Urban Sprawl and Residential Carbon Emissions: Evidence from Indonesia and the Philippines*

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Abstract

This paper uses detailed data from cities in Indonesia and the Philippines to study how variation in density within urban areas affects residential carbon emissions. To address simultaneity, we instrument density with soil characteristics, and to address sorting, we control for community averages of observed characteristics. Unlike cities in developed countries, we find that density is positively correlated with residential energy use. After controlling for sorting, we find that increasing density does not reduce residential carbon emissions. Our results suggest that policies to control urban sprawl may not be successful in reducing residential carbon emissions in developing country cities.

JEL Classifications: R11, O13, O18, Q41, L94, Q54

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> But as India and China get richer, their people will face a choice that could dramatically affect all our lives. Will they follow America and move towards car-based exurbs or stick with denser urban settings that are far more environmentally friendly? ... Driving and urbanization patterns in these countries may well be the most important environmental issues of the twenty-first century.
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> — Glaeser (2011)

1 Introduction

Over the next 30 years, much of the world's growth in energy demand is expected to come from developing countries. According to the EIA (2019), energy consumption in non-OECD countries is expected to increase by nearly 70 percent from 2020-2050, in contrast to an expected increase of 15 percent in OECD countries over the same period. Some of the rise in energy demand will be due to poverty reduction. As the world's poor grow increasingly affluent, they invest in durable household appliances and motor vehicles, and these extensive margin purchases could sustain increased energy consumption for decades (Wolfram et al., 2012; Gertler et al., 2016).

The same rising incomes that are fueling energy demand in the developing world are also increasing urban sprawl. Globally on average, cities are expanding spatially twice as fast as their population growth rates (Angel et al., 2011). Fueled by motorization, rapidly sprawling developing country cities raise concerns that low-density development may further exacerbate residential carbon emissions.

As cities sprawl, they can enable higher income commuters to escape from the massive density levels and crowding experienced in inner cities (Henderson and Turner, 2020). When more affluent households sort into the suburbs, they purchase larger homes that need to be cooled in hot tropical weather, and they need to commute further away to their jobs, often using private modes of transportation instead of public transit alternatives. As a consequence, these newly constructed, large homes in the suburbs could be particularly harmful for the environment. If rapid sprawl is associated with rising carbon intensity, policies to regulate the spatial extent of cities could be justified as ways to mitigate negative environmental externalities. Such policies could include growth controls, binding limits on new construction, or open space dedications (Cunningham, 2007; Glaeser and Ward, 2009; Brueckner and Sridhar, 2012).

At the same time, income sorting patterns vary greatly across cities throughout the world (Brueckner et al., 1999). Many central cities in developing countries are home to higher income households, while slums and lower income housing lie on the outskirts of those cities (Deffebach et al., 2025). The relative locations of the rich and the poor within cities are driven by the income elasticity of housing demand, the income elasticity of commuting expenditures, and differences in amenities, and as these factors differ across cities, they may alter the relationship between density and carbon emissions.

In this paper, we investigate how urban form shapes residential carbon emissions, using the experiences of rapidly sprawling cities in Indonesia and the Philippines as a case study. Indonesia and the Philippines are both lower-middle income countries that have experienced rapid industrialization. Because both countries have electricity grids that rely heavily on coal, they have some of the most emissions-intensive electricity sectors in the world (IEA, 2022a). Residential energy demand and transportation also comprise large shares of total energy use in both countries. To quantify the extent of residential carbon emissions across households, we use detailed cross-sectional data on households from various waves of both Indonesia's National Socioeconomic Survey (*Survei Sosial Ekonomi Nasional*, or *Susenas*) and the Family Income and Expenditure Survey (FIES) in the Philippines.

Our primary objective is to estimate how within cities, a community's population density affects residential carbon emissions. We want to understand how an average household's emissions would change if that household moved from a dense neighborhood in the center of the city to a low density suburb of the same city. To estimate the causal place effect of density on residential carbon emissions, we confront two fundamental identification challenges. First, omitted, place-specific variables may drive correlations between both density and carbon emissions, creating simultaneity problems. For example, favourable natural amenities may facilitate the construction of power lines and also attract more people.

Prior research has confronted the simultaneity problem by instrumenting for population density using geologic instruments (e.g Black et al., 2002; Rosenthal and Strange, 2008; Combes et al., 2010). We follow a similar approach here, instrumenting density within urban areas using soil characteristics and depth to bedrock. Soil characteristics were determined millions of years ago, and favorable soils lead to the formation of denser settlements historically because they facilitated greater agricultural productivity. We document that these initial advantages within cities persist even today, despite the fact that most workers in cities do not depend on agricultural production for income. We measure soil characteristics and depth to bedrock using data from SoilGrids, a global dataset providing high-resolution measures of many soil properties (Hengl et al., 2017).

Because we work with a large vector of candidate instruments, many of which may be weak on their own, we use post-double-selection lasso techniques to select instruments, following Belloni et al. (2012). This approach obtains the efficiency gains from optimal instruments while reducing problems associated with many instruments. A key concern with our IV strategy is that even within urban areas, soil characteristics could affect residential carbon emissions through channels other than density. We undertake several robustness checks to provide evidence in favor of the exclusion restriction.

After addressing simultaneity, there is still a second identification problem, which is that estimates of the relationship between density and carbon emissions could be confounded with sorting. If higher income individuals sort into denser neighborhoods, as we show that they do in cities in Indonesia and the Philippines, this can bias estimates of the relationship between density and carbon emissions. To tackle sorting, we combine instruments for density with controls for community averages of observed individual characteristics. We include a rich vector controls for observed population and demographic characteristics, computed from census microdata in both countries. Altonji and Mansfield (2018) show that under certain assumptions, these controls for sorting on observables will also control for sorting on unobservables. We follow Civelli et al. (2023) who combine their approach—which obtains partial identification of overall group effects—with instruments, to point-identify the place effects of density in a way that is unconfounded by sorting or simultaneity.

We find that in Indonesia and the Philippines, less dense areas within cities tend to contain households with lower overall total expenditures and households with lower levels of educational attainment. Consequently, when we estimate the relationship between density and different measures of residential energy use, including quantities of consumption expenditures on electricity, liquified petroleum gas (LPG), gas for motor vehicles, and kerosene, we find significant positive associations. These correlations also typically survive simultaneity bias in instrumental variables specifications. However, after we introduce controls for sorting, the positive relationship between density and energy consumption tends to disappear. Our point estimates decline, and we generally cannot detect significant effects of density on residential carbon emissions.

We find similar patterns using data on household asset ownership: households in denser neighborhoods of cities in both countries tend to own refrigerators, air conditioners, and LPG cylinders, but once we control for sorting and address simultaneity, the effects of density on asset ownership disappear. We investigate exactly how the sorting controls we use impact our estimates, and we find that controlling for sorting on economic dimensions, as opposed to ethnic or religious sorting, seems to eliminate significant effects of density on carbon emissions.

Using carbon intensity weights, carefully calculated to reflect differences in electricity grids across countries and cities, we aggregating our coefficient estimates to a single elasticity of carbon emissions with respect to density. We find that increasing density by 1 percent leads to a reduction of carbon emissions by -0.005 percent in Indonesian cities and an increase in emissions by 0.004 percent in Philippines cities. Both null results are precise and statistically indistinguishable from zero. We also find that this precise null density elasticity of residential carbon emissions is remarkably stable over time.

Because of concerns surrounding the exclusion restriction, we conduct a number of identification checks, including dropping agricultural households and controlling for historical measures of infrastructure. In both cases, our point estimates remain largely unchanged. We also investigate the effect of soil characterstics in rural areas where they do not predict density, and we find little evidence for any reduced form effects of the soil characteristics on residential carbon emissions outcomes (Altonji et al., 2005; van Kippersluis and Rietveld, 2018). We take the weight of this evidence as favoring the exclusion restriction.

From 2000-2010, carbon emissions increased by 63 percent in Indonesia, and from 2010-2018, emissions increased by 71 percent in the Philippines (Friedlingstein et al., 2024). Given our lack of significant density effects, we attempt to explain drivers of these large increases in emissions. To do so, we use a growth decomposition, which combines our estimated parameters with census data on the average characteristics of households in different communities. We find that apart from a few cities, such as Jakarta, population growth is generally not responsible for large emissions increases by city. Instead, changes in the mapping between household characteristics and emissions play a more prominent role in Indonesia, while changes in characteristics themselves play a larger role in cities in the Philippines. Overall, changes in density that owe to increases in urban sprawl explain only 1.1-1.8 percent of the changes in overall emissions for large cities in Indonesia and the Philippines.

In seminal work, Glaeser and Kahn (2010) and Zheng et al. (2011) study the relationship between city location choices and residential carbon emissions, but they tend not to focus on the impact of neighborhood choice within cities. de Thé et al. (2021) use data from French cities to study how urban forms affect car usage and emissions. They find a bell-shaped relationsihp between city size and car emissions, so that smaller and larger cities tend to be greener than medium-sized cities. Borck and Schrauth (2021) use panel data from German cities and find that air quality decreases with population density, while Carozzi and Roth (2023) use U.S. data to study the effect of urban density on air pollution. Our work complements this literature by extending the focus to a rapidly sprawling developing country setting, and to emphasizing the role of income sorting in mediating the findings.

In a related paper, Lyubich (2025) studies spatial heterogeneity in carbon emissions across census tracts in the U.S. and finds a large role for place effects. Her work uses a movers design to separate place effects from cross-sectional sorting, while we work with cross-sectional data, an instrumental variables design, and a control function approach to address sorting. Our paper identifies a component of overall place effects—namely the effect of neighborhood density—and while we find that this particular place effect is small, other components of place may be more important drivers of spatial heterogeneity.

The rest of this paper is organized as follows. Section 2 presents background information on economic development, urbanization, and residential carbon emissions in Indonesian cities. Section 3 describes the different datasets we analyze. Section 4 describes our empirical strategy, and Section 5 presents our results. Section 6 presents the results from a decomposition exercise to understand what factors are responsible for driving the growth in residential carbon emissions in Indonesia. Section 7 concludes.

2 Background: Growth, Urbanization, and Residential Emissions

After World War II, the Philippines was one of the wealthiest countries in East and Southeast Asia. In 1960, its real GDP per capita of $1,123.78 (in constant 2015 USD) was similar to South Korea's (Lucas Jr, 1993; Boquet, 2017). At that time, Indonesia had a much lower standard of living, with a real per capita GDP of $597.73, just over half that of the Philippines. However, from 1960-2010, Indonesia's GDP per capita grew by an average of 6.9 percent per year, while the Philippines grew by only 2.2 percent per year. Hence, Indonesia is now roughly 12.5 percent wealthier than the Philippines in GDP per capita terms.

From 1960-2010, Indonesia experienced rapid economic growth, and its structural transformation was accompanied by rapid urbanization and substantial rural to urban migration. Today, 151 million people, or roughly 56 percent of Indonesia's population, live in urban areas (Roberts et al., 2019). In 1975, commensurate with its relatively higher level of development, the Philippines was more urbanized than Indonesia, and 67 percent of Filipinos lived in urban areas. By 2020, 95.3 million people—or 85 percent of the population—lived in cities in the Phillipines (Santillan and Heipke, 2024).

As populations moved to urban areas in both countries, the share of built up surfaces also grew substantially. In 1975, only 0.28 percent of the Philippines' land area consisted of built up surfaces, but this share increased to 0.80 percent in 2020, more than doubling (Santillan and Heipke, 2024). In 1990, 0.46 percent of Indonesia's land area consisted of built-up surfaces, but by 2014, this figure had nearly doubled to 0.75 percent (Civelli et al., 2023). The faster rates of built up area expansion, relative to urban population growth, are suggestive of high rates of urban sprawl in both countries (Angel et al., 2005).

Although different rates of sprawl can be explained by variation in demographic, geographic, and economic characteristics (Burchfield et al., 2006), national policies in both countries also played an important role. The Philippines lacks a comprehensive national land use law, and this facilitates the conversion of agricultural land on the urban fringe into residential land. While the Philippines removed the majority of its gasoline subsidies in the late 1990s, Indonesia has maintained its fuel subsidies, favoring motorization. Policymakers in both countries have also seldom enacted land use regulations to curb sprawl, such as open space dedications, limits on new construction, or environmental regulations (Rukmana, 2015).

Emissions and Electrification. Indonesia is now the world's twelth-largest consumer of energy (IEA, 2022b). In 2022, Indonesia's energy sector was responsible for contributing 1.9 percent of global carbon emissions, and Indonesia was the largest emitter in the ASEAN region at 651.7 metric tons of CO_2 equivalents (IEA, 2022a).[1] The Philippines only contributed 0.4 percent of global carbon emissions in 2022. However, as the country grew wealthier over the past two decades, CO_2 emissions per capita increased by 40 percent from 2000-2022. Together, residential energy and transportation constitute a large share of total energy use in both countries (50.8 percent in Indonesia and 63.3 percent in the Philippines). The especially large share in the Philippines is partly due to its sizeable share of employment in the service sector (Boquet, 2017).

As the economies of Indonesia and the Philippines both expanded, so too have the growth of their electricity networks. Most of Indonesia's electricity is provided by *Perusahaan Listrik Negara* (PLN), the state electricity company. According to data from Indonesia's Village Potential Survey (or *Podes*), in 1983, only 21.7 percent of Indonesia's population had access to electricity provided by PLN. By 2011, 78.8 percent of households had access to electricity from PLN. In 1993, 65.4 percent of Filipino households had access to electricity, but this share rose to 98 percent by 2023, according to World Bank Data. However, electricity prices are relatively high in the Philippines, potentially dampening demand despite widespread access (Ravago et al., 2019).

Because of their heavy reliance on coal to produce power, Indonesia and the Philippines also have some of the most emissions-intensive electricity sectors in the world. According to CTR (2020), in 2020, Indonesia's electricity grid produced 804 grams of CO_2 per kWh, while the Philippines produced 691 grams of CO_2 per kWh. This compares to 556 g CO_2/kWh in China, 684 g CO_2/kWh in India, and 383 g CO_2/kWh in the United States. Only 12 percent of Indonesia's electricity came from renewable sources, while 23 percent came from renewables in the Philippines.

Residential Energy Use. Indonesia's tremendous economic growth was accompanied by rising rates of vehicle ownership and growing expenditures on gasoline. Using data from various waves of Indonesia's Transportation Statistics (*Statistik Transportasi*), published by the Central Bureau of Statistics (*Badan Pusat Statistik*, or BPS), Appendix Figure A.1 plots the number of registered vehicles in Indonesia over time.[2] In 1982, there were only 5.3 million registered vehicles in Indonesia, or roughly 1 vehicle for every 29 people. By 2015, there were over 121 million registered vehicles in Indonesia (roughly 1 vehicle for every 2 people). Motorization is somewhat lower in the Philippines; according to the Department of Transportation, there were only 14.6 million vehicles registered in 2024 (roughly 1 vehicle for every 8 people). Note that in the U.S., there was roughly 1 vehicle for every 1.2 people in 2020, so as development in both countries continues, rates of vehicle ownership could grow even further.

Cooking fuel is another important source of residential emissions. Although kerosene has historically been important for Indonesian households, in 2007, the nation began a large-scale conversion program designed to help households transition to liquid petroleum gas (LPG) (Thoday et al., 2018). At the

[1] The Association of Southeast Asian Nations (ASEAN) includes Brunei Darussalam, Burma, Cambodia, Indonesia, Laos, Malaysia, the Philippines, Singapore, Thailand, and Vietnam.

[2] The data compiled by BPS are based on vehicle registrations that come from Indonesia's State Police (*Kepolisian Republik Indonesia*). They include all kinds of motor vehicles except those belong to the Indonesian Army Force, the Indonesian State Police and the Diplomatic Corps.

time, increased subsidies for kerosene were straining government finances, and promoting LPG would be more environmentally friendly (Dwi Cahyani et al., 2020). Between 2000 and 2016, the number of Indonesians using LPG increased by 4 fold and reached 100 million urban residents (IEA, 2017). Per-capita usage of LPG increased from 4.7 kg in 2007 to 24.4 kg in 2015 (Thoday et al., 2018). By 2021, almost 85 percent of households used LPG as their primary cooking fuel (BPS, 2022).

In the Philippines, the fuel mix is somewhat different. According to the 2018 Family Income and Expenditure Survey (FIES), urban households' consumption of LPG constituted 20 percent of their total energy demand, electricity constituted 63 percent, and kerosene constituted 1 percent. Firewood and charcoal constituted 15 percent, but this share has declined substantially over time as LPG penetration has increased.

Sprawl and Income Sorting. In many U.S. cities, higher income households sort into suburban areas, while lower income households remain in the center. However, the relationship between income and distance to the city center is very different in other countries (e.g. Brueckner et al., 1999; Glaeser et al., 2008; Gaigné et al., 2022; Deffebach et al., 2025). Figure 2 plots the relationship between a community's distance to the central business district (CBD) and several community-level variables. Panels A-C focus on Indonesia, using 2010 Census data and *Susenas* data, while Panels D-F focus on the Philippines, using data from the 2020 Census. In Indonesia, our definition of a community is a *desa*, while in the Philippines, it is a *barangay*. Both communities constitute the smallest level of local government in both countries, and within cities appropriately represent neighborhoods.

This figure only uses data from our sample of metropolitan areas (described in more detail below). Estimated local polynomial regression lines are plotted in blue, along with 95% confidence bands in gray. Panel A shows that in Indonesian cities, population density declines rapidly as distance to the CBD increases.[3] Panel B uses *Susenas* data to show that households with higher total expenditures tend to locate closer to city centers, although this relationship is not very strong. Another indicator of affluence is secondary school completion, and Panel C shows that households with more highly educated individuals also tend to cluster in city centers.

In the Philippines, the sorting patterns are somewhat different. Panel D shows that density peaks at around 10 km from the distance to the CBD, perhaps suggestive of higher levels of commercial real estate in city centers. High school completion rates are higher in the Philippines than Indonesia (72.6 percent vs 57.5 percent in Indonesia), and the variation across distance to the CBD is somewhat muted (Panel E). But Panel F shows that head of household college completion rates decline substantially with distance to the CBD, suggesting that wealthier households tend to cluster in the center of Filipino cities.

Based on Figure 2, we might expect households living in denser areas in both Indonesian and Filipino cities would produce more residential emissions. Our empirical approach, described in more detail below, aims to identify the place effects of neighborhood density on residential carbon emissions, disentangling them from the effects of income and taste-based sorting.

[3] Panel A reproduces Figure 4 from Civelli et al. (2023).

3 Data

Delineating Urban Areas. We use nighttime lights satellite imagery to demarcate the spatial extent of urban areas in Indonesia and the Philippines, following Jiang (2021). The U.S. Air Force's Defense Meteorological Satellite Program (DMSP) collected data from Operational Linescan System (OLS) sensors to measure the intensity of Earth-based light from 1992-2013. Raw DMSP-OLS data were aggregated to an annual panel at a 30 arc second resolution from 1992-2013. In 2013, the DMSP-OLS data were replaced by a different set of sensors, known as the Visible and Infrared Imager/Radiometer Suite (VIIRS). VIIRS data are available at a higher resolution, with each pixel equal to about 0.22 km2 at the equator. VIIRS data are also not top-coded, unlike the DMSP-OLS data.

We first deblur and merge these data, following Abrahams et al. (2018). Then, we delineate human settlements based on a luminosity threshold equal to zero, which means that pixels with positive luminosity are all considered human settlements. We then aggregate clusters of luminous pixels, allowing for small gaps between them (1 km for DMSP-OLS data and 0.5 km for VIIRS data), into a single polygon. Many polygons are quite small and discrete, so we cross-reference them with place-names from the Global Rural Urban Mapping Project (GRUMP), focusing on urban settlements containing a population of more than 100,000 in 2000. These polygons constitute our set of urban areas.

Figure 1 presents a map of the locations of these cities and their defined urban spatial extents. Panel A shows that in Indonesia, half of the 91 cities identified are located on Java and Bali, roughly a quarter are on the island of Sumatra, and the remainder are located in the remaining Outer Islands.[4] The largest metropolitan area is Greater Jakarta (*Jabodetabekpunjur*), the economic and political center of Indonesia, which is a megacity with over 30 million people in 2010. Three other cities have more than 2 million inhabitants—these are Bandung, Surabaya, and Medan—while others have between 100,000 and 2 million people. Panel B shows the locations of the 42 cities in our sample from the Philippines.[5] The Greater Manila Area is far and away the largest city, with a population of over 24 million in 2016. Three other cities have populations above 1 million (Cebu, Angeles, and Davao).

Measures of Residential Carbon Intensity. We construct measures of residential carbon emissions from the consumption modules of various waves of Indonesia's National Socioeconomic Survey (*Survei Sosial Ekonomi Nasional*, or *Susenas*). The consumption data in the *Susenas* were matched on household identifiers and to individual-level data from the *Susenas* core survey.[6] Our primary analysis uses three waves of *Susenas* data (2010, 2011, and 2012), which we pool together into a single 2010 epoch.[7]

We derive similar measures for the Philippines using the Family Income and Expenditure Survey (FIES). The Philippine Statistics Authority (PSA) fields this survey every 3 years to provide information on citizens' socio-economic status and expenditure patterns. For Filipino cities, we predominantly work with data from the 2018 FIES. A sample of 170,917 households was interviewed in the FIES 2018 round for this survey, a substantially larger sample size than previous surveys (PSA, 2018).

[4] Appendix Table A.1 summarizes the cities in our sample from Indonesia.

[5] Appendix Table A.2 summarizes the Philippines cities in our sample.

[6] Note that in household-level regressions, we sometimes use individual-level data for the head of household to construct covariates like age, sex, education level and employment status.

[7] Surbakti and Statistik (1995) provides an overview for the design of the *Susenas* survey. Historically, consumption modules were only included every 3 years, but beginning in 2005, consumption modules were included every year.

The key variables used to measure residential carbon emissions, which are available in both countries across all waves of data, include consumption quantities and total expenditures on the following items: (1) electricity; (2) kerosene; (3) liquefied petroleum gas (LPG); and (4) vehicle gas. Our primary specifications use total quantities of consumption of different energy sources as dependent variables. While total expenditures are very often reported, quantities are sometimes missing in the Indonesia data (less than 3 percent of observations).[8] To account for this, we impute missing quantities by first estimating unit values (i.e. expenditures / quantities) for each item separately at the city-survey year level. We then impute missing quantities by dividing reported expenditures by the average unit values we recover. In our results below, we explore the sensitivity of our findings to the use of imputed quantity data.[9]

Table 1 presents summary statistics for monthly energy consumption variables across households in our urban sample, in the 2010 epoch for Indonesia and in 2018 for the Philippines. Filipino households in 2018 consumed nearly twice as much electricity as Indonesian households in 2010, but they also consumed relatively lower amounts of LPG, vehicle gas, and kerosene. The final row shows estimates of residential carbon emissions that are implied by these expenditure quantities. To obtain these estimates, we multiply each category's monthly fuel consumption by carbon emissions factors (reported in Appendix Table A.3). Different factors are used for households that source their electricity from different types of power plants.[10]

Both surveys asked questions about monthly energy consumption. Ignoring seasonal differences in energy consumption, we find that urban households produced an average of 0.924 tons of CO_2 per year in Indonesia and 0.972 tons of CO_2 in the Philippines. According to Goldstein et al. (2020), the average household in the U.S. produces 2.83 tons of CO_2 per year from residential emissions sources. Based on this, in 2010, Indonesian households produced about 33 percent of residential emissions of U.S. households, while Philippines households in 2018 produced about 34 percent of the emissions of U.S. households.

Community-Level Demographic Characteristics. We construct community-level demographic characteristics using Census data. For Indonesia, we merge *desa / kelurahan*-level aggregates from the 2010 Census to our pooled *Susenas* sample. For the Philippines, we work with *barangay*-level aggregates from the 2020 Census.[11] These census data allow us to construct multiple measures, including population density at the community level, the share of community members with different levels of educational attainment, the share belonging to different ethnic groups, and the share that is married or migrated from another district. As we describe below, community averages of individual-level characteristics, which we calculate with these data, are crucial for our empirical strategy.

Geospatial Data on Administrative Boundaries and Topography. Our analysis relies on adminis-

[8]For all items, we interpret any observations with zero expenditures and missing quantities as zeroes. For kerosene, LPG, and vehicle gas consumption, we interpret observations that are missing both quantities and expenditures as zeros. We also drop households that have zero consumption across all categories of energy expenditures and quantities.

[9]For the 2010 epoch in Indonesia, we imputed: (1) 2.4 percent of missing electricity quantities; (2) 1.1 percent of missing LPG quantities; (3) 2.7 percent of missing vehicle gas quantities; and (4) essentially 0 percent (2/119485) of missing kerosene quantities.

[10]We use government data from both countries on the locations of different types of power plants, and we match households to their nearest power plants to obtain the appropriate emissions factor for their electricity consumption.

[11]The community, or *desa / kelurahan*, is the 4th level administrative unit in Indonesia, below the province, district, and subdistrict. The *barangay*—historically referred to as the *barrio*—is the smallest administrative division in the Philippines.

trative boundary shapefiles that identify community borders. These datasets are created by Indonesia's national statistical agency, *Badan Pusat Statistik* (BPS), and the Philippine Statistics Authority (PSA). We use these boundaries in combination with data from the Harmonized World Soil Database (HWSD) to construct basic topographic characteristics (e.g., ruggedness, slope, and elevation).

Soil Characteristics and Depth to Bedrock. We use data from SoilGrids to measure the characteristics of soils in urban communities of Indonesia and the Philippines. Hengl et al. (2017) train machine learning algorithms to predict soil attributes on hand-collected soil profiles from roughly 150,000 sites. This produces a global dataset—at a 250-meter resolution—of several soil properties, including: (1) bulk density; (2) water content; (3) sand content; (4) clay content; (5) texture classification; and (6) soil taxonomy information. Absolute depth to bedrock (in cm), which is also predicted using the global compilation of soil ground observations, is also available from SoilGrids.[12]

Although SoilGrids also provides measures of organic carbon content and soil pH, we did not use these measures as instruments because they can be directly manipulated by human activity. We also only use soil characteristics measured at a depth of 60 cm or more, as these reflect variation in the subsoils and parent material of soils which were determined millions of years ago.

4 Empirical Strategy

The goal of this paper is to estimate how population density affects residential carbon emissions within cities. Our thought experiment is to imagine that an average household—with fixed demographic and employment characterstics—moves from a low density area in the suburbs to a higher density area in the center of the same city. How would that household's residential emissions change?

This section explains our approach for addressing the two key identification challenges that confound estimates of the relationship between a community's population density and household residential carbon emissions: (1) sorting of households with different income levels or different tastes for carbon intensity; and (2) place-specific unobservables that may simultaneously determine density and residential energy use. Altonji and Mansfield (2018) show that in a certain class of sorting models, adding controls for sorting on observables can help to bound the variance of overall community-level treatment effects when households sort into communities. Following Civelli et al. (2023), we combine these sorting controls with instruments to point identify the effect of density on residential carbon emissions. We first sketch the sorting model, and we provide key features of the sorting controls and instrumental variables procedure below.[13]

4.1 Sorting into Communities

Let i index households and let $v \in \{1, ..., V\} \equiv \mathcal{S}$ index a discrete set of communities that comprise different cities. The set $\mathcal{S}$ includes both suburban and central neighborhoods that constitute all cities throughout a country.[14] We assume that household i's consumer surplus from living in community v is

[12]SoilGrids data are publicly available and can be processed using Google Earth Engine and ISRIC Data Hub.
[13]Many details on this empirical strategy—used for a different research question—can also be found in Civelli et al. (2023).
[14]We estimate the effects of community-level population density on residential carbon emissions separately in both countries, so we do not allow households to migrate across countries in the model.

given by the following:

$$U_i\left(v\right) = \mathbf{W}_i \mathbf{A}_v - P_v + \varepsilon_{iv}\,, \tag{1}$$

where $\mathbf{A}_v$ represents a $(K \times 1)$ vector of amenities in community v, P_v measures the cost of living in community v, and ε_{iv} is an idiosyncratic preference term. The $(1 \times K)$ vector $\mathbf{W}_i$ captures preference weights that measure household i's willingness to pay for different components of the amenity vector. While $\mathbf{A}_v$ may contain exogenous amenities, such as a community's natural features, it may also include endogenous amenities, like density, school quality, or congestion, which are determined in equilibrium through the sorting process.

Following Altonji and Mansfield (2018), we partition $\mathbf{W}_i$ into three additively separable components:

$$\mathbf{W}_i = \mathbf{X}_i \boldsymbol{\Theta} + \mathbf{X}_i^U \boldsymbol{\Theta}^U + \mathbf{Q}_i \boldsymbol{\Theta}^Q\,. \tag{2}$$

This partition includes the following terms: (1) $\mathbf{X}_i$, a vector of household-level observables that may influence tastes for amenities and also impact residential carbon emissions; (2) $\mathbf{X}_i^U$, a vector of household-level unobservables that shape tastes for amenities and carbon emissions; and (3) $\mathbf{Q}_i$, a vector of variables (both observed and unobserved) that may influence preferences over amenities—and therefore impact sorting—but have no impact on residential energy usage. In equation (2), the vectors $\boldsymbol{\Theta}$, $\boldsymbol{\Theta}^U$, and $\boldsymbol{\Theta}^Q$ measure each component's respective willingness to pay coefficients.

Note that the partition in equation 2 defines $\mathbf{X}_i$, $\mathbf{X}_i^U$, and $\mathbf{Q}_i$ so that they represent the complete set of household-level factors that determine sorting and residential carbon emissions. This formulation is fairly general and allows for arbitrary correlations between household characteristics—both observable and unobservable—and tastes for amenities. The major caveat is that indirect utility function, equation (1), is additively separable.

When making location decisions, we assume that households take prices, P_v, and amenities, $\mathbf{A}_v$, as given. We also assume that households choose the community that maximizes (1) using all information available to them. This information set includes housing prices in different communities of different cities, the vectors of amenities in those locations, their full set of preference weights, $\mathbf{W}_i$, and realizations of their idiosyncratic component, ε_{iv} for all $v \in \{1, ..., V\}$. Because prices and amenities of communties may be endogenous, we assume that agents form expectations about the levels of P_v and $\mathbf{A}_v$ that will prevail in each community before moving. When agents move, they act atomistically, ignoring their impact on prices and endogenous amenities that emerge in equilibrium. Let $v(i)$ denote the optimal community choice for household i.

Altonji and Mansfield (2018) prove that given this setup and under a relatively weak set of additional assumptions, the community-level expectation of household-level unobservables that influence residential carbon emissions, denoted by $\mathbf{X}_v^U \equiv \mathbb{E}[\,\mathbf{X}_i^U \,|\, v(i) = v\,]$, is linearly dependent on community-level average observables, $\mathbf{X}_v \equiv \mathbb{E}[\,\mathbf{X}_i \,|\, v(i) = v\,]$. The intuition behind this result is that sorting creates two vector-valued mappings: (1) a mapping between community-level average observables and amenities, denoted by $\mathbf{X}_v = \mathbf{f}\left(\mathbf{A}_v\right)$; and (2) a mapping between community-level average unobservables in community v and amenities, denoted by $\mathbf{X}_v^U = \mathbf{f}^U\left(\mathbf{A}_v\right)$. The authors provide conditions under which the first mapping, $\mathbf{f}$, is invertible, so we can write: $\mathbf{X}_v^U = \mathbf{f}^U\left(\mathbf{f}^{-1}\left(\mathbf{X}_v\right)\right)$. Under an additional assumption, the relationship between $\mathbf{X}_v^U$ and $\mathbf{X}_v$ induced by composing these vector-valued functions is actually linear.

The strongest of these assumptions is a "spanning" assumption (assumption A5 in Altonji and Mansfield, 2018) which states that in equation (2), the coefficient vectors $\mathbf{\Theta}^U$ that relate tastes for amenities to elements of $\mathbf{X}_i^U$, need to be linear combinations of $\mathbf{\Theta}$, which relate tastes for amenities to both elements of $\mathbf{X}_i$.[15] If $\mathbf{f}$ is invertible, this spanning assumption holds, and a necessary condition for invertibility is that the dimension of $\mathbf{A}^{\mathbf{X}}$, the subset of amenities that affect sorting on observables, is less than the number of elements in $\mathbf{X}_v$. This would occur if $\mathbb{V}(\mathbf{X}_v)$ is rank deficient.

These results suggest that with a sufficiently rich dataset, we can use community-level averages of household-level observable characteristics to effectively control for sorting on both observables and on unobservables. In our empirical implementation, we use a vector of 38 variables constructed from Indonesian census data to measure $\mathbf{X}_v$, and we use a different vector of 38 variables constructed from Philippines census data to measure $\mathbf{X}_v$. These variables include the community's average age, years of schooling, household size, the percentage of the community that is female, the percent who self-identify with different religions or ethnicities, the share of different types of employment status and marital status.[16]

Appendix Table A.4 reports a principal components analysis of the $\mathbf{X}_v$ variables in Indonesia and the Philippines. In our urban *Susenas* sample for Indonesia (column 2), 27 factors explain 95 percent of the total variation in $\mathbf{X}_v$ and 31 factors explain 99 percent of the total variation in $\mathbf{X}_v$. In the urban FIES sample from the Philippines (column 4), 28 factors explain 95 percent of the total variation in $\mathbf{X}_v$, while 33 factors explain 99 percent of the total variation in $\mathbf{X}_v$.

Appendix Table A.5 also formally tests hypotheses about the rank of the $\mathbf{X}_v$ covariance matrix, using a test proposed by Kleibergen and Paap (2006). In the Indonesian urban sample (column 2), we cannot reject the null hypothesis that the rank of the variance-covariance matrix of $\mathbf{X}_v$ is 14 against the alternative that it is 15 or greater (p-value = 0.237). In urban areas of the Philippines (column 4), we cannot reject the null hypothesis that the rank of the variance-covariance matrix of $\mathbf{X}_v$ is 17 against the alternative that it is 18 or greater (p-value = 0.228). Taken together, the results from Appendix Tables A.4 and A.5 suggest that $\mathbf{X}_v$ is rank deficient in both countries. This implies that $\mathbf{f}$ will be invertible, so that $\mathbf{X}_v$ can be used as a linear control function for sorting on unobservables.

4.2 Production of Residential Carbon Emissions

After choosing locations, we assume that an energy consumption outcome for household i living in community v, denoted by y_{vi}, is produced according to the following log-linear, additively separable function:

$$\log y_{vi} = \mathbf{X}_i\beta + x_i^U + \theta \log \text{density}_v + \mathbf{C}_v\mathbf{\Gamma} + c_v^U + \eta_{vi} + \xi_{vi}\,. \tag{3}$$

In our application, $\log y_{vi}$ will denote logs of the total quantity of electricity used per month, or the logs of the total quantity of different types of fuel used per month (e.g. vehicle gasoline, kerosene, or LPG). Equation (3) is composed of three sets of terms: (1) a household-level component; (2) a community-level component; and (3) an idiosyncratic component. We describe each of these components in detail.

[15]Note that from equation (2), $\mathbf{\Theta}$ also measures tastes for elements of $\mathbf{X}_i^U$ that are correlated with $\mathbf{X}_i$.

[16]We discuss the exact variables used to construct $\mathbf{X}_v$ for different countries below in Section 5.

The household component, $\mathbf{X}_i\beta + x_i^U$, includes a row vector, $\mathbf{X}_i$, collecting household i's observed attributes, and the parameter β measures how those attributes affect y_{vi}. The second part consists of a scalar, $x_i^U \equiv \mathbf{X}_i^U\beta^U$, which summarizes the contribution of unobserved household characteristics ($\mathbf{X}_i^U$) to residential carbon emissions outcomes.

The community-level component, $\theta \log \text{density}_v + \mathbf{C}_v\mathbf{\Gamma} + c_v^U$, contains three terms. The first measures log population density at the community level, where density is defined as the population of community v in the survey year divided by the area of that community (in square km). The key object of interest, θ, measures the elasticity of residential carbon emissions outcomes with respect to density. The second component is a row vector, $\mathbf{C}_v$, capturing the influence of other observed community-level characteristics on carbon emissions outcomes. We include urban-area fixed effects in $\mathbf{C}_v$. Finally, the third term, $c_v^U \equiv \mathbf{C}_v^U\mathbf{\Gamma}^U$, represents a scalar that summarizes the contribution of unobserved neighborhood characteristics to y_{vi}.

The idiosyncratic component, $\eta_{vi} + \xi_{vi}$, also contains two terms. The first term, η_{vi}, captures unobserved variation in community-level contributions to carbon intensity among households who live in that community. Some factors correlated with η_{vi} may be captured by observed and unobserved community-level variables. The second term, ξ_{vi}, captures other factors influencing y_{vi} that are determined after the household arrives in community v, but are unpredictable given $\mathbf{X}_i$, x_i^U, log density$_v$, $\mathbf{C}_v$, c_v^U, and η_{vi}. Such factors could include local labor market shocks that increase or decrease residential emissions in the community, or shocks to infrastructure that affect the prevailing levels of emissions in certain areas.

We partition the group-level observables (excluding log density) into $\mathbf{C}_v = [\mathbf{X}_v, \mathbf{C}_{2v}]$, and we partition their coefficients analogously, so that $\mathbf{\Gamma} = [\mathbf{\Gamma}_1, \mathbf{\Gamma}_2]$. The term $\mathbf{X}_v$ includes community averages of household-level observables (our sorting controls), while the term $\mathbf{C}_{2v}$ includes community-level characteristics that are not mechanically related to community composition. In our baseline specifications, these include pre-determined, exogenous natural amenities, such as elevation, ruggedness, and distance to the coast or rivers, which may affect the provision of infrastructure and affect the pricing of different energy sources. This notation lets us we rewrite equation (3) as follows:

$$\log y_{vi} = \mathbf{X}_i\beta + x_i^U + \theta \log \text{density}_v + \mathbf{X}_v\mathbf{\Gamma}_1 + \mathbf{C}_{2v}\mathbf{\Gamma}_2 + c_v^U + \eta_{vi} + \xi_{vi}\,. \tag{4}$$

Note that because of the assumptions described in Section 4.1 above, adding $\mathbf{X}_v$ effectively controls for sorting on both observables and unobservables in the production of residential carbon emissions. A typical control function procedure would use a non-linear or semi-parametric control function, but the spanning assumption (assumption A5 in Altonji and Mansfield, 2018) implies that we just need to include these controls linearly.

4.3 An Instrumental Variables Estimator for θ

Altonji and Mansfield (2018) use $\mathbf{X}_v$ controls to partially identify the contribution of total group treatment effects (e.g., school or neighborhood effects) to outcomes. When estimating this overall group treatment effect, controlling for group averages eliminates the sorting bias, but it may also control for too much, absorbing peer effects that depend on these group-averages. Consequently, they can only obtain a lower bound on the overall importance of school or neighborhood effects in explaining the variance in outcomes.

Civelli et al. (2023) extend their approach by adding instruments for a particular group attribute (namely density) to point-identify the effect of that attribute on outcomes in a way that is unconfounded by sorting. Let $\widetilde{\mathbf{X}}_{iv} \equiv [\mathbf{X}_i, \mathbf{X}_v, \mathbf{C}_{2v}]$ collect the observed variables that do not include log density, and let $\widetilde{\beta} = [\beta, \mathbf{\Gamma}_1, \mathbf{\Gamma}_2]$ collect their parameters. Also let $u_{iv} \equiv x_i^U + c_v^U + \eta_{vi} + \xi_{vi}$ collect all of the unobserved components. Using this notation, we can simplify (4) even further:

$$\log y_{vi} = \theta \log \text{density}_v + \widetilde{\mathbf{X}}_{iv}\widetilde{\beta} + u_{iv} \,.$$

Let $\mathbf{Z}$ denote a vector of instruments for density and let $\widetilde{\mathbf{X}}_{iv}$ act as instruments for themselves. An IV estimator for θ can be written as:

$$\widehat{\theta}_{IV} = \left(\mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \text{density}\right)^{-1} \mathbf{Z}'\mathbf{M}_{\widetilde{\mathbf{X}}} \log \mathbf{y} \,, \tag{5}$$

where $\mathbf{M}_{\widetilde{\mathbf{X}}}$ is an orthogonal projection matrix for $\widetilde{\mathbf{X}}$.[17] Civelli et al. (2023) show that $\widehat{\theta}_{IV}$ is an unbiased estimator of θ if our vector of instruments, $\mathbf{Z}$, satisfies the following moment condition:

$$\mathbb{E}\left[c_v^U \mid \mathbf{Z}, \widetilde{\mathbf{X}}, \log \text{density} \right] = 0 \,. \tag{6}$$

In other words, the vector of instruments needs to be uncorrelated with omitted community-level factors that influence overall residential carbon emissions in the community.

Soil Characteristics as Instruments for Density. We propose that within urban areas, deep soil characteristics satisfy the moment condition in equation (6). To measure soil attributes, we use data from SoilGrids to capture various features of the different soils predominant in urban areas of Indonesia and the Philippines. These include: (1) bulk density; (2) water content; (3) sand content; (4) clay content; (5) texture; and (6) soil taxonomy information. For robustness, we also include depth to bedrock as a possible exogenous shifter of density.

Stable, fertile soils historically attracted greater numbers of people to settle in specific areas, and these soils affected both traditional settlements and also colonial investments, including those by the Dutch in Indonesia (Dell and Olken, 2019). Below, we show that within cities, certain soil characteristics also have a strong first stage relationship with population density today. Similar geologic instruments for density have also been used in prior work (e.g Hoxby, 2000; Black et al., 2002; Rosenthal and Strange, 2008; Combes et al., 2010; Ahlfeldt et al., 2024).

Despite a strong first stage relationship, there are several concerns with using soil features as an instrument for density. One issue is that soil characteristics recorded in cities today may reflect human activity, so our estimates could introduce reverse causality or simultaneity concerns. As discussed in Section 3, we only use soil attributes measured at a depth of 60 cm or more, helping to ensure that they are unaffected by human activity. We also do not consider certain measures that are easily changed by human activity, such as organic carbon content or acidity (pH).

[17]This matrix is given by: $\mathbf{M}_{\widetilde{\mathbf{X}}} = \mathbf{I} - \widetilde{\mathbf{X}}\left(\widetilde{\mathbf{X}}'\widetilde{\mathbf{X}}\right)^{-1}\widetilde{\mathbf{X}}'$.

A second, larger concern is the exclusion restriction, namely that within cities, soil attributes need to only affect energy consumption expenditures today through their effects on density. Even though soil mineralogy and the parent materials of soils were determined millions of years ago, fertile soils may still drive local wealth within cities, particularly if parts of urban areas contain agricultural employment. In the analysis that follows, we take care to examine this and several other potential threats to the exclusion restriction.

Sorting Controls and the Interpretation of θ. We think that θ is a useful object of interest for evaluating how policies that shape the density of a community may impact its residential carbon emissions. For example, policymakers in the U.S. and other developed countries use many tools to directly regulate the level of density that is permitted to emerge in a community. Such policies include: (1) minimum-lot size zoning; (2) binding limits on new construction; (2) open space dedications; (3) growth controls; (4) environmental regulations; (5) septic system regulations; (6) subdivision requirements; and (7) historic preservation (Glaeser and Ward, 2009). These policies alter the levels of density that are allowed to emerge in a community, but they do not directly control who gets to live where. Our estimates capture the extent to which density impacts different components of carbon emissions conditional on the spatial distribution of the population, which is more relevant for evaluating the effects of such policies.

5 Results

First Stage. We begin by using post-double-selection lasso techniques, following Belloni et al. (2012), to predict log density of urban communities in Indonesia and the Philippines using soil characteristics. Table 2 reports parameter estimates from the following regression equation:

$$\text{log density}_{iv} = \alpha_c + \mathbf{z}_v'\beta + \mathbf{X}_i\mathbf{\Theta}_1 + \mathbf{C}_{2v}\mathbf{\Theta}_2 + \varepsilon_{iv}\,, \tag{7}$$

where i indexes households, v indexes communities and c indexes urban areas. The dependent variable, log density$_{iv}$ is the log of the density of the community in which household i resides. The term α_c denotes a city-specific intercept, $\mathbf{z}_v$ denotes the selected vector of soil characteristics, $\mathbf{X}_i$ is a vector of household-level controls, $\mathbf{C}_{2v}$ denotes a vector of additional exogenous community-level characteristics (including ruggedness, elevation, and distance to the nearest coast and river), and ε_{iv} is an error term.

Out of 67 candidate soil characteristics instruments for density, all measured at a depth of 60 cm or more, the post-double-selection lasso procedure selected only 5 instruments for Indonesian cities and 3 instruments for Filipino cities. Table 2 reports their first-stage coefficients. The overall F-statistics for Indonesian cities (77.2 from column 2) and Filipino cities (96.0 from column 4) are large, and the first stages explain 58-67 perent of the variation in density within cities.

Columns 1 and 2 show that within cities in Indonesia and conditional on $\mathbf{C}_{2v}$ controls, population density in 2010 was positively related to the bulk density of soils' parent material. Columns 3 and 4 show similar results for cities in the Philippines, although with a slightly greater depth of bulk density selected (200 cm vs. 60 cm selected in Indonesia). These results are reasonable, given that more compact soils are more favorable for construction.

We also find that in Indonesian cities, sand content of soils' parent material is negatively related to density, while in Philippines cities, water content of soils' parent material is negatively related to density. Although sandy soils may be favourable for construction, they are also difficult for growing crops and likely reduced historical agricultural productivity. Watery soils can also be unstable, making it harder to build residential or commercial floorspace.[18]

In addition, four soil types were also significant predictors of population density. Haplustolls (from the order Mollisols) are grassland soils used for growing grains and feed crops. Chromusterts (Vertisols) are fertile soils that are often used for growing grains. Haplustalfs (Alfisols) are also naturally productive soils with high fertility (USDA, 2015). Each of these soil types are prominent in areas that were initially favorable for rice production and influenced historical settlement patterns, and as expected, these soil characteristics have positive effects on modern density within urban areas. On the other hand, Tropodults (Ultisols) are predominant in tropical forests and may have disuaded historical settlements (USDA, 1975), and the density coefficient for this soil type is negative. In summary, the selected soil characteristics within cities are either associated with attracting historical development through favourable agricultural production or with the ease of constructing buildings.[19]

In columns 2 and 4, we add controls for sorting on observables and unobservables, $\mathbf{X}_v$, to equation (7). The coefficients on the selected soil characteristics retain their signs and statistical significance. Overall, the results from Table 2 suggest that conditional on city fixed effects, the selected soil characteristics have strong first stage relationships with community-level population density, the key dependent variable in our analysis.[20]

Baseline Results. To estimate the impact of density on residential energy consumption expenditures, we run linear instrumental variable regressions of the following form:

$$\log\left(1+y_{vi}\right)=\alpha_c+\mathbf{X}_i\beta+\theta\log\text{density}_v+\mathbf{X}_v\mathbf{\Gamma}_1+\mathbf{C}_{2v}\mathbf{\Gamma}_2+\varepsilon_{vi}\,, \tag{8}$$

where α_c denotes a city fixed effect, $\mathbf{X}_i$ is a vector of household-level observables, $\mathbf{X}_v$ is a vector of community averages of the characteristics of people who live in community v (described above), $\mathbf{C}_{2v}$ are controls for community characteristics that are not mechanically related to sorting, and ε_{vi} is an error term. We estimate separate effects for urban households in both Indonesia and the Philippines. To illustrate our empirical strategy, Table 3 shows results for a single outcome variable, namely the log total quantity of electricity consumed by household i last month. Panel A shows results for households in Indonesian cities, while Panel B focuses on households in urban areas of the Philippines. For inference, we report robust standard errors, clustered at the sub-district level in Panel A and at the municipality level in Panel B, in parentheses.[21]

We begin by reporting estimates of θ from specifications that omit controls for sorting, setting $\mathbf{\Gamma}_1=0$

[18]Elevation, ruggedness, and distance to the coast and rivers are also correlated with density as one might expect. However, we include them in $\mathbf{C}_{2v}$ but not as instruments, because they could directly impact residential carbon emissions. For example, elevation may directly affect energy demand by reducing the need to use AC for cooling in higher altitudes.

[19]Note that Civelli et al. (2023) selected a slightly different set of soil characteristics to predict density within Indonesian cities. The differences between these two papers owe to different definitions of urban areas, and to the fact that this paper uses an expanded sample of urban Susenas communities because we pool data from 2010, 2011, and 2012.

[20]First-stage regression results at the community-level can be found in Appendix Table A.6.

[21]Indonesian cities are collections of urban *desa / kelurahan*, which span multiple sub-districts (*kecamatan*), the third-level of administrative division. Philippines cities are collections of urban *barangay*, which span possibly multiple municipalities, also the third-level of administrative division.

as a baseline. In column 1, our OLS specification finds that increasing density by 1 percent increases electricity consumption by 0.08 percent in Indonesian cities. Although highly significant, this is a moderate effect size, equivalent to roughly 0.1 percent of a standard deviation in electricity consumption. The OLS coefficient for cities in the Philippines is also positive (0.06, from Panel B).

Column 2 reports the relationship between density and electricity consumption estimated from IV-Lasso specifications, where we instrument density with soil characteristics. Overall, the estimate of θ grows larger, increasing to 0.099 in Indonesia and 0.181 in the Philippines. In column 2, the Kleibergen and Paap (2006) Wald Rank F-Stat, a generalization of the first-stage F-statistic for multiple instrumental variables, is large at over 92 in Indonesia and 27 in the Philippines. The Kleibergen-Paap rank LM test also strongly rejects the null of weak instruments for the endogenous density variable in both countries.

Appendix Table A.7 reports coefficients on household and community-level controls for Indonesian households (columns 1 and 2 of Table 3), while Appendix Table A.8 does the same for Filipino households (Table 3, Panel B). We see that relative to no schooling (the omitted category in Indonesia) and relative to no secondary education (the omitted category in the Philippines), higher levels of educational attainment are associated with greater quantities of electricity use. As expected, household size also increases electricity use, and electricity consumption has an inverse U-shaped relationship with the age of the household head.

In Table 3, column 3, we report results of the full model, where we include household-level covariates, $\mathbf{X}_i$, community-specific characteristics, $\mathbf{C}_{2v}$, and averages of different individual-level variables at the community level, $\mathbf{X}_v$, to control for sorting. The addition of sorting controls reduces the elasticity of electricity consumption with respect to density to 0.027 in Indonesia and 0.068 in the Philippines. In both cases, the effect becomes statistically insigificant. Although the Kleibergen-Paap Wald Rank F-Stat falls to 26 in Panel A and to 15 in Panel B, the Kleibergen-Paap LM tests still reject the null of weak instruments of the endogenous density variable. Moreover, the Sargan-Hansen J-test statistic for overidentifying restrictions is also relatively small in both countries, and we cannot reject the null that the soil characteristics instruments are correctly excluded from the estimation equation at the 1 percent significance level. Overall, the results in Table 3 suggests that the IV models are well specified, even after introducing controls for sorting.

In Appendix Table A.9, we report the estimated coefficients on Indonesian sorting controls (Table 3, Panel A), and in Appendix Table A.10, we report estimated coefficients for sorting controls for Philippines cities. Some ethnic group shares are negatively correlated with electricity use, but these are typically weak correlations. However, average years of schooling in the community seems to be strongly predictive of increased electricity use, suggesting that educational sorting and income sorting may be responsible for the naive OLS findings. Overall, the results from Table 3 suggest that while greater density is associated with higher electricity consumption, this effect is not causal and is not robust to controls for sorting on observables and unobservables.

Full Results. Table 4 shows parameter estimates from equation (8) for all of the residential carbon intensity outcomes we study. Columns 1-3 replicate the results on electricity from Table 3. Columns 4-6 report estimates of the relationship between density and LPG consumption. We obtain similar results to electricity: in both countries, density is positively associated with LPG consumption, and the effects increase after instrumenting for density. However, once we control for sorting, the relationships with density attenuate. Column 6 suggests that a 1 percent increase in density reduces LPG consumption by 0.05 percent in Indonesia and increases LPG consumption by 0.01 percent in the Philippines, but neither estimate is statistically significant.

Columns 7-9 report estimates of the relationship between density and vehicle gas consumption. Despite what one might expect from a monocentric city model, density and vehicle gas consumption are positively correlated in Indonesian cities in the OLS and IV specifications (column 6-7, Panel A). We also find a positive, though insignificant, correlation between density and vehicle gas consumption for urban households in the Philippines in the IV specification. However, after we control for sorting, in both countries, we cannot reject that the coefficient on density is statistically indistinguishable from zero. These results are quite different from findings in the U.S., where lower density neighborhoods are associated with increased miles traveled and fuel consumption (e.g. Brownstone and Golob, 2009).

Columns 10-12 show the results for kerosene, an important source of fuel for Indonesian households but less so for the Philippines. Here, we do find a significant relationship between kerosene consumption and density in Indonesia, but the effect is positive. The estimate in column 12 suggests that a 1 percent increase in density is associated with a 0.1 percent increase in kerosene consumption. However, the coefficient is quite small in the Philippines and is statistically insignificant.

Density and Asset Ownership. Given that we find an insignificant relationship between many aspects of residential carbon emissions and population density, we would also expect this finding to hold for measures of asset ownership. The 2010-2012 waves of the *Susenas* ask Indonesian households about ownership of several assets, including: (1) refrigerators; (2) motorcycles; (3) cars; (4) air conditioning; (5) gas cylinders; and (6) water heaters. Similar, but not all, asset ownership outcomes are available in the Philippines' FIES. These variables are summarized in Appendix Table A.11.

Table 5 presents IV estimates of the relationship between community-level population density and household asset ownership, using linear probability models based on the same specification as equation (8). These estimates suggest that refrigerator and AC ownership are positively associated with density in both Indonesia and the Phillipines, but those effects are not robust to controls for sorting.

Although one might expect that density would be negatively related to car and motorcycle ownership, we do not find statistically significant relationships between density and vehicle ownership outcomes in either Indonesia or the Philippines. If anything, car ownership is positively associated with density in Philippines cities, but neither vehicle outcome is significantly related to density after controlling for sorting. We also do not find significant relationships between density and ownership of LPG cylinders or hot water heaters, but these variables are only measured in Indonesia.

In summary, just as in the case of residential carbon emissions measures, many of the relationships between asset ownership and density reflect income sorting. After accouting for income sorting, we find no role for neighborhood population density in shaping household-level asset ownership.

Intensive vs. Extensive Margin Effects. Our main expenditure results rely on outcome variables that combine extensive and intensive margin effects. Given that we do not find significant relationships between density and asset ownership after controlling for sorting, we should expect to see similar null results on the extensive margin of expenditure. Appendix Table A.12 uses a linear probability model specification and reports estimates of the effects of density on indicators for whether or not the household reported any expenditures on electricity, vehicle gas, natural gas, or kerosene. The density effects in IV results with controls for sorting are not statistically significant at conventional levels, and these null results hold for all outcomes and for both countries.

Appendix Table A.13 drops the $\log(1+y_{iv})$ transformation in our main specification and examines the effect of density on $\log y_{iv}$. Movement in this outcome reflects intensive margin changes in residential energy expenditures for households who report positive expenditure values. For Indonesian cities, we report null results on electricity, vehicle gas consumption, and kerosene in IV specifications with sorting controls. We do find that density reduces LPG consumption, though the coefficient only marginally significant. For the Philippines, we find insigificant results for electricity, kerosene, and vehicle gas consumption. However, we also find positive, but small and significant effects of density on LPG consumption.

Probing the Effect of Sorting. In Figure 3, we explore the role that different types of sorting controls have on our IV estimates of the relationship between density and different sources of residential carbon emissions. Each point reports the coefficient on log population density from equation (8) where the dependent variable is listed in the panel header. The bars depict 95 percent confidence intervals.

The first set of estimates ("None") replicate our estimates from Table 4 without controls for sorting, which tend to be positive and significant. In the second row of estimates ("Non-Econ"), we add non-economic sorting controls, including ethnic composition shares and shares of different members of the community in different religious groups. The positive estimates of the effects of density on sources of residential carbon emissions do not change much in terms of magnitude or significance.

However, in the third set of rows ("Econ"), we replace the non-economic sorting controls with variables that capture sorting on economic factors, including education shares, household size, and employment characteristics. These controls dramatically reduce many of our coefficients, often making them insignificant. This suggests that economic sorting is playing a substantial role in mediating the observed relationship between density and residential carbon emissions. The fourth set of rows ("All") reproduce our preferred estimates from Table 4 with the full set of $\mathbf{X}_v$ controls.

The Density Elasticity of Residential Emissions. To more precisely estimate how density impacts overall residential carbon emissions, we aggregate the separate effects of density on different categories of residential energy-related expenses. Let CE_{iv} denote the total carbon emissions of household i in community v:

$$\text{CE}_{iv} = \sum_{k} \omega_v(k) y_{iv}(k)\,, \tag{9}$$

where $y_{iv}(k)$ is the total annual quantity of energy consumed by household i from source k, and $w_v(k)$ is a carbon intensity weight for source k. We allow the carbon intensity weights to differ by community because electricity generation sources differ across grids, and different types of power plants can vary in their carbon intensity.[22]

Estimating equation (8) for different outcome variables, indexed by $k = 1, ..., K$, provides different estimates of $\theta_k = \partial \log(1+y_{iv}) / \log \text{density}_v$, which is the elasticity of quantities of energy category k with respect to density. It is easy to show that we can write the elasticity of total household carbon

[22]See our discussion of carbon intensity weights in Section 3 for more details. Appendix Table A.3 shows the various emissions factors used to calculate $\omega_v(k)$.

emissions with respect to density as:

$$\mathcal{E}_{\text{CE}_{iv},\text{density}} = \sum_{k=1}^{K} \left(\frac{w_v(k) y_{iv}(k)}{\text{CE}_{iv}} \right) \theta_k \quad . \tag{10}$$

This is just a sum across energy sources of different density elasticities, where each elasticity is weighted by that source's share in total household carbon emissions.

Table 6 provides estimates of $\mathcal{E}_{\text{CE}_{iv},\text{density}}$, using national average carbon intensity weights, separately for urban households in Indonesia and the Philippines. We estimate all equations simultaneously using a seemingly unrelated regressions system to calculate standard errors. Panel A shows that a 1 percent increase in density is associated with a 0.007 percent increase in carbon emissions in Indonesia and a nearly 0 percent increase in carbon emissions in Philippines households. Column 2 shows that these effects increase to roughly 0.01 in both countries after instrumenting for density. However, in column 3, we add controls for sorting, and the elasticity falls to -0.005 in Indonesia and 0.004 in the Philippines. In both cases, the density elasticity of residential emissions becomes statistically insigificant.

Figure 4 plots estimates of $\mathcal{E}_{\text{CE}_{iv},\text{density}}$ for different cities, where we replace the national carbon intensity weights with city-specific weights to calculate equation (10). Because the carbon intensity weights for LPG, kerosene, and vehicle gas are fixed internationally (see Appendix Table A.3), our city-specific weights allow electricity consumption to contribute differently to emissions depending on where the city is located in the electricity grid and the carbon intensity of electricity production nearby. Despite allowing for more heterogeneity, nearly every city's density elasticity of residential carbon emissions is statistically indistinguishable from zero after we include sorting controls.

5.1 Probing Internal Validity and Robustness

Agriculture Households. A major concern with the results presented so far is the exclusion restriction: for soil characteristics to be a valid instrument, they must only affect residential carbon emissions through their impact on population density. One potential violation of the exclusion restriction is that if favorable soils were important for agricultural productivity in cities today, they could affect residential carbon emissions by affecting income or wealth. This is clearly an issue, since approximately 19 percent of households in Indonesian cities and 3 percent of urban households in the Philippines report employment in agriculture.

In Appendix Table A.14, we examine the sensitivity of our estimates to dropping agricultural households and to dropping communities with large shares of employment in agriculture. Each cell in this table reports results from a different regression, focusing on Indonesian cities.[23] Different panels focus on different emissions outcomes, and different rows denote estimates with and without sorting controls. Column 1 reports our baseline IV-Lasso estimates (from columns 2 and 3, Table 4). In column 2, we drop all households that report any employment in agriculture, and our results are mostly unchanged. In columns 3-6, we drop different communities based on the share of households that are employed in agriculture. While the magnitudes of density's effects vary slightly, qualitatively our results remain

[23] A similar table for households in cities in the Philippines can be found in Appendix Table A.15.

unchanged. We continue to find that unconditionally, greater energy use takes place in denser communities, but these results do not survive the inclusion of sorting controls.

Controlling for Historical Infrastructure. Although our results are robust to dropping agricultural households, the soil characteristics IVs may still be correlated with omitted community characteristics that affected historical sorting patterns and explain today's carbon emissions outcomes. We already control for certain aspects of geography (e.g. ruggedness, elevation, distance to the coast and rivers), but other omitted community characteristics may have affected the development of historical infrastructure and be correlated with modern density. This infrastructure may have induced people of different types to sort into different neighborhoods, determining persistent income sorting that lingers today.

In Appendix Table A.16, we show that our main estimates of the elasticity of residential carbon emissions with respect to density in Indonesia (reported in Table 6, Panel A), are robust to controlling for different types of historical infrastructure. To measure these controls, we use *Podes* data from 1983 to measure the number of education facilities, health facilities, religious facilities, irrigation facilities, electricity coverage, as well as the number of agricultural and social organizations. We also include controls for distance to major historical roads.[24] In all cases, our main estimate of the density elasticity of residential carbon emissions is nearly unchanged. While we lack data from the 1980s for the Philippines, Appendix Table A.17 shows how the 2018 density elasticity results (reported in Table 6, Panel B) are robust to controlling for measures of infrastructure from the 2000 census, including education, health, and religious facilities as well as distance to major roads.

Soil Characteristics in Rural Areas. If the exclusion restriction is satisfied, then in a subsample with no first stage relationship, there should also be no reduced-form relationship (Altonji et al., 2005; van Kippersluis and Rietveld, 2018). To provide more evidence in favor of the exclusion restriction, we performed a placebo exercise, estimating the effect of soil characteristics on residential energy consumption in rural communities where those IVs do not predict population density.

To implement this exercise, we identified rural communities in Indonesia and the Philippines with a population density of less than 300 inhabitants per square km.[25] Appendix Table A.18 shows that in these communities, soil characteristics IVs are not predictive of density. In the last row of each panel, we show that the first stage relationship between the selected soil characteristics and density is quite weak, with Kleibergen-Paap Wald F-stats of 2.4 in Indonesia and 0.06-0.1 in the Philippines. The table also reports p-values for tests of the joint significance of the soil characteristics in predicting each dependent variable. Of the four dependent variables we study, the soil characteristics IVs are only significant in predicting LPG consumption in the Philippines (p-value $= 0.01$), while the other p-values are above conventional significance levels. We take this evidence as weighing in favor of the exclusion restriction.

Depth-to-Bedrock Instruments. So far, our IVs have focused solely on soil characteristics. However, depth to bedrock has also been used as an IV for density in prior work, and it may be even more likely to be excludable, given that bedrock depth may not be as impactful for agricultural productivity as other soil characteristics. In Appendix Table A.19, we add depth to bedrock to the instrument choice set, together with other soil characteristics, before implementing the post-double-selection IV lasso estimator.

[24] For more details on these variables, see the Online Appendix to Civelli et al. (2023).

[25] This definition of rural areas is consistent with the definition used by the UN Statistical Commission (UN, 2020).

The first-stage F-statistics are similar to our preferred estimates reported in Table 4. Moreover, the estimates of the effect of density on residential energy use are also qualitatively similar, showing that our estimates are robust to expanding the instrument set.

Unit Values and Exact Quantity Measurements. As discussed in Section 3, for the Indonesian data, we sometimes impute missing quantity measures based on estimates of unit values. To explore the sensitivity of our results to this choice, Appendix Table A.20 re-estimates our main specification but drops observations with predicted quantities. Although point estimates differ slightly, the results are qualitatively similar to our baseline estimates, suggesting that our imputation procedure is not responsible for the results we obtain.

5.2 Mechanisms and Heterogeneity

Floor Area and Commuting Distance. One reason why many policymakers are concerned about urban sprawl is the tendency for homes to get larger as they move away from city centers, because larger homes require more energy consumption. However, the relationship between distance to the city center and home size may be different in cities with different income sorting patterns. In Table 7, we examine how population density affects a household's floor area, using self-reported data from the *Susenas* 2010-2012. In Indonesia, we find that conditional on household size, increasing density reduces floor area as expected, with a 1 percent increase in density reducing floor area by 0.76 percent in the IV specification (Panel A, column 2). When we add the sorting controls, the density coefficient loses some significance, but the density coefficient remains similar and negative. In the Philippines, the OLS specification also suggests that increasing density reduces floor area, and the IV estimates, while no longer significant, are still negative and similarly sized. These results suggest that households in denser urban neighborhoods do tend to use smaller amounts of residential floorspace, but despite this, there are no differences in residential energy consumption.

Another surprising finding from Table 4 is that density is unrelated to vehicle gas consumption after controlling for sorting and simultaneity. If anything, the coeffients in Table 7, columns 4-6 also suggest that commuting distances *increase* in denser neighborhoods, at least for households in Indonesian cities. These patterns reinforce the idea that monocentric city models may lack explanatory power for cities in lower-middle income countries.[26]

Heterogeneity by City Size. As countries grow richer, one concern is that they may converge towards more U.S. style income sorting, with richer households who own cars and move into bigger homes in the suburbs (Glaeser, 2011). On the other hand, if neighborhood amenities are persistent, richer households may bid up housing prices in the center and take advantage of those amenities. Some of these central amenities may even become more desireable through endogenous sorting of higher income households (Brueckner et al., 1999).

In Appendix Table A.21, we examine the extent to which the effect of density on residential carbon emissions differs in large, affluent cities with more than 1 million residents (e.g. Jakarta and Manila) vs. other smaller cities. We generally find that the effect of density is not significantly different in larger cities relative to other smaller cities, suggesting that our results are invariant to size and potentially

[26]Unfortunately, we lack similar commuting distance variables in the Philippines FIES data.

income differences across cities. The one exception to this finding is that the positive effects of density on kerosene consumption seem to come from smaller cities in Indonesia.

Time Stability of the Density Elasticity. Finally, we document that the elasticity of residential carbon emissions with respect to density is remarkably stable over time, despite large changes in urban populations and rapid migration experienced in Indonesia and the Philippines. To do so, we estimate the density elasticity using two older waves of data: a 2000 epoch for Indonesia and a 2010 epoch for the Philippines. In Indonesia, we combine data on residential energy expenditures from the 1996 *Susenas* with neighborhood sorting controls calculated from the 2000 Census. In the Philippines, we pool data from the 2006, 2009, and 2012 FIES together with sorting controls from the 2010 Census.

Appendix Table A.22 shows the results of using these earlier waves of cross-sectional data to estimate $\mathcal{E}_{\text{CE}_{iv},\text{density}}$ as defined in equation (10). We use national average carbon intensity weights and report separate for urban households in Indonesia and the Philippines. As before, to calculate standard errors, we estimate the individual energy expenditure equations simultaneously using a seemingly unrelated regressions system. Panel A shows that in the OLS and IV-Lasso specifications without sorting controls, a 1 percent increase in density is associated with a 0.02 percent increase in carbon emissions in Indonesia, with a similar effect size in the Philippines. However, in column 3, when we add controls for sorting, the effect sizes fall and become statistically insignificant. These precise zero effect sizes in models with sorting controls are very similar to what we found in Table 6 using more recent data waves.

6 Decomposing Overall Changes in Residential Emissions

So far, we have shown that energy demand in Indonesian and Philippines cities does not seem to be related to changes in community-level population density. Our estimates of the density elasticity are small, and the null density elasticity appears to be stable over time. If urban sprawl—as proxied by changes in population density—does not seem to play a role in driving increased residential carbon emissions, what is driving growth instead? In this section, we develop a novel Oaxaca-Blinder type of decomposition to explain growth in residential carbon emissions across cities. We calculate the components of this decomposition by combining multiple waves of detailed census data with our parameter estimates.

Decomposition. Let $c = 1, ..., C$ index cities in our sample, and let $v = 1, ..., N_v$ index communities in city c. Let $s \in \mathcal{S}$ also index types of households.[27]

Appendix B explains how we combine our parameter estimates averages from census data, taken for each household type s in each neighborhood v, to predict city c's total residential carbon emissions at time t. Our estimate can be expressed as follows:

$$\widehat{\text{CE}}_{ct} = \sum_{v=1}^{N_c} \sum_{i \in s} N_{sv,t} \cdot \widehat{\text{CE}}_{sv,t}$$

where $N_{sv,t}$ measures the number of type s households in community v at time t and $\widehat{\text{CE}}_{sv,t}$ is the pre-

[27]For this analysis, we group households into 3 size groups (1-2 person households, 3-4 person households, and households with more than 4 members) and 4 household-head education groupings (no schooling, some schooling, only completed high school, greater than high school completion). Therefore, there are 12 household types in our analysis (i.e. $|\mathcal{S}|$ = 12).

dicted average residential carbon emissions for a type s household in community v at time t. Our predictions combine census averages with estimates of the parameters in equation (8). Because our primary regression equations are log linear, we use a "smearing estimate" to predict emissions levels (Duan, 1983).

The growth in predicted total residential carbon emissions from census wave t to $t+1$ in city c is given by:

$$\Delta\widehat{\mathrm{CE}}_c \equiv \widehat{\mathrm{CE}}_{c,t+1} - \widehat{\mathrm{CE}}_{c,t} = \sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\left(N_{sv,t+1}\cdot\widehat{\mathrm{CE}}_{sv,t+1} - N_{sv,t}\cdot\widehat{\mathrm{CE}}_{sv,t}\right)$$

Appendix B shows that $\Delta\widehat{\mathrm{CE}}_c$ can be decomposed into three terms, as follows:

$$\Delta\widehat{\mathrm{CE}}_c = \sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\underbrace{(N_{sv,t+1}-N_{sv,t})\cdot\widehat{\mathrm{CE}}_{sv,t}}_{(\mathbf{A})} + \underbrace{\Delta\widehat{\mathrm{CE}}_{sv}\,(\Delta\mathbf{x})\cdot N_{sv,t+1}}_{(\mathbf{B})} + \underbrace{\Delta\widehat{\mathrm{CE}}_{sv}\,(\Delta\beta)\cdot N_{sv,t+1}}_{(\mathbf{C})} \tag{11}$$

In this expression, term A reflects *population growth* of type s households in community v, multiplied by the predicted levels of carbon emissions in time t for those household types in those communities. Term B reflects growth in emissions due to *changes in the mapping* between $\mathbf{x}_{v,s}$ characteristics and emissions over time. Term C reflects growth in emissions due to *changes in characteristics* over time. Because we are fixing household types in this analysis, one source of these changes will be changes in community-level population density. The last two terms of the decomposition in equation (11) are similar to a Oaxaca-Blinder decomposition, but for time periods as opposed to groups. They also need adjustments in how they are calculated because of the log linear model we use.

Results. According to Global Carbon Budget Data (Friedlingstein et al., 2024), from 2000 to 2010, Indonesia produced an additional 175.0 million metric tons (MMT) of CO_2. This represents a 63 percent increase in emissions from a baseline of 276.6 MMT in 2000. Over a similar time period, from 2010 to 2018, the Philippines produced an additional 58.9 MMT of CO_2, which was a 71 percent increase from emissions in 2010 (83.0 MMT).

In Figure 5, we plot the overall changes in emissions for the 10 largest cities in Indonesia (from 2000-2010, Panel A) and for some of the largest cities in the Philippines (from 2010-2018, Panel B).[28] The figure shows both overall changes in emissions as well as changes in emissions by energy source. In most of Indonesia's largest cities, overall emissions increased despite large reductions in emissions from kerosene over this period. The decline in kerosene emissions was offset by even larger increases in emissions from vehicle gas and electricity. In cities in the Philippines, emissions also grew, but these were driven largely by increases in electricity consumption.

In Indonesia, the 10 largest cities shown in Figure 5, Panel A, produced an additional 2.38 million metric tons of CO_2 per month from electricity, vehicle gas, LPG, and kerosene consumption. If we assume these emissions trends—which are based on monthly data—are constant throughout the year, this would account for an additional 28.6 MMT of CO_2 per year, or about 16 percent of Indonesia's total emissions growth from 2000-2010. In the Philippines, the cities in Figure 5, Panel B, produced an additional 0.71 million metric tons of CO_2 per month—or 8.6 million metric tons per year—from 2010-2018. This

[28]We show the 10 largest cities with coverage in the FIES in our results for the Philippines.

accounts for 14.6 percent of the total emissions growth in the Philippines over this period.

Figure 6 shows the results of decomposing this overall emissions growth by city into the different components described in equation (11). Panel A shows that in Indonesia, apart from Jakarta, overall emissions growth is typically not explained by changes in population. On average across the top 10 cities, 66.4 percent of the total absolute changes in emissions come from changes due to the mapping between community and household characteristics and emissions (term C). A further 18.6 percent comes from changes in characteristics (term B), while the remaining 15 percent comes from population growth (term A).

Figure 6, panel B shows somewhat different results for the Philippines. For a typical city in this panel, population growth only explains 18.1 percent of total emissions growth, and only 21.6 percent is explained by changes due to the mapping between community and household characteristics and emissions. Instead, changing characteristics explains 60.3 percent of the growth of emissions.

A key message of the paper is that density only modestly contributes to changes in emissions. Appendix Figure A.2 shows the results of further separating the effects of changes in characteristics (term B in equation 11)into a component owing to changes in density and a component due to changes in other factors.[29] On average, across the largest Indonesian cities, changing density explains only 1.1 percent of the changes in overall emissions by city. For the Philippines, although changing charateristics explains a larger share of total emissions growth, density changes still only explain 1.8 percent of the changes in overall emissions by city.

7 Conclusion

This paper presents causal estimates of the effect of neighborhood population density on residential carbon emissions, using data from cities in Indonesia and the Philippines. Estimating the effect of a place-specific feature like population density is plagued by two key identification problems: (1) simultaneity, in which omitted variables may drive correlations between both density and residential carbon emissions; and (2) sorting, where individuals with specific tastes for different emissions-based lifestyles may sort systematically into low or high density places. We confront the first identification challenge by instrumenting for density within cities using characteristics of the soils prevalent in different neighborhoods. We address sorting using a control function approach, following Altonji and Mansfield (2018).

We find that unlike many wealthier cities in the U.S. and Europe, higher income individuals tend to sort closer to the city center, and they also settle in denser neighborhoods. Consequently, neighborhoods with higher levels of density tend to produce greater carbon emissions. Our IV specifications suggest that this positive correlation survives simultaneity bias. However, after we control for sorting, the effect of density attenuates and becomes statistically insignificant. Our preferred estimates suggest that increasing density by 1 percent reduces carbon emissions by -0.005 percent in Indonesian cities and increases emissions by 0.004 percent in Philippines cities, but these effects are statistically indistinguishable from zero.

We also find that this precise null density elasticity of residential carbon emissions is remarkably stable over time. Our results are robust to many threats to the exclusion restriction, and we find similar

[29]The details of this additional decomposition can be found in Appendix B.

patterns using data on asset ownership. We also find surprisingly similar estimates in cities of different sizes. When probing the effect of sorting, economic sorting controls seem to dampen effect sizes instead of social or ethnic sorting controls.

If urban sprawl leads to undesireable externalities, it may be prudent to use growth controls as a policy to reduce these outcomes (Brueckner and Largey, 2008). Given that we do not find much scope for density-based place effects in Indonesia and the Philippines, such growth controls may not be warranted on these grounds, and it would be far better to use carbon pricing to better align marginal social costs with average private costs. However, other work has found a larger role for place effects in explaining spatial heterogeneity in residential carbon emissions (Lyubich, 2025). While population density is correlated with many important aspects of sprawl (Ewing and Cervero, 2001; Brownstone and Golob, 2009), other aspects of place may be more important. Further work should try to causally identify the effect of these other place-specic effects, including access to public transit, walkability, and neighborhood composition, to determine whether other policies may successfully reduce residential carbon emissions.

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Table 1: Summary Statistics on Monthly Energy Consumption

	Indonesia (2010)		Philippines (2018)	
Variable	**Mean (Std. Dev)**	N	**Mean (Std. Dev)**	N
Electricity (kWh)	77.844 (53.858)	40,920	138.687 (136.884)	47,635
LPG (kg)	5.027 (4.069)	40,920	5.621 (3.883)	47,635
Vehicle Gas (L)	13.149 (14.819)	40,920	9.692 (23.912)	47,635
Kerosene (L)	1.219 (4.531)	40,920	0.137 (0.899)	47,635
Carbon emissions (tons)	0.077 (0.053)	40,920	0.081 (0.091)	47,635

Notes: This table provides summary statistics on our main energy consumption outcomes for urban households in the Indonesia (2010) sample and for urban households in the Philippines (2018) sample. The Indonesian data are pooled from three *Susenas* rounds in 2010, 2011, and 2012, while the Philippines data come from the 2018 FIES. The final row summarizes estimates of the household residential carbon emissions implied by these expenditure quantities. Carbon emissions estimates are obtained by multiplying each category's fuel consumption by carbon emissions factors (reported in Appendix Table A.3).

Table 2: First Stage: Density and Soil Characteristics

	Indonesia		Philippines	
	(1)	(2)	(3)	(4)
Soil bulk density at 60cm depth	0.033***	0.015***		
	(0.002)	(0.002)		
Sand content at 60 cm depth (% (kg / kg))	-0.049***	-0.020***		
	(0.006)	(0.004)		
Great Group: Haplustolls (Mollisols)	0.676***	0.123*		
	(0.106)	(0.068)		
Great Group: Tropudults (Ultisols)	-1.119***	-0.848***		
	(0.196)	(0.173)		
Great Group: Chromusterts (Vertisols)	0.745***	0.473***		
	(0.107)	(0.092)		
Soil bulk density at 200cm depth			0.020***	0.012***
			(0.003)	(0.003)
Soil water content at 200cm depth			-0.037***	-0.017**
			(0.009)	(0.007)
Great Group: Haplustalfs (Alfisols)			0.377***	0.164*
			(0.096)	(0.085)
N	40,207	40,207	41,249	41,249
N Clusters	1,329	1,329	212	212
Adj. R^2	0.517	0.755	0.586	0.740
Adj. R^2 (Within)	0.342	0.666	0.335	0.582
Regression F-Stat	78.4	77.2	28.9	96.0
City FE	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	Yes	No	Yes

Notes: This table reports estimates of equation (7), the household-level first stage relationship between log population density (the dependent variable) and different soil characteristics variables. We use post-double-selection lasso regressions, following Belloni et al. (2012), to select instruments in these regressions from a set of 67 soil characteristics. Columns 1 and 2 are limited to the sample of urban communities in Indonesia covered by the 2010 *Susenas* epoch, while columns 3 and 4 are limited to urban communities in the Philippines covered by the 2018 FIES. All regressions include controls for household characteristics, city fixed effects, elevation, ruggedness, distance to the nearest point on the coast, and distance to the nearest river. In columns 2 and 4, we add village-level controls for sorting on observables and unobservables, denoted by $\mathbf{X}_v$. Robust standard errors, clustered at the subdistrict-level in columns 1-2 and clustered at the municipality level in columns 3-4, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 3: The Effect of Density on Electricity Use

	OLS	IV-Lasso	
Panel A: Indonesia	**(1)**	**(2)**	**(3)**
Log Density (2010)	0.082***	0.099***	-0.002
	(0.009)	(0.019)	(0.040)
N	40,207	40,207	40,207
N Clusters	1,329	1,329	1,329
Adjusted R^2	0.221	0.217	0.232
Adjusted R^2 (within)	0.129	0.125	0.142
Kleibergen-Paap Wald Rank F Stat		92.079	26.289
Under Id. Test (KP Rank LM Stat)		181.466	84.511
p-Value		0.000	0.000
Sargan-Hansen Test (Overidentification)		11.889	3.905
p-Value		0.018	0.419
Panel B: Philippines	**(1)**	**(2)**	**(3)**
Log Density (2018)	0.057***	0.181***	0.068
	(0.010)	(0.033)	(0.042)
N	41,249	41,249	41,249
N Clusters	212	212	212
Adjusted R^2	0.283	0.283	0.296
Adjusted R^2 (within)	0.193	0.193	0.208
Kleibergen-Paap Wald Rank F Stat		27.066	14.546
Under Id. Test (KP Rank LM Stat)		31.607	20.518
p-Value		0.000	0.000
Sargan-Hansen Test (Overidentification)		1.641	3.280
p-Value		0.440	0.194
City FE	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	No	Yes

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is the log quantity of electricity (kWh) consumed last month. Panel A reports results for households in Indonesian cities, while Panel B reports results for households in Philippines cities. Column 1 reports OLS estimates, while Columns 2 and 3 apply a post-double-selection IV-lasso estimator, following Belloni et al. (2012). All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Column 3 additionally includes $\mathbf{X}_v$ controls for sorting. The specific variables we include in $\mathbf{X}_i$, $\mathbf{C}_{2v}$ and $\mathbf{X}_v$, as well as their coefficients, are reported in Appendix Tables A.7 and A.9 for Indonesia (and Appendix Tables A.8 and A.10 for the Philippines). Robust standard errors, clustered at the subdistrict-level in Panel A (and the municipality level in Panel B), are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 4: Density and Residential Energy Use

	Electricity			LPG			Vehicle Gas			Kerosene		
	OLS	IV-Lasso		OLS	IV-Lasso		OLS	IV-Lasso		OLS	IV-Lasso	
Panel A: Indonesia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Log Density (2010)	0.082***	0.099***	-0.002	0.086***	0.070***	-0.052	0.002	0.027	-0.050	0.037***	0.056***	0.100**
	(0.009)	(0.019)	(0.040)	(0.009)	(0.019)	(0.041)	(0.012)	(0.023)	(0.049)	(0.008)	(0.018)	(0.041)
N	40,207	40,207	40,207	40,207	40,207	40,207	40,207	40,207	40,207	40,207	40,207	40,207
N Clusters	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329
Kleibergen-Paap Wald Rank F Stat		92.079	26.289		92.079	26.289		92.079	26.289		92.079	26.289
Panel B: Philippines	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Log Density (2018)	0.057***	0.181***	0.068	0.014	0.091***	0.007	-0.106***	0.025	0.047	-0.000	-0.002	-0.001
	(0.010)	(0.033)	(0.042)	(0.009)	(0.029)	(0.037)	(0.013)	(0.033)	(0.055)	(0.000)	(0.002)	(0.003)
N	41,249	41,249	41,249	43,687	43,687	43,687	42,887	42,887	42,887	45,312	45,312	45,312
N Clusters	212	212	212	212	212	212	212	212	212	212	212	212
Kleibergen-Paap Wald Rank F Stat		27.066	14.546		27.163	14.117		26.841	13.915		27.747	15.646
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is listed in the column header. Panel A reports results for households in Indonesian cities, while Panel B reports results for households in Philippines cities. Columns 1, 4, 7, and 10 report OLS estimates, while the other columns apply a post-double-selection IV-Lasso estimator, following Belloni et al. (2012). All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Columns 3, 6, 9, and 12 additionally include $\mathbf{X}_v$ sorting controls. Robust standard errors, clustered at the subdistrict-level in Panel A (and the municipality level in Panel B), are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 5: Density and Asset Ownership: IV-Lasso Estimates

	Indonesia		**Philippines**	
	(1)	**(2)**	**(3)**	**(4)**
Refrigerator (0 1)	0.051***	-0.017	0.065***	0.016
	(0.009)	(0.019)	(0.016)	(0.021)
AC (0 1)	0.021***	0.021	0.049***	0.010
	(0.005)	(0.015)	(0.011)	(0.014)
Motorcycle (0 1)	0.001	-0.010	-0.006	0.030
	(0.008)	(0.019)	(0.013)	(0.021)
Car (0 1)	0.008	0.002	0.018**	-0.008
	(0.006)	(0.018)	(0.008)	(0.012)
LPG Cylinder (0 1)	0.029***	-0.007		
	(0.009)	(0.027)		
Water Heater (0 1)	-0.001	0.005		
	(0.007)	(0.021)		
N	40,207	40,207	46,754	46,754
N Clusters	1,329	1,329	212	212
City FE	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	Yes	No	Yes

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is listed in the row header. All columns report results from post-double-selection IV-Lasso estimators, following Belloni et al. (2012). Columns 1-2 report results for households in Indonesian cities, while columns 3-4 show results for households in Philippines cities. All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Columns 2 and 4 additionally include $\mathbf{X}_v$ sorting controls. Robust standard errors, clustered at the subdistrict-level in Columns 1-2 and the municipality level in Columns 3-4, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 6: The Average Density Elasticity of Residential Carbon Emissions

	OLS	IV-Lasso	
Panel A: Indonesia	**(1)**	**(2)**	**(3)**
Log Density (2010)	0.007***	0.008***	-0.005
	(0.001)	(0.002)	(0.004)
N	40,207	40,207	40,207
Panel B: Philippines	**(1)**	**(2)**	**(3)**
Log Density (2018)	0.000	0.012***	0.004
	(0.001)	(0.002)	(0.003)
N	43,284	43,284	43,284
City FE	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	No	Yes

Notes: This table reports estimates of the average density elasticity of residential carbon emissions for urban households in Indonesia (Panel A) and the Philippines (Panel B). The object estimated is described in equation (10). To obtain this, we estimate the density elasticity for our four carbon intensity outcomes simultaneously, using a SUR system and national carbon intensity weights. All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Columns 2 and 3 report results from post-double-selection IV-lasso estimators, following Belloni et al. (2012), and column 3 additionally includes $\mathbf{X}_v$ controls. Robust standard errors, clustered at the subdistrict-level in Panel A and the municipality level in Panel B, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table 7: Mechanisms of Density: Floor Area and Commuting Distance

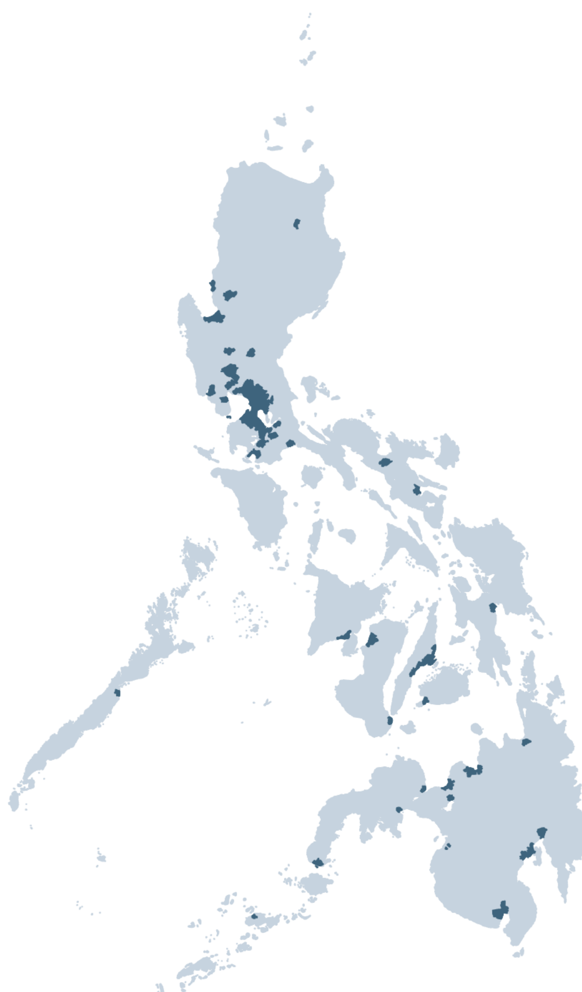
	log(Floor Area Per Capita)			log(Commuting Distance)		
	OLS	IV-Lasso		OLS	IV-Lasso	
Panel A: Indonesia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Log Density (2010)	-0.071***	-0.058***	-0.020	0.008	0.004	0.006
	(0.006)	(0.013)	(0.028)	(0.014)	(0.032)	(0.056)
N	40,207	40,207	40,207	40,056	40,056	40,056
N Clusters	1,329	1,329	1,329	1,325	1,325	1,325
Kleibergen-Paap Wald Rank F Stat		91.999	26.265		92.006	26.201
Panel B: Philippines	**(1)**	**(2)**	**(3)**			
Log Density (2018)	-0.080***	-0.027	-0.057			
	(0.011)	(0.029)	(0.039)			
N	46,754	46,754	46,754			
N Clusters	212	212	212			
Kleibergen-Paap Wald Rank F Stat		26.864	14.807			
City FE	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	No	Yes	No	No	Yes

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is listed in the column header. Panel A reports results for households in Indonesian cities, while Panel B reports results for households in Philippines cities. Columns 1 and 4 report OLS estimates, while the other columns apply a post-double-selection IV-Lasso estimator, following Belloni et al. (2012). All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Columns 3 and 6 additionally include $\mathbf{X}_v$ sorting controls. Robust standard errors, clustered at the subdistrict-level in Panel A (and the municipality level in Panel B), are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Figure 1: Urban Areas in Indonesia and the Philippines

(a) Indonesia

(b) Philippines

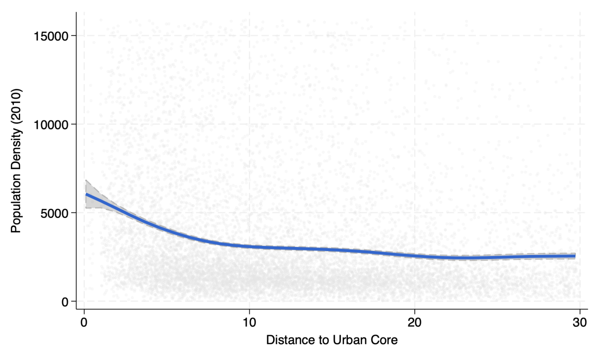


Notes: This figure presents a map of 91 urban areas in Indonesia and 42 urban areas in the Philippines, following Jiang (2021) and using nighttime lights satellite imagery to delineate cities.

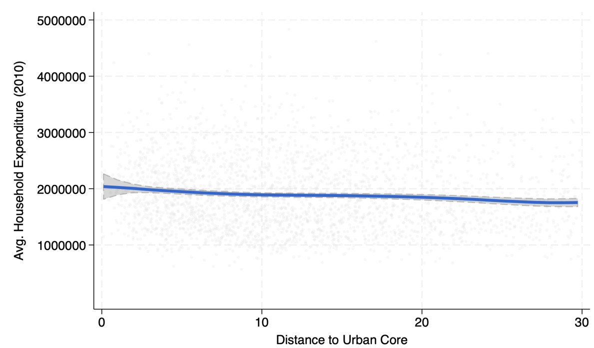
Figure 2: Population Density, Income, Skill, and Distance to the CBD

Indonesia (2010)

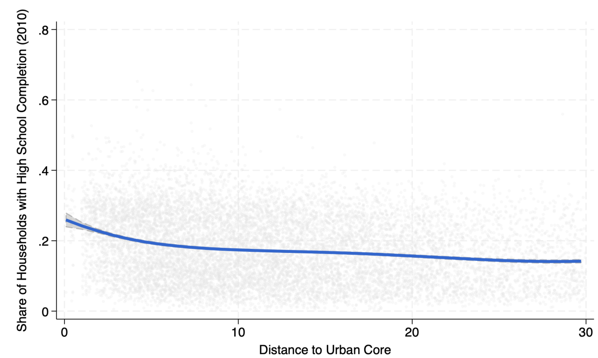
(A) Density



(B) Total Expenditures

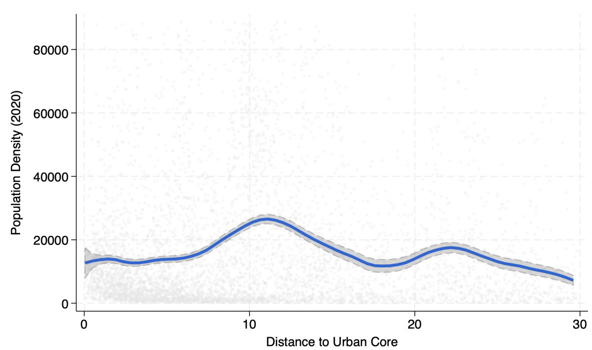


(C) High School Completion

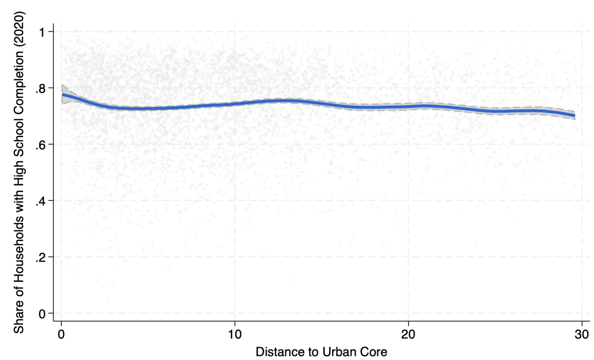


Philippines (2018)

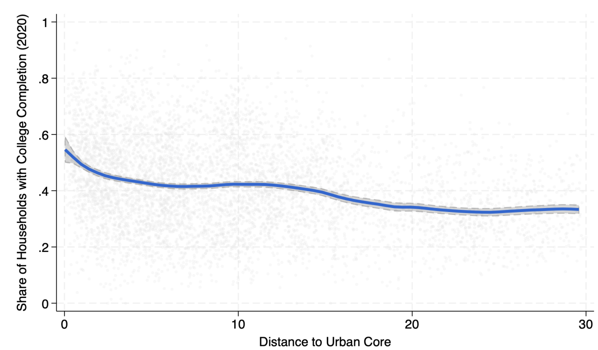
(D) Density



(E) High School Completion

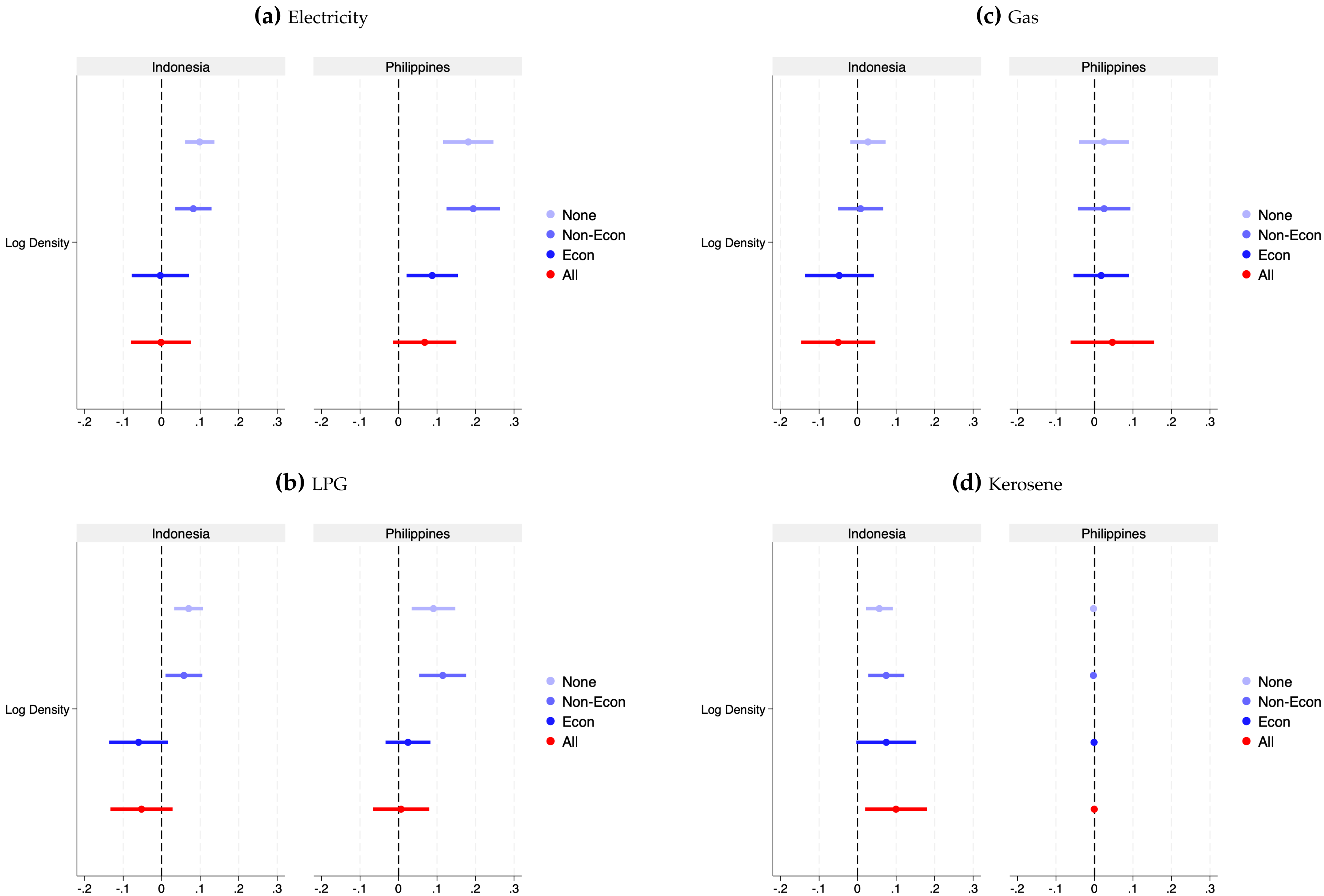


(F) College Completion



Notes: These figures plot local polynomial regressions of census community aggregates against distance to the CBD, pooled across cities. Regression lines are plotted in blue, along with 95% confidence bands in gray. Panels A-C focus on *desa*-level data from Indonesia, using the 2010 Census and *Susenas* data, while Panels D-F focus on *barangay*-level data from the Philippines, using data from the 2020 Census and *FIES* data. Local polynomial regressions use an Epanechnikov kernel, rule-of-thumb bandwidth and a local cubic function, and are estimated on data from our sample of metropolitan areas.

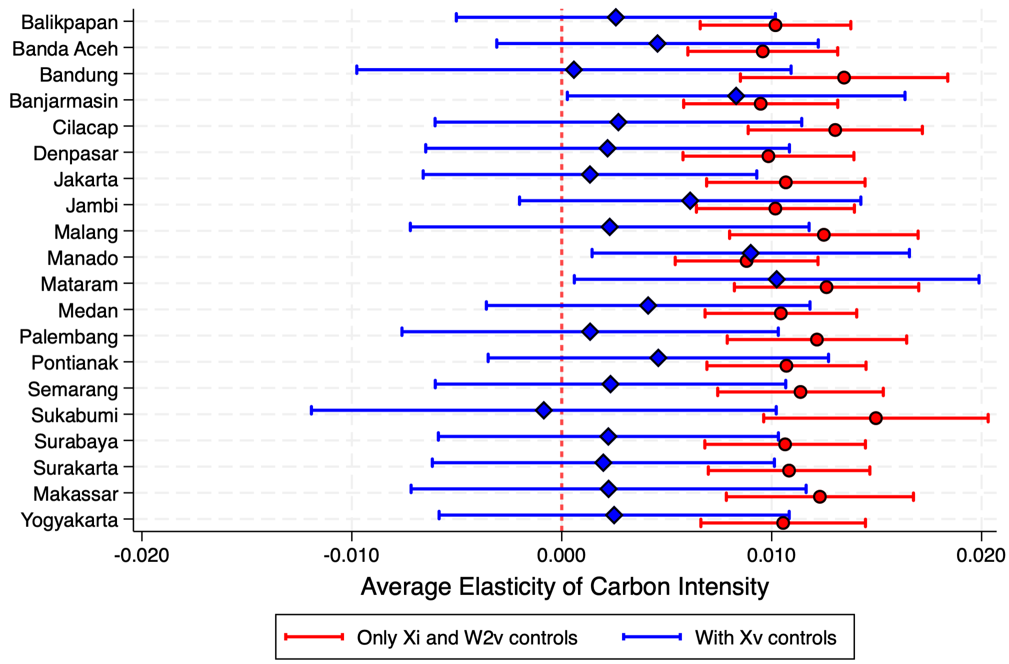
Figure 3: Density and Residential Energy Consumption: Probing the Effect of Sorting



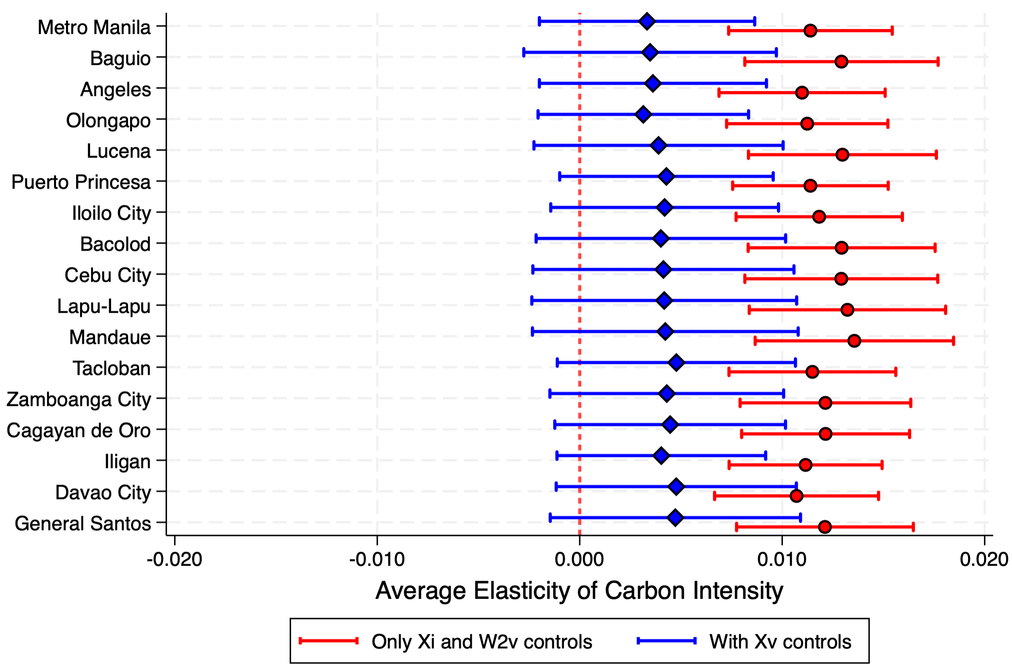
Notes: Each point reports the coefficient on log population density in 2010 from equation (8) where the dependent variable is listed in the panel header. The lines report 95% confidence intervals. All estimates are results from a post-double-selection IV-lasso estimator, following Belloni et al. (2012). The left sub-panels results for households in Indonesian cities, while the right sub-panels show results for households in Philippines cities. All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. The "non-econ" bars include non-economic $\mathbf{X}_v$ controls (e.g. ethnic composition shares and shares of different members of the community in different religious groups). The "econ" bars include economic $\mathbf{X}_v$ controls (e.g. education shares, household size, and employment characteristics). The "All" bars include the full set of $\mathbf{X}_v$ controls.

Figure 4: The Density Elasticity of Residential Carbon Emissions, by City

(a) Indonesia



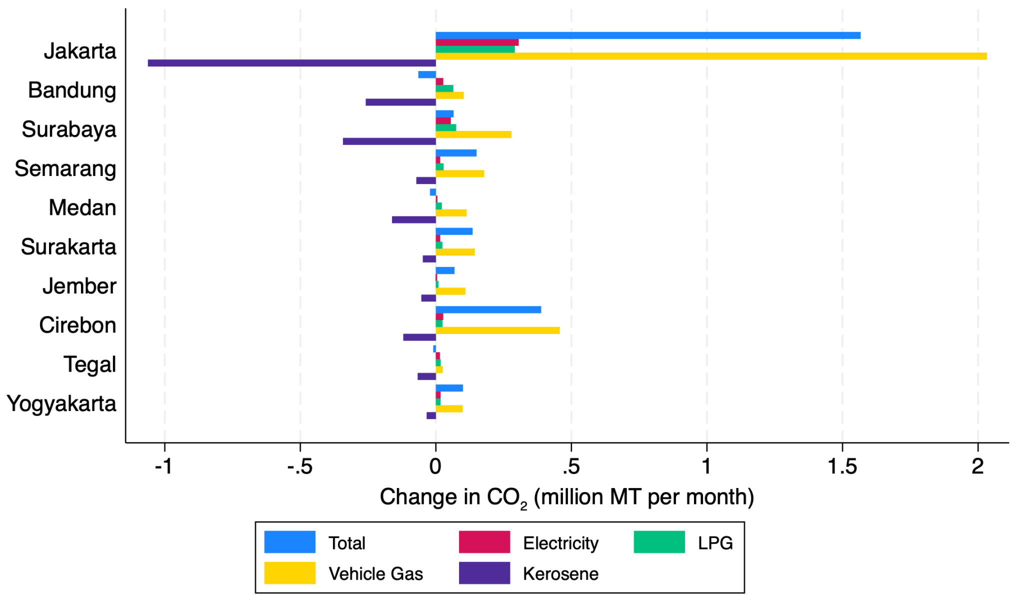
(b) Philippines



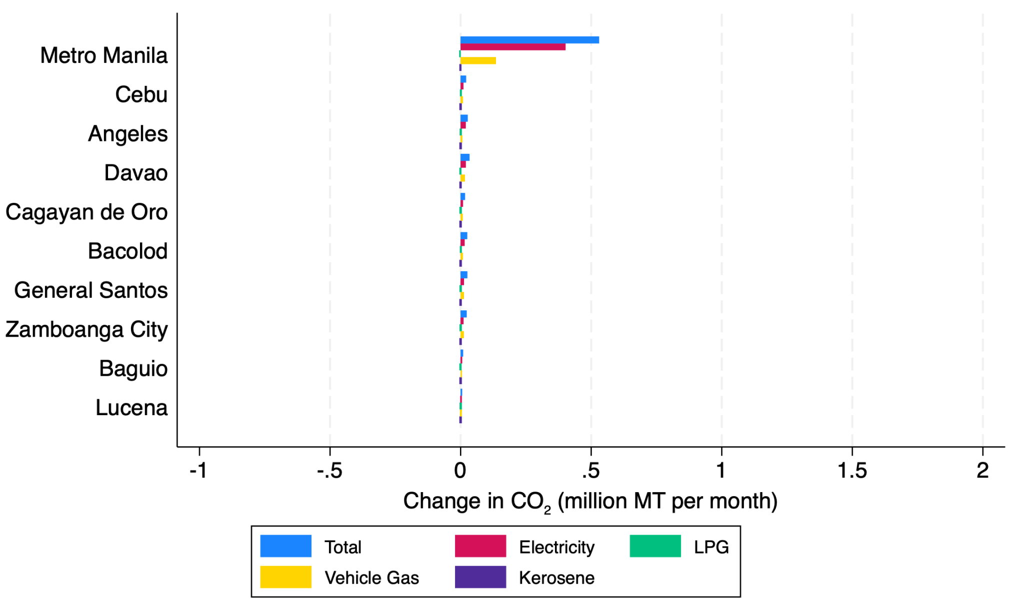
Notes: This figure reports estimates of the average density elasticity of residential carbon emissions for urban households in Indonesia (Panel A) and the Philippines (Panel B). The object estimated is described in equation (10), but with city-specific carbon intensity weights. To obtain these results, we estimate the four carbon intensity outcomes simultaneously, using a SUR system and city-specific carbon intensity weights. The point estimates (in dots) and 95 confidence intervals (lines) come from post-double-selection IV-lasso estimators, following Belloni et al. (2012). The red lines report IV-Lasso estimates without $\mathbf{X}_v$ controls, while the blue lines include $\mathbf{X}_v$ controls. The 95 percent confidence intervals account for clustering at the subdistrict-level in Panel A and the municipality level in Panel B.

Figure 5: Changes in Emissions by City and Emissions Type

(A) INDONESIA



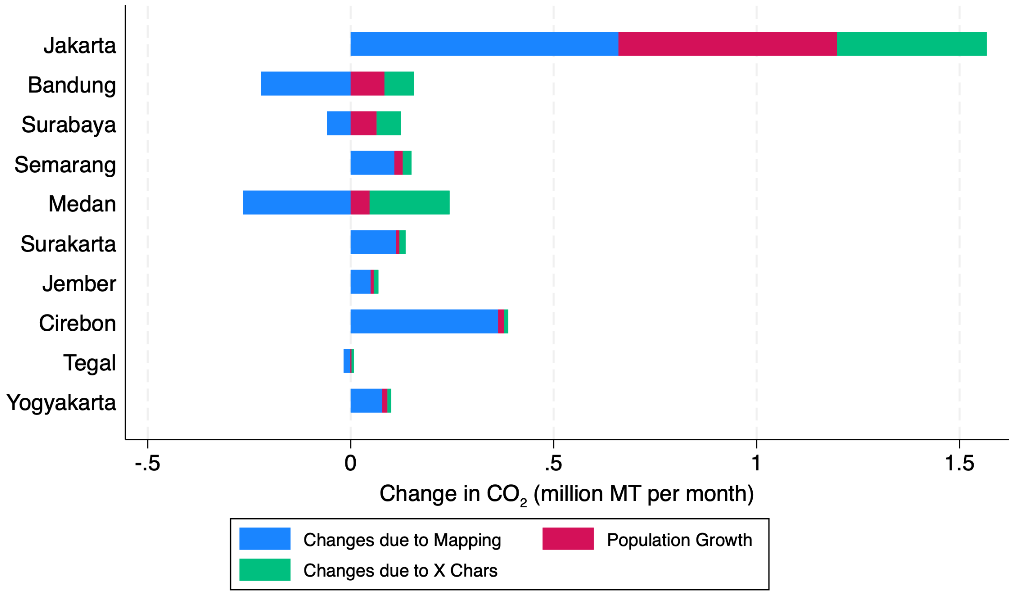
(B) PHILIPPINES



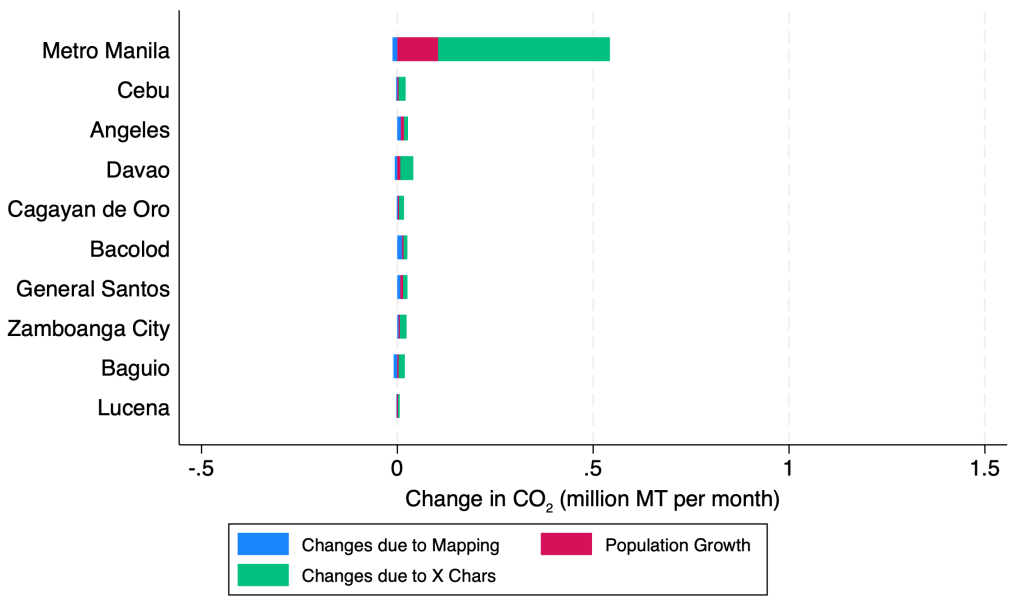
Notes: This figure presents estimates of changes in overall residential carbon emissions by city, $\Delta\widehat{CE}_c$, and growth in emissions by different sources.

Figure 6: Overall Emissions Growth Decomposition: Results for Top 10 Cities

(A) Indonesia



(B) Philippines



Notes: This figure presents our overall decomposition of changes in predicted emissions by city, using equation (11). Appendix B explains how we calculate each of these terms in detail.

Online Appendix

Lathrop, T., Rothenberg, A., and Wang, Y. (2025): "Urban Sprawl and Residential Carbon Emissions: Evidence from Indonesian Cities"

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A Additional Tables and Figures

Table A.1: List of Cities in Indonesia

	2000 Population		2000 Population
Jakarta	5,127,473	Tulungagung	95,777
Bandung	1,484,094	Indramayu	95,151
Surabaya	1,433,148	Jepara	94,263
Semarang	658,314	Lumajang	93,386
Medan	649,630	Cilegon	92,873
Surakarta	589,262	Balikpapan	92,142
Jember	543,040	Blitar	88,946
Cirebon	504,302	Salatiga	86,834
Tegal	498,389	Pemalang	81,700
Yogyakarta	470,434	Samarinda	79,404
Malang	458,454	Cilacap	78,083
Jombang	409,646	Pematangsiantar	58,047
Mataram	398,043	Subang	54,266
Denpasar	379,644	Palu	53,445
Kudus	356,318	Pacet	53,020
Tasikmalaya	313,207	Kebumen	49,449
Ujung Pandang	305,483	Batu	48,088
Bandar Lampung	303,906	Kupang	46,673
Palembang	301,191	Batang	44,209
Karawang	299,240	Metro	43,562
Bojonegoro	287,307	Tebingtinggi	40,446
Mojokerto	203,336	Singaraja	40,106
Pekalongan	191,050	Ponorogo	37,676
Purwokerto	186,173	Gorontalo	35,351
Banjarmasin	182,916	Brebes	32,707
Pamekasan	157,778	Bukit Tinggi	31,273
Magelang	147,106	Banda Aceh	30,558
Pasuruan	143,879	Tanjung Balai	30,199
Padang	142,733	Kisaran	29,429
Banyuwangi	140,900	Bengkulu	28,713
Karangampel	140,868	Bitung	27,233
Probolinggo	140,019	Duri	25,835
Sukabumi	138,848	Singkawang	25,082
Pekan Baru	136,808	Tarakan	23,219
Garut	132,871	Sibolga	21,873
Kediri	128,398	Parepare	21,447
Kuningan	124,874	Bontang	18,225
Purwakarta	121,901	Tanjungpinang	16,674
Pontianak	120,646	Palopo	16,132
Batam	117,086	Watampone	15,341
Cikampek	110,976	Rantauprapat	15,183
Binjai	109,401	Dumai	11,161
Manado	107,863	Pangkalpinang	5,910
Cianjur	106,793	Lhokseumawe	3,486
Jambi	100,081	Padangsidempuan	3,131
Madiun	99,994		

Notes: This table provides a list of 91 urban areas in Indonesia, identified following the procedure in Jiang (2021) that uses nighttime lights satellite imagery to delineate cities.

Table A.2: List of Cities in the Philippines

	2010 Population	2016 Population
	(1)	(2)
Metro Manila	21,311,087	24,253,738
Cebu	2,723,639	2,801,102
Angeles	1,359,184	1,569,482
Davao	1,541,418	1,545,521
Cagayan de Oro	535,353	777,611
Bacolod	577,894	667,295
General Santos	540,925	639,191
Zamboanga	476,398	585,040
Iloilo	970,750	537,811
Batangas	330,740	486,125
Baguio	408,934	451,965
Dagupan	165,954	383,634
Naga	304,559	373,422
Cotabato	127,976	361,203
Lipa	257,457	338,079
Iligan	289,897	331,163
Olongapo	373,833	326,828
Tarlac	280,650	312,772
Lucena	260,131	290,920
Tacloban	218,439	258,498
San Pablo	208,077	218,385
Butuan	123,440	182,180
Dumaguete	125,164	170,545
San Pedro	107,102	159,905
Marawi	48,439	147,534
Tuguegarao	59,701	129,505
Urdaneta	64,406	123,855
Silay	78,247	119,167
San Fernando	63,665	112,496
Ormoc	77,643	92,578
Calapan	59,350	89,885
Roxas	53,635	76,138
Ozamis	56,552	74,127
Surigao	26,351	47,994
Toledo	8,353	43,836
Kidapawan	3,635	43,413
NegrosOccidental San Carlos	23,332	38,182
Calbayog	15,356	33,272
Cadiz	13,403	33,242
Kabankalan	16,404	22,650
Pangasinan San Carlos	9,561	22,451
Bago	64	12,548

Notes: This table provides a list of 42 urban areas in the Philippines, identified following the procedure in Jiang (2021) that uses nighttime lights satellite imagery to delineate cities.

Table A.3: Carbon Dioxide Emissions Factors

Emissions Source	Factor	Unit	Source
Propane (LPG)	5.750	kilograms of CO_2 per gallon	EIA (2023)
Motor Gasoline	8.780	kilograms of CO_2 per gallon	EIA (2023)
Kerosene	9.880	kilograms of CO_2 per gallon	EIA (2023)
Electric Power Source	**Factor**	**Unit**	**Source**
Diesel Power	0.264	U.S. tons of CO_2 per MW hour (Fuel = Fuel Oil)	Sari et al. (2021)
Gas Machine Power	0.200	U.S. tons of CO_2 per MW hour (Fuel = Natural Gas)	Sari et al. (2021)
Gas Turbine Power	0.200	U.S. tons of CO_2 per MW hour (Fuel = Natural Gas)	Sari et al. (2021)
Geothermal Power	0.134	U.S. tons of CO_2 per MW hour	Bertani and Thain (2002)
Hydro Power	0.000		
Micro Hydro Power	0.000		
Steam Gas Power	0.404	U.S. tons of CO_2 per MW hour (Fuel = Coal)	Sari et al. (2021)
Steam Power	0.404	U.S. tons of CO_2 per MW hour (Fuel = Coal)	Sari et al. (2021)
Wind Power	0.000		

Notes: This table reports carbon emissions factors by source that we use to estimate household residential carbon emissions. Different factors are used for households that obtain their electricity from different types of power plants. We use government data from both countries on the locations of different types of power plants, and we match households to their nearest power plants to obtain the appropriate emissions factor for their electricity consumption. We assume that hydro, micro-hydro, and wind power produce zero tons of CO_2 per MW hour.

Table A.4: Principal Components Analysis of $\mathbf{X}_v$

	Indonesia (*Susenas*)		Philippines (*FIES*)	
	Full (1)	Urban (2)	Full (3)	Urban (4)
# of Variables in $\mathbf{X}_v$	38	38	38	38
# of factors needed to explain:				
... 75% of total $\mathbf{X}_v$ variation	16	16	19	17
... 90% of total $\mathbf{X}_v$ variation	23	23	26	24
... 95% of total $\mathbf{X}_v$ variation	27	27	29	28
... 99% of total $\mathbf{X}_v$ variation	31	31	35	33
... 100% of total $\mathbf{X}_v$ variation	36	36	38	38

Notes: This table reports a principal components analysis of the 38 $\mathbf{X}_v$ variables for the Indonesia analysis and the 38 variables in the Philippines analysis, both for the full *Susenas* / FIES samples (columns 1 and 3) and for our urban *Susenas* / FIES samples described in Section 3 (columns 2 and 4). The first row lists the number of variables in $\mathbf{X}_v$. The next set of rows report the number of factors needed to explain 75%, 90%, 95%, 99% and 100% of the total variation in $\mathbf{X}_v$.

Table A.5: Kleibergen and Paap (2006) Cluster-Robust Tests of the Rank of the $\mathbf{X}_v$ Covariance Matrix

# Factors		Indonesia		Philippines	
		Full *Susenas* (p-value)	**Urban *Susenas* (p-value)**	**Full FIES (p-value)**	**Urban FIES (p-value)**
H_0	H_A	**(1)**	**(2)**	**(3)**	**(4)**
0	1+	0.000	0.000	0.000	0.000
1	2+	0.000	0.000	0.000	0.000
2	3+	0.000	0.000	0.000	0.000
3	4+	0.000	0.000	0.000	0.000
4	5+	0.000	0.000	0.000	0.000
5	6+	0.000	0.000	0.000	0.000
6	7+	0.000	0.000	0.000	0.000
7	8+	0.000	0.000	0.000	0.000
8	9+	0.000	0.000	0.000	0.000
9	10+	0.000	0.000	0.000	0.000
10	11+	0.000	0.000	0.000	0.000
11	12+	0.000	0.004	0.000	0.000
12	13+	0.000	0.025	0.000	0.000
13	14+	0.000	0.039	0.000	0.000
14	15+	0.005	0.237	0.000	0.000
15	16+	0.004	0.436	0.000	0.000
16	17+	0.036	0.452	0.028	0.028
17	18+	0.325	0.748	0.228	0.228
18	19+	0.412	0.855	0.542	0.542
19	20+	0.793	0.939	0.870	0.870
20	21+	0.733	0.956	0.967	0.967
21	22+	0.939	0.930	0.895	0.895

Notes: Each element of this table reports a p-value from a test of the null hypothesis that the rank of the covariance matrix of $\mathbf{X}_v$ is equal to the value associated with the row label, against the alternative that the rank exceeds this value. The test statistic is described in Kleibergen and Paap (2006), and the p-values we report are robust and account for clustering at the sub-district level in Indonesia and clustering at the muncipality level in the Philippines. Column 1 performs these tests on the full *Susenas* sample in Indonesia, while column 2 restricts the sample to urban areas in Indonesia. Column 3 performs these tests on the full FIES sample in the Philippines, while column 4 restricts the sample to urban areas in the Philippines.

Table A.6: First Stage, Community Level

	Indonesia		Philippines	
	(1)	**(2)**	**(3)**	**(4)**
Soil bulk density at 60cm depth	0.027***	0.014***		
	(0.002)	(0.002)		
Sand content at 60 cm depth (% (kg / kg))	-0.042***	-0.020***		
	(0.005)	(0.004)		
Great Group: Haplustolls (Mollisols)	0.488***	0.123*		
	(0.103)	(0.069)		
Great Group: Tropudults (Ultisols)	-1.026***	-0.799***		
	(0.174)	(0.167)		
Great Group: Chromusterts (Vertisols)	0.678***	0.430***		
	(0.105)	(0.085)		
Sand content % 200cm depth median			0.046***	0.042***
			(0.013)	(0.010)
Soil water content % at 33kPa 200cm depth median			-0.047***	-0.032***
			(0.009)	(0.008)
Great Group: Haplustalfs (Alfisols)			0.372***	0.212**
			(0.103)	(0.085)
N	3,502	3,502	1,844	1,844
N Clusters	1,328	1,328	209	209
Adj. R^2	0.548	0.734	0.614	0.719
Adj. R^2 (Within)	0.405	0.650	0.442	0.594
Regression F-Stat	83.4	76.6	39.3	70.4
City FE	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	Yes	No	Yes

Notes: This table reports estimates of a community-level version of equation (7), the relationship between log population density (the dependent variable) and different soil characteristics variables. We use post-double-selection lasso regressions, following Belloni et al. (2012), to select instruments in these regressions from a set of 67 soil characteristics. Columns 1 and 2 are limited to the sample of urban communities in Indonesia covered by the 2010 *Susenas* epoch, while columns 3 and 4 are limited to urban communities in the Philippines covered by the 2018 FIES. All regressions include controls for city fixed effects, elevation, ruggedness, distance to the nearest point on the coast, and distance to the nearest river. In columns 2 and 4, we add village-level controls for sorting on observables and unobservables, denoted by $\mathbf{X}_v$. Robust standard errors, clustered at the subdistrict-level in columns 1-2 and clustered at the municipality level in columns 3-4, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels. A version of this table at the household level can be found in Table 2.

Table A.7: Density and Electricity Use: Indiv. and Exog. Community Controls, Indonesia

Panel A: Indonesia	OLS (1)	IV-Lasso (2)
Log Density (2010)	0.082***	0.099***
	(0.009)	(0.019)
Age	0.033***	0.033***
	(0.002)	(0.002)
Age^2	-0.000***	-0.000***
	(0.000)	(0.000)
Female (0 1)	0.018	0.021
	(0.018)	(0.018)
not completed high school	0.279***	0.272***
	(0.018)	(0.018)
completed high school	0.549***	0.531***
	(0.021)	(0.023)
college and higher education	0.787***	0.768***
	(0.025)	(0.028)
Married (0 1)	0.334***	0.346***
	(0.034)	(0.034)
Divorced (0 1)	0.163***	0.170***
	(0.041)	(0.041)
Widowed (0 1)	0.267***	0.273***
	(0.036)	(0.036)
Non-employed (0 1)	0.052***	0.044***
	(0.013)	(0.013)
Household Size	0.081***	0.081***
	(0.003)	(0.003)
Elevation	-0.000**	-0.000
	(0.000)	(0.000)
Ruggedness	0.043	0.093*
	(0.052)	(0.053)
Distance to the coast	-0.003	-0.004
	(0.014)	(0.015)
Distance to nearest river	-0.002	-0.000
	(0.008)	(0.008)
N	40,207	40,207
N Clusters	1,329	1,329
Adjusted R^2	0.221	0.217
Adjusted R^2 (within)	0.129	0.125
Kleibergen-Paap Wald Rank F Stat		92.079
Under Id. Test (KP Rank LM Stat)		181.466
p-Value		0.000
Sargan-Hansen Test (Overidentification)		11.889
p-Value		0.018
City FE	Yes	Yes

Notes: This table reports the the main density coefficient, the coefficients on the individual-level controls ($\mathbf{X}_i$), and the coefficients on the exogenous community controls ($\mathbf{C}_{2v}$) from the regressions reported in Table 3, Panel A, Columns 1-2. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.8: Density and Electricity Use: Indiv. and Exog. Community Controls, Philippines

Panel B: Philippines	OLS (1)	IV-Lasso (2)
Log Density (2018)	0.057***	0.181***
	(0.010)	(0.033)
Household size	0.081***	0.079***
	(0.002)	(0.002)
Age of HH head	0.029***	0.030***
	(0.002)	(0.002)
Age of HH head (sq)	-0.000***	-0.000***
	(0.000)	(0.000)
HH head is female (1 0)	0.081***	0.075***
	(0.012)	(0.012)
HH head has secondary educ (1 0)	0.349***	0.341***
	(0.019)	(0.018)
HH head has tertiary educ (1 0)	0.766***	0.763***
	(0.040)	(0.038)
HH head is married (1 0)	0.249***	0.255***
	(0.024)	(0.024)
HH head is widowed (1 0)	0.064**	0.067***
	(0.025)	(0.025)
HH head is divorced/separated (1 0)	0.012	0.009
	(0.029)	(0.028)
HH head is self employed (1 0)	0.091***	0.096***
	(0.016)	(0.016)
HH head is an employer (1 0)	0.417***	0.429***
	(0.039)	(0.038)
HH head is not employed (1 0)	0.187***	0.192***
	(0.017)	(0.016)
HH head is employed in agriculture (1 0)	-0.229***	-0.163***
	(0.055)	(0.046)
HH head is employed in services (1 0)	0.101***	0.093***
	(0.014)	(0.015)
Elevation (m)	-0.000	-0.000
	(0.000)	(0.000)
Slope (deg)	-0.013	-0.001
	(0.018)	(0.023)
Ruggedness (m)	0.000	0.001**
	(0.000)	(0.000)
Distance to coast (km)	-0.006***	-0.001
	(0.002)	(0.002)
Distance to river (km)	-0.002	-0.001
	(0.003)	(0.003)
N	41,249	41,249
N Clusters	212	212
Adjusted R^2	0.283	0.283
Adjusted R^2 (within)	0.193	0.193
Kleibergen-Paap Wald Rank F Stat		27.066
Under Id. Test (KP Rank LM Stat)		31.607
p-Value		0.000
Sargan-Hansen Test (Overidentification)		1.641
p-Value		0.440
City FE	Yes	Yes

Notes: This table reports the the main density coefficient, the coefficients on the individual-level controls ($\mathbf{X}_i$), and the coefficients on the exogenous community controls ($\mathbf{C}_{2v}$) from the regressions reported in Table 3, Panel B, Columns 1-2. Robust standard errors, clustered at the municipality-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.9: Density and Electricity Use: Sorting Controls, Indonesia

Panel A: Indonesia	OLS (1)	IV-Lasso (2)
Log Density (2010)	0.011	-0.002
	(0.012)	(0.040)
Percent Jawa	-0.019	-0.057
	(0.100)	(0.095)
Percent Sunda	-0.105	-0.163**
	(0.084)	(0.079)
Percent Batak	-0.167	-0.246
	(0.326)	(0.318)
Percent Ethnicities from Nusa Tenggara	-1.928**	-1.884**
	(0.756)	(0.747)
Percent Madura	-0.171	-0.201
	(0.166)	(0.165)
Percent Betawi	0.149	0.100
	(0.123)	(0.118)
Percent Aceh	-1.100	-1.111
	(0.880)	(0.878)
Percent Minangkabau	-0.271	-0.402
	(0.544)	(0.562)
Percent Bugis	-0.976**	-1.013**
	(0.406)	(0.393)
Percent Malay	0.142	0.041
	(0.284)	(0.276)
Percent Ethnicities from South Sumatra	0.114	0.003
	(0.516)	(0.523)
Percent Ethnicities from Banten	-0.052	-0.128
	(0.117)	(0.109)
Percent Banjar	-0.025	-0.077
	(0.639)	(0.635)
Percent Dayak	-0.978	-1.098
	(0.885)	(0.877)
Percent Chinese	-0.738	-0.638
	(0.624)	(0.617)
Percent Ethnicities from Central Sulawesi	-1.118	-1.068
	(1.510)	(1.546)
Percent Ethnicities from Papua	-3.716	-4.221
	(6.168)	(5.983)
Percent Makassar	-0.385	-0.405
	(0.370)	(0.357)
Avg. Age	-0.008	-0.008
	(0.009)	(0.009)
Percent Female	-0.706	-0.659
	(0.885)	(0.873)
Avg. Household Size	-0.000	-0.000*
	(0.000)	(0.000)
Percent Single	-1.000	-0.850
	(1.406)	(1.425)
Percent Married	-0.444	-0.293
	(1.316)	(1.362)
Percent Divorced	-0.572	0.355
	(2.811)	(2.753)
Percent Religion: Islam	10.802**	9.611**
	(4.819)	(4.759)
Percent Religion: Christian	10.551**	9.397**
	(4.846)	(4.792)
Percent Religion: Catholic	11.225**	9.961**
	(4.848)	(4.781)
Percent Religion: Hindu	11.017**	9.794**
	(4.832)	(4.775)
Percent Religion: Buddhist	11.626**	10.291**
	(4.940)	(4.871)
Percent Religion: Confucian	9.284*	7.524
	(5.585)	(5.463)
Percent Unemployed	0.293	0.318
	(0.200)	(0.196)
Percent Self-employed	0.398	0.416
	(0.252)	(0.257)
Percent Employer	0.053	0.059
	(0.307)	(0.302)
Avg. Years of Schooling	0.040***	0.043***
	(0.013)	(0.015)
Percent Ever Migrants	0.119	0.137
	(0.103)	(0.120)
Percent Recent Migrants	0.233	0.186
	(0.201)	(0.234)
Percent Working in Agriculture	-0.301***	-0.321***
	(0.081)	(0.109)
N	40,207	40,207
N Clusters	1,329	1,329
Adjusted R^2	0.232	0.232
Adjusted R^2 (within)	0.142	0.142
Kleibergen-Paap Wald Rank F Stat		26.289
Under Id. Test (KP Rank LM Stat)		84.511
p-Value		0.000
Sargan-Hansen Test (Overidentification)		3.905
p-Value		0.419
City FE	Yes	Yes

Notes: This table displays the coefficients on log density and the community-level sorting controls ($\mathbf{X}_v$) from the regression reported in Table 3, Panel A, Column 3. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.10: Density and Electricity Use: Sorting Controls, Philippines

	OLS	IV-Lasso
Panel B: Philippines	**(1)**	**(2)**
Log Density (2018)	0.031***	0.068
	(0.011)	(0.042)
Average family size in the barangay	0.001***	0.001***
	(0.000)	(0.000)
Percent females	0.108	-0.326
	(0.773)	(0.812)
Percent 7-15 years old	-1.191	-1.122
	(0.836)	(0.830)
Percent 16-24 years old	-2.816***	-2.680***
	(0.735)	(0.745)
Percent 25-54 years old	-1.191	-0.738
	(0.745)	(0.847)
Percent 55-64 years old	-2.080**	-1.603*
	(1.036)	(0.951)
Percent 65 years old and up	-1.532	-0.759
	(0.937)	(1.473)
Percent highest grade completed secondary	0.412	0.181
	(0.425)	(0.448)
Percent highest grade completed tertiary	1.833***	1.527***
	(0.304)	(0.500)
Percent single	-91.211	-41.662
	(115.275)	(109.422)
Percent married	-0.905	-0.286
	(0.601)	(1.183)
Percent widowed	-2.365	-3.949
	(1.784)	(2.425)
Percent common-law	-0.243	-0.856
	(0.665)	(0.940)
Percent overseas workers	0.676	1.118
	(0.823)	(0.925)
Percent Roman Catholics	0.408	0.450*
	(0.256)	(0.250)
Percent Muslims	1.075***	1.092***
	(0.368)	(0.330)
Percent Iglesia ni Cristo	0.133	0.074
	(0.393)	(0.368)
Percent other religious affiliations	-0.557	-0.765
	(0.567)	(0.534)
Percent Aglipay	0.184	0.433
	(0.535)	(0.546)
Percent Seventh Day Adventists	1.155**	1.251**
	(0.558)	(0.573)
Percent Tagalog	0.662***	0.611***
	(0.144)	(0.149)
Percent Bisaya	0.362**	0.302*
	(0.155)	(0.163)
Percent Cebuano	0.582**	0.521**
	(0.228)	(0.236)
Percent Ilocano	-0.006	-0.097
	(0.177)	(0.194)
Percent Ilonggo	0.542	0.458
	(0.385)	(0.390)
Percent Bikol	1.127***	1.127**
	(0.433)	(0.443)
Percent Waray	1.719***	1.622***
	(0.526)	(0.527)
Percent Kapampangan	0.851***	0.820***
	(0.201)	(0.211)
Percent Boholano	-0.660	-0.789
	(1.020)	(0.958)
Percent Pangasinan	-0.368	-0.648
	(0.444)	(0.463)
Percent Maguindanao	-0.028	-0.105
	(0.187)	(0.181)
Percent Maranao	-0.321	-0.533
	(0.380)	(0.349)
Percent Tausug	-1.630***	-1.710***
	(0.293)	(0.282)
Percent Capizeno	-6.339	-6.653
	(6.368)	(6.353)
Percent Masbatenon	3.853	4.297*
	(2.589)	(2.602)
Percent Karay-a	76.675	76.446
	(59.334)	(57.366)
Percent Manobo	15.529	14.473
	(11.384)	(10.920)
Percent Subanen	167.223	159.520
	(134.352)	(134.143)
N	41,249	41,249
N Clusters	212	212
Adjusted R^2	0.296	0.296
Adjusted R^2 (within)	0.209	0.208
Kleibergen-Paap Wald Rank F Stat		14.546
Under Id. Test (KP Rank LM Stat)		20.518
p-Value		0.000
Sargan-Hansen Test (Overidentification)		3.280
p-Value		0.194
City FE	Yes	Yes

Notes: This table displays the coefficients on log density and the community-level sorting controls ($\mathbf{X}_v$) from the regression reported in Table 3, Panel B, Column 3. Robust standard errors, clustered at the municipality-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.11: Summary Statistics on Asset Ownership

	Indonesia (2010)		Philippines (2018)	
Asset	**Mean (Std. Dev)**	**N**	**Mean (Std. Dev)**	**N**
Fridge	0.35 (0.48)	40,920	0.59 (0.49)	47,742
Air Conditioner	0.02 (0.14)	20,705	0.22 (0.41)	47,742
Motorcycle	0.59 (0.49)	40,920	0.24 (0.43)	47,742
Car	0.05 (0.22)	20,705	0.12 (0.32)	47,742
Gas Cylinder (<15kg)	0.09 (0.29)	20,705		
Water Heater	0.02 (0.14)	20,705		

Notes: This table provides summary statistics for different asset ownership outcomes for households in the Indonesia (2010) sample and for households in the Philippines (2018) sample. The Indonesian data are pooled from three *Susenas* rounds in 2010, 2011, and 2012, while the Philippines data come from the 2018 FIES.

Table A.12: Density and Residential Energy Consumption: Extensive Margin

Panel A: Indonesia	**Any Electricity? (1)**	**Any LPG? (2)**	**Any Vehicle Gas? (3)**	**Any Kerosene? (4)**
Log Density (2010)	-0.001	-0.018	-0.012	0.011
	(0.003)	(0.019)	(0.014)	(0.018)
N	40,207	40,207	40,207	40,207
N Clusters	1,329	1,329	1,329	1,329
Kleibergen-Paap Wald Rank F Stat	26.289	26.289	26.289	26.289
Panel B: Philippines	**(1)**	**(2)**	**(3)**	**(4)**
Log Density (2018)	0.002	-0.034*	0.013	-0.002
	(0.005)	(0.019)	(0.024)	(0.011)
N	46,754	46,754	46,754	46,754
N Clusters	212	212	212	212
Kleibergen-Paap Wald Rank F Stat	14.785	14.785	14.785	14.785
City FE	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	Yes	Yes	Yes	Yes

Notes: This table replicates columns 3, 6, 9, and 12 of Table 4 but replaces the dependent variable to be an indicator for whether the household consumed any quantity of residential energy. The dependent variable is listed in the column header. Panel A reports results for households in Indonesian cities, while Panel B reports results for households in Philippines cities. All columns apply a post-double-selection IV-Lasso estimator, following Belloni et al. (2012), and they include city fixed effects, controls for $\mathbf{X}_i$, $\mathbf{C}_{2v}$, and $\mathbf{X}_v$. Robust standard errors, clustered at the subdistrict-level in Panel A (and the municipality level in Panel B), are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.13: Density and Residential Energy Use, Intensive Margin

Panel A: Indonesia	**Electricity (1)**	**LPG (2)**	**Vehicle Gas (3)**	**Kerosene (4)**
Log Density (2010)	0.011	-0.045*	-0.025	-0.017
	(0.040)	(0.026)	(0.030)	(0.087)
N	40,081	29,289	25,121	6,166
N Clusters	1,322	1,299	1,323	873
Kleibergen-Paap Wald Rank F Stat	26.083	19.274	29.846	25.799
Panel B: Philippines	**(1)**	**(2)**	**(3)**	**(4)**
Log Density (2018)	0.040	0.050**	-0.195	0.119
	(0.035)	(0.021)	(0.148)	(0.075)
N	46,163	39,593	19,846	2,378
N Clusters	212	211	212	154
Kleibergen-Paap Wald Rank F Stat	14.527	17.528	3.108	17.064
City FE	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	Yes	Yes	Yes	Yes

Notes: This table replicates columns 3, 6, 9, and 12 of Table 4 but replaces the dependent variable to be $\log y_{iv}$ instead of $\log(1 + y_{iv})$. The dependent variable is listed in the column header. Panel A reports results for households in Indonesian cities, while Panel B reports results for households in Philippines cities. All columns apply a post-double-selection IV-Lasso estimator, following Belloni et al. (2012), and they include city fixed effects, controls for $\mathbf{X}_i$, $\mathbf{C}_{2v}$, and $\mathbf{X}_v$. Robust standard errors, clustered at the subdistrict-level in Panel A (and the municipality level in Panel B), are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.14: Density and Residential Energy Use: Dropping Agricultural HHs, Indonesia

	Baseline IV-Lasso	Dropping Households Employed in Agriculture	Dropping Communities with Agricultural Household Share >80%	>60%	>40%	>20%
Panel A: Electricity	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
1. Only Xi and W2v Controls	0.099***	0.090***	0.097***	0.096***	0.101***	0.106***
	(0.019)	(0.020)	(0.019)	(0.020)	(0.019)	(0.021)
2: Adding Xv controls	-0.002	0.006	-0.005	-0.006	0.017	0.020
	(0.040)	(0.039)	(0.039)	(0.039)	(0.038)	(0.042)
N	40,207	32,441	40,125	39,872	38,965	35,870
N Clusters	1,329	1,328	1,324	1,318	1,294	1,201
Kleibergen-Paap Wald Rank *F* Stat	26.289	27.661	26.390	26.208	27.187	23.345
Panel B: LPG	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
1. Only Xi and W2v Controls	0.070***	0.044**	0.069***	0.068***	0.076***	0.064***
	(0.019)	(0.018)	(0.019)	(0.019)	(0.020)	(0.020)
2: Adding Xv controls	-0.052	-0.059	-0.051	-0.057	-0.038	-0.053
	(0.041)	(0.039)	(0.041)	(0.041)	(0.040)	(0.040)
N	40,207	32,441	40,125	39,872	38,965	35,870
N Clusters	1,329	1,328	1,324	1,318	1,294	1,201
Kleibergen-Paap Wald Rank *F* Stat	26.289	27.661	26.390	26.208	27.187	23.345
Panel C: Vehicle Gas Consumption	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
1. Only Xi and W2v Controls	0.027	-0.003	0.027	0.029	0.034	0.054**
	(0.023)	(0.025)	(0.023)	(0.024)	(0.025)	(0.025)
2: Adding Xv controls	-0.050	-0.024	-0.048	-0.049	-0.020	0.029
	(0.049)	(0.050)	(0.049)	(0.049)	(0.049)	(0.052)
N	40,207	32,441	40,125	39,872	38,965	35,870
N Clusters	1,329	1,328	1,324	1,318	1,294	1,201
Kleibergen-Paap Wald Rank *F* Stat	26.289	27.661	26.390	26.208	27.187	23.345
Panel D: Kerosene Consumption	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
1. Only Xi and W2v Controls	0.056***	0.063***	0.056***	0.056***	0.059***	0.067***
	(0.018)	(0.019)	(0.018)	(0.018)	(0.018)	(0.020)
2: Adding Xv controls	0.100**	0.108***	0.097**	0.097**	0.103**	0.108**
	(0.041)	(0.042)	(0.041)	(0.041)	(0.041)	(0.045)
N	40,207	32,441	40,125	39,872	38,965	35,870
N Clusters	1,329	1,328	1,324	1,318	1,294	1,201
Kleibergen-Paap Wald Rank *F* Stat	26.289	27.661	26.390	26.208	27.187	23.345

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is listed in the panel header. All coefficients are obtained from a post-double-selection IV-Lasso estimator, following Belloni et al. (2012). The first row in each panel includes city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. The second row in each panel additionally includes $\mathbf{X}_v$ controls. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.15: Density and Residential Energy Use: Dropping Agricultural HHs, Philippines

	Electricity		LPG		Vehicle Gas		Kerosene	
	Baseline IV-Lasso	**Dropping Households Employed in Agriculture**	**Baseline IV-Lasso**	**Dropping Households Employed in Agriculture**	**Baseline IV-Lasso**	**Dropping Households Employed in Agriculture**	**Baseline IV-Lasso**	**Dropping Households Employed in Agriculture**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
1. Only Xi and W2v Controls	0.181***	0.237***	0.091***	0.098***	0.025	0.030	-0.002	0.000
	(0.033)	(0.060)	(0.029)	(0.029)	(0.033)	(0.036)	(0.002)	(0.002)
2. Adding Xv controls	0.068	0.234	0.007	0.024	0.047	0.058	-0.001	0.001
	(0.042)	(0.145)	(0.037)	(0.037)	(0.055)	(0.058)	(0.003)	(0.005)
N	41,249	39,734	43,687	42,186	42,887	41,390	45,312	43,812
N Clusters	212	212	212	212	212	212	212	212
Kleibergen-Paap Wald Rank F Stat	14.546	5.871	14.117	14.074	13.915	13.859	15.646	6.409

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is listed in the panel header. All coefficients are obtained from a post-double-selection IV-Lasso estimator, following Belloni et al. (2012). The first row in each panel includes city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. The second row in each panel additionally includes $\mathbf{X}_v$ controls. Robust standard errors, clustered at the municipality-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.16: Density and Residential Energy Use: Controlling for Historical Infrastructure, Indonesia

	Baseline		**Infrastructure Controls**							
Panel A: Only $\mathbf{X}_i$ controls	**OLS (1)**	**IV-Lasso (2)**	**IV-Lasso (3)**	**IV-Lasso (4)**	**IV-Lasso (5)**	**IV-Lasso (6)**	**IV-Lasso (7)**	**IV-Lasso (8)**	**IV-Lasso (9)**	**IV-Lasso (10)**
1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls	0.008***	0.011***	0.013***	0.013***	0.012***	0.012***	0.012***	0.012***	0.011***	0.012***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Panel B: Adding $\mathbf{X}_v$ controls	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
2. Adding $\mathbf{X}_v$ Controls	0.001	0.003	0.004	0.004	0.003	0.004	0.003	0.004	0.003	0.003
	(0.001)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Education Facilities (1983)	.	.	Yes	.	.	.	.	.	.	Yes
Historical Medical Facilities (1983)	.	.	.	Yes	.	.	.	.	.	Yes
Places of Worship(1983)	.	.	.	.	Yes	.	.	.	.	Yes
Irrigation and PLN (1983)	.	.	.	.	.	Yes	.	.	.	Yes
Agricultural Organizations (1983)	.	.	.	.	.	.	Yes	.	.	Yes
Social Activities (1983)	.	.	.	.	.	.	.	Yes	.	Yes
Distance to Major Road	.	.	.	.	.	.	.	.	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	151,520	151,520	151,520	151,520	151,520	151,520	151,520	151,520	151,260	151,260

Notes: Each cell reports estimates of the average density elasticity of residential carbon emissions for urban households in Indonesia (Panel A). The object estimated is described in equation (10). Column 1 and 2 reproduce the OLS estimates and IV-Lasso estimates from Table 6, Panel A. Notice that the estimates are slightly different due to imperfect merging with the historical infrastructure data. In Panel A, we only control for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Panel B reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas in Indonesia and include city-fixed effects. From Column 3-9, we separately includes different groups of historical infrastructure variables, as indicated from the bottom panel. In Column 10, we include all historical infrastructure controls. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% level.

Table A.17: Density and Residential Energy Use: Controlling for Historical Infrastructure, Philippines

	Baseline		**Infrastructure Controls**				
	OLS	**IV-Lasso**	**IV-Lasso**	**IV-Lasso**	**IV-Lasso**	**IV-Lasso**	**IV-Lasso**
Panel A: Only $\mathbf{X}_i$ controls	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
1. Only $\mathbf{X}_i$ and $\mathbf{W}_{2v}$ Controls	0.000	0.012***	0.011***	0.011***	0.012***	0.012***	0.011***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Panel B: Adding $\mathbf{X}_v$ controls	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
2. Adding $\mathbf{X}_v$ Controls	-0.001*	0.004	0.003	0.003	0.003	0.003	0.003
	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Education Facilities (2000)	.	.	Yes	.	.	.	Yes
Medical Facilities (2000)	.	.	.	Yes	.	.	Yes
Places of Worship(2000)	.	.	.	.	Yes	.	Yes
Access to Major Road (2000)	.	.	.	.	.	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	173,135	173,135	169,873	170,820	170,892	170,112	168,755

Notes: Each cell reports estimates of the average density elasticity of residential carbon emissions for urban households in Indonesia (Panel A). The object estimated is described in equation (10). Column 1 and 2 reproduce the OLS estimates and IV-Lasso estimates from Table 6 (Panel B). Notice that the estimates are slightly different due to imperfect merging with the historical infrastructure data. In Panel A, we only control for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. Panel B reports the full, unrestricted model. All regressions are limited to the sample of villages within urban areas in Indonesia and include city-fixed effects. From Column 3-6, we separately includes different groups of historical infrastructure variables, as indicated from the bottom panel. In Column 7, we include all historical infrastructure controls. Robust standard errors, clustered at the municipality-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% level.

Table A.18: The Effects of Soil Characteristics on Energy Consumption in Rural Areas

	Electricity	**LPG**	**Vehicle Gas**	**Kerosene**	**CO_2**
Panel A: Indonesia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Soil bulk density at 60 cm depth (kg / m3)	-0.001	-0.001	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Sand content at 60 cm depth (% (kg / kg))	-0.005	-0.000	0.010**	0.003	0.001**
	(0.004)	(0.003)	(0.004)	(0.003)	(0.000)
Great Group: Haplustolls (Mollisols)	-0.171*	-0.006	-0.021	-0.100	-0.009
	(0.096)	(0.052)	(0.089)	(0.079)	(0.007)
Great Group: Tropudults (Ultisols)	0.006	-0.011	0.040	-0.023	0.002
	(0.029)	(0.023)	(0.030)	(0.026)	(0.003)
N	30,435	30,435	30,435	30,435	
N Clusters	1,894	1,894	1,894	1,894	
Adj. R^2	0.289	0.341	0.341	0.451	
Adj. R^2 (Within)	0.056	0.066	0.162	0.019	
$H_o : \beta = 0$ (p-value)	0.131	0.801	0.093	0.545	
Kleibergen-Paap Wald Rank F Stat	2.438	2.438	2.438	2.438	
Density Cutoff	300	300	300	300	
Fixed Effects	Kabu	Kabu	Kabu	Kabu	
Panel B: Philippines	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Soil bulk density at 200cm depth	0.001	-0.001	-0.001	-0.000*	-0.000
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Soil water content at 200cm depth	0.009	-0.002	0.003	-0.000	0.001
	(0.006)	(0.002)	(0.003)	(0.001)	(0.000)
Great Group: Haplustalfs (Alfisols)	0.164	-0.062	-0.089	-0.062	-0.000
	(0.177)	(0.038)	(0.267)	(0.040)	(0.018)
N	37,579	36,718	36,959	34,634	
N Clusters	82	82	82	82	
Adj. R^2	0.332	0.426	0.208	0.235	
Adj. R^2 (Within)	0.227	0.146	0.152	0.040	
$H_o : \beta = 0$ (p-value)	0.345	0.006	0.784	0.139	
Kleibergen-Paap Wald Rank F Stat	0.094	0.085	0.106	0.068	
Density Cutoff	300	300	300	300	
Fixed Effects	Province	Province	Province	Province	

Notes: This table reports reduced-form regression coefficients of the dependent variable (listed in the column headers) on our selected soil characteristics in rural areas with a population density of less than 300 inhabitants per km^2. Panel A focuses on rural areas in Indonesia, while Panel B focuses on rural areas in the Philippines. All columns include city fixed effects and controls for $\mathbf{X}_i$, $\mathbf{C}_{2v}$, and $\mathbf{X}_v$. Robust standard errors, clustered at the subdistrict-level in Panel A and the municipality level in Panel B, are reported in parentheses. The "Ho : $\beta = 0$ (p-value)" row reports the p-value of an F-test for the null hypothesis that the coefficients on the soil characteristics variables are all equal to zero. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.19: Density and Residential Energy Use, Using Depth to Bedrock + Selected Soil IVs

	Electricity			LPG			Vehicle Gas			Kerosene		
	OLS	IV-Lasso		OLS	IV-Lasso		OLS	IV-Lasso		OLS	IV-Lasso	
Panel A: Indonesia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Log Density (2010)	0.082***	0.099***	0.017	0.086***	0.086***	-0.003	0.002	0.041*	-0.011	0.037***	0.029*	0.035
	(0.009)	(0.018)	(0.035)	(0.009)	(0.018)	(0.037)	(0.012)	(0.022)	(0.043)	(0.008)	(0.016)	(0.036)
N	40,207	40,180	40,180	40,207	40,180	40,180	40,207	40,180	40,180	40,207	40,180	40,180
N Clusters	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329	1,329
Kleibergen-Paap Wald Rank F Stat		84.072	25.886		84.072	25.886		84.072	25.886		84.072	25.886
Panel B: Philippines	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Log Density (2018)	0.057***	0.167***	0.055	0.014	0.087***	0.022	-0.106***	-0.015	0.062	-0.000	-0.003**	-0.005*
	(0.010)	(0.030)	(0.042)	(0.009)	(0.023)	(0.036)	(0.013)	(0.029)	(0.045)	(0.000)	(0.002)	(0.003)
N	41,249	41,249	41,249	43,687	43,687	43,687	42,887	42,887	42,887	45,312	45,312	45,312
N Clusters	212	212	212	212	212	212	212	212	212	212	212	212
Kleibergen-Paap Wald Rank F Stat		22.905	12.083		23.193	11.658		23.119	11.462		23.135	8.682
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is listed in the column header. Panel A reports results for households in Indonesian cities, while Panel B reports results for households in Philippines cities. Columns 1, 4, 7, and 10 report OLS estimates, while the other columns apply a post-double-selection IV-Lasso estimator, following Belloni et al. (2012). All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Columns 3, 6, 9, and 12 additionally include $\mathbf{X}_v$ sorting controls. Robust standard errors, clustered at the subdistrict-level in Panel A (and the municipality level in Panel B), are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.20: Density and Residential Energy Use: Only Reported Quantities, Indonesia

	Electricity			LPG			Vehicle Gas			Kerosene		
	OLS	**IV-Lasso**		**OLS**	**IV-Lasso**		**OLS**	**IV-Lasso**		**OLS**	**IV-Lasso**	
Panel A: Indonesia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
Log Density (2010)	0.081***	0.113***	0.006	-0.003	-0.024	-0.097***	-0.016	0.021	-0.026	0.031***	0.021*	0.011
	(0.009)	(0.023)	(0.054)	(0.009)	(0.016)	(0.032)	(0.010)	(0.019)	(0.038)	(0.006)	(0.012)	(0.027)
N	40,612	40,612	40,612	53,845	53,845	53,845	51,073	51,073	51,073	55,045	55,045	55,045
N Clusters	1,329	1,329	1,329	1,405	1,405	1,405	1,405	1,405	1,405	1,405	1,405	1,405
Kleibergen-Paap Wald Rank F Stat		124.229	32.902		81.240	25.042		81.634	25.099		70.164	22.682
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes

Notes: Each cell reports the coefficient on log population density from equation (8) where the dependent variable is listed in the column header. Columns 1, 4, 7, and 10 report OLS estimates, while the other columns apply a post-double-selection IV-Lasso estimator, following Belloni et al. (2012). All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Columns 3, 6, 9, and 12 additionally include $\mathbf{X}_v$ sorting controls. For the sample, unlike our main Indonesia results (reported in Table 4, Panel A), we drop observations without reported quantities in the consumption expenditures data. Robust standard errors, clustered at the subdistrict-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

Table A.21: Heterongeneity Analysis: Big City (> 1 million) VS Other Cities

	Electricity				**LPG**				**Vehicle Gas**				**Kerosene**			
	Big Cities		**Other**		**Big Cities**		**Other**		**Big Cities**		**Other**		**Big Cities**		**Other**	
	IV	**IV control $\mathbf{X}_v$**	**IV**	**IV control $\mathbf{X}_v$**	**IV**	**IV control $\mathbf{X}_v$**	**IV**	**IV control $\mathbf{X}_v$**	**IV**	**IV control $\mathbf{X}_v$**	**IV**	**IV control $\mathbf{X}_v$**	**IV**	**IV control $\mathbf{X}_v$**	**IV**	**IV control $\mathbf{X}_v$**
Panel A: Indonesia	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
Log Density (2010)	0.100***	0.033	0.059**	-0.007	0.046**	-0.037	0.044	-0.011	0.083**	-0.014	-0.031	-0.089	0.008	-0.007	0.136***	0.133**
	(0.024)	(0.046)	(0.030)	(0.042)	(0.021)	(0.042)	(0.031)	(0.049)	(0.033)	(0.061)	(0.032)	(0.058)	(0.016)	(0.024)	(0.035)	(0.056)
N	27,620	27,620	12,587	12,587	27,620	27,620	12,587	12,587	27,620	27,620	12,587	12,587	27,620	27,620	12,587	12,587
N Clusters	874	874	471	471	874	874	471	471	874	874	471	471	874	874	471	471
Kleibergen-Paap Wald Rank F Stat	57.559	19.848	64.885	30.631	57.559	19.848	64.885	30.631	57.559	19.848	64.885	30.631	57.559	19.848	64.885	30.631
Panel B: Philippines	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**
Log Density (2018)	0.072***	0.046	0.122	0.089	0.003	-0.015	0.029	0.011	-0.147***	-0.112**	-0.023	-0.108**	-0.000	0.000	0.001	-0.001
	(0.021)	(0.034)	(0.100)	(0.056)	(0.024)	(0.039)	(0.045)	(0.033)	(0.026)	(0.049)	(0.072)	(0.047)	(0.001)	(0.003)	(0.005)	(0.002)
N	25,565	25,565	15,684	15,684	26,303	26,303	17,384	17,384	25,880	25,880	17,007	17,007	27,411	27,411	17,901	17,901
N Clusters	176	176	36	36	176	176	36	36	176	176	36	36	176	176	36	36
Kleibergen-Paap Wald Rank F Stat	30.970	18.920	19.508	37.087	30.909	19.825	19.513	35.924	37.817	21.672	20.207	37.892	38.968	22.318	19.099	38.898
$\mathbf{X}_v$ Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

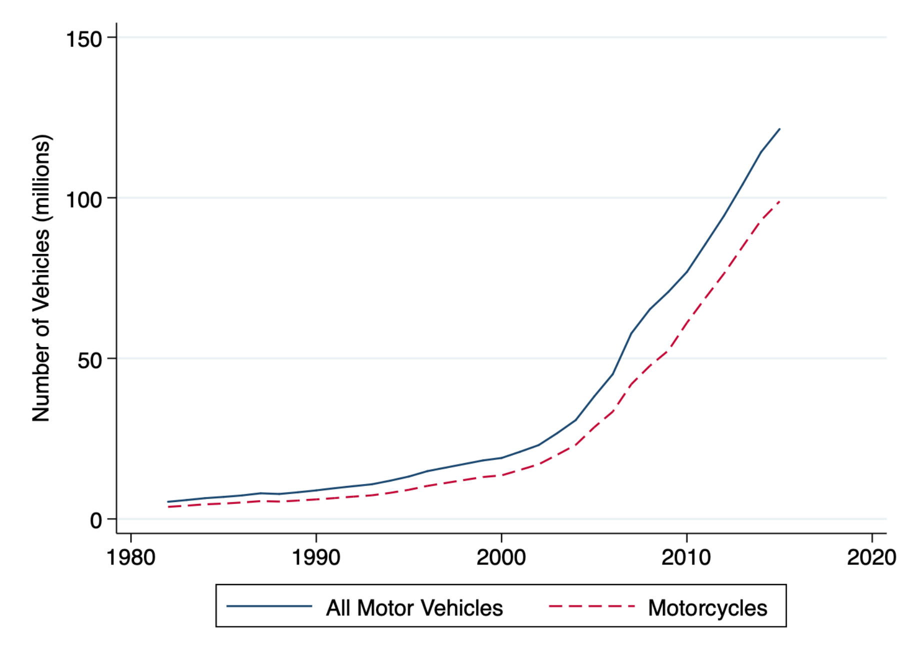
Notes: Each cell reports estimates of the effect of density on different types of residential energy consumption, with the type of energy listed in the column header. All coefficients are obtained from a post-double-selection IV-Lasso estimator, following Belloni et al. (2012). The odd columns only control for city fixed effects, $\mathbf{X}_i$, and $\mathbf{C}_{2v}$, setting $\mathbf{\Gamma}_1 = 0$. The even columns add the $\mathbf{X}_v$ sorting controls. Columns 1-2, 5-6, 9-10, and 13-14, restrict the sample to urban areas with populations greater than 1 million, while the other columns restrict the sample to smaller urban areas. Robust standard errors, clustered at the municipality-level, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% level.

Table A.22: The Average Density Elasticity of Residential Carbon Emissions: Previous Waves

	OLS	IV-Lasso	
Panel A: Indonesia	**(1)**	**(2)**	**(3)**
Log Density (2000)	0.017***	0.020***	-0.002
	(0.002)	(0.005)	(0.009)
N	16,847	16,833	16,833
Panel B: Philippines	**(1)**	**(2)**	**(3)**
Log Density (2010)	0.003**	0.014***	0.005
	(0.001)	(0.003)	(0.004)
N	11,376	11,376	11,376
City FE	Yes	Yes	Yes
$\mathbf{X}_i$ Controls	Yes	Yes	Yes
$\mathbf{C}_{2v}$ Controls	Yes	Yes	Yes
$\mathbf{X}_v$ Controls	No	No	Yes

Notes: This table reports estimates of the average density elasticity of residential carbon emissions for urban households in Indonesia (Panel A) and the Philippines (Panel B). The object estimated is described in equation (10). To obtain this, we estimate the density elasticity for our four carbon intensity outcomes simultaneously, using a SUR system and national carbon intensity weights. All regressions include city fixed effects and controls for $\mathbf{X}_i$ and $\mathbf{C}_{2v}$. Columns 2 and 3 report results from post-double-selection IV-lasso estimators, following Belloni et al. (2012), and column 3 additionally includes $\mathbf{X}_v$ controls. Robust standard errors, clustered at the subdistrict-level in Panel A and the municipality level in Panel B, are reported in parentheses. */**/*** denotes significant at the 10% / 5% / 1% levels.

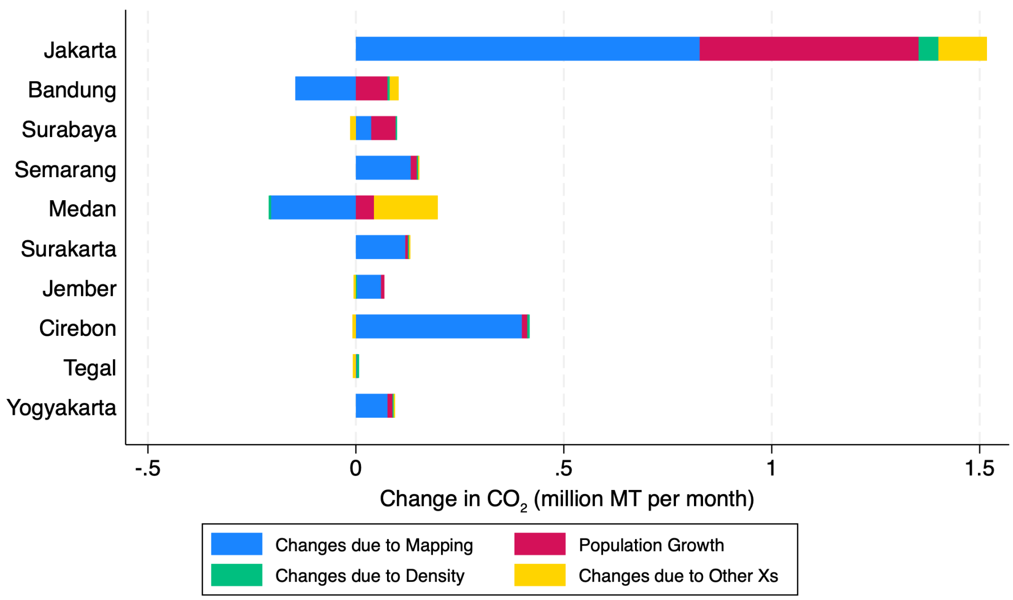
Figure A.1: Number of Registered Vehicles in Indonesia



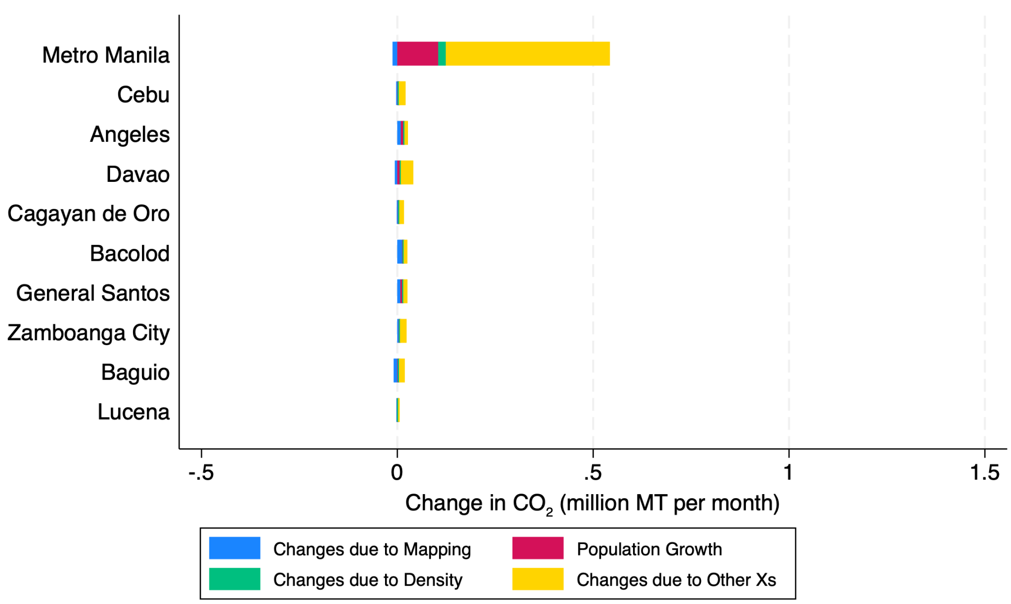
Notes: This figure uses data from various waves of Indonesia's Transportation Statistics (*Statistik Transportasi*), published by BPS, to plot the number of registered vehicles in Indonesia over time. The data compiled by BPS are based on vehicle registrations that come from Indonesia's State Police (*Kepolisian Republik Indonesia*).

Figure A.2: Overall Emissions Growth Decomposition: Results for Top 10 Cities + Density

(A) INDONESIA



(B) PHILIPPINES



Notes: This figure presents our overall decomposition of changes in predicted emissions by city. This decomposition further separates term B in equation (11) into density and non-density characteristic effects. To do so, we follow equation (B.2) in Appendix B.

B Growth Decomposition

Predicting Total Residential Emissions. Let $c = 1, ..., C$ index cities in our sample, and let $v = 1, ..., N_v$ index communities in city c. Let $s \in \mathcal{S}$ also index types of households. In our analysis, we group households into 3 size groups (1-2 person households, 3-4 person households, and households with more than 4 members) and 4 household-head education groupings (no schooling, some schooling, only completed high school, greater than high school completion). Therefore, there are 12 household types in our analysis (i.e. $|\mathcal{S}|$ = 12).

We can express city c's estimated total residential carbon emissions at time t as follows:

$$\widehat{\text{CE}}_{ct} = \sum_{v=1}^{N_c} \sum_{i \in s} N_{sv,t} \cdot \widehat{\text{CE}}_{sv,t}$$

where $N_{sv,t}$ measures the number of type s households in community v at time t and $\widehat{\text{CE}}_{sv,t}$ is the predicted average residential carbon emissions for a type s household in community v at time t. From equation (9), we can write:

$$\widehat{\text{CE}}_{sv,t} = \sum_{k} w_v(k) \cdot \widehat{y}_{sv,t}(k)$$

where k indexes residential energy outcomes, $w_v(k)$ are carbon intensity weights, and $\widehat{y}_{sv,t}(k)$ are the predicted *levels* of consumption for household type s in community v at time t.

Our main regression model, shown in equation (8), is a log linear regression. Abusing notation, let $\mathbf{x}_{sv,t}$ be a vector of variables in that regression (including city-specific intercepts, individual controls, log density, and community-level controls), and let β be a vector collecting their respective parameters (i.e. $\beta = [\alpha_c, \beta', \theta, \mathbf{\Gamma}_1', \mathbf{\Gamma}_2']'$. We can rewrite equation (8) as:

$$\log\left(1 + y_{sv,t}(k)\right) = \mathbf{x}_{sv,t}'\beta_{k,t} + \varepsilon_{sv,t}(k)$$

where k indexes the type of energy consumption, and t indicates the time period for the cross-sectional regression analysis. We can write:

$$\begin{aligned}
\log\left(1 + y_{sv,t}(k)\right) &= \mathbf{x}_{sv,t}'\beta_k + \varepsilon_{sv,t}(k) \\
\implies \exp\left\{\log\left(y_{sv,t}(k) + 1\right)\right\} &= \exp\left\{\mathbf{x}_{sv,t}'\beta_k\right\} \exp\left\{\varepsilon_{sv,t}(k)\right\} \\
\implies y_{sv,t}(k) &= \exp\left\{\mathbf{x}_{sv,t}'\beta_{k,t}\right\} \exp\left\{\varepsilon_{sv,t}(k)\right\} - 1
\end{aligned}$$

So we can use our regression results, which provide estimates of β_k, to calculate a "smearing estimate" of the predicted levels of y (Duan, 1983):

$$\begin{aligned}
\widehat{y}_{sv,t}(k) &= \exp\left\{\mathbf{x}_{sv,t}'\widehat{\beta}_{k,t}\right\} \left(\frac{1}{N}\sum_{i=1}^{N} \exp\left\{\mathbf{e}_{sv,t}(k)\right\}\right) - 1 \\
&= \exp\left\{\mathbf{x}_{sv,t}'\widehat{\beta}_{k,t}\right\} \widehat{\mathbf{s}}_t - 1
\end{aligned}$$

where $\mathbf{e}_{sv,t}(k) = \log\left(y_{sv,t}(k) + 1\right) - \mathbf{x}_{sv,t}'\widehat{\beta}_{k,t}$ is the residual of the log linear regression for outcome k for a type s household in community v, and $\widehat{\mathbf{s}}_t$ is defined as the average of the exponentiated residuals:

$$\widehat{\mathbf{s}}_t \equiv \frac{1}{N}\sum_{i=1}^{N} \exp\left\{\mathbf{e}_{sv,t}(k)\right\}$$

Therefore, we can express our estimate of average residential carbon emissions for a type s household in community v at time t is given by:

$$\begin{aligned}
\widehat{\text{CE}}_{sv,t} &= \sum_k w_v(k) \cdot \widehat{y}_{sv,t}(k) \\
&= \sum_k w_v(k) \cdot \left[\exp\left\{ \mathbf{x}'_{sv,t} \widehat{\beta}_{k,t} \right\} \left(\frac{1}{N} \sum_{i=1}^{N} \exp\left\{ \mathbf{e}_{sv,t}(k) \right\} \right) - 1 \right] \\
&= \sum_k w_v(k) \cdot \left[\exp\left\{ \mathbf{x}'_{sv,t} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t - 1 \right]
\end{aligned}$$

We calculate this expression for each community v, household type s, and census wave t. To do so, we combine our parameter estimates with community-specific, household-type averages of the characteristics included in $\mathbf{x}_{sv,t}$. These average characteristic variables are calculated directly from census data, and we combine them with the same geographic and community-level variables that we include in our main regressions.

Growth Decomposition. The growth in predicted total residential carbon emissions from t to $t+1$ in city c is given by:

$$\Delta\widehat{\text{CE}}_c \equiv \widehat{\text{CE}}_{c,t+1} - \widehat{\text{CE}}_{c,t} = \sum_{v=1}^{N_c} \sum_{s \in \mathcal{S}} \left(N_{sv,t+1} \cdot \widehat{\text{CE}}_{sv,t+1} - N_{sv,t} \cdot \widehat{\text{CE}}_{sv,t} \right)$$

Adding and subtracting $N_{sv,t+1} \cdot \widehat{\text{CE}}_{sv,t}$ and rearranging, it is straightforward to show that ΔCE_c can be written as the sum of two terms:

$$\Delta\widehat{\text{CE}}_c = \underbrace{\sum_{v=1}^{N_c} \sum_{s \in \mathcal{S}} (N_{sv,t+1} - N_{sv,t}) \cdot \widehat{\text{CE}}_{sv,t}}_{(\mathbf{I})} + \underbrace{\sum_{v=1}^{N_c} \sum_{s \in \mathcal{S}} \left(\widehat{\text{CE}}_{sv,t+1} - \widehat{\text{CE}}_{sv,t} \right) \cdot N_{sv,t+1}}_{(\mathbf{II})} \tag{B.1}$$

This equation decomposes the overall growth in predicted carbon emissions for city c into two terms. Term I reflects growth in the population of type s households in community v, multiplied by the predicted levels of carbon emissions in time t for those types of households in those communities. Changes in predicted emissions growth in term II owe to population growth or changes in the composition of households in community v. Term II instead reflects growth in average carbon emissions for type s households.

We can make more progress on Term II by noting:

$$\begin{aligned}
\left(\widehat{\text{CE}}_{sv,t+1} - \widehat{\text{CE}}_{sv,t} \right) &= \sum_k w_{v,t}(k) \cdot \widehat{y}_{sv,t+1}(k) - \sum_k w_v(k) \cdot \widehat{y}_{sv,t}(k) \\
&= \sum_k w_v(k) \left[\widehat{y}_{sv,t+1}(k) - \widehat{y}_{sv,t}(k) \right] \\
&= \sum_k w_v(k) \left[\left(\exp\left\{ \mathbf{x}'_{sv,t+1} \widehat{\beta}_{k,t+1} \right\} \widehat{\mathbf{s}}_{t+1} - 1 \right) - \left(\exp\left\{ \mathbf{x}'_{sv,t} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t - 1 \right) \right] \\
&= \sum_k w_v(k) \left[\exp\left\{ \mathbf{x}'_{sv,t+1} \widehat{\beta}_{k,t+1} \right\} \widehat{\mathbf{s}}_{t+1} - \exp\left\{ \mathbf{x}'_{sv,t} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t \right]
\end{aligned}$$

Focusing on the $\widehat{y}_{sv,t+1}(k) - \widehat{y}_{sv,t}(k)$ terms, and adding and subtracting $\exp\left\{ \mathbf{x}'_{sv,t+1} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t$, we obtain:

$$\begin{aligned}
\Delta\widehat{y}_{sv}(k) &\equiv \widehat{y}_{sv,t+1}(k) - \widehat{y}_{sv,t}(k) \\
&= \exp\left\{ \mathbf{x}'_{sv,t+1} \widehat{\beta}_{k,t+1} \right\} \widehat{\mathbf{s}}_{t+1} - \exp\left\{ \mathbf{x}'_{sv,t} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t \\
&= \left(\exp\left\{ \mathbf{x}'_{sv,t+1} \widehat{\beta}_{k,t+1} \right\} \widehat{\mathbf{s}}_{t+1} - \exp\left\{ \mathbf{x}'_{sv,t+1} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t \right) + \left(\exp\left\{ \mathbf{x}'_{sv,t+1} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t - \exp\left\{ \mathbf{x}'_{sv,t} \widehat{\beta}_{k,t} \right\} \widehat{\mathbf{s}}_t \right)
\end{aligned}$$

$$= \underbrace{\left(\exp\left\{\mathbf{x}'_{sv,t+1}\widehat{\beta}_{k,t+1}\right\}\widehat{\mathbf{s}}_{t+1} - \exp\left\{\mathbf{x}'_{sv,t+1}\widehat{\beta}_{k,t}\right\}\widehat{\mathbf{s}}_{t}\right)}_{(*)} + \underbrace{\left(\exp\left\{\mathbf{x}'_{sv,t+1}\widehat{\beta}_{k,t}\right\} - \exp\left\{\mathbf{x}'_{sv,t}\widehat{\beta}_{k,t}\right\}\right)\widehat{\mathbf{s}}_{t}}_{(**)}$$

Using the $(*)$ and $(**)$ terms, we define the following:

$$\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\mathbf{x}\right) \equiv \sum_k w_v(k)\left(\exp\left\{\mathbf{x}'_{sv,t+1}\widehat{\beta}_{k,t}\right\} - \exp\left\{\mathbf{x}'_{sv,t}\widehat{\beta}_{k,t}\right\}\right)\widehat{\mathbf{s}}_{t}$$
$$\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\beta\right) \equiv \sum_k w_v(k)\left(\exp\left\{\mathbf{x}'_{sv,t+1}\widehat{\beta}_{k,t+1}\right\}\widehat{\mathbf{s}}_{t+1} - \exp\left\{\mathbf{x}'_{sv,t+1}\widehat{\beta}_{k,t}\right\}\widehat{\mathbf{s}}_{t}\right)$$

Here, $\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\mathbf{x}\right)$ denotes the change in predicted residential carbon emissions for a type s household in community v that owe to changes in the $\mathbf{x}$ characteristics. The expression $\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\beta\right)$ reflects changes in emissions that owe to changes in the mapping between characteristics and outcomes. Using these definitions, it is straightforward to show that:

$$\begin{aligned}
\Delta\widehat{\mathrm{CE}}_c &= \sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\left(N_{sv,t+1} - N_{sv,t}\right)\cdot\widehat{\mathrm{CE}}_{sv,t} + \sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\left(\widehat{\mathrm{CE}}_{sv,t+1} - \widehat{\mathrm{CE}}_{sv,t}\right)\cdot N_{sv,t+1} \\
&= \underbrace{\sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\left(N_{sv,t+1} - N_{sv,t}\right)\cdot\widehat{\mathrm{CE}}_{sv,t}}_{(\mathbf{A})} + \underbrace{\sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\mathbf{x}\right)\cdot N_{sv,t+1}}_{(\mathbf{B})} + \underbrace{\sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\beta\right)\cdot N_{sv,t+1}}_{(\mathbf{C})}
\end{aligned}$$

This expression shows that we can decompose the growth in carbon emissions per household into two additional terms. Term B reflects growth in emissions due to changes in the $\mathbf{x}_{v,s}$ characteristics over time. Because we are fixing household types in this analysis, one source of these changes will be changes in community-level population density. Term C reflects growth in emissions due to changes in the mapping between $\mathbf{x}_{v,s}$ characteristics and emissions over time.

Using a similar add and subtract trick, we can also split term B into two separate terms:

$$\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\text{density}\right) \equiv \sum_k w_v(k)\left(\exp\left\{\mathbf{x}'_{sv,t}\widehat{\beta}_{k,t}\right\} - \exp\left\{\mathbf{x}_{sv,t}(\text{density}_{t+1})'\widehat{\beta}_{k,t}\right\}\right)\widehat{\mathbf{s}}_{t}$$
$$\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\text{other}\right) \equiv \sum_k w_v(k)\left(\exp\left\{\mathbf{x}_{sv,t}(\text{density}_{t+1})'\widehat{\beta}_{k,t+1}\right\} - \exp\left\{\mathbf{x}'_{sv,t+1}\widehat{\beta}_{k,t}\right\}\right)\widehat{\mathbf{s}}_{t}$$

where $\mathbf{x}_{sv,t}(\text{density}_{t+1})$ denotes the vector of $\mathbf{x}_{sv,t}$'s using density_{t+1} in place of density_{t}. It is easy to show that we can write:

$$\underbrace{\sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\mathbf{x}\right)\cdot N_{sv,t+1}}_{(\mathbf{B})} = \sum_{v=1}^{N_c}\sum_{s\in\mathcal{S}}\left[\Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\text{density}\right) + \Delta\widehat{\mathrm{CE}}_{sv}\left(\Delta\text{other}\right)\right]\cdot N_{sv,t+1} \tag{B.2}$$