Institut d'Economia de Barcelona

IEB Working Paper 2023/07

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Version October 2023

Energy Sustainability

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The **Chair of Energy Sustainability of the University of Barcelona-IEB** is funded by the following enterprises ACS, CEPSA, CLH, Enagas, Endesa, FCC Energia, HC Energia, Gas Natural Fenosa, and Repsol) through FUNSEAM (Foundation for Energy and Environmental Sustainability).

Postal Address:
Institut d’Economia de Barcelona
Facultat d’Economia i Empresa - Universitat de Barcelona
C/ John M. Keynes, 1-11
(08034) Barcelona, Spain
Tel.: + 34 93 403 46 46
ieb@ub.edu
http://www.ieb.ub.edu

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ABSTRACT: Developing countries are making great efforts to electrify residences to reduce dependence on fossil fuels and deal with climate change. In 2014, Ecuador launched a clean-cooking program known as the *Programa de Cocción Eficiente* (PCE) aimed at replacing liquefied petroleum gas (LPG)-fired cookstoves and LPG-fired boilers with electric devices. Using an original dataset of monthly information (2015-2021) at the parish level, we study several important determinants of participation in this program that have not yet been addressed. We first model spatial spillovers and then investigate the impact of regional power quality and the effect of other subsidized programs related to electricity consumption. Our results show spillover effects for PCE participation with regard to cooking but not for the overall PCE participation rate. Higher participation is associated to better supply quality and with the use of other power subsidies. Policy recommendations include the need to perform detailed spatial analyses of the determinants of participation in these programs, instead of using surveys, and designing programs using a placed-based approach, in addition to evaluating cross-sectional effects between subsidies in advance in order to avoid unforeseen trade-offs and considering the regulatory framework for utilities to provide effective incentives to improve supply quality.

JEL Codes: Q01, Q43, Q52, Q56
Keywords: Clean-cooking programs, Energy poverty, Spatial spillover effects, Power quality, Electrical reliability, Latin America, Developing countries, Ecuador.

Moisés Obaco
Universidad Católica del Norte & FACEA & Departamento de Economía, Antofagasta, Chile
E-mail: moises.obaco@ucn.cl

Daniel Davi-Arderius
Copenhagen School of Energy Infrastructure (CSEI), Copenhagen Business School, Denmark & University of Barcelona and Chair of Energy Sustainability & Barcelona Institute of Economics (IEB), Spain.
Email: daniel_davi@ub.edu

Nicola Pontarollo
Department of Economics and Management, University of Brescia, Brescia, Italy.
Email: nicola.pontarollo@unibs.it

*Disclaimer: The opinions expressed within the contents are solely the authors' and do not reflect those of institutions or companies with which they are affiliated. Daniel Davi-Arderius works at e-Distribucion Redes Digitales, SLU (Endesa) and is also part of the EU DSO Entity.

1. Introduction

In 2020, approximately 2 billion people were still using biomass for cooking despite having access to electricity (Energy Sector Management Assistance Program, 2020). The United Nations (UN) estimates that household air pollution from cooking kills over four million people every year and causes millions more to become ill.[1] Cooking smoke can lead to stroke, cancers, pneumonia, chronic lung diseases and heart disease, especially in women and children in low- and middle-income regions (World Health Organization, 2014, 2021). The adoption of clean technologies based on electricity produced by renewal energy sources (RES) is thus a priority related to 10 of the 17 Sustainable Development Goals (SDGs). In particular, SDG 7.1 aims to ensure universal access to affordable, reliable, and modern energy services. Indeed, in recent years, global investment in clean energy has been increasing around the world, outpacing that of fuel fossils.[2]

In developing countries, access to electricity in rural areas can improve the socioeconomic conditions of citizens and is strongly related to income and human development (Niu et al., 2016). In 2020, the level of access to electricity in Sub-Saharan Africa and in Latin America was 48.2% and 98.5%, respectively.[3] As both regions face similar problems in the adoption of clean technologies powered by electricity, many rural households in Latin America are still using coal or wood for cooking.

In Ecuador, for example, the main sources of household energy consumption in 2021 were liquefied petroleum gas (LPG) (52.9%), electricity (37.9%), wood (9.2%), and natural gas (0.1%). Moreover, 70.4% of national LPG consumption was by households; the electrification of residential consumption is thus considered a priority (Mi et al., 2020; IIGE, 2022; Yuan et al., 2022). In this context, the country presents an interesting case study as in 2014 the government launched the *Programa de Cocción Eficiente* [Efficient Cooking Program] (PCE) aimed at replacing LPG-fired cookstoves and LPG-fired boilers with electric devices. The PCE began in 2015, when households accounted for 75% of national LPG consumption. The Ecuadorian government expected 3 million families to join to PCE, but uptake was below 700,000 families. A main reason for this is that the low price of LPG cylinders did not provide enough of an economic incentive to switch from LPG to electricity (Gould et al., 2020a). More specifically, subsidies of LPG covered almost 90% of its final price (IIGE, 2022). Another reason for the low uptake pointed out by Davi-Arderius et al. (2023) is that the PCE program did not employ a regional approach to tailor the program to the socioeconomic characteristics of potential participants.

To the best of our knowledge, participation in the PCE program has not been analyzed in terms of the spatial dependence between parishes, i.e. the presence of spillover effects, referring to the effect of participation in a given parish being explained by participation in neighboring parishes (LeSage and Pace, 2009). The quantification of these spatial effects is useful in order to design effective strategies to engage participants: with high spatial dependence, the most optimal strategy could be to prioritize the engagement of

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[1] https://unfoundation.org/what-we-do/issues/sustainable-development-goals/; https://news.un.org/en/story/2014/11/484422.

[2] https://www.iea.org/news/clean-energy-investment-is-extending-its-lead-over-fossil-fuels-boosted-by-energy-security-strengths

[3] World Bank. 2023. Access to electricity (% of population). https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS

people through a place-based approach that creates opportunities to facilitate experience- and knowledge-sharing among peers and stakeholders.

In addition to spatial spillovers, the potential impact of power quality (the reliability of electricity infrastructure) on the engagement rate in these types of electrification programs has not been explored in depth. A negative impact of supply quality on PCE program participation would highlight the need to implement complementary policies to improve the quality of supply provided by utilities in combination with these types of electrification programs (Jamasb et al., 2017; Poudineh and Jamasb, 2015, 2017; Fowlie and Meeks, 2021; Macmillan et al., 2023).

In this context, regional differences in energy consumption within a country should not be underestimated (Zhou and Yang, 2016; Wu et al., 2017). However, very few studies in the literature on clean-cooking programs have considered spatial dependence across small regions as this requires detailed subnational datasets (Clements et al., 2020; Kapsalyamova et al., 2021; Sedai et al., 2021; Adjei-Mantey et al., 2022).

In this study, we build a monthly dataset for all parishes in Ecuador (2015-2021) using electricity data provided by the regulator (ARCONEL, 2023).[4] This allows us to consider population (number of residential points of connection), economic activity (average electricity consumption for industrial and economic activities), the implementation of subsidized programs (consumption subject to subsidized tariffs), and the quality of supply (number of power interruptions and length of interruption) in each parish. We merge this dataset with a spatial dataset that identifies neighboring parishes. To our knowledge, similar analyses considering spatial and temporal dependencies have not been carried out, although many authors have suggested it (Dharshing, 2017; Bharadwaj et al., 2022; De Siano and Sapio, 2022).

We use a spatial autoregressive model (SAR) to study participation in the PCE program and potential spillover effects between parishes (Anselin, 2022). Our main hypothesis is that participation in the PCE program is characterized by spatial dependence at the parish level and that the quality of supply provided by each utility also affects participation. Although our empirical analysis focuses on Ecuador, our results are of great interest for other developing countries aiming to implement electrification programs for cooking, water heating, or mobility.

Our results show that local participation in the clean-cooking program is positively correlated with local economic activity, with the richest areas having a higher participation rate. However, electricity consumption subject to subsidized tariffs is also positively correlated with participation, showing cross-effects between different subsidized programs. The quality of the power provided by utilities matters and clearly affects participation, and spillover effects between parishes are also significant and relevant, with local residents being positively influenced by what their neighbors do.

Based on our results, we provide some policy recommendations. First, it is essential to perform highly detailed spatial analyses of the determinants of participation in electrification programs, instead of using traditional surveys. Second, the design of electrification programs should always consider local particularities instead of taking a uniform and “space-blind” national approach. Third, cross-sectional effects between

[4] Ecuador had 17.5 million inhabitants in 2020 and is divided into 24 provinces, 221 cantons or municipalities, and 1228 parishes. In our study, we use the administrative divisions of the year 2020. The country, as shown in Figure I.1 in Appendix I, has four climatic areas: the coastal region, the sierra region, the oriental or Amazon region, and the Galápagos region.

different subsidized programs should always be considered. Fourth, the promotion of electrification programs should be prioritized in the largest parishes within each canton as these create spillover effects to other parishes. Finally, the quality of supply should also be considered in the implementation of electrification programs, with the efficiency of the regulatory framework applied to utilities affecting the success of these.

The remainder of the paper is organized as follows. Section 2 reviews the literature, and Section 3 introduces the PCE program. Section 4 outlines our empirical strategy, while Section 5 describes our dataset. Section 6 presents our results. Finally, Section 7 provides our conclusions and policy recommendations.

2. Literature review

The causal relationship between energy consumption, economic growth, human development, and trade has been verified in both the short and long run (Apergis and Payne, 2010; Akkemik and Göksal, 2012; Sadorsky, 2012). Employment, economic growth, education, gender empowerment, industrialization, and health are some of the potential channels through which access to energy can influence global income inequality (Mamidi et al., 2021). In poor countries, access to energy improves human development, and there is evidence that electricity and clean-cooking programs can promote economic and human development, as well as improve cognitive reasoning (Maji, 2019; Acheampong et al., 2021a, 2021b; Mamidi et al., 2021; Liu and Teng, 2022).

The literature on clean cooking shows that wood is still used by poor populations in many low-income countries and in rural areas (Akintan et al., 2018). However, in recent years there has been significant improvement in the use of LPG as a clean cooking technology (Sreeja et al., 2023). Countries are also making a strong effort to promote the adoption of clean cooking technologies based on electricity produced by renewable energy sources (RES), with the additional aim of mitigating climate change. Several studies have investigated the use of these clean cooking technologies in developing countries (Banerjee et al., 2016; Gould et al., 2018; al Irsyad et al.; 2023). Participation in clean-cooking programs depends on several regional drivers such as economic and sociodemographic factors and the awareness of the potential health risks associated with traditional cooking fuels (Vigolo et al., 2018; Dendup and Arimura, 2019). The rural-urban divide reflects the clearest differences in adopting clean energy (Gould et al., 2020b). Banerjee et al. (2016) find that in locations with a high level of electrification, the adoption of induction cookers is facilitated, and Das et al. (2018) find that households in India use firewood due to lower costs and potential barriers related with the access to alternative energy sources, particularly in rural regions. Martínez et al. (2020) explore cooking patterns and factors influencing LPG use in rural Andean Peru. The results of surveys and focus group discussions show that LPG is the second-preferred source of cooking energy after firewood in rural areas and that women only use LPG to prepare quick meals such as soups or to reheat meals. The main barrier to LPG is related to the purchasing costs and the technologies, which often do not match local cooking needs. There is also a perception that LPG affects the taste of food. Culture and tradition thus seem to be important determinants, especially in rural areas. Moreover, participation in clean-cooking programs might be constrained by affordability, ineffective information dissemination, the unavailability of clean cooking technologies, and the presence of easy substitutes such as wood or coal (Gould et al., 2018; Aemro et al., 2021; Davi-Arderius et al., 2023). There are also regional differences in household consumption behavior.

Some authors explain the low success of clean cooking in rural areas by pointing to the fear of expensive electricity bills (Banerjee et al., 2016). As a solution, social networks can help promote adoption by way of influencers (Kumar and Igdalsky, 2019). In this context, information and communications technology (ICT) facilitates consumer access to information about the pros and cons of alternative clean cooking systems (Murshed, 2020).

Cultural differences in cooking practices and energy use are a feature of countries across the globe. Akintan et al. (2018) analyze how cultural norms might influence household cooking practices, energy choices, and perceptions in Nigeria. This research, based on household surveys, participant observation, and semi-structured interviews with householders from four different ethnic origins in nineteen villages demonstrate that “ethnic-specific” fuel choice, wood fuel harvesting, and cooking practices are mainly influenced by traditional norms and taboos. Twumasi et al. (2020) analyses the impact of credit accessibility on rural household clean cooking energy consumption in Ghana. Their results based on survey data show that the impact is not uniform across the different regions of Ghana. In addition, individual household characteristics matter. An increase in household income or wealth in Sub-Saharan Africa, for example, leads to an increased likelihood of a household adopting modern energy sources (Behera et al., 2016).

The impact of energy poverty on electricity consumption is an open issue in developing countries. In the past, monitoring and evaluation indicators have focused largely on outputs, service delivery, or dissemination. Nowadays, new analyses are needed to adequately identify potential beneficiaries and describe the living conditions of families or communities targeted by such programs and initiatives. Until now, most studies have used surveys to collect information, creating potential a gap in terms of ex-post analyses of clean-cooking programs (Bielecki and Wingenbach, 2014; Ferrer-Martí, 2018).

Along this line, Jia et al. (2022) analyze regional differences in the impact of clean energy development on carbon dioxide emissions and economic growth in China. They find significant differences in consumption between western, central, and eastern regions. They point to accessibility and poverty as the mechanisms behind these differences, mainly due to the lack of massive electrification, installation costs, and lack of proper information. The evidence suggests that poor households choose low-cost cooking methods even though they have a higher environmental impact. Puzzolo and Pope (2017) and Quinn et al. (2018) point out that non-RES fuels are the primary energy sources for cooking in developing countries. In this context, energy poverty determines the potential for cooking stoves (Pachauri and Spreng, 2011). Gill-Wiehl et al. (2021) indicate that the affordability of electrical energy plays a relevant role in the use of electric cooking appliances by poor households.

Regarding the performance of electrical utilities, Gegiant and Ramalho (2018) find that in low-income countries the cost of electricity connection is 70 times higher than in high-income countries. They also show that the procedures for connection to the national grid tend to be more cumbersome in countries where other regulatory processes are also complex, suggesting a persistence of bureaucracy across public sector entities in some countries. Finally, they find that simpler and less costly electricity connection processes are associated with better firm performance in industries with high electricity needs. The quality of the electrical supply can be affected by the operation of equipment connected to the public electricity supply network, however (Elphick et al., 2015). According to Elphick et al. (2015), quantifying consumer costs related to power quality is an important metric to justify grid investment. Thus, regulators have tried to implement efficiency incentives to improve the quality of supply, but in developing countries there is scant literature about the potential impacts of the quality of supply, with most studies having been conducted in developed economies (Meles, 2020).

The quality of supply can impact a household's choice of fuel (Sedai et al., 2021). For example, Kapsalyamova et al. (2021) use survey data to investigate why the use of clean energy is not strongly adopted in India, Kazakhstan, and Kyrgyzstan. They find that the quality of electricity supply is relevant for the choice of cooking fuel, with households in rural areas facing more frequent power supply disruptions being more likely to adopt coal and wood for cooking rather than gas and electric cooking. Moreover, households in urban areas with more frequent power supply disruptions are more likely to consume gas.

Regarding spatial dependence, Mamidi et al. (2021) consider the direct and indirect effects of energy accessibility on income inequality in Latin America and the Caribbean. Along this line, Nan et al. (2022) study spatial spillover effects related to globalization and carbon emissions, showing that there is a positive spatial externality of CO_2 emissions from neighboring countries and that spillover effects are important to consider in these types of analyses. Furthermore, a strand of the literature has found peer effects in the diffusion of household renewable energy technologies such as residential solar photovoltaics, electric vehicles, and water heaters (Graziano and Gillingham, 2015; Irwin, 2021; Kucher et al., 2021; Zhang et al., 2023). Peer effects can be considered from two perspectives. The first refers to the influence of members of a peer group on an individual's attitudes, values, or behaviors (Wolske et al. 2020). The second is related the tendency for people to rely on what others tell them, especially for those with little information or prior experience on which to base expectations (Rai and Henry, 2016). In such cases, information from peers plays an important role in shaping the perceptions and expectations of individuals and, ultimately, their behavior (Henry and Vollan, 2014).

3. The PCE in Ecuador

Ecuador is a developing country with a huge informal sector, many ethnicities, and spatial heterogeneity between natural regions as well as between urban and rural areas, in addition to high deprivation levels (Matano et al., 2020; Obaco et al., 2021; Mendieta Muñoz et al., 2022). The country has historically depended on revenue from oil extraction, and its energy market is highly subsidized. In 2014, the Ecuadorian government launched the PCE program aiming to replace LPG cookstoves and LPG boilers with electric devices, in an attempt to reduce the large financial burden associated with LPG subsidies and make better use of the country's strong hydropower potential. Initially, the government planned to enroll 3 million families,[5] but only 0.7 million families participated at the peak of the program.

The main benefits for residential participants in the PCE program were the following (Davi-Arderius et al., 2023):[6]

[5] https://unfccc.int/climate-action/momentum-for-change/activity-database/efficient-cooking-program-ecp (last accessed May 30th 2023)

[6] Ministerial Agreement no. 230-2014: *Programa de Eficiencia Energética para Cocción por Inducción y Calentamiento de Agua con Electricidad en sustitución del gas licuado de petróleo en el sector residencial*, published in Registro Oficial No. 359 – 22/10/2014. https://www.gob.ec/sites/default/files/regulations/2018-09/Documento_Delegaciones-direcciones-provinciales-268.pdf

- Free monthly electricity supply: 20 KWh for water-heating devices, 80 KWh for induction cooking, or 100 KWh for water heating and induction cooking;
- Specific tax exemptions to purchase an induction stove;
- Credit (between 150 USD and 600 USD) to purchase an induction stove (Gould et al. 2018);
- The connection of one's home to the electricity grid.

The program also included specific agreements with national manufacturers of induction stoves and compatible pots and pans.

There have been few studies of the Ecuadorian electricity sector. Ponce-Jara et al. (2020) consider the evolution of the electricity generation fuel mix between 2007 and 2017 and the implementation of energy-efficiency programs and technological solutions to the electricity networks. They observe that hydropower capacity in the country increased by 81%, while biomass, biogas, wind, and solar farms played only a marginal role in total electricity generation. Martinez et al. (2017) analyze the theoretical CO_2 emissions and economic impacts of the implementation of the Efficient Cooking Program, with the results indicating that that the future PCE program could be successful in practice. Gould et al. (2018) use a survey to understand cooking technology consumption patterns in rural Ecuador, where the availability of alternative fuels affects fuel choice. More than three quarters of those interviewed reported weekly wood-fuel use. Induction stove ownership (17%) and its use as a primary cooking appliance (1%) was low among the rural households surveyed, and households owning induction stoves reported very low satisfaction. Finally, Davi-Arderius and Obaco (2023) find that the PCE program saved 978,470 ktons of CO_2 and reduced Ecuadorian LPG consumption by 3,845,808 barrels (2015-2021). They also find that the rate of return of the subsidies spent on the program was 0.72463.

However, most of the above studies are based on surveys, limiting the ability to account for potential spatial dependence in the PCE program, i.e., spillover effects. Moreover, to the best of our knowledge the impact of power quality on the engagement rate in the PCE program has not yet been analyzed. Table 1 summarizes the main studies of the PCE program.

Table 1. Summary of studies on the PCE in Ecuador, sorted by publication year.
Source: own elaboration

Reference	Aim	Dataset	Methodology	Scope	Main results
Martínez et al., 2017	Analyze potential CO_2 emissions and cost savings related to the PCE program	Dataset published by ARCONEL	Data projections based on several scenarios	National aggregated data	The PCE program could save USD 1.162 billion in annual government expenditure and reduce CO_2 emissions by 1.8 tn per year.
Martínez-Gómez et al., 2017	Analyze potential impacts on electricity demand, energy consumption and CO_2 emissions related with the introduction of a clean-cooking program in Ecuador (Plan Fronteras)	Dataset from experiments on induction devices and other energy dataset	National projections	National aggregated data	Peak electricity consumption of 2,860 MW at 7pm CO_2 emissions decreased by 40.8 million tones (2016-2032).
Gould et al., 2018	Assess the effect of LPG subsidies on household energy use	Household surveys	Probit model	Rural areas in northern Ecuador	Acceptance and use of LPG is very high. Very low satisfaction with induction stoves.
Gould et al., 2020a	Analyze the cooking technologies in peri-urban and rural Ecuador	Household surveys	ANOVA linear model	Peri-urban and rural communities in coastal and Andean Ecuadorian provinces	Firewood for cooking is used by a large number of houses. Induction stoves are scarcely used due to the lack of electrical infrastructure and the fear of high electricity bills.
Davi-Arderius et al., 2023	Analyze household socioeconomic determinants of the adoption of different cooking technologies	Official surveys (ENEMDU)	Logit and multinomial logit models	National, urban, and rural area dwelling information	Significant differences across regions, urban/rural areas, age, income, ethnic, and type of house, which were not considered by the PCE program.
Davi-Arderius and Obaco, 2023	Assess the effect of the PCE program on national LPG consumption, the savings on CO_2 emissions, and the rate of return of PCE subsidies	Dataset published by ARCONEL	Time series estimations	National aggregated data	The PCE program saved 978,470 ktons of CO_2 and reduced LPG consumption by 3,845,808 barrels (2015-2021). The rate of return of PCE subsidies was 0.72463.

4. Empirical approach

In this section, we explain the empirical approach we follow for our analysis. We test two distinct dependent variables. The first, $PCE80_{it}$, is the most relevant because it refers to the share of participants receiving 80 KWh for induction cooking. The second variable, PCE_{it}, is the share of participants benefitting from any of the three consumption types in the PCE program, i.e., 20 KWh for water-heating devices, 80 KWh for induction cooking, and 100 KWh for water heating and induction cooking.

In the first empirical estimation, we study local cooking-only participation in the PCE program ($PCE80_{it}$) using a spatial lag model (SLM), as is shown in Equation 1:

$$PCE80_{it} = \alpha_i + \rho \boldsymbol{W}_T PCE80_{it} + \beta_1 \log(NRES_{it}) + \beta_2 \log(NRES_{it}^2) + \beta_3 \log(eELD_{it}) + \beta_4 \log(ePOV_{it}) + \beta_5 \log(eACTV_{it}) + \beta_6 \log(FMIk_{jt}) + T + \theta + u_{it}, \quad (1)$$

where $NRES_{it}$ is the number of residential points of consumption, which is a proxy of the size of parish *i*; $eELD_{it}$ is the monthly average residential expenditure subject to the subsidized tariff for the poor (dignity tariff); $ePOV_{it}$ is the monthly average residential expenditure subject to the tariff for the elderly; $eACTV_{it}$ is the average monthly electricity consumption of industrial and commercial activities, as a proxy of the economic activity of parish *i*; $FMIk_{jt}$ is the monthly frequency of power interruptions for each utility *j* corresponding to each Ecuadorian province (see Note 4). We add the square of $NRES_{it}$ to capture potential non-linearity in our dependent variable and use logs to interpret as elasticities the coefficients of our independent variables, as described in the next section.

Moreover, ρ is the spatial autoregressive coefficient, which ranges between –1 and 1; $\boldsymbol{W}_T$ is a space-time spatial weight matrix defined as $\boldsymbol{W}_T = \boldsymbol{I}_T \otimes \boldsymbol{W}$, with $\otimes$ referring to the Kronecker product; and $\boldsymbol{I}_T$ is an identity matrix of dimension *T*. The definition of $\boldsymbol{W}$ is in Appendix II. α_i is the intercept, and $\beta_1 \ldots \beta_6$ are coefficients to be estimated. *T* represents month or year fixed effects, θ is the parish fixed effects, and $u_{i,t}$ are the i.i.d. error terms. In our estimates, we also use the monthly length of power interruptions, $\log(TTIk_{jt})$, as an alternative to $\log(FMIk_{jt})$. We expect that the sign and significance are the same.

In the second empirical estimation, we study the local participation rate in the PCE program (PCE_{it}) using a spatial error model (SEM) as in Equation 2:

$$PCE_{it} = \alpha_i + \beta_1 \log(NRES_{it}) + \beta_2 \log(NRES_{it}^2) + \beta_3 \log(eELD_{it}) + \beta_4 \log(ePOV_{it}) + \beta_5 \log(eACTV_{it}) + \beta_6 \log(FMIk_{jt}) + T + \theta + u_{it}, \quad (2)$$

where $u_{it} = \lambda \boldsymbol{W_T} u_{i-1t} + e_{it}$. λ is the coefficient of the spatially lagged error term, which ranges between –1 and 1, and e_{it} is the i.i.d. error term. As before, we also alternatively use the variable $\log(TTIk_{jt})$ instead of $\log(FMIk_{jt})$. Again, we expect that the sign and significance are the same.

The process to select between the SLM and SEM is the following. First, we validate the potential spatial autocorrelation of our dependent variables $PCE80_{it}$ and PCE_{it} using Moran's I (see Appendix II). Once spatial autocorrelation is confirmed, we select the appropriate spatial econometric model by means of Lagrange multiplier (LM) tests on the residuals of the standard (a-spatial) model. In Appendix III, we show that for $PCE80_{it}$ the preferred model is the spatial lag model (SLM), while the spatial error model (SEM) is preferred for PCE_{it}.

We must stress that for Equation 1, the interpretation of marginal effects is not straightforward. The spatial autoregressive parameter $|\rho| < 1$ signals the existence of global externalities due to how the spatial multiplier is defined, i.e., $(\boldsymbol{I}_{NT} - \rho \boldsymbol{W}_T)^{-\mathbf{1}} = \boldsymbol{I}_{NT} + \rho \boldsymbol{W}_T + \rho^2 \boldsymbol{W}_T^2 + \ldots + \rho^N \boldsymbol{W}_T^N$, where $\boldsymbol{I}_{NT}\mathbf{I}$ is an *NT*×*NT* identity matrix. Thus, the participation rate in the PCE (only for cooking) is determined by a parish's own characteristics as well as those of immediate neighbors ($\rho \boldsymbol{W}_T$), second-order neighbors ($\rho^2 \boldsymbol{W}_T^2$), and so forth. Indeed, a shock in parish *i* is transmitted to its neighbors by parameter *ρ* related to *participation rate in the PCE by neighbors* and, in turn, this is transmitted back to parish *i* through $\boldsymbol{W}$, reinitiating the process until the effect becomes negligible for *N* tending towards infinity (LeSage and Fischer, 2008). With respect to the marginal effects, we can thus distinguish between direct and indirect effects:

$$\frac{\partial Y}{\partial X_i'} = (\boldsymbol{I}_{NT} - \rho \boldsymbol{W}_T)^{-1} \boldsymbol{I} \beta_i = (\boldsymbol{I}_{NT} + \rho \boldsymbol{W}_T + \rho^2 \boldsymbol{W}_T^2 + \ldots + \rho^N \boldsymbol{W}_T^N) \beta_i. \tag{3}$$

LeSage and Pace (2009) define the direct effect as the mean of the diagonal elements of (3) and the indirect effect as the mean of the off-diagonal elements, where the off-diagonal row elements are summed up and averaged. The sum of the direct and indirect effects gives the average total effect.

5. Dataset

Our dataset is based on the following information: monthly parish-level data from 2015 to 2021 by electric utility, provided by the Ecuadorian regulator and the Ministry of Energy and Resources (ARCONEL, 2023), and parish-level shapefiles gathered from the National Institute of Statistics and Censuses of Ecuador (INEC) in 2020. We selected 753 parishes for which we have complete information for all 84 months considered.

5.1 Variable definitions

In defining the variables, it is important to highlight that each parish *i* belongs to each utility *j*. First, we consider the following variables at the parish level *i* and at time *t*:

1. **Size**: number of residential points of consumption ($NRES_{it}$);[7]

2. **Local Participation in the PCE**: PCE participation rate for each parish *i*, constructed by dividing the monthly number of participants in the PCE program ($NPCE_{it}$) by the number of residential points of consumption ($NRES_{it}$):

$$PCE_{it} = \frac{NPCE_{it}}{NRES_{it}}. \tag{4}$$

   Moreover, we calculate the specific parish-level PCE participation rate for cooking only, dividing the monthly number of participants in the PCE program ($NPCE80_{it}$) by the number of residential points of consumption ($NRES_{it}$):

$$PCE80_{it} = \frac{NPCE80_{it}}{NRES_{it}}. \tag{5}$$

3. **Local subsidized households**: average residential expenditure subject to the subsidized tariff cost for the poorest (dignity tariff), $ePOV_{it}$, and the tariff for elderly people (elderly tariff),[8] $eELD_{it}$ per household:

$$ePOV_{it} = \frac{EPOV_{it}}{NRES_{it}}, \tag{6}$$

$$eELD_{it} = \frac{EELD_{it}}{NRES_{it}}, \tag{7}$$

   where $EPOV_{it}$ is the number of households enjoying the dignity tariff and $EELD_{it}$ is the number of persons enjoying the elderly tariff.

4. **Local economic activity**: average electricity consumption in industrial, $EIND_{it}$ and commercial activities, $ECOM_{it}$, over the number of residential points of connection:

$$eACTV_{it} = \frac{EIND_{it}+ECOM_{it}}{NRES_{it}}. \tag{8}$$

Second, we use the following variables at the utility *j* level and at time *t*:

1. **Quality of power supply**: monthly power supply quality for each utility *j*, using two different indicators (ARCONEL, 2023). The monthly frequency of power interruptions is calculated as follows:

$$FMIK_{jt} = \frac{\sum KVAfs_{jt}}{KVAinst_{jt}}, \tag{9}$$

[7] Each point of consumption corresponds to a metering device. Therefore, a point of consumption is equivalent a household or similar.

[8] The dignity tariff refers to a subsidy for residential consumers whose electricity consumption is up to 110 kWh per month in the Sierra Region and up to 130 kWh per month in the Coast/East/Insular Regions. Thus, it is a proxy for the number of poor households in each municipality. The elderly tariff applies to residents 65 years of age or older. (ARCONEL, 2023).

where $\sum KVAfs_{jt}$ is the sum of installed capacity that was subject to power supply failure during period t and $KVAinst_{jt}$ is the sum of installed capacity for utility j in the same period t.

We also consider the monthly length of power interruptions for each utility j, calculated as in Equation (7):

$$TTIK_{jt} = \frac{\sum KVAfs_{jt} \cdot Tfs_{jt}}{KVAinst_{jt}}, \tag{10}$$

where, Tfs_{jt} is the interruption time of each $KVAfs_{jt}$.[9]

In our dataset, we assign power quality to each parish according to the quality of supply provided by the utility feeding its residential points of connection.

5.2 Descriptive analysis

Tables 2 and 3 show summary statistic for our dataset at the parish and utility level, respectively.

Table 2. Summary statistics for our variables at the parish level

First level: Parish (NUTS3) (N=753 ×T=84)

Description	Variable	Units	Mean	Std. Dev.	Min.	Max.
Residential points of electricity connection	$NRES_{it}$	Number	4,524.0510	29,570.8700	0.0000	681931.0000
Number of PCE participants (cooking only)	$NPCE80_{it}$	Number	428.1650	3,371.6800	0.0000	114,638.0000
Number of PCE participants	$NPCE_{it}$	Number	521.1714	4,256.9300	0.0000	115,223.0000
PCE participation rate	PCE_{it}	p.u.	0.08061	0.1928	0.000	0.97612
PCE participation rate (cooking only)	$PCE80_{it}$	p.u.	0.07223	0.0718	0.000	0.95622
Electricity expenditure with poverty tariffs	$EPOV_{it}$	USD	3,844.0030	16,613.6700	-56,287.6900	508,095.1000
Average electricity consumption with poverty tariffs	$ePOV_{it}$	USD	1.0893	0.4757	0.0017	26.2669
Electricity expenditure with elderly tariffs	$EELD_{it}$	USD	1,268.3590	10,092.2100	-4,290.1300	305,873.20000
Average electricity expenditure with elderly tariffs	$eELD_{it}$	USD	0.2121	0.1494	0.0001	6.410
Electricity consumption by industrial consumers	$EIND_{it}$	KWh	423,197.2000	4,090,3250.0000	-995,020.0000	1.4400e+08
Electricity consumption by commercial consumers	$ECOM_{it}$	KWh	318,588.5000	3,530,163.0000	-388,540.000	1.1900e+08
Average electricity consumption by industrial and commercial consumers	$eACTV_{it}$	KWh	2,089.3000	17,255.2400	-19,689.9000	847,410.4000

Note: i corresponds to the parish and t to the month.

[9] In both cases, $FMIK_{jt}$ and $TTIK_{jt}$ only consider power interruptions longer than 3 minutes or those related with to a major force (unpredictable adverse weather conditions)

Table 3. Summary statistics for our variables at the utility level

Second level: Utilities (N=20 × T=84)

Description	Variable	Units	Mean	Std. Dev.	Min.	Max.
Frequency of power interruptions	$FMIk_{jt}$	Number	10.34	6.29	0.83	41.71
Length of power interruptions	$TTIk_{jt}$	Hours	14.29	9.79	0.78	55.50

Notes: j corresponds to the utility and t to the month.

Figures 1 and 2 show the average values of our endogenous variables for PCE participation rate, $PCE80_{it}$ and PCE_{it}, respectively. It is important to note that parishes located in the Sierra and coastal regions (Appendix I) have higher participation rates.

Figure 1. Average value of our endogenous variable $(PCE80_{it})$ *in each parish (2015-2020)*

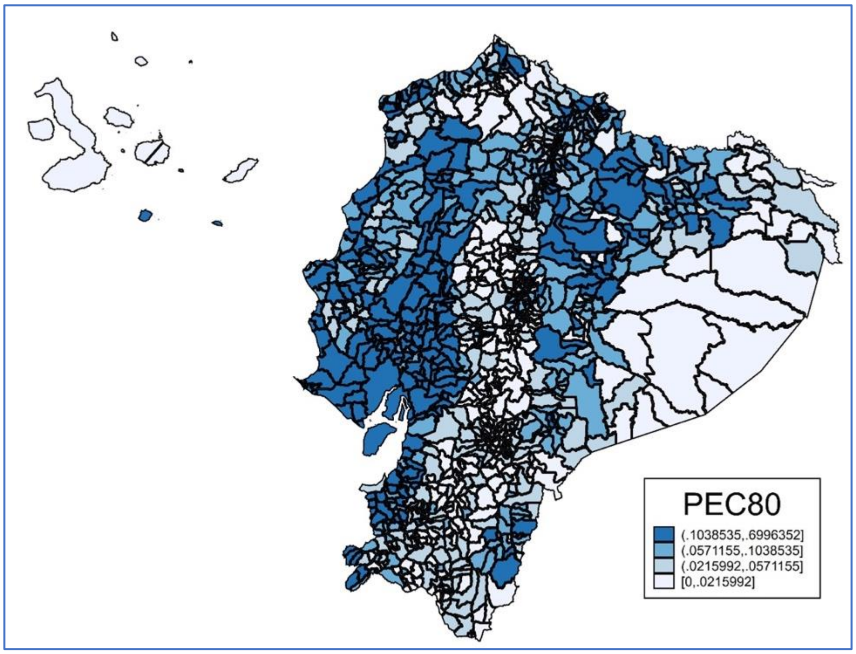
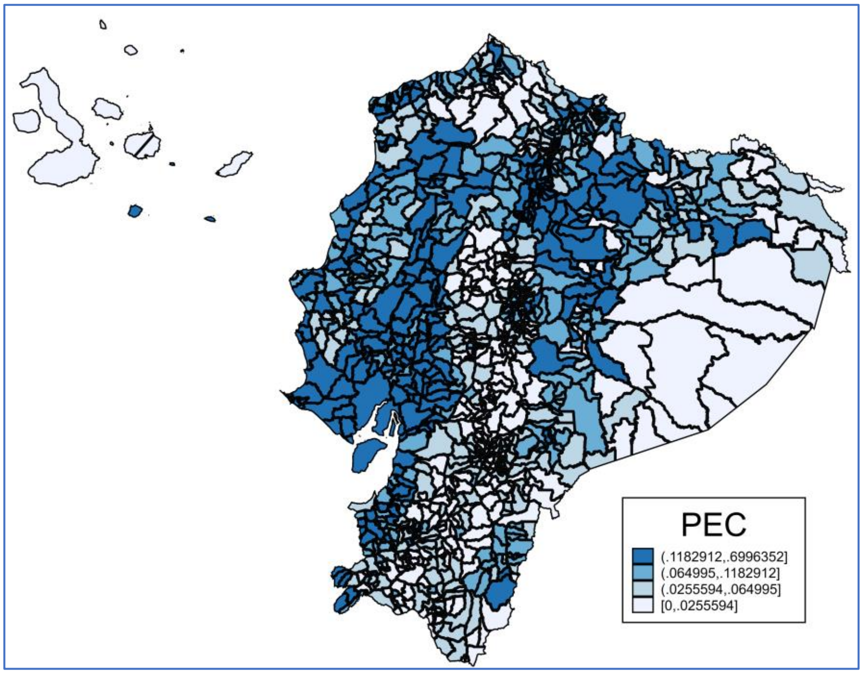


Figure 2. Average value of our endogenous variable (PCE_{it}) in each parish (2015-2020)



Figures 3 and 4 show utility quality of supply ($FMIk_{jt}$) and the corresponding PCE participation rate at the utility level. It is important to note that the coast suffers from poorer power supply quality compared to other areas, but the number of interruptions decreased substantially in almost all utilities between 2015 and 2021. Blue Bars are the average of participation rate in the PEC program by utility. The concentration in the coastal areas is higher in PEC participation rate. The utility that gives service to the capital has a participation rate relatively higher in all three PEC programs.

Figure 3. Average number of power interruptions ($FMIk_{jt}$) and PCE participation rate by utility, population size, and parish administrative boundaries in 2015

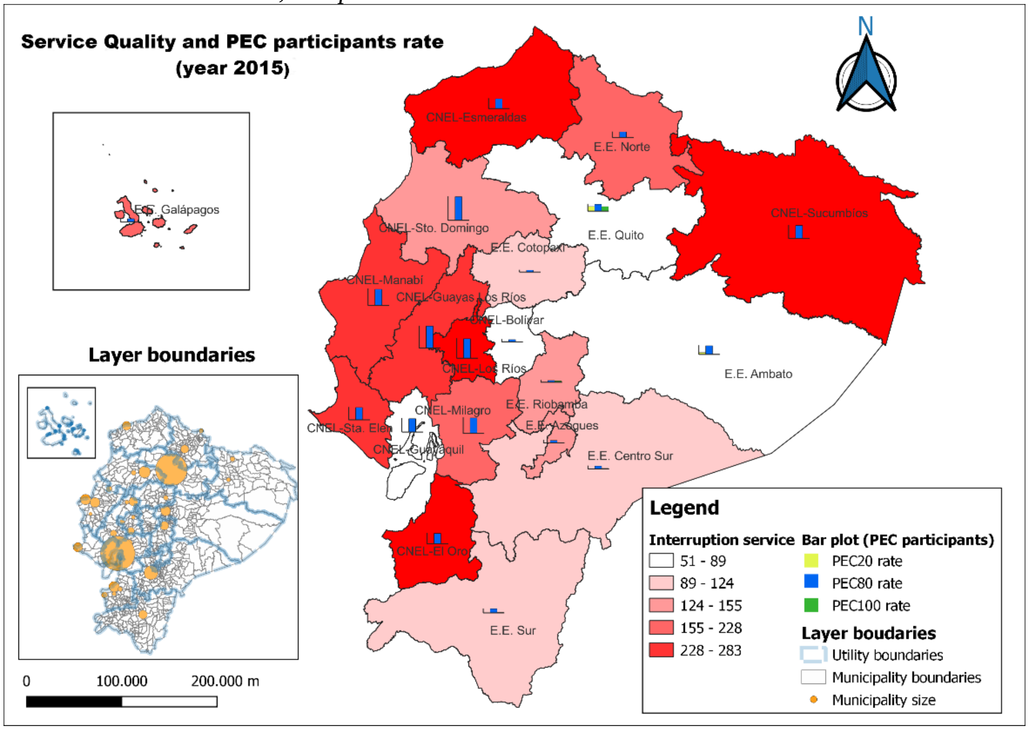
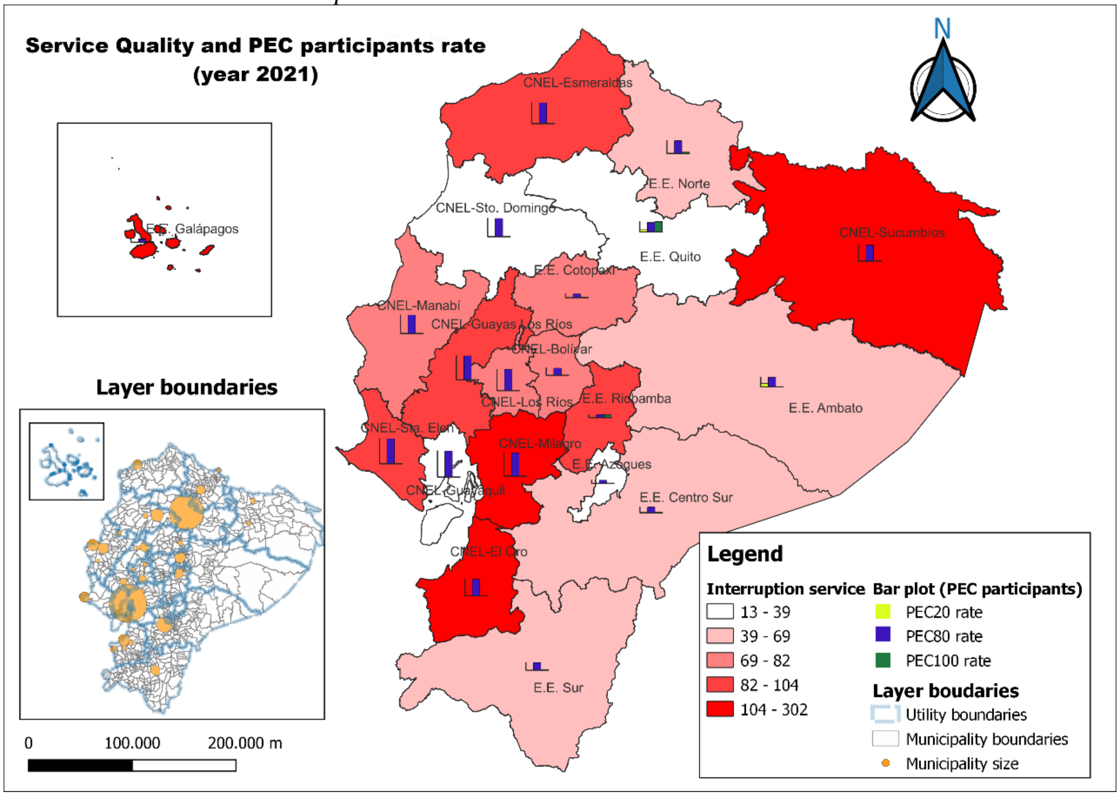


Figure 4. Average number of power interruptions and PCE participation rate by utility, population size, and parish administrative boundaries in 2021



As shown in Figure II.1 in Appendix II, spatial autocorrelation has grown markedly over time, i.e., after the launch of the PCE program. From January 2015 to December of the same year, spatial autocorrelation rose from around zero to 0.35. From 2018, it stabilized at around 0.5.

6. Results

In this section, we present the results of our empirical estimations for $PCE80$, including the calculation of the indirect and direct effects.

6.1. Spatial autoregressive estimations

We estimate the SLM (Equation 1) and the SEM (Equation 2) for *PCE*80 and *PCE*, respectively, with individual and monthly time dummies. However, as a robustness check we estimate *PCE*80 by means of an SEM and *PCE* using SLM, alternatively employing month and year fixed effects. The results are shown in Appendix IV.

Table 4. Selected spatial panel regressions for PCE participation

	(1) PCE_{it} (SEM)	(2) PCE_{it} (SEM)	(3) $PCE80_{it}$ (SLM)	(4) $PCE80_{it}$ (SLM)
$\log(NRES_{it})$	0.0182***	0.0182***	0.0143***	0.0144***
	(0.001)	(0.0001)	(0.0009)	(0.0009)
$\log(NRES_{it}^2)$	-0.0023***	-0.0023***	-0.002***	-0.002***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\log(eELD_{it})$	-0.0001	0.00004	-0.0004*	-0.0003
	(0.0002)	(0.00002)	(0.0002)	(0.0002)
$\log(ePOV_{it})$	0.0012***	0.0012***	0.0005*	0.0006*
	(0.0004)	(0.0002)	(0.0003)	(0.0003)
$\log(eACTV_{it})$	0.0012***	0.0012***	0.0015***	0.0015***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(FMIk_{\mathrm{j}t})$	-0.0038***		-0.0024***	
	(0.0007)		(0.0004)	
$\log(TTIk_{\mathrm{j}t})$		-0.0036***		-0.0023***
		(0.0006)		(0.0003)
λ	0.5309***	0.5307***		
	(0.0042)	(0.0042)		
ρ			0. 5757***	0. 5754***
			(0. 0039)	(0. 0039)
Time and individual dummies	yes	yes	yes	yes
Observations	63,252	63,252	63,252	63,252

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

Some interesting results emerge from Table 4. First, participation in the PCE program is characterized by strong spatial dependence, as the coefficients ρ and λ are significant, capturing the spatial autocorrelation in a different form. In particular, as the spatial autoregressive parameter ρ is equal to 0.57 for $PCE80$ (columns 3 and 4), it corresponds, in scalar terms, to a spatial multiplier of 2.32. This implies that around 60% (i.e., 1/2.32) of $PCE80$ is explained by the so-called indirect or spillover effect, referring to the effect arising from variation in a variable in neighbors. The remainder is explained by the direct effects, i.e., the impact of variation in a variable in the same parish *i*. Note that if spatial dependence is in the form of a spatial lag and is not accounted for, the regression coefficients are upward-biased.

On the other hand, with respect to *PCE* (column 1 and 2) the spatial dependence is in the error term, meaning that there may be spatially autocorrelated variables not accounted for in the model, such as cultural factors, for example, which are captured by the error term (Anselin et al., 1998). This seems to make sense as the variable *PCE* includes heating water and water in combination with heating in addition to electricity for cooking. This means that *PCE* intrinsically includes several dimensions potentially related to a wide set of explanatory factors that may not be accounted for due to the limitations of our data. The fact that spatial autocorrelation exists confirms our initial hypothesis and highlights a very interesting point related to the design of electrification programs.

Second, the analysis of the coefficients associated with each explanatory variable also reveals some interesting results. We find that parishes with a higher number of residential points of connection (*NRES*) show a higher participation rate. However, the impact is non-linear, as the coefficient related to the square of *NRES* is also significant with a negative sign. In other words, parish size fits better with a polynomial function, implying that the share of PCE participants increases with the size of the parish, but at a decreasing rate until *NRES* equals 52[10] and then becoming negative. Considering that the average value of *NRES* is 4,524, this means that the benefits of larger parish size are only applicable to a few parishes. The reason may be that residents begin to distrust the reliability of the power grid if many users are connected.

The coefficients related with local economic activity (*ACTV*) are positive, showing that in parishes with a higher level of industrial or commercial activities people tend to participate more in the Efficient Cooking Program. This highlights that local economic activity is relevant and that there may be a potential affordability problem for participating in the PCE program, which may be related to the purchase of the induction cookstove or the need to live in dwellings in good condition, as was found regarding the use of electricity for cooking in Ecuador (Daví-Arderius et al., 2023).

The coefficient for expenditure subject to the tariff for the elderly *ELD* is negative and marginally significant only for PCE participation for cooking (column 3). Regarding the coefficient associated with expenditure subject to the poverty tariff *ePOV*, it is always positive but significant at the 1% level only for *PCE* (columns 1 and 2), while for *PCE*80 the significance is at the 10% level. This shows that parishes in which a higher share of expenditure is subsidized also show a higher participation rate in the PCE program. This is true for *PCE* in general, but less important when we only consider cooking. This result can be explained by several complementary reasons. These subsidized electricity tariffs are subject to a maximum monthly electricity expenditure, so customers may decide to join the clean-cooking program to receive additional free electricity. These subsidized tariffs can also implicitly lower the cost of purchasing an induction stove.[11] Finally, the poorest people do not have electricity metering and, as a result, often opt for alternative cooking technologies such as firewood or coal, especially in rural areas. These people therefore do not receive the

[10] Considering the coefficients in column 1 of Table 4, the calculation is as follows: $0.0182 \times \log(NRES_{it}) - 0.0023 \times 2 \times \log(NRES_{it}) = 0$, thus $NRES_{it} = \exp(0.0182 / (2 \times 0.0023)) = 52.27$.

[11] Our dataset does not allow us to conclude that all poor families consume electricity using poverty tariffs.

subsidized tariffs. From a policy perspective, these results show potentially relevant cross-subsidy effects that should not be underestimated in the design of electrification programs.

Regarding the quality of power supply, i.e., *FMIK* and *TTIK*, it is important to note that the coefficients are always negative and highly significant, showing a relevant impact on the engagement rate in the PCE program. This suggests that customers are reluctant to electrify their consumption if they do not feel that the power system is reliable. From the point of view of policy, this highlights that the performance of utilities can limit or boost engagement with electrification programs such as the clean-cooking program. In other words, these programs may not be successful on their own and require a reliable power grid as a necessary condition. As utilities are highly regulated activities, the efficiency of the regulatory framework applied to these utilities should incentivize improvements in energy quality.

6.2. Indirect and direct effects

In Table 5, we show the direct, indirect, and total spatial effects for cooking, calculated according to Equation 3.

Table 5. Direct, indirect, and total spatial effects related to the coefficients from Table 4 for PEC80

	(1) dy/dx	(2) dy/dx
Direct effect		
$\log(NRES_{it})$	0.0158***	0.0156***
$\log(NRES_{it}^2)$	-0.0022***	-0.0022***
$\log(eELD_{it})$	-0.0003*	-0.0004*
$\log(ePOV_{it})$	0.0006**	0.0006*
$\log(eACTV_{it})$	0.0016***	0.0016***
$\log(FMIk_{\mathrm{j}t})$	-0.0025***	
$\log(TTIk_{\mathrm{j}t})$		-0.0026***
Indirect effect (spillover)		
$\log(NRES_{it})$	0.0181***	0.0180***
$\log(NRES_{it}^2)$	-0.0025***	-0.0025***
$\log(eELD_{it})$	-0.0004	-0.0004*
$\log(ePOV_{it})$	0.0007**	0.0007**
$\log(eACTV_{it})$	0.0018***	0.0018***
$\log(FMIk_{\mathrm{j}t})$	-0.0028***	
$\log(TTIk_{\mathrm{j}t})$		-0.003***
Total effect		
$\log(NRES_{it})$	0.0339***	0.0336***
$\log(NRES_{it}^2)$	-0.0048***	-0.0047***
$\log(eELD_{it})$	-0.0007	-0.0008*
$\log(ePOV_{it})$	0.0013**	0.0013**
$\log(eACTV_{it})$	0.0034***	0.0030***
$\log(FMIk_{\mathrm{j}t})$	-0.0053***	
$\log(TTik_{\mathrm{j}t})$		-0.0056***

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors are in parentheses.

Regarding power quality, we find that the frequency of power interruptions has a coefficient of –0.0053, meaning that a 1% increase in *FMIk* implies a 0.0053% reduction in the share of PCE participants. Regarding the length of power interruptions, when the average length increases by 1%, the PCE participation rate (for cooking) decreases by 0.0056%. However, these effects are mainly due to the spillovers, meaning that a shock occurring in parish *I* or in a neighboring parish is transmitted to neighbors and then to the neighbors of these neighbors, and so on, and then and back again.

We can understand the rest of the effects in the same way. For instance, the coefficient for economic activity is between +0.0030 and +0.0034, meaning that increasing the average electricity consumption of industrial and commercial activities by 1% increases the PCE participation rate (for cooking only) by 0.0030% and 0.0034%.

7. Conclusions and policy implications

In this paper, we study the factors affecting participation in the PCE program in Ecuadorian parishes, taking into account spatial dependence. Our hypotheses are that the spatial dependence across parishes is relevant and the quality of supply provided by each utility affects participation in the PCE. Neither of these aspects have been fully assessed in the empirical literature on the implementation of clean cooking in developing countries due to a lack of highly detailed datasets. Here, we use an official dataset provided by the Ecuadorian regulator instead of the surveys typically used in studies of developing countries. This allows us to produce more consistent and replicable outcomes than those provided by surveys, where the selection of observations might constrain the results and limit replicability.

We find that local participation in the PCE program is positively correlated with local economic activity, meaning that income from locals sets the local participation rate. The subsidized electricity tariff for the poorest (dignity tariff) is positively correlated with participation in the PCE program, meaning that already subsidized customers are more likely to join. The quality of power provision matters and clearly constrains participation. Finally, we find that spillover effects between parishes are also very significant and relevant for this cooking program, with local residents being positively influenced by what their neighbors do.

Based on these results, we provide several policy recommendations. First, it is essential to perform detailed spatial analyses of the determinants of participation in electrification programs. To this end, there are efficient and less costly alternatives to traditional surveys, where sample selection can be a limitation. In this paper, we use data from the electricity sector as a proxy for local socioeconomic characteristics. This type of data should be analyzed using advanced econometric methodologies such as spatial econometrics, the approach used here.

Second, the design of electrification programs should always consider local particularities and avoid taking a uniform national approach. As uncovered here, certain local characteristics are significant and relevant to participation in such programs. For instance, parishes with more economic activity have a higher participation rate, highlighting a potential economic cost related with the procurement of an induction cookstove, which residents from the wealthiest areas can most easily afford. For other parishes, specific subsidies for the procurement of induction cookstoves could be implemented as a complementary solution to deal with this economic barrier.

Third, cross-sectional effects between different subsidized programs cannot be neglected. We find that parishes with a higher use of subsidized electricity tariffs also show higher participation rates in the PCE program. This seems to complement the results related to parish economic activity, as these participants may face a lower economic barrier to procuring a cookstove or join this program to enjoy additional free electricity. Therefore, existing subsidy programs should be considered when programs are designed and launched, as unforeseen trade-offs might arise between them.

Fourth, the promotion of electrification programs should take into account social ties, which can often involve peer comparison and a tendency to influence each other's attitudes, values, or behaviors. Thus, a place-based approach that contributes to creating opportunities to facilitate experience- and knowledge-sharing among peers and stakeholders should be prioritized. Based on these results, the dissemination process for electrification programs should study these spillover effects between parishes beforehand and incorporate these effects into their strategy. Fifth, the quality of supply should also be considered in the implementation of electrification programs. We find that the quality of supply provided clearly constrains participation, as consumers may feel the need to have a reliable power system before they are willing to join such programs. This links the design of electrification programs with the regulatory framework for utilities. Regulators should prioritize power quality improvements that can be made in different complementary ways. Grid investments that improve the reliability of the power system should be prioritized, such as replacing the oldest assets, upgrading the insulation of aerial cables, and ensuring the N-1 criteria in case of failure of an element, among others. In addition, efficient economic incentives associated with the quality of supply provided by each utility should be implemented to improve their internal operational processes. Finally, power interruptions should be closely monitored in order to determine their root causes and prevent these in the future.

In summary, we found that local and regional issues should be considered in the design of electrification programs in developing countries such as Ecuador. However, our results also apply to electrification programs already being implemented in many developed countries, such as the electrification of private mobility. As with cooking, consumers will only switch to electrical vehicles if they are connected to a reliable power system. Moreover, as in developing countries they will often see and possibly replicate what their neighbors do.

Future analyses of these electrification programs would benefit from incorporating different combinations of additional spatial data such as parish censuses or other similar information. These results would complement our findings and provide deeper insights to enable the design of efficient electrification programs in the future.

Funding

The work was supported by the Universidad Católica del Norte, *Fondo Semilla*. [RESOLUCION N°071/2022] and the Chair of Energy Sustainability (IEB, University of Barcelona), FUNSEAM and 2017-SGR-739 (Government of Catalonia-Next Generation Funds EU).

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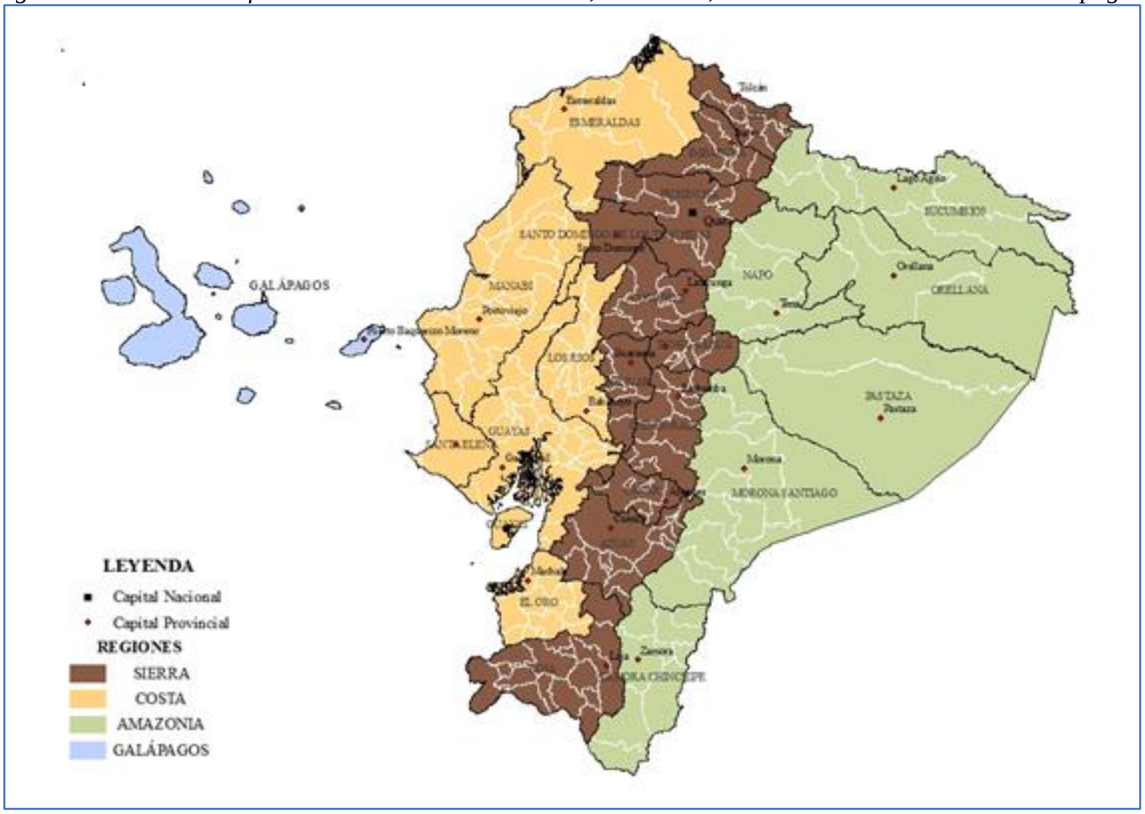
Appendix I. Ecuadorian Regions

Figure I.1: Ecuadorian four climatic areas: the Coastal, the Sierra, the Oriental or Amazon and Galápagos.

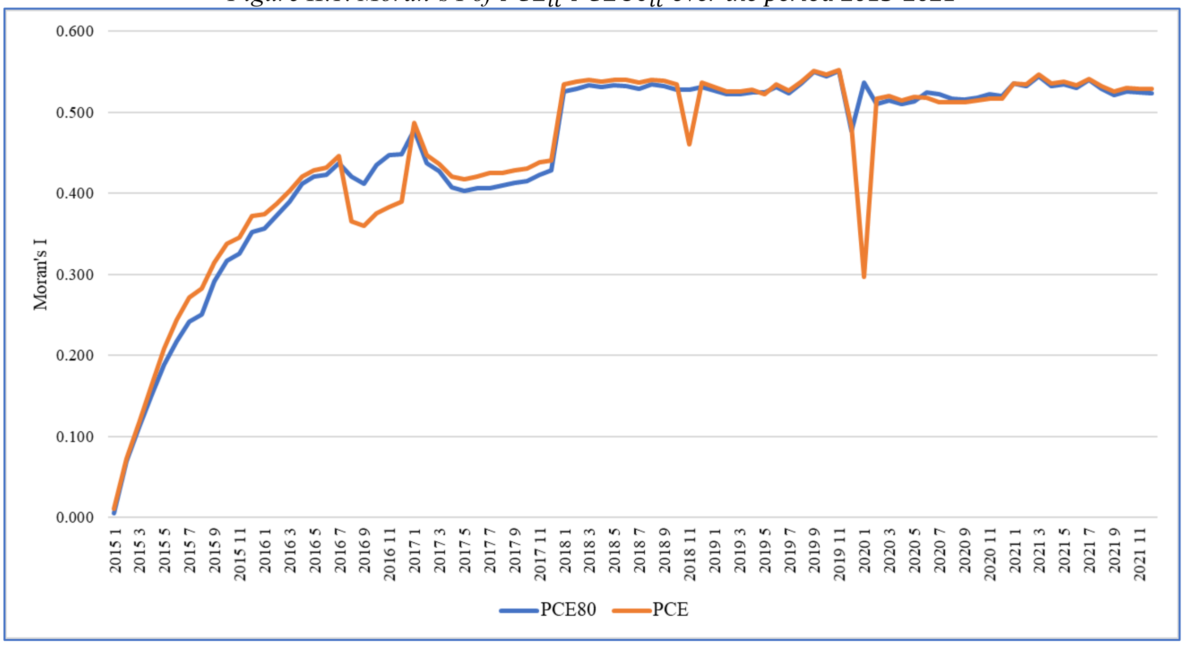


Source: Own elaboration.

Appendix II – Moran's I Test for Spatial Autocorrelation

As our hypothesis is that spatial autocorrelation is present for$PCE80_{it}$ and PCE_{it}, we test for this using the Moran'I based on a row standardized queen spatial weight matrix $\boldsymbol{W}$, that considers neighbours parishes with at least a point of their border in common. Parishes without connections are linked to the nearest one. Moran's I varies between -1 and 1, where 1 means positive spatial autocorrelation, i.e. locations with similar value of a variable are located close each other, and -1 means negative spatial autocorrelation, i.e. locations with dissimilar value of a variable are located close each other. Values close to zero denote the absence of spatial autocorrelation, which means that a variable is randomly distributed in space.

Figure II.1. Moran's I of PCE_{it} $PCE80_{it}$ over the period 2015-2021



Appendix III – Lagrange Multiplier test

According to the decision rule (Anselin et al., 1996), if the LM lag is more significant than the LM error, and the robust LM lag is significant, but the robust LM error is not, then the appropriate model is the spatial lag model. Conversely, if the LM error is more significant than the LM lag, and the robust LM error is significant, but the robust LM lag is not, then the appropriate model is the spatial error model.

Regarding the $PCE80_{it}$, in the Table II.1, we find that the preferred model is the spatial lag, as the Robust LM lag is preferred to Robust LM err. This is true also when substituting our independent variable $\log(TTIk_{\mathrm{j}t})$ with $\log(FMIk_{\mathrm{j}t})$ and independently from using of year of month fixed effects.

Table III.1. Lagrange Multiplier test for PEC80
(Panel data with Municipality Fixed Effects)

	$\log(TTIk_{\mathrm{j}t})$				$\log(FMIk_{\mathrm{j}t})$			
	Year FE		Month FE		Year FE		Month FE	
	Statistic	p-val.	Statistic	p-val.	Statistic	p-val.	Statistic	p-val.
LM err	21028.299	0.000	16861.253	0.000	21003.200	0.000	16955.082	0.000
LM lag	21230.047	0.000	17157.295	0.000	21234.480	0.000	17244.304	0.000
Robust LM err	3.438	0.064	3.859	0.049	0.741	0.389	3.733	0.053
Robust LM lag	**205.186**	**0.000**	**299.901**	**0.000**	**232.025**	**0.000**	**292.954**	**0.000**

Regarding the PCE_{it}, in Table II.2, we find that the Robust LM err is preferred to Robust LM lag for both $\log(TTIk_{\mathrm{j}t})$ and $\log(FMIk_{\mathrm{j}t})$. Consequently, we select a spatial error model. This holds also when we use year fixed effects instead of month fixed effects.

Table III.2. Lagrange Multiplier test for PEC
(Panel data with Municipality Fixed Effects)

	$\log(TTIk_{\mathrm{j}t})$				$\log(FMIk_{\mathrm{j}t})$			
	Year FE		Month FE		Year FE		Month FE	
	Statistic	p-val.	Statistic	p-val.	Statistic	p-val.	Statistic	p-val.
LM err	16152.400	0.000	12423.556	0.000	16071.242	0.000	12470.202	0.000
LM lag	16047.510	0.000	12370.482	0.000	15999.891	0.000	12419.779	0.000
Robust LM err	**105.299**	**0.000**	**58.720**	**0.000**	**76.199**	**0.000**	**56.204**	**0.000**
Robust LM lag	0.414	0.520	5.646	0.018	4.848	0.028	5.781	0.016

Appendix IV – OLS, SLM and SEM Estimations

Table IV.1. OLS estimations for PEC80

Variable	Year FE	Month FE	Year FE	Month FE
$\log(NRES_{it})$	0.0124 ***	0.0118 ***	0.0124 ***	0.0118 ***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
$\log(NRES_{it}^2)$	-0.0020 ***	-0.0020 ***	-0.0020 ***	-0.0020 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\log(eELD_{it})$	-0.0013 ***	-0.0011 ***	-0.0013 ***	-0.0011 ***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(ePOV_{it})$	-0.0004	0.0004	-0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\log(eACTV_{it})$	0.0017 ***	0.0015 ***	0.0017 ***	0.0015 ***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(TTIk_{\mathrm{jt}})$	-0.0041 ***		-0.0041 ***	
	(0.0003)		(0.0003)	
$\log(FMIk_{\mathrm{jt}})$		-0.0066 ***		-0.0066 ***
		(0.0004)		(0.0004)
Time and Individual dummies	yes	yes	yes	yes
Observations	63,252	63,252	63,252	63,252
R^2 (Adj.)	0.495 (0.489)	0.526 (0.519)	0.495 (0.489)	0.526 (0.519)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table IV.2. OLS estimations for PEC

Variable	Year FE	Month FE	Year FE	Month FE
$\log(NRES_{it})$	0.0100 ***	0.0093 ***	0.0100 ***	0.0093 ***
	(0.0012)	(0.0011)	(0.0012)	(0.0011)
$\log(NRES_{it}^2)$	-0.0016 ***	-0.0017 ***	-0.0016 ***	-0.0017 ***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\log(eELD_{it})$	-0.0019 ***	-0.0017 ***	-0.0019 ***	-0.0017 ***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\log(ePOV_{it})$	0.0012	0.0004 ***	0.0012	0.0004 ***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$\log(eACTV_{it})$	0.0009 **	0.0007 ***	0.0009 **	0.0007 ***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(TTIk_{\mathrm{jt}})$	-0.0048 ***		-0.0048 ***	
	(0.0004)		(0.0004)	
$\log(FMIk_{jt})$		-0.0082 ***		-0.0082 ***
		(0.0005)		(0.0005)
Time and Individual dummies	yes	yes	yes	yes
Observations	63,252	63,252	63,252	63,252
R^2 (Adj.)	0.487 (0.481)	0.516 (0.509)	0.487 (0.481)	0.516 (0.509)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table IV.3. SLM estimations for PEC80

Variable	Year FE	Month FE	Year FE	Month FE
$\log(NRES_{it})$	0.0144***	0.0139***	0.0143***	0.0137***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$\log(NRES_{it}^{2})$	-0.0020***	-0.0020***	-0.0020***	-0.0020***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\log(eELD_{it})$	-0.0003	-0.0003	-0.0004*	-0.0004*
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(ePOV_{it})$	0.0006*	0.0002*	0.0005*	0.0002*
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$\log(eACTV_{it})$	0.0015***	0.0014***	0.0015***	0.0014***
	(0,0002)	(0.0002)	(0.0002)	(0.0002)
$\log(TTIk_{\mathrm{j}t})$	-0.0023***	-0.0018***		
	(0.0003)	(0.0003)		
$\log(FMIk_{\mathrm{j}t})$			-0.0024***	-0.0012***
			(0.0004)	(0.0004)
ρ (sp. Lag)	0.5754***	0.5421***	0.575***	0.5430***
	(0.0039)	(0.0041)	(0.0039)	(0.0041)
Time and Individual dummies	yes	yes	yes	yes
Observations	63,252	63,252	63,252	63,252

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table IV.4. SLM estimations for PEC

Variable	Year FE	Month FE	Year FE	Month FE
	0.0151***	0.0142***	0.015***	0.0141***
$\log(NRES_{it})$	(0.001)	(0.0009)	(0.001)	(0.0001)
	-0.0021***	-0.0020***	-0.0020***	-0.002***
$\log(NRES_{it}^{2})$	(0.0001)	(0.0001)	(0.0001)	(0.0001)
	-0.0006**	-0.0006***	-0.0007***	-0.0007*
$\log(eELD_{it})$	(0.0002)	(0.0002)	(0.0002)	(0.0002)
	0.001**	0.0006*	0.001***	0.0006*
$\log(ePOV_{it})$	(0.0002)	(0.0003)	(0.0003)	(0.0003)
	0.0010***	0.0009***	0.0011***	0.0009***
$\log(eACTV_{it})$	(0,0002)	(0.0002)	(0.0002)	(0.0002)
	-0.0030***	-0.0024***		
$\log(TTIk_{\mathrm{j}t})$	(0.0003)	(0.0003)		
			-0.0036***	-0.0022***
$\log(FMIk_{\mathrm{j}t})$			(0.0004)	(0.0004)
ρ (sp. Lag)	0.5257***	0.4870***	0.5255***	0.4878***
	(0.0042)	(0.0044)	(0.0042)	(0.0044)
Time and Individual dummies	yes	yes	yes	yes
Observations	63,252	63,252	63,252	63,252

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table IV.5. SEM estimations for PEC80

Variable	Year FE	Month FE	Year FE	Month FE
$\log(NRES_{it})$	0.0160***	0.0156***	0.0160***	0.0156***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$\log(NRES_{it}^2)$	-0.0021***	-0.0021***	-0.0021***	-0.0021***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\log(eELD_{it})$	0.0000	-0.0000	-0.0000	-0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(ePOV_{it})$	0.0008**	0.0005	0.0008**	0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$\log(eACTV_{it})$	0.0015***	0.0014***	0.0015***	0.0014***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(TTIk_{\mathrm{jt}})$	-0.0025***	-0.0019***		
	(0.0005)	(0.0005)		
$\log(FMIk_{\mathrm{jt}})$			-0.0017***	-0.0012***
			(0.0007)	(0.0004)
λ (sp. Err.)	0.5803***	0.5472***	0.5811***	0.5484***
	(0.0039)	(0.0041)	(0.0039)	(0.0041)
Time and Individual dummies	yes	yes	yes	yes
Observations	63,252	63,252	63,252	63,252

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

Table IV.6. SEM estimations for PEC

Variable	Year FE	Month FE	Year FE	Month FE
$\log(NRES_{it})$	0.0182***	0.0175***	0.0182***	0.0175***
	(0.001)	(0.0010)	(0.001)	(0.0010)
$\log(NRES_{it}^2)$	-0.0023***	-0.0023***	-0.0023***	-0.0023***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$\log(eELD_{it})$	-0.0001	-0.0001	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(ePOV_{it})$	0.0012***	0.0009**	0.0012***	0.0009**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$\log(eACTV_{it})$	0.0012***	0.0011***	0.0012***	0.0011***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
$\log(TTIk_{\mathrm{jt}})$	-0.0025***	-0.0019***		
	(0.0005)	(0.0005)		
$\log(FMIk_{\mathrm{jt}})$			-0.0038***	-0.0019***
			(0.0007)	(0.0007)
λ (sp. Err.)	0.5307***	0.4924***	0.5309***	0.4934***
	(0.0042)	(0.0044)	(0.002)	(0.0044)
Time and Individual dummies	yes	yes	yes	yes
Observations	63,252	63,252	63,252	63,252

Notes: *** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses.

2019

2019/1, Mediavilla, M.; Mancebón, M. J.; Gómez-Sancho, J. M.; Pires Jiménez, L.: "Bilingual education and school choice: a case study of public secondary schools in the Spanish region of Madrid"
2019/2, Brutti, Z.; Montolio, D.: "Preventing criminal minds: early education access and adult offending behavior"
2019/3, Montalvo, J. G.; Piolatto, A.; Raya, J.: "Transaction-tax evasion in the housing market"
2019/4, Durán-Cabré, J.M.; Esteller-Moré, A.; Mas-Montserrat, M.: "Behavioural responses to the re)introduction of wealth taxes. Evidence from Spain"
2019/5, Garcia-López, M.A.; Jofre-Monseny, J.; Martínez Mazza, R.; Segú, M.: "Do short-term rental platforms affect housing markets? Evidence from Airbnb in Barcelona"
2019/6, Domínguez, M.; Montolio, D.: "Bolstering community ties as a means of reducing crime"
2019/7, García-Quevedo, J.; Massa-Camps, X.: "Why firms invest (or not) in energy efficiency? A review of the econometric evidence"
2019/8, Gómez-Fernández, N.; Mediavilla, M.: "What are the factors that influence the use of ICT in the classroom by teachers? Evidence from a census survey in Madrid"
2019/9, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "The long-run redistributive power of the net wealth tax"
2019/10, Arribas-Bel, D.; Garcia-López, M.A.; Viladecans-Marsal, E.: "Building(s and) cities: delineating urban areas with a machine learning algorithm"
2019/11, Bordignon, M.; Gamalerio, M.; Slerca, E.; Turati, G.: "Stop invasion! The electoral tipping point in anti-immigrant voting"

2020

2020/01, Daniele, G.; Piolatto, A.; Sas, W.: "Does the winner take it all? Redistributive policies and political extremism"
2020/02, Sanz, C.; Solé-Ollé, A.; Sorribas-Navarro, P.: "Betrayed by the elites: how corruption amplifies the political effects of recessions"
2020/03, Farré, L.; Jofre-Monseny; J., Torrecillas, J.: "Commuting time and the gender gap in labor market participation"
2020/04, Romarri, A.: "Does the internet change attitudes towards immigrants? Evidence from Spain"
2020/05, Magontier, P.: "Does media coverage affect governments'preparation for natural disasters?"
2020/06, McDougal, T.L.; Montolio, D.; Brauer, J.: "Modeling the U.S. firearms market: the effects of civilian stocks, crime, legislation, and armed conflict"
2020/07, Veneri, P.; Comandon, A.; Garcia-López, M.A.; Daams, M.N.: "What do divided cities have in common? An international comparison of income segregation"
2020/08, Piolatto, A.: "'Information doesn't want to be free': informational shocks with anonymous online platforms"
2020/09, Marie, O.; Vall Castello, J.: "If sick-leave becomes more costly, will I go back to work? Could it be too soon?"
2020/10, Montolio, D.; Oliveira, C.: "Law incentives for juvenile recruiting by drug trafficking gangs: empirical evidence from Rio de Janeiro"
2020/11, Garcia-López, M.A.; Pasidis, I.; Viladecans-Marsal, E.: "Congestion in highways when tolls and railroads matter: evidence from European cities"
2020/12, Ferraresi, M.; Mazzanti, M.; Mazzarano, M.; Rizzo, L.; Secomandi, R.: "Political cycles and yardstick competition in the recycling of waste. evidence from Italian provinces"
2020/13, Beigelman, M.; Vall Castelló, J.: "COVID-19 and help-seeking behavior for intimate partner violence victims"
2020/14, Martínez-Mazza, R.: "Mom, Dad: I'm staying" initial labor market conditions, housing markets, and welfare"
2020/15, Agrawal, D.; Foremny, D.; Martínez-Toledano, C.: "*Paraísos fiscales*, wealth taxation, and mobility"
2020/16, Garcia-Pérez, J.I.; Serrano-Alarcón, M.; Vall Castelló, J.: "Long-term unemployment subsidies and middle-age disadvantaged workers' health"

2021

2021/01, Rusteholz, G.; Mediavilla, M.; Pires, L.: "Impact of bullying on academic performance. A case study for the community of Madrid"
2021/02, Amuedo-Dorantes, C.; Rivera-Garrido, N.; Vall Castelló, J.: "Reforming the provision of cross-border medical care evidence from Spain"

2021/03, Domínguez, M.: "Sweeping up gangs: The effects of tough-on-crime policies from a network approach"
2021/04, Arenas, A.; Calsamiglia, C.; Loviglio, A.: "What is at stake without high-stakes exams? Students' evaluation and admission to college at the time of COVID-19"
2021/05, Armijos Bravo, G.; Vall Castelló, J.: "Terrorist attacks, Islamophobia and newborns'health"
2021/06, Asensio, J.; Matas, A.: "The impact of 'competition for the market'regulatory designs on intercity bus prices"
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