Will Urbanization in Developing Countries Reduce Carbon Emissions?

Panel Data Evidence from Pakistani Household Surveys

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Abstract: Using four rounds of nationwide household survey data from the Pakistan Social and Living Standards Measurement Survey from 2005 to 2014, we provide the first empirical estimates of districts' carbon emissions and their changes over time based on representative households' energy consumption. We find that hotspots for carbon emissions in Pakistan tend to cluster around megacities—Islamabad has the highest per capita carbon emissions. This is contradictory to the compact city hypothesis that denser cities are greener, with lower per-capita carbon emissions, than remote cities, and suggest that urbanization in developing countries may not reduce carbon emissions. Our results also show that ignoring household garbage would underestimate the urban carbon footprint by at least 15%. Finally, our results demonstrate the importance of incorporating rural households and their primary energy usage such as firewood, and the fluid nature of carbon emissions and greenness ranking over time in developing countries like Pakistan.

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

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

1. Introduction

Urbanization is sweeping the globe. The United Nations estimates that by 2030 60% of the world's population will live in cities—twice the proportion that lived in cities in 1950 (UN 2014). As they migrate, their household energy use patterns will 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, and in many rural parts of low-income developing countries it is the only domestically available and affordable source of energy (FAO 2017). Firewood use will, likely, substantially decrease when rural households move to cities. However, systematic understandings of the interplay between household energy use, carbon emissions, and the environmental footprint of growing cities, especially for cities and peri-urban areas in developing countries remains lacking. The compact city hypothesis holds that households' carbon emissions decline, at least on a per-capita basis, when they move to an urban area, denser places are more energy efficient (Duany et al. 2001). Nonetheless cities now account for at least 43% of global primary energy-related carbon dioxide emissions (Seto et al. 2014). This article investigates the compact city hypothesis and its efficacy for cities in developing countries. In so doing it asks, how do firewood 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? Likewise, we ask whether cities in developing countries are greener than cities in developed countries due to lower energy consumptions. Using longitudinal data, we examine whether they are getting greener over time.

The relationship between energy use, urban growth, and carbon emissions has been extensively analyzed, 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, recent efforts have been made to understand urban households' carbon emissions for cities in the United States (Glaeser and Kahn 2010), China (Zheng et al. 2011), the United Kingdom (Minx et al. 2013), the Philippines (Serino and Klasen 2015), and India (Ahmad et al. 2015); this is the first such study for Pakistan. This is important because Pakistan is the sixth-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 United Nations estimates that by 2030 half of Pakistan's population will live in urban areas, which means roughly 60 million Pakistanis will move from rural areas to cities over the next decade (UN 2014).

The previous studies reveal significant gaps in our knowledge even about those countries they study. First, the compact city hypothesis seems to hold in the U.S. (Glaeser and Kahn 2010) but not in developing countries such as India (Ahmad et al. 2015). Second, most studies have ignored the roles of household garbage and firewood in household energy use and subsequent carbon emissions. However, 32% of the world's rural populations lack access to electricity and other modern energy sources (Intergovernmental Panel on Climate Change [IPCC] (2014); International Energy Agency [IEA] 2010). Third, past studies ignored households in rural and peri-urban areas and focused on urban households only. Finally, all past studies have used cross-sectional data collected at a single point in time, rather than longitudinal data.

The primary objective of our article is to quantify, for the first time, districts' carbon emissions and their changes over time based on a representative household's energy consumption for both urban and rural districts in Pakistan. We used the four most recent rounds of micro-level data from the Pakistan Social and Living Standards Measurement (PSLM) Survey

from 2005 to 2014, which is the most comprehensive nationwide data set at the household level in Pakistan in terms of household demographics, socioeconomic characteristics, and disaggregated energy consumption expenditures. We first estimated a series of Heckman selection models of household energy consumption 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). Then we constructed a district-level panel data set of carbon emissions by energy types, Using this data set, we examined the validity of the compact-city hypothesis for Pakistani cities and evaluated the contributions of previously ignored energy types, such as firewood and household garbage, in explaining cross-district differences in total and per-capita emissions.

Our main findings yield several insights that contribute to our understanding of carbon accounting, sustainable development, and the interplay between urbanization and carbon emissions both in Pakistan and around the world. First, we reject the compact city hypothesis for Pakistan, showing that hotspots for carbon emissions tend to cluster around megacities—Islamabad has the highest per capita carbon emissions at one ton per year. This conforms to research on Indian households (Ahmad et al. 2015) but not research in the U.S. and other developed countries in Europe (Brownstone and Golob, 2009; Kahn, 2007). Along with those past studies, it suggests that the compact city hypothesis may not hold in the urbanizing developing countries. 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 energy types largely ignored by previous studies –household garbage and firewood. Specifically,

household garbage accounts for at least 15% of urban households' carbon footprint, and firewood accounts for half of all carbon emissions in some rural areas. This finding complements the current movement on food waste and shows that it is important to incorporate the carbon emissions from household garbage even when the per-capita household waste levels are low in developing countries. This also indicates that it is important to include households in rural and peri-urban areas, which past studies have often ignored, as well as energy types such as firewood. Fourth, our findings reveal a fluid and dynamic path over time in district-level greenness rankings. Just over half, 52% of Pakistani districts experienced noticeable changes in their greenness rankings between 2005 and 2014, with 18% becoming significantly greener and 34% becoming less green. Finally, by using multiple rounds of household surveys in Pakistan, we demonstrated the fluid nature of carbon emissions and household energy use in urbanizing developing countries, and thus improve on previous studies that rely on cross-sectional data collected at a single point in time.

2. Background

As the sixth-most populous country in the world and the most rapidly urbanizing South Asian nation (Kugelman 2015), Pakistan offers an excellent laboratory for examining the compact city hypothesis and the dynamic 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's World Development Indicators (WDIs), the annual urbanization rate for Pakistani cities is 2.6% (World Bank 2016). The WDI database also shows that Pakistan's carbon dioxide intensity relative to gross domestic product is 0.83 kg/dollar, which puts it very close 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. International Energy Agency (2016) found that at least 51 million people in Pakistan—27% of the population—do not have access to electricity, and 90% of urban households and 61% in rural areas are believed to not have reliable access to electricity (World Bank 2017). As well, more than 50% of the population, mainly in rural Pakistan, relies on traditional biomass for cooking, including firewood, agricultural waste and, dung cakes. This is in part due to inefficient and insufficient 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 and Bhada-Tata 2012) due to 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 obvious impact on carbon emissions. All of these factors make Pakistan more or less typical of developing countries.

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 the last 20 years, with its 200 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, which was 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 where proper abatement technologies are frequently not available and this will likely increase urbanization.

3. Data and Methodology

We aim to quantify the household- and district-level carbon emissions in Pakistan between 2005 and 2014. 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 several nationwide household surveys; (*b*) predict district-level energy consumption for all districts using the characteristics of representative household 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 in more detail, as well as the data used to implement these estimations.

Step 0. Data preparation and validation

First, 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 from July 2004 to June 2015. Survey data collection is based on stratified sampling of both urban and rural areas. . Specifically, we use household-level data for 64,760 households from the PSLM surveys conducted in fiscal years 2005–6, 2007–8, 2011–2, and 2013–4. Of particular interest to our study, PSLM data have disaggregated household-level expenditures for various fuel and energy types, including cooking fuel, lighting fuel, 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 2005 to 2014 (Pakistan Economic Survey 2014). In particular, we obtain energy and fuel consumption quantities for electricity, natural gas, gasoline, compressed natural gas (CNG), liquid petroleum gas (LPG), and firewood.

Unfortunately, the PSLM survey does not cover public transportation usage for all households from 2005 to 2014. Therefore, we rely on the newly added section on household expenditure on public transport in the 2015–2016 PSLM survey. We first obtain 2015–2016 average expenditures across low, medium, and high-income household types for all districts on four modes of public transportation—cab, bus, rickshaw, and minivan. 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 2005 to 2014 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 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. However, to estimate emissions, we only include garbage quantity for households that have no formal system of garbage collection, because in such cases open burning is the usual method of disposal.

[Insert Table 1 Here]

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 24% of households consist of agricultural producers and workers. The average household size is close to seven, which is much larger than the norm in the developed world. Of particular significance to our study, Table 1 shows that almost no households rely on coal for heating or cooking, although this is likely to change because the energy projects under China Pakistan Economic Corridor are adding coal-based power plants. On average, 35% of households have connections to electricity, 35% have natural gas connections, 18% live in a municipality that collects household garbage, and only 5% own a private car.

Step 1. 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 the household surveys for each energy type (Heckman 1976). It is important 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 35% of Pakistani households have access to electricity or natural gas, and only 5% of households own motor vehicles.

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 as exclusion restrictions.

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

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

where 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, gasoline, kerosene oil, charcoal, and dung cake—as well as fuels used for public transportation. 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 city 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, 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 (3) 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 and use full-information maximum-likelihood estimation techniques instead of the limited-information maximum-likelihood estimation imbedded in the original Heckman two-step approach.

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

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

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

Step 2. Predict district-level energy consumption for representative households

The next step is to predict district-level energy consumption for representative households using median demographic and socioeconomic characteristics. For the median 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 restriction for the representative household in district d.

Step 3. 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. At present, the EFDB contains IPCC default data, such as the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (IPCC 2006), as well as data from peer-reviewed journals and other publications, including National Inventory Reports and data from the IEA (2012). With these emissions factors, we convert the predicted district-level energy consumption shown in equations (4) and (5) using the following method:

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

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

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

Step 4: 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 80 (out of 124 total) 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:

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

And the per-capita carbon emissions for a district and for each particular 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 as greener when it has 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 policy makers, urban city planners, and the general public in visualizing the impacts and linkages between urban growth and city-level household carbon footprint through the use of charts and spatial city maps.

Step 5: Examining the compact city hypothesis using district-level regressions

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:

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

In equation (9), there are two sets of district-level characteristics:$\boldsymbol{S_{dt}}$, which represents district-level socioeconomic characteristics such as average household and income, percentage of low-income groups, share of household car ownership, percentage of agricultural workers, population density, and built-up area; 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 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:

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

By estimating equations (9) and (10) using panel data model techniques, we explicitly test the validity of the compact city hypothesis in Pakistan and examine whether the per-capita carbon emissions decrease when the population density rises. We disentangle this relationship not only using district-level carbon emissions aggregated across multiple energy types, but also

examining how district-level characteristics drive per-capita carbon emission from a particular energy type.

4. Results and Discussion

[Insert Table 2 Here]

Tables 2 and 3 present the emission estimates from household energy consumptions of two energy types and everyday garbage: electricity and firewood in Table 2 and household garbage in Table 3, of which the latter two previous studies have often ignored. The energy consumption regressions for other energy types are omitted for brevity. The first four columns of Table 2 present results on electricity consumptions separately estimated for each survey year, with the household's connection to electricity supply as the exclusion restriction. It shows that on average, household income, size of household, education, and employment correlates with electricity use levels. In contrast, households in rural areas consume less electricity. This is unsurprising given half of the rural population in Pakistan did not have access to electricity in 2018 (International Renewable Energy Agency 2018). The coefficient for the exclusion restriction variable—has electricity connection—is always positive and significant in the selection equation, suggesting that it is important to control for sample selection issues using electricity connections. Reliable electricity supply is critical and will likely shape future household energy consumption patterns. A decade ago more than 75% of Pakistan's population was suffering from occasional blackouts and there is no reason to think the situation has significantly improved as yet (World Bank 2010). However, the major 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).

[Insert Table 3 Here]

The last four columns of Table 2 show that rural residence and household size consistently correlate with firewood use. In contrast, households in which the head is either self-employed or works as a paid employee or agricultural worker, as well as those with higher household income, consume less firewood in general. The selection equation also shows that households with a cooking range are less likely to use firewood, as such stoves usually use natural gas fuel. A comparison across all four provinces 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 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, both of which emit either dangerous levels of carbon or other poisonous gases. Recently, some scholars have claimed firewood is a carbon neutral fuel, but this is wishful thinking (Johnson, 2009). In fact 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 large environmental costs of deforestation (Specht, 2015).

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, and as IPCC (2006) argues, 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, are larger in size, and the head of the household is female. Yet higher education is negatively correlated with household garbage generation. Likewise households in rural areas tend to produce much less household garbage than urban households, mainly due to the use of food waste and other recyclables for backyard livestock or manure production. Given the average household size at close to seven in Pakistan and the country's annual population growth rate of 2.4%, household garbage in Pakistan will likely continue to add significantly to carbon emissions. 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).

[Insert Figure 1 Here]

Using the household energy consumption coefficients and provincial-level representative household characteristics, Figure 1 presents the district-level predicted total and per capita carbon emissions for both urban and rural areas of all four provinces in Pakistan from 2005-6 to 2013-4. It shows that urban centers typically dominate total carbon emissions due to their large

population base. When focusing on per capita carbon emissions, megacities and urban centers in the two more urbanized provinces, Punjab and Sindh, contain the most emission hotspots. This provides suggestive evidence that the compact city hypothesis put forward by Glaeser and Kahn (2010) for US cities does not apply to Pakistan. We also note that the remote, higher-elevation rural areas in northern KP province depend on firewood for heating.

[Insert Figure 2 Here]

Figure 2 examines the evolution of district-level carbon emissions from another angle and shows the percent change in district-level per capita and total carbon emissions from 2005 to 2014. Specifically, red and orange areas in Figure 2a represent districts that have witnessed significant growth in per capita emissions, while green areas in Figure 2b represent districts that have become greener when measured by their aggregate carbon emissions. In general, Figure 2 echoes Figure 1 in the sense that per capita emissions increase more sharply in urbanizing cities over time, which is likely driven by income-induced higher energy consumption. Declines in total emissions from rural areas reflect the out-migration of rural residents and, in some cases (e.g., rural areas in northern KP province) reflect the gradual shift from firewood use to natural gas.

[Insert Table 4 Here]

We finally rank districts' greenness based on the level of per capita carbon emissions for each survey year, and assign a higher ranking if the district has lower carbon emissions and thus is greener. Table 4 shows per capita emissions for 2005-6 and 2013-4, greenness rankings for 2013-4, and an indicator for change in districts' rankings from 2005 to 2014. In particular, 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 2005 to 2014, "red" if it emits significantly higher per-capita emissions and moves to a lower quintile in 2013-4 compared to the previous decade, and "green" if the district moves up by at least one quintile in its greenness ranking. For example, the Karak district in KP province had per-capita carbon emissions of 668/kgs in 2005-6 and a greenness ranking of 25 out of 77 districts. In 2013-4, Karak managed to cut per capita emissions by half because of increased provision of natural gas and better municipal services. Karak's current rank is 2, and thus it is labeled green. Table 4 reveals the significance of examining the greenness of districts over time rather than relying solely on a snapshot, especially for developing countries. Pakistan's population grew from 154 million to 190 million, and urbanization increased from 34% to 38% from 2005 to 2014 (Worldometers 2017). These substantial changes have led to extensive shifts in inter-district greenness ranking—18% became greener, while 34% became less green, from 2005 to 2014.

Examining the hotspots for household per-capita carbon emissions in Pakistan revealed by Figure 1 and Table 4, we find that in contrast with the compact-city hypothesis (high population density makes you green) put forward by Glaeser and Kahn (2010) for US cities, Table 4 reveals that 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 efficient public transport system (International Growth Centre 2011). The factors have contributed to lower population density in urbanizing Pakistani cities than even in other developing countries.

The impact of urbanization in Pakistan should not distract us from the fact that Pakistani household carbon emissions are still radically lower than those in developed countries such as the United States. Islamabad had the highest per capita carbon emissions in 2013–4, roughly 1 ton per year (about 7 tons per household), which is similar to Delhi and Greater Mumbai (Ahmad et al. 2015), and comparable to Shanghai (1.8 tons) and Beijing (4 tons) (Zheng et al. 2011). However, 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 city, Islamabad, a standardized household emits only one-fourth the carbon produced by a standardized household in America's greenest cities.

Table 4 also provides insights on the impact of rural-urban migration on Pakistan's future carbon emissions. A recent survey shows that in 2015 the percentage of rural migrants in urban populations is highest in Punjab province (7.5%), followed by Sindh (2%), KP (2%), and Balochistan (0.08%) (Urban Unit 2018). Table 4 shows that on average, urban-to-urban migration by a representative household from KP to Punjab would not yield any significant change in emissions, whereas rural-to-urban migration would increase emissions by 37% from 640/kgs per person for a rural resident in KP to 879/kgs for a Punjab urbanite. In the case of intra-provincial rural-to-urban migration in Sindh province, emissions would rise by 6% assuming no change in household characteristics. Migrants cut firewood use, but household energy consumption and carbon emissions do not necessarily drop because they consume more electricity and gasoline.

Next we present the results on the decomposition of carbon emission across different energy types. Across the study period, natural gas and electricity contribute 20% and 15% to Pakistani carbon emissions, respectively. Firewood and household garbage also contribute 30% and 15% respectively. Firewood's impact is decreasing over time, but even in the final survey it contributes 22% of carbon emissions. Thus it is clear that omitting these two sources significantly underestimates total household carbon footprint.

[Insert Figure 3 Here]

Figure 3 further illustrates the relative importance of household garbage and firewood in total carbon emissions for each district and shows that firewood use is more concentrated in high elevation areas and rural districts. Over time, however, it becomes less important, especially in rural districts in Punjab province. Heavy reliance on firewood for energy consumption could be a result of 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 is heavily geared toward the urban provinces of Punjab and Sindh, even though Balochistan has the largest reservoirs of natural gas. In contrast, the share of carbon emissions resulting from household garbage noticeably increases in urban districts in KP and Sindh provinces and rural districts in Punjab province. It is worth noting that the share of emissions from firewood use significantly increased from 2011–2 to 2013–4, but this is likely due to acute shortages in the electricity supply. Similarly, the sharp increase in gasoline use by urban and rural residents in 2011–12 is a result of low energy prices. Focusing on the northwest tip of the country in Figure 3, we also

notice a reduction in reliance on firewood for heating in northern KP province, which is consistent with the lower-emissions story illustrated in Figure 2.

[Insert Figure 4 Here]

Figure 4 presents the per-capita carbon emissions over time for three types of regions. Based on the national average of 37%, we distinguish districts where the proportion of urban households exceeds 50% as “urban”; districts where 37%-50% of households are urban as “emerging urban” districts; and all others as rural areas. The urban districts by definition include mega cities such as Lahore, which have more than 1 million residents. Figure 4 provides strong evidence to reject the compact city hypothesis: in each of the four survey years, urban districts consistently have higher per-capita emissions than rural districts, especially from 2005 to 2012. Over time, Figure 4 shows that most districts, especially emerging urban and rural areas, exhibit reduction in per-capita carbon emissions. The rural areas show a declining trend of per-capita emissions due to gradual improvement in the provision of cleaner fuels. Combining the findings in Figure 2 reveals that population growth determines the increase in total carbon emissions over time for many Pakistani districts. In fact, a simple scatterplot reveals that a 1% increase in a district’s population will on average lead to a 1% increase in total carbon emissions.

[Insert Figure 5 Here]

By presenting the per-capita carbon emission by energy types over time, Figure 5 reveals several interesting patterns: First, consistent with Figure 3, it shows that the use and emissions from firewood decreased dramatically over time. In general, from 2005 to 2014, emissions from firewood use declined in most urban regions and in rural areas in Punjab and Sindh provinces. However, carbon emissions from firewood use in rural areas in the two rural provinces, KP and Balochistan, are still more than 50% as of 2013–4. Second, Figure 5 shows that emissions from household garbage in urban areas is at least 50% greater than in rural areas. This is in part due to the ability of rural households to use the food waste as feed. It also reflects poor services for garbage collection and disposal in many urban areas. Third, Figure 5 shows growing emissions over time from gasoline use for private cars and cabs. In particular, gasoline consumption is heavily concentrated in urban cities such as Karachi and Lahore, and disproportionately used by households with higher income or salary. The role of public transportation is heterogeneous across cities—a ratio of predicted carbon emissions from public transportation relative to private vehicle usage based on our analysis shows that the proportion of carbon emissions from public transport to private transport is 30% in Karachi, 16% in Islamabad, and just 7% in Lahore in 2013–4. Finally, Figure 5(a) shows declining carbon emissions from electricity, which is likely a result of a shortage of electricity supply and daily blackouts that were especially prevalent in the 2010s. It is also worth mentioning that the per-capita carbon emissions from electricity are similar to previous findings for urban households in India (Ahmed et al. 2015). The average Pakistani household size is seven, which means that 11%–15% of emissions from electricity and a per capita emission of close to 1 ton would translate into 0.5–1 ton per year in emissions from electricity for Pakistan, comparable to 1.3 tons for India (Ahmed et al. 2015), 2.3 tons for China

(Zheng et al. 2011), and much lower than the 13 tons for the United States (Glaeser and Kahn 2010).

[Insert Table 5 Here]

Using predicted carbon emissions for representative households at the district level, we construct a series of panel regressions to explain inter-district variations in per capita carbon emissions and per capita carbon emissions by energy type. Table 5 shows the results and reveals several interesting findings. First, districts with a higher share of car ownership have higher per-capita carbon emissions, mainly resulting 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 greater heating needs at higher elevations. Third, higher-income districts typically have more total and per-capita carbon emissions, and hence could potentially 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. Figures 1 and 2 also confirm regional variations—Islamabad has the highest electrical and natural gas emissions due to urbanization, high affluence, and a relatively abundant energy supply, whereas districts in mountainous regions rely heavily on firewood in their energy portfolio.

5. Conclusions

Using four 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 use of all energy types from 2005 to 2014 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 is contrary to the compact city hypothesis put forward by Glaeser and Kahn (2010) 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 half of all carbon emissions across households' energy consumption in rural provinces and ignoring household garbage would lead to a 15% underestimate of household carbon emissions, especially for cities. Finally, our analysis shows that 20% of Pakistani districts changed their greenness rankings by at least one quintile from 2005 to 2014. This suggests that it is not advisable to rely solely on a single year's survey data, especially for developing countries like Pakistan that experience pressure from urbanization and population growth.

Our paper makes several important contributions to the literature of sustainable development, carbon accounting, and the interplay between urbanization, energy use, and carbon emissions, and has important policy implications for adaptations to climate change, especially in the developing world. By focusing on Pakistan—the sixth most populous country in the world—and firewood, which is the main 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 the compact city hypothesis with larger cities showing lower per-capita carbon emissions does not apply to Pakistan, and likely in other developing countries. Furthermore, changes in the greenness

rankings of 52% of Pakistani districts within one decade confirms the importance of monitoring the climate profiles of a district, region, and country 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, a recent study in China reveals that households' energy consumption will likely increase with higher temperatures (Li et al. 2018), and this is likely also true for Pakistan, which is facing some of the most significant climate risks. Second, ongoing projects, such as coal power plants along the China Pakistan Economic Corridor, are projected to significantly alter Pakistan's energy consumption and carbon emissions profile.

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, but a comparison between 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. Third, PSLM surveys did not always cover the same districts. However, out of roughly 100 districts, we were able to match the majority as 77 districts were surveyed in all four 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.

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Tables

Variables	N	mean	Sd	Min	max
Annual Income (PKR, 1USD~100PKR)	64,760	172,221	334,538	0	5.134e+07
Household Size	64,761	6.850	3.406	1	61
Age (years)	64,681	45.900	13.630	10	99
Married	64,761	0.902	0.290	0	1
Employer	52,908	0.018	0.133	0	1
Self-Employed	52,908	0.187	0.390	0	1
Paid Employee	52,908	0.553	0.497	0	1
Agri Worker	52,908	0.236	0.425	0	1
Educated	62,821	0.903	0.295	0	1
Household with Electricity Connection	64,761	0.349	0.476	0	1
Annual Electricity (KWh)	57,564	1,723	1,625	0	74,213
Household with Gas Connection	64761	0.346	0.475	0	1
Annual Natural Gas (MMBTU)	24,564	48.840	32.190	0	681.8
Car Ownership (Yes/No)	64,761	0.051	0.220	0	1
District Gasoline(for Cab liters)	57,486	5	9	0	163
District HSD(for Bus liters)	57,486	21	20	0.097	270
District LPG(for Rickshaw kgs)	57,486	1.419	1.237	0	17
District CNG(for Minivan kgs)	57,486	3.742	9.234	0	151
District Garbage Generation (kgs)	57,486	887	514	102	9,817
District Coal Use	64,761	0.004	0.064	0	1
Waste Collection by Municipality	64,757	0.184	0.387	0	1
Rural	64,761	0.605	0.488	0	1
Elevation (meters)	63897	412.101	615.553	9	3377

Table 1: Summary statistics of household characteristics and energy consumption

Energy Type	Electricity consumption				Firewood Consumption			
Year	2005-06		2013-14		2005-06		2013-14	
Model	Heckman	Probit	Heckman	Probit	Heckman	Probit	Heckman	Probit
Age	0.003***	-0.002*	0.0038***	-0.005***	0.0022	-0.008***	0.006***	-0.008***
	(0.0004)	(0.0011)	(0.0005)	(0.0011)	(0.0018)	(0.0008)	(0.0008)	(0.0008)
Income (Log)	0.258***	0.047***	0.325***	0.122***	0.095	-0.366***	0.225***	-0.410***
	(0.0100)	(0.0181)	(0.0107)	(0.0223)	(0.0805)	(0.0190)	(0.0196)	(0.0161)
HH Size	0.023***	0.013***	0.004**	0.013***	0.039***	0.059***	0.015***	0.074***
	(0.0018)	(0.0048)	(0.0022)	(0.0051)	(0.0124)	(0.0037)	(0.0039)	(0.0036)
Gender	0.156***		0.251***		0.080		0.116**	
	(0.0356)		(0.0363)		(0.0579)		(0.0566)	
Married	-0.004	-0.055	0.055**	-0.060	0.0363		0.047	
	(0.0231)	(0.0566)	(0.0265)	(0.0594)	(0.0307)		(0.0368)	
Employer	0.110		0.111		-0.218*		-0.296*	
	(0.0770)		(0.1150)		(0.1200)		(0.1770)	
Paid Employee	-0.099		-0.036		-0.181*		-0.259*	
	(0.0651)		(0.1080)		(0.1040)		(0.1360)	
Self-employed	-0.039		-0.020		-0.223**		-0.246*	
	(0.0657)		(0.1080)		(0.1050)		(0.1380)	

Agri Worker	0.001		-0.046		-0.077		-0.114	
	(0.0654)		(0.1080)		(0.1040)		(0.1370)	
Educated	0.068***	0.173***	-0.202***	0.398***	-0.024		0.269***	
	(0.0179)	(0.0364)	(0.0323)	(0.0588)	(0.0216)		(0.0500)	
Rural region	-0.181***	-0.729***	-0.344***	-0.482***	0.071***		0.117***	
	(0.0132)	(0.0395)	(0.0140)	(0.0411)	(0.0210)		(0.0279)	
Province								
Sindh	-0.187***		-0.217***		0.407***		-0.019	
	(0.0133)		(0.0138)		(0.0205)		(0.0187)	
KP	-0.183***		-0.298***		0.450***		0.125***	
	(0.0149)		(0.0156)		(0.0239)		(0.0321)	
Balochistan	-0.355***		-0.232***		0.148***		0.245***	
	(0.0172)		(0.0176)		(0.0234)		(0.0284)	
Have Electricity		1.265***		1.134***				
		(0.0549)		(0.0431)				
Cooking Range						-1.417***		-1.350***
						(0.1340)		(0.1610)
Constant	4.435***	0.652***	3.081***	-0.411	5.932***	4.134***	4.319***	4.730***
	(0.1260)	(0.2060)	(0.1690)	(0.2760)	(0.4540)	(0.1990)	(0.2510)	(0.188)
Observations	12,886	12886	14,815	14,815	13,470	13,470	15,770	15,770

Significance

arthrho	-1.007***	-0.918***	-0.352	-1.073***
	(0.0438)	(0.0315)	(0.5901)	(0.0697)
lnsigma	-0.503***	-0.394***	-0.401***	-0.153***
	(0.0125)	(0.0074)	(0.1090)	(0.0292)

Note: Robust standard errors in parentheses. The dependent variable in the selection equation is a binary variable that equals one when the household uses firewood, and the dependent variable in the outcome equation is the log of annual firewood consumption. *** p<0.01, ** p<0.05, * p<0.1. *arthrho* represents the inverse hyperbolic tangent of the correlation between the errors for selection equation and outcome equation.

Table 2: Heckman selection model results of household gasoline and firewood consumption

Variables Year	Garbage Quantity 2005-06	Garbage Quantity 2007-08	Garbage Quantity 2010-11	Garbage Quantity 2013-14
Age	9.22e-05	-4.39e-06	1.24e-04	6.58e-04**
	(0.000293)	(0.0002)	(0.0002)	(0.0002)
Income (Log)	0.022***	0.0256***	0.031***	0.040***
	(0.0046)	(0.0046)	(0.0047)	(0.0046)
HH_size	0.256***	0.272***	0.276***	0.275***
	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Gender (F)	0.134***	0.132***	0.141***	0.118***
	(0.0232)	(0.0202)	(0.0189)	(0.0188)
Married	0.214***	0.198***	0.194***	0.205***
	(0.0137)	(0.0131)	(0.0128)	(0.0130)
Employer	0.006	-0.004	0.0422	0.006
	(0.0514)	(0.0611)	(0.0678)	(0.0600)
PaidEmployee	0.060	0.066	0.061	-0.006
	(0.0466)	(0.0536)	(0.0642)	(0.0557)
Self-employed	0.058	0.064	0.053	-0.005
	(0.0470)	(0.0539)	(0.0644)	(0.0561)
AgriWorker	0.068	0.0629	0.065	0.010
	(0.0467)	(0.0537)	(0.0644)	(0.0559)
Educated	-0.004	0.001	-0.019*	0.008
	(0.0101)	(0.0107)	(0.0108)	(0.0149)
Region (Rural)	-0.545***	-0.530***	-0.563***	-0.561***
	(0.0080)	(0.0072)	(0.0069)	(0.0070)
2.province	0.020**	-0.016**	0.016**	0.015**
	(0.0086)	(0.0078)	(0.0073)	(0.0070)
3.province	0.019*	0.032***	0.063***	0.069***
	(0.0100)	(0.0090)	(0.0087)	(0.0086)
4.province	-0.086***	-0.074***	-0.130***	-0.095***
	(0.0109)	(0.0095)	(0.0111)	(0.0106)
Constant	6.552***	6.410***	6.330***	6.223***
	(0.0701)	(0.0758)	(0.0859)	(0.0798)
Observations	12,701	12,681	12,649	14,679
R-squared	0.853	0.868	0.875	0.867
Year	2005-06	2007-08	2010-11	2013-14

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: OLS model of carbon emissions from household garbage

District	Province	Per Capita Emission (kgs) 2005-06	Per Capita Emission (kgs) 2013-14	District Type	Rank 2005-06	Rank 2013-14	Ranking Change
Rajanpur	Punjab	389.0	306.5	Rural	4	1	No change
Karak	KP	668.4	327.0	Rural	25	2	Green
Lodhran	Punjab	341.6	328.2	Rural	2	3	No change
Layyah	Punjab	399.0	369.1	Rural	5	4	No change
Upper Dir	KP	1554.4	403.6	Rural	76	5	Green
Chitral	KP	1447.4	416.1	Rural	74	6	Green
Bannu	KP	697.5	419.0	Rural	31	7	Green
Thatta	Sindh	569.3	424.1	Rural	11	8	No change
Lower Dir	KP	1230.3	428.7	Rural	70	9	Green
Bahawalnagar	Punjab	402.5	438.1	Rural	6	10	No change
Lakki Marwat	KP	646.3	444.5	Rural	22	11	Green
Vehari	Punjab	493.5	450.8	Rural	8	12	No change
Shangla	KP	1398.4	451.6	Rural	73	13	Green
Bonair	KP	671.1	451.7	Rural	28	14	Green
Bahawalpur	Punjab	559.9	463.4	Rural	9	15	No change
Zhob	Balochistan	643.6	471.2	Rural	20	16	Green
Muzaffar Garh	Punjab	403.7	474.5	Rural	7	17	Red
Khanewal	Punjab	375.3	477.7	Rural	3	18	Red
Hangu	KP	565.8	478.8	Emerging Urban	10	19	Red
R.Y.Khan	Punjab	264.9	481.5	Rural	1	20	Red
Malakand	KP	1033.4	491.7	Rural	64	21	Green
Tharparkar	Sindh	668.6	500.2	Rural	26	22	No change
Khairpur	Sindh	745.7	513.0	Rural	37	23	Green
Nawabshah	Sindh	638.8	530.9	Rural	18	24	No change
Shikarpur	Sindh	670.8	542.1	Rural	27	25	No change
Sukkar	Sindh	709.9	546.0	Emerging Urban	33	26	Green
D.G.Khan	Punjab	573.4	548.8	Rural	12	27	Red
Mirpur Khas	Sindh	822.9	563.6	Rural	46	28	Green
Swabi	KP	587.1	564.0	Emerging Urban	14	29	Red
Sanghar	Sindh	722.9	573.5	Rural	34	30	Green
Swat	KP	1195.4	575.4	Emerging Urban	69	31	Green
Ghotki	Sindh	755.4	579.2	Rural	40	32	No change
Dadu	Sindh	742.2	583.0	Rural	36	33	No change
Jaccobabad	Sindh	661.2	591.8	Rural	24	34	Red

Hyderabad	Sindh	746.9	604.3	Mega Cities	38	35	No change
Multan	Punjab	765.6	619.6	Mega Cities	43	36	No change
Charsada	KP	605.1	628.6	Emerging Urban	16	37	Red
Kohat	KP	836.9	631.3	Emerging Urban	50	38	Green
Sibbi	Balochistan	578.2	637.7	Rural	13	39	Red
Nowshero Feroze	Sindh	760.4	640.8	Rural	41	40	No change
Jehlum	Punjab	829.0	680.7	Rural	48	41	Green
Badin	Sindh	1005.3	682.0	Rural	63	42	Green
Tank	KP	627.2	684.1	Rural	17	43	Red
Larkana	Sindh	599.9	688.0	Rural	15	44	Red
Mardan	KP	687.6	688.5	Emerging Urban	30	45	Red
Pakpatten	Punjab	770.8	712.7	Rural	44	46	No change
Attock	Punjab	706.0	721.5	Rural	32	47	No change
Nowshera	KP	765.2	730.4	Urban	42	48	Red
Sahiwal	Punjab	793.0	771.3	Rural	45	49	Red
Okara	Punjab	639.9	788.4	Rural	19	50	Red
Gujrat	Punjab	948.6	797.5	Rural	61	51	No change
Sialkot	Punjab	938.3	817.1	Emerging Urban	59	52	No change
Chakwal	Punjab	869.3	818.8	Rural	55	53	No change
Peshawar	KP	747.4	819.2	Mega Cities	39	54	Red
Hafizabad	Punjab	1316.7	825.5	Rural	72	55	Green
Kasur	Punjab	675.2	833.4	Rural	29	56	Red
Mandi Bahuddin	Punjab	1125.6	838.9	Rural	67	57	Green
Faisalabad	Punjab	837.4	847.9	Mega Cities	51	58	No change
T.T.Singh	Punjab	726.2	853.9	Rural	35	59	Red
Khushab	Punjab	864.0	855.2	Rural	54	60	No change
Gujranwala	Punjab	854.5	860.3	Mega Cities	52	61	No change
Karachi	Sindh	870.9	863.8	Mega Cities	56	62	No change
Jhang	Punjab	832.4	870.6	Rural	49	63	Red

Rawalpindi	Punjab	928.7	870.6	Mega Cities	58	64	Red
Quetta	Balochistan	644.9	902.2	Mega Cities	21	65	Red
Bhakar	Punjab	655.0	905.9	Rural	23	66	Red
Mianwali	Punjab	857.5	921.4	Rural	53	67	Red
Narowal	Punjab	1297.5	928.4	Rural	71	68	No change
Sargodha	Punjab	944.5	933.9	Emerging Urban	60	69	Red
Sheikhupura	Punjab	828.2	987.4	Emerging Urban	47	70	Red
Kohistan	KP	1895.7	995.9	Rural	77	71	No change
Haripur	KP	1140.0	1079.4	Rural	68	72	No change
Lahore	Punjab	901.8	1089.3	Mega Cities	57	73	Red
Manshera	KP	1093.2	1097.8	Rural	66	74	No change
Batagram	KP	1463.6	1147.2	Rural	75	75	No change
Abbotabad	KP	950.1	1182.0	Emerging Urban	62	76	Red
Islamabad	Punjab	1056.6	1275.0	Mega Cities	65	77	No change

Table 4: Greenness rankings of Pakistani districts and changes from 2005-06 to 2013-14

Variables	Total CO_2	Per Capita CO_2	Per Capita Electricity	Per Capita Nat. Gas	Per Capita Gasoline	Per Capita Firewood	Per Capita Dungcake	Per Capita Cab	Per Capita Garbage
Average Household Size	-0.051	-0.120***	-0.019	-0.300***	-0.033	-0.131***	0.340***	-0.152**	-0.018***
	(0.0397)	(0.0210)	(0.0267)	(0.0650)	(0.0438)	(0.0468)	(0.0807)	(0.0676)	(0.0052)
Average Car Ownership	-1.438	1.011*	0.207	-0.224	6.591***	0.914	-8.588***	6.068***	-0.044
	(1.0910)	(0.5790)	(0.7340)	(1.7670)	(1.196)	(1.2880)	(2.3190)	(1.8690)	(0.1440)
Low-income Household Proportion	0.015	0.013	0.687**	2.076**	-0.005	-1.142*	-1.039	2.970***	0.118*
	(0.4991)	(0.2650)	(0.3360)	(0.8260)	(0.5501)	(0.5901)	(1.0390)	(0.8601)	(0.0659)
Agri Worker Proportion	0.119	0.489***	-0.537***	-0.628	-0.091	0.572*	3.933***	0.264	-0.068*
	(0.2630)	(0.1390)	(0.1770)	(0.4440)	(0.2940)	(0.3110)	(0.5560)	(0.4690)	(0.0347)
Elevation (log)	0.168***	0.121***	-0.023	0.248***	-0.180***	0.139***	-0.211**	0.327***	0.0003
	(0.0425)	(0.0225)	(0.0285)	(0.0702)	(0.0473)	(0.0501)	(0.0866)	(0.0775)	(0.0056)
Waste-burning Proportion	1.214***	0.062	0.311*	0.928**	-0.087	-0.948***	-0.267	-0.391	0.516***
	(0.2540)	(0.1350)	(0.1710)	(0.4500)	(0.2780)	(0.3010)	(0.5620)	(0.4290)	(0.0335)
Population Density (log)	0.326***	0.040*	0.184***	0.334***	0.040	-0.237***	0.244***	-0.119*	0.023***
	(0.0396)	(0.02101)	(0.0266)	(0.0663)	(0.0437)	(0.0467)	(0.0827)	(0.0676)	(0.0052)

Average Income (log)	0.546***	0.202*	0.443***	1.448***	0.784***	-0.435*	0.548	1.225***	0.0893***
	(0.2070)	(0.1101)	(0.1390)	(0.3401)	(0.227)	(0.2440)	(0.4310)	(0.3550)	(0.0273)
Rural	-0.188**	0.010	-0.037	-0.084	-0.179*	0.089	-0.089	-0.112	-0.111***
	(0.0862)	(0.0457)	(0.0579)	(0.1390)	(0.0939)	(0.1020)	(0.1780)	(0.1470)	(0.0114)
Constant	5.030**	4.054***	-1.094	-13.651***	-5.278**	11.801***	-5.214	-15.340***	3.743***
	(2.3560)	(1.2490)	(1.5840)	(3.8880)	(2.5960)	(2.7801)	(4.8810)	(4.0280)	(0.3110)
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	351	351	351	325	342	350	332	321	351
R-squared	0.558	0.304	0.701	0.540	0.702	0.487	0.483	0.629	0.834

Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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

Figures

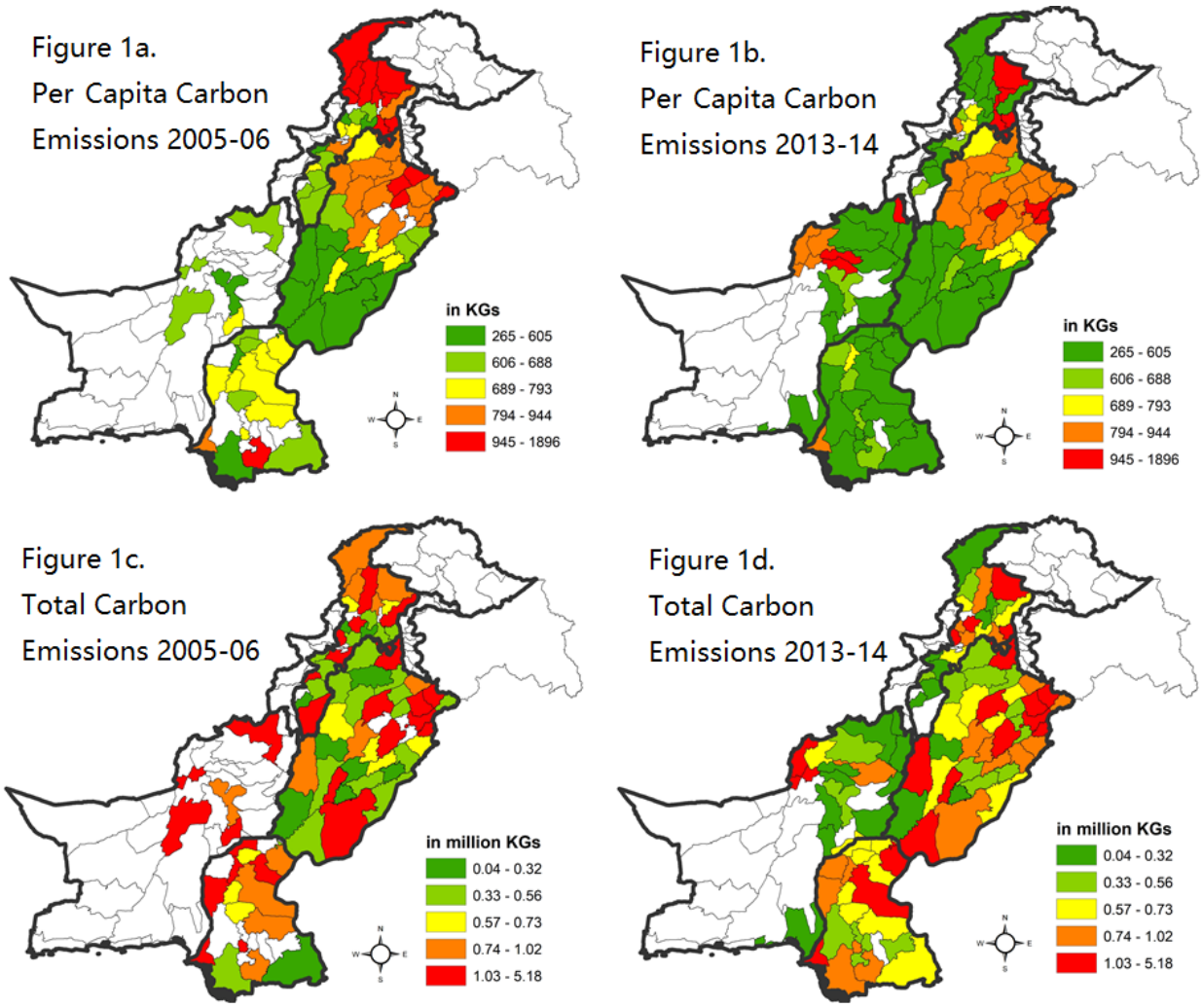

Figure 1. Total and per capita carbon emissions by districts for 2005-06 and 2013-14

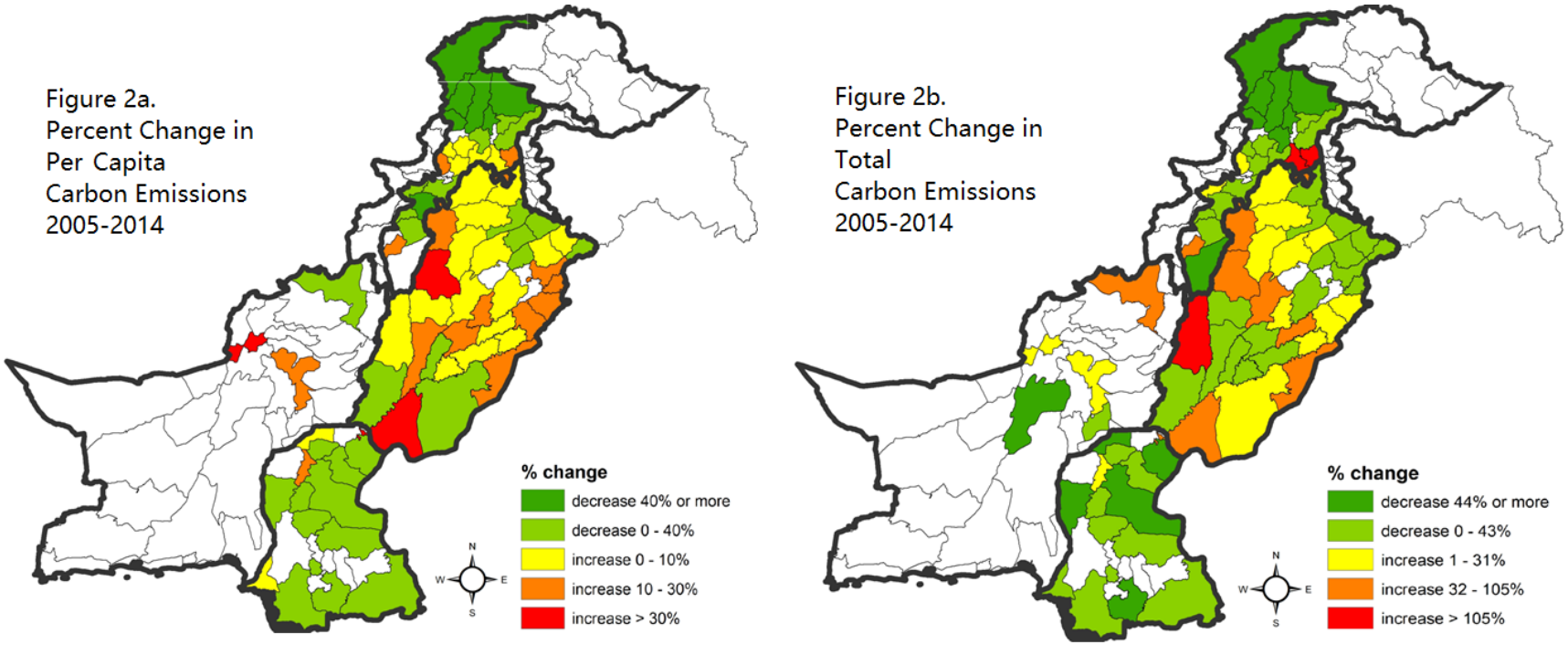

Figure 2. Percent change in per capita and total carbon emissions from 2005-06 to 2013-14

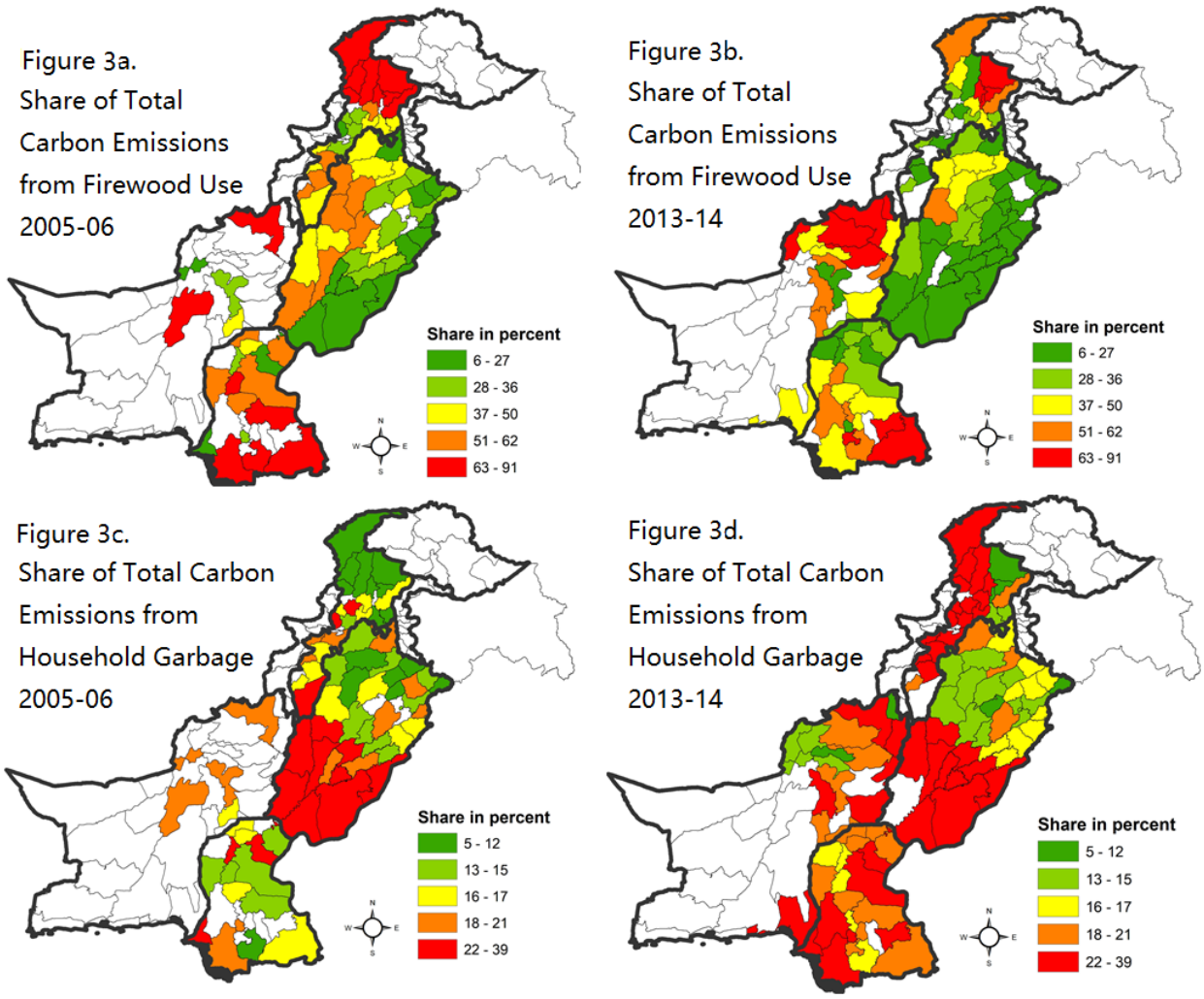

Figure 3. Share of district total carbon emissions from firewood use and household garbage 2005-06 vs. 2013-14

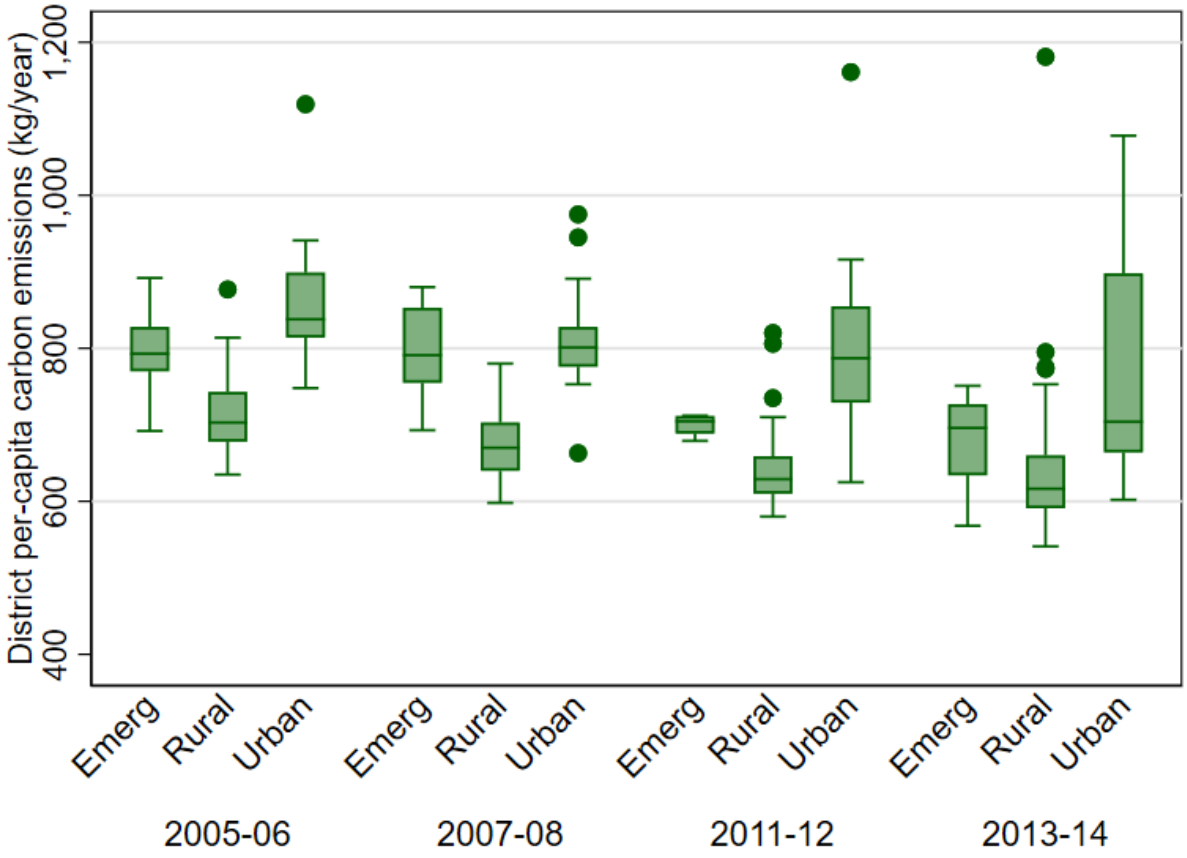

Figure 4. Evolution of per capita carbon emissions over time by district types

Note: *Emerg* in the Figure represents *Emerging Urban* districts shown in Table 4, and *Urban* represents the *Urban* and *Mega Cities* districts shown in Table 4.

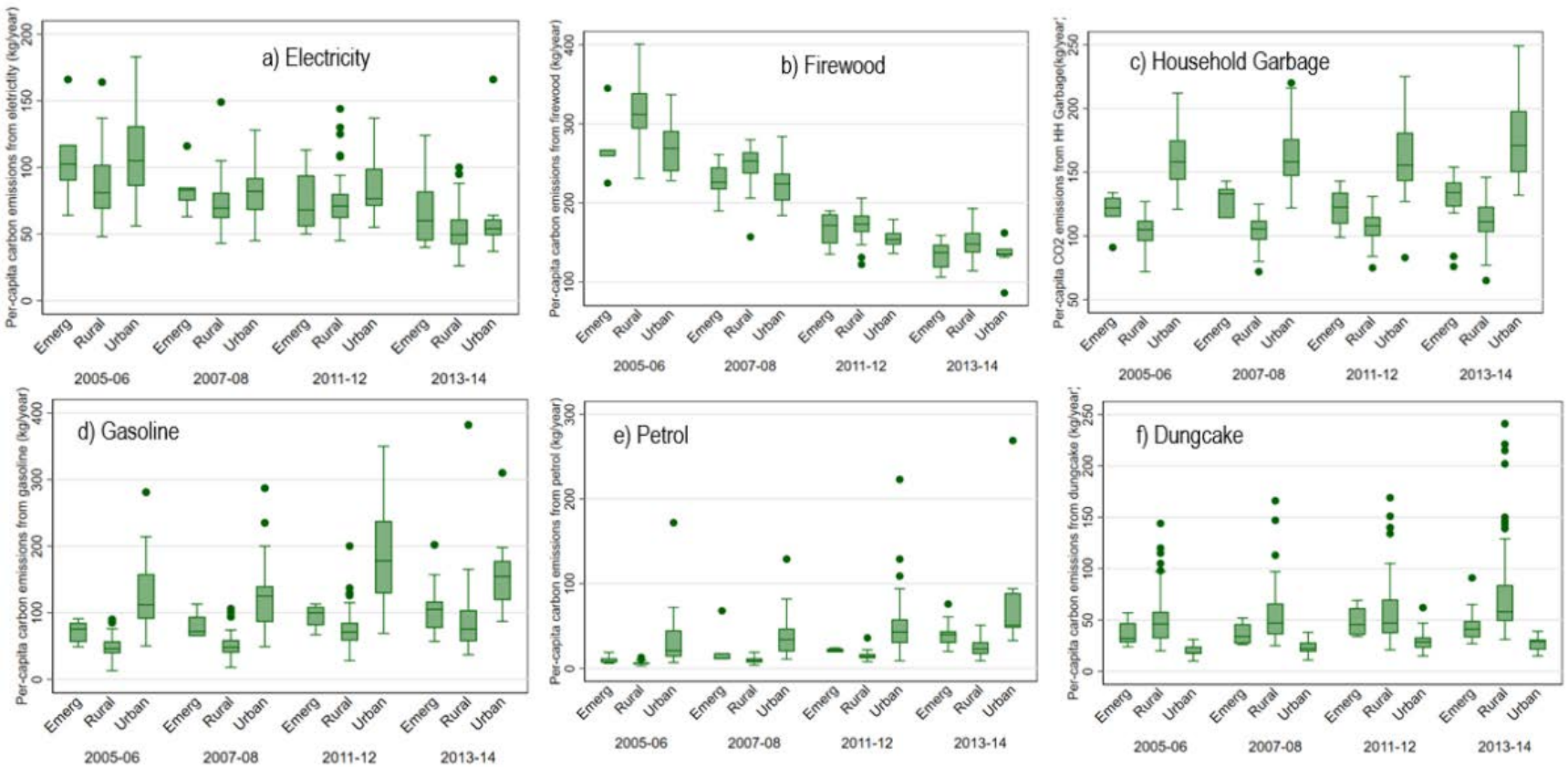

Figure 5. Evolution of per capita carbon emissions over time by district types and energy types

Note: *Emerg* in the Figure represents *Emerging Urban* districts shown in Table 4, and *Urban* represents the *Urban* and *Mega Cities* districts shown in Table 4.