot{x}_{itk} = x_{itk} - \bar{x}_{ik}$, $\bar{u}_{it} = u_{it} - \bar{u}_i$.

These models are not able to show the coefficient dynamics which can be corrected using a time-varying coefficients panel data model. Recent developments in this kind of models can be found in the literature with the general model:

$$y_{it} = \alpha_i + x_{it}^\top \beta(z_t) + u_{it} \quad i = 1, \ldots, N, \quad t = 1, \ldots, T. \tag{13}$$

Note that the smoothing variable only changes over time, not like in the SURE model where it changed over i and t. The three correspondent estimators are:

1. The time-varying pooled ordinary least squares (TVPOLS) has the same expression as estimator (5) with the following terms:

$$S_{T,a}(z_t) = X^\top K_{b,t} X(Z - z_t)^s T_{T,s}(z_t) = X^\top K_{b,t}^* Y(Z - z_t)^s, \tag{14}$$

where $K_{b,t}^* = I_N \otimes \text{diag}\{K_b(z_1 - z_t), \ldots, K_b(z_T - z_t)\}$. Note that it is not possible to ignore the panel structure in the semiparametric model because the coefficients change over time. The consistency and asymptotic normality of this estimator need the classical assumptions about the kernel and the regularity of the coefficients, available in the related literature.

2. The time-varying random effects (TVRE) estimator is also given by Equation (7) with a non-identity Σ:

$$S_{T,s}(z_t) = X^\top K_{b,t}^{*1/2} \Sigma_t^{-1} K_{b,t}^{*1/2} X(Z - z_t)^s \quad T_{T,s}(z_t) = K_{b,t}^{*1/2} \Sigma_t^{-1} K_{b,t}^{*1/2} Y(Z - z_t)^s. \tag{15}$$

The variance-covariance matrix is estimated using the residuals from the TVPOLS, and it may be an iterative algorithm until convergence of the coefficients:

Step 1: Estimate Σ_t based on the residuals of a line-by-line estimation (i.e., when Σ_t is the identity matrix, and with the same bandwidth for all equations). If Σ_t is known to be constant, the sample variance-covariance matrix from the residuals is a consistent estimator of it. If Σ_t changes over time, an alternative consistent nonparametric estimator should be considered.

Step 2: Estimate the coefficients of the TVSURE by plugging in $\hat{\Sigma}_t$ from Step 1 into Equation (8)

3. The time-varying fixed effects (TVFE) estimator. Unfortunately, the transformation for the within estimation does not work in the time-varying coefficients model because the coefficients depend on time. Therefore, it is necessary to make the assumption that $\sum_{i=1}^{N} \alpha_i = 0$ for identification. The terms in the TVFE estimator are:

$$S_{T,s}(z_t) = X^\top W_{b,t} X (Z - z_t)^s T_{T,s}(z_t) = X^\top W_{b,t} Y (Z - z_t)^s, \tag{16}$$

where $W_{b,t} = D_t^\top K_{b,t}^* D_t$, $D_t = I_{NT} - D(D^\top K_{b,t}^* D)^{-1} D^\top K_{b,t}^*$, $D = (-1_{N-1}, I_{N-1})^\top \otimes 1_T$, and 1_k is the unity vector of length k. The fixed effects are given by,

$$\hat{\alpha} = (D^\top K_{b,t}^* D)^{-1} D^\top K_{b,t}^* (Y - X^\top \beta).$$

Finally, $\hat{\alpha}_i = \frac{1}{T} \sum_{t=1}^{T} \alpha_{it}$ for $i = 2, \ldots, N$.

References

Abbasi, K. R., Abbas, J., and Tufail, M. (2021). Revisiting electricity consumption, price, and real gdp: A modified sectoral level analysis from pakistan. *Energy Policy*, 149:112087.

Acheampong, A. O., Boateng, E., Amponsah, M., and Dzator, J. (2021). Revisiting the economic growth–energy consumption nexus: does globalization matter? *Energy Economics*, 102:105472.

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

Baležentis, T., Butkus, M., Štreimikienė, D., and Shen, Z. (2021). Exploring the limits for increasing energy efficiency in the residential sector of the european union: Insights from the rebound effect. *Energy Policy*, 149:112063.

Berner, A., Bruns, S., Moneta, A., and Stern, D. I. (2022a). Do energy efficiency improvements reduce energy use? empirical evidence on the economy-wide rebound effect in europe and the united states. *Energy Economics*, 110:105939.

Berner, A., Lange, S., and Silbersdorff, A. (2022b). Firm-level energy rebound effects and relative efficiency in the german manufacturing sector. *Energy Economics*, 109:105903.

Bielig, M., Kacperski, C., Kutzner, F., and Klingert, S. (2022). Evidence behind the narrative: Critically reviewing the social impact of energy communities in europe. *Energy Research & Social Science*, 94:102859.

Brockway, P. E., Sorrell, S., Semieniuk, G., Heun, M. K., and Court, V. (2021). Energy efficiency and economy-wide rebound effects: A review of the evidence and its implications. *Renewable and sustainable energy reviews*, 141:110781.

Burke, P. J. and Csereklyei, Z. (2016). Understanding the energy-gdp elasticity: A sectoral approach. *Energy Economics*, 58:199–210.

Cabral, J., Cabral, M. V., and Júnior, A. O. P. (2020). Elasticity estimation and forecasting: An analysis of residential electricity demand in brazil. *Utilities Policy*, 66:101108.

Canh, N. P., Schinckus, C., Thanh, S. D., and Chong, F. H. L. (2021). The determinants of the energy consumption: a shadow economy-based perspective. *Energy*, 225:120210.

Casas, I. and Fernández-Casal, R. (2022). tvreg: Time-varying coefficients in multi-equation regression in r. *R Journal*, 14(1).

Casas, I., Gao, J., Peng, B., and Xie, S. (2021). Time-varying income elasticities of healthcare expenditure for the oecd and eurozone. *Journal of Applied Econometrics*, 36(3):328–345.

CEER (2021). Ceer views on electricity distribution network development plans. Technical report, CEER, Tech. Rep., Nov. 2021.[Online].

Chen, Y., shen, B., Ali, A., and reyes, S. (2024). Econometric analysis of factors influencing electricity consumption in spain: Implications for policy and pricing strategies. *Heliyon*, 10(17):e36217.

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

Costa-Campi, M. T., Garcia-Quevedo, J., and Trujillo-Baute, E. (2018). Electricity regulation and economic growth. *Energy Policy*, 113:232–238.

Csereklyei, Z. (2020). Price and income elasticities of residential and industrial electricity demand in the european union. *Energy Policy*, 137:111079.

Csereklyei, Z., Rubio-Varas, M. d. M., and Stern, D. I. (2016). Energy and economic growth: the stylized facts. *The Energy Journal*, 37(2):223–256.

Dall-Orsoletta, A., Ferreira, P., and Dranka, G. G. (2022). Low-carbon technologies and just energy transition: Prospects for electric vehicles. *Energy Conversion and Management: X*, 16:100271.

DGEG (2023). National energy and climate plans 2021-2030.

E-Redes (2022). Distribussion network development plan - update 2023-25.

ERSE (2003). *Caracterizacao do sector do gas natural EM PORTUGAL*. ERSE.

ERSE (2023). Proveitos permitidos e ajustamentos para 2024 das empresas reguladas do setor elétrico.

ERSE (2024). Relatório de análise de mercado - 2024. Technical report, ERSE.

EuropeanCommission (2022). Repower eu plan.

EuropeanCommission (2024). Report on energy prices and costs in europe. Technical report, European Commission.

EuropeanParliament (2012). Directive 2012/27 - energy efficiency.

EuropeanParliament (2018a). Directive 2018/2002 - energy efficiency.

EuropeanParliament (2018b). Regulation 2018/1999 - governance of the energy union and climate action.

EuropeanParliament (2019). Directive (eu) 2019/944: Common rules for the internal market for electricity.

EuropeanParliament (2023). Directive 2023/1791 - energy efficiency.

Felício, L., Henriques, S. T., Guevara, Z., and Sousa, T. (2024). From electrification to decarbonization: Insights from portugal's experience (1960–2016). *Renewable and Sustainable Energy Reviews*, 198:114419.

Frieden, D., Tuerk, A., Antunes, A. R., Athanasios, V., Chronis, A.-G., d'Herbemont, S., Kirac, M., Marouço, R., Neumann, C., Pastor Catalayud, E., et al. (2021). Are we on the right track? collective self-consumption and energy communities in the european union. *Sustainability*, 13(22):12494.

Fuinhas, J. A., Koengkan, M., Leitão, N. C., Nwani, C., Uzuner, G., Dehdar, F., Relva, S., and Peyerl, D. (2021). Effect of battery electric vehicles on greenhouse gas emissions in 29 european union countries. *Sustainability*, 13(24):13611.

Gryparis, E., Papadopoulos, P., Leligou, H. C., and Psomopoulos, C. S. (2020). Electricity demand and carbon emission in power generation under high penetration of electric vehicles. a european union perspective. *Energy Reports*, 6:475–486.

Guevara, Z. and Domingos, T. (2017). Three-level decoupling of energy use in portugal 1995–2010. *Energy Policy*, 108:134–142.

Haberl, H., Wiedenhofer, D., Virág, D., Kalt, G., Plank, B., Brockway, P., Fishman, T., Hausknost, D., Krausmann, F., Leon-Gruchalski, B., et al. (2020). A systematic review of the evidence on decoupling of gdp, resource use and ghg emissions, part ii: synthesizing the insights. *Environmental research letters*, 15(6):065003.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica*, 46(6):1251–1271.

Huntington, H. G. (2010). Structural change and us energy use: recent patterns. *The Energy Journal*, 31(3):25–40.

IEA (2023). Electrification:tracking clean energy progress.

Inci, M., Çelik, Ö., Lashab, A., Bayındır, K. Ç., Vasquez, J. C., and Guerrero, J. M. (2024). Power system integration of electric vehicles: A review on impacts and contributions to the smart grid. *Applied Sciences*, 14(6):2246.

International Energy Agency (IEA) (2023). *Energy Efficiency 2023: Overview of policies and measures to improve energy efficiency globally*. IEA, Paris, France.

Judson, R. A., Schmalensee, R., and Stoker, T. M. (1999). Economic development and the structure of the demand for commercial energy. *The Energy Journal*, 20(2):29–57.

Kan, S., Chen, B., and Chen, G. (2019). Worldwide energy use across global supply chains: decoupled from economic growth? *Applied energy*, 250:1235–1245.

Lange, S., Pohl, J., and Santarius, T. (2020). Digitalization and energy consumption. does ict reduce energy demand? *Ecological economics*, 176:106760.

Lee, R. and Brown, S. (2021). Social & locational impacts on electric vehicle ownership and charging profiles. *Energy Reports*, 7:42–48.

Levin, A., Lin, C.-F., and James Chu, C.-S. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, 108(1):1–24.

Liddle, B. and Hasanov, F. (2022). Industry electricity price and output elasticities for high-income and middle-income countries. *Empirical Economics*, 62(3):1293–1319.

Liddle, B., Parker, S., and Hasanov, F. (2023). Why has the oecd long-run gdp elasticity of economy-wide electricity demand declined? because the electrification of energy services has saturated. *Energy Economics*, 125:106832.

Liddle, B., Smyth, R., and Zhang, X. (2020). Time-varying income and price elasticities for energy demand: Evidence from a middle-income panel. *Energy economics*, 86:104681.

Lindner, J. and Clements, M. (2020). Modeling and forecasting time-varying volatility with the time-varying parameter model. Technical report, Tinbergen Institute.

Liu, H., Khan, A. R., Aslam, S., Rasheed, A. K., and Mohsin, M. (2022). Financial impact of energy efficiency and energy policies aimed at power sector reforms: mediating role of financing in the power sector. *Environmental Science and Pollution Research*, pages 1–14.

Mangipinto, A., Lombardi, F., Sanvito, F. D., Pavičević, M., Quoilin, S., and Colombo, E. (2022). Impact of mass-scale deployment of electric vehicles and benefits of smart charging across all european countries. *Applied Energy*, 312:118676.

Martins, F., Moura, P., and de Almeida, A. T. (2022). The role of electrification in the decarbonization of the energy sector in portugal. *Energies*, 15(5):1759.

Matthess, M., Kunkel, S., Dachrodt, M. F., and Beier, G. (2023). The impact of digitalization on energy intensity in manufacturing sectors – a panel data analysis for europe. *Journal of Cleaner Production*, 397:136598.

Mulder, P. and de Groot, H. L. (2004). Decoupling economic growth and energy use: An empirical cross-country analysis for 10 manufacturing sectors. *Tinbergen Institute Discussion Paper*.

NationalParliament (2022). Decree-law no. 15/2022.

Ozturk, I. and Arisoy, I. (2016). An estimation of crude oil import demand in turkey: Evidence from time-varying parameters approach. *Energy Policy*, 99:174–179.

Pablo-Romero, M. d. P., Sánchez-Braza, A., and González-Jara, D. (2023). Economic growth and global warming effects on electricity consumption in spain: a sectoral study. *Environmental Science and Pollution Research*, 30(15):43096–43112.

Papież, M., Rubaszek, M., Szafranek, K., and Śmiech, S. (2022). Are european natural gas markets connected? a time-varying spillovers analysis. *Resources Policy*, 79:103029.

Pesaran, M. H. (2015). *Time Series and Panel Data Econometrics*. Oxford University Press.

Priest, G. L. (1993). The origins of utility regulation and the" theories of regulation" debate. *The Journal of Law and Economics*, 36(1, Part 2):289–323.

Rajabi, M. M. (2022). Dilemmas of energy efficiency: A systematic review of the rebound effect and attempts to curb energy consumption. *Energy Research & Social Science*, 89:102661.

REN (2021). Transmission network development plan 2022-31.

Ribeiro, A. C. P. (2023). Determinants of household electricity consumption in nuts ii regions of portugal. *Master Thesis*.

Roberts, M. B., Sharma, A., and MacGill, I. (2022). Efficient, effective and fair allocation of costs and benefits in residential energy communities deploying shared photovoltaics. *Applied Energy*, 305:117935.

Saldivia, M., Kristjanpoller, W., and Olson, J. E. (2020). Energy consumption and gdp revisited: A new panel data approach with wavelet decomposition. *Applied energy*, 272:115207.

Schäfer, A. (2005). Structural change in energy use. *Energy Policy*, 33(4):429–437.

Schreiner, L. and Madlener, R. (2022). Investing in power grid infrastructure as a flexibility option: A dsge assessment for germany. *Energy Economics*, 107:105843.

Sedmíková, E., Vasylieva, T. A., Karpenko, I. V., and Navickas, M. (2021). Energy consumption in assessment of shadow economy. *European Journal of Interdisciplinary Studies*.

Sharma, D. and Saini, R. (2020). Impact of modernization on energy consumption in agriculture: A review. *Energy Reports*, 6:100–108.

Silva, S., Soares, I., and Pinho, C. (2018). Electricity residential demand elasticities: Urban versus rural areas in portugal. *Energy*, 144:627–632.

Sorrell, S. and Dimitropoulos, J. (2008). The rebound effect: Microeconomic definitions, limitations and extensions. *Ecological Economics*, 65(3):636–649.

Sousa, J., Silva, S., and Almeida, M. (2012). Energy framework for the portuguese residential sector. *Seminar on Energy Rehabilitation of Buildings*, pages 49–57.

Sun, Y., Carroll, R. J., and Li, D. (2009). Semiparametric estimation of fixed-effects panel data varying coefficient models. In *Nonparametric econometric methods*, pages 101–129. Emerald Group Publishing Limited.

Triollet, R., Alvazer, M. A. F., Mortara, B., et al. (2021). Jrc annual report 2022.

Wang, N. and Mogi, G. (2017). Industrial and residential electricity demand dynamics in japan: How did price and income elasticities evolve from 1989 to 2014? *Energy Policy*, 106:233–243.

Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data*. The MIT Press, Cambridge, MA, 2nd edition.

Wu, Y., Zhu, Q., and Zhu, B. (2018). Comparisons of decoupling trends of global economic growth and energy consumption between developed and developing countries. *Energy Policy*, 116:30–38.

Zhu, X., Li, L., Zhou, K., Zhang, X., and Yang, S. (2018). A meta-analysis on the price elasticity and income elasticity of residential electricity demand. *Journal of Cleaner Production*, 201:169–177.