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THE OPTIMAL INVESTMENT SIZE IN THE ELECTRICITY SECTOR IN EU COUNTRIES

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IES Working Paper 24/2024

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The Optimal Investment Size in the Electricity Sector in EU Countries

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Abstract:
This paper aims to estimate the optimal environmental policy in the elektricity generation sector for each of the EU countries maximizing total welfare. The study uses a recently proposed theoretical corporate finance model and empirically estimate each of its components using the current state of the literature to derive the estimated optimal investment size and greenhouse gas abatement activities. Results indicate that a social planner would not significantly reduce the carbon intensity of the EU electricity generation sector but rather keep its industry size well below current levels.

JEL: C54, G38, Q41, Q54
Keywords: investment size, abatement activity, electricity demand, social cost of carbon, carbon intensity, marginal abatement cost curve

1. Introduction

Global climate change impacts are well established (IPCC, 2022). Considered as a threat, governments must take both mitigation and adaptation measures (IPCC, 2022). As part of the former, a control of the net concentration of carbon dioxide in the atmosphere is an essential part of controlling climate change (Begum et al., 2022). This control can be achieved by reducing emissions, capturing carbon dioxide at production, or taking it out of the carbon cycle using negative emission technologies such as growing forests (Parmesan et al., 2022). Firms will have to invest in such abatement activities and adopt more sustainable technologies requiring new investment and capital (Heider and Inderst, 2023). Narrowing to the power sector, our main research question asks which industry size and how much abatement activities a social planner would set to maximize total welfare.

Heider and Inderst (2023) proposed a corporate finance model incorporating emission externalities and industry equilibrium. Particularly, they proposed a theoretical framework to determine what a social planner would choose in terms of investment size (in terms of produced quantity) and abatement activity in a single sector of the economy in order to maximize total welfare. In Heider and Inderst (2023), the outcome obtained within the above framework is referred to as the first-best outcome.

In this paper, we choose to use the above-mentioned framework to estimate the optimal investment size in the electricity generation sector for each of the European Union (EU) countries assuming a closed European market. As detailed in Section 2.3, other frameworks such as The Integrated MARKAL-EFOM1 System (TIMES) energy systems models or multi-objective models can be used to answer the same research question. Our choice among the different frameworks was motivated by the desire to provide feedback on this newly

proposed theoretical framework.

At the time the current paper is written, the above-mentioned theoretical framework was still being developed. Therefore, a key point to keep in mind is that our paper will discuss the empirical results of each of the two latest versions of the above-mentioned theoretical framework (Heider and Inderst, 2021, 2023).

These theoretical frameworks include a number of components, which will have to be estimated from real-world data and the existing literature as part of its application to the electricity sector. The set of components to be estimated include the electricity demand function, the social cost of carbon (SCC), the carbon intensity of electricity for all firms and low-polluting firms, and the marginal abatement cost curve (MACC).

The rest of this paper is structured as follows. In the second section, a brief review of literature on the estimation of electricity demand, the SCC, and the MACC as well as models generating optimal environmental policy are provided. In the third section, data sources and variable measurements involved are described. In the fourth (resp. fifth) section, the results from the application of the first (resp. second) version of Heider and Inderst (2023), are presented. The sixth section quantitatively compares our empirical results with those of the existing literature. The last section concludes.

2. Literature review

The first two subsections are intended to provide lights on the existing literature for the electricity demand modelling and the estimation of the SCC and the MACC, all of which are essential components of the theoretical framework proposed by Heider and Inderst (2021). The last subsection reviews the current state of the literature on determining the optimal environmental policy maximizing the total welfare.

2.1. Electricity demand in the EU

Eskeland and Mideksa (2010) studied the relationship between the European electricity consumption and outdoor temperature as well as other variables such as income, demography, and technology. The results show that the outdoor temperature has a significant effect on electricity consumption, however the authors argue that a change in temperature will have a smaller impact on electricity consumption compared to the other variables mentioned above.

Damm et al. (2017) provided information on the impact of a +2°C global warming scenario on the heating and cooling electricity demand for 26 European countries. Findings reveal that energy policy is a more important factor than climate in electricity consumption for heating and cooling.

Cialani and Mortazavi (2018) examined the determinants of both residential and industrial electricity demand in 29 European countries using data on a relatively long period (1995-2015). Using the Generalized Method of Moments (GMM) and the Maximum Likelihood (ML) approaches, they found very small price elasticities and relatively large income elasticities. It is worth mentioning that the data and methods used in Cialani and Mortazavi (2018) to model the electricity demand are replicated in our present paper.

2.2. Social Cost of Carbon and Marginal Abatement Cost Curve

The SCC represents the economic cost caused by an additional ton of carbon dioxide emissions or its equivalent (Nordhaus, 2017). Pearce (2003), Tol (2011), and Havranek et al. (2015) are three meta-analyses providing an overview of past estimates of the SCC. Tol (2011) concludes that estimates are highly uncertain and are very sensitive to the researcher's assumptions with respect to the people's views on the far future. However, it is found that estimates of the Willingness-To-Pay (WTP) to avoid greenhouse gas emissions at the margin are similar to the estimates of the SCC. Havranek et al. (2015) examined potential

bias in the literature on the SCC using a set of 809 estimates from 101 studies and found the mean reported SCC corrected for the selective reporting bias to be between USD 0 and 134 per ton of carbon at 2010 prices for emission year 2015. Nordhaus (2007, 2011, 2014) progressively valued the SCC at 28.1 USD/tC, 44.0 USD/tC, and 18.6 USD/tCO_2, respectively, at 2005 price levels. Based on a revised Dynamic Integrated model of Climate and the Economy (DICE), Nordhaus (2017) estimated the SCC to be at USD 31 per ton of carbon dioxide at 2010 prices for emission year 2015, consistent with the findings of Havranek et al. (2015). In a recent study, Barrage and Nordhaus (2023) documented a significant rise in the estimated social cost of carbon dioxide, which was assessed 61 USD/tCO_2 at 2019 price levels.

The MACC reflects the required carbon tax level for certain emission reduction targets. Enkvist et al. (2007) have developed cost curves for various environmental policy scenarios, globally and by region and sector, including the power generation sector. For the latter, the author argues that low-tech abatement is more important than technological R&D in a 2030 perspective. Additionally, reducing demand, carbon capture and storage, renewables, nuclear power, and improving the greenhouse gas efficiency of fossil fuel plants are the five key groups of abatement measures which would cost less than EUR 40 per ton of carbon dioxide. Notably, Liu and Feng (2018) investigated the factors influencing the marginal abatement costs of carbon dioxide emissions using data from 165 countries from 2000 to 2014. They found that the relationship between the marginal abatement costs and the economic development is represented by a U-shaped curve. Furthermore, it is found that energy and industrial structure and carbon dioxide emissions are negatively correlated with marginal abatement costs. Tang et al. (2020) simulated the marginal abatement cost curves of various sectors in China's carbon emission trading system

(ETS) and found a negative relationship between the marginal abatement cost and the sector involvement. Finally and particularly, Yue et al. (2020) derived a system-wide MACCs using scenario ensembles from TIMES energy systems model. It is found that MACCs are highly dependent on the model assumptions and the availability of abatement technologies. A ranking and classification of key mitigation measures is also provided.

2.3. Optimal environmental policy and the power sector

As explained in the introduction, our paper directly applies to the electricity sector the two latest versions of the theoretical framework generating the first-best outcome proposed by Heider and Inderst (2021, 2023). In the first version (Heider and Inderst, 2021), the authors provided the set of equations determining the industry/investment size and abatement activity set by an unconstrained social planner maximizing aggregate welfare. These equations involve four key components: the demand function, the SCC, the carbon intensity, and the MACC. In the second version (Heider and Inderst, 2023), the authors have simplified this set of equations into a single equation solving for total investment involving three key components: the demand function, the SCC, and the carbon intensity of low-polluting firms. To our knowledge, there is no existing literature on the application of this specific framework.

Another approach to determine the optimal environmental policy is to generate the outcomes from a TIMES energy system model. Mondal et al. (2019) used this approach to examine Egypt's energy policy goals with a focus on the electricity generation sector. Results suggested a greater diversification in the electricity generation mix to improve energy security, reduce the usage of fossil fuel-based power plants, and reduce carbon dioxide emissions.

Lastly, there exist other alternative models for optimizing social welfare. Geng et al. (2017) explores mitigating air pollution in China via power sector

strategies. Three stochastic scheduling models and a multi-objective model are discussed, offering insights for policymakers on balancing societal welfare, emissions, and renewables. Lykidi and Gourdel (2015) determined how flexible nuclear power plants have to be operated in order to maximize social welfare. The authors found that such power production management involves a constant thermal production and a totally flexible nuclear production through sufficient nuclear capacity.

To the authors' knowledge, there is no existing literature on determining the level of power production and the level of carbon dioxide emissions that maximize social welfare utilizing a theoretical framework such as the ones proposed by Heider and Inderst (2021, 2023), at least for EU countries and most likely for any part of the globe.

3. Data sources and variable measurements

Although shifting of the carbon emission costs between global regions certainly exists, we assume a closed European market. We applied this theoretical framework on the power sector in EU countries at the country-level on the 2000-2020 time period. In other words, for each country in the EU and for each year in the above-mentioned time range, our objective was to determine the investment size (in terms of produced quantity, e.g., Kilowatt-hour (kWh)) and to some extent the abatement activities (in terms of reduced greenhouse gas emission per unit of output, e.g., tCO_2eq/kWh) that an unconstrained social planner would choose to maximize total welfare. The electricity demand function, the SCC, the MACC, and the carbon intensity of electricity generation are key components of the theoretical framework to be estimated. Their estimation requires data collection. For each of these quantities, the data used to estimate them are described in the following subsections.

3.1. Electricity demand

The electricity demand function is one of the key components of the theoretical framework that have to be estimated. With this regard, we replicated the work of Cialani and Mortazavi (2018) requiring the variables described in Table 1. Yearly data were collected from Eurostat and the International Energy Agency (IEA) for 20 countries with observable time period depending on the available data of each country (see Table 8 in the Appendix A). Typical descriptive statistics are provided in Table 2.

Variable	Abbreviation	Description	Source	Unit
Electricity price for household consumers	$price^{hh}$	Average national price in Euro per kWh including taxes and levies applicable for the first semester of each year for medium size household consumers (Consumption Band Dc with annual consumption between 2500 and 5000 kWh). Until 2007 the prices are referring to the status on 1st January of each year for medium size consumers (Standard Consumer Dc with annual consumption of 3500 kWh.	Eurostat, until 2007 and from 2007 onwards	€/kWh
Electricity price for industrial consumers	$price^{ind}$	Average national price in Euro per kWh without taxes applicable for the first semester of each year for medium size industrial consumers (Consumption Band Ic with annual consumption between 500 and 2000 MWh). Until 2007 the prices are referring to the status on 1st January of each year for medium size consumers (Standard Consumer Ie with annual consumption of 2000 MWh).	Eurostat , until 2007 and from 2007 onwards	€/kWh
Electricity consumption by households	$elect^{hh}$	Electricity consumption by households, which is accounted at the same heat value as electricity in final consumption (i.e. 1 GWh = 0.0036 PJ).	International Energy Agency (IEA), Households	PetaJoule (PJ)
Electricity consumption by industry	$elect^{ind}$	Electricity consumption by industries, which is accounted at the same heat value as electricity in final consumption (i.e. 1 GWh = 0.0036 PJ).	International Energy Agency (IEA), Industry	PetaJoule (PJ)
Gross Domestic Product	gdp	Total final output of goods and services produced by an economy within a year in billions of euros (real value at 2010 prices)	Eurostat, GDP	$€_{2010}$
Gross Domestic Product per capita	gdpcap	Real GDP divided by the average population within a year (real value at 2010 prices)	Eurostat, GDP and Population	$€_{2010}$
Population	pop	Population of a Member State on 31st December	Eurostat, Population	
Heating degree day	hdd	Weather-based index designed to assess the energy requirements for heating buildings	Eurostat, HDD	
Cooling degree day	cdd	Weather-based index designed to assess the energy requirements for cooling buildings	Eurostat, HDD	

Table 1: Variable description.

Statistic	N	Mean	St. Dev.	Min	Max
elechh	417	30.252	39.627	0.634	168.129
elecind	417	42.776	53.384	1.506	239.307
pricehh	417	0.179	0.064	0.043	0.390
priceind	417	0.101	0.037	0.033	0.266
gdpcap	417	28,621.020	17,179.270	6,533.997	87,559.120
gdp	417	499.966	694.066	11.954	2,986.827
pop	417	18.541	23.029	0.412	83.194
cdd	417	50.122	77.504	0.000	409.640
hdd	417	3,186.154	1,063.845	1,007.580	6,179.750

Table 2: Electricity demand estimation: Descriptive statistics of explanatory variables. *elechh*, *elecind*, and *gdp* were divided by one bilion; *pop* by one million.

3.2. Social Cost of Carbon

Table 3 contains the SCC estimates directly derived from baseline scenarios in Pearce (2003); Nordhaus (2007, 2011, 2014); Barrage and Nordhaus (2023).

Emission period	Social Cost of Carbon
1991-2000	6.4 USD_{2000}/tC
2001-2005	28.1 USD_{2005}/tC
2006-2015	31.0 USD_{2010}/tCO_2
2016-2020	61.0 USD_{2019}/tCO_2

Table 3: Social Cost of Carbon from baseline scenarios in Pearce (2003); Nordhaus (2007, 2011, 2014); Barrage and Nordhaus (2023).

Incorporating these SCC estimates into our framework necessitates converting units to nominal prices in euros per ton of carbon dioxide, EUR/tCO_2. Firstly, any instances of tC units are transformed into tCO_2 units units by dividing by a factor of 3.67 [1]. Secondly, fixed USD prices are converted into nominal prices in euros using the yearly average USD/EUR exchange rates sourced from Eurostat, along with calculations of the inflation factor for the European Union (EU) as a whole for each year between 1995 and 2020. These inflation

[1] Carbon dioxide is composed of one atome of carbon and two atomes of oxygen with atomic weights 12 and 16, respectively. Therefore 1 tCO_2 contains $\frac{12}{2\times16+12}\ tC \approx \frac{1}{3.67}\ tC$. As a result, $\frac{priceUSD}{1tC} = \frac{priceUSD}{3.67tCO_2}$.

factors are computed concerning the price levels of reference years such as 2000, 2005, 2010, and 2019. Specifically, the inflation factor for each year, A with respect to the reference year, $refY$ is calculated as follows:

$$(1 + \frac{avg_{inf}^{A}}{100})^{A-refY}, \tag{1}$$

where avg_{inf}^{A} denote the average inflation between the reference year $refY$ and year A.

The resulting inflation factors are represented in the Appendix in Figure 11.

3.3. Carbon intensity of electricity generation

Lastly, the carbon intensity of electricity generation is another key component of the theoretical framework. In our case, carbon intensity must be understood as the quantity of greenhouse gases emitted per unit of output, e.g., tCO_2eq/kWh (Heider and Inderst, 2021). However, there is an important distinction between the one in Heider and Inderst (2021) and in Heider and Inderst (2023) to consider. The former uses the averaged carbon intensity of electricity generation among all firms while the later uses the averaged carbon intensity of electricity generation of low-polluting firms.

Keeping these two distinctions in mind, we first present the observed yearly averaged carbon intensity of electricity generation (all firms included) expressed in tCO_2eq/kWh retrieved from Our World in Data for 26 countries from 2000 to 2021. As an example, Figure 1 showcases the carbon intensity of power generation for five EU countries (namely, Germany, Spain, France, Italy, and Netherlands).

The approach used to approximate the yearly average carbon intensities of electricity generation of low-polluting firms for each country will be discussed in section 5.1. This assumption requires data on time-variant country-specific power generation mixes. Figure 2 showcases the electricity generation mix for

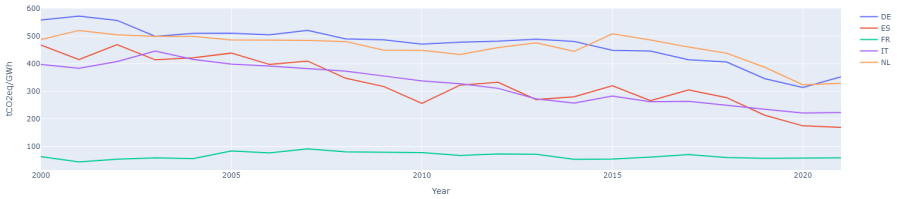


Figure 1: Carbon intensity of electricity generation - all firms. Data downloaded from Our World in Data.

Germany.

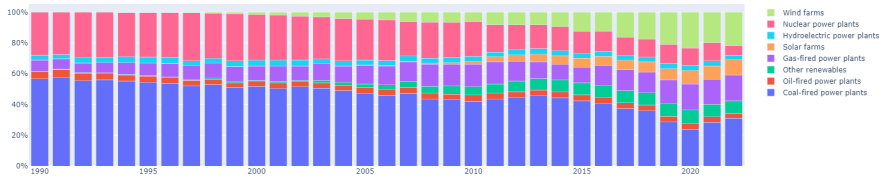


Figure 2: Electricity generation mix of Germany. Data downloaded from Our World in Data.

4. The first-best outcome: including abatement activity

Heider and Inderst (2021) hypothesize Lemma 1.

Lemma 1. *An unconstrained social planner maximizing aggregate welfare would implement monitoring, an abatement activity s_{FB} as given by $c'(s_{FB}) = v$, and industry size I_{FB} as given by $P(I_{FB}) = 1 + v(y - s_{FB}) + c(s_{FB})$.*

In this section, we provide an empirical framework to estimate time-variant electricity demand functions, $P(.)$, for each EU country, the time-variant EU's MACC, $c(.)$, and the time-variant EU's SCC, v. Using Heider and Inderst (2021)'s lemma, the observed time-variant country-level historical carbon intensities and our estimations mentioned above, we derive an estimation of the

first-best investment size, I_{FB}, and the abatement activities, s_{FB}, in section 4.3.

4.1. Electricity demand

The electricity demand function is estimated for each country and year following the empirical framework developed by Cialani and Mortazavi (2018). Specifically, we decompose the electricity consumption into the household and industrial consumptions as follows:

$$e = e^{hh} + e^{ind}, \tag{2}$$

where e, e^{hh}, e^{ind} represent the total, household, and industrial electricity consumption, respectively.

We posit that the formulations presented in Cialani and Mortazavi (2018) accurately capture the characteristics of the broader population under consideration, i.e.,

$$\begin{aligned} ln(e^{hh}_{i,t}) = \beta^{hh}_1 + \beta^{hh}_2 ln(e^{hh}_{i,t-1}) + \beta^{hh}_3 ln(price^{hh}_{i,t}) + \beta^{hh}_4 ln(gdpcap_{i,t}) \\ + \beta^{hh}_5 ln(pop_{i,t}) + \beta^{hh}_6 cdd_{i,t} + \beta^{hh}_7 hdd_{i,t} + \beta^{hh}_8 year_t + \epsilon^{hh}_{i,t} \end{aligned} \tag{3}$$

$$\begin{aligned} ln(e^{ind}_{i,t}) = \beta^{ind}_1 + \beta^{ind}_2 ln(e^{ind}_{i,t-1}) + \beta^{ind}_3 ln(price^{ind}_{i,t}) + \beta^{ind}_4 ln(gdp_{i,t}) \\ + \beta^{ind}_5 cdd_{i,t} + \beta^{ind}_6 hdd_{i,t} + \beta^{ind}_7 year_t + \epsilon^{ind}_{i,t} \end{aligned} \tag{4}$$

which can be rewritten as follows:

$$
\begin{aligned}
ln(e^{hh}_{i,t}) - \beta^{hh}_2 ln(e^{hh}_{i,t-1}) =& \beta^{hh}_1 + \beta^{hh}_3 ln(price^{hh}_{i,t}) + \beta^{hh}_4 ln(gdpcap_{i,t}) \\
&+ \beta^{hh}_5 ln(pop_{i,t}) + \beta^{hh}_6 cdd_{i,t} + \beta^{hh}_7 hdd_{i,t} \\
&+ \beta^{hh}_8 year_t + \epsilon^{hh}_{i,t} \\
ln(e^{ind}_{i,t}) - \beta^{ind}_2 ln(e^{ind}_{i,t-1}) =& \beta^{ind}_1 + \beta^{ind}_3 ln(price^{ind}_{i,t}) + \beta^{ind}_4 ln(gdp_{i,t}) \\
&+ \beta^{ind}_5 cdd_{i,t} + \beta^{ind}_6 hdd_{i,t} + \beta^{ind}_7 year_t + \epsilon^{ind}_{i,t},
\end{aligned}
$$

where $e^{hh}_{i,t}$, $e^{ind}_{i,t}$, $price^{hh}_{i,t}$, $price^{ind}_{i,t}$ represent the household and industry electricity consumption and price for household and industry in country i at year t respectively, $gdp_{i,t}$, $gdpcap_{i,t}$, $pop_{i,t}$, $cdd_{i,t}$, $hdd_{i,t}$ are the GDP, GDP per capita, population, Cooling and Heating Degree Days in country i at year t respectively, $year_t$ is the year at t, and $\epsilon^{hh}_{i,t} \sim \mathcal{N}(0, \sigma^{hh})$ and $\epsilon^{ind}_{i,t} \sim \mathcal{C}(0, \gamma^{ind})$ are the error terms with $\sigma^{hh} > 0$ and $\gamma^{ind} > 0$.

At equilibrium $e^j_t = e^j_{t-1}$, $j \in \{hh, ind\}$, equation (2) can be rewritten as

$$
e = (h^{hh})^{-1} \circ m^{hh}(p) + (h^{ind})^{-1} \circ m^{ind}(p), \tag{5}
$$

where

$$
h^j(e) = (1 - \beta^j_2) ln(e), \text{ for j in } \{hh, ind\} \tag{6}
$$

$$
\begin{aligned}
m^{hh}(p) = \beta^{hh}_1 &+ \beta^{hh}_3 ln(p) + \beta^{hh}_4 ln(gdpcap) + \beta^{hh}_5 ln(pop) + \beta^{hh}_6 cdd \\
&+ \beta^{hh}_7 hdd + \beta^{hh}_8 year + \epsilon
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
m^{ind}(p) = \beta^{ind}_1 &+ \beta^{ind}_3 ln(p) + \beta^{ind}_4 ln(gdp) + \beta^{ind}_5 cdd + \beta^{ind}_6 hdd \\
&+ \beta^{ind}_7 year + \epsilon.
\end{aligned} \tag{8}
$$

Equation (5) leads to the inverse total electricity demand function

$$P(e) = \left((h^{hh})^{-1} \circ m^{hh} + (h^{ind})^{-1} \circ m^{ind}\right)^{-1}(e). \tag{9}$$

Detailed derivations leading to Equation (5) are provided in the Appendix B.1. Using equations (6), (7), (8), and (9), we have

$$P^{-1}(p) = exp(A)exp\left(\frac{\beta_3^{hh}}{1-\beta_2^{hh}} ln(p)\right) + exp(B)exp\left(\frac{\beta_3^{ind}}{1-\beta_2^{ind}} ln(p)\right),$$

where

$$A = \frac{1}{1-\beta_2^{hh}}\left(\beta_1^{hh} + \beta_4^{hh} ln(gdpcap) + \beta_5^{hh} ln(pop) + \beta_6^{hh} cdd + \beta_7^{hh} hdd + \beta_8^{hh} year + \epsilon\right)$$
$$B = \frac{1}{1-\beta_2^{ind}}\left(\beta_1^{ind} + \beta_4^{ind} ln(gdp) + \beta_5^{ind} cdd + \beta_6^{ind} hdd + \beta_7^{ind} year + \epsilon\right),$$

which can simply be rewritten as

$$P^{-1}(p) = \tilde{A}p^a + \tilde{B}p^b, \tag{10}$$

where

$$\begin{aligned} \tilde{A} &= exp(A) \\ \tilde{B} &= exp(B) \\ a &= \frac{\beta_3^{hh}}{1-\beta_2^{hh}} \\ b &= \frac{\beta_3^{ind}}{1-\beta_2^{ind}}. \end{aligned} \tag{11}$$

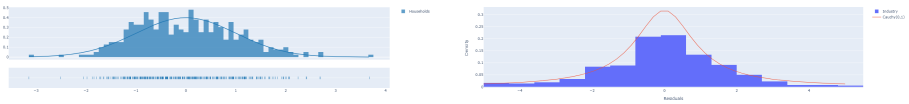
The function $P^{-1}(.)$ in Equation (10) is the total electricity demand function that we want to estimate. Its estimation requires the estimation of quantities

$\tilde{A}$, $\tilde{B}$, a, and b through the estimation of the coefficients β_j^i.

Similar to Cialani and Mortazavi (2018), the above-mentioned coefficients in equations (3) and (4) are estimated by taking the estimate having the highest likelihood among 100 Maximum Likelihood (ML) estimates on the data described in section 3.1 for each of the households and industry sector. Figure 3 shows the estimated total power demand function for five EU countries (namely, Germany, Spain, France, Italy, and Netherlands).

Figure 3: Estimated total power demand functions for five EU countries in 2020.

In addition to Cialani and Mortazavi (2018), we provide a residual analysis for both households and industry estimations. Coefficients in the household electricity demand model equation (3) are estimated assuming independence and normal distribution of its residuals. Table 4 and Figure 4a support these assumptions. As for the industry, coefficients in the industry electricity demand model equation (4) are estimated assuming independence and Cauchy distribution of its residuals to allow for tighter tails. Similarly, Table 5 and Figure 4b support these assumptions.



(a) Households: distribution against $\mathcal{N}(0,1)$ (b) Industry: distribution against $\mathcal{C}(0,1)$

Figure 4: Observed distributions of reduced residuals against their distribution assumption.

Statistic	Overall	DE	ES	FR	IT	NL
N	395	16	15	17	25	16
Mean	0.002	−0.531	0.071	0.271	−0.022	−0.448
St. Dev.	1.001	0.655	0.781	0.906	0.849	0.651
Min	−3.145	−1.447	−1.130	−1.424	−1.250	−1.169
Median	−0.045	−0.690	−0.073	0.408	0.012	−0.620
Max	3.680	0.611	1.764	1.588	1.296	0.910
Skewness	0.282	0.234	0.444	−0.186	−0.122	0.631
Kurtosis	2.940	1.864	2.608	1.882	1.668	2.220
Shapiro	0.990**	0.952	0.970	0.944	0.923	0.909
Jarque-Bera	5.301*	1.005	0.588	0.983	1.910	1.468
ARCH-LM	67.442***	2.224	0.496	2.144	6.563*	3.192
ADF	−7.612***	−0.614	−3.844***	−0.058	−0.604	−1.390
KPSS	0.088*	0.623**	0.714**	0.762***	0.722**	0.583**

Table 4: Households electricity demand estimation: the descriptive statistics, diagnostics, and unit root tests results of reduced residuals.
Note: *, **, and *** represents significance at 10%, 5% and 1% level respectively. ARCH-LM test performs the LM test for Autoregressive Conditional Heteroskedasticity with the null assumption of no ARCH effects. Unit roots are tested using the Augmented Dicky and Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

Statistic	Overall	DE	ES	FR	IT	NL
N	395	16	15	17	25	16
Mean	−0.411	0.524	−1.688	−0.459	−0.256	−0.497
St. Dev.	2.747	2.535	3.260	2.077	2.030	2.396
Min	−12.061	−6.476	−10.101	−6.535	−7.759	−6.531
Median	−0.070	0.596	−1.330	−0.070	−0.010	−0.116
Max	18.052	6.258	2.350	2.419	2.642	3.099
Skewness	−0.126	−0.655	−1.190	−1.636	−2.005	−1.306
Kurtosis	9.765	6.053	4.051	5.603	8.714	4.360
ARCH-LM	5.753	1.160	0.168	0.096	0.277	0.348
ADF	−20.123***	−0.524	−2.866**	−3.827***	−4.446***	−1.096
KPSS	0.122*	0.151*	0.211*	0.080*	0.199*	0.183*

Table 5: Industry electricity demand estimation: the descriptive statistics, diagnostics, and unit root tests results of reduced residuals.
Note: *, **, and *** represents significance at 10%, 5% and 1% level respectively. ARCH-LM test performs the LM test for Autoregressive Conditional Heteroskedasticity with the null assumption of no ARCH effects. Unit roots are tested using the Augmented Dicky and Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

4.2. Social Cost of Carbon and Marginal Abatement Cost Curve

Another key component of the first-best outcome framework is the SCC. In our analysis, its estimation over time is provided for the EU as a whole gathering all the prepared elements from section 3.2. The estimed SCCs from Table 3 are first converted into euros using the USD/EUR yearly average exchange rates and then spread out over time using the inflation factors for the respective emission periods. Figure 5 shows the assumed evolution of the SCC over time.

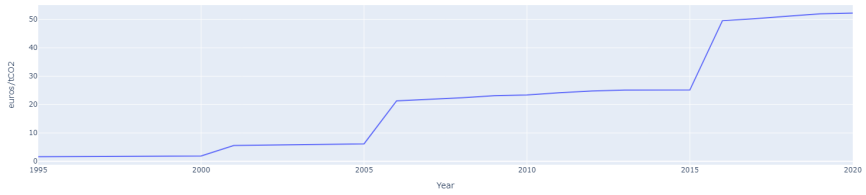


Figure 5: Estimated SCC for the EU as a whole.

MACCs, the last key component, are modelled for the EU as a whole and for each year using the constraints from Heider and Inderst (2021), the estimations from Yue et al. (2020) and additional empirical assumptions, that is:

Assumption 1. *For all* $\alpha > 0$, $\beta > 1$, *and any carbon intensity reduction* $s_i \geq 0$, *the MACC is in the form* $c(s_i) = \alpha s_i^{\beta}$.

Assumption 2. *Denoting* y_{2000}^{max} *the highest country-level carbon intensity observed in the EU in 2000,* $c'(y_{2000}^{max}) = 10^{12}$, *assuming that* 10^{12} *is an infinite number.*

Assumption 3. $c\left(\frac{y_{2000}^{max}}{2}\right) = 200€_{2018}/tCO_2$.

The above assumptions may be interpreted as follows. First, EU countries face the same marginal abatement costs and therefore share the same technology at the same price. Second, 10^{12} is supposed to be an infinite number: at the

y_{2000}^{max} carbon intensity reduction level, an additional reduction of 1 tCO_2/kWh requires an investment of 1 trillion euros. Third, the unconstrained social planner begins to manage abatement activities in the year 2000. Lastly, Ireland estimated MACCs are a proxy for those of the EU.

From Assumption 1., Assumption 2., and Assumption 3., α and β are derived using a standard calculator. The reader is encouraged to note that since Assumption 3 involves 2018 prices, $200€_{2018}/tCO_2$ is converted in nominal prices[2] and therefore there is one MACC for each year. Figure 6 showcase the estimated MACCs for the EU as a whole for the subset of years 2000, 2012, and 2021.

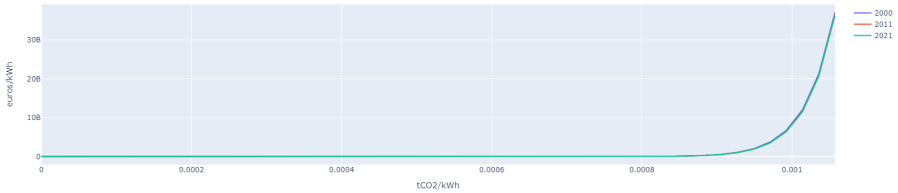


Figure 6: Estimated MACCs for the EU as a whole for the subset of years 2000, 2012, and 2021.

4.3. Investment size and Abatement activity

As a final step, we derive an estimation of the first-best investment size, I_{FB}, measured in kWh and the abatement activities s_{FB} measured in tCO_2/kWh from our estimations in sections 4.1 and 4.2, the observed historical country-level carbon intensity, and Heider and Inderst (2021)'s Lemma 1.

One can show that Heider and Inderst (2021)'s Lemma 1, Equations (1), (10), and (11) imply the following system of equations (12)

[2] $200€_{2018}/tCO_2$ is converted in nominal prices for each year in the period 2000-2021 using a similar formula for the inflation factor as in Equation (1), replacing year 2010 by 2018.

$$
\begin{aligned}
I_{FB} &= \tilde{A}(p^*)^a + \tilde{B}(p^*)^b \\
s_{FB} &= exp\left(\frac{1}{\beta - 1} ln\left(\frac{v}{\alpha\beta}\right)\right),
\end{aligned}
\tag{12}
$$

where

$$
p^* = 1 + v\left[y - exp\left(\frac{1}{\beta - 1} ln\left(\frac{v}{\alpha\beta}\right)\right)\right] + \alpha \times exp\left(\frac{\beta}{\beta - 1} ln\left(\frac{v}{\alpha\beta}\right)\right),
$$

and $\tilde{A}$ and $\tilde{B}$ are time-variant country-specific parameters, a and b are time-fixed country-fixed parameters, and β and α are time-variant country-fixed parameters, all defined in the system of equations (11) and Assumption 1.

With estimations in section 4.1 and 4.2 at hand, Figure 7 showcases the estimated investment size in TWh set by an unconstrained social planner for five EU countries (namely, Germany, Spain, France, Italy, and Netherlands) for the country's specific longest available period. A social planner would set the investment size much lower than the observed historical electricity production, especially in the 2000-2015 period.

These results should however be taken with a grain of salt given the uncertainty of the estimation of the power demand functions. The later is achieved by repeating 100 estimations of β_1^{hh}, β_2^{hh}, ... , β_6^{ind}, and β_7^{ind} using the Limited-memory Broyden–Fletcher–Goldfarb–Shanno Bound optimizer (L-BFGS-B) and the initial parameter distributions provided in Appendix B.2. Among these 100 estimations, the one producing the highest Log-likelihood is retained as the final estimate for the β coefficients. The authors repeated this estimation procedure 100 times and descriptive statistics of the estimated β coefficients, provided in Table 6, clearly show that there is a large uncertainty in the estimation.

As shown in Figure 8, the estimated carbon intensity set by an unconstrained social planner would remain roughly constant over time, keeping large differences

Statistic	N	Mean	St. Dev.	Min	Max
β_1^{hh}	100	−14.998	4.444	−28.972	−10.085
β_2^{hh}	100	0.971	0.076	0.571	1.174
β_3^{hh}	100	−0.079	0.068	−0.239	0.074
β_4^{hh}	100	0.042	0.050	−0.077	0.274
β_5^{hh}	100	0.033	0.082	−0.188	0.467
β_6^{hh}	100	0.00002	0.0001	−0.0002	0.0003
β_7^{hh}	100	0.00002	0.00002	−0.00004	0.0001
β_8^{hh}	100	0.007	0.002	0.005	0.014
β_1^{ind}	100	1.654	3.434	0.017	18.075
β_2^{ind}	100	0.975	0.028	0.862	0.993
β_3^{ind}	100	−0.040	0.069	−0.270	0.078
β_4^{ind}	100	0.018	0.029	−0.0003	0.130
β_5^{ind}	100	0.0001	0.0001	0.0001	0.0003
β_6^{ind}	100	0.00000	0.00001	−0.00001	0.00004
β_7^{ind}	100	−0.001	0.002	−0.009	0.0001

Table 6: The estimation procedure of the power demand functions was repeated 100 times. The table shows descriptive statistics of the estimated beta coefficients.

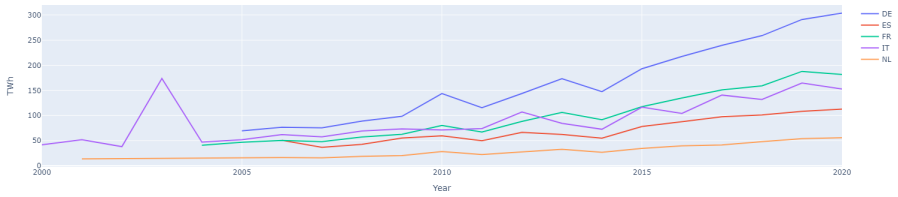


Figure 7: Estimated investment size for five EU countries over time.

in carbon intensity between countries.

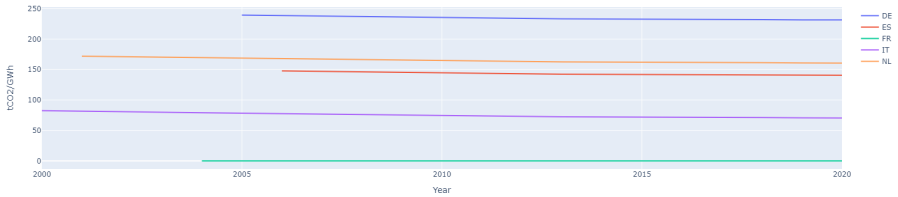


Figure 8: Carbon intensities deducting social planner's abatement activities for five EU countries over time.

5. The first-best outcome: with low-polluting firms only

Heider and Inderst (2023) hypothesize Lemma 2.

Lemma 2. *Given the linear production technology, only low-polluting firms, $j = l$, should be active, and marginal social surplus should be zero at investment and output I_{FB}, $P(x = I_{FB}) = 1 + vy_l$, which equates marginal consumer welfare to marginal social costs of production.*

We employ the empirical framework from section 4 to estimate time-variant electricity demand functions, $P(.)$, for each EU country and the time-variant EU's SCC, v. Compared to the theoretical framework in section 4, the difference resides in the marginal social cost of production, $1 + vy_l$, from the addition of the carbon intensity of low-polluting firms, y_l, expressed in tCO_2/kWh, and the deletion of the marginal abatement activities, s_{FB}. In this section 5, we extend our empirical framework to estimate the carbon intensity of low-polluting firms, y_l, in section 5.1, and discuss the resulting estimated first-best investment sizes, I_{FB}, in section 5.2.

5.1. Carbon intensity of low-polluting firms

Switching to the delicate case of carbon intensity of electricity generation of low-polluting firms, we are not aware of any data which measures this quantity. Therefore, we first assume that low-polluting firms generate electricity from all of the existing low-carbon technologies (namely, hydro and nuclear power plants, solar and wind farms, and other renewables) in a given country and year, leaving the high-polluting firms with all of the existing high-carbon technologies (coal, oil, and gas power plants). As for our second assumption, we quantify the averaged carbon intensity for each low-carbon electricity generation type as described in Table 7. From the above two assumptions and the time-variant country-specific power generation mix data provided in section 3.3, we define

the averaged carbon intensity of electricity generation of low-polluting firms, y_l, expressed in tCO_2eq/kWh, as

$$y_l = \frac{hydro \times 24 + nuc \times 12 + solar \times 30 + wind \times 11.5 + otherrenew \times 100}{hydro + nuc + solar + wind + otherrenew},$$

where $hydro$, nuc, $solar$, $wind$, $otherrenew$ are the hydroelectric, nuclear, solar, wind, and other renewables production shares in a given country and year, respectively.

Production type	Assumed carbon intensity (tCO_2eq/GWh)
Hydroelectricity power plants	24
Nuclear power plants	12
Solar farms	30
Wind farms	11.5
Other renewables (includes biomass)	100

Table 7: Carbon intensities by low-carbon electricity production type in the EU.

Figure 9 showcases the estimated carbon intensities of low-polluting firms, y_l, over time for five EU countries.

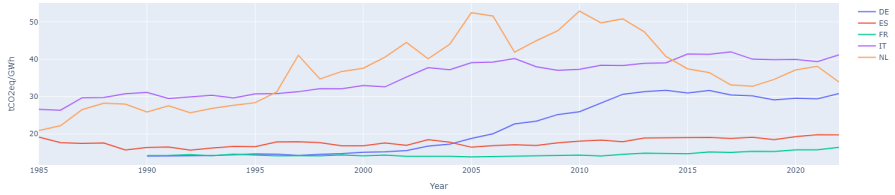


Figure 9: Estimated carbon intensities of low-polluting firms over time for five EU countries.

5.2. Investment size

Similar to section 4.3, we derive an estimation of the first-best investment size, I_{FB}, measured in kWh from our estimations in sections 4.1, 4.2 (leaving the estimated MACCs aside), 5.1, and Heider and Inderst (2023)'s Lemma 2.

We show that Heider and Inderst (2023)'s Lemma 2, Equations (10), and (11) imply the time-variant country-specific investment size in Equation (13)

$$I_{FB} = \tilde{A}(p^*)^a + \tilde{B}(p^*)^b, \tag{13}$$

where

$$p^* = 1 + vy_l,$$

and $\tilde{A}$ and $\tilde{B}$ are time-variant country-specific constants, and a, b are time-fixed country-fixed constants, all defined in the system of equations (11).

With the estimated time-variant country-specific electricity generation demand functions from section 4.1, the estimated time-variant SCC from section 4.2, and the estimated carbon intensities of low-polluting firms from section 5.1 at hand, Figure 10 showcases the estimated first-best investment size, I_{FB}, set by an unconstrained social planner for five EU countries (namely, France, Germany, Italy, Netherlands, and Spain). Similar to section 4.3, a social planner would set the investment size much lower than the observed historical electricity production.

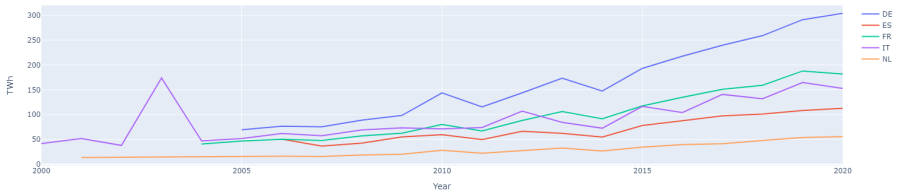


Figure 10: Estimated industry sizes for five EU countries over time.

6. Empirical Results Versus Literature Comparison

In this section, we contrast our results with studies that provide estimates of the power generation industry size for EU countries, focusing on maximizing social welfare.

Carraro et al. (2013) analyzes various scenarios for European energy markets to assess their alignment with economic incentives and climate goals, focusing on the role of natural gas in different climate policy contexts. Their welfare maximizing power generation in the EU27 under various scenarios and policy assumptions exceed our estimates by a factor of three to five.

Su et al. (2020) explored EU's 2030 climate goals, applying Pinch Analysis to identify renewable energy pathways for major electricity producers, considering socio-economic and technological factors. While their objective focused on maximizing the deployment of renewable electricity sources, we align our study results with theirs, even though our goal is broader in optimizing total welfare. Their country-level estimates of the electricity production exceed our estimates by a factor of two to five.

Misconel et al. (2022) employ diverse model approaches, including the PowerACE model, which encompasses modeling of the Germany electricity system. PowerACE is an agent-based simulation model developed for analyzing European spot electricity markets at hourly resolution using long-term scenarios. All supply agents within this framework prepare hourly supply and demand bids that are auctioned across the market area, with the overarching goal of maximizing welfare. Their projections for German electricity production exceed our findings by a margin ranging from 15 to 98%.

Overall, our socially optimal power output estimates fall significantly lower than those found in the existing literature. This study consequently questions either the theoretical frameworks of Heider and Inderst (2021, 2023), or the

empirical techniques used to quantity their individual components, or the empirical findings from the existing literature on the optimal power production in EU countries. Given the results from repeated estimation of the power demand functions and their importance in the estimation of the optimal investment size, the authors conclude that further research is required to accurately estimate power demand functions.

7. Conclusion and Policy Implications

Climate change mitigation can be achieved by reducing emissions, capturing carbon dioxide at production, or taking out of the carbon cycle using negative emission technologies. In this context, firms require new investments in such abatement activities. Focusing on the power sector, this empirical paper estimates the industry size and how much abatement activities an unconstrained social planner would set in each EU country from 2000 to 2020 to maximize aggregate welfare. To this extent, we estimate EU time-variant country-level power demand functions, time-variant social cost of carbon, time-variant marginal abatement cost curves and apply the theoretical framework of Heider and Inderst (2021) as well as its updated version in Heider and Inderst (2023) under the closed European market assumption.

Findings suggest that an unconstrained social planner would not significantly reduce the carbon intensity of the EU electricity generation sector but rather keep the industry size well below current levels. Assuming the empirical findings are valid, implications for investors and policymakers include the introduction of energy saving policies, such as renovating buildings, and lower investments in costly carbon dioxide abatement activities in the electricity generation sector.

Additionally, our empirical study essentially tests whether the theoretical frameworks proposed by Heider and Inderst (2021, 2023) are empirically relevant and can be operationalized, providing feedback to the authors mentioned above. Our

estimates of power generation are significantly lower than those reported in the existing literature. This discrepancy may partly stem from inaccuracies in the estimation of the power demand functions. The authors therefore advocate for further research in the power demand function estimation.

CRediT authorship contribution statement

Mathieu Petit: Conceptualization, Data Curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing - Original Draft. **Karel Janda:** Project administration, Supervision, Writing - Review & Editing.

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Appendix A Data Sources

	Start	End
AT	2004	2020
BE	1995	2020
CZ	2000	2020
DE	2004	2020
DK	1995	2020
EE	2002	2020
ES	2005	2020
FI	1995	2020
FR	2003	2020
HU	1995	2020
IE	2005	2020
IT	1995	2020
LT	2004	2020
LU	1995	2020
LV	2004	2020
NL	2000	2020
PL	2001	2020
PT	2005	2020
SE	1997	2020
SI	1995	2020

Table 8: Electricity demand estimation: Observable time period by country.

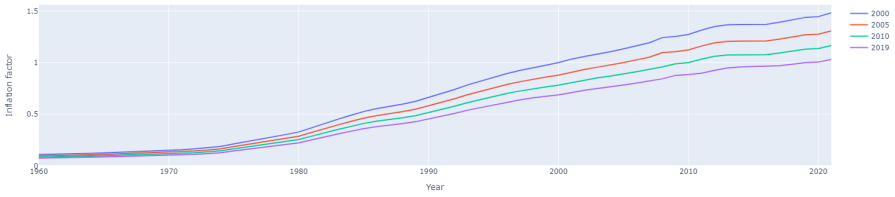

Figure 11: The calculated EU inflation factors. Inflation rates are downloaded from Eurostat.

Appendix B The first-best outcome: including abatement activity

B.1 Derivation of the power demand function

The following derivations are provided for the households (hh) as an example but these are obviously adjustable for the industry (ind).

Proposition 1. *If* $\forall t \in \mathbb{N}+, \forall e_t^{hh} \in \mathbb{R}_+^*, \exists p_t^{hh} \in \mathbb{R}_+^*$,

$$\begin{aligned} ln(e_t^{hh}) - \beta_2^{hh} ln(e_{t-1}^{hh}) =& \beta_1^{hh} + \beta_3^{hh} ln(p_t^{hh}) + \beta_4^{hh} ln(gdpcap_t) \\ &+ \beta_5^{hh} ln(pop_t) + \beta_6^{hh} cdd_t + \beta_7^{hh} hdd_t \\ &+ \beta_8^{hh} year_t + \epsilon_t, \end{aligned}$$

then $\forall e^{hh} \in \mathbb{R}_+^*, \exists p \in \mathbb{R}_+^*, e^{hh} = (h^{hh})^{-1} \circ m^{hh}(p)$ *at equilibrium, where* h^{hh} *is invertible on* $\mathbb{R}_+^*$ *and*

$$h^j(e) = (1 - \beta_2^j) ln(e), \text{ for } j \text{ in } \{hh, ind\},$$

$$\begin{aligned} m^{hh}(p) = \beta_1^{hh} + \beta_3^{hh} ln(p) + \beta_4^{hh} ln(gdpcap) + \beta_5^{hh} ln(pop) + \beta_6^{hh} cdd \\ + \beta_7^{hh} hdd + \beta_8^{hh} year + \epsilon. \end{aligned}$$

Proof:

$$\begin{aligned} &\forall t \in \mathbb{N}+, \forall e_t^{hh} \in \mathbb{R}_+^*, \exists p_t^{hh} \in \mathbb{R}_+^*, \\ &\quad ln(e_t^{hh}) - \beta_2^{hh} ln(e_{t-1}^{hh}) = \beta_1^{hh} + \beta_3^{hh} ln(p_t^{hh}) + \beta_4^{hh} ln(gdpcap_t) \\ &\qquad + \beta_5^{hh} ln(pop_t) + \beta_6^{hh} cdd_t + \beta_7^{hh} hdd_t \\ &\qquad + \beta_8^{hh} year_t + \epsilon_t, \end{aligned}$$

$$
\begin{aligned}
& \forall e^{hh} \in \mathbb{R}_+^*, \exists p^{hh} \in \mathbb{R}_+^*, \\
e_t^{hh}=e_{t-1}^{hh}=e^{hh} \implies \quad & ln(e^{hh}) - \beta_2^{hh} ln(e^{hh}) = \beta_1^{hh} + \beta_3^{hh} ln(p^{hh}) + \beta_4^{hh} ln(gdpcap) \\
& \qquad + \beta_5^{hh} ln(pop) + \beta_6^{hh} cdd + \beta_7^{hh} hdd \\
& \qquad + \beta_8^{hh} year + \epsilon
\end{aligned}
$$

$$
\begin{aligned}
& \forall e^{hh} \in \mathbb{R}_+^*, \exists p^{hh} \in \mathbb{R}_+^*, \\
\implies \quad & (1 - \beta_2^{hh}) ln(e^{hh}) = \beta_1^{hh} + \beta_3^{hh} ln(p^{hh}) + \beta_4^{hh} ln(gdpcap) \\
& \qquad + \beta_5^{hh} ln(pop) + \beta_6^{hh} cdd + \beta_7^{hh} hdd \\
& \qquad + \beta_8^{hh} year + \epsilon
\end{aligned}
$$

$$
\begin{aligned}
\implies \quad & \forall e^{hh} \in \mathbb{R}_+^*, \exists p^{hh} \in \mathbb{R}_+^*, \\
& h^{hh}(e^{hh}) = m^{hh}(p^{hh})
\end{aligned}
$$

$$
\begin{aligned}
\implies \quad & \forall e^{hh} \in \mathbb{R}_+^*, \exists p^{hh} \in \mathbb{R}_+^*, \\
& e^{hh} = (h^{hh})^{-1} \circ m^{hh}(p^{hh}).
\end{aligned}
$$

B.2 Power demand function estimation: Optimization

When performing the estimation of the β coefficients involved in the power demand function population equation, the authors used the L-BFGS-B optimizer and the distributions for the initial parameters,

$$
\begin{aligned}
\beta_1^{hh} &\sim -10^{\mathcal{U}[1,3]},\\
\beta_2^{hh} &\sim 10^{\mathcal{U}[-1,1]},\\
\beta_3^{hh}, \beta_3^{ind} &\sim -10^{\mathcal{U}[-3,-1]},\\
\beta_4^{hh}, \beta_5^{hh}, \beta_2^{ind}, \beta_4^{ind}, \beta_5^{ind} &\sim 10^{\mathcal{U}[-2,0]},\\
\beta_6^{hh}, \beta_7^{hh}, \beta_6^{ind} &\sim 10^{\mathcal{U}[-3,-1]},\\
\beta_8^{hh}, \beta_7^{ind} &\sim -10^{\mathcal{U}[-4,-2]},\\
\sigma^{hh}, \gamma^{ind} &\sim \mathcal{U}[0,1],\\
\beta_1^{ind} &\sim 10^{\mathcal{U}[-2,2]}.
\end{aligned}
$$

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