Climate and health benefits of a transition from gas to electric cooking

Carlos F. Gould[1,◇], M. Lorena Bejarano[2], Brandon De la Cuesta[3,6], Darby W. Jack[4], Samuel B. Schlesinger[5], Alfredo Valarezo[2], and Marshall Burke[1,6,7]

[1]Doerr School of Sustainability, Stanford University
[2]Institute for Energy and Materials Research, Universidad San Francisco de Quito, Quito, Ecuador
[3]Center for Democracy, Development and the Rule of Law, Stanford University
[4]Dept. of Environmental Health Sciences, Columbia University
[5]Independent consultant, Quito, Ecuador
[6]Center on Food Security and the Environment, Stanford University
[7]National Bureau of Economic Research
[◇]Communicating author: gould.cf@gmail.com

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Abstract

Household electrification is thought to be an important part of a carbon neutral future, and could also have additional benefits to adopting households such as improved air quality. However, the effectiveness of specific electrification policies in reducing total emissions and boosting household livelihoods remains a crucial open question in both developed and developing countries. We investigated a transition of more than 750,000 households from gas to electric cookstoves – one of the most popular residential electrification strategies – in Ecuador following a program that promoted induction stoves, and assessed its impacts on electricity consumption, greenhouse gas emissions, and health. We estimate that the program resulted in a 5% increase in total residential electricity consumption between

2015 and 2021. By offsetting a commensurate amount of cooking gas combustion, we find that the program likely modestly reduced national greenhouse gas emissions, thanks in part to the country's electricity grid being 89% hydropower in later parts of the time period. Increased induction stove uptake was also associated with declines in all-cause and respiratory-related hospitalizations nationwide. These findings suggest that when the electricity grid is largely powered by renewables, gas-to-induction cooking transitions represent a promising way of amplifying the health and climate co-benefits of net-carbon-zero policies.

Significance statement The potential for replacing household gas appliances with electric ones to reduce greenhouse gas emissions and improve health is often cited as a motivating factor for residential electrification policies, but ex post evaluations of such efforts do not yet exist. Here, we assess the climate and health impacts of Ecuador's nationwide induction stove promotion program. Between 2015 and 2021, one-tenth of all Ecuadorian households acquired an induction stove. Residential electricity consumption increased by 5% and residential gas sales declined by about the same magnitude. Taken together, we find evidence that both greenhouse gas emissions and hospitalization rates likely fell over the first six years of the program in lockstep with increased induction stove adoption and use.

Main

Residential electrification is a key component of most net-carbon-zero strategies. Globally, residential buildings are responsible for 10% of greenhouse gas emissions.[1] Household electrification coupled with electricity grid decarbonization are also increasingly thought to have co-benefits in terms of improved indoor air quality and health.[2–6] Thus, most plans to get societies on low-carbon pathways include ambitious residential electrification policies.[7,8] The approach to reducing emissions from residential buildings is straightforward: electrify everything and decarbonize electricity production.[9] Modeling studies suggest that residential electrification could yield large "win-win" reductions in both greenhouse gas and air pollution emissions in both wealthy and resource-poor regions of the world.[2,10–12]

However, despite substantial policy attention on residential electrification in general, we still lack careful ex-post evaluation of to what extent available residential electrification policies actually spur adoption, reduce emissions, and generate co-benefits. Ex post policy evaluation is important, given the frequent gulf in findings between ex ante and ex post analyses of energy policies, with differences often driven by behavioral responses to these policies.[13–17] For example, in an experimental evaluation of 30,000 homes participating in the Weatherization Assistance Program in Michigan, USA, Fowlie, Greenstone, and Wolfram (2018)[15] show that model-projected savings exceeded observed savings by more than three times, at least partly due to low take up[18] and smaller-than-predicted energy efficiency gains. In another example, Davis, Fuchs, and Gertler (2014)[16] show that a program that helped 1.9 million households in Mexico replace their refrigerators and air conditioners with energy efficient units reduced electricity consumption by 8%, only one-quarter of the ex ante predictions. These differences are explained by most retired appliances being comparatively younger and more efficient than expected and an increased use of air conditioners among enrollees (the "rebound effect"). In some cases, lower-than-expected benefits lead the costs of these programs to outweigh the benefits. And yet, despite their clear limitations, ex ante engineering estimates are widely used to measure the benefits of energy efficiency programs, with little attention to rigorous ex post evaluation.[19]

While the specific policies that will maximize both climate and health benefits remain unknown, one promising strategy is replacing gas cookstoves with electric induction cookstoves.[20,21] When the grid is powered by renewables, induction is the gold-standard for clean cooking because it has zero combustion at the point of use and produces minimal greenhouse gas emissions.[6] Induction is also more efficient than gas cooking. Cooking with gas has a typical energy efficiency of 50% (i.e., half the energy from the gas is transferred to usable heat for cooking).[22] In comparison, induction stoves use electromagnetic induction to directly heat ferromagnetic cookware and can have an efficiency of 90% when used, well above even a typical electric coil stove (60% to 75% efficiency). Cooking with induction could also improve health for residents as compared to cooking with gas. Gas-based cooking has been identified as an environmental health risk factor for several decades[23–26] because it increases indoor concentrations of air pollutants – especially nitrogen dioxide (NO_2) – that have been linked to poor health outcomes.[27–32] Recent research has also documented both the presence of toxic chemicals like volatile organic compounds and benzene in natural gas samples from US homes and substantial leakage of these chemicals even when stoves are not in use.[33–35] Somewhat more limited evidence has directly documented associations between cooking with gas and poor health,[36–39] though studies with strong causal identification are lacking.

Given these potential benefits, governments are promoting the transition from gas to electric cooking in many regions around the world, including in parts of the US, the Netherlands, Nepal, Indonesia, and Australia.[40] However, the extent to which such transitions will yield climate and health benefits once implemented, and whether the benefits of policies that induce these transitions exceed costs, remains unknown. Benefits depend on a range of factors, including human behaviors such as the extent to which households take up the new program, the extent to which they use new technologies, and the extent to which the new technology displaces the old one. These behavioral responses cannot be quantified ex ante.

Here, we evaluate the impact of a large program in Ecuador, the "Program for efficient cooking" (PEC), which aimed to reduce LPG consumption and replace it with electricity powered by the nation's growing hydroelectric capacity by subsidizing households to adopt and use induction stoves. As in many other developing and middle income countries, the Ecuadorian government has a history of subsidizing cooking fuel – although to a greater extent than most other countries. These subsidies have encouraged a transition away from more polluting cooking fuels,[41] but at large budgetary cost.[42] While LPG was originally subsidized in the midst of a petroleum boom in the 1970s, Ecuador now imports roughly 80% of all its LPG. Volatile international petroleum prices, a fixed internal sale price, and growing demand have combined to result in ballooning government expenditures on the LPG subsidy, at times reaching 60 million USD per month (Figure S1). Begun in 2014, PEC aimed to connect 3 million households, and by 2020 it had induced about 750,000 households (or 12% of the population) to purchase an induction cookstove. This program represents one of the most ambitious of such programs to date in a middle income country, yet there have been no evaluations of its impact on household energy use, greenhouse gas emissions, or health.

Using multiple datasets and two approaches to isolating the causal impact of the program, we evaluate the effect of PEC on electricity consumption, LPG consumption, greenhouse gas emissions, and health. We quantify changes in electricity consumption from PEC using a combination of 130 million monthly household utility bills from Ecuador's two largest utilities over the last eight years, monthly nationwide parish level data on electricity consumption changes, and administrative data on program enrollment. We use both an event study design and a differences-in-differences analysis to estimate the effects of program enrollment on household electricity consumption. Next, we quantify the changes to net greenhouse gas emissions from household fuel combustion nationwide associated with induction stove uptake. To do so, we directly estimate how much PEC-related electricity consumption is associated with reduced LPG sales in panel fixed effects regressions. Then we combine these data with detailed information on Ecuador's electricity grid fuel mix to provide estimates of how greenhouse gas emissions have changed with program expansion.

Next, we examine how population health has changed with program enrollment. We join data covering all 9.6 million hospitalizations in Ecuador between January 2012 and March 2020 with program enrollment, both aggregated to the canton level, to estimate the response of both all-cause and respiratory-related hospitalization rates to program enrollment in panel fixed effects regressions. We assess the robustness of the association to alternative approaches, including in a difference-in-differences model, modeling the outcome as a count, accounting for potential confounding by measures of wealth, healthcare resources, and political support, and implementing recent statistical techniques that inform the likelihood that estimated treatment effects are likely explained by factors other than program enrollment. Finally, combining our results with global data, we detail countries and regions where residential electrification programs are likely to be carbon neutral based on the intensity of greenhouse gas emissions of the operating margin in that area and the extent to which electricity can be expected to replace gas.

Results

Patterns of induction stove program enrollment PEC enrollment grew quickly after its inception in 2015, reaching its existing size – about 600,000 active customers in a given month – within three years. In 2021, 12.6% of all residential electricity customers were enrolled in PEC (Figure 1, Table S1). Given that PEC did not target specific demographics for enrollment, intuition might suggest that enrollment would be most common among wealthy households in urban centers. However, multiple measures suggest that the program was taken up by households across the wealth spectrum. While the majority of PEC enrollees reside in or near Ecuador's two major cities, Quito and Guayaquil, many rural parishes across the country have similar enrollment rates as their urban counterparts (Figure S2). Canton level enrollment in PEC was negatively associated with the prevalence of a needs-based poverty alleviation program (a proxy for deprivation), but not with other measures of socio-economic status like income-based poverty or extreme poverty (Table S2; Figure S3). Finally, leveraging our billing data, we observe that program adoption was positively correlated with pre-enrollment baseline electricity consumption but that both low- and high-baseline energy users also adopted at meaningful rates (Figure S4).

Program enrollment and increased electricity consumption To understand program impacts on electricity consumption, we first use customer level billing records from all customers in Ecuador's two largest utilities – the Corporacion Nacional de Electricad - Guayaquil (CNEL-Guayquil) and the Empresa Electrica de Quito (EEQ) – which together cover 40% of all households in Ecuador – to estimate the impact of enrollment in PEC on average monthly household electricity consumption. Enrolling in PEC is associated with a 31.3 kWh per month increase in total electricity consumption (95% CI, 30.6 to 32.0) in the CNEL-Guayaquil sample and 23.6 kWh per month (95% CI, 23.0 to 24.1) in the EEQ sample, controlling for month, year, month-by-year, and customer fixed effects with standard errors clustered at the customer level (Figure 2). In other words, customers in both samples increased their electricity consumption by roughly 15% after enrollment. In an event study analysis, customers increased their overall electricity consumption by 10 kWh three months after enrollment relative to the month of enrollment, 15 kWh six months after enrollment, and steadily increased consumption until reaching a 20 kWh increase about 24 months after enrollment (Figure 2). The observed increasing effect of enrollment in PEC on electricity consumption appear to be partially explained by an increasing number of customers beginning to use their induction stoves over time, in addition to adaptive behaviors whereby individual customers increase their consumption over time (Figure S5), though we cannot be certain exactly how households use their electricity. These findings are robust to a range of alternative sample selections and modeling choices (Methods).

We also analyze program impacts using nationwide parish-level data on the universe of household electricity use. In these data, general customers and PEC beneficiaries both consumed roughly 140 kWh per month in 2016 (Table S1), but by 2019, PEC beneficiaries were consuming an average of 25 kWh per month more than the average general customer (165 kWh vs. 140 kWh) (Table S1). We estimate that each percentage point increase in the percent of all residential electricity customers that are enrolled in PEC is associated with an increase in average monthly kWh per customer of 0.64 (95% CI, 0.14 to 1.20) (Table S3). In total, we estimate that increased PEC enrollment is associated with an excess consumption of 2.9 billion kWh of electricity between January 2015 and October 2021, a 5% increase in residential electricity consumption (Figure 3A-B; median estimate 5.2% increase, interquartile range 3.5% to 6.5% increase). Our model-based estimate exceeds the utility-calculated PEC subsidy amount over the same time period of 1.9 billion kWh (171 million USD), which is estimated as the kWh a household consumes over and above its 12-month average prior to PEC enrollment to overcome a lack of appliance-specific metering. Thus, absent this empirical analysis, total impacts of the program on electricity consumption would be underestimated by one-third. Our results are consistent when this analysis is repeated at the canton level and when controlling for measures of income, wealth, and voting patterns are included (Table S3, S4).

Reduced LPG sales from increased induction stove use Increased electricity consumption for cooking is largely a substitute for LPG consumption. To understand the extent of substitution induced by PEC, we first regress aggregate country-level total kilograms of domestic LPG sales on monthly total kWh of PEC-related electricity subsidized, using fixed effects for month and year (subnational data on LPG sales is unavailable for our full study period). We find that each additional kWh of PEC electricity is associated with a decline of 0.27 kg LPG sold (95% CI, 0.09 to

0.45) (Figure 3C), equivalent to an estimated total reduction in LPG sales of 689 million kg (median estimate, IQR: 505 to 878) (Figure 3D). Using monthly province-level sales data that begin in 2018, which miss half of our study period including the critical first three years when PEC enrollment grew most, we find that an additional estimated kWh of PEC electricity is associated with a decline in 0.16 kg LPG sold for residential purposes (95% CI, 0.01 to 0.22) – somewhat smaller than our national estimate. This implies an estimated national-level total LPG sales reduction of 423 million kg LPG (IQR, 388 to 2,630). An alternate approach using Government of Ecuador data on conversion factors between electricity and LPG yield estimates of reduction in LPG sales between the national and provincial estimates (see Methods for more details on these approaches).

Program impacts on greenhouse gas emissions Ecuador emits around 40,000 kilotons carbon dioxide equivalent (CO2e) each year, with electricity production responsible for about 5% of all CO2e emitted.[43] Given that household electricity consumption accounts for one-third of all electricity consumed in the country, this sector is responsible for about 1.6% of the Ecuador's yearly CO2e emissions (roughly 640 ktCO2e yearly). Whether PEC has reduced greenhouse gas emissions depends on not only our estimates of excess electricity consumption and associated reductions in LPG consumption, but also on the intensity of emissions from the electricity grid on the margin and gas combustion.

Using yearly marginal emissions factors (MEFs), defined as kg CO2e emitted per additional kW electricity consumed, we estimate that the PEC program was responsible for 1,450 kt CO2e between January 2015 and November 2021; over the same time frame, reduced LPG sales led to 2,351 ktCO2e averted (Figure 3E). Net, across the full combination of 1,000 bootstrapped runs of monthly excess electricity consumption and 1,000 runs of monthly reduced LPG consumption, we estimate a median net reduction of 771 ktCO2e (IQR, 144 to 1,519) between January 2015 and November 2021, or a 1.5% reduction in household electricity and LPG related greenhouse gas emissions (Figure 3F). Net declines in CO2e emitted have come since 2019, in particular, when Ecuador's electricity grid reached more than 80% renewable power. Alternative approaches led to similar, albeit smaller, estimated declines in CO2e emitted nationwide (Methods).

Impacts of induction program on health To estimate program impacts on health, we used administrative data on the universe of hospitalizations between January 2012 and March 2020 (representing 9.5 million hospitalizations) (Figure S6, Table S8). We analyzed the association between monthly cause-specific canton-level hospitalization rates and PEC enrollment using fixed effect regression that controlled for canton and month-of-sample fixed effects (Methods), with confidence intervals estimated by block-bootstrapping (1000 runs, sampling cantons with replacement).

We found that each additional percentage of the customers in a canton enrolled in PEC was associated with a 0.73 percent decline (95% CI, 0.20 to 1.21) in the all-cause hospitalization rate, a 0.72 percent decline (95% CI, 0.04 to 1.38) respiratory-related hospitalization rates, and 2.15 percent decline (95% CI, 0.69 to 3.39) for chronic obstructive pulmonary disorder (COPD) hospitalization rates (Figure 4). Estimates for associations with the rate of hospitalizations for influenza and pneumonia and asthma were negative but had wide confidence intervals. We observed no clear associations between PEC enrollment and hospitalizations for other cause-specific outcomes (Figure S7).

These observed effect sizes imply substantial improved public health from induction stove uptake and warrant close attention. We address concerns about time-trending unobservables driving both induction uptake and declines in hospitalization rates using three tests (Methods). First, we isolated cantons that had high PEC enrollment at the end of the study period (>85th percentile from June 2019 to March 2020; 18% average enrollment in $N = 33$ cantons) and compared them to those that had low PEC enrollment (<15th percentile; 4% average enrollment $N = 33$) over the same time frame. Prior to PEC's inception in January 2015, these cantons had similar trends in all-cause hospitalization rates after conditioning on covariates, i.e., had parallel trends (Figure S8). Second, we identified and directly controlled for a set of canton-level time-varying factors that might plausibly covary with enrollment and health, including measures of wealth, urbanization, and political targeting (i.e., areas that may have received attention due to political motivations). Adjusting for per capita cantonal incomes, the fraction of households that benefit from a needs-based poverty alleviation program, the cantonal rate of doctors and nurses and medical facilities per person, population size, and voting patterns marginally attenuated the observed effects (Figure 4, Figure S7, Table S9). Third, we implemented a formal approach to bound the potential influence of any remaining unobserved confounders[44,45] (Methods). The results from this procedure indicated that if there existed an unobserved confound with the same predictive power as all of the included covariates currently in the regression, we would still conclude that PEC enrollment had a negative effect on all-cause hospitalization rates (Figure S9). To drive our effect size to zero, we calculate that a confound would have to be so strong as to yield an overall regression model that explained 95% of the total variance in hospitalization rates. We view this possibility as unlikely, given that several important drivers of hospitalization rates and PEC enrollment (particularly population) are already included, and that there is likely substantial idiosyncratic variation in local hospitalization rates unlikely to be explained by any model.

We also tested the association between PEC and hospitalization rates in a difference-in-differences

(DiD) approach in which we compared high-enrollment cantons to lower-enrollment cantons (Methods). In comparison to our preferred model described above, the DiD approach may have greater internal validity because, based on recent advancements in the econometrics literature, implementing the DiD estimator of Callaway and Sant'Anna (2021)[46] eliminates so-called "negative weights"[47] and produces valid estimates of the average treatment effect on the treated (Methods). The DiD approach presented here serves as a complement to our main approach because we use only a subset of all cantons, and thus it might not represent the larger sample. We found that high enrollment cantons had 11% (95%, 2% to 20%) and 8% (95%, 0% to 17%) lower hospitalization rates in the post-PEC period as compared to low enrollment cantons in unadjusted and adjusted models, respectively (Figure S10). The event study plot illustrates that there are no pre-PEC trends in hospitalization rates and that hospitalization rates decline over the first year following PEC's inception and stabilize thereafter (Figure S10).

Results were additionally robust to controlling for long-term time trends using a natural spline and month of year and year fixed effects, to alternative choices for potential confounding variables, and to alternate temporal or geographic aggregations (Methods) (Figures S11-S16, Table S10). Hospitalization rates were more negatively associated with PEC enrollment in cantons where the average household PEC-related electricity subsidy use was higher, providing suggestive evidence that our observed associations are driven by induction stove use (Figure S17).

The direction and patterns of reductions in hospitalizations with cause-specific outcomes were consistent with our expectations for PEC enrollment reducing indoor air pollution and improving health, i.e., we observed our largest effects for respiratory-related causes known to be impacted by NO_2 exposures. Still, given wide confidence intervals in bootstrapped analyses, we cannot rule out smaller effects. We conclude that, at the canton level, increased PEC enrollment is negatively associated with hospitalization rates, especially for respiratory conditions like COPD.

Potential global emissions benefits from residential electrification programs We sought to understand whether a residential electrification program like PEC would likely reduce total emissions in other countries outside of Ecuador. To do so, we first developed a simple model to estimate net GHG emissions as households substitute from one energy source to another. The model relied on three basic parameters: marginal emissions factors (MEFs) for electricity grids (i.e., the kg CO2e associated with each additional kWh of electricity generated on top of existing base loads), a static emissions factor associated with gas combustion (kg CO2e per unit LPG or natural gas), and the extent to which an additional unit of electricity consumption would be expected to displace gas combustion. A program can be considered viable from an emissions perspective if increased emissions from additional electricity consumption are equaled or outweighed by expected reductions in emissions from gas combustion. We model these substitutions using a set of common energy conversions and assumptions about efficiencies of gas and electric cooking (Methods).

Figure 5A maps the extent to which a country-level residential electrification program would have to displace gas to achieve a combustion-related CO2e neutral transition based on the marginal emissions factors for regional grids, and highlights some existing and proposed residential electrification programs. In large part, we see that transitions are already technically viable in much of western Europe, central and South America, and parts of sub-Saharan Africa where grids are clean. However, these country-wide averages likely mask subnational heterogeneity in emissions factors, as illustrated in Figure 5B and C in the US and India, two of the world's largest countries that both have large reliance on gas for cooking. In the US, New England, California, Idaho, and Florida have sufficiently clean grids to support a combustion-related emissions-neutral transition (Figure 5B); in India, much of north and eastern India, along with Kerala, have sufficiently clean grids (Figure 5C). However, the large geographic majority of these countries require reductions in MEFs before a program to electrify cooking would reduce net emissions.

Discussion

Although substantial policy attention and investments have been made in increasing residential electrification and promoting clean cooking in recent decades, there is remarkably little real-world evidence on both the climate and health impacts of such efforts. Instead most investments and policies have been motivated by engineering estimates of the purported benefits of electrification policies and cleaner cooking solutions. Cleaner cooking, in particular transitioning away from inefficient combustion of biomass like firewood, has long been heralded as an opportunity to reap both climate and health benefits.[2,48] However, many ex post evaluations of efforts – in particular those that focus just on one dimension of a program (i.e., climate or health) – have found much more limited benefits (and even zero benefits) relative to ex ante estimates.[17] Thus, the ex post analysis presented here of a large gas-to-electric cooking program represents a substantial advancement for our understanding of the potential climate and health benefits of residential electrification programs. We capitalize on a remarkable policy environment in Ecuador where several decades of subsidies have led to the majority of the country using gas for cooking and natural resources have enabled the country's electricity grid to be 90% renewables. Across multiple approaches and leveraging both micro and publicly-available administrative data, our results illustrate that Ecuador's recent initiative to replace gas with induction electric cooking has indeed both reduced greenhouse gas emissions and yielded health co-benefits.

The potential for residential electrification programs to provide climate benefits depends on both the extent to which they offset fossil fuel combustion, the carbon-intensity of the relative operating margin of the grid that supplies electricity, and certain aspects of grid readiness to deliver sufficient electricity for household use at scale. Based on marginal emissions factors, we illustrate that much of the world can already support gas-to-electric cooking transitions that would be emissions reducing. The further growth in renewable energy capacity expected in the near term should make this true in even more regions. However, beyond facilitating shifts toward electricity generated from renewable resources, investments must also be made to ensure that electrical grids can support the temporally-correlated demand associated with a widespread transition to electric cooking.[49,50] In the past decade, Ecuador has invested more than a billion dollars in grid upgrades to broadly support electrification efforts and ensure consistent, reliable electricity for the population, although these upgrades may have been made in the absence of PEC. Similarly, households themselves may need to make changes to support induction cooking. In Ecuador, households must have 220 volt connections and dedicated circuits installed to use induction stoves. Delays in installing these connections has reportedly been a barrier to using induction stoves after purchase.[41] Emerging economies with recently expanded electricity grids should recognize the additional capital investments required to support large-scale residential electrification projects. Indeed, it is possible that some countries with sufficiently clean grids cannot yet support widespread residential electrification projects because of inadequate service and reliability concerns.[51,52]

Mindful of the limitations of ecological analyses, our findings suggest that widespread replacement of gas with induction cooking could yield health benefits, especially for the acute exacerbation of chronic respiratory diseases. To our knowledge, no study has analyzed the health gains from widespread replacement of gas with electricity as we do here, which makes it difficult to compare our work to existing literature. One meta-analysis of 19 studies concluded that children living in households with gas stoves had a 32% higher risk of having asthma as compared to those living in households with electric stoves.[53] Using this meta-analytic estimate, one study calculated that about 13% of all pediatric asthma cases in the US were attributable to gas cooking.[54] Elsewhere, a simulation study estimated that replacing gas stoves would reduce severe asthma attacks by 7% in an urban population.[55] Our effect estimates are larger than what we might expect given anticipated air pollution exposure reductions from gas to induction cooking transitions and existing estimates of the health effects from NO_2 exposures (Methods). We urge caution in directly interpreting our effect estimates as they have wide confidence intervals and we cannot rule out smaller effects. The large benefits observed here, and the body of evidence supporting the relationships between gas cooking, elevated air pollution exposures, and health, emphasize the need for randomized or quasi-experimental evaluations of gas to electric cooking transitions, especially at the household or individual level.

Our study has additional limitations. First, we analyze the impacts of enrollment in PEC on total household electricity consumption using customer-level data from Ecuador's two largest utilities and using aggregated data with nationwide coverage; however, both datasets lack a direct, objective measure of stove use. Second, our estimation of the changes in greenhouse gas emissions associated with PEC are somewhat sensitive to our calculation of the reduction in cooking-related gas combustion associated with the program. With that said, across a range of specifications we observe that either the program has been roughly combustion-related-emissions neutral or yielded small but meaningful reductions in GHG emissions. Our approach to evaluating combustion-related emissions may underestimate the benefits of the electrification program because the emissions associated with life cycle of gas typically exceed those for electricity (e.g., gas is transported on trucks in cylinders); however, estimates for life cycle emissions for gas combustion in Ecuador are unavailable. This limitation – i.e., our inability to directly quantify the CO2e associated with gas transport – extends to our analysis of whether hypotethetical global residential electrification programs are technically viable. Third, our analysis is focused on a single middle-income country and our results may not be generalizable to other contexts. Still, it is plausible that the transition in Ecuador represents a conservative estimate for the potential climate and health benefits of similar programs elsewhere because it is likely that a substantial proportion of PEC enrollees continue to use gas to some extent, in part because gas continues to be so heavily subsidized. Transitions that are driven by policies focused on preventing gas appliance use in new construction would more completely replace gas with electricity leading to potentially greater cooking-related air pollution exposure reductions and health benefits than we observe in our study.

While Ecuador's induction promotion program remains unique as of 2022, other residential electrification projects are likely to follow. Gas remains the most popular cooking fuel in the world, with roughly three billion daily users, and demand is increasing in many low- and middle-income countries. However, policies around the world in high-income countries and cities propose to eliminate gas appliances from residential homes as a means of reaching net-zero greenhouse gas emissions. Investments in clean electricity and flexible and robust electricity systems that can meet the necessary projected increased electricity demand are essential to reach a net zero emissions future. Here we show that when these renewable energy investments do come, capitalizing on the opportunity and replacing gas with electricity in residential homes holds promise for achieving both climate and health benefits.

Methods

Estimating changes to customer electricity consumption after induction stove promotion program enrollment

We obtained all residential customer monthly electricity consumption and cost records from Ecuador's two largest electricity providers through a private use agreement. Data from the Electricity Utility of Quito (EEQ) totaled 1.07 million unique customers – 161,000 of whom enrolled in PEC at some point – and ranged from January 2015 to July 2021, yielding 65 million observations. Data from the National Electricity Corporation for Guayaquil (CNEL) totaled 818,692 unique customers – of whom 115,832 enrolled in PEC at some point – and ranged from January 2013 to July 2021, yielding 66 million observations. Together, the two data sets cover approximately 40% of all electricity customers in Ecuador. For each customer, we have data on whether they enrolled in PEC at some point during the study period (and, if so, the date of enrollment), whether they benefit from a reduced electricity tariff, and their location. For PEC customers in EEQ, we additionally have a utility-provided measure of PEC-specific electricity subsidy consumption in kWh, which is defined as excess household electricity consumption over and above their pre-enrollment 12-month average consumption. Customer data were provided in two files by both electricity utilities, with the first file covering the period until December 2017 and the second file covering the period after, due to the utilities switching billing management systems.

We estimate the effect of PEC enrollment on electricity consumption using the following fixed effects regression separately for customers in EEQ and CNEL:

$$y_{imd} = \beta E_{imd} + \mu_i + \gamma_m + \delta_d + \epsilon_{imd} \tag{1}$$

using ordinary least squares where i indexes customers, m indexes month-of-study, and d indexes the billing system the data were collected under. y_{im} is the electricity consumption in kWh for customer i in month m and E_{im} is a dummy variable for whether customer i is enrolled in PEC in month m ("Not enrolled" vs. "Enrolled"). The reference category of "Not enrolled" includes customers that never enroll (general customers) and customers that eventually enroll but are not yet enrolled in month m. In this approach, the impact of program enrollment on electricity consumption is identified by using within-household variation over time in consumption, after accounting for any average differences in consumption between months in the study sample. The coefficient β can be interpreted as the effect of the program on consumption under the assumption that program adoption is not correlated with other unobserved household level behavior or characteristics that vary over time and also affect electricity consumption. Any average differences in consumption between early and later (or non-) adopting customers are accounted for by the customer fixed effect.

We next estimate the change in electricity consumption in each month relative to enrollment in PEC among customers that enroll in PEC at some point using an event study design, estimated with the following equation:

$$y_{itmy} = \sum_{t=-q}^{r} \beta M_{it} + \lambda_m + \gamma_y + \epsilon_{itmy} \tag{2}$$

using ordinary least squares where i indexes customers, t indexes month relative to enrollment, m indexes month of year, and y indexes year. Our outcome y_{itmy} is the electricity consumption in kWh for customer i in month m, year y, and month relative to enrollment t. M_{it} is a vector of dummy variables for each month relative to that customer's month of enrollment (reference group: month before enrollment t=-1). -q is the customer's earliest month observed and r is the customer's latest month observed. The resulting 80 βs (from 20 months before enrollment to 60 months after enrollment) can be interpreted as the average difference in monthly electricity consumption relative to electricity consumption in the month before enrollment.

We use these event study plots to illustrate two key facts: (1) electricity consumption among PEC enrollees does not change meaningfully in the months leading up to PEC enrollment (i.e., point estimates and their 95% confidence intervals are relatively flat) and (2) electricity consumption increases dramatically in the months following PEC enrollment (i.e., point estimates steadily increase and 95% confidence intervals do not include zero as time moves forward). The resulting event study plot gives us confidence that our study design isolated the causal effect of PEC enrollment on household electricity consumption; however, it is worth noting that this extension of our main analysis only includes customers that eventually enroll in PEC (roughly one-tenth of our total sample). Furthermore, in the case of the EEQ sample, we only have data from 2016 onward, meaning that our "pre-enrollment" period is substantially more limited because many customers had already enrolled prior to the data beginning.

Results were robust to a number of alternative specifications and subsamples generated during data cleaning processes (Supplemental Information Section 1).

Parish level electricity consumption and enrollment in induction stove program

As a complement to the individual customer level data, we obtained data from the Agency for the Regulation and Control of Energy and Non-Renewable Natural Resources (ARCONEL) on monthly residential electricity consumption for all parishes in Ecuador since 2015, detailing: 1) the total kWh of residential electricity consumption and associated USD billed; 2) total residential customers; 3) total kWh of residential electricity consumption for PEC customers and associated USD billed; 4) total kWh of PEC-related electricity subsidized and associated USD subsidized; and 5) total PEC customers. Data cleaning procedures focused on identifying and unifying parishes across the study time period by manual matching to address different spelling, capitalization, and use of accents. In total, there were 1,188 unique parishes and 94,972 parish-month observations in our sample.

We estimate the change in average household electricity consumption associated with changes in PEC enrollment using the following fixed effects regression:

$$y_{pcm} = \beta P_{pcm} + \mu_p + \delta_{cm} + \epsilon_{pcm} \tag{3}$$

via ordinary least squares where p indexes parishes in canton c (parishes are smaller than cantons). y_{pcm} is the average household electricity consumption in kWh per month in each parish-month observation and P_{pcm} is the proportion of customers enrolled in PEC in the same parish-month. μ_p is a vector of parish fixed effects to account for locality-specific time-invariant characteristics drivers of PEC enrollment and household electricity use. To account for both seasonal and longer-term trends in PEC enrollment and household electricity use that could differ across regions, we include a vector of canton-by-month-of-study fixed effects δ_{cm} (e.g., "Cuenca, Azuay January 2015"). To aid in interpretability, we estimate the change in average household electricity consumption per 10 percentage point increase in PEC enrollment, with standard errors clustered at the parish level.

We develop a counterfactual scenario without PEC enrollment to estimate excess kWh of electricity consumed by households from increased PEC enrollment. To do so, we subtract the product of our estimated coefficient of interest (the change in average household electricity consumption per unit increase in PEC enrollment) and the number of PEC customers from total parish-month kWh. We quantify uncertainty in this analysis by bootstrapping the estimates of the relationship between PEC enrollment and electricity consumption (1,000 times, sampling parishes with replacement) and applying these coefficients to observed consumption to construct 1,000 total excess electricity consumption estimates.

Estimating trade-offs with LPG consumption

We estimate the trade-off between electricity for cooking and LPG a few different ways. First, we obtained monthly national-level data since 2007 on the volume of Ecuador's LPG imports, the volume of Ecuador's internal LPG production, the volume total internal LPG sales, the cost of LPG imports per barrel, and the country's internal sales price. To estimate the extent to which LPG consumption has declined from PEC enrollment, we combine these monthly national data on LPG sales (our measure of national LPG consumption) with our predicted excess kWh consumed using ordinary least squares regression with fixed effects for year and month of year to account for seasonal and longer-term drivers of LPG and electricity consumption. Similar to our approach for estimating excess electricity consumption, we use the coefficient from this regression to estimate reduced LPG sales from the additional electricity consumed from PEC enrollment. We repeat this analysis 1,000 times sampling months of observation with replacement and apply these resulting coefficients to observed sales to yield 1,000 estimates of total averted LPG sales.

We also tested three alternative strategies. In the first, we obtained monthly province-level LPG sales data by sector (residential, industry, vehicular, agricultural industry) between 2018 and 2021 and repeat our principal approach of directly regressing PEC-related electricity consumption on LPG sold, here using province level aggregations and province and month of study fixed effects. Second, we draw on an engineering approach to assessing the expected trade-off between cooking with electricity and with gas. Third, the Government of Ecuador has equated 80 kWh with 1.2 15 kg LPG tanks in designing its PEC-related electricity subsidy. Results from all three approaches support the conclusion that PEC reduced household LPG consumption.

Net changes to greenhouse gas emissions associated with the induction stove promotion program

To estimate GHG emissions impacts, we first estimate additional emissions from PEC-related electricity consumption using a yearly operating margin emissions factor (MEF) for public electricity generation in Ecuador;[43] the MEF represents the CO2e emitted per additional kWh consumed over the base load, which is appropriate for our exercise since we aim to assess emissions due to PEC as compared to a counterfactual scenario where PEC did not exist. For example, from Equation 2, we estimated that excess electricity consumption in July 2016 was 24 million kWh. In 2016, the emissions factor was 0.6431 kilograms CO2e per kWh produced. Therefore, in July 2016, excess electricity consumption from PEC was estimated to result in 15.5 kilotonnes CO2e. At the same time, excess kWh electricity consumption was associated with declines in LPG sales. We infer this association to imply averted LPG combustion from PEC enrollment; therefore, we can estimate associated declines in CO2e from reduced LPG sales using a standard emissions factor of 2.992 kg CO2e per kg LPG. We quantify uncertainty in this analysis of net changes to greenhouse gas emissions by combining the 1,000 bootstrapped sets of monthly estimates of excess electricity consumption and the 1,000 bootstrapped sets of monthly reduced LPG sales. This procedure yields 1,000,000 estimates of total net changes to greenhouse gas emissions from PEC. Across the full combination of 1,000 bootstrapped runs of monthly excess electricity consumption and 1,000 runs of monthly reduced LPG consumption, we estimate a median net reduction of 771 ktCO2e (IQR, 144 to 1,519) January 2015 and November 2021, or a 1.5% reduction in household electricity and LPG related greenhouse gas emissions (Figure 3F). While our preferred specification finds a small net reduction in greenhouse gas emissions due to PEC, our analysis may be sensitive to our approach to estimating declines in LPG consumption. Across potential specifications, we estimate changes in greenhouse gas emissions to range from a 0.4% increase (20 ktCO2e) to a 3.5% decrease (1,827 ktCO2e) from January 2015 to November 2021. While yearly marginal emissions factors are a historical simplification of numerous short-term changes to electricity generation determined by dispatch models, recent modeling studies suggest that they perform reasonably well at predicting emissions from demand shifts.[56]

Changes to hospitalizations associated with PEC

Hospitalization data come from the statistical registry of hospital beds and visits which details morbidity across Ecuador, managed by the National Statistical Agency (INEC). Our visit level data intend to capture all hospitalizations in Ecuador between January 1, 2012 and March 1, 2020 (truncated because of the COVID-19 pandemic). Each hospitalization contains data on the age and sex of the patient, the date of admission and release, the location (province, canton, parish) of the patient's residence and the healthcare facility (public or private), and the International Classification of Disease (ICD-10) code for the reason for the hospitalization. Summaries of the hospitalizations by ICD grouping are shown in Figure S6. In total, the data cover 9.6 million hospitalizations across 21,319 canton-month observations (216 unique cantons and 99 months studied). The data included in our final analysis cover 99% of all recorded hospitalizations during the study period, with most data losses coming due to missing canton-level data on PEC enrollment.

We calculated monthly canton-level all-cause and cause-specific hospitalization rates by dividing the total canton-level visits by canton-level population in that month. We assign yearly canton-level population estimates from the Ecuadorian statistical agency to January of every year and linearly interpolate to develop monthly canton-level population across the study period. Country-wide, the average monthly hospitalization rate was 589 per 100,000 across the study period. Beyond all-cause hospitalizations, we additionally focused on respiratory-related conditions (influenza and pneumonia, COPD, and asthma), which are most likely to respond to reductions in air pollution from declines in gas cooking.

To estimate the impacts of program take-up on hospitalizations, we estimate the following regression:

$$log(y_{cm}) = \beta P_{cm} + \mu_c + \gamma_m + \theta_{cm} + \varepsilon_{cmf} \tag{4}$$

using ordinary least squares, where c indexes cantons and m indexes month-of-study. y_{cm} is the log of the monthly canton-level cause-specific hospitalization rate, and P_{cm} is the proportion of customers enrolled in PEC in the same canton-month. μ_c is a vector of canton fixed effects that account for all locality-specific time-invariant characteristics correlated with either PEC enrollment or hospitalization rates. To account for seasonal and longer-term trends in PEC enrollment and hospitalization rates we include a vector of month-of-study fixed effects γ_m, which account for any seasonal- or time-trending differences in either PEC enrollment or hospitalization rates that are common to all parishes. Regressions were weighted by canton population and standard errors were clustered at the canton level.

Our analysis assesses the association between a one percentage point increase in PEC enrollment at the canton level on average canton level hospitalization rates. Previously, we showed that PEC enrollment leads to increased canton-level household electricity consumption and reduced gas consumption. Our inference is thus that PEC enrollment's impact on health is through reduced gas cookstove use which improves indoor air quality. Our approach is focused on making inferences about average effects at the canton level and we do not draw any inferences on the risk reduction that any individual may experience when replacing their gas stove with an electric one.

Given that PEC was not a randomized policy experiment, we may be concerned that cantons with higher rates of enrollment are different from those with lower rates of enrollment in ways that influence population health (i.e., hospitalization rates) independent from the impact of PEC on induction stove use and its replacement of gas. Given our unit of analysis (canton-month) and the use of canton and month of study fixed effects, potential confounding variables would have to be canton-level factors that vary differentially over time across cantons and covary with both hospitalization rates and PEC enrollment. We take three approaches to address concerns about time-trending unobservables. See Supplemental Information Section 5 for more details.

First, we test for parallel trends in health outcomes using pre-program data to assess if outcomes were trending differentially prior to PEC's initiation in January 2015. If outcomes trend differentially between cantons than eventually had high PEC enrollment as compared to those who had relatively little PEC enrollment, then we would have concerns that some other unobserved variables are driving associations between PEC enrollment and hospitalization rates. We define the low enrollment group as those that have $<$15th percentile average enrollment from June 2019 to March 2020, while the high enrollment group is those with $>$85th percentile enrollment. We formally test for parallel trends in our outcome conditional on covariates using the 'did' package in R, finding no evidence of differences in trends in all-cause hospitalization rates before PEC (Cramer von Mises Test Statistic = 0.798; Critical Value = 3.827; P-Value $\approx$ 1). We see similarly non-significant differences in trends for key covariates prior to PEC initiation, as illustrated in Figure S8 where trends are tested at the canton-month level by interacting month of the study (as a continuous number) with a dummy variable for high or low enrollment canton, with fixed effects for canton.

Our second approach is to identify and directly control for a set of canton-level time-varying factors that might plausibly covary with enrollment and health, including wealth (areas that get wealthier may be more likely to differentially take up induction stoves and improve their health than poorer areas), healthcare quality (which can be considered both a measure of wealth and urbanization while also more directly measuring quality of healthcare which can determine hospitalization use patterns), and political support (which, through various programs and investment targeting, could drive PEC enrollment and healthcare utilization). As described in *Additional data sources*, we define the following variables to cover these domains: the fraction of individuals that benefit from the Bono Desarollo Humano (a needs-based cash transfer program), the fraction of households considered to be in poverty and extreme poverty based on incomes, median household income, the number of healthcare facilities, the number of doctors, the number of nurses, and voting histories. Our preferred adjusted model includes a set of potential confounders that are only weakly correlated with one another (see Figure S3): % BDH, % extreme poverty, healthcare facilities per capita, doctors and nurses per capita, and canton-level voting histories for the party that initially developed and promoted PEC (President Rafael Correa and associated subsequent candidates). Effect sizes did not meaningfully change across all 130,000 potential confounding variable combinations (Figure S15).

Third, we formally bounded the potential influence of unobserved variables. Drawing on the work of Cinelli and Hazlett (2020)[44] and Oster (2019),[45] this approach poses the following question: how strongly related would an unobserved confounder have to be – both to our treatment (PEC enrollment) and our outcome (hospitalization rates) – to account for the effect we observe? Results are relative to the jointly predictive power of all already-included covariates. We use the R pacakge 'sensemakr' to implement this test.

Difference-in-differences approach. While our approach illustrated in Equation is typical of studies examining time-varying exposures and outcomes in environmental epidemiology and econometrics literature, we can additionally leverage the implementation of the PEC program as an event fixed in time and apply a difference-in-differences (DiD) approach. Here, we effectively dichotomize the treatment and change the sample (taking only the high enrollment and low enrollment cantons). Doing so enables us to have an arguably 'cleaner' inference relative to the approach using the full sample of cantons and continuous treatment. In the DiD case, the treatment and control groups are better defined and more intuitive: the control group consists of cantons whose PEC enrollment changed little over time (<15th percentile average enrollment from June 2019 to March 2020), while the treatment group consists of the highest-uptake cantons (>85th percentile). These groups are equally sized at 33 cantons and 3,234 and 3,211 canton-month observations in the treatment and control groups, respectively. Our dependent variable (log of all-cause hospitalization rate) satisfies parallel trends across the treatment and control group conditional on included covariates, indicating that the DiD design is valid. We split our sample at these quantiles rather than the median to create a more valid 'control' group that closer approximates being untreated.

The tradeoff in the DiD approach relative to our preferred two-way fixed-effects (TWFE) model above is one of external versus internal validity. The TWFE model retains all of the data as well as the continuous nature of our treatment – the percentage of households in a canton enrolled in the PEC program – and thus has greater external validity. However, recent advances in the literature have demonstrated that the TWFE estimator does not recover the average treatment effect (ATE) but rather a weighted average group-time effects (see e.g., refs[46,47]). Critically, some units may be weighted, including receiving negative weight, such that the recovered estimate is significantly different from the true causal effect.[47] To address this threat to inference, we implement the difference-in-difference estimator of Callaway and Sant'Anna (2021),[46] which eliminates negative weights and produces valid estimates of the average treatment effect on the treated (ATT). The DiD estimate thus has greater internal validity – provided the identifying assumptions of the design are met – and a slightly different but nonetheless substantively meaningful interpretation: the estimated coefficient represents the effect of moving from the average PEC enrollment in the "low-uptake" group (canton-level mean 1.7% enrollment from January 2015 to March 2020) to the "high-uptake" average (17.6% enrollment). Pre-period estimates and confidence intervals include zero and the averaged treatment effect is in line with estimates from our preferred approach. Taken together, these results are encouraging because they illustrate that, while high enrollment cantons do have some levels differences across our potential confounders, their trends are overall similar to low-enrollment cantons absent treatment.

Uncertainty and robustness of results to alternative approaches. To quantify uncertainty in our results, we bootstrapped equation 1,000 times, sampling cantons with replacement. Figure 4 illustrates the distribution of the obtained effect estimates for key outcomes from bootstrapped analyses. We observed consistently negative effect estimates for associations between increased PEC enrollment and all-cause hospitalizations, respiratory-related hospitalizations, and COPD in adjusted and unadjusted models. Estimates for associations with influenza and pneumonia and asthma had wider distributions. We observed no clear associations between PEC enrollment and hospitalizations for other cause-specific outcomes (Figure S12). Next, we bootstrap eight total models based on combinations of adjustment for our preferred set of potential confounding variables, population weights, and the full sample (January 2012 to March 2020) and a restricted sample post-PEC (January 2015 to March 2020) (Figure S13). Further, we show robustness of our results under a range of alternative approaches. We repeat our main approach (full sample, population-weighted) using all combinations of potential confounding variables (Figure S15). Our main approach is additionally robust to controlling for long-term time trends using a natural spline and month of year and year fixed effects, as well as alternative choices for potential confounding variables (Figure S14). We also model canton-month hospitalizations as counts in

Poisson regressions to account for overdispersed outcomes, both in a fixed effects approach and using a conditional Poisson regression. In the conditional Poisson regression we match on canton and month of year to control for seasonality and other non-time varying factors across cantons, and control for long-term trends using a natural spline for month-of-study with nine knots (one for each year) (Figure S14). Results are robust to aggregating data to two-month periods, which substantially decreases canton-months with low numbers of hospitalizations in cause-specific analyses (Figure S16) and, similarly, to aggregating data to the province level (Table S10).

Assessing global viability of carbon-neutral residential electrification

We develop a simple model to assess the viability of residential electrification programs that displace gas use from households in different regions of the world:

$$CO2e_{net} = \gamma * MEF - \delta * \mu \tag{5}$$

where the net CO2e emissions from a residential electrification project are equivalent to excess emissions from new electricity consumption (γ; kWh) multiplied by the marginal emissions factor (MEF; gCO2e/kWh) minus the change in gas consumption due to additional electricity use (δ) multiplied by the emissions factor for gas (either 62.0 kgCO2e/mmBTU LPG or 53.1 kgCO2e/mmBTU natural gas converted to 0.211 kgCO2e/kWh and 0.181 kgCO2e/kWh, respectively). We assess viability based on CO2e$_{net}$ being equal to or less than 0; in other words, the program would be carbon neutral in terms of combustion-related emissions.

Unfortunately, we cannot know ex ante the extent to which a given residential electrification program will displace gas with electricity. Thus, we rely on a set of theoretical energy conversions and assumptions about the energy efficiency of gas and induction cooking. When we use the same units of energy (like kWh), the conversion between gas and electricity is simply the ratio between electric induction cooking efficiency (between 85-90%) and gas cooking efficiency (between 35-50%).[22] Using these efficiency scenarios, a residential electrification program that replaces gas cookstoves with induction electric cooking can be expected to displace between 1.7 kWh and 2.6 kWh gas with 1 kWh electricity (see Supplemental Information). Thus, a program can be considered technically viable if the grid is less polluting than 0.385 kg CO2e/kWh (i.e., 1/2.6) or, somewhat less stringently 0.588 kg CO2e/kWh (i.e., 1/1.7).

To conduct this analysis, we compile a dataset of national and subnational MEFs, relying on the most recent government-provided estimates where possible (available in Table S11). Our compiled dataset covers 107 countries that represent 80% of the global population, though the lack of subnational data in large countries (e.g., Brazil, China, Russia) limits the accuracy of country-specific inferences.

We additionally illustrate subnational heterogeneity in MEFs using state-specific estimates for the US (ref[57]) and India (ref[58]) (shown in Table S12, S13). We present these state-specific results in terms of reduction in MEF needed to meet the theoretical energy equivalence trade-off between electricity and natural gas and LPG for the US and India, respectively. Furthermore, we include data on the prevalence of gas cookstoves in US and Indian states based on the Residential Energy Consumption Survey (ref.[59]) and the National Family Health Survey - 5 (ref.[60]), respectively, which represent the most recent nationally-representative surveys of cooking fuels in these countries.

Additional data sources

Socioeconomic conditions surveys We use public use survey data on socioeconomic conditions in nationally-representative samples of Ecuadorian households from the Survey on Employment, Unemployment, and Underemployment from 2012 to 2020. This survey has been administered to a rotating panel of households quarterly since 2012 and contains a set of basic parameters on individual employment status and household living conditions that we utilize. Specifically, we use average household per capita incomes, a binary designation of poverty or extreme poverty based on mean per capita household incomes, and whether individuals receive the "Bono Desarrollo Humano" (a needs-based cash transfer program). Surveys within a given calendar year were pooled together. We estimate average canton socio-economic conditions each year using provided survey weights. To generate monthly estimates, we assign yearly estimates to January of the given year and linearly interpolate.

Healthcare resources We develop measures of canton level healthcare resources based on a yearly census of the healthcare system that detail available personnel and resources for every healthcare facility in Ecuador. Our primary measures of interest are the number of nurses and physicians per capita per canton and the number of healthcare facilities per capita per canton.

These measures were then linearly interpolated to develop monthly measures where we assigned yearly values to January of that year.

Voting results The longstanding nature of fuel subsidies in Ecuador, and the significant social unrest that accompanied multiple attempts in the past reduce these subsidies, have positioned cooking fuels as an inherently political topic in Ecuador.[42] While eventually consigned to internal PEC documentation in favor of more convenience-focused messaging, initial government efforts to promote the PEC program centered on the program's ability to reduce government expenditure on LPG subsidies and replace imported fuels with nationally-produced electricity. Anecdotally, electoral support for former President Rafael Correa has been correlated with PEC enrollment and induction stove use, though formal evidence of this is not available. We evaluate this hypothesis using public use elections data. We estimate the share of votes for Correa in the 2009 and 2013 elections, for his former Vice President Lenin Moreno in 2017 (the winner of the election), and for Andres Arauz in the first round of the 2021 election (whose voters mirror the bloc supporting Correa and Moreno in contrast to voters for the eventual winner of the 2021 election Guillermo Lasso). Values were then linearly interpolated after assigning values to January of that year.

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Competing interests

The authors have no competing interests to declare.

Data and materials availability

This study primarily relies on public use datasets. Only customer level billing records are not publicly available; requests can be made to the electric utilities directly. Code and data to replicate all other analyses will be made publicly available upon publication.

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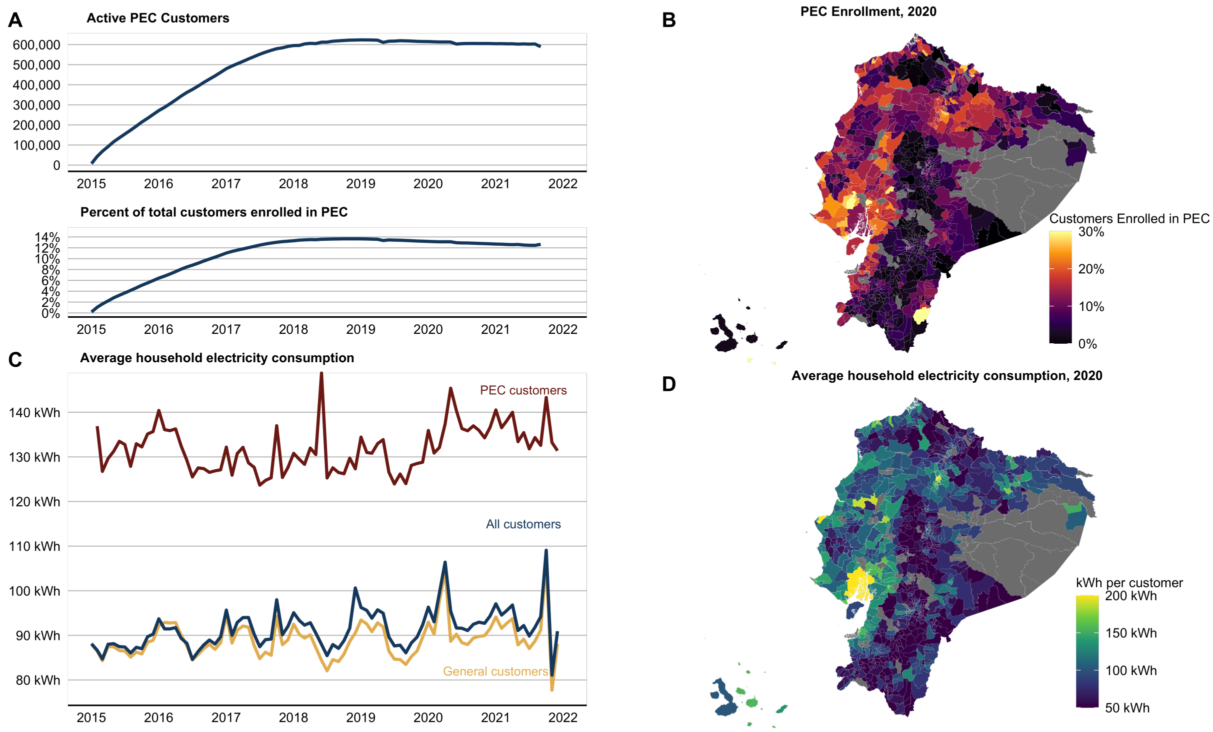


Figure 1: **Enrollment in Ecuador's induction promotion program (PEC) and average household electricity consumption among enrollees and non-enrollees**. **A**, Temporal variation of PEC enrollment across Ecuador in terms of total customers and the fraction of residential customers from January 2015 to September 2021. **B**, Spatial variation in the fraction of residential customers enrolled in PEC across parishes averaged between September 2019 and September 2020 (N=935). Grey parishes are missing data (N=106). **C**, Temporal variation of average household electricity consumption in kilowatt-hours (kWh) by PEC customers, general (non-PEC) customers, and all customers (combined PEC and general customers) from January 2015 to October 2021. **D**, Spatial variation in average kWh per all customers between September 2019 and September 2020 (N=935). Grey parishes are missing data (N=106).

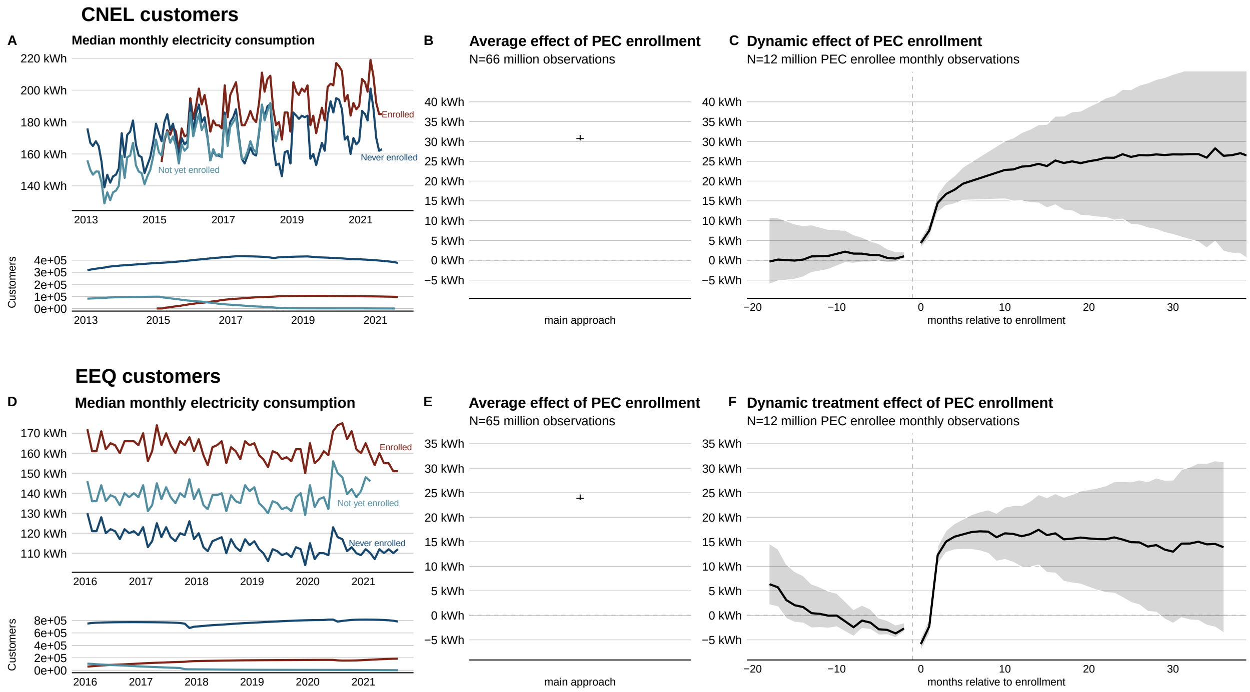


Figure 2: **PEC enrollment is associated with higher household electricity consumption across Ecuador's two largest electricity utilities.** **A,** Temporal variation in median monthly electricity consumption among never enrolled, not yet enrolled, and enrolled customers in the Corporacion Nacional de Electricidad (CNEL-Guayaquil) from January 2013 to July 2021. Electricity consumption only shown when the group is larger than 2,000 customers. Temporal variation in the monthly numbers of customers are shown below. Peak sizes for each group are never enrolled 434,554 customers, enrolled 104,817 customers, and not yet enrolled 97,751 customers. **B,** Main estimate and 95% CI (which are small and difficult to see) from a two-way fixed effects model where the reference group is not yet enrolled and never enrolled customers, with fixed effects for customer and month of study and standard errors clustered at the customer level. **C,** Monthly change in average household electricity consumption relative to the month of PEC enrollment among PEC enrollees where the reference group is not yet enrolled customers with fixed effects for customers and month of study period, with standard errors clustered at the customer level. The solid black line indicates month-specific estimates and the grey ribbon indicates the 95% confidence interval. **D**, **E**, and **F,** illustrate the same as **A**, **B**, and **C** but for customers in the Empresa Electrica de Quito from January 2016 to August 2021. Peak sizes for customers enrolled in each group for EEQ are never enrolled 815,224 customers, enrolled 185,925 customers, and not yet enrolled 105,640 customers.

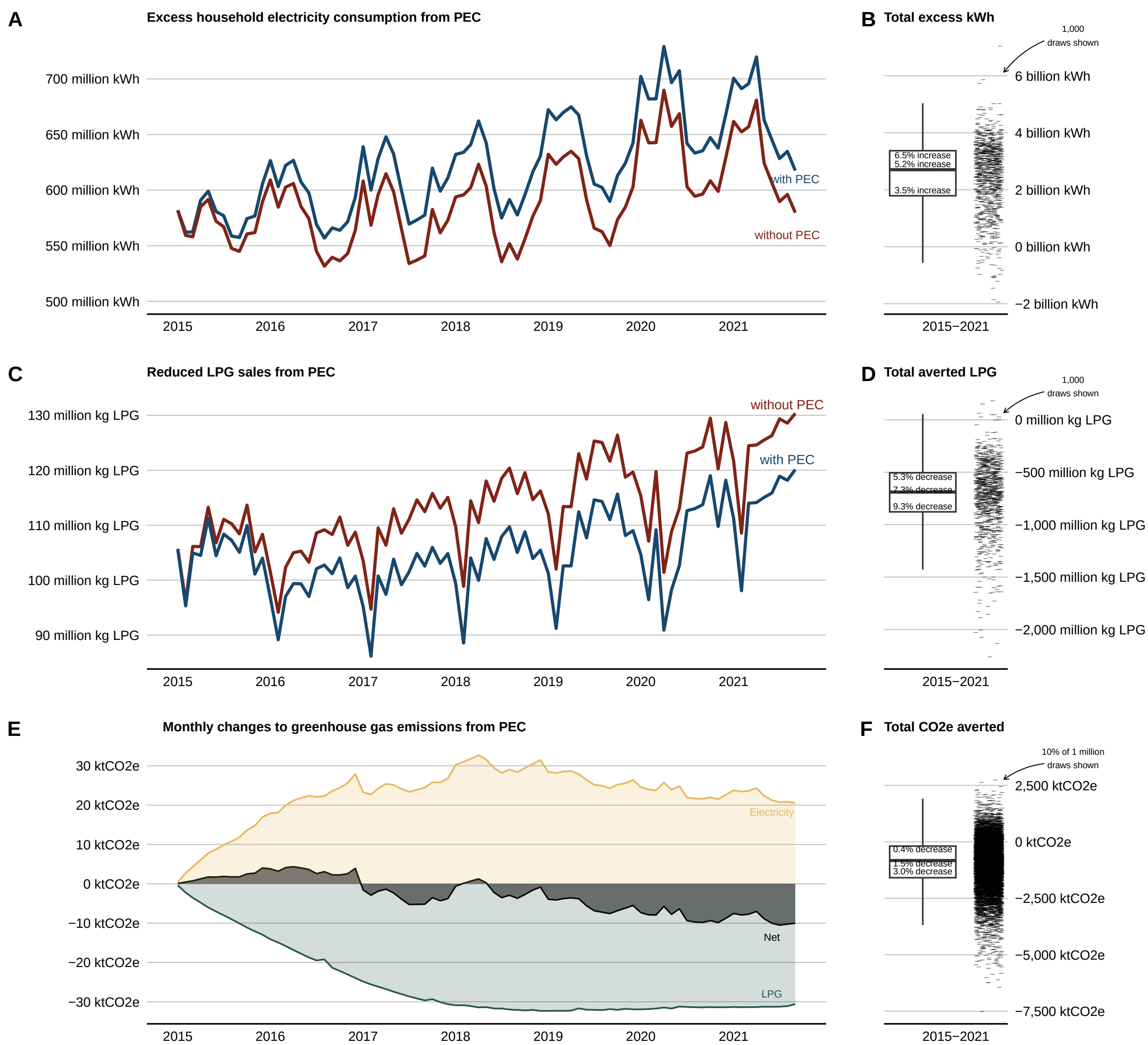


Figure 3: **Excess household electricity consumption, reduced LPG sales, and changes to greenhouse gas emissions attributable to increased induction stove enrollment and use**. **A,** Illustrates a counterfactual scenario of household electricity consumption in the absence of PEC enrollment derived from Equation . N=94,982 parish-month observations. **B,** Summarizes the total excess kWh consumed from PEC enrollment across 1,000 bootstrapped runs of the analysis using random sampling of parishes with replacement in a boxplot and with dashes for each total estimate. **C,** Illustrates a counterfactual scenario of LPG sales in the absence of the PEC program using an OLS regression with the outcome total monthly national LPG sales in kilograms and the independent variable is the model-based monthly excess kWh from PEC, with fixed effects for year and month-of-year. N=83 observations. **D,** Summarizes total reduced LPG sales from PEC-associated increased electricity consumption across 1,000 bootstrapped runs of the analysis using random sampling of months with replacement. **E,** Shows changes to national greenhouse gas emissions associated with excess electricity consumption and reduced LPG sales based on monthly emissions factors for the Ecuadorian grid and an average emissions factor for CO2e emitted from burning LPG from Equation . **F,** Combines the monthly estimates of excess kWh consumed and reduced LPG sales from the 1,000 bootstrapped runs shown in **B** and **D**, respectively, to produce 1,000,000 estimates of the total changes to greenhouse gas emissions.

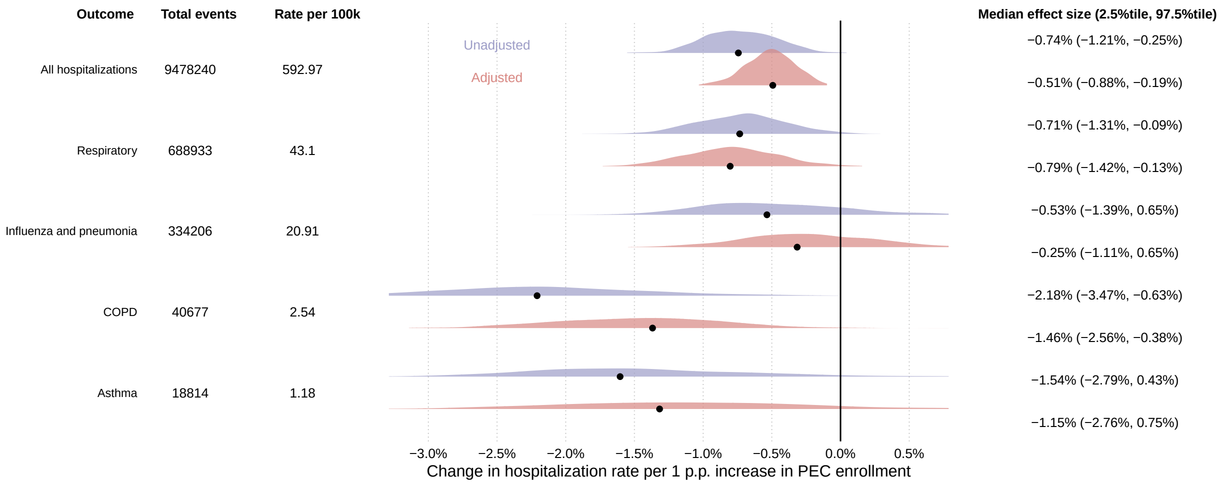
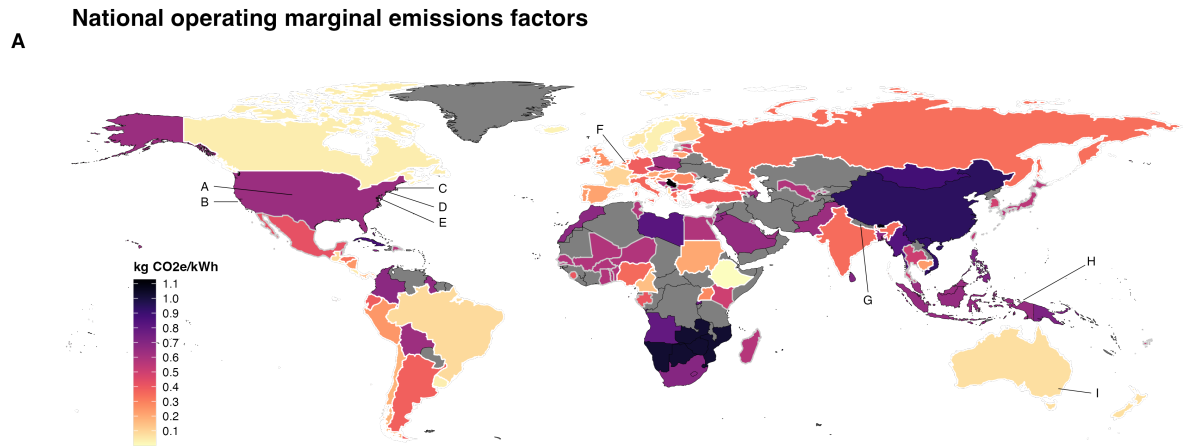


Figure 4: **Change in monthly respiratory related hospitalizations associated with increased canton level PEC enrollment.** The response in all-cause, respiratory-related hospitalizations, and cause-specific hospitalization rates are estimated from canton-level linear models and the fraction of electricity customers that are enrolled in PEC in the same month, with fixed effects for canton and month and standard errors clustered at the canton level (Methods). Adjusted models control for time-varying canton-level median income per capita, the fraction of individuals that receive money from a a poverty alleviation program, per capita nurses and doctors, per capita healthcare facilities, and voting patterns. Coefficient estimates represent the percent change relative to the national monthly base rate, with 95% confidence intervals shown. N=21,885 and N=19,800 canton-month observations in the unadjusted and adjusted main specification, respectively.



Select proposed and established building electrification plans

Label	Region	Aim	Label	Region	Aim
A	Denver, USA	Phase out gas appliances at end of life in commercial and multifamily homes 2023-2027.	F	The Netherlands	No gas heating in new construction after 2023; Phase out all fossil fuel heating by 2040.
B	State of California	Approved energy code to incentive all-electric residential home construction starting 2023. 50 cities and counties taken steps to restrict gas in new constructions.	G	Nepal	Plan for all households to have electric cookstove by 2030.
C	Boston, USA	Proposal to restrict natural gas use in new buildings starting 2027.	H	Indonesia	Plan to transition 58 million households from gas to induction cooking by 2050, with interim target of 28 million by 2035.
D	New York, USA	Ban on new fossil fuel hookups in commercial and residential buildings for heat, hot water, and cooking starting 2024-2027.	I	Canberra, Australia	No gas or oil heating in new buildings after 2025; Phase out all gas or oil heating by 2035.
E	Washington DC, USA	Plan to restrict natural gas use in new commercial and larger residential buildings starting 2027.			

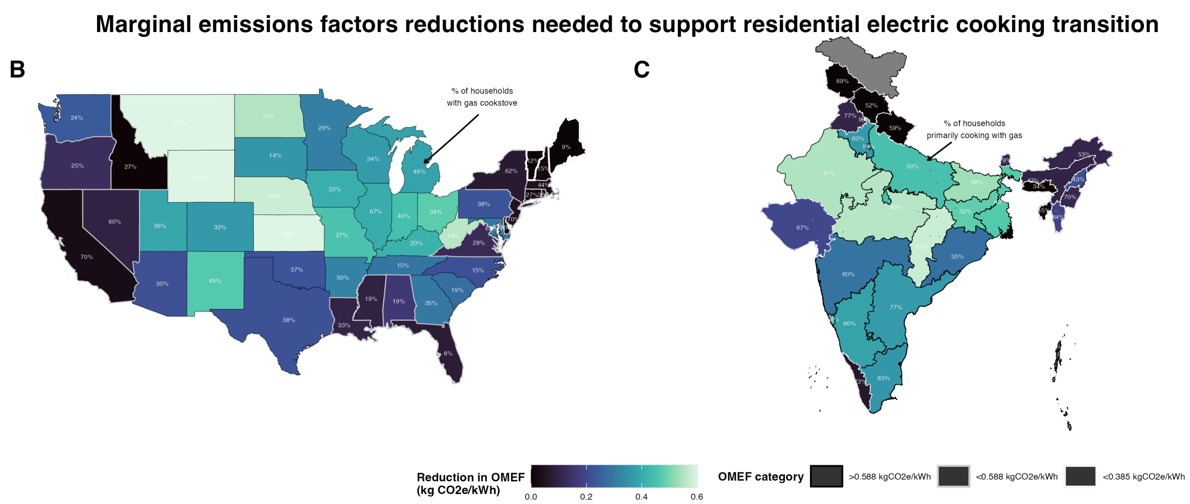


Figure 5: **Global viability of residential electrification programs based on emissions factors.** **A**, Maps national operating marginal emissions factors (OMEFs) in kg CO2e per kWh. Regions with bolded white outlines are those where the grid is clean enough to theoretically support a transition and be combustion-related emissions neutral in our more stringent scenario (i.e., <0.385 kg CO2e / kWh) and with grey outlines are less stringent scenario (i.e., 0.385 kg CO2e / kWh < OMEF < 0.588 kg CO2e / kWh). Labels describe a select number of proposed and established building electrification programs around the world shown. **B and C**, Map the reductions in marginal emissions factors in kg CO2e per kWh in US and Indian states needed to achieve combustion-related CO2e neutral transitions from natural gas (US) and LPG (India) to electricity (both). White bolded states have OMEFs <0.385 kg CO2e / kWh as of 2020. Also shown are the percentage of households that have gas cookstoves in US states and the percentage of households that primarily cook with LPG in Indian states. See Methods for more details.

Supplemental information

1 Data cleaning procedures for customer level billing records

With the objective of precisely estimating changes to monthly electricity consumption among residential customers after enrolling in PEC, we cleaned these data in a few steps: (1) dropping long runs of 0 kWh consumption that we infer to be before or after accounts were activated, (2) removing extremely high consuming customers that we infer to be small businesses (median consumption of greater than 3000 kWh per month), (3) handling duplicated customer identifiers associated with the same meter identifiers that we interpret to be different customers moving in or out of a residence, (4) averaging rare instances of multiple consumption records for the same customer in November 2017, (5) handling extreme consumption readings by top coding consumption at 5000 kWh, removing consumption records below 0 kWh, and removing values if they were greater than three standard deviations above or below the six month running average and if they were an absolute change of greater than 40% consumption and 200 kWh from the running average, and (6) recoding customers whose date of PEC enrollment was earlier than January 1, 2015 as non-PEC due to apparent data entry error.

Our preferred specification included fixed effects (FE) for customer, month of study, and the dataset (in the CNEL model) and limited analyses to the above-defined subsample.

We additionally conducted regressions where we: (1) used month FE and year FE instead of month of study FE, (2) removed data after March 2020, which could be affected by the pandemic, (3) dropped the dataset FE in the CNEL sample, (4) dropped the dataset FE and data after March 2020, (5) included a linear time trend in addition to month and year FE, and (6) included a linear time trend and a squared time trend in addition to month and year FE, dropped customers with median consumption above 2500 kWh, and included the dataset FE.

We also conducted these data on two additional subsamples: (1) where dropped customers with median consumption above 2500 kWh and (2) where we where dropped customers with median consumption above 2500 kWh and included only customers with a complete time series across the full study period.

We additionally conducted all regressions with kWh top coded at 1500 kWh instead of 5000 kWh, instead of top coding at 1500 kWh or 5000 kWh dropping this observations, and raw kWh.

Effect estimates did not substantively change in any specification or subsample (Table S7).

2 Additional details on observed effects of PEC enrollment on customer level electricity consumption over time

We explore two potential mechanisms that explain increased effects of PEC enrollment over time since enrollment. Increases in use over time could indicate evidence of adaptive behaviors after enrollment, whereby households increase their use of induction stoves over time as they gain greater familiarity with the stove or program subsidy benefits. It is also plausible that the observed trends observed are due to some number of customers not using their induction stoves after enrollment whatsoever, with that proportion of customers declining over time. We explore this hypothesis by using utility-provided PEC subsidy data for EEQ customers after they enrolled in PEC. While more than half of customers are estimated to use the full 80 kWh subsidy each starting the first month after enrollment, a declining proportion of customers had 0 kWh subsidized each month after PEC enrollment, falling from 35% of all PEC beneficiaries in the first month after enrollment to 20% one year after enrollment, though there appears to be some rebound in the 0 kWh group after two years of enrollment hovering around 30% of PEC enrollees between years two and five (Figure S5).

3 Energy-equivalence approach to converting LPG consumption to induction-related electricity consumption for cooking

We separately calculate an equivalent amount of energy transferred to cook the meals using LPG and electricity.

In Ecuador, LPG is a mixture of Propane (C3H8) (30%) and Butane (C4H10) (70%). The chemical reactions of these two gases with oxygen are exothermic and the amount of energy is calculated according to the equations where both gases are considered as ideal gases, the temperature is 25 degrees C, and pressure is 1 atmosphere.

Propane:

$$\text{C3H8} + \text{5O2} \rightarrow 3\ \text{CO2} + \text{4H2O}$$

In this reaction, 1 mol of propane produces 2220 kJ per mol

Dividing this value by its molar mass 44 g/mol, we have: 50.45 kJ/g

Propane is 30% of LPG, so: 50.45 kJ/g * 0.3 = 15.135 kJ/g

Butane:

$$\mathrm{C4H10+6.5\ O2 \rightarrow 4\ CO2+5\ H2O}$$

In this reaction, 1 mol of butane produces 2877 kJ/mol

Dividing this value by its molar mass 58 g/mol, we have: 49.6 kJ/g

Butane is 70% of LPG, so: 49.6 kJ/g * 0.70 = 34.72 kJ/g

The total heat capacity (also known as energy density) of LPG is thus 15.135 kJ/g + 34.72 kJ/g = 49.85 kJ/g (or 49.85 MJ/kg).

However, it is worth noting that LPG stoves have an average efficiency of between 30% and 50%, with the remainder of the energy dissipated to the surroundings. For example, if an average household of four members consumes 1.2 15-kg LPG tanks (as stated by the Government of Ecuador), this household consumes the following total energy per month in LPG:

15 kg LPG * 1.2 = 18 kg LPG consumed

18 kg LPG * 49.85 MJ/kg LPG = 897.3 MJ per month

Actual energy transferred to cooking = 897.3 MJ per month * 35% efficiency = 314.1 MJ per month

We can estimate the equivalent amount of kWh to this amount of energy transferred to meals for cooking from LPG. First, it is known that 1 MJ = 0.2778 kWh. Second, induction stoves have energy efficiencies of around 90%. Thus:

$$49.85 \text{ MJ/kg} * 35\% * 0.2778 \text{ kWh / MJ} = \gamma * 90\%$$

$$4.85 \text{ kWh / kg} = \gamma \text{ kWh} * 90\%$$

$$4.85 \text{ kWh / kg / } 90\% = \gamma$$

$$5.39 \text{ kWh / kg} = \gamma$$

Therefore, 1 kg LPG for cooking = 5.39 kWh induction electricity for cooking

Estimating the energy-equivalence between gas and induction in the same units (namely, kWh) reduces to a ratio between the energy efficiency associated with cooking. Thus, when induction cooking has 90% efficiency and gas cooking has 35% efficiency, 1 kWh induction electricity is equivalent to 2.57 kWh LPG.

If LPG cooking had an efficiency of 50% these conversion factors would be:

- 1 kg LPG = 7.69 kWh

- 1 kWh induction electricity = 1.8 kWh LPG

Like LPG, the precise composition of natural gas varies from region to region and as such so does the energy density. Estimates of the energy density of natural gas vary between 40 MJ/kg and 55 MJ/kg. Conversion factors are therefore as follows, assuming 90% induction efficiency:

- 1 kg natural gas = 5.94 kWh induction electricity (35% efficiency, 55MJ/kg)
- 1 kg natural gas = 8.49 kWh induction electricity (50% efficiency, 55MJ/kg)
- 1 kWh induction electricity = 2.57 kWh natural gas (35% efficiency)
- 1 kWh induction electricity = 1.8 kWh natural gas (50% efficiency)

4 Calculating CO2e emissions associated with LPG combustion for cooking

We use the US EPA's greenhouse gas emissions factors for LPG combustion, which specifies a range of relevant parameters:

- 0.092 mmBtu per gallon
- 61.71 kg CO2 per mmBtu
- 3.0 g CH4 per mmBtu
- 0.60 g N20 per mmBtu
- 5.68 kg CO2 per gallon
- 0.28 g CH4 per gallon
- 0.06 g N20 per gallon

Additionally, from the Intergovernmental Panel on Climate Change, Fourth Assessment, the 100-year global warming potentials for CH4 and N20 are 25 and 298, respectively. Together, these factors enable the calculation of combustion-related CO2e from LPG used for cooking. For our analysis we are interested in estimating (1) the CO2e emitted per kg LPG burned and (2) the CO2e emitted per kWh-equivalent LPG burned.

Therefore:

CO2e per mmBtu LPG = 61.71 kg CO2 +
(25 GWP * 0.003 kg CH4) +
(298 GWP * 0.0006 kg N20)
61.9638 kg CO2e per mmBtu LPG

Next, we estimate that 22.91 kg LPG is equal to 1 mmBtu.

Therefore:

61.9638 kg CO2e per mmBtu LPG * (1 mmBtu / 22.91 kg)
2.992 kg CO2e per kg LPG

Additionally, it is known that 1 mmBtu is equivalent to 293.3 kWh.

Therefore:

61.9638 kg CO2e per mmBtu LPG * (1 mmBtu / 293.3 kWh)
0.211 kg CO2e per kWh LPG

These calculations do not account for upstream GHG emissions involved in the production and transport of LPG. However, estimates suggest that these upstream emissions are associated would only account for 10% of lifecycle emissions associated with LPG combustion. Furthermore, LPG is a byproduct of petroleum production and in the absence of LPG being used for cooking in Ecuador, it is likely that the upstream emissions associated with using LPG for cooking in Ecuador would occur in any case. Therefore, we conclude that omitting upstream GHG emissions associated with LPG is both unlikely to impact the overall findings we present here (which can thus be considered a lower-bound estimate for the climate benefits from gas to induction cooking transitions) and an appropriate representation of the impacts of marginal changes to gas consumption for cooking.

5 Additional information on inferences related to the association between PEC enrollment and hospitalizations

Because PEC was not a randomized experiment, a concern we might have in our analysis of the associations between PEC enrollment and hospitalizations is that cantons that adopted PEC at higher rates were also changing in other ways that affected health outcomes over time, and thus that we would attribute the resulting health benefits to PEC rather than these other unobserved changes (note that any time-invariant average differences between high-adopting and low-adopting parishes are not a concern in our analysis, as these differences are always absorbed by unit fixed effects). Given our unit of analysis (canton-month) and use of canton and month of study fixed effects, such confounds would need to vary differentially over time across cantons. For instance, we might be concerned that cantons with higher PEC enrollment were becoming differentially wealthier or more urbanized than cantons with lower PEC enrollment – which could yield both better access to health-improving resources and factors that might contribute higher PEC uptake – and these changes in wealth or connectivity had independent effects on health outcomes.

To help address concerns about time-trending unobservables, we take three approaches. The first is to test for parallel trends in health outcomes using pre-program data, using a difference-in-difference setup that makes such tests straightforward. In this standard test, if outcomes were trending differentially prior to the initiation of PEC between cantons that were rapid adopters of PEC versus slower adopters, then this would raise clear concerns that some other variable could be driving the association between program adoption and health outcomes; the absence of trend differences prior to treatment reduces these concerns. To implement this test, we divide cantons into a high-enrollment and low enrollment groups (based on enrollment rates between June 2019 and March 2020), and test whether both hospitalization outcomes and covariates were trending differentially in the years 2012-2014, prior to program initiation in 2015. Results from this test are shown in Figure S8, with coefficients and p-values reported in each figure panel. Cantons with higher eventual enrollment if anything have all-cause and respiratory hospitalization rates that are trending relatively higher than low-enrollment cantons prior to program initialization, although differences in trends between the two groups are not statistically significant after conditioning on covariates (Cramer von Mises Test Statistic = 0.798; Critical Value = 3.827; P-Value $\approx$ 1). We similarly see non-significant differences in trends in key covariates prior to PEC initiation.

Our second approach is to identify and directly control for a set of canton-level time-varying factors that might plausibly covary with enrollment and health, including wealth, urbanization, and political targeting (i.e., the idea that due to political motivations certain areas may receive attention that would affect both PEC enrollment and healthcare resources). Specifically, we identified the following canton-level variables: the fraction of individuals that benefit from the Bono Desarollo Humano (a needs-based poverty alleviation program), the fraction of households considered to be in poverty and extreme poverty based on incomes, the median household income, the number of healthcare facilities, the number of doctors, the number of nurses, and voting histories. In our main approach, we include canton-month values for a select number of these covariates as well as canton and month of study fixed effects. We find that our estimated effect of PEC enrollment on hospitalization is not affected by the inclusion of these control variables (Table S9). Any additional confounding would have to be uncorrelated with these variables, correlated with PEC enrollment over time, affect health outcomes; we are unable to identify any such plausible mechanism.

Third, we implement a formal approach to test the potential influence of unobserved variables. This approach aims to bound the relative strength of the potential influence of unobserved confounders such that, given our observed effects, the true effect of PEC on hospitalization rates is zero. The approach we use relies on comparing both effect sizes and the variance explained in unadjusted and adjusted models, and seeks to answer an intuitive selection question: how strongly related would an unobserved confounder have to be related to both our treatment (PEC enrollment) and our outcome (hospitalization rates) to account for the effect we observe? If the estimated effect of PEC enrollment on hospitalization rates remains negative and statistically significant even in the presence of a set of confounders strongly related to both measures – that is, highly predictive in an R^2 sense – we can be relatively confident that our estimated effect is indeed causal. To formally test for omitted variable bias, we draw on the work by Cinelli and Hazlett (2020)[44] as implemented in the R package 'sensemakr.' This approach is similar to that advocated in Oster (2019) (ref.[45]) but yields more substantively interpretable quantities of interest.

Results are presented in Figure S9. First, we consider three different scenarios: what if the confounder explained the outcome half as well as the *jointly predictive power* of all time-varying covariates (the solid line), equally as well (long dashed line), or twice as well (short dashed line). For each, we consider how predictive the confounder would have to be about the treatment (in R^2 terms, shown on the x-axis) to produce different estimated treatment effects (y-axis). The red dashed line is the 0 effect, i.e., the point at which the estimated effect is no longer negative. The red bars on the bottom of that plot represent partial R^2 values of the treatment $\sim$ confounder relationship that represent one-half, equal and twice the selection we actually observe in the data. The plot demonstrates that even with a treatment $\sim$ confounder relationship equally as strong as the one we observe (the red bar farthest to the right among the three) and an outcome $\sim$ confounder similarly as strong (the short dotted line labeled 5% in the legend), we would still observe a negative treatment effect. The second figure is an isocurve demonstrating the same relationship but visualizes scenarios where you have unequal selection – that is, where the treatment $\sim$ confounder relationship is stronger than the outcome $\sim$ confounder relationship, or vice versa. The red curve indicates the amount of variance that the confounder would have to explain in both the treatment $\sim$ confounder relationship (x-axis) and outcome $\sim$ confounder relationship (y-axis) to push the estimated coefficient to zero. The diamond points represent the position of the confounder if it explained one-half, equal, and twice as much variance in both the treatment and the outcome as we observe in practice.

The relatively narrow range of partial R^2 values is driven by the fact that the canton and month fixed-effects explain nearly 80% of the total variance in hospitalization rates. Thus, a scenario in which the confounder explains, for example, 10% of the residual variance in hospitalization rates implies a model in which over 95% of the total variance is explained – 80% from the fixed effects, roughly 5% from included covariates, and 10% from the confounder. Put another way, for the confounder to push the estimated effected to zero, accounting for fixed effects, it would have to explain half of the remaining variance. In light of the included covariates – particularly population, which is strongly related to both PEC enrollment and hospitalization rates – we view that possibility as unlikely. We note that fixed-effects are not included in the basket of benchmark covariates because they fully account for all potential canton- and month-level unobservables and are not time-varying; as a result, even strong selection based on month or canton is not a threat to inference.

We additionally extend our analysis of PEC's association with hospitalization rates in a difference-in-differences analysis (as outlined above). Here, we effectively dichotomize the treatment and change the sample (taking only the high enrollment and low enrollment cantons). Doing so enables us to have a 'cleaner' inference over the full sample, continuous treatment approach. In the DiD case, the treatment and control groups are better defined and more intuitive: the control group consists of cantons whose PEC enrollment changed little over time, while the treatment group consists of the highest-uptake cantons. Moreover, because the treatment indicator was constructed using quantiles, these groups are equally sized at 33 cantons and 3,234 and 3,211 canton-month observations in the treatment and control groups, respectively.

The tradeoff here relative to our preferred two-way fixed-effects (TWFE) model above is one of external versus internal validity. The TWFE model retains all of the data as well as the continuous nature of our treatment – the percentage of households in a canton enrolled in the PEC program – and thus has greater external validity. However, recent advances in the literature have demonstrated that the TWFE estimator does not recover the average treatment effect (ATE) but rather a weighted average group-time effects (see e.g., refs[46,47]). Critically, some units may weights such that the recovered estimate is significantly different from the true causal effect. The biggest concern here is what are termed "negative weights".[47] In our approach, the average effect of PEC enrollment on hospitalization rates are the weighted average of both population size (which we directly weight) and the implicit weight of the size of treatment effects for each canton and how much variation there is in both the exposure and the outcome in that canton. In an extreme example, some units can receive negative weights, such that it is in principal possible for units to make a positive contribution to the estimated coefficient even if the true effect is negative. The observed regression output is then average of these heterogeneous effects according to the implicit weights.

To address this threat to inference, we implement the difference-in-difference estimator of Callaway and Sant'Anna (2021),[46] which eliminates negative weights and produces valid estimates of the average treatment effect on the treated (ATT). The DiD estimate thus has greater internal validity, and a slightly different but nonetheless substantively meaningful interpretation: the estimated coefficient represents the effect of moving from the average PEC enrollment in the "low-uptake" group (canton-level mean 1.7% enrollment from January 2015 to March 2020) to the "high-uptake" average (17.6% enrollment). This comes at the cost of external validity, as the population being used for estimation is a (potentially unrepresentative) subset of all cantons. However, as the omitted confounders analysis above suggests, PEC enrollment is in general weakly related (if at all) to other covariates, and as such there is little to suggest the DiD estimate would be a poor estimate for the larger sample.

Our DiD analysis finds that in the post-PEC period, hospitalization rates fell by an average of 11.4% (95% CI, 2.2% to 20.5%) in the high enrollment group as compared to the low enrollment group. The event study plot illustrates (1) that there are no pre-PEC trends in hospitalizations and (2) that hospitalization rates decline over the first year since PEC's inception and largely stabilize thereafter (Figure S10). We can divide 11.4% by the average enrollment difference in high vs. low enrollment cantons (18.0% minus 3.9%) to obtain an estimate of a decline in hospitalization rates of 0.81% per 1 percentage point increase in PEC enrollment. Although an imperfect comparison, this estimate is remarkably similar to our primary specification which yielded an estimate of 0.74% decline in hospitalization rates per 1 percentage point increase in PEC enrollment. Allowing for heterogeneous timing of treatment – that is, rather than treatment starting for all high enrollment cantons January 2015, allowing treatment to "turn on" when cantons reach a threshold level of enrollment – increases our estimated effect sizes somewhat (-14.8%, 95% -20.7% to -8.9%) (Figure S10).

6 Benchmarking and interpreting observed health benefits.

It is difficult to compare our observed effect estimates with other studies because only limited work has examined the health impacts of gas cooking (and none have studied the health gains from widespread replacement of gas with electricity to our knowledge). One meta-analysis of

19 studies concluded that children living in households with gas stoves had a 32% higher risk of having asthma as compared to those living in households with electric stoves.[53] Additionally, while there is substantial epidemiological literature linking NO_2 exposures to negative health outcomes, estimates of the air quality gains from eliminating or substantially reducing household gas cookstove use are not available in the broader literature, so it is not possible to compare our results with the anticipated benefits from gas to electric transitions. However, in a forthcoming pilot study we found a reduction of 9.5 parts per billion (95% CI, 5.4 to 13.5) (roughly a 17.8 μgm^{-3} decline) in two-day average NO_2 exposures when households switched from gas to induction for cooking, which we can use to benchmark anticipated risk reductions from the existing literature. Other studies have documented differences in personal NO_2 exposures participants in households that rely on gas vs electric stoves (e.g., refs,[23,24,26,61,62] though relatively few have done so in the last 15 years (see ref[63]). Estimates for the impacts of increases in NO_2 exposures on hospitalizations and other outcomes vary across recent meta-analyses: 0.57% and 0.65% increases in respiratory and cardiovascular hospitalizations per 10 μgm^{-3} increase in short-term average NO_2 from 68 and 52 studies, respectively,[64] a 1.6% increase in mortality per 10 μgm^{-3} increase in short-term average NO_2 from 123 studies,[64] and a 1.3% increase in COPD-related hospitalizations from 10 μgm^{-3} increase in short-term average NO_2 exposure from 14 studies.[65] Our estimate of the marginal effect of an additional percentage point increase in PEC enrollment on hospitalizations are thus substantially larger than what we might expect given previous estimates. We urge caution in directly interpreting our effect estimates as they have wide confidence intervals and we cannot rule out smaller effects. Our inferences are further restricted to the range of data in this study: 0% PEC enrollment (and very little baseline electric cookstove use) to roughly 35% of households in a canton being enrolled in PEC.

7 Supplemental figures and tables

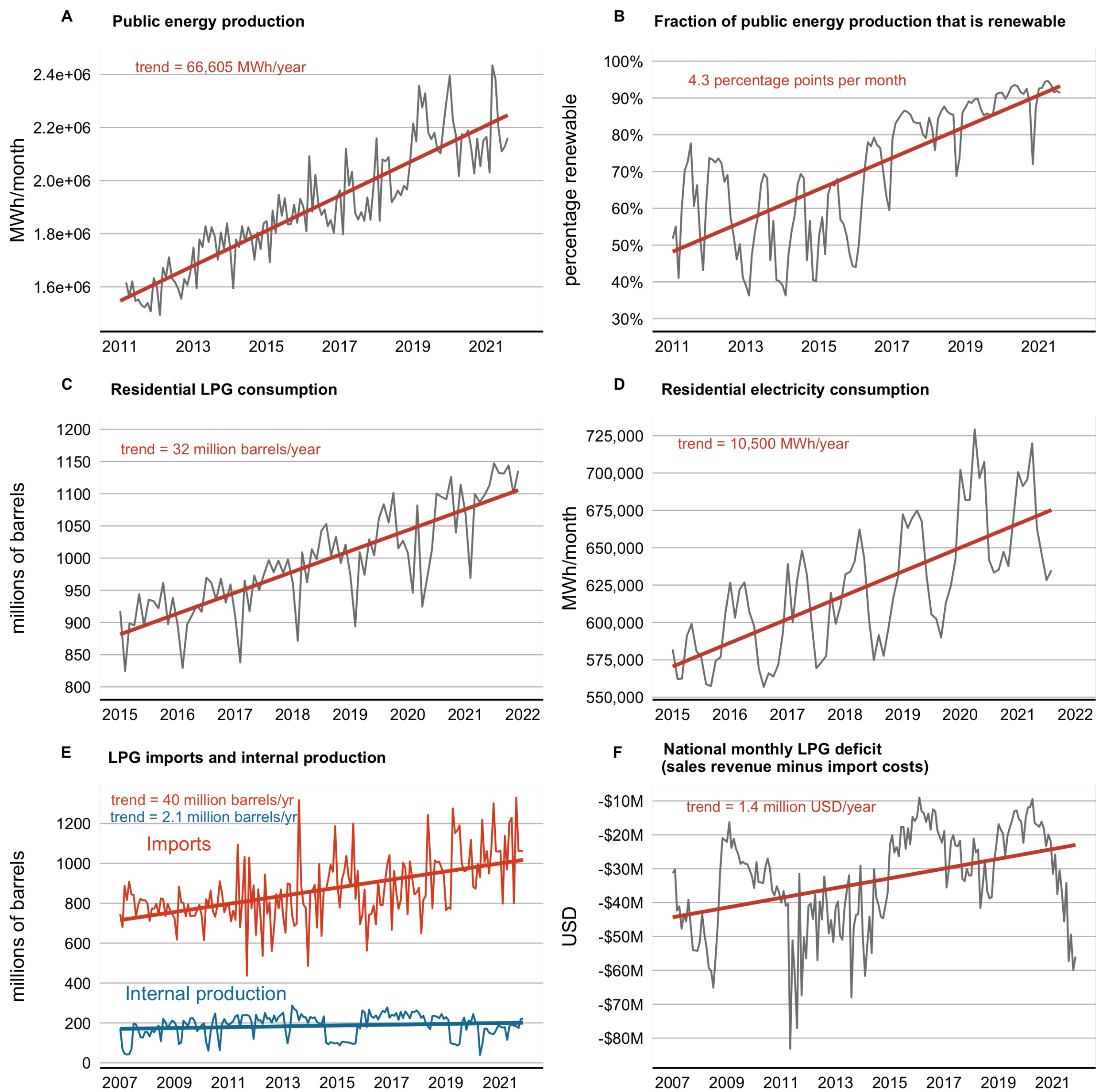


Figure S1: **Trends in cooking fuel consumption and costs, and electricity generation**. **A** Overall public electricity production is increasing in Ecuador. **B** An increasing proportion of electricity produced in Ecuador is from renewable sources due to investments in hydroelectric capacity, especially since 2018. **C** and **D**, Residential LPG and electricity consumption have both been increasing in recent years. **E** An increasing proportion of Ecuador's LPG stock is imported, which has led to **F** a persistent and highly variable national deficit (where import costs exceed sales revenue) due to international petroleum price fluctuations.

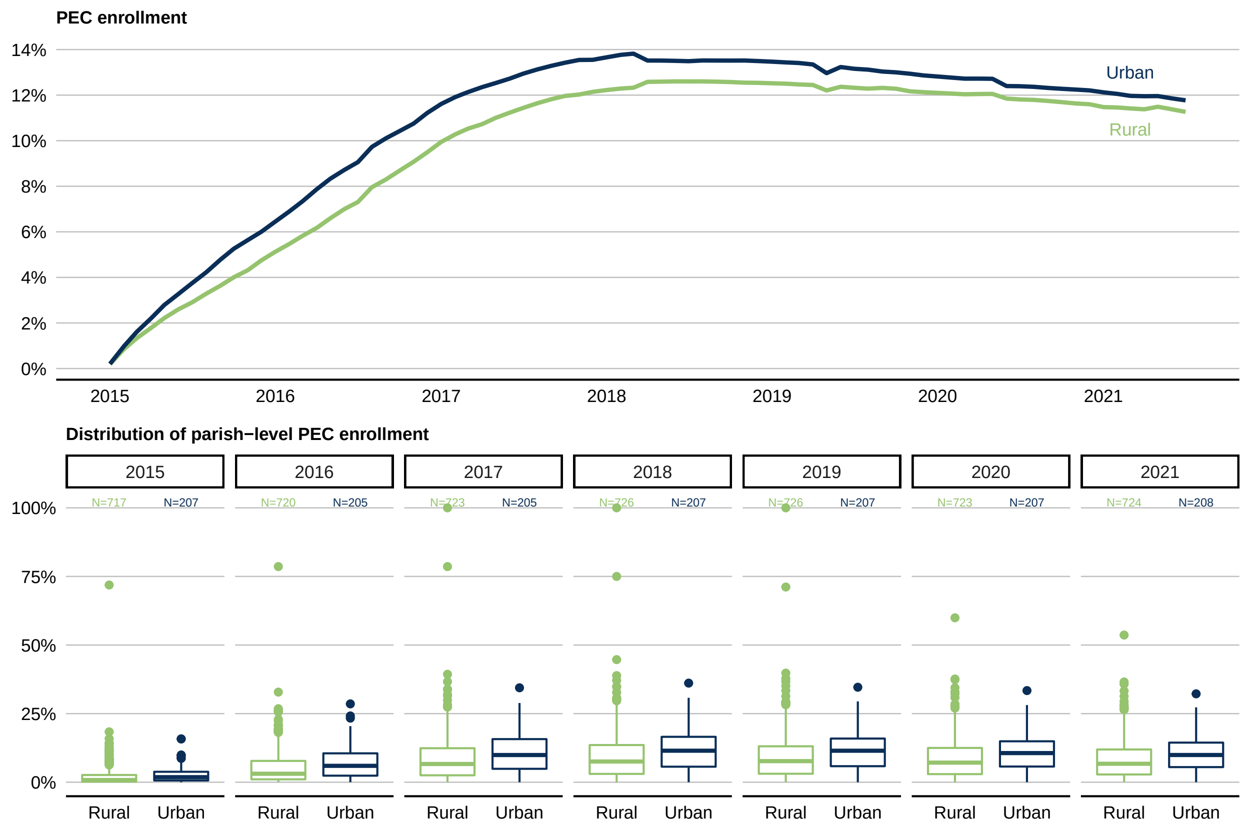


Figure S2: **Trends in PEC enrollment by urban and rural parishes.** **Top** panel shows the total fraction of customers that are enrolled in PEC in each month since January 2015 in urban and rural parishes. **Bottom** panel shows the distribution of parish-level yearly average enrollment in box-and-whisker plots where bottom, middle, and top lines of the boxes represent the 25th, 50th, and 75th percentiles, respectively. Whiskers extend to two times the interquartile range and remaining outliers are shown as points. Sample sizes indicate the number of parishes contributing data in that year.

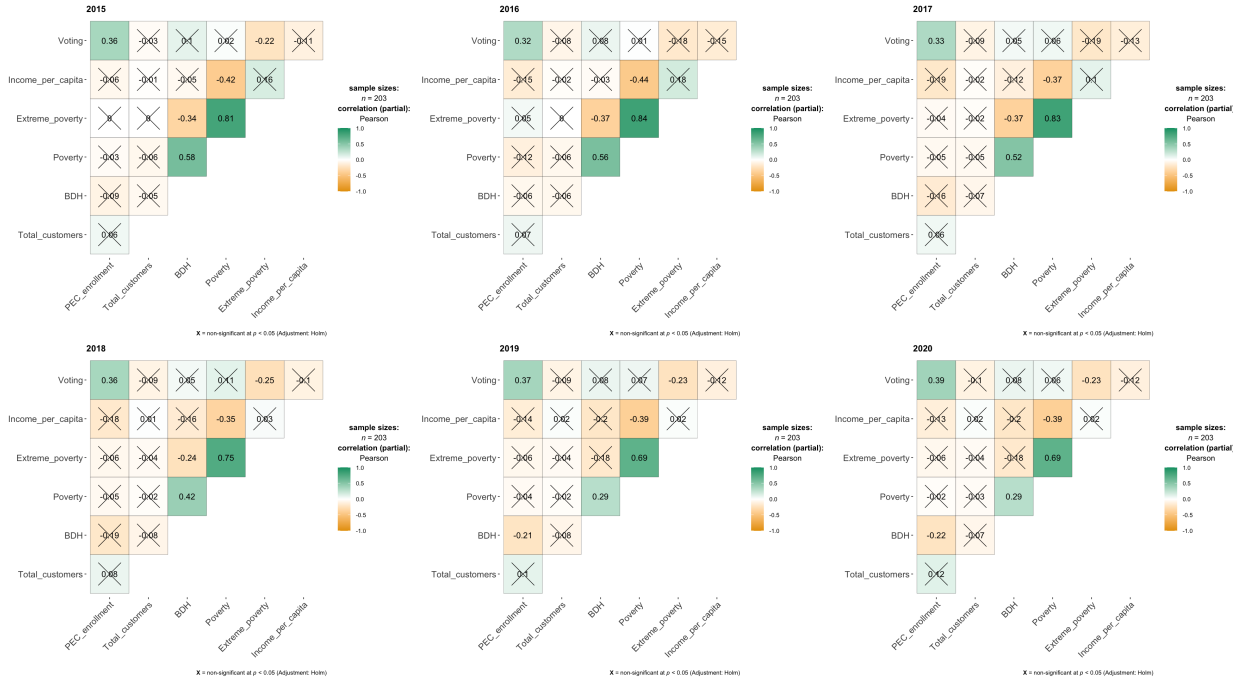


Figure S3: **Correlates of the parish-level PEC enrollment, by year.** Correlates are described in Additional data sources. BDH = Bono desarollo humano (needs-based poverty alleviation program).

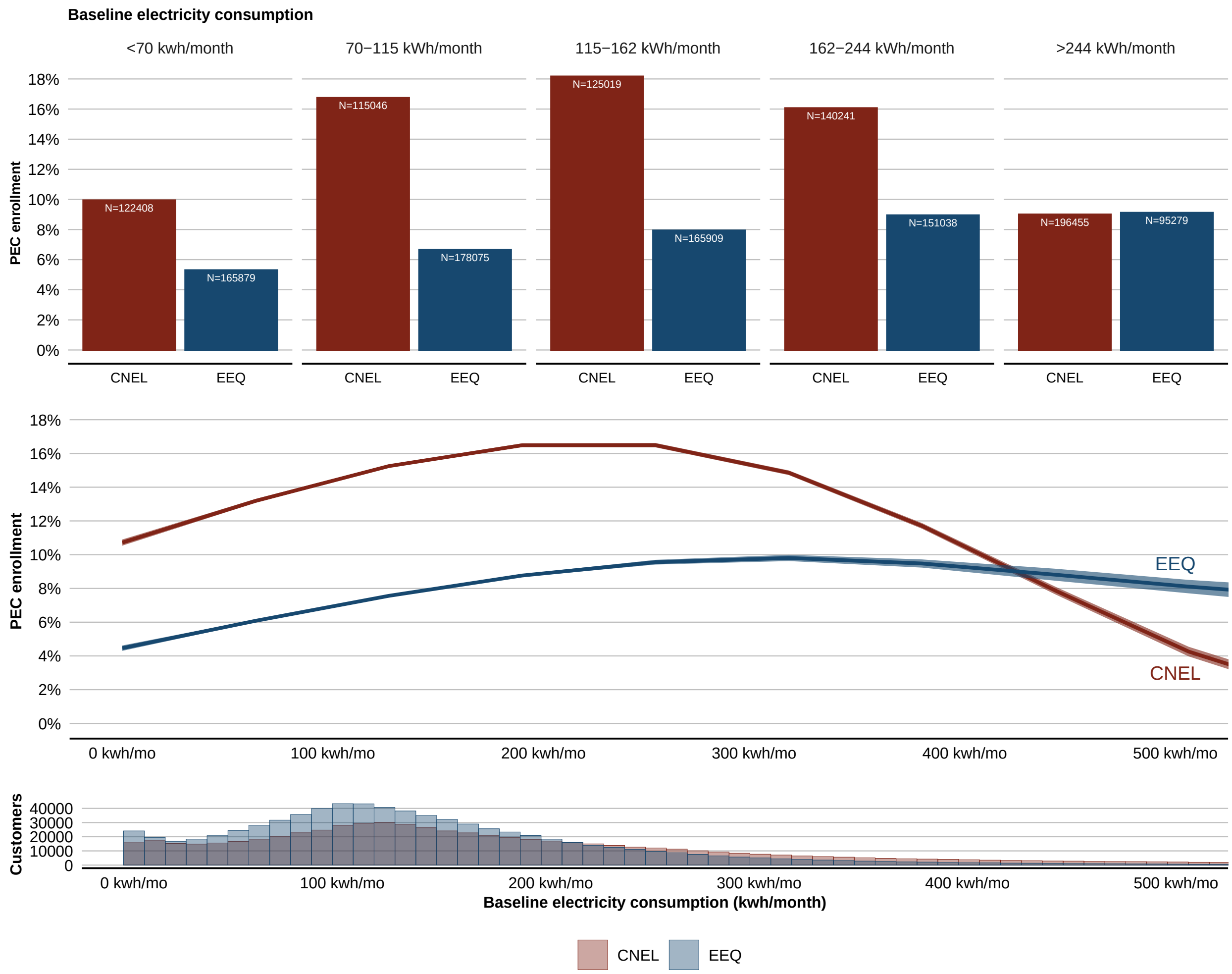


Figure S4: **Trends in PEC enrollment by baseline electricity consumption in customer level billing records from Ecuador's two largest utilities**. **Top** panel shows the fraction of customers that eventually enrolled in PEC based on their pre-enrollment baseline electricity consumption. Groups represent quintiles for all customers combined across the utilities. For CNEL customers the baseline period is 2013 to 2015. For EEQ customers the baseline period is 2016 and 2016 enrollees were dropped in this analysis. Sample sizes indicate the group size in each quintile. **Middle** panel runs a flexible smoothing function through customer-level observations where the x-axis is average baseline electricity consumption and the y-axis is whether the customer eventually enrolls in PEC using the geom_smooth function in R, which employs a generalized additive model with no restrictions on degrees of freedom. **Bottom** panel shows the distribution of customer level baseline electricity consumption.

	2015	2016	2017	2018	2019	2020	2021
Total parish-month observations	10249	12366	13063	13267	13280	13315	12763
Total electricity customers							
Mean (SD)	4708 (25101)	4115 (19661)	4014 (11501)	4065 (11162)	4151 (11213)	4217 (11376)	4222 (11616)
Median (IQR)	1559 (602, 3746)	1306 (505, 3480)	1323 (508, 3652)	1351 (525, 3808)	1385 (534, 3842)	1407 (554, 3876)	1440 (583, 3880)
Total PEC customers							
Mean (SD)	164 (988)	354 (1783)	496 (1804)	551 (1988)	558 (2015)	547 (2001)	528 (2002)
Median (IQR)	20 (4, 89)	52 (13, 222)	92 (26, 358)	106 (31, 407)	106 (32, 412)	104 (31, 401)	103 (31, 385)
All customers total electricity consumption (kWh/month)							
Mean (SD)	95 (57)	92 (50)	92 (54)	92 (48)	92 (51)	95 (57)	95 (47)
Median (IQR)	87 (62, 116)	85 (60, 114)	85 (60, 115)	85 (59, 115)	85 (60, 116)	88 (62, 118)	89 (63, 117)
General customer total electricity consumption (kWh/month)							
Mean (SD)	94 (57)	90 (50)	89 (54)	88 (48)	88 (50)	91 (60)	91 (46)
Median (IQR)	86 (61, 115)	82 (58, 111)	81 (57, 110)	80 (56, 109)	81 (57, 110)	84 (59, 112)	85 (60, 111)
PEC customer total electricity consumption (kWh/month)							
Mean (SD)	134 (82)	131 (60)	128 (53)	128 (47)	129 (50)	137 (52)	135 (50)
Median (IQR)	129 (98, 163)	127 (100, 157)	124 (97, 152)	125 (99, 152)	125 (99, 154)	132 (104, 163)	133 (105, 160)
PEC subsidy per customer (kWh/month)							
Mean (SD)	28 (16)	31 (13)	31 (11)	32 (11)	32 (10)	35 (11)	34 (10)
Median (IQR)	27 (18, 37)	30 (23, 38)	31 (25, 37)	31 (26, 37)	32 (26, 37)	35 (29, 41)	34 (29, 39)

Table S1: Descriptive statistics related to parish level PEC enrollment, by year. Data source: ARCONEL.

Dependent Variable:	Canton level electricity customers enrolled in PEC (percentage)											
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
Bono Desarollo Humano (%)	-0.0465	-0.0717*									-0.0676**	-0.0974***
	(0.0284)	(0.0370)									(0.0316)	(0.0364)
Poverty (%)			0.0089	0.0216							0.0144	0.0215
			(0.0092)	(0.0157)							(0.0161)	(0.0209)
Extreme poverty (%)					0.0050	0.0101					-0.0094	-0.0240
					(0.0137)	(0.0233)					(0.0206)	(0.0304)
Mean income per capita (USD)							-1.51×10^{-5}	3.39×10^{-6}			-2.15×10^{-5}	-3.09×10^{-6}
							(1.71×10^{-5})	(2.7×10^{-5})			(2.36×10^{-5})	(3.19×10^{-5})
Voting patterns									-0.1353	-0.6126***	-0.1484	-0.6298***
									(0.1218)	(0.2258)	(0.1205)	(0.2179)
Fixed-effects												
Canton	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of study	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Customer weights												
Canton	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Fit statistics												
Observations	13,544	13,544	13,544	13,544	13,544	13,544	13,544	13,544	12,853	12,853	12,788	12,788
R^2	0.90692	0.92594	0.90658	0.92580	0.90647	0.92554	0.90655	0.92552	0.90709	0.92867	0.90777	0.92985
Within R^2	0.00501	0.00572	0.00132	0.00384	0.00019	0.00035	0.00103	3.51×10^{-5}	0.00613	0.12090	0.01810	0.13820

Clustered (canton) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S2: Associations between canton-level socio-economic characteristics and canton-level PEC enrollment.

Dependent Variable:	mean kwh per customer							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
% PEC enrollment (per 10 p.p. increase)	6.420**	6.420**	4.714***	4.817***	7.150***	7.034***	6.749***	6.591***
	(2.584)	(2.583)	(1.685)	(1.626)	(2.199)	(2.248)	(2.286)	(2.221)
Fixed-effects								
Parish	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of study	Yes		Yes		Yes	Yes	Yes	Yes
Canton by month of study	Yes	Yes			Yes	Yes	Yes	Yes
Month of year		Yes		Yes				
Year		Yes		Yes				
Fit statistics								
Observations	94,972	94,972	94,972	94,972	94,197	87,932	83,374	82,228
R^2	0.52437	0.52437	0.43804	0.43652	0.86692	0.86406	0.89402	0.89326
Within R^2	0.00054	0.00054	0.00048	0.00052	0.00453	0.00438	0.00566	0.00539

Clustered (parish) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S3: Robustness of results from parish level analysis of PEC enrollment and average household electricity consumption to alternative fixed effects and study samples. Model (1) is our preferred specification with all data included and parish FE, month of study FE, and canton by month of study FE.
Alternative FEs. Model (2) replaces month of study FE with month FE and year FE. Model (3) drops canton by month of study FE. Model (4) drops canton by month of study FE and replaces month of study FE with month FE and year FE.
Alternative samples. Model (5) omits parishes that had total electricity consumption less than or equal to 0, and omits parishes that are identified as 'outliers' (see Supplemental information for more details). Model (6) further restricts the the sample to before July 2021. Model (7) further omits potentially pandemic-affected months (March 2020 to June 2020). Model (8) further omits May 2019 where some parishes had implausible parish total electricity consumption.

Dependent Variable:	Average household electricity consumption (kwh/month)			
Model:	(1)	(2)	(3)	(4)
Variables				
% PEC enrollment (per 10 p.p. increase)	6.420**	5.274***	4.701***	3.226***
	(2.584)	(0.9355)	(0.9481)	(0.9828)
Bono desarollo humano (0 to 1)				-11.89**
				(4.781)
Extreme poverty (0 to 1)				3.562
				(3.332)
Voting patterns (0 to 1)				10.05
				(24.39)
Fixed-effects				
Parish	Yes			
Month of study	Yes	Yes	Yes	Yes
Canton x month of study	Yes			
Canton		Yes	Yes	Yes
Fit statistics				
Observations	94,972	18,571	15,678	12,179
R^2	0.52437	0.82577	0.92692	0.94329
Within R^2	0.00054	0.00231	0.00533	0.00503

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S4: Alternative approaches to estimating area level changes in household electricity consumption associated with PEC enrollment. Model (1) is our preferred specification (described in Table S3. Model (2) aggregates data to the canton level rather than the parish level. Model (3) restricts differentiates itself from Model 2 based on being run on the dataset that was combined with the hospitalizations data, and thus some canton-month observations were lost due to lack of hospitalizations outcomes. Model (4) includes a set of canton-level socio-economic characteristics. We illustrate these canton-level regressions to motivate our interpretation of the impacts of PEC enrollment on hospitalizations as acting via increased electricity consumption that displaces gas.

	General Customer	PEC Enrollee	
		Pre enrollment	Post enrollment
Mean (SD)	304 (448)	222 (194)	251 (219)
Median (IQR)	192 (109-307)	175 (110-273)	206 (129-317)
Customers	703,611	10,016	109,838
Observations	28,836,030	366,982	2,243,592

Table S5: Summary of CNEL customer data

	General Customer	PEC Enrollee	
		Pre enrollment	Post enrollment
Mean (SD)	143 (130)	164 (122)	181 (122)
Median (IQR)	118 (71-180)	141 (92-208)	161 (105-232)
Customers	839,990	118,485	215,376
Observations	44,541,217	18,290,111	9,339,396

Table S6: Summary of EEQ customer data

CNEL

Dependent Variable:	kWh per month											
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
Enrolled	31.09***	31.31***	31.09***	31.09***	31.01***	31.26***	31.01***	31.01***	32.13***	32.40***	32.13***	32.13***
	(0.3703)	(0.3687)	(0.3703)	(0.3703)	(0.3570)	(0.3560)	(0.3569)	(0.3569)	(0.4151)	(0.4141)	(0.4151)	(0.4151)
Fixed-effects												
Customer	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of study	Yes		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes
Month of year		Yes				Yes				Yes		
Year		Yes				Yes				Yes		
Fit statistics												
Observations	67,241,269	67,241,269	67,241,269	67,241,269	66,022,380	66,022,380	66,022,380	66,022,380	36,622,692	36,622,692	36,622,692	36,622,692
R^2	0.91429	0.91410	0.91429	0.91429	0.72176	0.72080	0.72177	0.72177	0.70077	0.69912	0.70077	0.70077
Within R^2	0.00081	0.00082	0.00082	0.00082	0.00139	0.00141	0.00143	0.00143	0.00277	0.00280	0.00277	0.00277

Clustered (customer) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

EEQ

Dependent Variable:	kWh per month											
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
Enrolled	24.13***	24.09***	24.11***	24.11***	24.15***	24.11***	24.12***	24.12***	25.72***	25.71***	25.72***	25.72***
	(0.2879)	(0.2875)	(0.2880)	(0.2880)	(0.2871)	(0.2867)	(0.2872)	(0.2872)	(0.3153)	(0.3144)	(0.3153)	(0.3153)
Fixed-effects												
Customer	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of study	Yes		Yes	Yes	Yes		Yes	Yes	Yes		Yes	Yes
Month of year		Yes				Yes				Yes		
Year		Yes				Yes				Yes		
Fit statistics												
Observations	65,158,584	65,158,584	65,158,584	65,158,584	65,141,038	65,141,038	65,141,038	65,141,038	48,802,724	48,802,724	48,802,724	48,802,724
R^2	0.20755	0.20741	0.20756	0.20756	0.19656	0.19642	0.19657	0.19657	0.65855	0.65786	0.65855	0.65855
Within R^2	0.00017	0.00017	0.00018	0.00018	0.00017	0.00017	0.00018	0.00018	0.00189	0.00190	0.00189	0.00189

Clustered (customer) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S7: **Robustness of estimates of the impact of PEC enrollment on customer level monthly electricity consumption among CNEL and EEQ customers.** Models are as follows.
Study samples: (1)–(4) use the main sample; (5)–(8) use a sample that removes customers with median kWh consumption above 2500 kWh per month; (9)–(12) also removes customers with median kWh consumption above 2500 kWh per month and only retains customers that are observed in all study months.
Model specifications: For each sample, the four columns use four model specifications. The first (i.e., models (1), (5), and (9)) is the main specification where we use customer and study month fixed effects. The second we drop study month FE and instead use month and year FE. The third we add a linear time trend (i.e., study month as a continuous variable as a control) and also use study month FE. The fourth we use a linear and a squared time trend (i.e., study month and study month squared as controls) and study month FE.

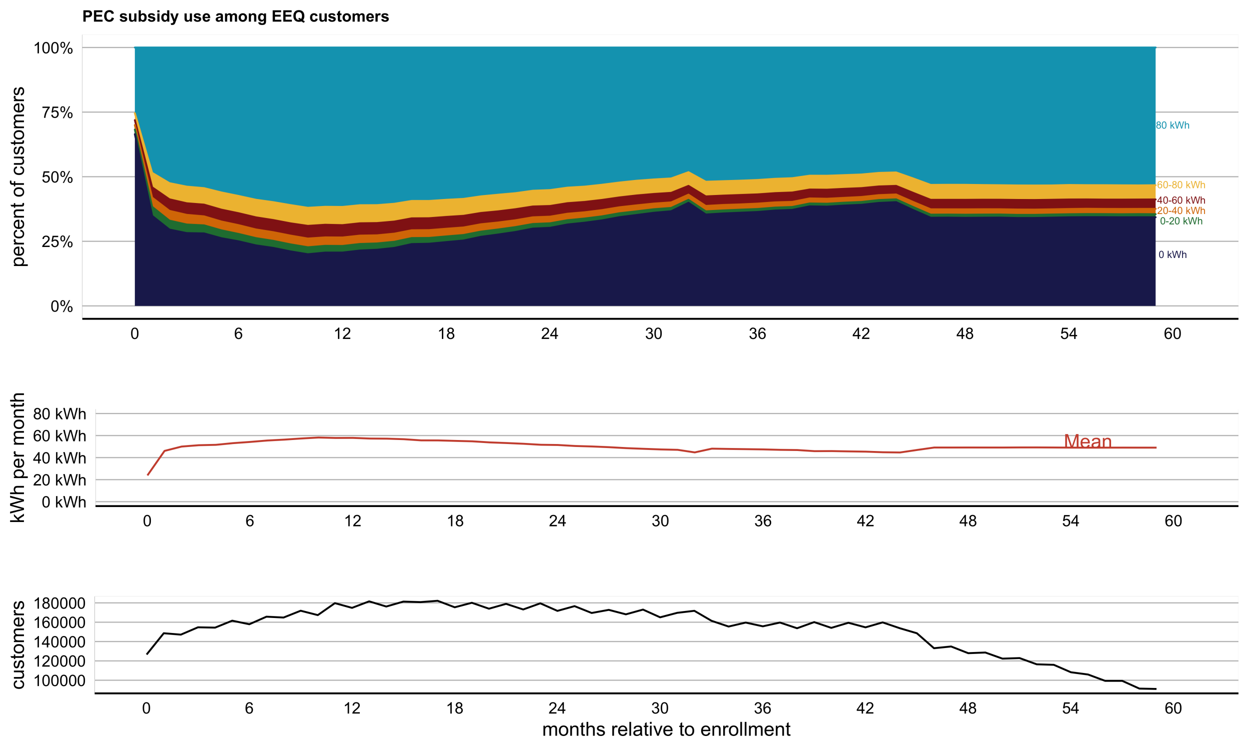


Figure S5: **Trends in PEC subsidy use among EEQ customers after enrollment.** These data summarize a unique feature of the EEQ customer-level data, which provides the utility-derived kWh subsidized for PEC customers in each month. **Top panel** We group customers into the amount of kWh subsidized in each month relative to enrollment. **Middle panel** We estimate the mean kWh subsidized in each month. **Bottom panel** Displays the number of customers contributing in each month relative to enrollment. Data source: EEQ.

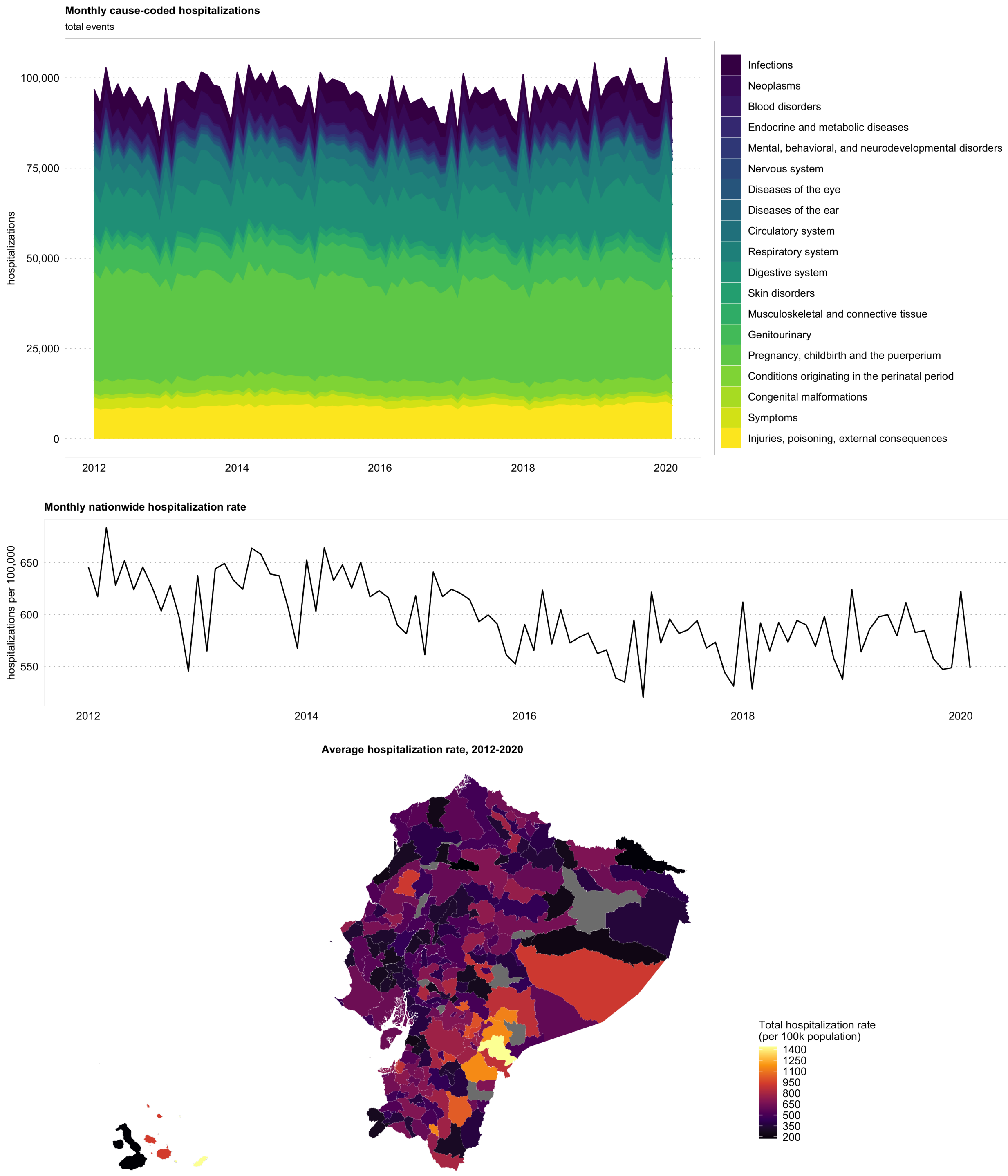


Figure S6: **Trends and distribution of hospitalizations across Ecuadorian cantons, 2012 to 2020. Top panel** In each month, we aggregate individual hospital visits by their cause in a stacked line chart to illustrate temporal trends in overall hospitalizations and cause-specific hospitalizations. **Middle panel** We sum all hospitalizations in each month and divide by the total national estimated population and standardize per 100,000 population. **Bottom panel** Maps canton-level average hospitalization rate over the full time period per 100,000 population. Data source: INEC.

Table S8: Summary of cause-coded hospitalizations, 2012-2020. Data source: INEC.

Outcome	**Total events**	**Hospitalization rate (per 100k)**	**Canton-month observations with 0 events**	**ICD Codes**
Total hospitalizations	9478240	497.08	0	All
Asthma	18814	1.18	0.73	J45
Chronic obstructive pulmonary disease	40677	2.54	0.54	J44
Influenza and pneumonia	334206	20.91	0.13	J09-J18
Infectious and parasitic diseases	457571	25.67	0.12	A00-B99
Neoplasms	557460	26.59	0.093	C00-D49
Disease of the blood	61184	3.26	0.46	D50-D89
Endocrine, nutritional, and metabolic diseases	244323	13.11	0.19	E00-E89
Mental, Behavioral and Neurodevelopmental disorders	72674	3.64	0.51	F01-F99
Diseases of the nervous system	99535	4.96	0.38	G00-G99
Diseases of the eye and adnexa	63802	2.28	0.59	H00-H59
Diseases of the ear and mastoid process	21928	1.08	0.71	H60-H95
Circulatory system	390314	19.47	0.12	I00-I99
Respiratory system	688933	37.83	0.06	J00-J99
Diseases of the digestive system	1251481	62.34	0.02	K00-K95
Diseases of skin and subcutaneous tissue	141055	9.18	0.27	L00-L99
Diseases of the musculoskeletal system and connective tissue	241266	9.34	0.26	M00-M99
Diseases of the genitourinary system	742504	39.24	0.05	N00-N99
Pregnancy, childbirth and the puerperium	2670647	150.55	0.01	O00-09A
Certain conditions originating in the perinatal period	396130	19.11	0.14	P00-P96
Congenital malformations, deformations and chromosomal abnormalities	103616	4.47	0.39	Q00-Q99
Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	225443	9.76	0.29	R00-R99
Injury, poisoning and certain other consequences of external causes	862943	47.94	0.03	S00-T88

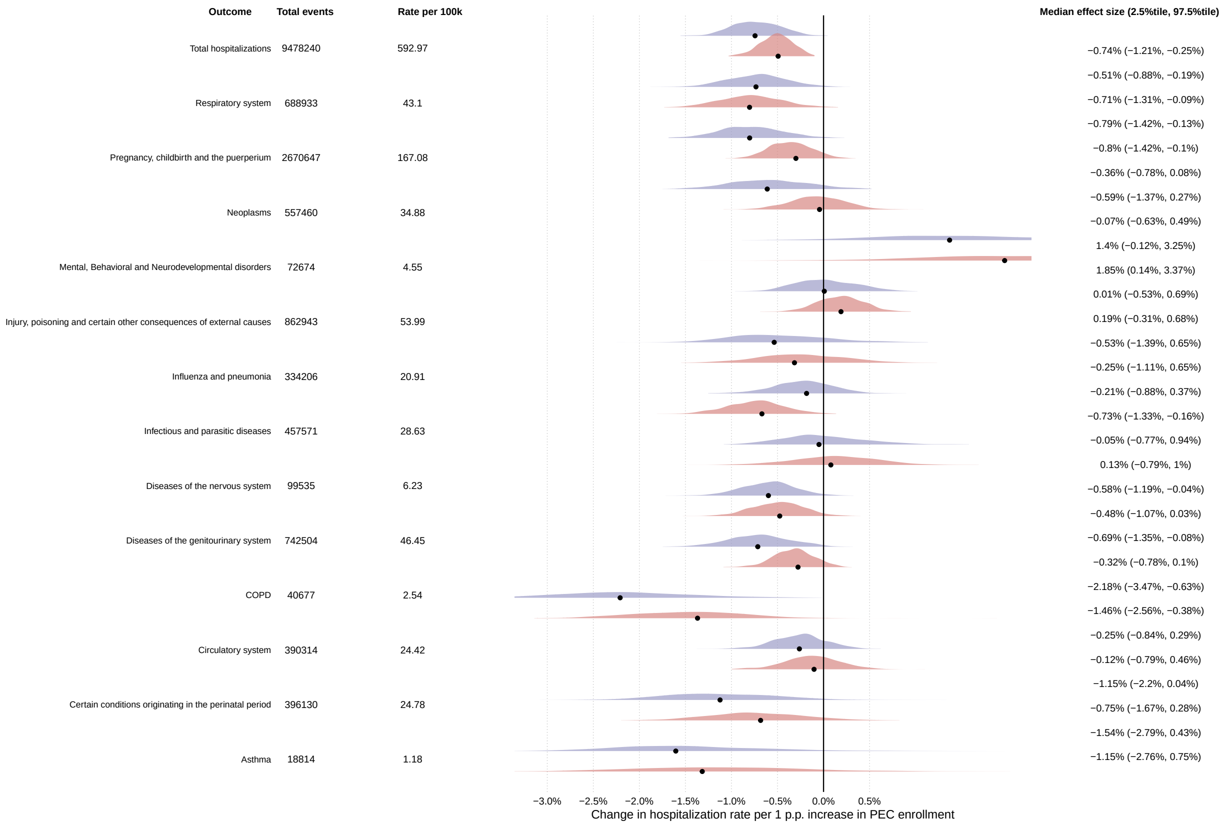


Figure S7: **Associations between cause-specific canton level hospitalization rates and PEC enrollment**. Replicates our preferred approach as shown in Figure 4 for specific cause groups. For each cause, we conduct unadjusted (top, purple) and adjusted (bottom, pink) regressions. The coefficient estimates are shown with black dots. Then, we draw 1,000 random cantons samples (sampling with replacement) and illustrate the density of coefficient estimates. For each cause, we also show the total number of hospitalizations and the average hospitalization rates per 100,000 over the full study period. Estimated effect sizes and 95% CIs shown are the median, 2.5th percentile, and 97.5th percentile.

Controls: % Bono Desarollo Humano, % extreme poverty, voting patterns, healthcare facilities with more than five doctors or nurses per capita, doctors plus nurses per capita, population.

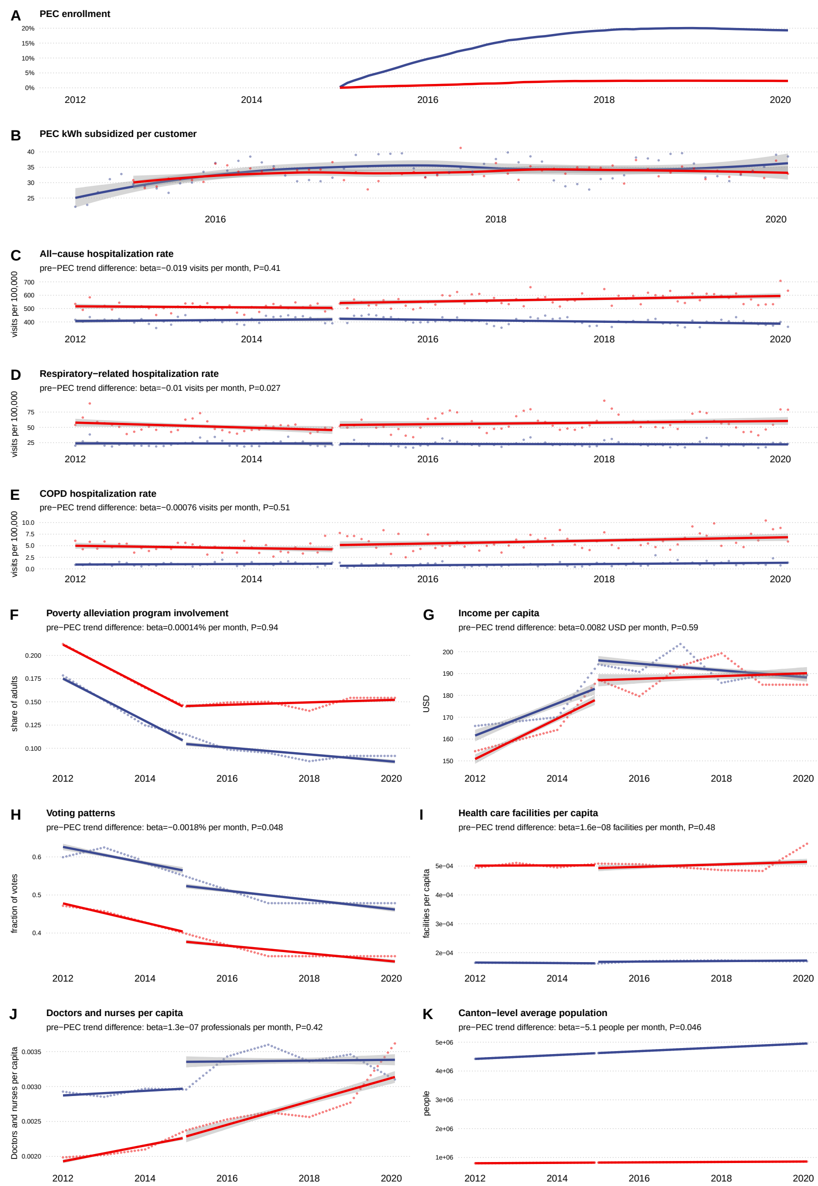


Figure S8: **Assessment of parallel trends in PEC enrollment, hospitalizations, and socio-economic characteristics among high and low enrollment cantons.** High enrollment cantons are those above the 85th percentile of average canton level enrollment between June 2019 and March 2020 (the last 9 months of the study period for hospitalizations), and low enrollment cantons are those below the 15th percentile. To test for parallel trends in high vs. low enrollment cantons we carry out an OLS panel fixed effects regression on canton level data where the outcome is the variable of interest and we interact a numeric variable for month with a dummy variable for whether the canton belongs to the high or low enrollment canton (binarized such that 1 = high enrollment), with the data restricted to the pre-PEC period. The interpretation of the coefficient is thus the difference in monthly trends of high enrollment cantons vs. low enrollment cantons in the pre-PEC period. Data points are estimates at the group-level (i.e., canton level data are aggregated to the group). For **A**, a line is drawn through data points. For **B**, we use the flexible 'loess' smoothing function in ggplot. For **C-K**, we separately fit lines for each group in the pre-PEC and post-PEC periods. See Methods for data sources.

Dependent Variables:	log(total rate)		total		log(total rate)			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Poisson	Poisson	OLS	OLS	OLS	OLS
Variables								
% PEC (per 1 p.p. increase)	-0.0074***	-0.0049***	-0.0130*	-0.0036				
	(0.0026)	(0.0017)	(0.0067)	(0.0023)				
ATT					-0.1126**	-0.0791*	-0.1462***	-0.1099**
					(0.0461)	(0.0432)	(0.0273)	(0.0354)
Controls								
		Yes		Yes		Yes		Yes
Fixed-effects								
Canton	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of sample	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	21,319	20,095	21,319	20,095	6,370	6,076	6,370	6,076
Squared Correlation	0.73244	0.73699	0.99721	0.99763	0.75362	0.76077	0.78038	0.78479
Pseudo R^2	1.0000	1.0000	1.0003	1.0003	1.0000	1.0000	1.0000	1.0000
BIC	2,771.2	2,563.5	4.05×10^{10}	2.39×10^{10}	1,731.6	1,735.1	9,494.8	9,543.2

Clustered (canton) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S9: **Comparing results from unadjusted and adjusted analyses of the association between PEC and hospitalizations across three principal approaches**. Columns (1) and (2) come from our preferred OLS specification where the outcome is the log of the all-cause canton-month hospitalization rate per 100,000 population. Coefficients are interpreted as the relative change (when multiplied by 100 the percent change) in average hospitalization rate per 1 percentage point increase in canton-level PEC enrollment. Columns (3) and (4) repeat this analytical approach, but replace the outcome with a count of canton-month all-cause hospitalizations modeled as a Poisson. Coefficients, when exponentiated, are interpreted as incidence rate ratios. Columns (5)-(8) are from our stylized Difference-in-differences approach (outlined in the Supplemental Information) that compares log average all-cause hospitalization rates in "high" and "low" enrollment cantons both after (5)-(6) January 2015 (the initiation of PEC) and (7)-(8) when high enrollment cantons reach 5% PEC enrollment.
Controls: % Bono Desarollo Humano, % extreme poverty, voting patterns, healthcare facilities with more than five doctors or nurses per capita, doctors plus nurses per capita, population.

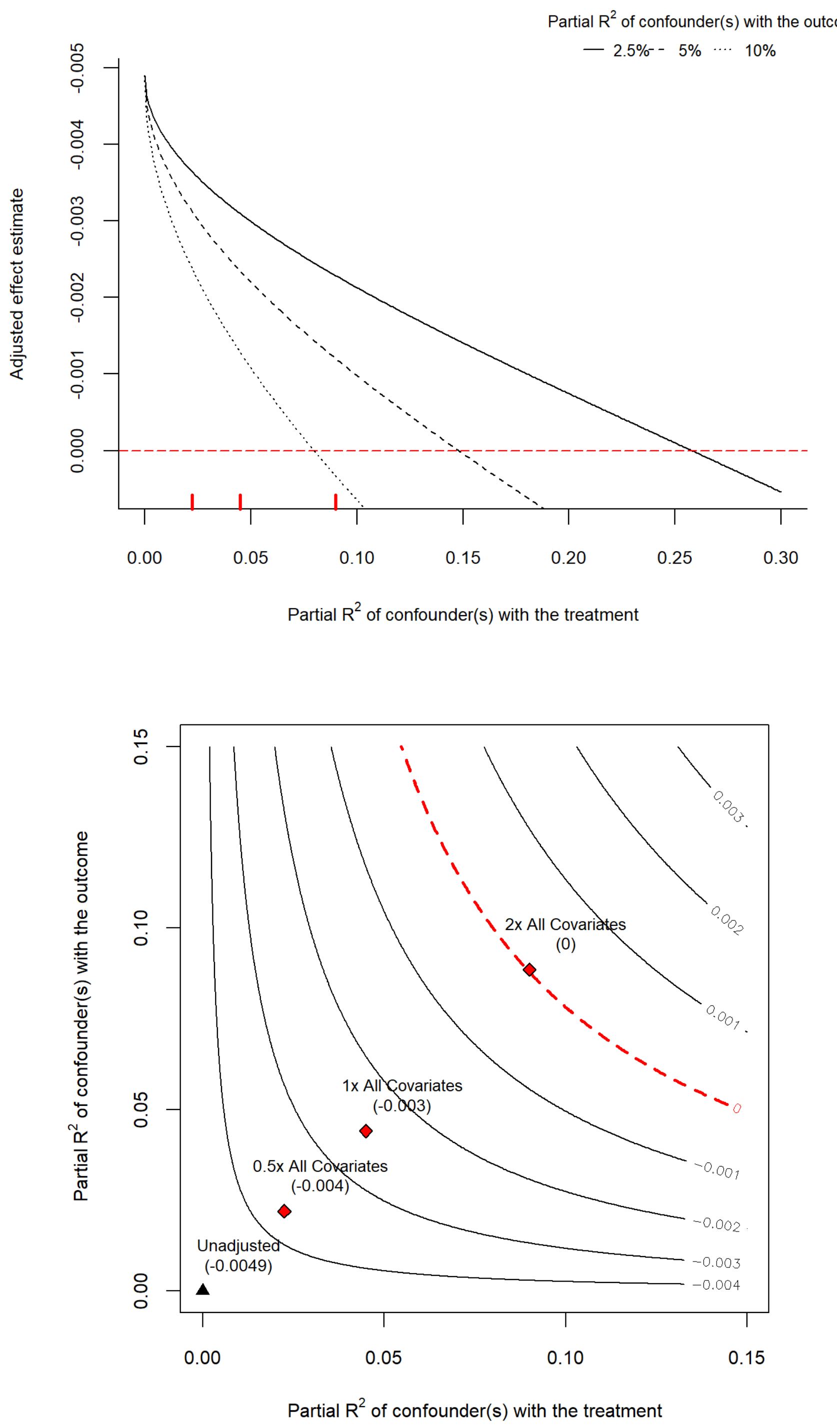


Figure S9: **Assessment of omitted variable bias as described in Supplemental Section 5**.

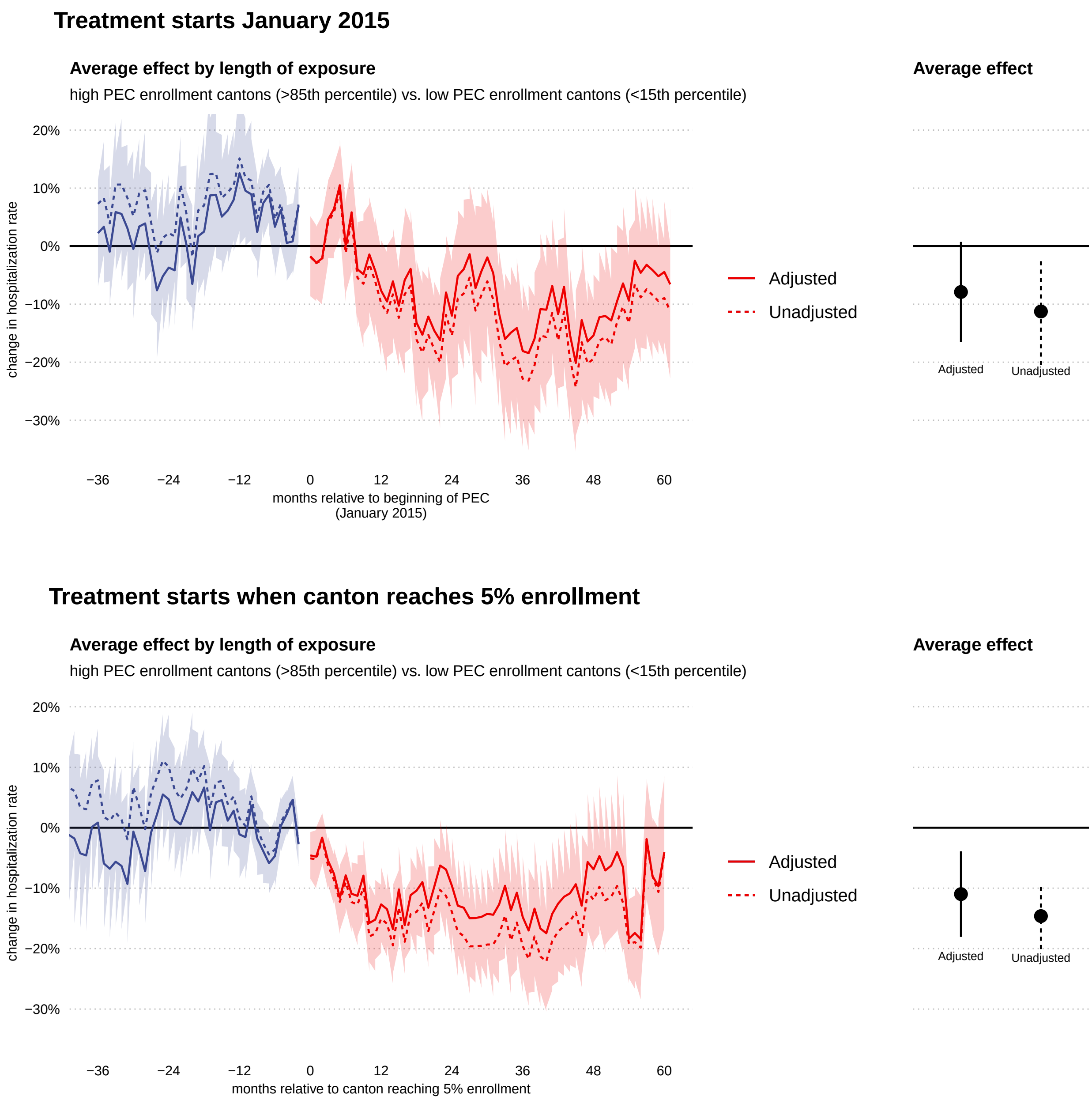


Figure S10: **Difference-in-differences approach to isolating the impact of PEC enrollment on hospitalization rates**. See Section SI section 5 for more details on approach. We compare average canton-month hospitalization rates across ‘high’ vs. ‘low’ PEC enrollment cantons (defined as above or below the 85th or 15th percentile of enrollment in the last 9 months of the study period, June 2019 to March 2020). **Top panel** Estimates the average treatment effect on the treated where treatment occurs in high enrollment cantons on January 2015 in an event study plot where coefficients are plotted and connected in a line with 95% confidence intervals shown relative to December 2014 (month before treatment). We also aggregate to estimate the total average effect on the treated. Solid lines show results from adjusted models. **Bottom panel** repeats the top panel’s approach but treatment occurs in the month where high enrollment cantons pass 5% PEC enrollment. We use the ‘sunab’ call within ‘fixest’ to generate estimates (estimates are similar when estimated using the ‘did’ package, which does not allow for inclusion of time-varying controls). *Controls:* % Bono Desarollo Humano, % extreme poverty, voting patterns, healthcare facilities with more than five doctors or nurses per capita, doctors plus nurses per capita, population.

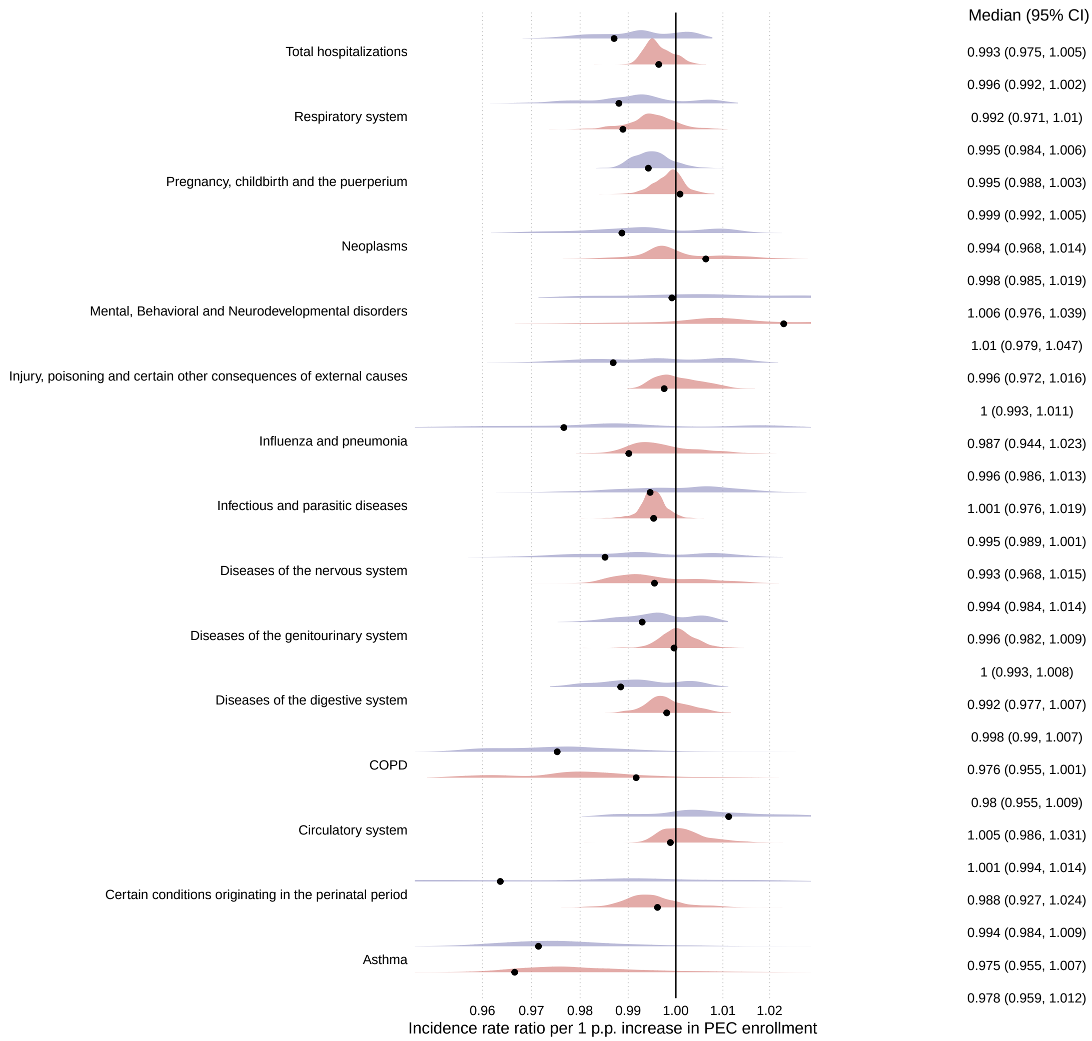


Figure S11: **Robustness of effects of PEC enrollment on cause-specific hospitalizations to modeling the outcome as a count in Poisson regressions**. Adjusted and unadjusted in main approach (2012-2020), FE for canton and month of study, by three outcome specifications: log hospitalization rate; hospitalization rate; and count of hospitalizations modeled as a Poisson. ICD code groupings are defined in Table S7.

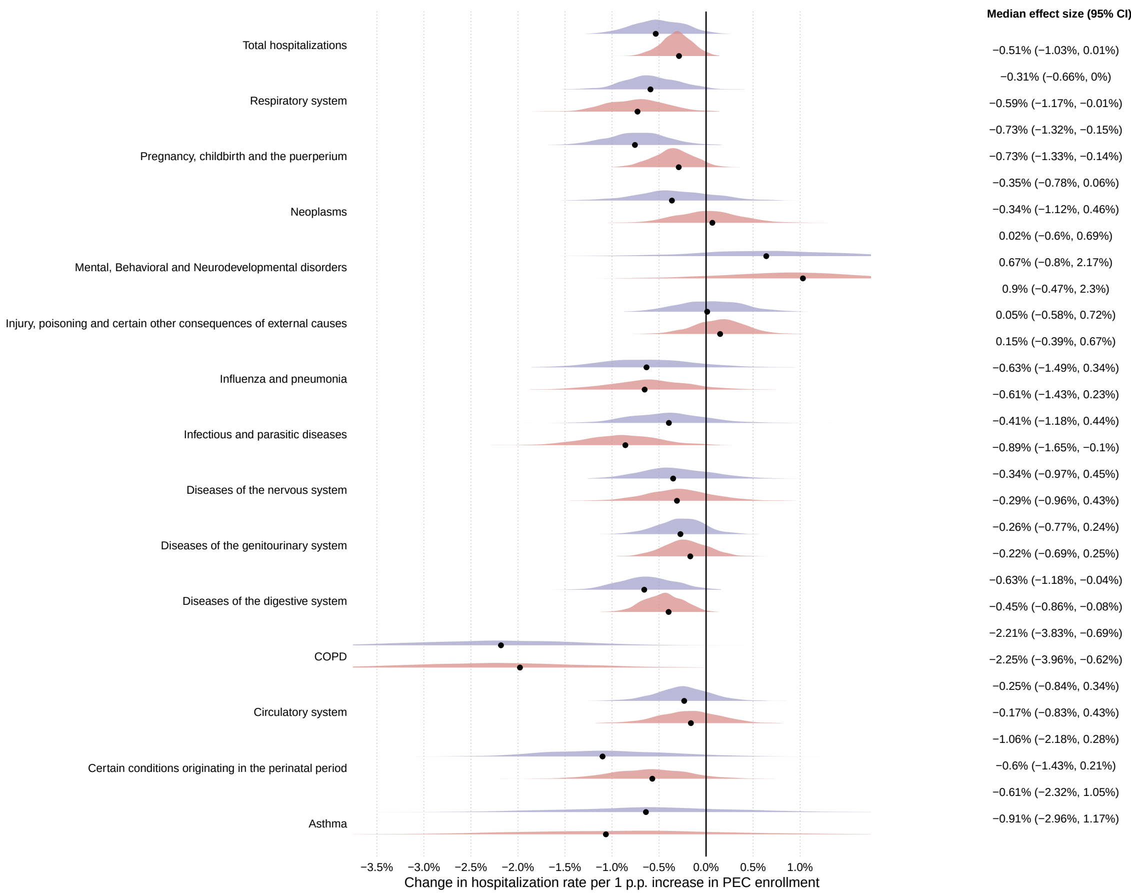


Figure S12: **Robustness of effects of PEC enrollment on cause-specific hospitalizations to modeling the outcome as a rate and converting to percent change**. Adjusted and unadjusted in main approach (2012-2020), FE for canton and month of study. ICD code groupings are defined in Table S7.

Sample	Adjusted for controls	Population weights	Median estimate (95% CI)
Full	Adjusted	Population-weighted	-0.51% (-0.92%, -0.19%)
Full	Adjusted	Unweighted	-0.92% (-1.3%, -0.61%)
Full	Unadjusted	Population-weighted	-0.74% (-1.23%, -0.17%)
Full	Unadjusted	Unweighted	-1.03% (-1.36%, -0.71%)
Post PEC	Adjusted	Population-weighted	-0.78% (-1.4%, -0.23%)
Post PEC	Adjusted	Unweighted	-1.04% (-1.52%, -0.6%)
Post PEC	Unadjusted	Population-weighted	-0.66% (-1.32%, -0.22%)
Post PEC	Unadjusted	Unweighted	-1.04% (-1.54%, -0.56%)

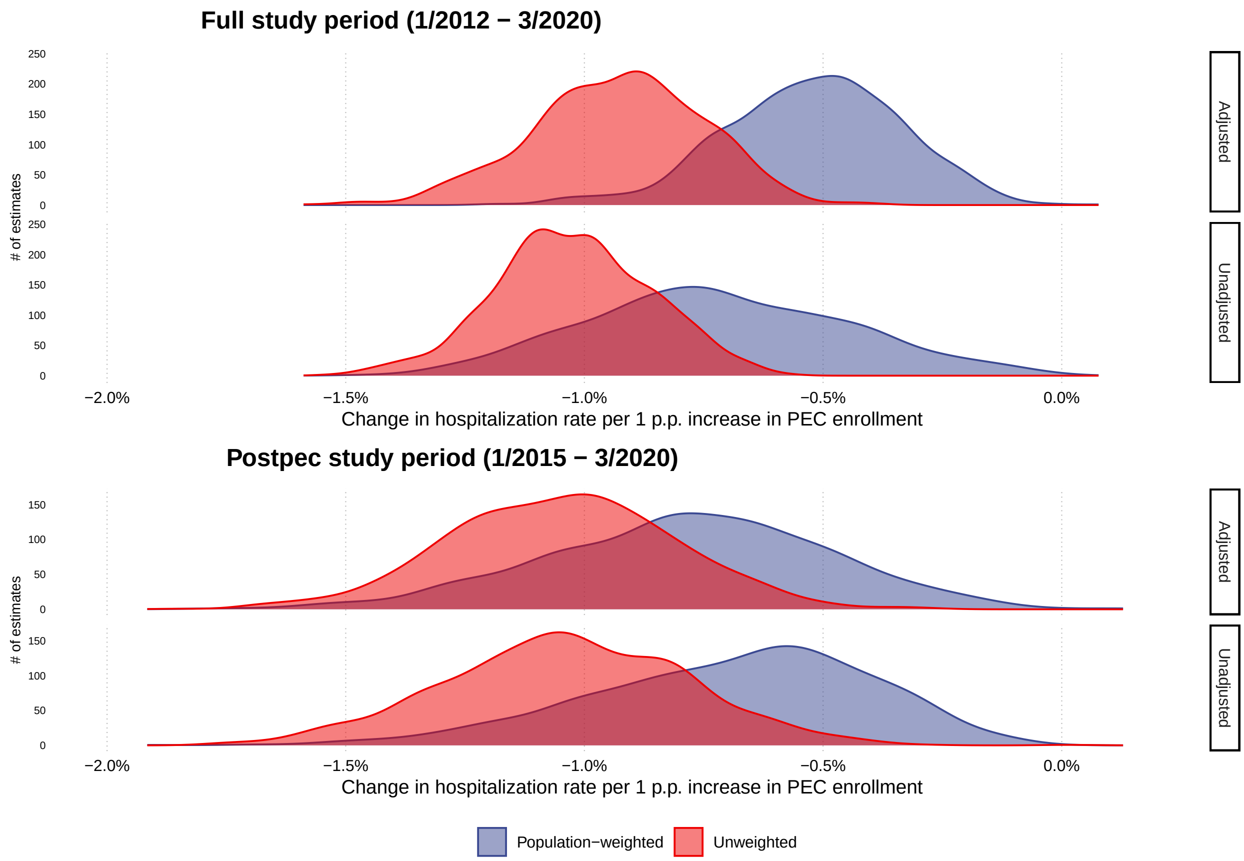


Figure S13: **Sensitivity of associations between total canton level hospitalization rates and PEC enrollment to population weighting**. **Table above** summarizes estimates. Density plots illustrate the distribution of estimates from 1,000 draws of cantons sampled with replacement. We further demonstrate the differences that result from weighting regressions by canton-level population. **Top panel** shows analyses using the full sample January 2012 to March 2020, which includes the pre-PEC period when enrollment is zero. **Bottom panel** restricts the sample to January 2015 to March 2020 (the period when PEC has been in effect).

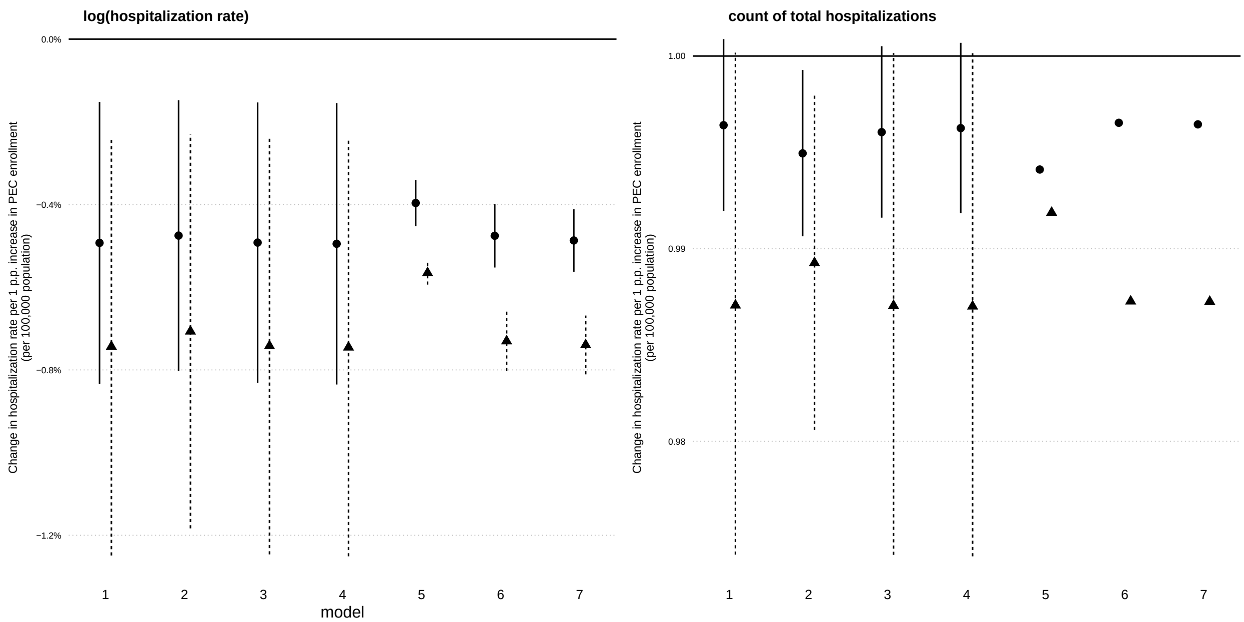


Figure S14: **Robustness of effects of PEC enrollment on total hospitalizations to alternative approaches**. Counts of hospitalizations are modeled in Poisson regressions. Circles are unadjusted and triangles are adjusted models. The models are (1) main model: month of study FE, (2) month of year and year FE; (3) nonlinear time trend (9 degrees of freedom), month of year and year FE, (4) non linear time trend (27 degrees of freedom), month of year and year FE, (5) conditional regression with canton by month of year strata, (6) conditional regression with nonlinear time trend (9 degrees of freedom) and strata are canton by month of year, (7) conditional regressions with nonlinear time trend (27 degrees of freedom) and strata are canton by month of year. All models have canton FE and have standard errors clustered at the canton-level. Counts were modeled in Poisson regressions. Conditional regressions were carried out using the 'gnm' package in R; Other regressions were carried out using 'fixest.'
Controls: % Bono Desarollo Humano, % extreme poverty, voting patterns, healthcare facilities with more than five doctors or nurses per capita, doctors plus nurses per capita, population.

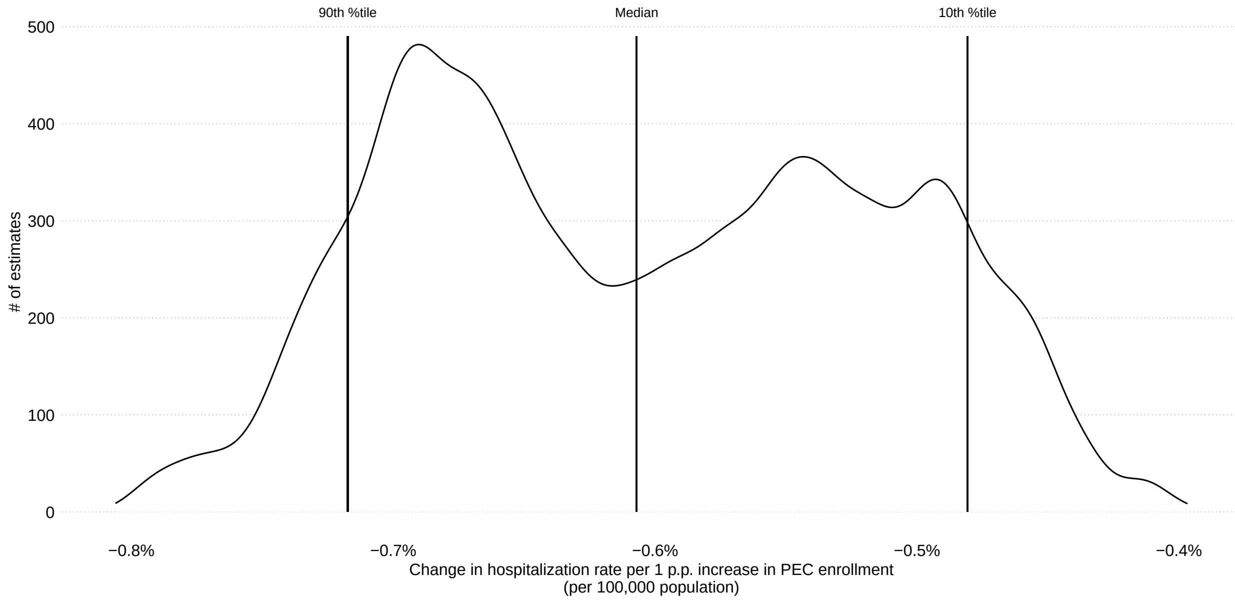


Figure S15: **Robustness of effects of PEC enrollment on total hospitalizations to all combinations of potential confounding variables**. $n = 131,078$ models

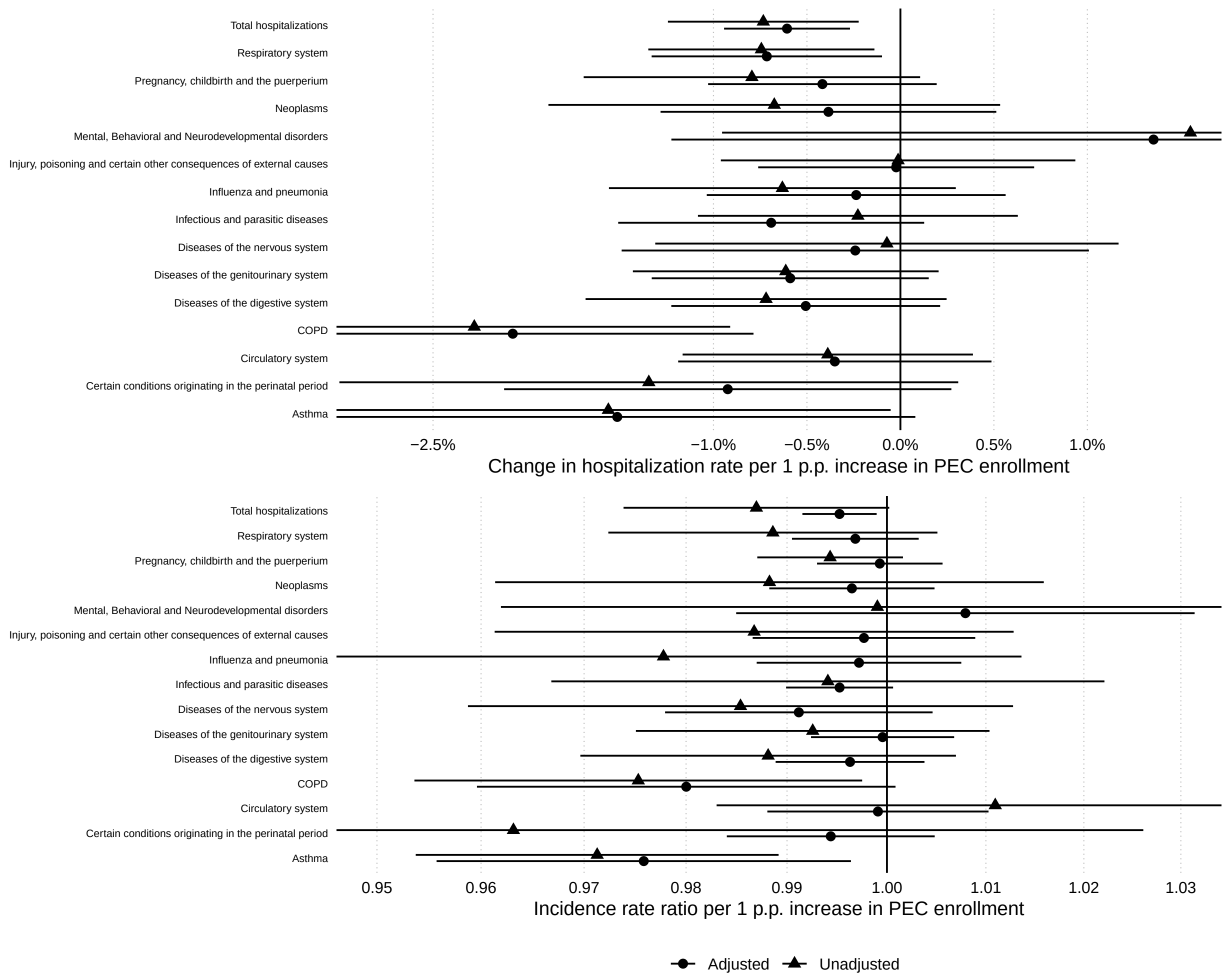


Figure S16: **Robustness of effects of PEC enrollment on cause-specific hospitalizations when data are aggregated to two-month periods**. We repeat our main approach but instead of canton-month unit level observations, all data (outcome, exposure, and controls) were aggregated to two month periods. In other words, instead of having two observations for each canton in January 2016 and February 2016, data were aggregated to January-February 2016 and so on.

Dependent Variables:	log(total rate)		total		log(total rate)		total	
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	OLS	Poisson	Poisson	OLS	OLS	Poisson	Poisson
Variables								
% PEC (1 p.p.)	-0.0090***	-0.0056*	-0.0098***	-0.0094***	-0.0088***	-0.0068**	-0.0098***	-0.0107***
	(0.0022)	(0.0029)	(0.0012)	(0.0025)	(0.0023)	(0.0025)	(0.0012)	(0.0025)
Controls								
		Yes		Yes		Yes		Yes
Fixed-effects								
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month of study	Yes	Yes	Yes	Yes				
Year					Yes	Yes	Yes	Yes
Fit statistics								
Observations	2,376	2,376	2,376	2,376	216	216	216	216
Squared Correlation	0.87634	0.88513	0.99816	0.99825	0.96908	0.97420	0.99891	0.99905
Pseudo R^2	0.99999	0.99999	1.0001	1.0001	1.0000	1.0000	1.0000	1.0000
BIC	-3,437.7	-3,567.9	2.93×10^{10}	2.84×10^{10}	-332.02	-338.82	1.2×10^{11}	1.11×10^{11}

Clustered (province) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table S10: **Adjusted association between PEC enrollment impacts and hospitalizations at the province-month and province-year level.**

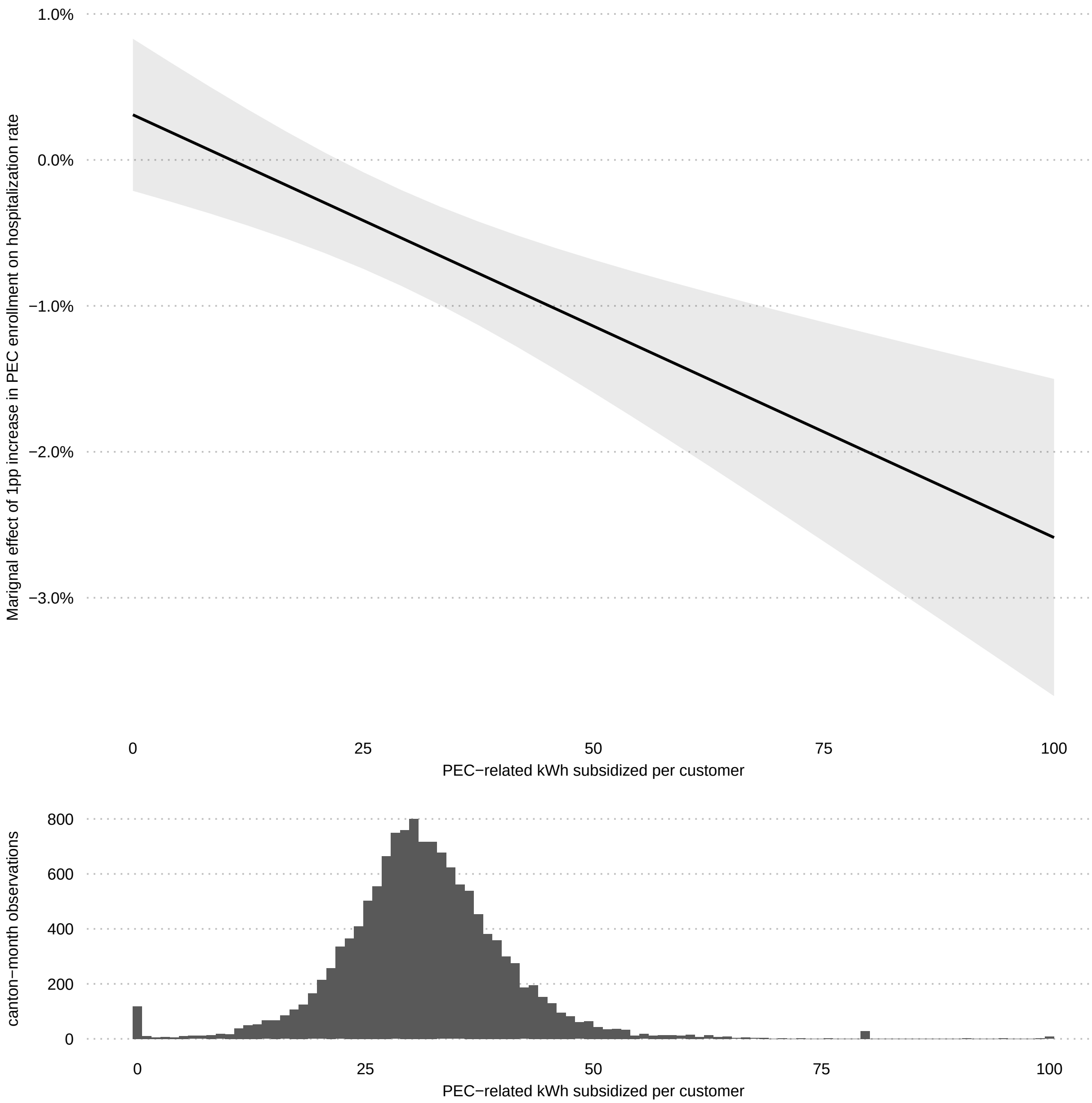


Figure S17: **PEC enrollment is associated with larger declines in hospitalization rates when more PEC-related electricity is subsidized per customer**. **Top panel** displays the marginal effect of a 1 percentage point increase in canton-level PEC enrollment on hospitalization rate in a percent change (generated using 'marginaleffects' package in R). To obtain these estimates, we directly interact the average kWh subsidized per PEC customer (obtained from ARCONEL data that contain the total kWh subsidized for PEC among PEC customers) with % PEC enrollment in our preferred adjusted specification. **Bottom panel** Shows the histogram of PEC-related kWh subsidized per customer from January 2015 to March 2020. Note that the model includes the pre-PEC period, where PEC enrollment and kWh PEC subsidized are all zeros. Data source: ARCONEL.

Table S11: Country and regional marginal emissions factors (MEFs)

Region	Country	MEF (gCO2e/kWh)	Source	Details
	Antigua	620	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Argentina	378	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Argentina	428.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Armenia	473	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Western Australia	Australia	426	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Queensland	Australia	684	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Tasmania	Australia	72	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
South Australia	Australia	225	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
New South Wales	Australia	633	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Victoria	Australia	527	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Austria	204	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Bangladesh	670	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Barbuda	960	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Belgium	156	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Belize	490	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Benin	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Bosnia and Herzegovina	593	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Botswana	1026.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
South Brazil	Brazil	85	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Central Brazil	Brazil	117	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
North-East	Brazil	42	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
North Brazil	Brazil	142	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Brazil	598.53	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Bulgaria	416	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Burkina Faso	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Cambodia	234	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Yukon	Canada	38	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Alberta	Canada	462	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Ontario	Canada	65	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Quebec	Canada	29	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Sal	Cape Verde	720	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
São Vicente	Cape Verde	690	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Santo Antão	Cape Verde	710	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Santiago	Cape Verde	650	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Brava	Cape Verde	790	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Fogo	Cape Verde	790	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Santo Maio	Cape Verde	790	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
São Nicolau	Cape Verde	790	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Boavista	Cape Verde	760	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Chile	180	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Chile	787	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
North China Grid	China	941.9	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Northeast China Power	China	1082.6	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
East China Grid	China	792.1	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Central China Power Grid	China	858.7	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Northwest China Power	China	892.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	China	804.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	China	797	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Colombia	680	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Costa Rica	49	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Côte d'Ivoire	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Croatia	267	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Cyprus	554	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Czechia	426	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Democratic Republic of the Congo (DRC)	995.8	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Denmark	168	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Dominican Republic	561	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Dominican Republic	630	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Ecuador	383.4	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	El Salvador	125	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Estonia	512	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Finland	93	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	France	100	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Gambia	713	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Georgia	276.57	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Germany	383	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Ghana	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Great Britain	280	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Greece	345	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Guatemala	83	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Guyana	666	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p

	Honduras	332	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Honduras	612.5	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Hungary	259	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Iceland	27	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Karnataka	India	344	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Maharastra	India	732	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Uttar Pradesh	India	732	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Himachal Pradesh	India	75	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Punjab	India	663	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Delhi	India	470	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	India	949.7	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	India	940.55	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Indonesia	652	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Ireland	354	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Israel	577	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Italy	356	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Jamaica	705	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Tokyo	Japan	553	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Kansai	Japan	456	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Kyushu	Japan	480	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Kenya	499.9	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Kosovo	683	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Kuwait	550	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Lao PDR	559.5	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Latvia	438	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Lesotho	995.8	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Lithuania	218	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Malaysia	644.8	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Mali	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Mauritius	1027.3	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Mexico	423	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Moldova	400	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Mongolia	884	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Montenegro	516	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Mozambique	1026.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Namibia	1026.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Netherlands	325	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Nevis	730	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	New Zealand	70	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Nicaragua	246	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Niger	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Nigeria	352	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Nigeria	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	North Macedonia	550	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Norway	52	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Pakistan	637.53	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Panama	167	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Peru	246	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Peru	685.7	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Luzon-Visayas Grid	Philippines	712.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Philippines	779.7	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Poland	636	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Portugal	237	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Romania	275	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Europe-Ural	Russia	338	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Siberia	Russia	409	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
East	Russia	318	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Rwanda	767	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Rwanda	771	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Saint Kitts	670	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Sao Tome and Principe	646	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Senegal	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Singapore	408	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Slovakia	278	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	South Africa	697	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	South Africa	1026.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	South Korea	490	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Spain	216	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Sri Lanka	708.4	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Sudan	206	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Swaziland	1026.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
	Sweden	30	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Switzerland	123	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
	Taiwan	532	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022

Thailand	502	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Thailand	529	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Togo	578	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Turkey	381	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Uganda	274	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Uganda	614	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Uruguay	35	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Uruguay	35	https://app.electricitymaps.com/map?aggregated=false	12 month average MEF retrieved on October 20, 2022
Viet Nam	924.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Zambia	1026.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p
Zimbabwe	1026.2	IGES Grid Emissions Factors v11.0 2022-10-12	Most recent government provided estimate of MEF (ex-p

Table S12: US State MEFs. Data source: EPA

Year	US State	MEF (kgCO2e/MWh)
2020	AK	615.272
2020	AL	547.907
2020	AR	705.397
2020	AZ	600.095
2020	CA	414.777
2020	CO	755.088
2020	CT	400.577
2020	DC	276.312
2020	DE	395.188
2020	FL	463.129
2020	GA	686.037
2020	HI	774.894
2020	IA	801.040
2020	ID	387.748
2020	IL	794.160
2020	IN	836.007
2020	KS	1,008.083
2020	KY	806.605
2020	LA	486.356
2020	MA	425.668
2020	MD	684.436
2020	ME	300.502
2020	MI	774.155
2020	MN	702.530
2020	MO	841.677
2020	MS	480.983
2020	MT	1,019.970
2020	NC	602.022
2020	ND	941.917
2020	NE	969.548
2020	NH	407.070
2020	NJ	431.680
2020	NM	855.984
2020	NV	480.410
2020	NY	456.861
2020	OH	865.906
2020	OK	609.776
2020	OR	518.533
2020	PA	612.644
2020	PR	761.496
2020	RI	410.805
2020	SC	662.630
2020	SD	745.635
2020	TN	678.610
2020	TX	603.923
2020	UT	782.253
2020	VA	510.139
2020	VT	126.185
2020	WA	625.115
2020	WI	759.778
2020	WV	948.474
2020	WY	1,084.742

Table S13: Indian State MEFs. Data source: Sengupta (2022)[58]

State	MEF (kgCO2e/MWh)
Puducherry	1051.83333
Chhattisgarh	960.66667
Rajasthan	932.25
Madhya Pradesh	939.16667
Bihar	917.58333
West Bengal	852.16667
Jharkhand	864.75
Goa	843.66667
Uttar Pradesh	832.58333
Telangana	793.08333
Karnataka	770.66667
Tamil Nadu	741.58333
Nct Of Delhi	774.16667
Andhra Pradesh	754.16667
Haryana	751.08333
Maharashtra	672.83333
Orissa	663.08333
Nagaland	597.66667
Gujarat	579.33333
Punjab	488.83333
Mizoram	569.33333
Kerala	445
Arunachal Pradesh	490.5
Assam	481.41667
Manipur	498.08333
Sikkim	500.58333
Chandigarh	403.41667
Tripura	387.58333
Uttarakhand	148.5
Jammu And Kashmir	70.75
Meghalaya	199.58333
Himachal Pradesh	39.16667