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

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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 reduced national greenhouse gas emissions, thanks in part to the country's electricity grid being 80% 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 cobenefits of net-carbon-zero policies.

residential electrification | climate change | environmental epidemiology | policy evaluation

Significance

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. We find evidence that both greenhouse gas emissions and hospitalization rates likely fell over the first 6 y of the program in lockstep with increased induction stove adoption and use.

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 and electricity grid decarbonization are also increasingly thought to have cobenefits 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 conceptually 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 cobenefits. Ex post policy evaluation is important, given the frequent gulf in results 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 et al. (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 et al. (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 comparatively 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

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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 (36–40), 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 United States, the Netherlands, Nepal, Indonesia, and Australia (41). 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 liquefied petroleum gas (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 (42), but at large budgetary cost (43). 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 (*SI Appendix*, Fig. 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 8 y, 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, political support, and air pollution, and implementing recent statistical techniques that inform the likelihood that estimated treatment effects are likely explained by factors other than program enrollment.

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 (Fig. 1 and *SI Appendix*, 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 (*SI Appendix*, Fig. 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 socioeconomic status like income-based poverty or extreme poverty (*SI Appendix*, Table S2 and Fig. 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 (*SI Appendix*, Fig. 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 Electricidad—Guayaquil (CNEL-Guayaquil) 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 (see *SI Appendix*, Tables S3 and S4 for summary statistics). 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-by-year, billing

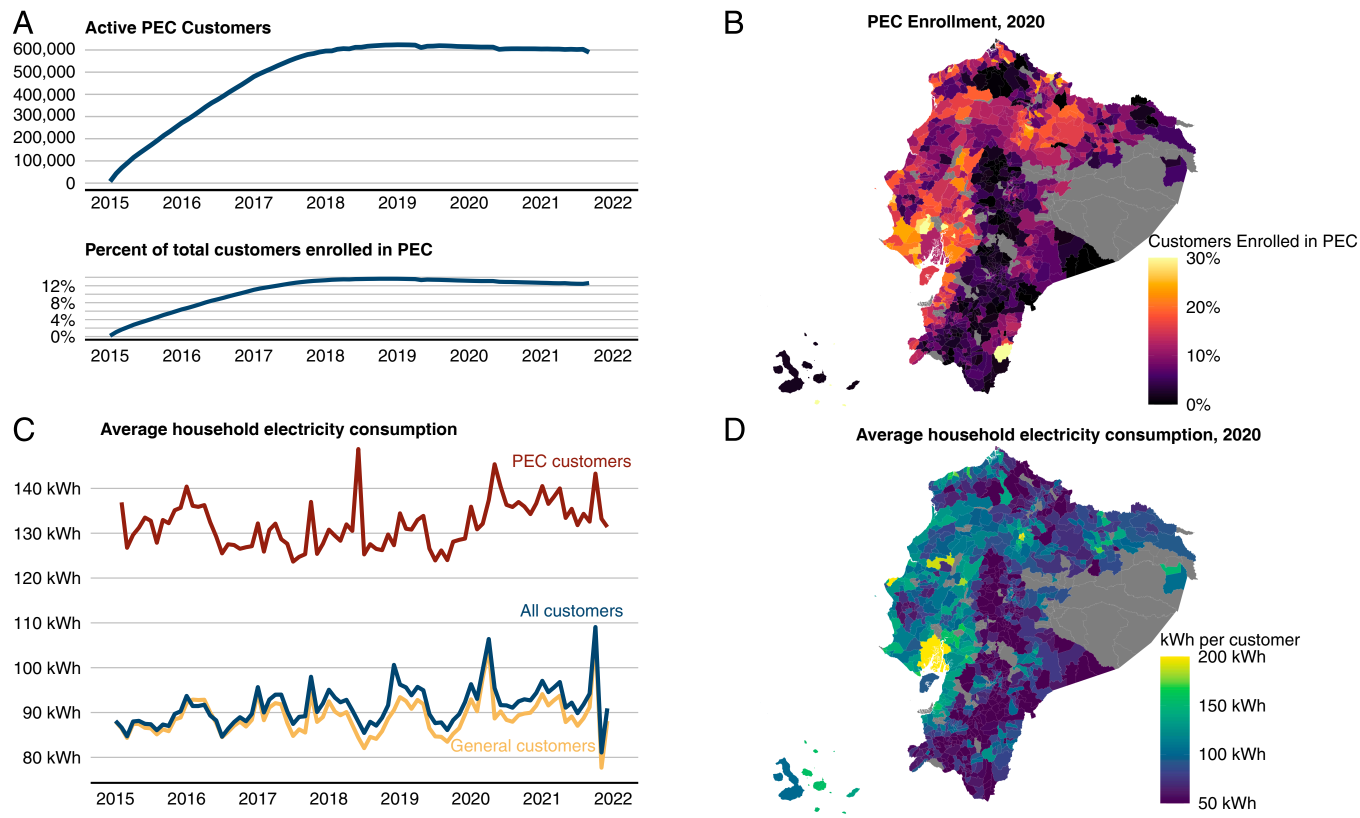

Fig. 1. Enrollment in Ecuador's induction promotion program (PEC) and average household electricity consumption among enrollees and nonenrollees. (*A*) Temporal variation of PEC enrollment across Ecuador in terms of total customers and the fraction of residential customers from January 2015 to September 2021. (*B*) Spatial variation in the fraction of residential customers enrolled in PEC across parishes averaged between September 2019 and September 2020 (N = 935). Gray 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). Gray parishes are missing data (N = 106).

system, and customer fixed effects with standard errors clustered at the customer level (Fig. 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 3 mo after enrollment relative to the month of enrollment, 15 kWh 6 mo after enrollment, and steadily increased consumption until reaching a 20-kWh increase about 24 mo after enrollment (Fig. 2). The observed increasing effect of enrollment in PEC on electricity consumption appears 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 (*SI Appendix*, Fig. 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 (*Materials and Methods*) (*SI Appendix*, Table S5).

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, 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). We estimate that each percentage point increase in the proportion 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 1.15) (*SI Appendix*, Table S6). 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 (Fig. 3 *A* and *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-mo 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 (*SI Appendix*, Table S6 and S7).

Reduced LPG Sales from Increased Induction Stove Use. Increased electricity consumption for cooking is likely a substitute for LPG consumption. To understand the extent of substitution induced by PEC, we regress monthly 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 are 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) (Fig. 3*C*). We propagate uncertainty in our chain of estimates by separately regressing LPG sales on the 1,000 bootstrapped estimates of excess kWH of PEC electricity; each of these is then bootstrapped 1,000 times sampling months with

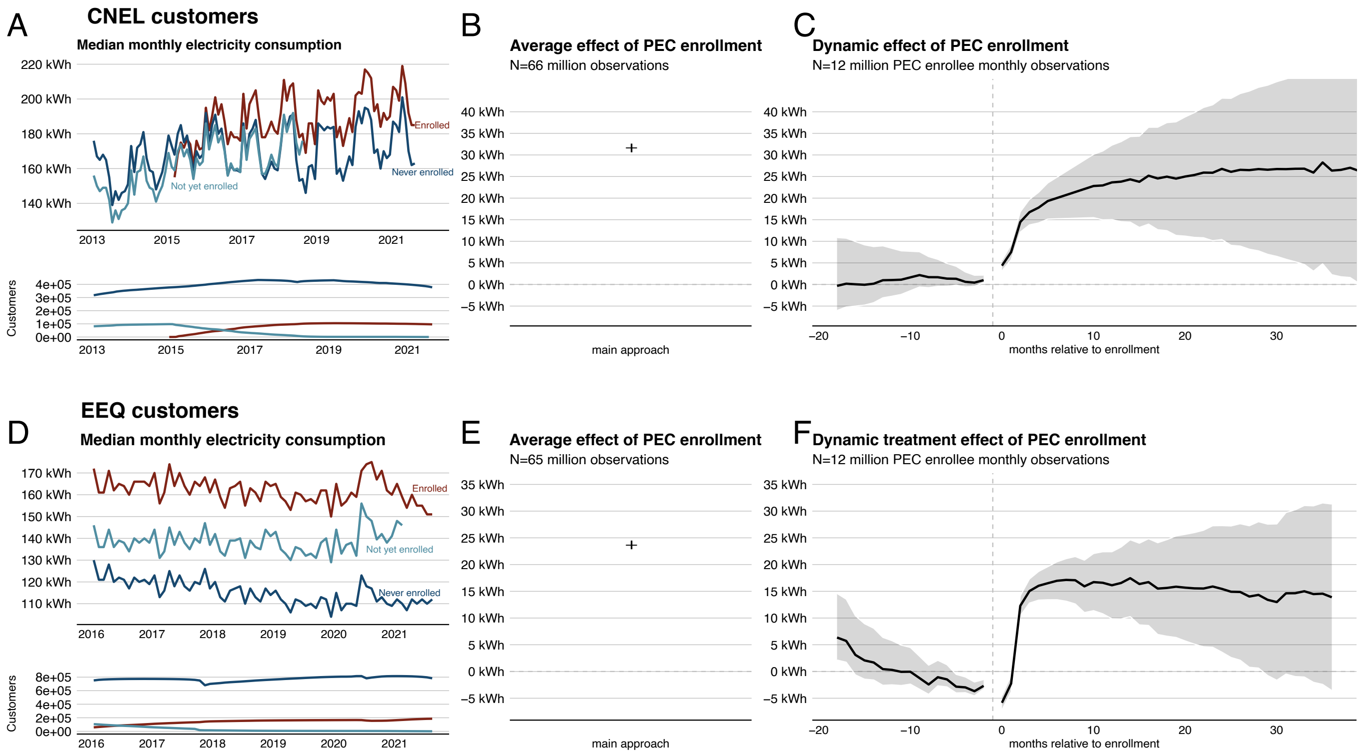

Fig. 2. PEC enrollment is associated with higher household electricity consumption across Ecuador's two largest electricity utilities. (*A*) Temporal variation in median monthly electricity consumption among never enrolled, not yet enrolled, and enrolled customers in the Corporacion Nacional de Electricidad (CNEL-Guayaquil) from January 2013 to July 2021. Electricity consumption is shown only when the group is larger than 2,000 customers. Temporal variation in the monthly numbers of customers is 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, billing system, and month of study and SEs 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 SEs clustered at the customer level. The solid black line indicates month-specific estimates, and the gray ribbon indicates the 95% CI. (*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.

replacement. Across these 1,000,000 draws, we estimate that PEC-related excess electricity consumption was associated with a total reduction in LPG sales of 706 million kg (median estimate, IQR: 522 to 927), equivalent to roughly a 7.5% decline (Fig. 3*D*). In a secondary approach, we use monthly province-level sales data that begin in 2018, which misses half of our study period including the critical first 3 y when PEC enrollment grew most. In this analysis, 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—resulting in an estimated national-level total LPG sales reduction of 423 million kg LPG (IQR, 388 to 2,630). A third approach using Government of Ecuador data on conversion factors between electricity and LPG yields an estimated reduction in LPG sales between the national and provincial estimates (*Materials and Methods*).

Program Impacts on Greenhouse Gas Emissions. Since 2015, Ecuador's energy sector has emitted around 40,000 kilotons of carbon dioxide equivalent (ktCO2e) each year, of which 8 to 10% come from residential energy consumption (44). While LPG and electricity account for 50% and 40% of residential energy consumed, respectively, LPG dominates emissions from this sector because Ecuador's national grid is largely hydropower. 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 and gas combustion.

Using a yearly emissions factor (EF) for Ecuador's national grid, defined as kg CO2e emitted per kWh electricity consumed, we estimate that the PEC program was responsible for about 400 additional ktCO2e between January 2015 and November 2021 from extra household electricity consumption. Over the same time frame, however, reduced LPG sales led to 2,070 ktCO2e averted (Fig. 3*E*). Net, across the 1 million paired estimates of PEC-associated increased residential electricity consumption and reduced LPG consumption, we estimate a median net reduction of 2,370 ktCO2e (IQR, 1,812 to 3,037) between January 2015 and November 2021—roughly a 7% decline in residential energy emissions (Fig. 3*F*). We observe small net increases of CO2e emissions in 0.2% of model estimates. Alternative approaches led to similar, albeit smaller, estimated declines in CO2e emitted nationwide (*Materials and 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) (*SI Appendix*, Fig. S5 and 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

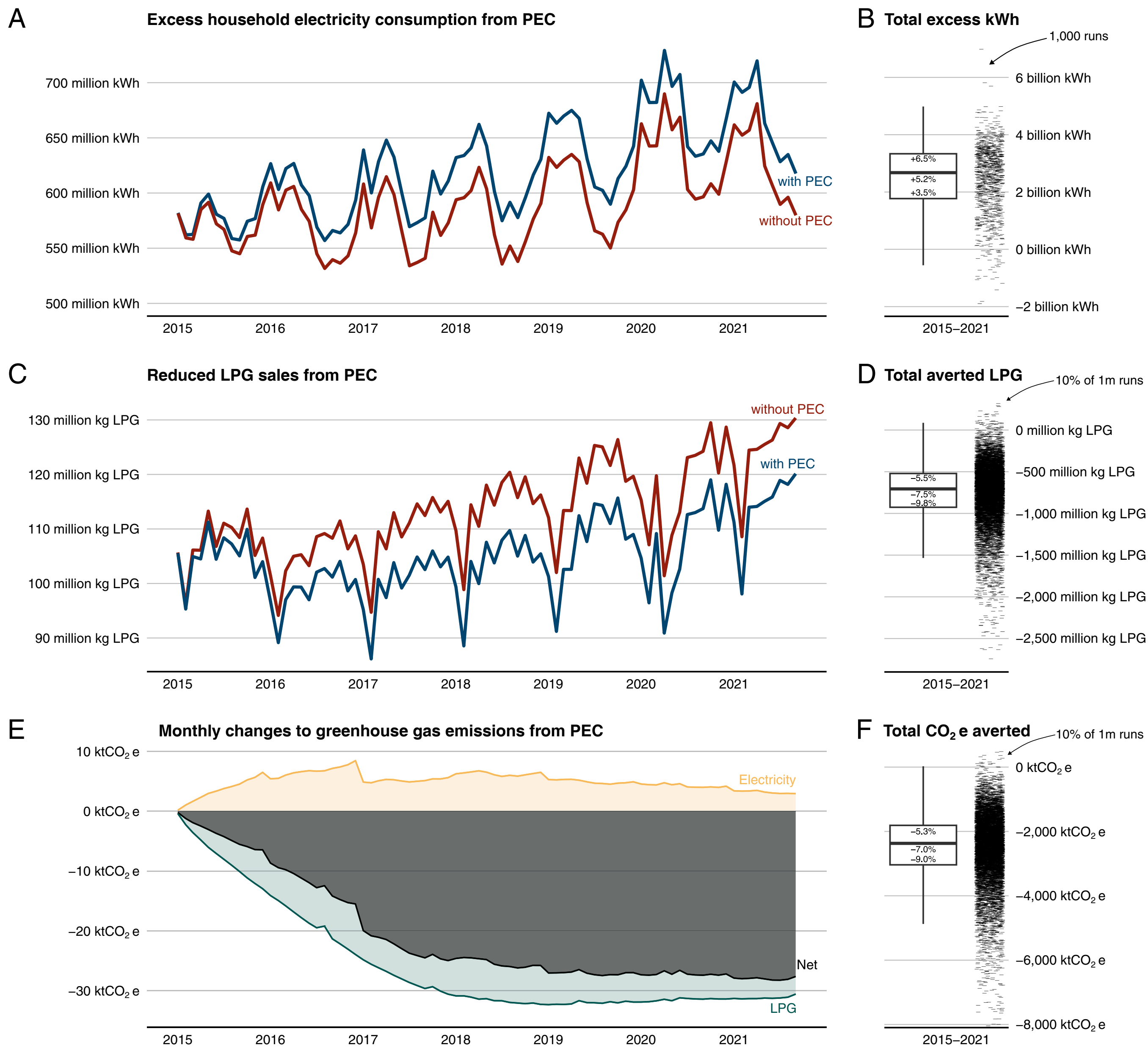

Fig. 3. Excess household electricity consumption, reduced LPG sales, and changes to greenhouse gas emissions attributable to increased induction stove enrollment and use. (*A*) illustrates a counterfactual scenario of household electricity consumption in the absence of PEC enrollment derived from Eq. **3**. 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 1,000,000 bootstrapped runs of the analysis produced from 1,000 estimates of excess PEC-related electricity consumption, each bootstrapped 1,000 times 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 Eq. **6**. (*F*) summarizes 1,000,000 estimates of the total changes to greenhouse gas emissions based on the paired excess kWh and averted LPG sales scenarios.

month-of-sample fixed effects (*Materials and Methods*), with CIs estimated by bootstrapping (1,000 runs, sampling cantons with replacement).

We found that each additional percentage of the customers in a canton enrolled in PEC was associated with a 0.74-percent decline (95% CI, 0.22 to 1.19) in the all-cause hospitalization rate, a 0.74-percent decline (95% CI, 0.11 to 1.38) in respiratory-related hospitalization rates, and 2.11 percent decline (95% CI, 0.64 to 3.37) for chronic obstructive pulmonary disorder (COPD) hospitalization rates (Fig. 4). Estimates for associations with the rate of hospitalizations for influenza and pneumonia and asthma were negative but had wide CIs. We observed no clear associations between PEC enrollment and hospitalizations for other cause-specific outcomes (*SI Appendix*, Fig. 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

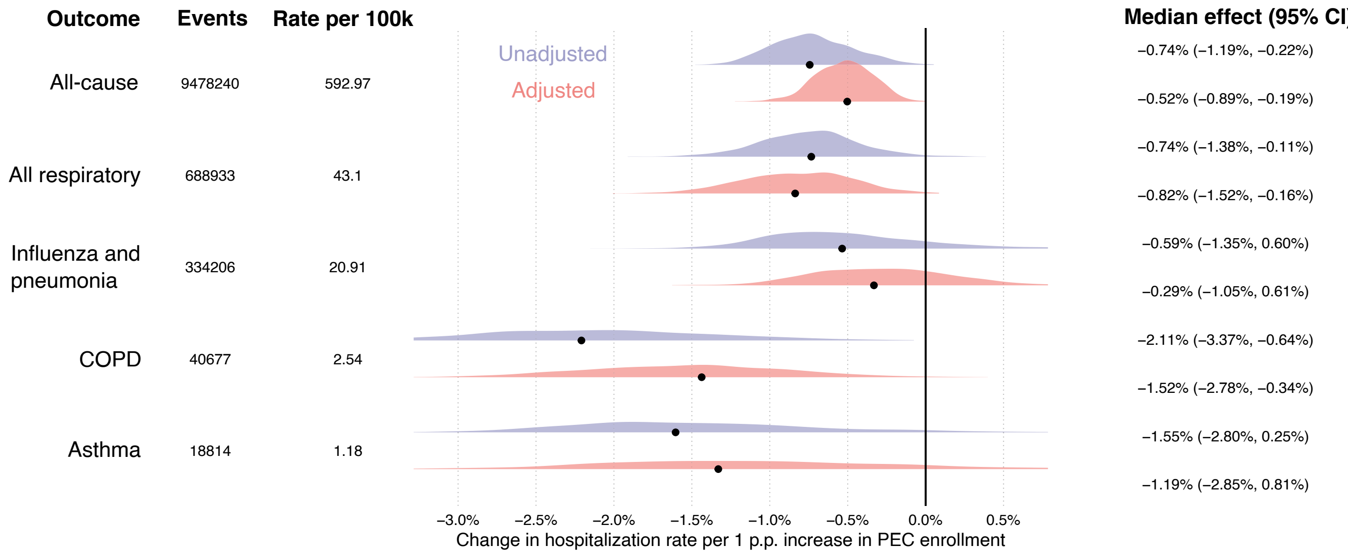

Fig. 4. Change in monthly all-cause and cause-specific respiratory-related hospitalizations associated with increased canton-level PEC enrollment. The response in all-cause, respiratory-related hospitalizations, and cause-specific hospitalization rates are estimated from canton-level linear models and the fraction of electricity customers that are enrolled in PEC in the same month, with fixed effects for canton and month and SEs clustered at the canton level (*Materials and Methods*). Adjusted models control for time-varying canton-level median income per capita, the fraction of individuals who receive money from a poverty alleviation program, per capita nurses and doctors, per capita healthcare facilities, voting patterns, and ambient $PM_{2.5}$ concentrations. Coefficient estimates represent the percent change relative to the national monthly base rate, with 95% CIs shown. N = 21,885 and N = 19,800 canton-month observations in the unadjusted and adjusted main specification, respectively.

three tests (*Materials and 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 (*SI Appendix*, Fig. 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, political targeting (i.e., areas that may have received attention due to political motivations), and ambient air pollution. Adjusting for time-varying canton-level mean per capita income, 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, voting patterns, and mean ambient $PM_{2.5}$ concentration marginally attenuated the observed effects (Fig. 4 and *SI Appendix*, Fig. S7 and Table S9). Third, we implemented a formal approach to bound the potential influence of any remaining unobserved confounders (45, 46) (*Materials and 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 (*SI Appendix*, Fig. 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 note that this test evaluated how much selection would be needed to drive the coefficient estimate to zero, which is distinct from selection needed to render the coefficient no longer statistically significant at a given level; less selection would be required for the latter.

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 (*Materials and 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 (47) eliminates so-called "negative weights" (48) and produces valid estimates of the average treatment effect on the treated (*Materials and 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 (*SI Appendix*, Fig. 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 (*SI Appendix*, Fig. 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 (*Materials and Methods*) (*SI Appendix*, Figs. S11–S17 and 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 (*SI Appendix*, Fig. S18).

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 CIs 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.

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, 49). 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 likely both reduced greenhouse gas emissions and yielded health cobenefits.

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 a set of common energy conversions and assumptions about efficiencies of gas and electric cooking (*Materials and Methods*), we estimate that much of western Europe, central and South America, and parts of sub-Saharan Africa have sufficiently clean grids such that a gas-to-induction cooking transition would be emissions-reducing in terms of cooking energy use (*SI Appendix*, Fig. S19); however, there is likely to be substantial subnational heterogeneity. For example, in the United States, New England, California, Idaho, and Florida have sufficiently clean grids to support a combustion-related emissions-neutral transition; in India, much of north and eastern India, along with Kerala, have sufficiently clean grids. However, the large geographic majority of these two example countries require cleaner grids before a program to electrify cooking would reduce net emissions.

While further growth in renewable energy capacity expected in the near term should make gas-to-induction cooking transitions viable in even more regions, 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 (50, 51). In the past decade, Ecuador has invested more than 1 billion USD 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-v connections and dedicated circuits installed to use induction stoves. Delays in installing these connections have reportedly been a barrier to using induction stoves after purchase (42). 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 (52, 53).

Our study lacked individual and household-level data on health outcomes and cooking appliance use, thus limiting us to an ecological analysis. Additionally, we are limited by a lack of representative longitudinal indoor air quality measurements. Therefore, we can make no inference about the individual household-level impacts of gas-to-induction cooking transitions on health risks. Nevertheless, 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 the 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 (38). Elsewhere, a simulation study estimated that replacing gas stoves would reduce severe asthma attacks by 7% in an urban population (54). 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 (*Materials and Methods*). We urge caution in directly interpreting our effect estimates as they have wide CIs, 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 and choice of emissions factors. With that said, across a range of specifications, we observe that either the program has been roughly emissions neutral or yielded reductions in GHG emissions. Nevertheless, our effort to propagate uncertainty from the chain of estimations of excess PEC-related kWh electricity consumed to LPG sales offset yielded a range of scenarios, including a small number where CO2e increased due to PEC—though even in these scenarios, we might expect PEC to result in emissions declines moving forward due to the increased role of hydropower in recent years. Our approach to evaluating combustion-related emissions may underestimate the benefits of the electrification program because the emissions associated with the 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 hypothetical 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 2023, 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.

Materials and 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 datasets 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-mo 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:

$$y_{imd} = \beta E_{imd} + \mu_i + \gamma_m + \delta_d + \epsilon_{imd}, \qquad [1]$$

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:

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

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 mo before enrollment to 60 mo 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% CIs are relatively flat) and 2) electricity consumption increases dramatically in the months following PEC enrollment (i.e., point estimates steadily increase, and 95% CIs 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 who 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 (*SI Appendix*, *Data Cleaning Procedures for Customer-Level Billing Records*).

Parish-Level Electricity Consumption and Enrollment in the 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:

$$y_{pcm} = \beta P_{pcm} + \mu_p + \delta_{cm} + \epsilon_{pcm}, \qquad [3]$$

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 SEs 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 of total internal LPG sales, the cost of LPG imports per barrel, and the country's internal sales price. We estimate the extent to which LPG consumption is associated with PEC enrollment in the following regression via OLS:

$$y_{ym} = \beta K_{ym} + \mu_y + \delta_m + \epsilon_{ym}, \qquad [4]$$

where y indexes year and m indexes month of year. The outcome y_{ym} is the total kilograms of LPG sold to residences in Ecuador each month between 2015 and 2020. The independent variable βK_{ym} is the total nationwide predicted kWh attributable to increased PEC enrollment in a given month from Eq. **1**. Given that βK_{ym} itself has uncertainty, in addition to our central estimate, we use the bootstrapped coefficients from Eq. **1** to generate 1,000 scenarios and trade-offs. For each of these 1,000 scenarios, we bootstrap 1,000 times sampling at the month-of-sample level with replacement. Similar to our approach for estimating excess electricity consumption, we then use the resulting 1 million coefficients from this regression to estimate reduced LPG sales from the additional electricity consumed from PEC enrollment.

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 residential 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 fifteen-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 average emissions factor for public electricity generation in Ecuador, calculated by dividing yearly total electricity consumed (kWh) by the CO2e emitted by electricity production (44).

As an illustration of our approach to inferring net CO2e changes from PEC, take our estimate of 24-million-kWh excess electricity consumption in July 2016. In 2016, the emissions factor was 0.195 kg CO2e per kWh produced. Therefore, we calculate that excess electricity consumption from PEC resulted in 4.7 kilotons CO2e in July 2016. At the same time, excess kWh electricity consumption was associated with declines in LPG sales and, we infer, averted LPG combustion. We 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 using the 1 million generated scenarios from Eq. **2**, representing 1,000 estimates of excess kWh from PEC and, for each scenario, 1,000 estimates of averted LPG sales, yielding 1 million estimates of total net changes to greenhouse gas emissions from PEC. While our preferred specification finds a 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.

Our results are additionally sensitive to our choice of grid emissions factors. We could apply a marginal emissions factor that estimates emissions for an additional unit of electricity consumed above the base load, which is commonly used in program evaluations similar to our own. However, there are two reasons we consider this approach to be inferior to our calculated average emissions factor. First, we estimate that PEC increased electricity consumption by roughly 5%, which we consider to be beyond consumption "on the margin." Ecuador's official marginal emission factor quantifies the emissions of electricity generation that are used to meet short-term fluctuations in electricity demand (i.e., it is a short-term marginal emission factor). We thus decide it is not appropriate to apply it to the PEC program since the program is rolled out over the course of multiple years, during which the underlying electricity system undergoes rapid transitions and development. Indeed, new installed capacity in Ecuador since PEC's inception has nearly entirely been hydropower, suggesting that if the program caused the need for expanded capacity, it would have been renewable, with emissions approaching zero. Second, given that Ecuador's marginal emissions factors exceed the average emissions factor by a factor of five to eight, applying the marginal emissions factor to excess electricity consumption results in estimates that electricity consumption from PEC would have to be responsible for roughly 20% of all electricity generation emissions despite comprising only 2 to 3% of total consumption. Nevertheless, applying the marginal emissions factor to PEC-related electricity consumption results in estimated declines in GHG emissions of 330 ktCO2e (IQR, 260-406).

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 *SI Appendix*, Fig. S6. In total, the data cover 9.6 million hospitalizations across 21,319 canton-month observations (216 unique cantons and 99 mo 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. Countrywide, 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:

$$log(y_{cm}) = \beta P_{cm} + \mu_c + \gamma_m + \theta_{cm} + \varepsilon_{cm}, \qquad [5]$$

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. θ_{cm} is a vector of time-varying controls described below. 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 SEs 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 of 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 *SI Appendix*, *PEC Enrollment and Hospitalizations* for more details.

First, we test for parallel trends in health outcomes using preprogram data to assess whether 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 = 0.701; P-Value $\approx$ 1). We see similarly nonsignificant differences in trends for key covariates prior to PEC initiation, as illustrated in *SI Appendix*, Fig. 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), political support (which, through various programs and investment targeting, could drive PEC enrollment and healthcare utilization), and ambient air pollution. As described in *Additional Data Sources*, we define the following variables to cover these domains: the fraction of individuals who benefit from the Bono Desarrollo 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, voting histories, and average ambient $PM_{2.5}$ concentrations. Our preferred adjusted model includes a set of potential confounders that are only weakly correlated with one another (*SI Appendix*, Fig. S3): % BDH, % extreme poverty, healthcare facilities per capita, doctors and nurses per capita, canton-level voting histories for the party that initially developed and promoted PEC (President Rafael Correa and associated subsequent candidates), and average ambient $PM_{2.5}$ concentration. Effect sizes did not meaningfully change across all 130,000 potential confounding variable combinations (*SI Appendix*, Fig. S15).

Third, we formally bounded the potential influence of unobserved variables. Drawing on the work of Cinelli and Hazlett (45) and Oster (46), 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 package "sensemakr" to implement this test.

Difference-in-differences approach. While our approach illustrated in Eq. **5** is typical of studies examining time-varying exposures and outcomes in the 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. 47 and 48). Critically, some units may be weighted, including receiving negative weight, such that the recovered estimate is significantly different from the true causal effect (48). To address this threat to inference, we implement the difference-in-difference estimator of Callaway and Sant'Anna (47), 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). Preperiod estimates and CIs 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 differ somewhat in levels across our potential confounders, their pre-treatment trends are similar to low-enrollment cantons.

Uncertainty and robustness of results to alternative approaches. To quantify uncertainty in our results, we bootstrapped Eq. **5** 1,000 times, sampling cantons with replacement. Fig. 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 (*SI Appendix*, Fig. S7). 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) (*SI Appendix*, Fig. 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 (*SI Appendix*, Fig. S15). To account for potential correlations among spatially or politically proximate cantons, we implement a block bootstrapping approach where we sample entire province-years with replacement, which yields similar results, albeit with slightly wider CIs (*SI Appendix*, Fig. S16). 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 (*SI Appendix*, Fig. 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) (*SI Appendix*, Fig. S14). Results are robust to aggregating data to 2-mo periods, which substantially decreases canton-months with low numbers of hospitalizations in cause-specific analyses (*SI Appendix*, Fig. S17) and, similarly, to aggregating data to the province level (*SI Appendix*, 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:

$$CO2e_{net} = \gamma * MEF - \delta * \mu, \qquad [6]$$

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 and 90%) and gas cooking efficiency (between 35 and 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 (*SI Appendix*). 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 *SI Appendix*, 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 United States (55) and India (56) (shown in *SI Appendix*, Tables S12 and 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 United States 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. 57) and the National Family Health Survey - 5 (58), 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 socioeconomic 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 to reduce these subsidies have positioned cooking fuels as an inherently political topic in Ecuador (43). 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.

Ambient air pollution. We acquired publicly available monthly ambient $PM_{2.5}$ concentrations at a $0.1^o \times 0.1^o$ spatial resolution derived from satellite-retrieved aerosol optical depth, chemical transport modeling, and ground-based measurements for South America available since 1998 from ref. 59. We averaged ambient pollution concentrations across canton polygons to estimate canton-month average ambient $PM_{2.5}$ concentrations over the study period, which was then used as a control in our analysis of the association between PEC scale-up and hospitalization rates.

Data, Materials, and Software Availability. Anonymized data (data frames) have been deposited at https://github.com/echolab-stanford/ecuador-climate-health-induction. Customer-level electricity billing records are not made available from the authors due to data use agreements made with the utilities. Parties interested in these data may contact Patricia Recalde at the Ministerio de Energia y Minas for further information (patricia.recalde@energiayminas.gob.ec).

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