Carbon Emissions from Household Energy Use in Pakistan:

Policy Implications for Climate Mitigation and Regional Development

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Abstract: Households in developing countries face two concurrent challenges: rising energy consumption but limited access to clean energy sources. Using national data from the Pakistan Social and Living Standards Measurement Survey (2013-14 and 2018-19), we provide the first empirical estimates of districts' carbon emissions based on representative households' energy consumption for all Pakistani districts. Following Glaeser and Kahn (2010), we estimate and predict energy consumption for eight energy types, and, using emission factors, convert the predicted energy consumption by representative households for each district to carbon emissions. Notably, we include three often-omitted energy types: household garbage, firewood, and public transport. Results indicate that carbon emissions hotspots tend to cluster around megacities, as household access to relatively cleaner energy sources are getting limited over time. Firewood use not only matter for rural households, but it also became more important for many urban households in 2018-19 due to recurrent disruptions to natural gas or electricity supplies. Finally, the greenness rankings of districts based on carbon emissions experienced considerable shifts from 2013-14 to 2018-19. Our results emphasize the importance of including all relevant energy sources for developing countries and highlight the necessity of accommodating the regional variation in shaping effective energy and climate policies.

JEL Codes: Q56, Q01, Q54, O13, O53

Keywords: Pakistan; sustainable development; carbon dioxide emissions; household energy use; urban development; South Asia

1. Introduction

Quantifying and understanding household carbon emissions from energy use across a country and over time lies at the heart of any energy policy that aims to address the multi-pronged problem of climate mitigation and simultaneously improving household access to clean energy sources. Progress on Sustainable Development Goal (SDG) 7 "ensuring access to clean and affordable energy" while also incorporating climate mitigation strategies poses a conundrum for developing countries like Pakistan that are not only energy poor but also susceptible to extreme climate events. Rising global temperatures leading to heatwaves, long summer spells, and harsh winters increase household energy demand (and hence, household emissions) at one hand, and climate change related flooding causes damage to infrastructure which further worsens the existing disparities in terms of energy provision to households. Nonetheless, residential emissions in Pakistan have increased from 7.0 MT CO_2 in 1990 to 19.0 MT CO_2 in 2020, comprising approximately 10% of the total emissions (International Energy Agency, 2020). This article provides the first empirical estimates of districts' carbon emissions and their changes over time based on representative households' energy consumption for Pakistan's rural and urban districts as well as megacities using two rounds of comprehensive nationwide data set from the Pakistan Social and Living Standards Measurement Survey (PSLM) from 2013–2014 and 2018–2019. Our methodology allows us to predict the consumption of each energy type by standardized households at the district level and then translate these predicted energy consumption values into carbon dioxide emissions using well-established emission conversion factors from the IPCC Emission Factors Database (EFDB; IPCC 2017) to assess how household emissions and their source have varied over time. We also evaluate the contributions of previously ignored energy types, such as firewood, public and private transport, and household garbage, in explaining cross-district differences in total and per-capita emissions. To the best of our knowledge, this is the first time this exercise has been done for Pakistan.

Urbanization is sweeping the globe, albeit there are differences in the patterns and hence, the consequences. The World Bank (2023) estimates that by 2050, seven out of ten people will be living in cities. A systematic understanding of the interplay between household energy use, carbon emissions, and the environmental footprint of growing population in developing countries is especially important given that the generally observed patterns of urbanization in developed countries have stark differences with developing countries (Zhang, 2016). Literature on how household emissions vary across regions, especially for cities and peri-urban areas in developing countries is still in infancy stage. While in developed countries, evidence suggests that households' carbon emissions decline, at least on a per-capita basis, when they move to an urban area: densely populated places are more energy efficient (Duany et al. 2001), this does not always hold true for developing countries. Urbanization in Pakistan, for instance, is often referred as messy and hidden (Elis & Roberts, 2015; Shaikh & Nabi, n.d.; World Bank (2015)). This paper attempts to understand how energy usage at household level varies across megacities, urban and rural regions in Pakistan, and the impact this has on household emissions.

The intersection of household energy usage, urbanization and household emissions is critical for energy policies in developing countries. As they migrate, household energy use patterns adapt, leading to dramatic changes in carbon emissions from rural and urban areas. For example, over two billion people globally rely on wood for heat. In many rural parts of low-income developing countries, firewood is the only domestically available and affordable source of energy (FAO, 2017). Though firewood use is likely to substantially decrease when rural households move to cities, the depletion of relatively cleaner fuel choices, such as natural gas[1], and frequent electricity outages (Gertler et al., 2017; Meles, 2020) can potentially restrict this possibility. Similarly, poor public transport systems in cities leads to greater reliance on environmentally inefficient private vehicle use. Finally, open air burning of household garbage can substantially add to cities' environment emissions, thereby making cities the growing hotspots of carbon emissions. These practices influence household energy usage, and when aggregated, impede the achievement of development goals due to failure to fully capitalize on development potential of urbanization.

Globally, cities account for approximately 70% of carbon dioxide emissions (Dasgupta, Lall & Wheeler, 2022). By understanding the intricate linkages between energy mix and carbon emissions, systemic decarbonization of cities is critical for staying below the 1.5° Celsius global warming target. This article investigates the distribution of hosuehold emissions in Pakistan stemming from different energy sources to understand regional variation to guide energy and urban policymaking in the purview of climate mitigation. We ask explicitly how firewood, transport fuels, and household garbage contribute differentially to urban and rural household carbon emissions in developing countries, which often lack adequate and cost-efficient abatement technologies and environmentally friendly regulatory environments. In doing so, we are also able to assess whether cities in developing countries are greener than those in developed countries Using longitudinal data from two rounds of surveys, we examine whether cities in

[1] According to National Electric Power Regulatory Authority's State of Industry Report 2020, in Pakistan the share of gas and oil in primary energy supply has reduced from 46.3 % and 34.4 % in 2013-14 to 35% gas and 26% oil respectively. Gas reserves in Pakistan are declining over the past years, while coal power plants have picked pace.

developing countries are getting greener over time and differentially analyze the impact of individual sources of emissions.

The literature has extensively analyzed the relationship between energy use, urban growth, and carbon emissions, but many previous studies focus on aggregate or sectoral direct energy use (e.g., Zhang 2000; Hertwich and Peters 2009; Han and Chatterjee 1997; Levitt et al. 2017) or aggregate land use change (e.g., Naughton-Treves 2004). Using household-level data and continuing the efforts recently made to understand urban households' carbon emissions in the United States (Glaeser and Kahn 2010), China (Zheng et al. 2011), the United Kingdom (Minx et al. 2013), the Philippines (Seriño and Klasen 2015), and India (Ahmad et al. 2015), we conduct the first such study for Pakistan. This research is important because Pakistan is the fifth-most populous country in the world and has the highest population and urbanization growth rate of all South Asian countries (Kedir et al. 2016). The growth in urban population has been tremendous already, almost doubling between 1998 and 2017 from 43 million to 75 million. According to United Nations, more than half of Pakistan's urban population reside in ten major cities with populations exceeding one million. However, more than 50 percent of the population of these major cities resides in slums and squatter settlements, i.e., *Katchi Abadi.*

Previous studies reveal significant gaps in our knowledge about the countries they analyze. First, most studies ignore the roles of traditional energy fuels like firewood and household garbage in household energy use and subsequent carbon emissions. However, according to the Encyclopedia of World Problems and Human Potential, up until 2020, approximately 40% of the total world population resorted to traditional cooking fuels like firewood and charcoal for basic needs like cooking and heating. The COVID-19 pandemic and the resultant exorbitant inflation and energy prices have further exacerbated access to electricity around the globe, which may further entrench the reliance on traditional cooking fuels. Second, past studies often ignore households in rural and peri-urban areas and focus on urban households only. Third, few past studies use longitudinal data rather than cross-sectional data collected at a single point. Fourth, that cities are greener holds in the context of a developed country like the United States (Glaeser and Kahn 2010) but not in developing countries such as India (Ahmad et al. 2015). Finally, the studies focused on understanding household energy emissions nexus in Pakistan have conducted their analysis on specific geographic regions, whereas our data and methodology provide us the flexibility to cover whole of Pakistan, over a period of five years.

Our main findings yield several insights contributing to our understanding of differential access of households to different energy sources, household energy usage and its impact on carbon emissions, sustainable development, and the interplay between urbanization and carbon emissions in Pakistan and worldwide. First, we find that contrary to generally held belief that urbanization leads to greening of a region, we find that hotspots for carbon emissions tend to cluster around megacities, particularly Islamabad, Lahore, and Rawalpindi. We find these cities carbon emissions increased over the study period, which conforms to research on Indian households (Ahmad et al. 2015) but not those in the United States and other European developed countries (Brownstone and Golob 2009; Kahn 2007). Second, Pakistan's major cities' household carbon emissions are drastically lower than in the United States but are comparable to, and sometimes even higher than, cities in India and China. Third, our results highlight the importance of accounting for two emission sources previous studies primarily ignore—household garbage and firewood. Specifically, household garbage accounts for at least 24% of urban households' carbon footprint, and firewood accounts for approximately half of all carbon emissions in some rural areas. This finding complements the current movement on food waste and shows that it is essential to incorporate the carbon emissions from household garbage even when the per-capita household waste levels are low in developing countries. The importance of firewood use even for urban households due to disruption of natural gas and electricity supplies also highlights the challenges for households in developing countries to maintain reliable access to cleaner energy sources. Results also indicate that it is crucial to segregate households in rural, urban, and megacities areas, which past studies often ignore, as well as including energy types such as firewood. Our findings reveal a fluid and dynamic path in district-level greenness rankings over time. Just over half, 56%, of Pakistani districts experienced noticeable changes in their greenness rankings between 2014 and 2019, with 26% becoming significantly greener and 30% becoming less green. Finally, using multiple rounds of household surveys in Pakistan, we demonstrate the fluid nature of carbon emissions and household energy use in urbanizing developing countries. We thus improve on previous studies that rely on cross-sectional data collected at a single point in time. Our findings have the potential to pave the path for urban policy making, policies targeted at improving clean energy access, and hence climate mitigation strategies.

2. Background

As the fifth-most populous country in the world and the most rapidly urbanizing South Asian nation (Kugelman, 2015), Pakistan offers an excellent laboratory for understanding the linkages between household energy use and carbon emissions. According to the 2017 Pakistani Census, Pakistan's population grows at 2.4% annually, and, measured by the World Bank (2018), the annual population growth rate for Pakistani cities is 2.7%. The WDI database shows that Pakistan's carbon dioxide intensity relative to gross domestic product is 0.83 kg/dollar, which is very close to the average of 0.88 for lower-middle-income countries.

Like most developing countries, Pakistan’s energy mix and technologies are more complex than those of the developed countries addressed in previous studies examining the impact of urbanization on household energy use and emissions. The WDI shows that in 2020, 75.38 % of the total population had access to electricity, even though the disparity between urban (100 %) and rural (60.82%) is drastic. Moreover, access to clean fuels and technology for cooking is not just low overall (49.3%) but shows an even greater regional disparity: 86.5 % of urban and only 26.10 % of the rural population had access to clean cooking fuels in 2020. This is partly due to inadequate public service provisions that force many rural households to use firewood and other biomass fuels (Kugelman, 2015). World Bank also estimated that household municipal solid waste in urban Pakistan is expected to increase from 0.84 kg/capita/day in 2012 to 1.05 kg/capita/day in 2025 (Hoornweg & Bhada-Tata, 2012) due to a projected increase in affluence. Due to a lack of waste management facilities, Pakistan’s waste collection rate is less than 60%. This prompts Pakistanis to burn their waste in open fires, with the apparent impact on carbon emissions. Together, these factors make Pakistan typical of developing countries. They also impede progress on development goals as these regions fail to fully capitalize on the potential of urbanization in terms of provision of clean energy and better services to its inhabitants.

At the same time, the Global Climate Risk Index developed by Germanwatch (Kreft et al., 2015) ranks Pakistan among the top 10 countries most affected by climate change during 1995-2014, with its more than 230 million residents among the world’s most vulnerable to the growing consequences of climate change (Salam, 2018). Pakistan has also suffered from increasingly frequent climate-induced catastrophes. For instance, in Karachi in 2015, about 1,200 people lost their lives due to an unprecedented heat wave partly caused by the urban heat island effect (Sajjad et al., 2015). Pakistan is not only expected to emit more carbon dioxide than many of its counterparts, it is also a victim of ongoing climate change, especially in rural areas The recent floods in 2022 and the destruction therein suggest that rural-urban migration will be a likely climate adaptation response by the rural households, further pushing urbanization in the country (Ishfaq, 2019).

The current research on household energy usage in Pakistan is either focused on estimating energy poverty using national level data (Mahmood & Shah, 2017; Awan, Bilgili, & Rahut, 2022), mixed methods research (Batool et al., 2022), or restricted to specific regions like Lahore and utilizes primary data to relate household energy consumption and GHG emissions (Khan & Siddiqui, 2017; Ghafoor et al, 2019). This paper, thus, builds on energy consumption and household emissions literature in Pakistan with nationwide empirical evidence to support urban and energy policy making while also unravels research curiosities for future.

3. Data and Methodology

We aim to quantify Pakistan's household- and district-level carbon emissions from 2013-14 to 2018-19. To do so, we follow a five-step approach in which we (*a*) explain household-level energy consumption using household demographic and socioeconomic characteristics based on two nationwide household surveys; (*b*) predict district-level energy consumption for all districts using the characteristics of representative households for a district; (*c*) convert predicted energy consumption to carbon emissions for all districts using well-established carbon emission factors; (*d*) rank districts' greenness based on predicted carbon emissions; and, (*e*) identify the determinants of changes in districts' greenness rankings over time using district-level panel data estimation. The subsections below discuss these methods and the data used to implement these estimations.

3.1. Data preparation and validation

We link multiple nationwide datasets for the first time to obtain a complete picture of energy consumption by Pakistani households for all energy types. The first data set is PSLM surveys conducted in alternate years at the provincial and district levels based on stratified urban and rural areas sampling. Specifically, we use household-level data for 35,094 households from the PSLM surveys conducted in fiscal years 2013–4 and 2018-19. Of particular interest to our study, PSLM data have disaggregated household-level expenditures for various fuel and energy types, including cooking fuel, transport fuels, and electricity. To convert these energy expenditures to energy consumption in quantity, we use the annual national energy prices provided by the Pakistan Economic Survey from 2014 to 2019 (Pakistan Economic Survey 2019). We obtain energy and fuel consumption quantities for electricity, natural gas, gasoline, compressed natural gas (CNG), and firewood.

Unfortunately, the PSLM survey does not cover public transportation usage for all households from 2014 to 2019. Therefore, we rely on the newly added section on household expenditure on public transport in the 2015–2016 PSLM survey. We first obtain the 2015–2016 average expenditures for all districts on three modes of public transportation—cab/taxi, bus, and rickshaw; based on these averages, we construct and calculate the share of total household energy expenditure for public transportation for 2015–2016, then draw out energy expenditure on public transportation from 2014 to 2019 by maintaining the same ratio. Finally, energy expenditure on public transportation was converted to consumption quantities using average national prices from the Pakistan Economic Survey in corresponding years.

A unique addition to our study is the carbon emissions generated by household garbage. To obtain this, we use Pakistani government data that separately reports the average garbage quantity generated by households in urban and rural regions, 0.453 kg/capita/day and 0.283 kg/capita/day, respectively, for all provinces in Pakistan. Using these figures, we estimate the amount of garbage generated by each household included in the analysis given its family size. However, to estimate emissions, we only include garbage quantity for households with no formal garbage collection system because, in such cases, open burning is the usual disposal method. Given data limitations on garbage generated by households across the country, these are the best possible estimates to be included in estimation.

Table 1 shows the summary statistics for household demographic and socioeconomic characteristics from the PSLM survey. On average, 60% of households are in rural areas, and 22% of households consist of agricultural producers and workers. The average household size is six, much larger than the norm in the developed world. Of particular significance to our study, the survey data shows that almost no households rely on coal for heating or cooking. However, this will likely change because the energy projects under China Pakistan Economic Corridor are adding coal-based power plants. Furthermore, on average, 43 % use gas as a cooking fuel, 74% live in a municipality that does not formally collect household garbage, and only 5% own a private car. In comparison, 48 % own either a car, a motorbike, or a scooter.

VARIABLES	(1) N	(2) mean	(3) min	(4) max
Socioeconomic Variables:				
Age of HH Head (Years)	35,094	45.88	15	90
Annual HH Income (Million PKR)	33,759	0.32	0	51.33
HH Size	35,094	6.32	1	30
HH Head is Currently Married	35,094	0.90	0	1
Basic Literacy	35,094	0.92	0	1
Employment and Location:				
employer	28,508	0.02	0	1
paidEmployee	28,508	0.56	0	1
selfEmployee	28,508	0.20	0	1
agriWorker	28,508	0.22	0	1
Dummy for Rural	35,094	0.60	0	1
Dummy for Urban	35,094	0.17	0	1
Dummy for MegaCity	35,094	0.22	0	1
Asset Ownership Proportion:				
Owns a Refrigerator	35,094	0.49	0	1
Use Gas as Cooking Fuel	35,094	0.43	0	1
Owns a Cooking Range or Stove	35,094	0.53	0	1
Garbage Not Collected Formally	35,094	0.74	0	1
Owns any Vehicle	35,094	0.48	0	1
Owns a Car	35,094	0.05	0	1
Dependent Variables:				
Annual Electricity Units (KWh)	32,182	1,355.72	30.00	39,052.39
Annual Gas Units by HH (MMBTU)	14,946	47.89	0.96	681.81
Annual Firewood by HH (KG)	13,348	1,413.55	0.00	48,000.00
Annual HH Garbage Quantity (KG)	35,094	842.12	102.20	6,132.00
Annual Petrol Quantity Consumed - Private Transport (Litres)	16,306	314.94	1.56	13,275.80

Annual Petrol Quantity Consumed on Taxi (Litres)	26,651	17.39	0.03	1,328.58
Annual CNG Quantity Consumed on Rickshaw (KGs)	26,651	30.31	0.02	799.10
Annual Diesel Quantity Consumed on Bus (Litres)	26,651	53.61	1.66	4,261.73

Table 1: Summary Statistics

3.2. Explaining household-level energy consumption

To understand and explain the determinants of household-level energy consumption, we follow Gleaser and Kahn (2010) and run a series of Heckman selection models using household surveys for each energy type (Heckman, 1976). It is essential to account for sample selection issues because not all energy types are available to all households in Pakistan. For example, our survey shows that only 43% of Pakistani households have access to natural gas, and only 5% of households own cars. The PSLM surveys have information on energy expenditure, asset ownership, and access to energy, which provides several natural exclusion restrictions for constructing two-stage Heckman selection models using sensible asset ownership and energy access variables.

For each survey year t, we estimate a probit model of the household $i's$ dichotomous energy consumption choice of each energy type j as follows:

$$C_{ijt} = \boldsymbol{I_{it}\gamma} + \delta * Z_{ijt} + u_{ijt} \qquad (1),$$

C_{ijt} is the dichotomous energy consumption choice variable that equals one when household i consumes energy type j in year t. Energy types mainly include seven sources—electricity, natural gas, firewood—and fuels used for private (petrol/gasoline) and public transportation (petrol on taxis, CNG on rickshaws, and diesel on buses). Explanatory variables have two parts: (*a*) the household's demographic and socioeconomic characteristics $\boldsymbol{I_{it}}$, which include the age, gender, and employment status of the household head, household income and size, and dummy variables indicating whether the household is in a megacity, urban or rural area; and, (*b*) an energy-specific exclusion restriction variable Z_{ijt}, such as car ownership or connection to electricity or natural gas supply. We also incorporate energy price r_{jt} in the model to account for price responsiveness in energy consumption.

In the second stage, we examine household-level energy consumption for each energy type j by incorporating the inverse Mills ratio derived from the selection equation shown in equation (1). In particular, the household *i*'s energy consumption of each energy type *j* can be explained as follows:

$$Y_{ijt} = E(Y_{ijt}|E^{*}_{ijt} > 0)$$

$$= \boldsymbol{I_{it}\beta} + \beta_{\lambda}\lambda_i\left({}^{-\boldsymbol{I_{it}\gamma} - \delta * Z_{ijt}}/_{\sigma_u}\right) + \nu_{ijt} \qquad (2)$$

In equation (2), the nonnegative energy consumption quantity Y_{ijt} for energy type j is explained by household-level demographic and socioeconomic characteristics $\boldsymbol{I_{it}}$. The familiar Heckman-style inverse Mills ratio $\lambda_i(Z_{ijt}) = \lambda_i\left({}^{-\boldsymbol{I_{it}\gamma} - \delta * Z_{ijt}}/_{\sigma_u}\right)$ is used to account for the sample selection bias introduced by the binary energy consumption choice. Equation (2) clearly shows that ignoring the selection issues in the household's energy consumption choices would lead to biased and inconsistent estimates, while the Heckman selection models shown in equation (3), which exploit access to an energy supply, mitigate and may eliminate bias. In the estimation, we convert the energy consumption quantity to its logarithm as the dependent variable. We use full-information maximum-likelihood estimation techniques instead of the limited-information maximum-likelihood estimation embedded in the original Heckman two-step approach.

Because every household generates a positive amount of household garbage, we can model it in a simple OLS form as follows:

$$G_{it} = \boldsymbol{I_{it}\beta} + e_{it} \qquad (3)$$

where G_{it} denotes the garbage generated by household I in year t.

3.3. Predict district-level energy consumption for representative households

The next step is to predict district-level energy consumption for representative households using mean demographic and socioeconomic characteristics. For the mean representative household in district d for energy type j, the predicted energy consumption $\widehat{y_{djt}}$ in year t can be obtained using the following equation for electricity, natural gas, kerosene oil, charcoal, and coal:

$$\widehat{y_{djt}} = \boldsymbol{I_{dt}\widehat{\beta}} + \hat{\gamma}\lambda_d(Z_{djt}) \qquad (4)$$

For household garbage, we use equation (3) in the district-level prediction, as follows:

$$\widehat{G_{djt}} = \boldsymbol{I_{dt}\widehat{\beta}} \qquad (5)$$

In equations (4) and (5), $\boldsymbol{I_{dt}}$ and Z_{djt} are the corresponding demographic characteristics and exclusion restrictions for the representative household in district d.

3.4. Convert predicted district-level energy consumption to carbon emissions

The next step is to convert predicted district-level energy consumption for the representative households in Step 2 into predicted district-level carbon emissions using well-established carbon emission factors. We use a set of emission conversion factors from the IPCC's Emission Factors Database (EFDB; IPCC, 2017), which the IPCC established to provide country-specific emission factors. The EFDB currently contains IPCC default data, such as the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC, 2006), and data from peer-reviewed journals and other publications, including National Inventory Reports and IEA (2012) data. With these emissions factors, we convert the predicted district-level energy consumption shown in equations (4) and (5) using the following method:

$$\widehat{E_{dJt}} = \widehat{y_{dJt}} * EF_j \qquad (6a)$$

$$\widehat{E_{dGt}} = \widehat{G_{dt}} * EF_G \qquad (6b)$$

Equation (6b) converts the predicted district-level household garbage quantities to predicted carbon emissions using the emission factors for Pakistan EF_G. In contrast, equation (6a) converts this energy consumption to carbon emissions for all other energy types.

3.5. Ranking the greenness of districts based on predicted per capita carbon emissions

We next aggregate district-level predicted carbon emissions for all energy types, then rank the greenness of about 90 districts in Pakistan based on district-level predicted total carbon emissions. Total carbon emissions for district d for each survey year t $\widehat{TE_{dt}}$ are aggregated as follows:

$$\widehat{TE_{dt}} = \sum_j \widehat{E_{dJt}} \qquad (7)$$

Moreover, the per-capita carbon emissions for a district and each energy type j could be derived by dividing the district-level total carbon emissions by its population:

$$\widehat{E_{dJt,pc}} = \widehat{E_{dJt}}/population_{dt} \qquad (8a)$$

$$\widehat{E_{dt,pc}} = \widehat{TE_{dt}}/population_{dt} \qquad (8b)$$

Intuitively, a district is ranked greener with lower per-capita carbon emissions, denoted as $\widehat{E_{dJt,pc}}$. In other words, these per-capita carbon emissions form the basis for our measure of the greenness of a Pakistani district at a particular time. These results will assist energy policymakers, urban city planners, and the public visualize the impacts and linkages between urban growth and city-level household carbon footprint through charts and spatial city maps.

3.6. Identifying the determinants of predicted district-level carbon emissions

First, for each district d and all survey years t, we estimate a district-level panel regression to explain what drives per-capita carbon emissions for a particular district:

$$\widehat{E_{dt,pc}} = \boldsymbol{S_{dt}}\boldsymbol{\phi} + \boldsymbol{G_{dt}}\boldsymbol{\mu} + \varepsilon_{dt} \qquad (9)$$

In equation (9), there are two sets of district-level characteristics:$\boldsymbol{S_{dt}}$, which represents district-level socioeconomic characteristics such as average household size, district-level percentage of low-income households, the share of household car ownership, percentage of agricultural workers, percentage of households that use gas as cooking fuel, percentage of urban population; and $\boldsymbol{G_{dt}}$, which includes geographic characteristics such as mean elevation. As we do not have district-level data for temperature or rainfall due to a limited number of weather stations, we proxy these with the district elevation level.

We can also run separate regressions for the per-capita emissions from each energy type *j* at the district level, as follows:

$$\widehat{E_{djt,pc}} = \boldsymbol{S_{dt}}\boldsymbol{\phi} + \boldsymbol{G_{dt}}\boldsymbol{\mu} + \varepsilon_{djt} \qquad (10)$$

By estimating equations (9) and (10) using panel data model techniques, we examine whether the per-capita carbon emissions decrease when the population density rises. We disentangle this relationship using district-level carbon emissions aggregated across multiple energy types and examining how district-level characteristics drive per-capita carbon emission from a particular energy type.

4. Results and Discussion

Tables 2 and 3 present the emission estimates from household energy consumption of three energy types and regular garbage: electricity, gas, and firewood in Table 2 and household garbage in Table 3, the latter two previous studies have often ignored. The energy consumption regressions for other energy types are omitted for brevity but attached in the Appendix Tables A1 and A2.

The first two columns of Table 2 present results on electricity consumption separately estimated for each survey year, with the household's connection to the electricity supply as the exclusion restriction. It shows that, on average, household income, size of household, education, and employment correlates with electricity use levels. Moreover, households in rural areas consume less electricity than their urban and Megacity counterparts. This is unsurprising, given that half of Pakistan's rural population had no reliable electricity access in 2018 (International Renewable Energy Agency 2018). The coefficient for the exclusion restriction variable, *household has an electricity connection* is always positive and significant in the selection equation, suggesting that it is essential to control for sample selection issues using electricity connections. A reliable electricity supply is critical and will likely shape future household energy consumption patterns. Almost a decade ago, more than 75% of Pakistan's population suffered from occasional blackouts, and there is no reason to think the situation has significantly improved yet (World Bank 2010). However, the significant investment in power infrastructure Pakistan is currently undertaking, including rural electrification projects, could significantly narrow the gap in electricity supply and increase electricity generation capacity by 50% between 2012 and 2018 (Pakistan Economic Survey, 2019).

Columns 3 and 4 of Table 2 show that the use of gas correlates positively with urban and Megacity locations and the gender of the household (females). Paid Employees and self-employee heads of households have an inverse correlation with gas use, even though the coefficients are not always statistically significant. The variable in the selection equation *use gas* *as a cooking fuel* is positive and highly significant. The last two columns of Table 2 show that rural residence and household size consistently correlate with firewood use. In contrast, households where the head is self-employed or works as a paid employee or employer consume less firewood. The coefficient on urban location (compared to rural) is positive but insignificant. The coefficient on Megacity was negative and significant in 2013/14 but not significant in 2018/19. The selection equation also shows that households with a cooking range are less likely to use firewood; stoves usually use natural gas.

A comparison across all four provinces from figure 1 shows higher firewood use in rural provinces, such as Balochistan and Khyber Pakhtunkhwa, consistent with the aggregate statistic that in 2013–14, more than half of energy consumption in these two rural provinces was from firewood use. This situation is further aggravated when political influence aggregates the provision of relatively cleaner energy sources like natural gas in more urbanized provinces, such as KP and Sindh. In contrast, many households in the largely rural Balochistan province, which contains the largest reservoirs of natural gas in Pakistan, lack access to natural gas. Rural residents without a natural gas connection often use firewood and cow dung, which emit dangerous levels of carbon or other poisonous gases.

Energy Type	*Electricity*		*Gas*		*Firewood*	
Year	*2013/14*	*2018/19*	*2013/14*	*2018/19*	*2013/14*	*2018/19*
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	(Log)Annual Electricity	(Log)Annual Electricity	(Log) Gas Natural	(Log) Gas Natural	(Log) Firewood	(Log) Firewood
Age of HH Head	0.002***	0.003***	0.003***	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Log of HH Annual	0.299***	0.390***	0.253***	0.195***	0.066***	0.143***
Income	(0.009)	(0.008)	(0.012)	(0.009)	(0.013)	(0.014)
HH Size	0.019***	0.011***	0.026***	0.024***	0.056***	0.041***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Gender of HH Head = 2,	0.193***	0.277***	0.101**	0.107***	0.120**	0.094**
female	(0.032)	(0.031)	(0.045)	(0.039)	(0.048)	(0.047)
HH Head Currently	0.044**	0.043**	0.044	0.007	0.014	0.046
Married	(0.022)	(0.020)	(0.032)	(0.023)	(0.034)	(0.032)
Category = 2, Urban	0.189***	0.138***	0.044	0.054***	0.032	0.025
	(0.016)	(0.015)	(0.027)	(0.018)	(0.028)	(0.026)
Category = 3,	0.249***	0.240***	0.015	0.054***	-0.244***	-0.083
MegaCities	(0.021)	(0.021)	(0.025)	(0.020)	(0.066)	(0.057)
Education	-0.074***	-0.058***	0.165***	0.020	0.139***	-0.028
	(0.028)	(0.019)	(0.043)	(0.022)	(0.038)	(0.026)
employer	0.103**	0.200***	0.033	0.018	-0.243**	-0.027
	(0.042)	(0.040)	(0.050)	(0.038)	(0.099)	(0.092)
Paid Employee	-0.113***	-0.102***	0.025	-0.057**	-0.095***	-0.128***
	(0.015)	(0.013)	(0.033)	(0.023)	(0.019)	(0.018)
Self-Employee	-0.045**	-0.054***	0.052	-0.022	-0.040	-0.097***
	(0.018)	(0.016)	(0.035)	(0.024)	(0.026)	(0.024)
Constant	2.385***	1.494***	0.446***	1.401***	6.706***	5.999***
	(0.119)	(0.117)	(0.171)	(0.127)	(0.175)	(0.183)
Select Equation:						

Education	0.992***	0.809***	-1.970***	-2.100***	0.343***	0.137***
	(0.0183)	(0.018)	(0.031)	(0.030)	(0.015)	(0.015)
Owns a Refrigerator	1.151***	1.023***				
	(0.0406)	(0.032)				
Use Gas as Cooking Fuel			3.545***	3.889***		
			(0.041)	(0.041)		
Owns a Cooking Range					-1.780***	-1.174***
or Stove					(0.027)	(0.0203)
Observations	12,385	16,460	13,763	18,187	13,999	18,779
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
athrho	-0.982***	-0.797***	-0.144***	0.133***	-0.118***	-0.443***
lnSigma	-0.511***	-0.489***	-0.694***	-0.881***	-0.614***	-0.497***

Table 2: Heckman Selection Model Results for Household Electricity, Gas, and Firewood Consumption

VARIABLES	*2013/14* (Log) HH Garbage	*2018/19* (Log) HH Garbage
Age of HH Head	-0.00006	-0.0004***
	(0.0001)	(0.0001)
Log of HH Annual Income	0.017***	0.028***
	(0.003)	(0.003)
HH Size	0.144***	0.148***
	(0.001)	(0.001)
Gender of HH Head = 2, female	0.040***	-0.022**
	(0.011)	(0.010)
HH Head is Currently Married	0.076***	0.108***
	(0.008)	(0.007)
Category = 2, Urban	0.566***	0.546***
	(0.006)	(0.005)
Category = 3, MegaCities	0.502***	0.553***
	(0.008)	(0.008)
Basic Literacy	0.018**	0.009
	(0.009)	(0.006)
Employer	-0.003	-0.009
	(0.017)	(0.017)
paidEmployee	-0.000	-0.005
	(0.005)	(0.004)
selfEmployee	-0.004	-0.008*
	(0.006)	(0.005)
Constant	5.197***	5.041***
	(0.040)	(0.038)
Observations	9,034	12,062
R-squared	0.895	0.894
District Fixed Effects	Yes	Yes

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 3: OLS Model of Household Garbage Generation

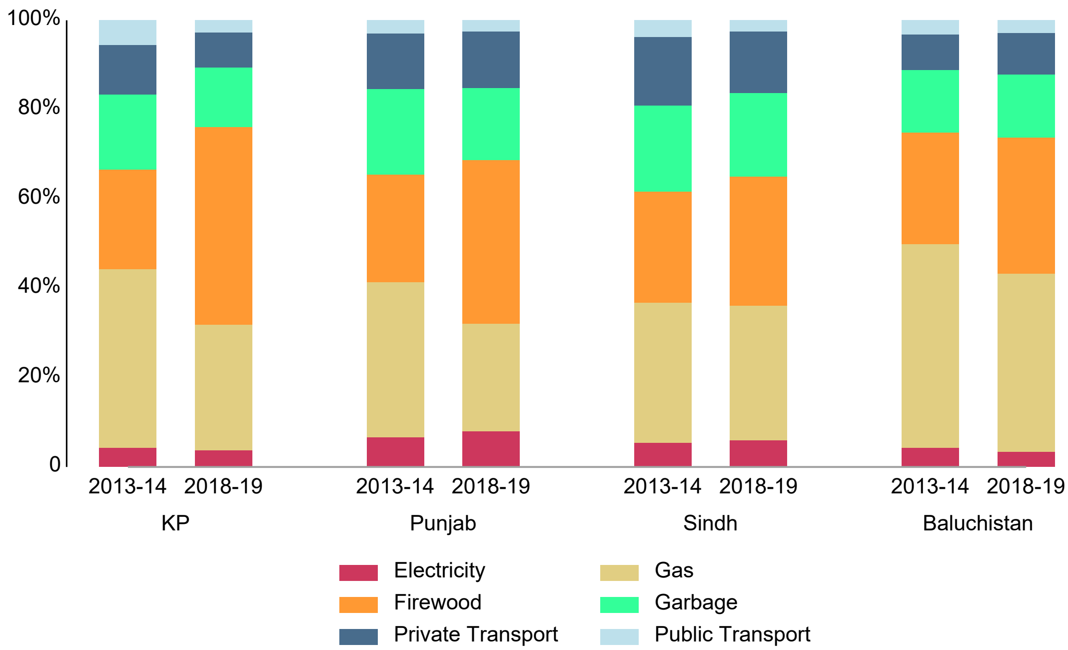

Figure 1: Distribution of Emissions for each Fuel Type for All Provinces

We also converted the consumption of each fuel type into emissions and aggregated them at the province level. This exercise reveals striking results. The use of firewood, and hence its contribution to province-level emissions, has visibly increased over the period studied. Recently, some scholars have claimed firewood is a carbon-neutral fuel, but this is wishful thinking (Johnson, 2009). The rate of carbon emissions in using firewood far exceeds the decades-long carbon sequestration process of forest growth (Schlesinger, 2018). Further, burning firewood for fuel often comes with enormous environmental costs of deforestation (Specht, 2015). This is an alarming finding and warrants more understanding.

Table 3 presents the OLS regression of household garbage separately for each survey year. We focus on household garbage because garbage collection by public and private agencies in Pakistan is limited. As IPCC (2006) argues, the open burning of garbage is a source of carbon emissions. Although households do not directly “consume” household garbage, it essentially serves as a proxy for the consumption of food (kitchen waste), paper and packing products, and recyclable items. Our regressions show that households tend to generate more household garbage when they have higher household income and are larger, even though basic literacy is positively correlated with household garbage generation but is not significant. Likewise, households in rural areas tend to produce much less household garbage than urban and Megacity households, mainly due to use of food waste and other recyclables for backyard livestock or manure production. Given the average household size of close to six in Pakistan and the country’s annual population growth rate of 2.4%, household garbage in Pakistan will likely continue to increase carbon emissions significantly. A key feature of Asian megacities, of which Pakistan has two, is that they include extensive peri-urban regions of mixed urban and rural land use but follow an urban lifestyle, which suggests household garbage generation will only increase (Hugo, 2014).

Figure 2 presents the district-level predicted total and per capita carbon emissions for both urban and rural areas of all four provinces in Pakistan from 2013-4 to 2018-19. Urban centers dominate total carbon emissions due to their large population base. Regarding per capita carbon emissions, megacities and urban centers in the two more urbanized provinces, Punjab and Sindh, contain the most emission hotspots. This suggests that the compact city hypothesis proposed for US cities (Gleaser & Kahn, 2010) only partly applies to Pakistan. Cities, despite their cleaner fuel choices, suffer from more transport fuel usage, high garbage generation and limited availability of natural gas for cooking. We also note that the remote, higher-elevation rural areas in northern KP province depend on firewood for heating have higher per capita emissions.

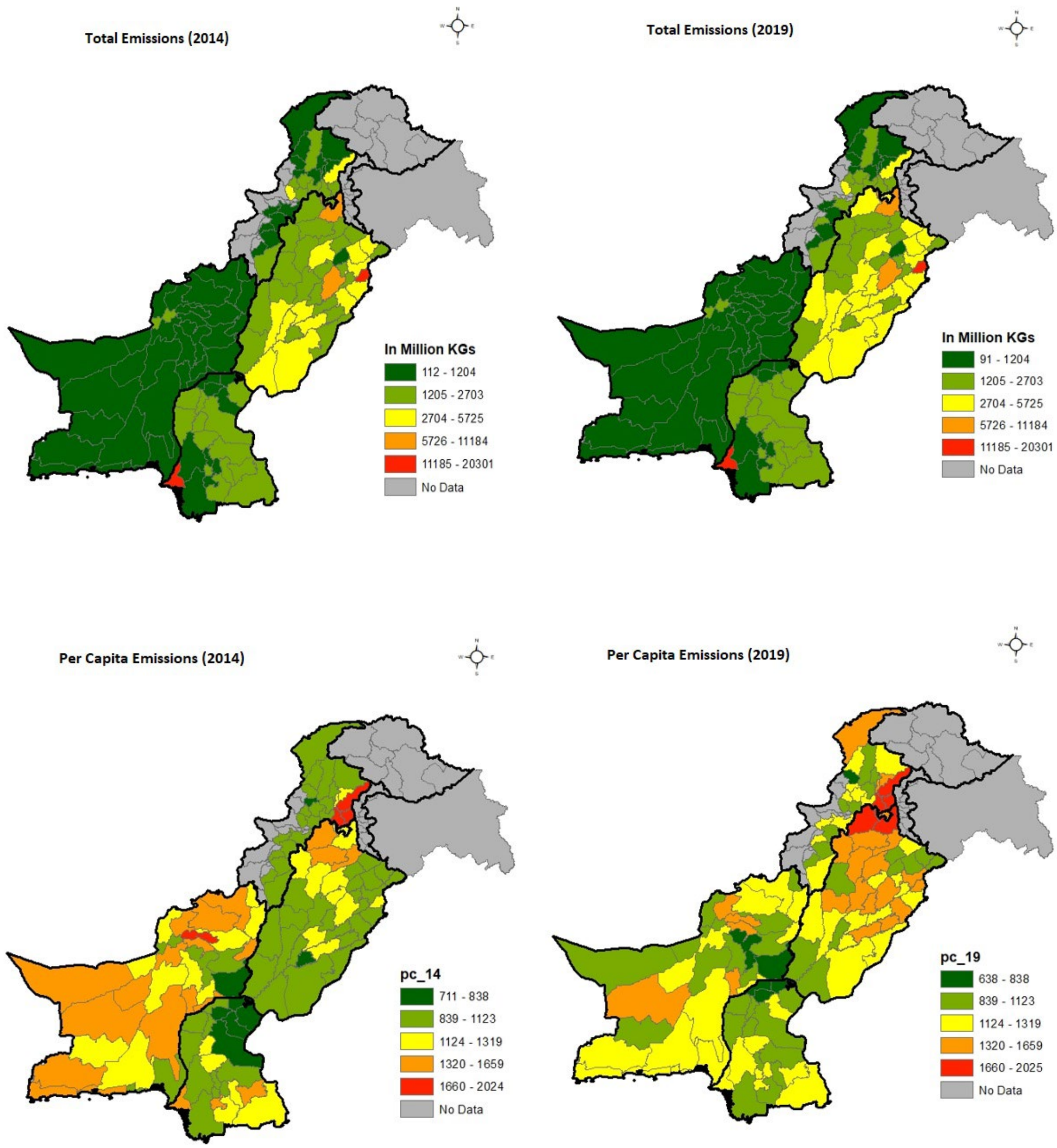

Figure 2: Predicted District-Level Total and Per Capita Carbon Emissions

We finally rank districts' greenness based on the per capita carbon emissions level for each survey year and assign a higher ranking if the district has lower carbon emissions and thus is greener. Table A3 in the Appendix shows per capita emissions for 2013-14 and 2018-19, the percent change in per capita emissions, greenness rankings for both years and an indicator for change in districts' rankings from 2014 to 2019. For every survey year, we rank all districts and divide them into five quintiles. We label a district as "no change" if it stays within the same greenness quintile from 2014 to 2019, "red" if it emits significantly higher per-capita emissions and moves to a lower quintile in 2018-19 compared to the previous decade, and "green" if the district moves up by at least one quintile in its greenness ranking. For instance, of the top 10 districts that rank the highest in per capita emissions, eight have had no change over the years, while two of them have turned red, i.e., experienced exacerbated ranking. Both districts, Khushab and Toba Tek Singh, are in Punjab province, which has been hard hit by the gas crisis ever since 2015. Domestic consumers were completely deprived of gas in these provinces, especially in the winter season (Hasnain, 2015), which explains the switch to unclean energy sources like firewood. Furthermore, although a rank change significant enough to classify as green is not observed for Chitral, its greenness ranking has improved from 81 in 2014 to 78 in 2019. Projects like Productive Uses of Renewable Energy (PURE) and Promotion of Energy Efficient Cooking, Heating and Housing Technologies (PEECH) in Chitral, can be credited for the same. On the contrary, the industrial city of Sheikhupra, which has been industrializing rapidly, faces a downward reduction in its greenness ranking from 56 in 2014 to 77 in 2019. The ongoing initiatives of business park establishment and coal-based power plant (Global Energy Monitor Wiki, 2023) will likely worsen the situation.

Examining the hotspots for household per-capita carbon emissions in Pakistan revealed by Figure 2 and Table 2 in Appendix 1, we find that in contrast with the compact-city hypothesis (high population density makes a city greener than its rural counterpart), large Pakistani cities are hotspots of carbon emissions with higher per-capita emissions. This may be due to the sprawling nature of the urbanization of Pakistani cities due to strict zoning laws that restrict floor area ratios and building heights (Planning Commission, 2011) and a lack of high-density core areas and an efficient public transport system (International Growth Centre, 2011). These factors have contributed to lower population density in urbanizing Pakistani cities than in other developing countries.

The discussion on the impact of urbanization in Pakistan should keep us mindful of the fact that Pakistani household carbon emissions are still radically lower than those in developed countries such as the United States and neighboring countries like India. Islamabad, Lahore, and Rawalpindi rank in the top 10 cities with the highest emissions in both the survey years, roughly 1 ton per year in 2013-14 (about 7 tons per household), which is like Delhi and Greater Mumbai (Ahmad et al. 2015), and comparable to Shanghai (1.8 tons) and Beijing (4 tons) (Zheng et al., 2011). Similarly, for 2018-19, the per capita carbon emissions of these megacities are approximately 1.6 tons per year. World Bank (2023) reports per capita carbon emissions for India in 2020 to be 1.6 tons per year, while Glaeser and Kahn (2010) report that in the cleanest US cities, San Diego and San Francisco, a standardized household emits around 26 tons of CO_2 per year. This means that even in Pakistan’s brownest cities, a standardized household emits only one-fourth of the carbon produced by a standardized household in America’s greenest cities.

We now discuss each province's per capita emissions and migration between the regions given Pakistan Bureau of Statistics (2020) migration data. Punjab ranks the highest in per capita emissions for 2018/19 and has the highest percentage of migrated population but 6.02 % of Punjab's 'migrated' population is Intra-province migration, while only 1.44 % is from other provinces. The highest percentage of Inter-province migration is in Sindh, i.e., 2.35 %. Based on these numbers, provincial migration is likely to increase emissions in the future.

Similarly, when we compare the per capita emissions for rural, urban, and megacity locations, unsurprisingly, the per capita emissions are higher for urban and megacities than for rural regions. The pattern holds for both survey years. The difference between urban and megacities is trivial and further corroborates our speculation that the compact city hypothesis may not hold in the case of Pakistan. The rural versus urban comparison of per capita emissions, when combined with the latest rural-to-urban migration distribution from Labor Force Survey, Pakistan (Government of Pakistan, 2021) reveal exciting dynamics. While the LFS reports overall rural-to-urban migration less in 2020/2021 (11.7 %) compared to 14.9 % in 2018/19, the provincial breakdown of the same interests us more. The rural-to-urban migration has decreased in all provinces except for Baluchistan, where it has dramatically increased from 1.9 % in 2018/19 to 10.1 % in 2020/21. Research also shows that internal migration (rural to urban) is a climate adaptation response. Rural-to-urban movement is likely to continue and increase in the future as changes in the climate unsettle rural livelihoods (Ishfaq, 2019).

Next, we present the results on the decomposition of carbon emission across different energy types for both years and the three regions. For rural regions, the highest share of emissions is of firewood (and increasing), while gas and garbage have decreased over the period studied. The most striking finding of our study is the increase in the share of firewood emissions in urban (33.36%) as well as mega cities regions (131.8%), accompanied by a corresponding decrease in the share of emissions from gas. The proportion of emissions from garbage has also increased over the period, but the increase is not huge. Thus, omitting these two sources significantly underestimates the total household carbon footprint. However, the increase in the share of emissions from firewood in urban regions is counter-intuitive and exacts an explanation of the country's overall energy mix. The natural gas provider in the country has seen a hit in the face of growing demand by power, commercial, fertilizer, and residential sectors as well as a decline in the indigenous gas production (Government of Pakistan, 2021). The power sector's shift from oil to gas and coal implies less availability of gas for residential consumers (Government of Pakistan, 2019). In 2015, the government had to resort to importing LNG to address the widening gap between supply and demand (Ministry of Planning, Development & Special Initiatives, 2023). Figure 3 reveals how the ongoing gas crisis resulted in a switch from a relatively cleaner fuel (i.e., gas) to firewood in even the more-urban regions of the city. We observe a marked increase in the usage of (and hence emissions from) firewood between 2014 and 2019.

Category	*Rural*		*Urban*		*MegaCity*	
Year	*2013/14*	*2018/19*	*2013/14*	*2018/19*	*2013/14*	*2018/19*
Fuel Type	*% of carbon emissions*					
Electricity	7.29	9.52	8.94	11.40	12.38	16.81
Gas	12.13	9.82	38.28	31.21	49.51	40.50
Firewood	43.20	44.94	10.82	14.4 3	0.88	2.04
Garbage	26.30	24.45	31.54	32.03	25.19	28.83
Private Petrol	5.29	8.06	5.40	8.09	6.69	9.51
Taxi	1.14	0.50	1.10	0.50	0.72	0.21
Bus	2.99	2.13	2.38	1.78	2.93	1.51
Rickshaw	1.66	0.58	1.54	0.56	1.68	0.59
	100.00	**100.00**	**100.00**	**100.00**	**100.00**	**100.00**
Per-capita emissions (lbs/year)	1026.24	1149.18	1148.70	1307.36	1112.12	1300.48

Table 4: Proportion of emissions from each fuel type for Rural, Urban, and Mega City Categories for 2013/14 and 2018/19

Figure 3 further illustrates the relative importance of including traditional energy sources such as firewood in total carbon emissions for a country like Pakistan. One would expect firewood used to be more concentrated in high-elevation areas and rural districts and a shift away from firewood over time. For 2013/14, heavy reliance on firewood for energy consumption could result from multiple factors, including higher elevation, greater forest cover in mountainous areas, lower household income, lack of access to cheaper alternatives such as natural gas, and weak enforcement of forest protection. In addition, the provision of natural gas was heavily geared toward the urban provinces of Punjab and Sindh, even though Balochistan has the largest reservoirs of natural gas. However, the gas shortage has visibly resulted in more widespread and intense use of firewood, even in districts in Punjab and Sindh, the two more urbanized provinces of Pakistan.

We now turn to the share of garbage in total emissions. For 2013/14, the rural areas have the least share of household garbage in total emissions. This is in part due to the ability of rural households to use food waste as feed. It also reflects poor garbage collection and disposal services in many urban areas. However, mega cities' share of garbage in total emissions is less than urban and comparable to rural, and this may indicate better waste disposal management systems as cities develop or a higher relative share of other energy sources such as electricity. However, for 2018/19, the share of garbage in total household emissions in megacities is more than in rural regions but still less than in urban.

Table 4 also shows growing emissions from gasoline use for private vehicles over time. This holds across the three regions. However, there is a decline in the proportion of emissions from public transport. Gasoline consumption is concentrated in urban cities such as Karachi and Lahore and disproportionately used by households with higher incomes or salaries. The role of public transportation is heterogeneous across cities and is demonstrated separately in Figure 4. The introduction of bus rapid transit (BRT) in the megacities of Lahore (2013), the twin cities of Rawalpindi – Islamabad (2015), and Multan (2017) has shifted the mix of public transport in all provinces over the years, shifting it to higher bus usage, while reducing the share of taxis and rickshaws.

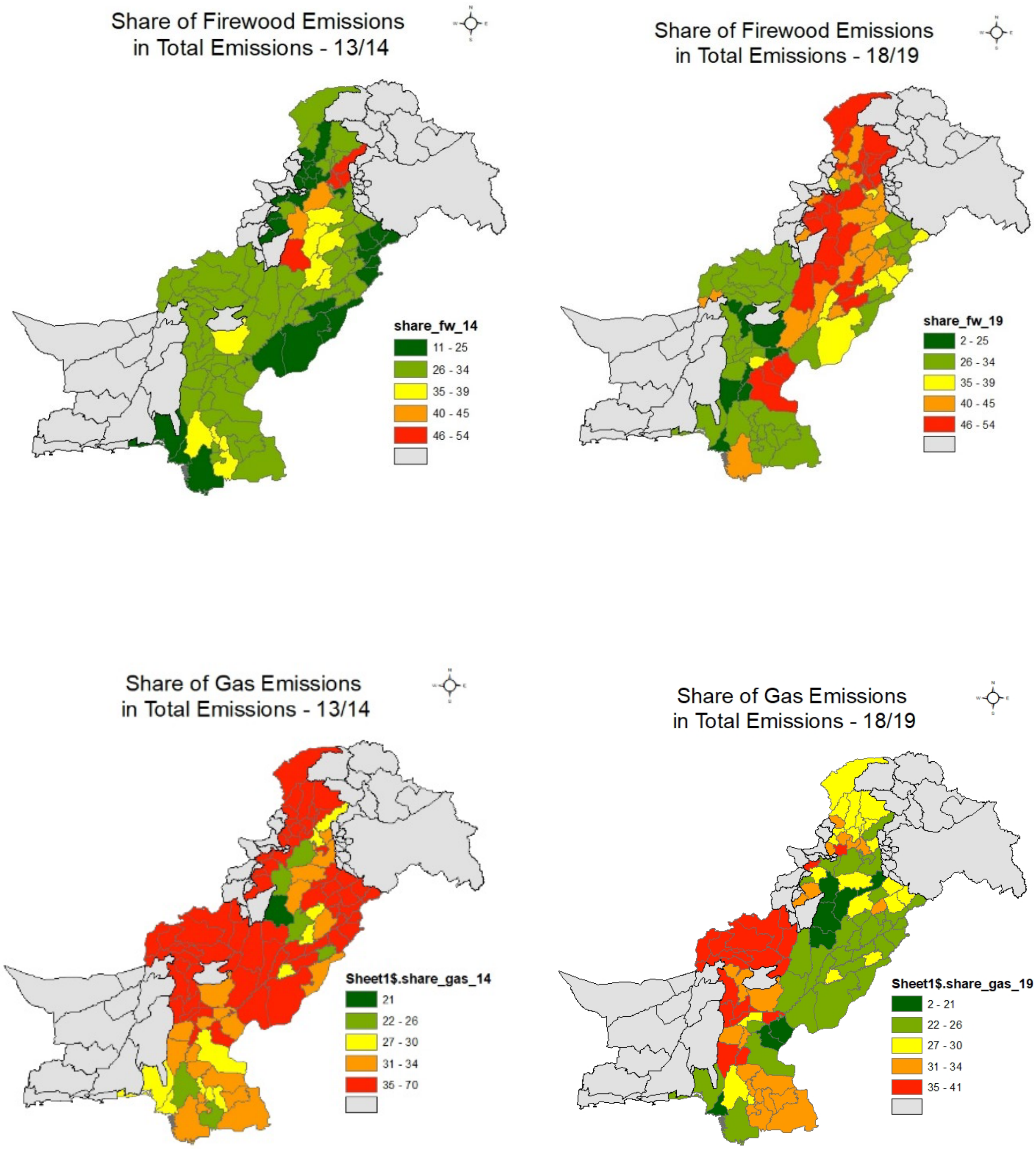

Figure 3: Share of Household Garbage and Firewood Use in Total Emissions

The same findings are echoed by Majid et al. (2018). There is robust evidence that the metro bus system (MBS) in Lahore has caused workers to change their mode of transport from private to public and has increased public transport use by 24 % in the nearby areas. Moreover, recent research (Shah et al, 2020) shows how the MBS Lahore is associated with a reduction of the same carbon footprint. Given the latest developments of the introduction of e-buses in Karachi, and their potential benefits for females, at least the emissions from the transport sector may take a better turn in the future, and for the benefit of the more vulnerable groups of the population to climate change, i.e., women.

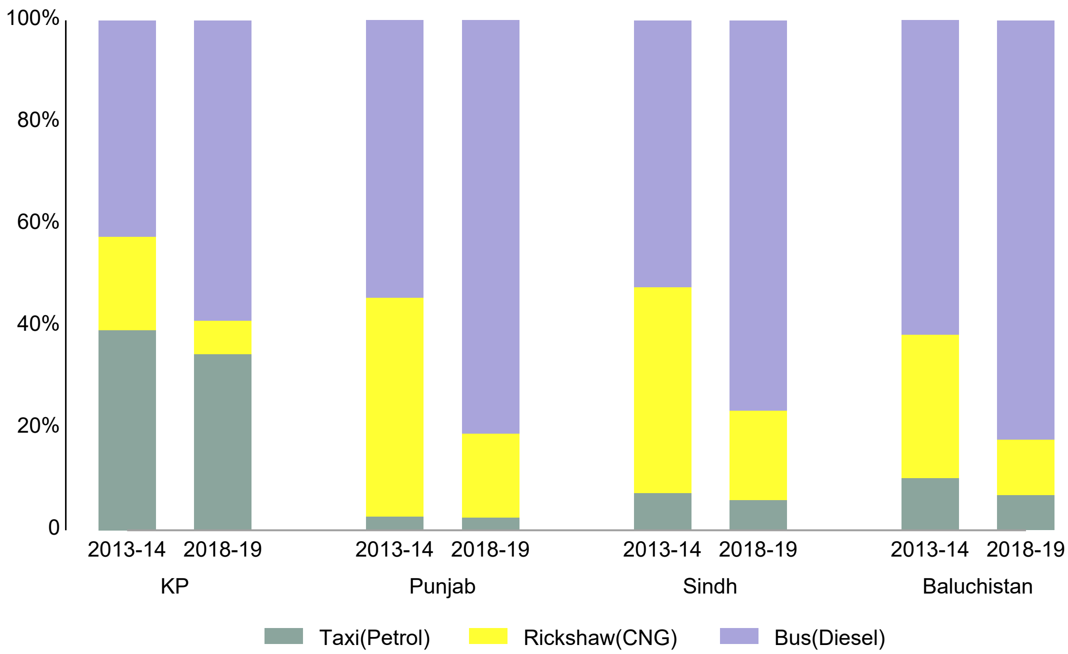

Figure 4: Distribution of Emissions from public transport use by households across provinces

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	(Log) Total Emissions	(Log) Per Capita Emissions	Log Per Capita Electricity	Log Per Capita Gas	Log Per Capita Firewood	Log Per Capita Garbage	Log Per Capita Petrol	Log Per Capita Taxi	Log Per Capita Rickshaw	Log Per Capita Bus
HH Size	-0.134***	-0.158***	-0.207***	-0.120***	-0.221***	-0.126***	-0.148***	-0.261***	-0.207***	-0.159***
	(0.0213)	(0.0133)	(0.0215)	(0.0188)	(0.0350)	(0.00792)	(0.0231)	(0.0526)	(0.0576)	(0.0325)
Car Prop	0.131	0.364	-0.223	0.459	0.573	0.0203	0.479	0.0736	-5.661***	1.310*
	(0.564)	(0.304)	(0.470)	(0.415)	(0.771)	(0.176)	(0.511)	(1.328)	(1.407)	(0.726)
Low Income Proportion	-0.323**	-0.241**	0.00314	-0.0771	-0.394	-0.00668	-0.0238	-0.134	-0.616	-0.0198
	(0.153)	(0.109)	(0.185)	(0.160)	(0.300)	(0.0669)	(0.197)	(0.392)	(0.441)	(0.274)
Agri Worker Proportion	0.184	0.154*	0.148	0.0322	0.382*	-0.0523	-0.101	-0.196	-0.147	0.221
	(0.112)	(0.0798)	(0.135)	(0.117)	(0.219)	(0.0489)	(0.144)	(0.288)	(0.324)	(0.201)
No Garbage Collection	-0.159	-0.0513	-0.225	-0.181	-0.109	0.0555	0.303**	-0.121	-0.747**	0.0927
	(0.119)	(0.0853)	(0.144)	(0.125)	(0.234)	(0.0522)	(0.154)	(0.306)	(0.345)	(0.214)
Cooking Fuel Gas	-0.0575	-0.0914	-0.163	0.0770	-0.205	-0.0302	-0.178	-0.0433	0.329	-0.256
	(0.107)	(0.0661)	(0.108)	(0.0941)	(0.176)	(0.0396)	(0.116)	(0.262)	(0.285)	(0.163)
Refrigerator Proportion	0.0830	0.193**	0.418***	0.185	0.524**	0.0306	-0.343**	-0.114	0.0852	0.231
	(0.149)	(0.0912)	(0.148)	(0.130)	(0.242)	(0.0545)	(0.159)	(0.363)	(0.395)	(0.224)
Elevation (Log)	0.0398	0.0388**	-0.0187	0.0477**	0.0817**	0.000250	0.00273	0.250***	-0.119	0.0686*
	(0.0690)	(0.0153)	(0.0222)	(0.0198)	(0.0366)	(0.00850)	(0.0244)	(0.0938)	(0.0848)	(0.0350)
Urban Proportion	2.032***	-0.0838	0.652***	-0.409***	-0.603**	0.606***	0.532***	0.337	0.0883	0.357

	(0.370)	(0.114)	(0.173)	(0.153)	(0.285)	(0.0653)	(0.189)	(0.592)	(0.573)	(0.269)
Punjab	0.433**	-0.163***	0.166**	-0.259***	-0.0860	0.0192	0.0138	-2.787***	-0.182	-0.0977
	(0.183)	(0.0437)	(0.0646)	(0.0575)	(0.106)	(0.0246)	(0.0708)	(0.256)	(0.235)	(0.101)
Sindh	-0.176	-0.0848	-0.241**	-0.108	0.146	0.0165	-0.0214	-1.682***	-0.333	-0.0614
	(0.278)	(0.0689)	(0.102)	(0.0907)	(0.168)	(0.0388)	(0.112)	(0.398)	(0.368)	(0.160)
Balochistan	-1.703***	-0.0699	0.0200	0.0734	0.0419	-0.104***	-0.227***	-1.559***	0.191	0.129
	(0.201)	(0.0530)	(0.0797)	(0.0707)	(0.131)	(0.0302)	(0.0871)	(0.293)	(0.276)	(0.124)
Constant	21.46***	7.955***	5.205***	6.754***	6.821***	5.706***	5.594***	3.316***	5.378***	3.349***
	(0.519)	(0.181)	(0.292)	(0.255)	(0.476)	(0.107)	(0.314)	(0.838)	(0.836)	(0.442)
Observations	180	180	180	180	180	180	180	180	180	180
Number of districts	90	90	90	90	90	90	90	90	90	90
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Overall R-squared	0.768	0.684	0.812	0.509	0.519	0.915	0.562	0.713	0.376	0.330

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The omitted province is KP. Province 2 is Punjab, 3 is Sindh, and 4 is Baluchistan.

Table 5. Pooled OLS regressions of district-level per-capita carbon emissions by energy type for Pakistan

Using predicted carbon emissions for representative households at the district level, we construct a panel regression to explain inter-district variations in total, per capita and per capita carbon emissions by energy type. Table 5 shows the results and reveals several interesting findings. First, total emissions are positively related to urban population share indicating that cities must be the center of focus for the policy. Interestingly the per capita emissions are higher in high income and high elevation districts, but these are negatively related to urban population (the result is insignificant due to lack of power). Moreover, districts with a higher share of car ownership have higher per-capita carbon emissions, mainly from higher gasoline emissions by private vehicles. Second, districts with higher population density, larger built-up areas, and higher average household income have higher emissions from the consumption of electricity, natural gas, gasoline, and household garbage and higher consumption of natural gas and firewood due to more significant heating needs at higher elevations. Third, higher-income districts typically have more total and per-capita carbon emissions and could benefit from more carbon abatement efforts. Fourth, rural households contribute significantly less household garbage due to better utilization of most household waste items as fodder for cattle.

5. Conclusions and Policy Implications

Using two rounds of nationwide household surveys for both rural and urban districts in Pakistan, we provide the first empirical estimate of Pakistan's household carbon emissions from using all energy types from 2014 to 2019 and examine the evolution of greenness rankings over time for each district. Our main results reveal that high-elevation rural districts in KP province, urban centers, and larger cities represent household carbon emission hotspots, even when measured as per capita emissions. This contradicts the compact city hypothesis Glaeser and Kahn (2010) put forward for US cities and suggests future increases in emissions for Pakistan, which faces massive rural-to-urban migration and rapid population growth. In addition, we find that firewood use accounts for roughly half of all carbon emissions across households' energy consumption in rural regions, and its share in total household emissions has drastically increased over time. Moreover, household garbage would lead to a 25% underestimate of household carbon emissions, especially for cities. Finally, our analysis shows that 56 % of Pakistani districts changed their greenness rankings by at least one quintile from 2005 to 2014, where 30 % became less green, and 26 % improved their greenness rank. This suggests that relying solely on a single year's survey data is not advisable, especially for developing countries like Pakistan that experience pressure from urbanization, population growth, and shifts in the energy mix.

Our paper makes several significant contributions to the literature on sustainable development, carbon accounting, and the interplay between urbanization, energy use, and carbon emissions. It has important policy implications for adaptations to climate change, especially in the developing world. By focusing on Pakistan—the fifth most populous country in the world—and firewood, the primary energy source for two billion people in lower-income developing countries, we highlight the importance of focusing on often-overlooked energy types when analyzing climate change impacts. We also provide strong evidence that urban areas are not necessarily greener. The policy focus required to facilitate clean energy transition in both rural and urban areas should also incorporate how and where carbon emissions are concentrated and the fundamental energy use practices deriving them. For instance, impact of policies like provision of alternate cooking sources to 14.03 million households by 2025 in Pakistan[2] can be

[2] Under the Sustainable Energy for All (SEforAll) National Action Plan 2019 mentioned in the Updated Nationally Determined Contributions 2021, Pakistan.

maximized by incorporating the spatial diversity dimension. Furthermore, changes in the greenness rankings of 56% of Pakistani districts within one decade confirm the importance of monitoring the climate profiles of a region over time, especially for urbanizing developing countries. Finally, imminent carbon emissions from Pakistan and similar developing countries merit further analysis for at least two reasons. First, Li et al, (2018) corroborate that that households' energy consumption will likely increase with higher temperatures, and this is likely also true for Pakistan. Second, ongoing projects, such as coal power plants along the China-Pakistan Economic Corridor, are projected to alter Pakistan's energy consumption and carbon emissions profile significantly.

Our analysis has limitations. First, because the PSLM surveys only have data on self-reported energy expenditures rather than the quantity of consumption, we had to use province-level energy prices to convert these measures, then use national-level emission conversion factors to derive corresponding predicted carbon emissions. These conversions and aggregations likely introduced measurement errors in our estimates. However, comparing the aggregate amount of our predicted energy consumption with official government statistics on energy use at the province level reveals that our measures are within 5% of these statistics. Second, Pakistan experienced significant electrical blackouts and shortages, especially in 2013–4, which forced many households to use firewood. This could result in an artificially higher share of carbon emissions from firewood due to unreliable electricity or natural gas supply, which may not translate to all developing countries. The same scenario repeated for gas shortages and hence the switch to firewood. Third, PSLM surveys did not always cover the same districts. Many PSLM 2018/19 districts were not surveyed in 2013/14. However, we matched the majority of roughly 100 districts, as 73 were surveyed in both rounds. Finally, our results, especially for remote rural areas, might not be statistically representative if surveys of the poorest or most remote areas were less likely. Future research is needed to further examine the distributional impacts of climate change on rural and underprivileged households who lack access to cheaper and consistent alternative energy or abatement technologies.

Our research has unraveled an interesting phenomenon that must be investigated in the context of Pakistan. The energy ladder hypothesis (Hanna and Oliva 2015) states that household cooking fuel choice transitions from traditional to modern as the household income improves. However, in the face of exogenous factors like gas shortages, we speculate that such explanations fail to hold, at least in our data. We, instead, observed a marked shift in cooking fuel choices, even in the better-off provinces of Pakistan. Policy implications of a shift towards traditional fuel, such as firewood at the nexus of gendered energy poverty (GEP) is also pertinent for sustainable development for all. GEP in the rural areas has exposed females to security concerns, health hazards, premature death, domestic fire accidents, time and income poverty at different levels of severity in selected rural electrified areas in South Asia (Longe, 2021). It would be interesting to explore the repercussions of this regression in the usage of cooking fuels in the face of overall development in the 21st century, with sustainable development goals in place for women's health, time, and income in Pakistan.

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The Appendix

Energy Type	*Fuel Consumption on Private Car*		*Fuel Consumption on public transport (Taxi)*	
Year	***2013/14***	***2018/19***	***2013/14***	***2018/19***
	(1)	(2)	(3)	(4)
VARIABLES	ln_cargasoline	ln_cargasoline	ln_taxi	ln_taxi
Age of HH Head	0.00117*	0.000989*	0.00298***	0.00205***
	(0.000630)	(0.000506)	(0.000551)	(0.000509)
Log of HH Annual Income	0.233***	0.349***	0.293***	0.338***
	(0.0117)	(0.0104)	(0.0104)	(0.0103)
HH Size	0.00710***	0.0102***	0.0175***	0.0223***
	(0.00237)	(0.00216)	(0.00238)	(0.00225)
Gender of HH Head = 2, female	0.0611	0.0835*	0.126***	0.257***
	(0.0444)	(0.0488)	(0.0377)	(0.0367)
HH Head is Currently Married	0.0192	-0.0271	0.0103	0.0241
	(0.0299)	(0.0247)	(0.0265)	(0.0246)
Category = 2, Urban	-0.0126	-0.0221	-0.0196	0.0218
	(0.0212)	(0.0175)	(0.0190)	(0.0168)
Category = 3, MegaCities	-0.00294	-0.0102	-0.0373	0.0325
	(0.0261)	(0.0241)	(0.0248)	(0.0259)
Education	0.258***	0.0458**	-0.131***	-0.128***
	(0.0493)	(0.0233)	(0.0348)	(0.0237)
employer	-0.0602	0.0316	-0.216***	-0.0302

	(0.0397)	(0.0430)	(0.0513)	(0.0512)
paidEmployee	-0.0457**	-0.0421***	-0.0471***	-0.00794
	(0.0200)	(0.0156)	(0.0173)	(0.0158)
selfEmployee	-0.0785***	-0.0888***	-0.0994***	-0.0807***
	(0.0216)	(0.0178)	(0.0208)	(0.0187)
Constant	2.290***	1.360***	0.793***	0.0253
	(0.201)	(0.163)	(0.141)	(0.139)
Select Equation				
Education	-0.527***	-0.0240**	1.343***	0.401***
	(0.0118)	(0.00967)	(0.0198)	(0.0144)
Owns a Car	1.670***	1.370***		
	(0.0684)	(0.0489)		
Owns any Vehicle			-0.563***	-0.156***
			(0.0275)	(0.0172)
Observations	14,214	18,157	12,527	17,497
District Fixed Effects	Yes	Yes	Yes	Yes
athrho	-0.532***	-1.696***	-0.644	-0.872
lnSigma	-0.722***	-0.139***	-0.396	-0.358

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A1: Heckman Selection Model Results for Household Consumption of Fuel in Private Cars and Public Transport-Taxi

Energy Type	***Fuel Consumption on Public Transport (Rickshaw)***		***Fuel Consumption on Public Transport (Bus)***	
Year	***2013/14***	***2018/19***	***2013/14***	***2018/19***
	(1)	(2)	(3)	(4)
VARIABLES	ln_rickshaw	ln_rickshaw	ln_bus	ln_bus
Age of HH Head	0.00305***	0.00214***	0.00304***	0.00204***
	(0.000551)	(0.000518)	(0.000551)	(0.000507)
Log of HH Annual Income	0.293***	0.347***	0.293***	0.339***
	(0.0104)	(0.0104)	(0.0104)	(0.0102)
HH Size	0.0176***	0.0218***	0.0176***	0.0223***
	(0.00238)	(0.00229)	(0.00238)	(0.00224)
Gender of HH Head = 2, female	0.125***	0.268***	0.125***	0.256***
	(0.0378)	(0.0374)	(0.0378)	(0.0366)
HH Head is Currently Married	0.00898	0.0208	0.00867	0.0225
	(0.0265)	(0.0250)	(0.0265)	(0.0245)
Category = 2, Urban	-0.0226	0.0177	-0.0227	0.0229
	(0.0190)	(0.0171)	(0.0190)	(0.0167)
Category = 3, MegaCities	-0.0333	0.0197	-0.0333	0.0167
	(0.0248)	(0.0264)	(0.0248)	(0.0258)
Education	-0.129***	-0.124***	-0.129***	-0.130***
	(0.0348)	(0.0239)	(0.0348)	(0.0237)
employer	-0.218***	-0.0162	-0.218***	-0.0340
	(0.0513)	(0.0522)	(0.0513)	(0.0510)

paidEmployee	-0.0461***	-0.00284	-0.0461***	-0.00668
	(0.0173)	(0.0161)	(0.0173)	(0.0157)
selfEmployee	-0.0984***	-0.0787***	-0.0984***	-0.0790***
	(0.0208)	(0.0191)	(0.0208)	(0.0187)
Constant	-1.908***	-2.975***	0.241*	-0.215
	(0.141)	(0.142)	(0.141)	(0.139)
Select Equation				
Education	1.342***	0.400***	1.343***	0.402***
	(0.0198)	(0.0143)	(0.0198)	(0.0145)
Owns any Vehicle	-0.562***	-0.154***	-0.563***	-0.157***
	(0.0275)	(0.0170)	(0.0275)	(0.0174)
Observations	12,527	17,497	12,527	17,497
District Fixed Effects	Yes	Yes	Yes	Yes
athrho	-0.651	-0.942	-0.648	-0.832
lnSigma	-0.394	-0.318	-0.395	-0.374

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A2: Heckman Selection Model Results for Household Consumption of Public Transport Fuels (Rickshaw and Buses).

District	Province	District Category	Per Capita Emissions 2014	Per Capita Emissions 2019	Rank in 2014	Rank in 2019	Ranking Change
Dera Bugti	Baluchistan	Urban	741	638	2	1	No Change
Sibi	Baluchistan	Rural	859	673	14	2	No Change
Jacobabad	Sindh	Rural	862	710	15	3	No Change
Jhal Magsi	Baluchistan	Rural	832	724	8	4	No Change
Ziarat	Baluchistan	Rural	977	759	35	5	Green
Kachhi	Baluchistan	Rural	1097	783	62	6	Green
Shikarpur	Sindh	Rural	784	812	4	7	No Change
Harnai	Baluchistan	Urban	1098	820	63	8	Green
Barkhan	Baluchistan	Rural	967	828	32	9	Green
Pishin	Baluchistan	Rural	883	831	20	10	Green
Kashmore	Sindh	Rural	711	838	1	11	No Change
Musakhel	Baluchistan	Rural	979	907	37	12	Green

Lakki Marwat	KP	Rural	937	946	26	13	Green
Dadu	Sindh	Rural	1011	975	45	14	Green
Narowal	Punjab	Rural	1020	988	47	15	Green
Ghotki	Sindh	Rural	831	1004	7	16	No Change
Swat	KP	Urban	1077	1020	58	17	Green
Gujranwala	Punjab	Mega City	856	1028	13	18	No Change
Tank	KP	Rural	875	1029	19	19	No Change
Sialkot	Punjab	Urban	847	1038	11	20	Red
Hafizabad	Punjab	Rural	854	1041	12	21	Red
R.Y.Khan	Punjab	Mega City	866	1042	17	22	Red
Larkana	Sindh	Rural	941	1045	27	23	No Change
Khairpur	Sindh	Rural	762	1050	3	24	Red
Peshawar	KP	Mega City	887	1055	21	25	No Change
Naushahro Feroze	Sindh	Rural	1186	1066	75	26	Green
Nowshera	KP	Urban	1101	1079	65	27	Green
Quetta	Baluchistan	Mega City	1107	1080	67	28	Green

Sherani	Baluchistan	Rural	1171	1092	73	29	Green
Mirpur Khas	Sindh	Rural	1204	1094	77	30	Green
Rajanpur	Punjab	Rural	932	1095	25	31	No Change
Thatta	Sindh	Rural	1057	1096	54	32	Green
Bhakkar	Punjab	Rural	1015	1097	46	33	Green
Tando Muhammad Khan	Sindh	Rural	818	1101	6	34	Red
Buner	KP	Rural	974	1102	33	35	No Change
Multan	Punjab	Mega City	994	1104	40	36	Green
Badin	Sindh	Rural	1148	1105	70	37	Green
Mandi Bahauddin	Punjab	Rural	950	1109	30	38	Red
Matiari	Sindh	Rural	1040	1119	51	39	No Change
Sanghar	Sindh	Rural	1104	1121	66	40	Green
Shangla	KP	Rural	1171	1121	72	41	Green
Tharparkar	Sindh	Rural	947	1123	29	42	Red
Sukkur	Sindh	Urban	833	1133	9	43	Red
Lasbela	Baluchistan	Rural	942	1134	28	44	Red

Swabi	KP	Urban	982	1138	38	45	No Change
Mardan	KP	Urban	975	1139	34	46	Red
Jamshoro	Sindh	Rural	998	1142	41	47	No Change
Tando Allahyar	Sindh	Rural	987	1143	39	48	No Change
Umer Kot	Sindh	Rural	1100	1146	64	49	Green
Bahawalnagar	Punjab	Rural	868	1149	18	50	Red
Gujrat	Punjab	Rural	1006	1152	44	51	No Change
Hyderabad	Sindh	Mega City	1032	1166	49	52	No Change
Charsadda	KP	Urban	998	1167	42	53	No Change
Bahawalpur	Punjab	Rural	956	1167	31	54	Red
Muzaffargarh	Punjab	Rural	1049	1167	52	55	Red
Karak	KP	Rural	1029	1190	48	56	Red
Kasur	Punjab	Rural	1088	1193	59	57	No Change
Bannu	KP	Rural	841	1199	10	58	Red
Sahiwal	Punjab	Rural	1073	1204	57	59	No Change
Khanewal	Punjab	Rural	1138	1209	68	60	No Change

Chiniot	Punjab	Rural	1287	1212	82	61	Green
Kohistan	KP	Rural	1035	1231	50	62	Red
Upper Dir	KP	Rural	1090	1231	61	63	No Change
Dera Ghazi Khan	Punjab	Rural	865	1248	16	64	Red
Lodhran	Punjab	Rural	786	1250	5	65	Red
Karachi	Sindh	Mega City	1336	1265	84	66	Green
Hangu	KP	Urban	901	1286	22	67	Red
Kohat	KP	Urban	909	1295	24	68	Red
Batagram	KP	Rural	1155	1317	71	69	No Change
Lower Dir	KP	Rural	1050	1343	53	70	Red
Okara	Punjab	Rural	1060	1362	55	71	No Change
Pakpattan	Punjab	Rural	906	1364	23	72	Red
Layyah	Punjab	Rural	977	1367	36	73	Red
Jhang	Punjab	Rural	1002	1393	43	74	Red
Faisalabad	Punjab	Mega City	1179	1420	74	75	No Change
Mianwali	Punjab	Rural	1198	1432	76	76	No Change

Sheikhupura	Punjab	Urban	1070	1448	56	77	Red
Chitral	KP	Rural	1252	1449	81	78	No Change
Jhelum	Punjab	Rural	1369	1507	85	79	No Change
Khushab	Punjab	Rural	1144	1518	69	80	Red
Toba Tek Singh	Punjab	Rural	1088	1519	60	81	Red
Sargodha	Punjab	Urban	1316	1546	83	82	No Change
Islamabad	Punjab	Urban	1238	1597	80	83	No Change
Lahore	Punjab	Mega City	1216	1602	78	84	No Change
Chakwal	Punjab	Rural	1409	1634	87	85	No Change
Rawalpindi	Punjab	Mega City	1236	1659	79	86	No Change
Attock	Punjab	Rural	1383	1712	86	87	No Change
Abbottabad	KP	Urban	1955	1970	90	88	No Change
Mansehra	KP	Rural	1905	2018	89	89	No Change
Haripur	KP	Rural	1763	2024	88	90	No Change

Table A3. District Ranking based on Per Capita Carbon Emissions for 2013-14 and 2018-19