In Search of a Spatial Equilibrium in the Developing World*

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Abstract

In most developing countries, there is a large gap in income per head between urban and rural areas. One appealing interpretation of this gap is that it reflects a spatial equilibrium, in which the higher incomes of urban areas are offset by lower non-monetary amenities. In this paper, we draw on new high-resolution evidence to document how amenities vary across space within twenty developing countries. We focus on measures of health, housing quality, crime and pollution. These vary substantially across space, and they can be carefully measured with highly comparable data. We find that in almost all countries, and for almost all measures, amenities are constant or increasing in population density. In addition, net internal migration flows are directed toward denser areas in every country. These findings are hard to reconcile with a spatial equilibrium. Instead, they suggest that developing countries are undergoing a reallocation of workers to densely populated areas, which offer higher living standards on average.

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1. Introduction

Economists have long recognized that there are large income differences across space within countries. A body of recent evidence has documented that urban-rural wage gaps are particularly large in developing countries (Ferré, Ferreira, and Lanjouw, 2012; Young, 2014), as, similarly, are gaps in average output between non-agricultural workers and agricultural workers (Gollin, Lagakos, and Waugh, 2014). In an accounting sense, these gaps are important for understanding why developing countries have such low aggregate income, since such a large fraction of workers in developing countries live in rural areas and work in agriculture (Caselli, 2005; Restuccia, Yang, and Zhu, 2008; Vollrath, 2009; McMillan and Rodrik, 2011).

One interpretation of these urban-rural income gaps is that they reflect a *spatial equilibrium*, in which the higher incomes of urban areas are offset by lower non-monetary amenities. A spatial equilibrium – in which utility levels are equalized across locations – is one of the simplest and most appealing concepts that economists have used to analyze how economic agents locate through space (Rosen, 1979; Roback, 1982). The rationale is simple: if any region offered a better bundle of consumption and amenities than the rest, then agents would move into the better region until any arbitrage opportunities were gone. The concept of a spatial equilibrium has proven useful in learning about a wide set of economic phenomena, including the wage and size distribution of U.S. cities (Baum-Snow and Pavan, 2012; Desmet and Rossi-Hansberg, 2013), the dynamics of U.S. manufacturing and service activity (Desmet and Rossi-Hansberg, 2014), and the welfare effects of infrastructure investments (Allen and Arkolakis, 2014; Kline and Moretti, 2014a; Donaldson and Hornbeck, 2016). It is thus with good reason that Glaeser and Gottlieb (2009, p.3) call a spatial equilibrium the "central theoretical tool" of urban economics.[1]

Almost all papers that assume a spatial equilibrium rely on models to infer the amenity values of different locations, rather than measuring the amenities directly (Glaeser and Gottlieb, 2009). This reflects the intrinsic difficulty of measuring amenities. But in the context of developing countries, this approach is particularly unsatisfying. Given that most developing countries have much higher incomes in urban areas, a spatial equilibrium implies that urban amenities must be much lower than rural amenities. If this is true, researchers and policy makers should know which amenities of urban areas are so much worse than in rural areas. If urban amenities are not lower, then a spatial equilibrium may not be the right interpretation of the significantly higher urban wages in developing countries – with important implications for policy. Distin-

[1] Numerous other papers assume a spatial equilibrium as part of their analysis. See Kline and Moretti (2014b) and Redding and Rossi-Hansberg (Forthcoming) for highly readable surveys of the recent quantitative literature in urban economics and studies of place-based policies more generally.

guishing between these two alternatives requires direct measures of amenities across space.

In this paper, we report on spatial patterns of amenities that we find from constructing a new database of amenity values across space in twenty developing countries in sub-Saharan Africa. We focus on real amenity measures based on health outcomes, housing quality, crime exposure and pollution exposure.[2] These measures are commonly cited in the literature on urban and regional economics, and they can be measured consistently within and across countries. To construct our database, we combine nationally representative household survey data, satellite-derived measures of pollution, and population density data coming from the Gridded Population of the World Version 4 (GPW). The main surveys we employ are the Demographic and Health Surveys (DHS) and Afrobarometer Surveys. The surveys also report the GPS coordinates or location names of each geographic region sampled, which we link to data on population density from the GPW. We draw on global estimates on the spatial distribution of air pollution concentrations for fine particulate matter (PM2.5) and nitrogen dioxide (NO2). An advantage of our approach is that we do not have to rely on reported categories of what is "urban" and "rural." These binary categories often reflect administrative boundaries and cut-offs that are not consistent across space and time. Our linked data allows us to examine in much greater detail how our amenities measures vary across population density within each country, using internationally comparable measures of density.

We find that in almost all countries, and for almost all measures, amenities are non-decreasing in population density. Housing quality metrics, such as roof and floor quality, electricity access, and the extent of indoor plumbing are strongly increasing in population density in virtually every country we consider. Measures of children's health, such as the consumption of a minimum acceptable diet, are almost everywhere increasing in density. Property crime and violent crime are, unfortunately, high throughout density space in most countries, and marginally higher in urban areas on average, though with statistically insignificant differences in most countries. The same is true for the percent of adults reporting fear of crime in their homes and feeling unsafe in their neighborhoods. In terms of magnitudes, we draw on previous studies of willingness to pay to avoid crime to estimate the monetary value of the higher crime rates in denser areas. We conclude that in monetary terms, the value of the crime-rate differences between rural and urban areas are dwarfed by the much larger differences in average income.

Perhaps surprisingly, we find that outdoor air pollution is largely unrelated to density in sub-Saharan Africa. Fine particulate matter is most prevalent in areas near the Sahara, due to dust and sand in the air. Even excluding dust and sea salt, PM2.5 concentrations are quite similar in

[2] By "real," we mean that we measure quantities rather than values. In the following section, we discuss how higher housing prices in urban areas are consistent with a spatial equilibrium only if housing quality or consumption levels (or both) are lower in urban areas; hence our analysis of housing quality.

urban areas and in rural areas on average, as are NO2 concentrations, to focus on two widely used measures of air quality. Overall magnitudes are also quite low, particularly relative to to other developing countries like India and China, which we view as a sad commentary on the lack of manufacturing activity in Africa. Arguably more relevant for many Africans is *indoor* air pollution, which comes about from cooking indoors with solid fuels such as coal or wood. In each of our countries, we find that the fraction of households using solid fuels to cook indoors falls sharply with population density. Thus, people in the rural areas of our countries face worse air quality on average than their urban counterparts.

Our findings provide little support for the existence of a spatial equilibrium in Africa. With few exceptions, measures of health, housing, crime and pollution are either similar across density space or strictly better in denser areas. Of course, our results do not imply that a spatial equilibrium does not exist. We did not – and could not – consider all possible amenities. In fact, by definition there is an "amenity" which is higher in denser areas: population density. It is possible that people could simply dislike living in denser areas.[3] One should view our findings so far as the most careful look to date at the "prime suspects" of amenities mentioned in the literature, rather than a proof of non-existence of a spatial equilibrium, which, even in principle, we could not produce.[4]

To complement our findings for these four amenities, we take two further steps. First, we look at data on internal migration rates within our countries. In a spatial equilibrium, net migration should not flow systematically toward denser areas or toward rural areas. What we find is that migration flows are in fact strongly oriented toward denser areas in every country we consider – consistent with a long-standing literature on rural-urban migration. Second, we look at some additional "secondary" measures of amenities, moving down the list of suspects; for these, we have fewer countries (and less data). Here we find one amenity that does seem to decrease with population density: trust in neighbors, though the magnitudes are not overwhelmingly higher in denser areas. For the other secondary metrics we consider – anxiety, reported lack of food, and reported lack of medicine – we again find worse outcomes in rural areas.

We conclude by offering a simple explanation for the facts we document, which is that living standards in developing countries are higher on average in denser areas, and that individuals migrate to denser areas to improve their living conditions. In other words, our facts are consis-

[3] Ciccone and Hall (1996), for example, argue that this is a simple and "realistic" description of the data. Still, there are reasons to believe people prefer to be in denser areas. In the developing world, Fafchamps and Shilpi (2009), for example, provide evidence that rural workers dislike the isolation that comes with rural life.

[4] In terms of policy, our findings question the view of urbanization as a phenomenon requiring intervention to be stopped or even reversed. We find no evidence supporting statements such as "In developing countries, the urban poor are often as bad as, or worse off than, the average rural family, and for many rural families, moving to the city may result in more - rather than less - hardship" (Save the Children, 2015).

tent with a more dynamic notion of spatial equilibrium, where individuals are not indifferent across space at any point in time, but migrate to better locations to close spatial gaps in living standards (Topel, 1986). The fact that we find few permanent amenities of cities that are systemically worse than rural areas does not imply that moving costs are small. Many related studies in fact point to large moving costs, such as from loss of social networks (Morten, 2013; Munshi and Rosenzweig, 2016), lack of skill transferability (Bazzi, Gaduh, Rothenberg, and Wong, 2016), risk of bad migration outcomes (Harris and Todaro, 1970; Bryan, Chowdhury, and Mobarak, 2014) or simply disutility from living in a new place away from one's family.

Our findings can also be squared with the recent work emphasizing sorting of heterogenous agents across space based on comparative advantage (Lagakos and Waugh, 2013; Herrendorf and Schoellman, 2014; Young, 2014). These theories do not have workers indifferent between all locations, and in fact each worker in general prefers one location to another. To reconcile these theories with the net migration rates to urban areas, however, one must consider a model where, on net, workers are moving to cities, rather than in a stationary equilibrium where urban inflows are equated with urban outflows of population.[5] As one step toward guiding these classes of models, we look *within* narrowly defined educational groups, including those without any education. There we find that amenities increase with density within each education category. This suggests that the patterns observed in the data cannot be explained simply by sorting along educational backgrounds – or indeed by sorting along any dimension that is highly correlated with education.

Our paper is perhaps closest to Chauvin, Glaeser, Ma, and Tobio (2016), who test the spatial equilibrium hypothesis in various forms in Brazil, China and India. They conclude that a spatial equilibrium assumption can be used, "if it is used warily," in Brazil and China, but reject a spatial equilibrium outright in India. Our data, which all come from countries less developed than India, coincide with their conclusions from India, suggesting that a spatial equilibrium is not the right description of the world's least developed countries. Our paper also builds on recent work measuring living standards, such as Henderson, Storeygard, and Weil (2012) and Henderson, Storeygard, and Deichman (2017), which uses satellite data on night lights to construct proxies for income at a fine level of geographic detail. One way our work differs in that it tries to isolate the effect of non-monetary amenities, which have not been studied systematically in the developing world. In emphasizing measurement of amenities, our work parallels that of Albouy (2012), and echoes his conclusion that denser areas do not appear to be undesirable places to live once one considers richer spatial data with better measurement.

[5] In this way, our findings are similar to the persistent transitional dynamics associated with large shocks, such as after the division of Germany post WWII, where workers reallocated away from border regions for decades (Redding and Sturm, 2008; Ahlfeldt, Redding, Sturm, and Wolf, 2015).

This paper is structured as follows. Section 2 provides a simple model with a spatial equilibrium and discusses the role of housing prices. Section 3 outlines our data and how we link our outcome measures with population density. Section 4 presents our main findings for amenities by population density. Section 5 looks at amenity measures for households by education group. Section 6 explores migration flows plus our secondary amenities metrics. Section 7 concludes.

2. Simple Spatial Equilibrium Model with Housing Prices

In this section we present a simple spatial model to illustrate how a spatial equilibrium works, particularly regarding how housing prices fit into our analysis. It is important to be clear on this point, as virtually all evidence on housing prices suggest that they increase with population density. We do not dispute this fact at all. Instead, we show that this is not enough to conclude that there is a spatial equilibrium. One needs to look at real quantities of consumption, housing quality and other amenities for that.

Environment: The economy is populated by identical households that each have a utility function $U(c,h,a)$, where c is non-housing consumption, h is housing consumption (or "housing quality"), and a is amenities. The utility function satisfies $\frac{\partial U}{\partial c} \geq 0$, $\frac{\partial U}{\partial h} \geq 0$ and $\frac{\partial U}{\partial a} \geq 0$ for all levels of c, h and a; i.e., utility is everywhere non-decreasing in each input.

The economy is partitioned into J regions. Households are freely mobile and must locate in exactly one region. Regions have three exogenous characteristics: wages, w^j, housing prices, p^j and amenities a^j. Any household locating in region j earns the wage w^j, may consume as much housing services as it wants at price p^j per unit, and enjoys amenities a^j. Households anywhere may consume non-housing consumption at a normalized price of one. The budget constraint of a household locating in region j is $w^j = c + p^j h$. We make no attempt to clear markets, but rather focus on the households' choice of where to locate.

Spatial Equilibrium: A spatial equilibrium implies that utility levels are equated across regions. Let this common utility level be denoted $\bar{u}$. The standard approach in the literature is to use the household's (and/or firms') optimality conditions, plus the common utility value $\bar{u}$, to impute amenities, a^j, given data on prices w^j and p^j. In contrast, our approach is to focus on quantities, and to assess whether utility levels are equated across regions. To this end, denote the common quantities of non-housing consumption and housing in j by c^j and h^j. Then, note the following basic, almost definitional, properties of the static spatial equilibrium:

1. Consider two regions u and r. If $c^u > c^r$, than either $h^u < h^r$ or $a^u < a^r$ or both.

2. Consider two regions u and r. Households do not prefer to migrate from u to r, or vice

versa.

Property one says simply that if non-housing consumption is higher in one region than a second region, then either housing consumption or amenities must be higher in the second. No region can have higher quantities of every input into the utility function, or that would violate the assumption that utility is equated across regions. Property two says that when offered the choice, households do not systematically prefer another region to the one they are in. This is heart of the logic of a spatial equilibrium: if households were systematically better off in another region than their current region, they would migrate to improve their well being. In what follows, we draw on new data on quantities of consumption, amenities and net migration flows to test these two basic predictions of a static spatial equilibrium.

The Role of Housing Prices: How do housing prices fit into this? Suppose region u has higher wages than region r, but also higher housing prices. That is, $w_u > w_r$ but $p_u > p_r$. Couldn't this mean there is a spatial equilibrium, even if amenities were the same, i.e. $a_u = a_r$? If there were a spatial equilibrium, then one of two basic patterns could be found in the quantity data. First, households use the higher wages in u to obtain higher consumption, so $c_u > c_r$, though consume lower quality housing, $h_u < h_r$. Second, households get lower consumption, $c_u < c_r$, but higher housing, $h_u > h_r$. If both were higher in r then there would not be a spatial equilibrium. The point is that the ubiquity of higher housing prices in high-wage regions is not sufficient to conclude there is a spatial equilibrium. A spatial equilibrium implies that the high-wage, high-price region must have either lower consumption or lower housing, where these are measured in real terms rather than value terms. If instead, as we later find, both housing quality and consumption are higher in the high-wage, high-price denser areas, it must be true that some other amenity is worse in the denser area, or there is not a spatial equilibrium.

Extension to Heterogenous Households: The assumption that all households are identical is quite stark. Indeed, many more recent spatial equilibrium models assuming that households are heterogenous in productivity or tastes and sort accordingly. Recent examples include Ahlfeldt, Redding, Sturm, and Wolf (2015), Caliendo, Dvorkin, and Parro (2015) and Faber and Gaubert (2016).

How would the assumption of heterogenous households affect our conclusions above? To answer this question, consider the following simple extension of our model based on the elegant formulation of Kline and Moretti (2014b). Suppose for simplicity there are two regions: u and r. Households are indexed by i, and the utility of household i be $U(c_j, h_j, a_j) + e_{i,j}$ for region j where c_j, h_j and a_j are the common consumption, housing and amenities of region j, and $e_{i,j}$ is an idiosyncratic taste term. The $e_{i,j}$ draws are independent and identically distributed

across households with mean zero in each region. For tractability, assume further that $e_{i,j}$ are drawn from a Gumbel (extreme value type I) distribution with shape parameter s (though this isn't necessary for our conclusion).

In this model, the workers that prefer a region u to a second region r are those that have $U(c_u,h_u,a_u)-U(c_r,h_r,a_r)>e_{i,r}-e_{i,u}$, and vice versa. As Kline and Moretti (2014b) show, the Gumbel assumption implies that the fraction of households locating in region u is given by

$$N_u = \Lambda\left(\frac{U(c_u,h_u,a_u)-U(c_r,h_r,a_r)}{s}\right), \tag{1}$$

where $\Lambda(\cdot)$ is a logistic(0,1) distribution.

In most developing countries, and each of the African countries studied in the current paper, the majority of the population lives in rural areas. Is there a way to square this observation, plus the higher consumption levels of urban areas, with a spatial equilibrium? As we show below, in this model the answer is only if either housing quality or amenities were higher in the *rural* area. To see this, suppose $N_u < 1/2$ as we see empirically. This implies that from (1) that $U(c_u,h_u,a_u)<U(c_r,h_r,a_r)$ for any value of the parameter s. If $c_u > c_r$, it must then be the case that either $h_u < h_r$ or $a_u < a_r$ (or both).

We conclude that adding heterogeneity in household preferences to our model doesn't change our basic conclusion. For there to be a spatial equilibrium with most households located in the rural area, as is empirically the case in most developing countries, amenities still have to be higher in rural areas. We now turn to measuring whether this is the case.

3. Measuring Amenities Across Space

This section describes our data and our method for matching the data on real outcome measures with population density.

3.1. Data on Consumption, Housing, Crime and Pollution

Until recently, measuring amenities and other living standards metrics across space in the developing world was not feasible. Exploiting progress in surveying and mapping technology, we construct a new dataset that spatially links household surveys on amenities, crime, mistrust and reported living standards with satellite-derived measures of pollution and gridded population density. To measure household welfare across space, we use data from Demographic and Health Surveys (DHS), Living Standards Measurement Surveys (LSMS), Afrobarometer and remotely sensed pollution data. The micro surveys are high-quality nationally representative

surveys and cover large numbers of households (typically more than 5,000 for DHS and LSMS, and 1200–2400 for Afrobarometer) in developing countries. The surveys are designed to use consistent methodologies and definitions across countries. DHS and LSMS focus on variables related to population, health, and nutrition, while Afrobarometer focuses on attitudes towards democracy and governance, including experiences of crimes. Our data on outdoor air pollution come from satellite-derived estimates of fine particulate matter, in particular PM2.5 concentrations from van Donkelaar, Martin, Brauer, and Boys (2015), NO2 concentrations from Geddes, Martin, Boys, and van Donkelaar (2016), and refer to DHS data for the source of cooking fuel that households use and the location where they undertake their cooking. We outline the main choices related to using these data here and in the following section when we present our results, while referring the reader to the detailed data appendices A - C for further details.

We select countries that satisfy four criteria: (i) the survey was conducted no earlier than 2005, (ii) spatial identifiers of the respondents or clusters were collected and are available, (iii) the country is larger than 50,000 square kilometers, and (iv) the country is classified as a low-income country by the World Bank in 2012 (meaning GNI per capita (Atlas method, current US$) below $4,126 in 2012.) For the DHS data, our main data to measure housing and non-housing consumption across space, this leaves us with a sample of 276,051 households across 20 African countries as listed in Tables 1 and A.1, covering countries with a combined population of about 770 million people. From these data, we use the following variables: durables owned by households (television, car and mobile/landline telephone), housing conditions (electricity, tap water, flush toilet, constructed floor, finished walls and finished roof), and child health (stunting, wasting, anemia, and minimum acceptable diet).

3.2. Population Density Measures

To measure population density, we use data from the Gridded Population of the World Version 4 (GPWv4), which provides population density estimates at a resolution of 30 arc-seconds, corresponding to about 1km at the equator (Center for International Earth Science Information Network, 2015). The gridded population data employ a minimal amount of modelling by equally distributing non-spatial population data from censuses among spatial datasets of administrative units (Doxsey-Whitfield, MacManus, Adamo, Pistolesi, Squires, Borkovska, and Baptista, 2015).

One attractive feature of GPWv4 for the purpose of this analysis is that the distribution of population data is transparent and performed without using further auxiliary data. This comes at a cost of a lower resolution than that available in some alternative data sources. For example, one higher resolution dataset is WorldPop, which uses a range of input data and has a resolu-

tion of 100m (Linard, Gilbert, Snow, Noor, and Tatem, 2012). For our analysis, one important consideration is that these other input data might introduce circularity in measurement. For example, if night-time lights data from satellites are used to assign populations to locations, in an effort to allocate population at a finer geographical resolution, then it would hamper our efforts to estimate the relationship between population density and electrification: by construction, higher densities would be associated with higher rates of electrification. We rule out this circularity by using population density data that are not modelled using further input data. The maximum dispersion assumption of GPWv4 within spatial administrative units therefore biases us towards finding no relationship between population density and outcome variables.

The resolution of the census data underlying the GPWv4 varies across countries due to availability of data. Some countries provide their data at the level of the enumeration area, while others only share data at the second administrative level. We restrict our analysis to countries for which the underlying census data have sufficiently high spatial detail, which corresponds approximately to those for which we have data on more than 40 regions per country.

3.3. Spatially Linking Living Standards and Density

We next combine the different sources of data step by step. To link the individual data from the DHS and Afrobarometer with population density, ideally we would have the GPS location of each household. The DHS readily collects GPS coordinates for survey clusters, but in order to preserve the anonymity of survey respondents, these have been displaced: i.e., re-assigned a GPS location that falls within a specified distance of the actual location. Urban DHS clusters are randomly displaced by 0-2km, and rural clusters are randomly displaced by 0-5km, with 1 percent of clusters randomly selected to be displaced by up to 10km (Perez-Heydrich, Warren, Burgert, and Emch, 2013). We take into account the random offset of DHS cluster locations when linking DHS GPS data with continuous raster data by taking 5 km buffers around both urban and rural DHS clusters, as suggested by Perez-Heydrich, Warren, Burgert, and Emch (2013). Appendix A provides more detail on this procedure. An important consideration is how representative our samples are across different levels of population density. We discuss the sampling protocol of the surveys in the Appendix and show in Figure A.2 that when we have geo-coded census data, the survey data cover a wide range of densities. All our results are robust to using the survey weights provided.

Unfortunately, the Afrobarometer did not collect the GPS location for respondents, but the location name was recorded. We develop an algorithm that performs a series of exact and fuzzy matches of location names relying on data from a global gazetteer that contains the latitude and longitude of a location. Depending on the survey round, this involves between

thirteen and twenty-one steps in which the village name, district name and region name are sequentially matched against the ascii names of locations, as well as up to four alternative names listed in the gazetteer. To catch mis-spellings, we perform fuzzy matches based on similar text patterns, using a similarity score of 0.7 and a vectorial decomposition algorithm (3-gram) (Raffo, 2015). Appendix B provides further detail on the matching procedure. Using this algorithm we are able to geo-locate 92–95% of village names in each round.[6] For each respondent we can then extract the population density value.

Both the pollution data and the population density data are gridded data, making it straightforward to link them. The estimated PM2.5 and NO2 concentrations are available at a resolution of 0.1 decimal degrees (about 10km at the equator) compared to the 30 arc-second resolution of the population data. We construct a fishnet grid of the same resolution of the pollution data (the coarser spatial resolution) and for each pixel compute the average pollution measure as well as the average population density from the GPWv4. PM2.5 is measured in $\mu g/m^3$ while NO2 is measured in ppb (parts per billion). Appendix C contains further details on how we link the pollution data with the population density data and discusses the joint distributions of these variables in detail for the Nigerian case.

With these different pieces of information in hand, we can test whether the data are consistent with a simple static spatial equilibrium model when considering this key set of real outcome measures.

4. Empirical Findings

In this section, we analyze how measures of living standards vary with population density in our set of twenty African countries. We begin with measures of durable good ownership across geographic space, largely as a frame of reference. As in previous studies, durable ownership rises dramatically with density. We next consider measures of housing quality and health, which are not direct amenity measures per se, but may reflect both household expenditures and public goods provision in the household's location. Last, we consider measures of pollution and crime, which are closest to pure amenities.

4.1. Durable Consumption

To illustrate our methodology, consider how telephone ownership varies through space. Figure 1 shows a kernel-weighted local polynomial regression of whether a household has a phone at

[6] Nunn and Wantchekon (2011) manually geo-locate the respondents of the 2005 Afrobarometer round. When we compare their locations with ours, we find that median distance is 10km.

different levels of the log of population density for Ethiopia, Nigeria, Senegal and Tanzania.[7] Several facts are worth noticing. First, there is a large dispersion in phone ownership – one of our real indicators of living standards – from the least populated areas to the most populated areas, with a support from zero to one. Second, across the whole range of densities, phone ownership is increasing almost monotonically and continuously. The pattern is not driven by our choice of countries: the bottom graph shows the same gradient for the entire sample, with the thick red lines representing Ethiopia, Nigeria, Senegal and Tanzania, and the light grey lines representing the remaining 16 countries in out data. We now show that these patterns hold across a range of other non-housing consumption measures and countries.

To present data in a compact fashion for our whole set of countries, we divide locations within each country into quartiles of population density, and we compute average durable ownership rates by quartile.[8] Table 2 presents the average differences between the least dense quartile (Q1) and the others. Telephone ownership rates are 42 percentage points higher in the densest quartile (Q4) than in Q1. The number beneath each difference is the number of countries in which the difference is statistically significant at the one-percent level. In the case of telephones, 20 out of 20 countries have a significant increase in telephone ownership from the least- to most-dense quartile.[9]

Televisions are similarly increasing sharply with density. The densest quartile has 47 percentage points higher television ownership rates than does the least dense quartile. Again, all twenty countries have a significant difference. Automobile ownership rates are also higher, by 8 percentage points, though motorcycles are lower by 1 percentage point. Households are likely substituting motorcycles for automobiles to some extent in denser areas, though overall they are increasing motorized transportation goods.

4.2. Child Health

We next look at measures of child health. Child health is informative about both the consumption of the household and also amenities like access to health facilities or medicine. One caveat of using child health measures is that household members living in urban areas might be more informed about health problems of children, thus affecting the propensity to report a health

[7] Each regression line shows a 95 percent confidence interval. The graphs exclude the top and bottom five percentile of the distribution.

[8] We use sample weights when computing quartiles and averages across quartiles; when looking at averages across quartiles within countries, we define these within countries; when we aggregate across countries, we define quartiles over the whole sample of countries.

[9] By looking at density quartiles, we avoid the problems of defining "urban" and "rural" locations, and we can be confident that our comparisons within countries have a certain consistency that would be harder to achieve with more arbitrary definitions based on administrative categories.

problem. Mindful of this, we only selected outcomes which are objectively measured; in other words, they are not dependent on reporting of caretakers and thereby possibly capturing a combination of differences in information as well as outcomes across space.

We look at four main objective measures of child health: stunting, wasting, anemia and consuming an acceptable minimum diet. Stunting is defined as having low height for age, and is perhaps the most commonly used indicator of poor child health calculated using the DHS (see e.g. Cummins, 2013). Wasting is defined as having low weight for height. The minimum acceptable diet is is defined by a minimum meal frequency and dietary diversity (World Health Organization, 2015). For all metrics we calculate the fraction of children that have the condition in question, and then aggregate by population density; see Appendix A for more detail on how these variables are defined.

Figure 2 shows the fraction of children with stunting, wasting, anemia and consumption below the acceptable minimum diet. For each metric, there is one point per country, capturing the average value in the lowest density (y-axis) and the highest density (x-axis) quartile. The upper panel covers the percent stunted (darker circles) and the percent wasted (lighter diamonds). The lower panel covers percent anemic (darker circles) and percent below an acceptable minimum diet (lighter diamonds).

Two main features stand out in Figure 2. First, for all four metrics, most countries lie near the 45 degree line. This implies that rates of child malnourishment are largely similar in the least dense and densest areas in most countries. Second, in all but a handful of countries, rural areas have higher rates of child malnourishment. Rates of stunting and wasting are similar or higher in rural areas in all countries but Madagascar. Anemia and dietary inadequacy are worse in rural areas for all countries except Zimbabwe and Tanzania, which have marginally worse values in the most densely populated areas.

Table 3 reports country average differences from the least dense quartile. Again, the bottom numbers in each row indicate for how many countries the differences are statistically significant. Rates of anemia, stunting, wasting and consumption below a minimum diet are all lower on average in denser areas. Differences in stunting rates are significantly lower in urban areas in 11 out of 20 countries, while around half of countries have significant differences in the other metrics. Its hard for us to conclude whether these findings are largely about better food consumption of urban children or better access to health care in urban areas. In either case, its safe to conclude that child health is substantially better in most countries in more densely populated areas.[10]

[10]We looked for geo-referenced data on infectious diseases as well, but found that they were largely unavailable for our set of countries. One exception are malaria test samples takes as part of the Demographic and Health

4.3. Housing Quality

We next ask how housing quality varies across population density. We focus on six measures of quality: the percentages of households having (1) a finished roof, (2) a constructed floor (as opposed to dirt), (3) finished walls, (4) electricity, (5) a flush toilet, and (6) tap water. Together these measures provide a fairly comprehensive view of housing quality for households in the developing world.

Figure 3 plots the fraction of households having each of these characteristics in the top and bottom quartiles of the density distribution. The top panel plots the results for finished roofs and finished walls, which are mostly the result of private investments. In most countries, three-quarters or more of residents in the densest regions have constructed floors and finished roofs, compared to half or fewer of residents of the least dense regions. Only Benin and Ethiopia are near parity, and differences are perhaps starkest for Zimbabwe, for which virtually all households in the densest areas have finished roofs and floors, compared to fewer than half of households in the least dense areas. In Liberia, more than eighty percent of households have finished walls in the densest quartile, compared to less than twenty percent of households in the lowest density quartile.

The bottom panel of 3 plots the fraction having electricity and flush toilets, which are housing amenities that have more of public-investment component. Differences between the densest and least dense areas are even starker here. In no single country do the least dense areas have more than half of households with access to electricity, or more than one quarter of households having flush toilets. In the densest areas, flush toilets are also quite uncommon, though still substantially higher than in the least dense areas in every country. Electricity has more variance but is again much more common in the densest areas.

Table 4 reports the differences between each quartile of the density distribution and the least dense quartile. The number of countries with a statistically different difference (at the one percent level) is reported below each difference. In addition to the housing metrics plotted in Figure 3, we look also at the fraction of households with constructed floor (rather than e.g. dirt), the fraction with tap water, the fraction with a finished roof and the average time collecting water. The table shows that, for each metric, housing quality rises with density on average. Differences between the second and first quartile are statistically significant for the majority of countries. Differences between the first and fourth (densest) quartiles are

Surveys, Malaria Indicator Surveys and AIDS Indicator Surveys. Using all data available for our countries from these surveys, we find that malaria incidence is decreasing with population density consistently in most of the countries. This is in line with Tatem, Gething, Smith, and Hay (2013) who document a negative relationship between malaria and urbanization on a global scale.

quite large in magnitude and statistically significant for all but a few countries. In the densest quartiles, people spend on average 17.2 few minutes a day collecting water and are 52 percent more likely to have tap water than in the least dense quartile. Households in the densest quartiles are 46–49 percent more likely to have finished walls, a finished roof or a constructed floor. We conclude that by these six measures, housing quality is unambiguously higher in denser areas in these developing countries.[11]

4.4. Crime

We next turn to measures of crime, which are a clear example of an amenity not already measured in consumption expenditure data. The challenge we face is that data on crime at small levels of geographic detail are difficult to obtain for African countries. Official administrative records are either not stored centrally, or they are not available to researchers.

The best and most comparable data on crime come from the Afrobarometer surveys, which were collected in in 2005, 2009 and 2011 for a large subset of our countries. The Afrobarometers are high quality micro surveys covering between 1200-2400 individuals in each of several African countries. Table A.2 in the appendix shows the number of rounds a country is part of the survey, as well as the number of observations per country. The surveys are designed to use consistent methodologies and definitions across countries. The questionnaire focuses on attitudes towards democracy and governance, and it includes questions on crime, safety and trust. An advantage of survey data over administrative data on crime is that the latter are likely to be biased towards areas with police presence or better record keeping capacity. In contrast, our surveys are asked in the same way within and across countries, and across the three years of our survey. Hence, our data are unlikely to be biased toward any particular geographic area.

We consider four main metrics: property crime, violent crime, feeling safe in one's neighborhood, and fear of crime in one's home. To measure property and violent crime, we use the survey questions *"Over the past year, how often (if ever) have you or anyone in your family had something stolen from your house?"* and *"Over the past year, how often (if ever) have you or anyone in your family been physically attacked?"* For each region, we compute the fraction of respondents reporting at least one theft (property crime) or attach (violent crime).

To measure feeling safe and fear of crime, the questions are *"Over the past year, how often, if ever, have you or anyone in your family felt unsafe walking in your neighborhood?"* and *"Over the past year, how often have you or anyone in your family feared crime in your own home?"* The

[11] Some measures of housing quality may already be incorporated into measured rural-urban income differences. For example, surveys reporting average consumption expenditures at the household level may deflate housing expenditure by regional quality-adjusted price indices. In practice, it is an open question how well quality adjustments are done in these surveys.

answer to these questions on experienced crime and perceived safety are classified as *"never," "just once or twice," "several times," "many times,"* and *"always."* We define a dummy variable as equal to one if a respondent's reply is anything more than "never."

Overall, we find that crime is quite common in Africa. About one-third of respondents report a theft from their house in the previous year. The highest rates of theft are in Liberia (49%), Uganda (42%) and Senegal (39%), and the lowest rates are in Madagascar (13%), Niger (18%) and Mali (21%). The heterogeneity in physical attacks follows a similar pattern for most countries, and the pairwise correlation coefficient at the country level between theft and attack is 0.7 and highly significant. Exceptions include Senegal, where theft is high but attacks are reported infrequently. Across the whole sample, more than one third of respondents report that they felt unsafe in their neighborhood at least once in the past year, and that they feared crime in their own home.

Figure 4 shows differences in experienced crime and fear of crime across space. We show both of these categories of variables, as fear of crime might matter at least as much as experiences of crime for location choices. Both figures illustrate that most countries are located close to the 45 degree line. Property crime appears to be slightly higher in denser areas, but the differences for most countries are fairly small when comparing them with observed differences in living standards, for example. One limitation of the theft variable is that it does not consider livestock theft, a type of crime common in rural areas. It is therefore likely that the difference is even smaller when taking into account livestock theft. The results are similar for fear of crime and perceived feeling of safety in the neighborhood, where most countries cluster around the 45 degree line.

Table 5 presents the average crime rates by density quartile across all the countries. Around 29 percent of households in the least dense quartile experience property crimes, compared to 33 percent in the densest quartile. Violent crime affects 10 percent of households in the least dense quartile compared to 12 percent in the densest quartile. Fear of crime and feeling unsafe are similarly increasing in population density on average, with similarly modest differences by density. Only a handful of countries have statistically significant differences in crime rates through density, with the majority insignificant.[12]

[12] Studies by Fafchamps and Moser (2003) and Demombynes and Ozler (2002) from Madagascar and South Africa point to somewhat higher crime rates in less dense areas. Crime information is also available in some LSMS surveys, though with questions that are hard to compare across countries. Appendix Figure A.6 shows the fractions of LSMS households having experienced a crime in the last twelve months, in five countries for which geo-references are available: Ethiopia (2013), Malawi (2010), Tanzania (2009-2010), Nigeria (2012) and Uganda (2010-2011). While patterns of crime across space are different in each of these five countries, one common theme is a lack of evidence that rates of crime are systematically increasing in density, or a lack of evidence that the densest areas have the highest rates of theft; visually, a constant rate of crime seems like it

Still, so far our evidence suggest that crime the leading contender for the amenity that gets worse with density. Could it be that crime rates are enough to offset the higher income and consumption levels of more urban areas? Several previous studies in the literature have estimated the value of living in an areas with less crime, proxied by willingness to pay. What is the value of having 33 percent chance of theft in the densest areas relative to just 29 percent in the least dense, as we find on average? Or having a 12 percent chance of violent crime in the densest areas compared to just 10 percent in the least dense areas?

Relative to the large differences in average income across space, the estimated valuations of crime implied by estimates in the literature are quite modest. For example, Bishop and Murphy (2011) estimate a dynamic model using crime data, and infer that San Francisco residents are willing to pay $472 per year to avoid a ten percent increase in violent crime. On an average income per head of $57,276, this amounts to 0.8% of average yearly income. Using direct survey questions, Cohen, Rust, Steen, and Tidd (2001) estimate that U.S. residents in 2000 were willing to pay $120 to reduce the chance of armed robbery by ten percent. This amounts to 0.4% percent of average income ($120 / $34,432). Similarly, Ludwig and Cook (2001) estimate that U.S. households in 1998 were willing to pay $240 per year to reduce the chance of gunshot injury by 30 percent, which amounts to 0.5% of average household income ($240 / $51,939). Taken together, these studies suggest that the modest differences in crime rates with density are nowhere near large enough to offset the much higher average incomes in urban areas.

4.5. Outdoor Air Pollution

Pollution is an widely studied amenity that varies through space. Sources of outdoor pollution include vehicles, electricity generation, industry, waste and biomass burning, and re-suspended road dust from unpaved roads. Banzhaf and Walsh (2008) find pollution to be an important determinant of locational choice in the United States, and exposure to pollutants significantly affects health, human capital and productivity (Adhvaryu, Kala, and Nyshadham, 2014; Currie and Walker, 2011; Currie, Hanushek, Kahn, Neidell, and Rivkin, 2009; Graff Zivin and Neidell, 2012).[13]

In this section we use satellite-derived estimates of two measures of outdoor air pollution: fine particulate matter (PM2.5) and nitrogen dioxide (NO2) and document how they vary with population density in our set of countries and several reference countries. We measure both pollution measures in micrograms per cubic meter ($\mu g/m^3$). For frame of reference, the World

would just about fit within the confidence intervals.

[13] For a comprehensive survey of the literature on pollution and individual welfare see Graff Zivin and Neidell (2013); on environmental amenities and city growth see Kahn and Walsh (2015).

Health Organization recommends mean annual exposures of 10 $\mu g/m^3$ or less for PM2.5 and 40 $\mu g/m^3$ or less for NO2, at the same time highlighting that there are no levels of pollution exposure that have been proven not to negatively affect health (Geddes, Martin, Boys, and van Donkelaar, 2016; WHO, 2006). Indeed, Pope and Dockery (2006) conclude from a meta analysis of dozens of studies that the relationship between particulate matter exposure and life expectancy is approximately linear.

The top panel Figure 5 plots (as black circles) the average PM2.5 concentrations for the highest and lowest population density quartiles. Countries with the highest overall concentrations of PM2.5 tend to have high concentrations both in the least and most dense areas. These countries are essentially the ones that border or contain parts of the Sahara desert, like Niger, Senegal, Mali and Nigeria. We therefore look plot PM2.5 concentrations with dust and sea salt removed (as black triangles).[14] There is no evidence suggesting that anthropogenic sources of PM2.5 are more or less harmful for health than natural sources, but it is possible that individuals perceive anthropogenic sources as more hazardous to their health. These lead to far lower levels of PM2.5, with again very modest apparent differences by population density. The bottom panel of Figure 5 plots NO2 by population density. While there is some variation across countries, there is again little apparent difference by density.

Table 6 reports the average differences between density quartiles. NO2 has relatively small average differences across density quartiles, and the variation is quite modest compared to the regional standard deviation. In other words, NO2 concentrations do vary across space in our countries, but that variation is largely not linked to density. PM2.5 on average is lower in denser areas, though the differences are statistically significant only in around half the countries, and the average differences are again modest relative to the regional standard deviation. We conclude that outdoor air pollution concentrations in Africa are at best loosely linked to population density.

What do these gradients look like in other parts of the world, known to suffer from high levels of urban pollution, such as China? The global coverage of the PM2.5 map as well as the population density map allows us to look at further countries. Figure 6 shows the relationship between pollution and population density in China, India, and the United States. The left-hand side axis denotes levels for India and China, while the level in the U.S. is illustrated on the right-hand side axis. All three countries show clearly positive density gradients. In China, PM2.5 levels for the top population density decile amount to 66 $\mu g/m^3$, more than six times the WHO recommended threshold; the lowest population density decile has a level

[14] About half of the population-weighted ten-year mean of PM2.5 concentration in Eastern Sub-Saharan Africa is estimated to be due to dust and sea salt; in Western Sub-Saharan Africa the proportion amounts to about three quarters (van Donkelaar, Martin, Brauer, and Boys, 2015).

of 13 $\mu g/m^3$. In India, the top decile has a level of 41 $\mu g/m^3$, still four times the WHO recommended threshold, compared to 6 $\mu g/m^3$ in the lowest decile. The bottom figure shows NO2 distribution for these other countries. The levels are much lower, but there are gradients again for China, India and the United States. These positive gradients are very much what we might expect of a world in which cities have high concentrations of industrial activity and automobile traffic. Although urban areas in Africa are growing rapidly, there is little industrial activity, and consequently industrial air pollution is relatively low.

To be clear, we are not making a claim that pollution does not matter in African cities. Our satellite-derived pollution estimates do not capture pollution exposure in some dimensions: they are annual series and therefore average over temporarily high values. At a 10km resolution they are spatially rather coarse, ignoring local effects such as proximity to roads which have been demonstrated to matter significantly. For example, Kinney, Gichuru, Volavka-Close, Ngo, Ndiba, Law, Gachanja, Gaita, Chillrud, and Sclar (2011) find average PM2.5 concentrations at four traffic sites between 7.30am and 6.30pm in Nairobi to amount to between 58.1 and 98.1 $\mu g/m^3$; the maximum multi-annual average PM2.5 concentration for Kenya in our sample is 13.9 $\mu g/m^3$, and this pixel is at Lake Turkana, the world's largest desert lake (Avery, 2012). Finally, satellite-derived measures reflect the column of pollution as observed from space, rather than the concentration experienced on the ground. Nevertheless, as the graphs from India, China, and the US illustrate, the two datasets still capture meaningful variation in concentrations levels across space. What emerges, rather, is that in Africa, cities are not large enough and concentration of industries is not significant enough to create large clouds of pollution around cities; however, background non-anthropogenic pollution is high. This combination produces different pollution gradients from those observed in more industrialized parts of the world.

4.6. Indoor Air Pollution

Arguably a more serious health risk in developing countries is indoor air pollution, largely related to the use of unvented fires for cooking. As a proxy for indoor air quality we examine the main material used for cooking as reported in the DHS. The World Health Organization estimates that over 4 million people suffer from pre-mature deaths due to illnesses attributable to cooking with solid fuels, such as wood and charcoal (WHO, 2014). Indoor air pollution is also estimated to contribute significantly to outdoor air pollution-related deaths.

Figure 7 shows the proportion of households using solid fuels for cooking across population density (as black squares). Across all of our countries, virtually everyone in the least dense areas uses a solid cooking fuel. In the urban area there is more variation, with the densest

areas ranging from 20 percent solid fuel in Zimbabwe up to around half in countries such as Nigeria, Cote d'Ivoire and Ghana, and the majority over 80 percent. Overall, the pattern is clear one of much higher use of solid fuels in rural areas than in urban areas.

One potential advantage of rural areas is that there might be more space to accommodate outdoor cooking, thereby somewhat mitigating the negative effect of using solid fuels. Therefore we also show the interaction effect: among the households using solid fuels, we look at the proportion cooking indoors (as black crosses). The fractions of people cooking primarily indoors with solids drops everywhere, and it is still higher in rural areas in almost every country (Benin being the sole exception). The last row of Table 6 shows that the fraction cooking inside with solid fuels is 6 percentage points lower in the third quartile than in the least dense quartile, and 25 percentage points lower in the densest quartile. All but one country have a significant difference. In summary, indoor air pollution is almost everywhere worse in rural areas than in African cities.

5. Gradients by Education Group

One explanation for the patterns we observe is that workers select into different regions and occupations according to comparative advantage. This type of sorting has recently been emphasized by e.g. Lagakos and Waugh (2013), Young (2014), Bryan and Morten (2015) and others as a way of explaining regional income differences in the developing world. To address this issue further, we compare how measured living standards vary by density within specific educational groups. Educational attainment is perhaps the simplest measure of skills or ability that is availability at the individual level in the data, though of course there are components of ability not well captured by educational attainment.

For simplicity, we divide households into two education groups: those whose head finished primary school, and those whose head did not finish primary school. Figure 8 plots one metric by educational group, namely electricity access. The top graph shows the proportion of households who have electricity by the highest education of the household head. The histograms show that the different educational groups are represented at various population density levels. Households with more educated household heads are experiencing better access to electricity at almost all levels of population density. Still, the urban-rural gradients documented earlier persist even within these education categories.

To study these slopes by education group for all metrics, we estimate the following linear

projection for households i in country c:

$$x_{ic} = \theta_0 + \theta_1 P_{ic} + \theta_2 E_{ic} + \theta_3 (P_{ic} * E_{ic}) + \epsilon_{ic}$$

where x_{ic} is a measure of consumption or amenities, P_{ic} is the log of population density and E_{ic} is a dummy variable that is equal to one if the household head has completed primary education or more.

Figure 9, Panel (a), shows the linear gradients for households with heads who have less than complete primary education, and panel (b) shows gradients for households with heads who have complete primary education or more. Each dot represents a slope estimate for one country. The y-axis indicates the size of the coefficient and the grey horizontal bars show the median slope coefficient. The figures show that in virtually all countries and for virtually all of our living standards measures, these urban-rural gradients persist *within* populations at similar educational levels. That is, almost without exception, the relationship between population density and housing consumption is positive for the two main education groups.

We do not argue against the relevance of sorting and selection mechanisms for differences in living standards across space. However, the data suggest that these mechanisms may not be *sufficient* to account for the observed patterns of difference. At the very least, sorting and selection would need to take place on dimensions that are not highly correlated with educational attainment. We note that our results hold if we divide educational attainment further; e.g., looking at those who complete secondary school as well as those who complete primary school. In sum, there are surely strong pressures for individuals to move to locations where their comparative advantages are rewarded. But the data suggest that such mechanisms do not in a simple sense explain the observed patterns.

6. Mobility Across Space, Slums and Secondary Amenities Measures

The descriptive statistics of outcomes across population densities in section 4 suggest there is no easily observable measure of consumption or amenity that is decreasing with population density. We turn now to measures of migration. Taken literally, the spatial equilibrium in our model predicts that we should observe no migration across regions. Taken more liberally, the model suggests that we should see roughly similar movements of workers from less dense to more dense regions, than from more dense to less dense parts. We ask whether this is the case. We then turn to some secondary amenities to ask how those vary across space.

6.1. Net Migration Rates

We now compute, for the subset of countries with appropriate data, the fraction of all surveyed individuals in the DHS that are rural-to-urban migrants, and the fraction of all individuals that are urban-to-rural migrants. Ideally, we would know the exact location an individual migrated from. Unfortunately the DHS data does not contain this information. However, we know if an individual moved from the capital or a large city, town, or the countryside. We define an urban-rural migrant to be someone who has been residing in the lowest density quartile for five years or less, and who previously lived in the capital or a large city. Similarly, we define a rural-urban migrant as someone who has been residing in the highest density quartile for five years or less, and who previously lived in the countryside.[15]

Table 7 displays the fractions of all individuals that are rural-to-urban migrants, urban-to-rural migrants, and their difference. In every country, there are substantially more rural-to-urban migrants than the vice versa. The differences are starkest in Kenya, where 7.6 percent are rural-urban migrants, compared to 0.6 percent urban-to-rural migrants, and Malawi, which has 7.2 percent rural-urban migrants and less than 0.5 percent moving the opposite direction. All other countries but one have positive net migration. [16]

The Table shows clearly that for all but one country, rural-urban migration is in absolute terms larger than urban-rural movements, and in all cases the net flows are significantly positive. This view is consistent with cities being seen as attractive places to live, and workers voting with their feet to move there. Its hard to reconcile this evidence with a spatial equilibrium. To most development economists, of course, this may not be a new or controversial claim; the literature has long emphasized the importance of rural-urban migration as one feature of structural transformation. But policy makers continue to worry about excessive urbanization, and many academic economists use models that explicitly or implicitly assume that population movements are associated with some kind of sorting that is consistent with a steady-state distribution of population. For these reasons, we find it useful to emphasize that the flow of people in our economies is clearly single directional.

[15]We do not consider individuals who reported that they previously lived in a town due to the difficulty of assigning the person to a high or low density area. We keep them in the sample to compute the appropriate population-weighted cut-off for density quartiles.

[16]Our finding is not in contrast with Young (2014), who finds urban-to-rural migration as a fraction of the originating population is as large as rural-to-urban migration as a fraction of the originating population. He states that the “differences in relative to shares of destination arises because of the smaller average urban population share (0.41 versus 0.59 for rural). Overall, net migration is in favor of urban areas with, on average, 0.126 of the aggregate young adult female population moving to urban areas and only 0.07 to rural areas.”

6.2. Migration destinations

Migration decisions are likely to be shaped by the conditions in arrival destinations, rather than averages of a population. It might be the case that conditions in location in which individuals would see themselves migrate to are much worse than the averages we have documented so far. Our data does not contain any information about whether a cluster is a migration destination, and the random displacement of clusters makes it infeasible to spatially merge the DHS data with secondary data (i.e. slum settlements). Still, we can use the individual-level migration data and construct a cluster-level average of in-migrants to explore whether differences in outcomes depend on the intensity of in-migration into a cluster. If outcomes are much worse in these ares, it would explain why individuals might be hesitant to move.

Tabel 8 shows durables and housing quality measures across quartiles for the sample used to study migration. Given that these DHS were collected earlier, the first three columns repeat the comparisons across quartiles we already carried out on the more recent data. The table shows that the different surveys yield very similar average differences across density quartiles. Columns 4 and 5 restrict the sample in the highest density quartile to clusters in which at least 25% and 40% of individual respondents have lived there for 5 years or less. The table shows that these clusters do not exhibit smaller differences compared to the most remote areas. If anything, the differences are larger.

6.3. Secondary Amenities Measures

We turn next to a set of issues that we view as secondary amenities, by which we mean that they are somewhat less tangible than e.g. pollution and crime, as considered above. In particular, we focus on measures of social networks, social insurance and stress. By bringing together large numbers of people, cities can create stress and lead to feelings of isolation and anonymity. Urban dwellers may find that they have weaker social links to supportive networks and communities than rural people. This may be important if would-be migrants worry about their access to the insurance provided by their social networks. If individuals have sufficiently strong preferences for the social integration – and perhaps also for smoother consumption or lower deviation from the consumption of those around them – then these characteristics of urban life could explain some of the stark differences in living standards that we observe.

The Afrobarometer asks a number of questions that allow us to further investigate these possible explanations related to shortages of necessities, stress and trust. To examine consumption variability we look at whether and how often a household has gone without enough food or medicines in the past year. Representing crucial consumption goods, these variables are possibly good proxies for insurance provided by community members. We define a household as

lacking food or medicines if they state that they lacked the good either several times, many times or always. Finally, the Afrobarometer asks *"In the past month, how much of the time: Have you been so worried or anxious that you have felt tired, worn out, or exhausted?"* If respondents reply with *"many times"* or *"always"* we take this as a measure of anxiety.

There are also a number of questions related to trust towards people in general, and also towards various distinct groups of people, including specifically neighbors and relatives. The questionnaire asks *"Generally speaking, would you say that most people can be trusted or that you must be very careful in dealing with people?"* We create a dummy variable that is equal to one if the individual responds with *"most people can be trusted"* and zero otherwise. The questions related to specific groups are framed slightly differently: whether respondents trust their neighbors or relatives on a scale from 0 to 3 (not at all, just a little, somewhat, a lot). In line with our framing of lower levels of trust as a downside of city life, we define a dummy variable equal to one if respondents say they trust their neighbors not at all or just a little.

The top panel of Figure 10 plots the proportion of individuals reporting a lack of medicines and food in the top and bottom quartile while the bottom panel shows trust in general and towards relatives. Table 9 shows the average differences for all of our secondary amenity measures between density quartiles. The data do not support the idea that people find cities to be places with less certain access to food or medicine. To the extent that this represents the effective functioning of social insurance and networks, the data are not consistent with the idea that people in cities face weaker insurance. Individuals residing in the highest density quartile are 8 percentage points less likely to have reported lacking food, and 12 percentage points less likely to have reported lacking medicine. In the majority of countries in our sample, this difference is significant. One explanation is that rural communities face covariate shocks, causing a failure of mutual insurance. But especially in the case of medicine, we would expect a significant idiosyncratic component. To further explore this question, we also used data from the Financial Inclusion Insights program which surveys a representative sample of individuals in Uganda, Kenya, Nigeria and Tanzania. The survey asks whether an individual could get extra money from relatives in an emergency. In all four countries the proportion answering "yes" is higher in the most densely populated quartile (31%) compared to the least densely populated quartile (25%). A parsimonious explanation is that higher income levels in urban areas lead to strengthening of insurance.

As for anxiety, measured levels appear generally to be higher in the countryside than in cities, weakening the argument that people prefer the countryside due to its higher level of tranquillity and reduced stress. However, the differences are significant only in a small number of countries.

For trust, however, the story is different. All measures of trust – trust towards anyone, relatives, neighbors and one's own ethnic group – are higher in the lowest population density quartile compared to the highest population density quartile: cities appear to be low-trust environments. Second, there appear to be very low levels of trust in general among the population: most trusting are individuals in Madagascar where 30% thinks that people can in general be trusted. Other countries have much lower levels of trust; for example, about 90% of respondents in Tanzania and Kenya report that "one must be very careful with people." One could imagine that the problem in cities is simply that people live with more diverse neighbors, including people from other ethnicities, whom they trust less than co-ethnics. But it is striking that trust in co-ethnics also declines in cities relative to rural areas. However, the difference is significant only for a handful of countries.[17]

There are many issues with these kinds of self-reported data, both within the same cultural contexts and even more so across different contexts. Still, the higher level of mistrust offers one possible compensating differential for the many tangible advantages of densely populated areas, but we lack a clear way of quantifying this in monetary terms, to compare with the higher income and other benefits of city life. Nevertheless, we think these results are interesting and potentially point towards avenues for further research.

7. Conclusion

One appealing explanation of the higher incomes of urban areas in the developing world is a "spatial equilibrium," where the higher amenities of rural life are enough to offset the greater monetary rewards of living in cities. In this paper we go searching for a spatial equilibrium in twenty African countries using numerous sources of spatial data. We focus on measures of consumption, housing quality, health, crime and pollution, which can be measured consistently across space within and across our countries. We find that almost all metrics in almost all countries are unrelated or improving with population density. The only real exception is crime, though when differences exist they are modest in magnitude and dwarfed in monetary value by the size of the rural-urban wage gaps. When looking at migration rates, every country for which we have data shows that rural-to-urban migrants are far more common than urban-to-rural migrants. That is, net migration is overwhelmingly towards denser areas.

[17]We are not the first to find that mistrust is higher in denser areas in Africa. Nunn and Wantchekon (2011) use the 2005 Afrobarometer survey, demonstrating that a higher historical exposure to the slave trade appears to be linked to reduced levels of trust in the present day. They control for urban location as classified by the survey, but the coefficient is not reported in the main paper. We geo-locate two further rounds of the same survey and link the data with spatial population density data. Replicating their results, we find that the coefficient on the urban dummy is negative in all their models and highly significant. The patterns found in the two papers are therefore similar in that urban location is associated with higher levels of mistrust.

Our findings are hard to reconcile with a spatial equilibrium in the developing world. Instead, they point to a world where individuals in developing countries are moving on net to cities, which offer a better mix of consumption and amenities on average.In this way, our conclusions are consistent with the hypothesis of Chauvin, Glaeser, Ma, and Tobio (2016) that a spatial equilibrium only emerges when economies are sufficiently developed. Our findings suggest that nonetheless assuming a spatial equilibrium in the developing world today will lead to misleading inferences about the extent of amenities in cities relative to rural areas. This in turn may lead to flawed policy recommendations regarding urbanization and internal migration. Instead, researchers should treat developing countries as dynamic economies undergoing structural change toward more-productive urban areas and life in denser areas.

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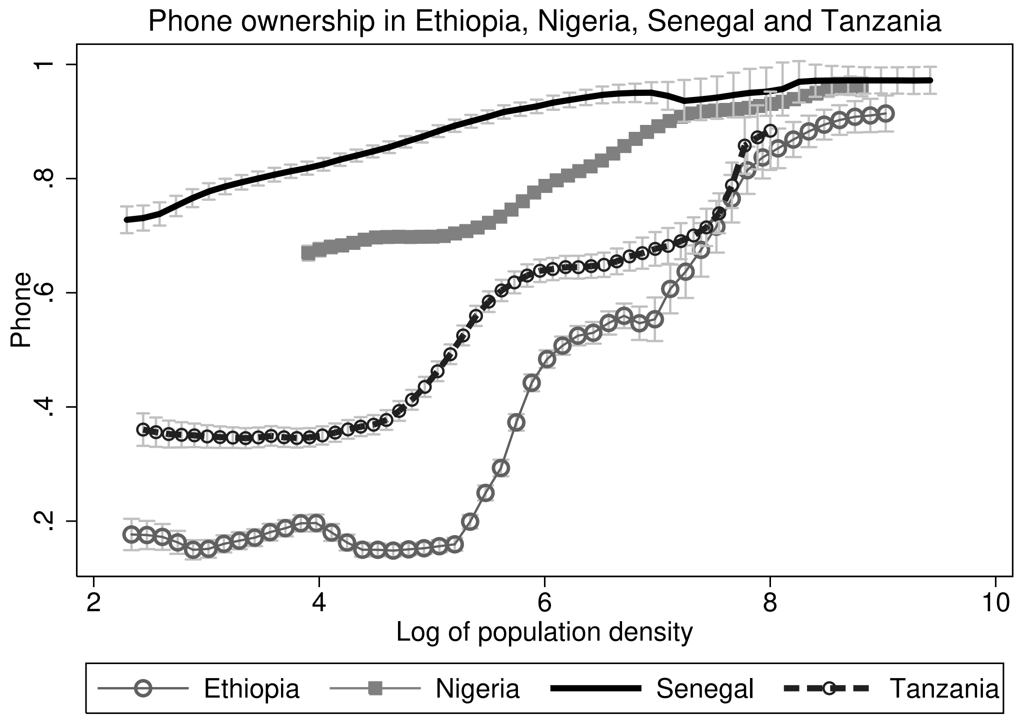
Figure 1: Telephone Ownership Gradients



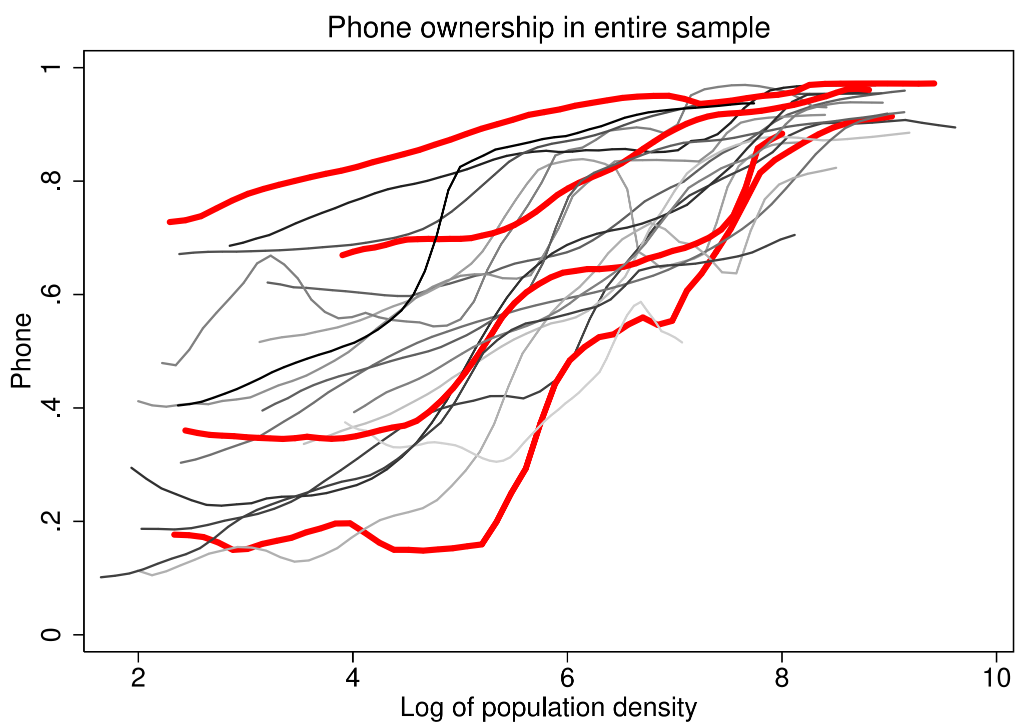


Figure 2: Child Health

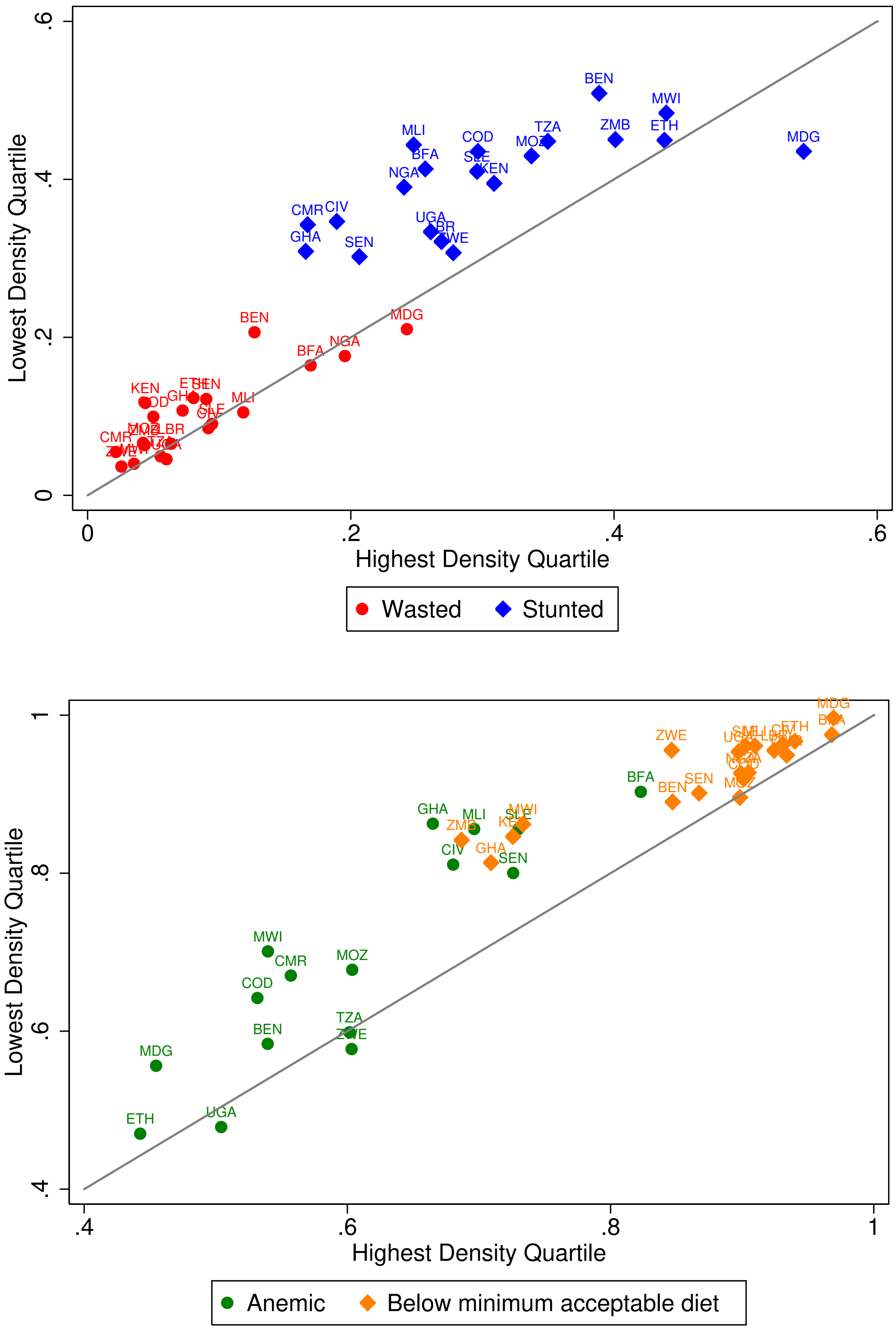
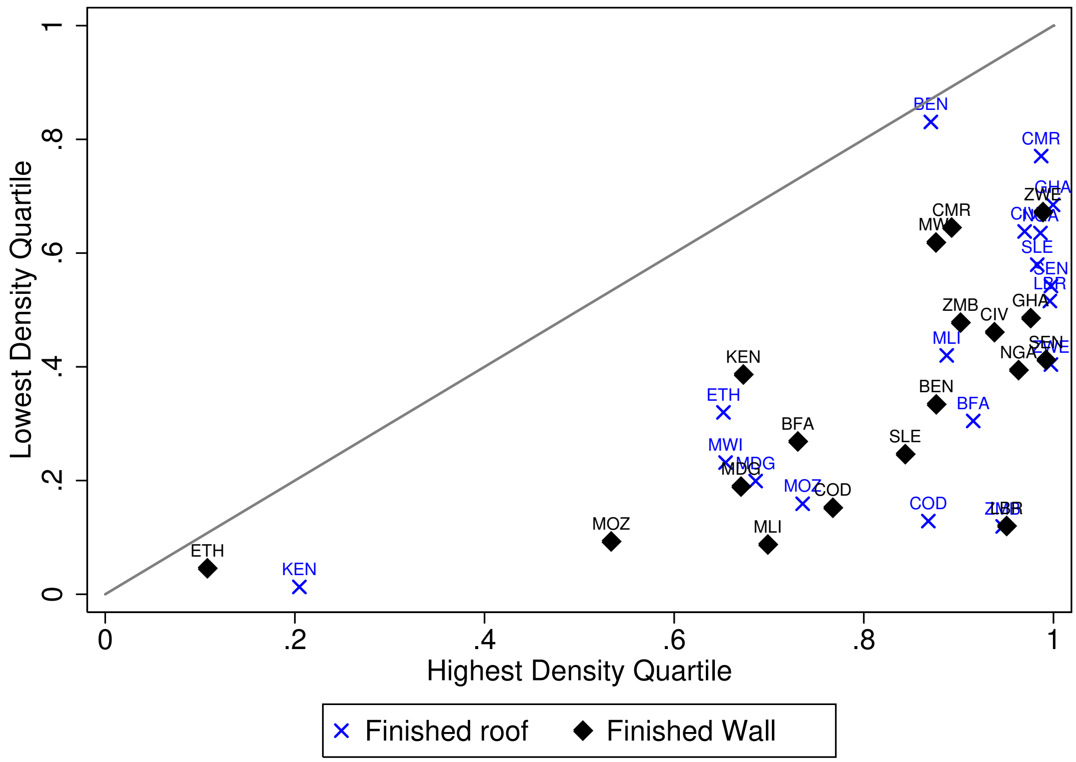


Figure 3: Housing Quality



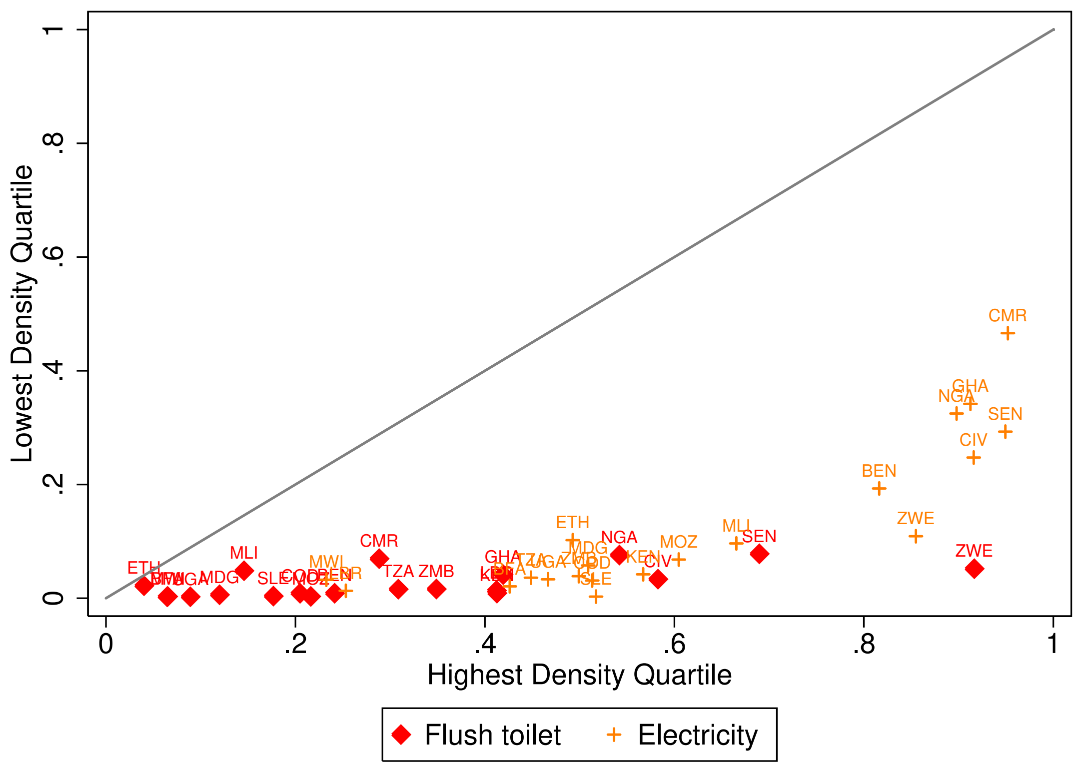
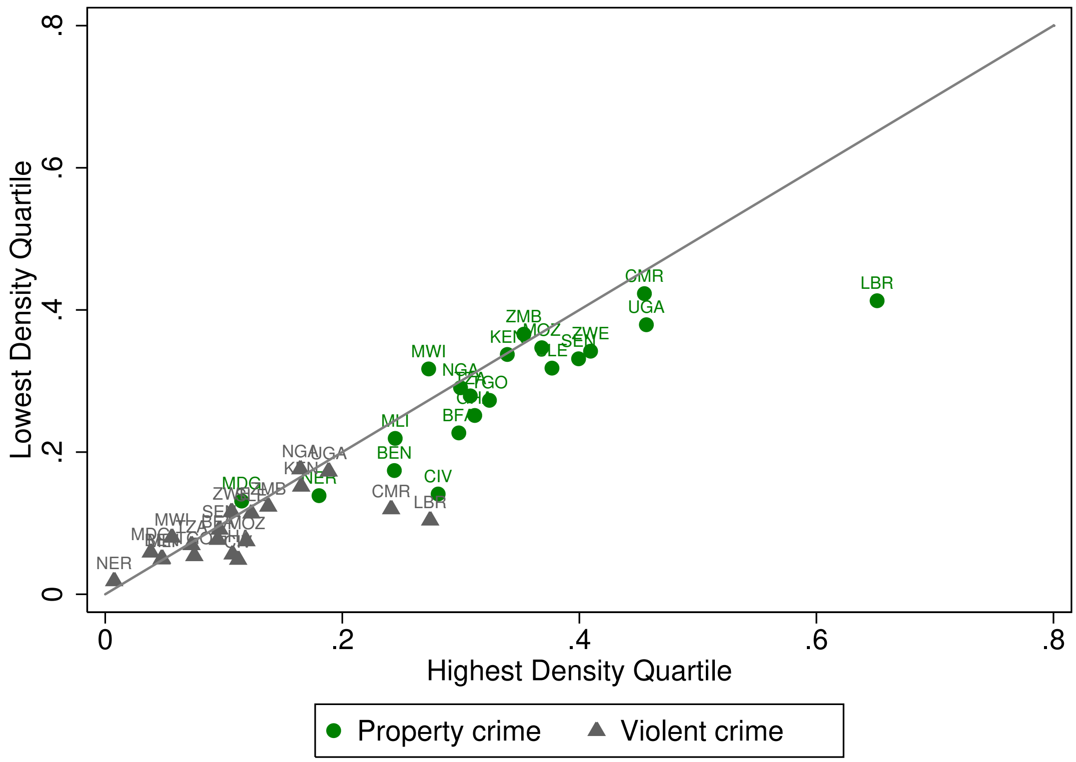


Figure 4: Crime



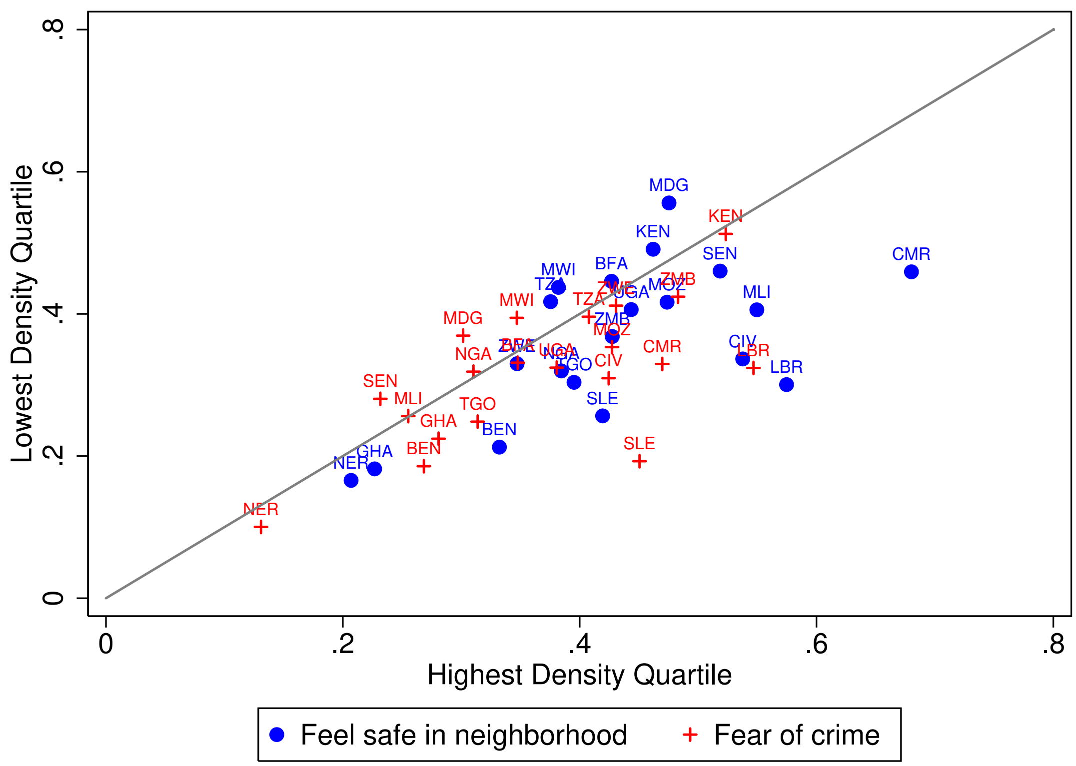
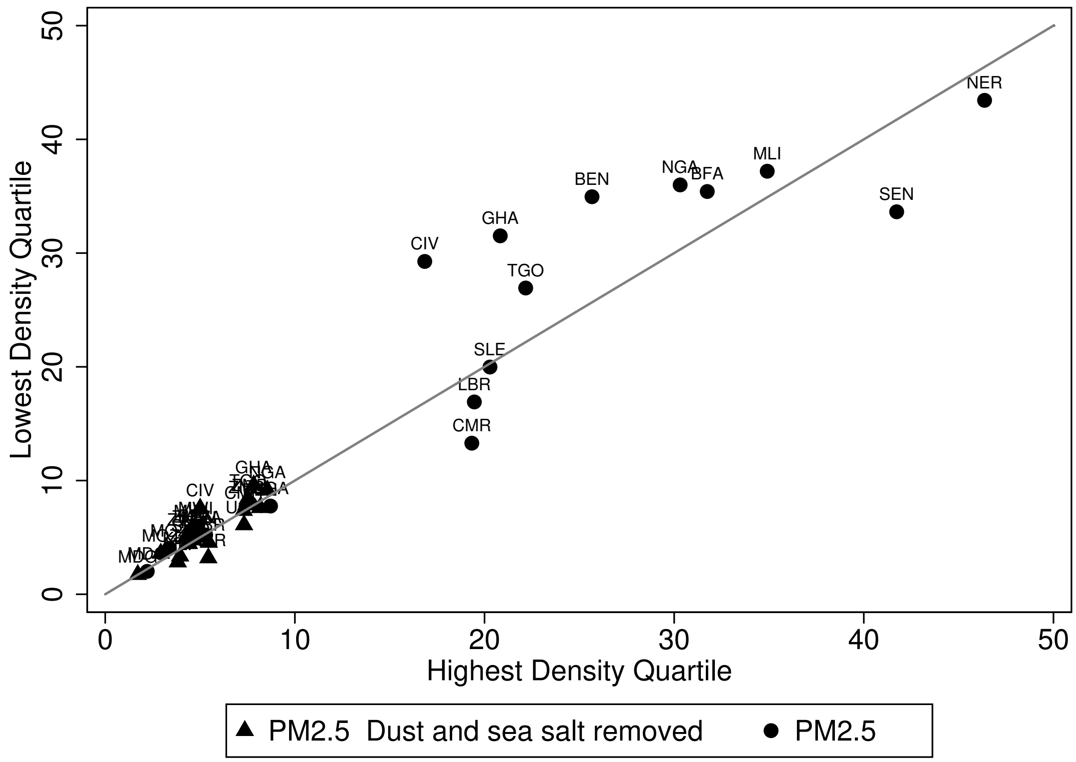


Figure 5: Outdoor Air Pollution



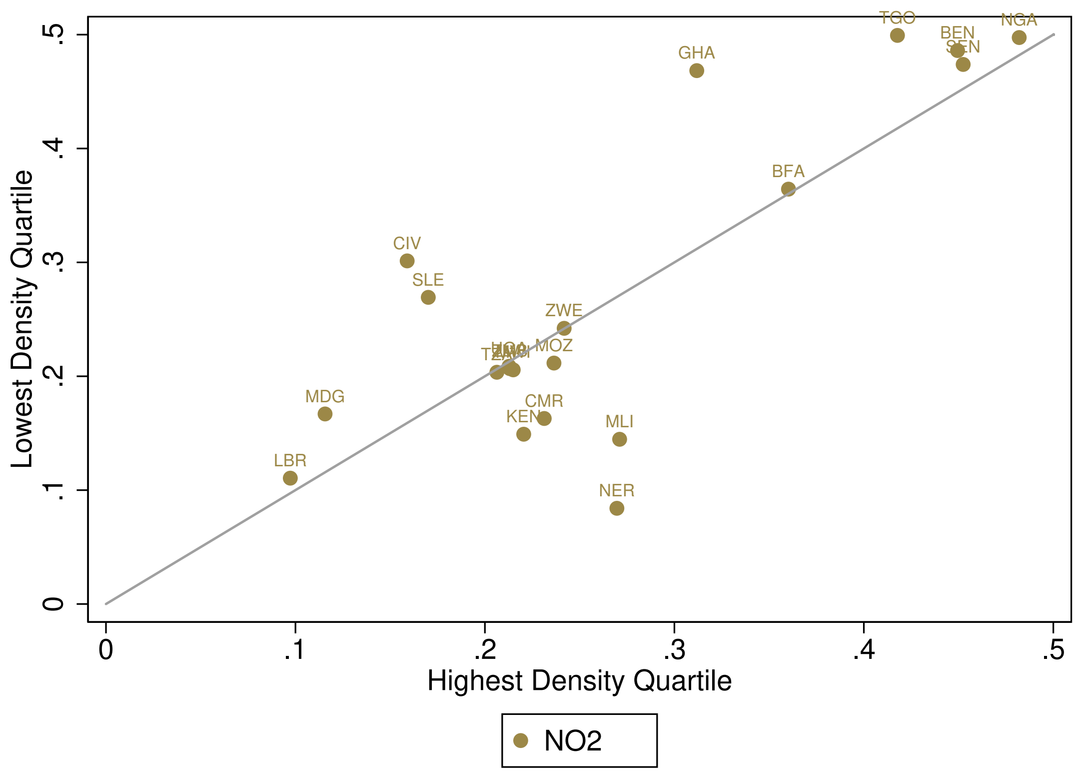
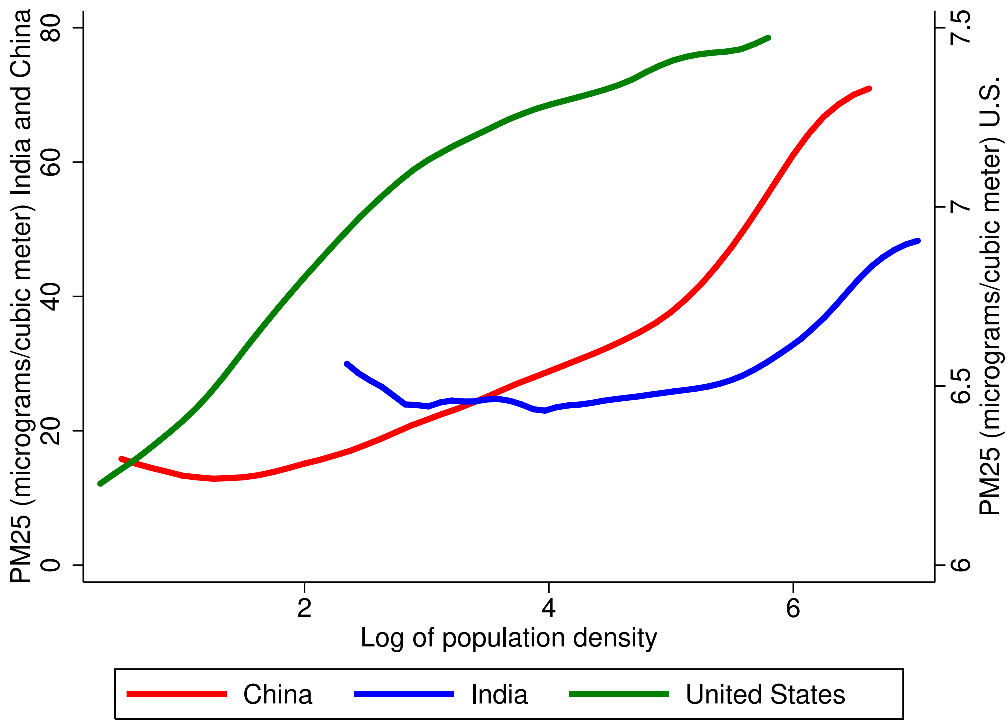


Figure 6: Outdoor Air Pollution in China, India and the United States



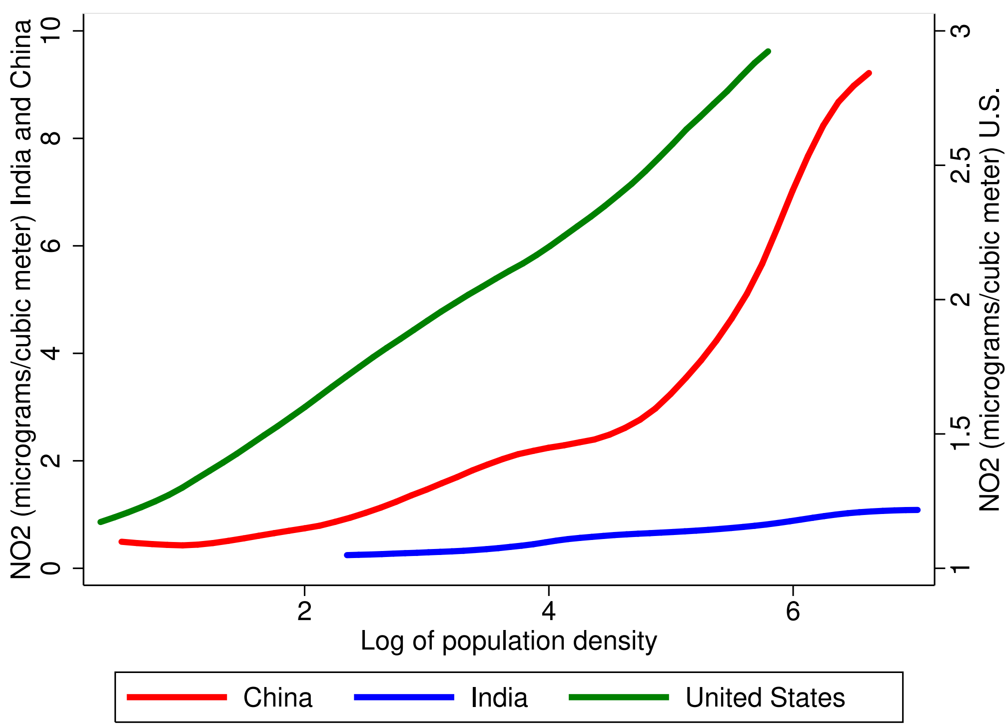


Figure 7: Indoor Air Pollution

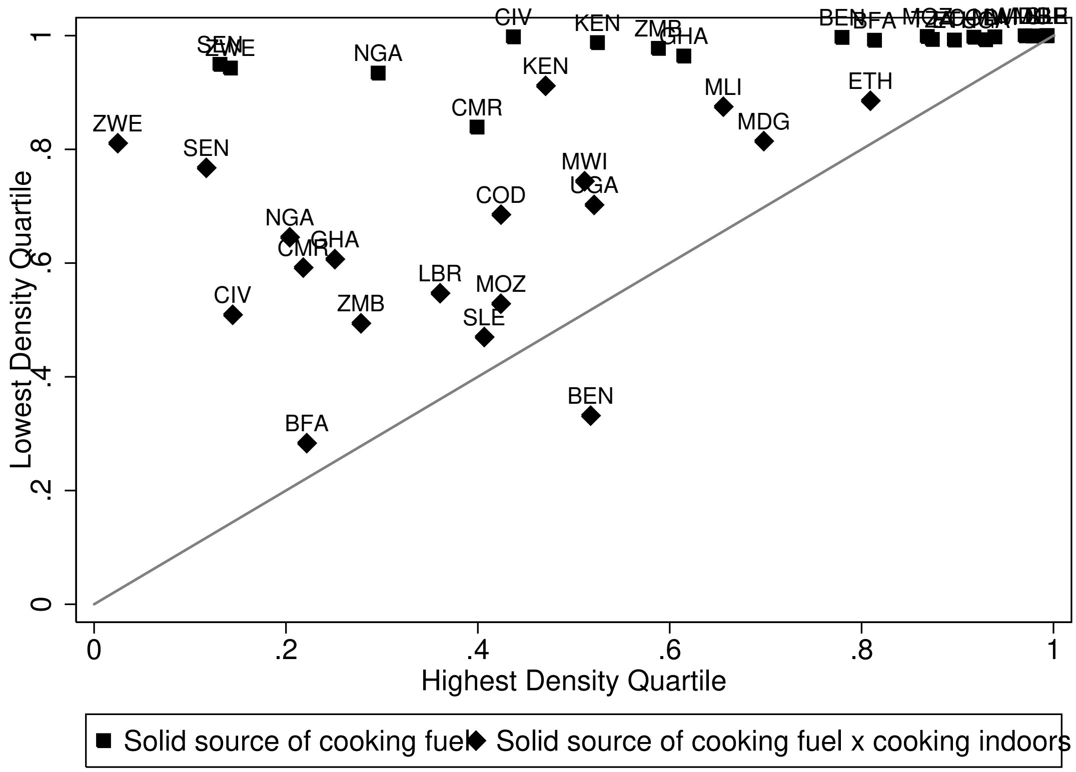


Figure 8: Electricity by Highest Education of Household Head in Nigeria

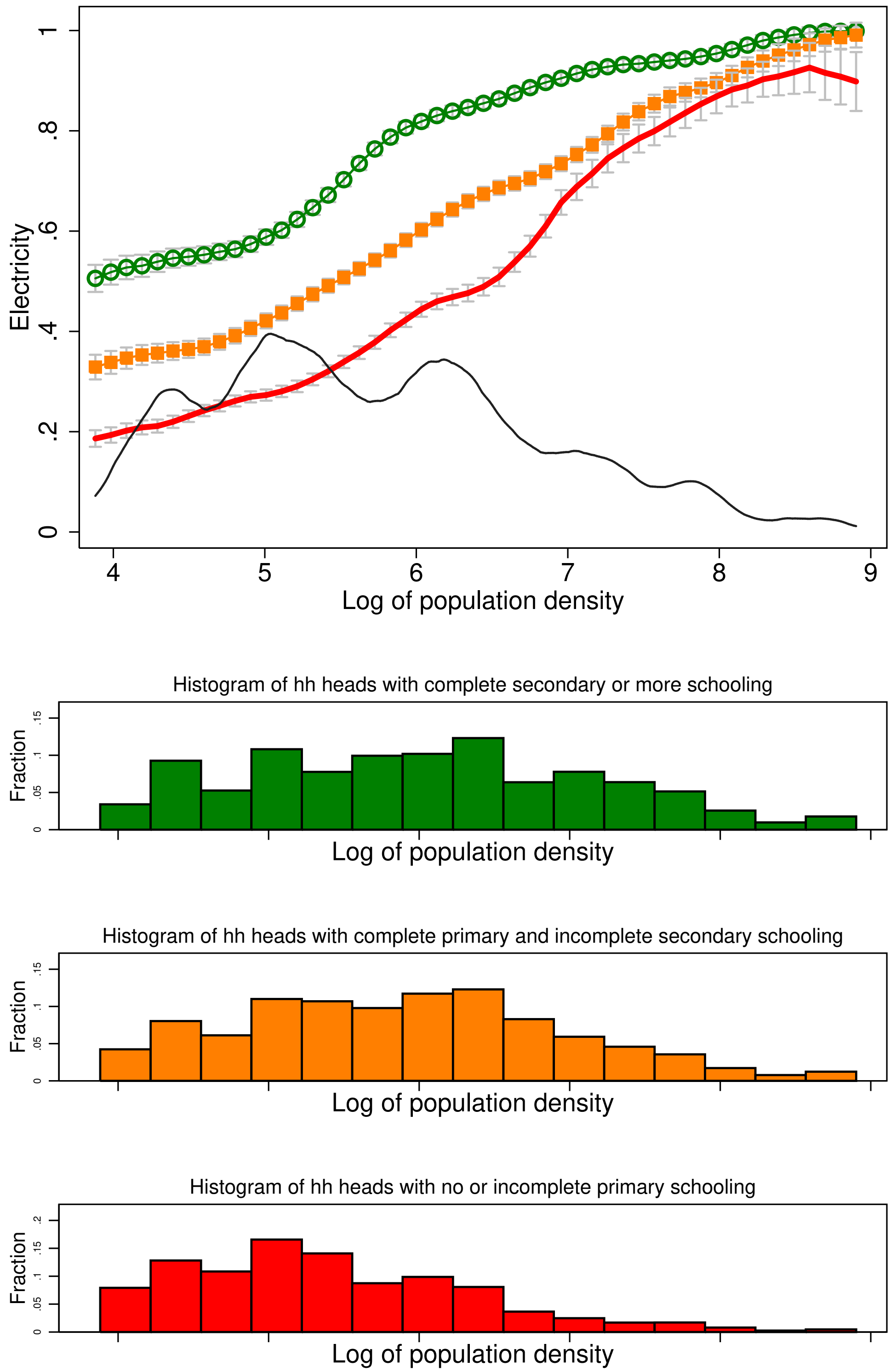
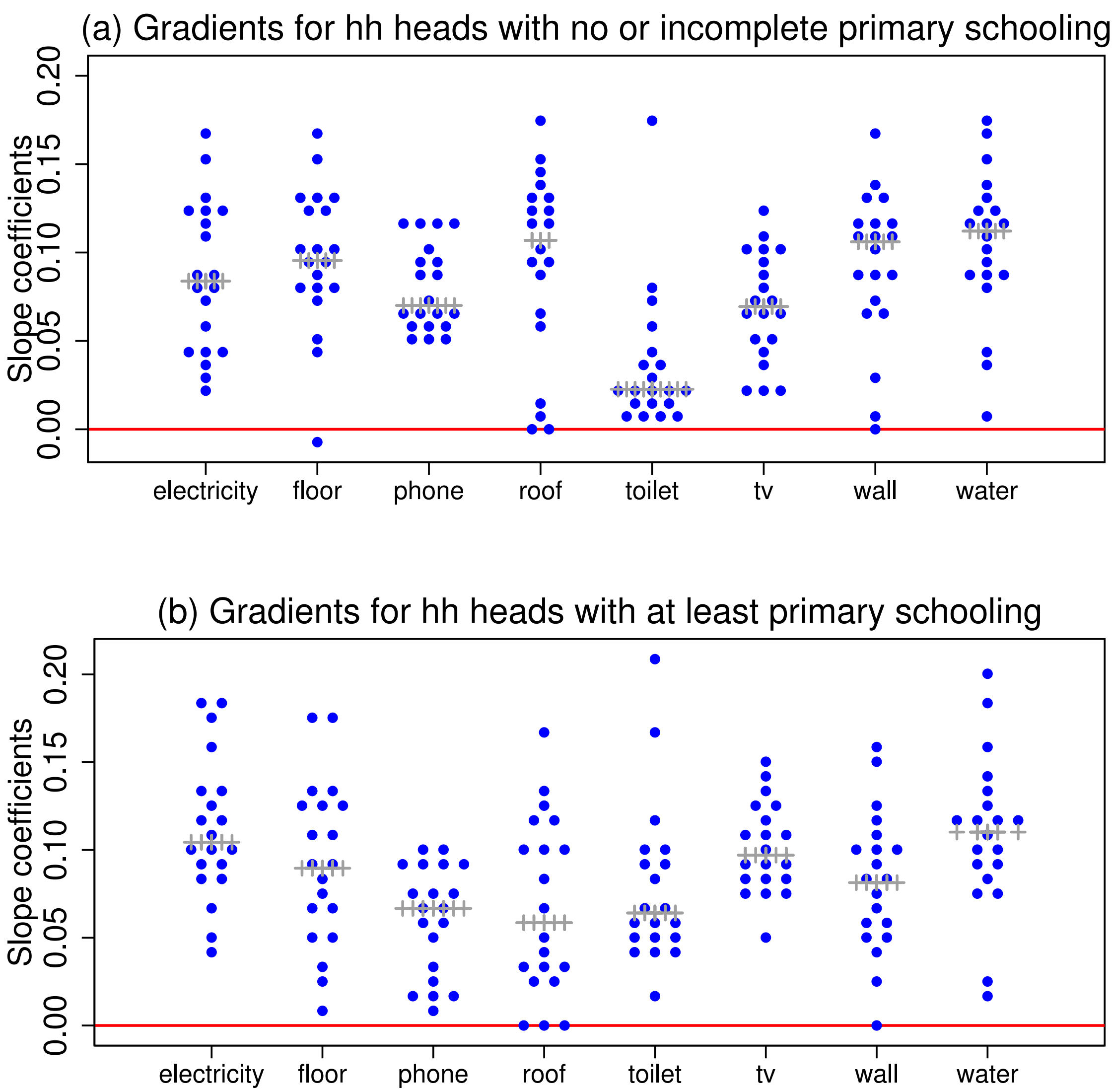


Figure 9: Density Gradients by Education of Household Head



Note: Each dot in the Figure represents the coefficient estimate of a linear projection for household i in country c: $x_{ic} = \theta_0 + \theta_1 P_{ic} + \theta_2 E_{ic} + \theta_3 (P_{ic} * E_{ic}) + \epsilon_{ic}$ where x_{ic} is a measure of consumption, P_{ic} is the log of population density and E_{ic} is a dummy variable that is equal to one if the household head has completed primary education or more. Panel (a) shows the linear gradients for households with household heads who have less than complete primary education, and panel (b) shows gradients for households with household heads who have complete primary education or more. The y-axis indicates the size of the coefficient and the grey horizontal bars show the median slope coefficient.

Figure 10: Social Insurance and Anxiety

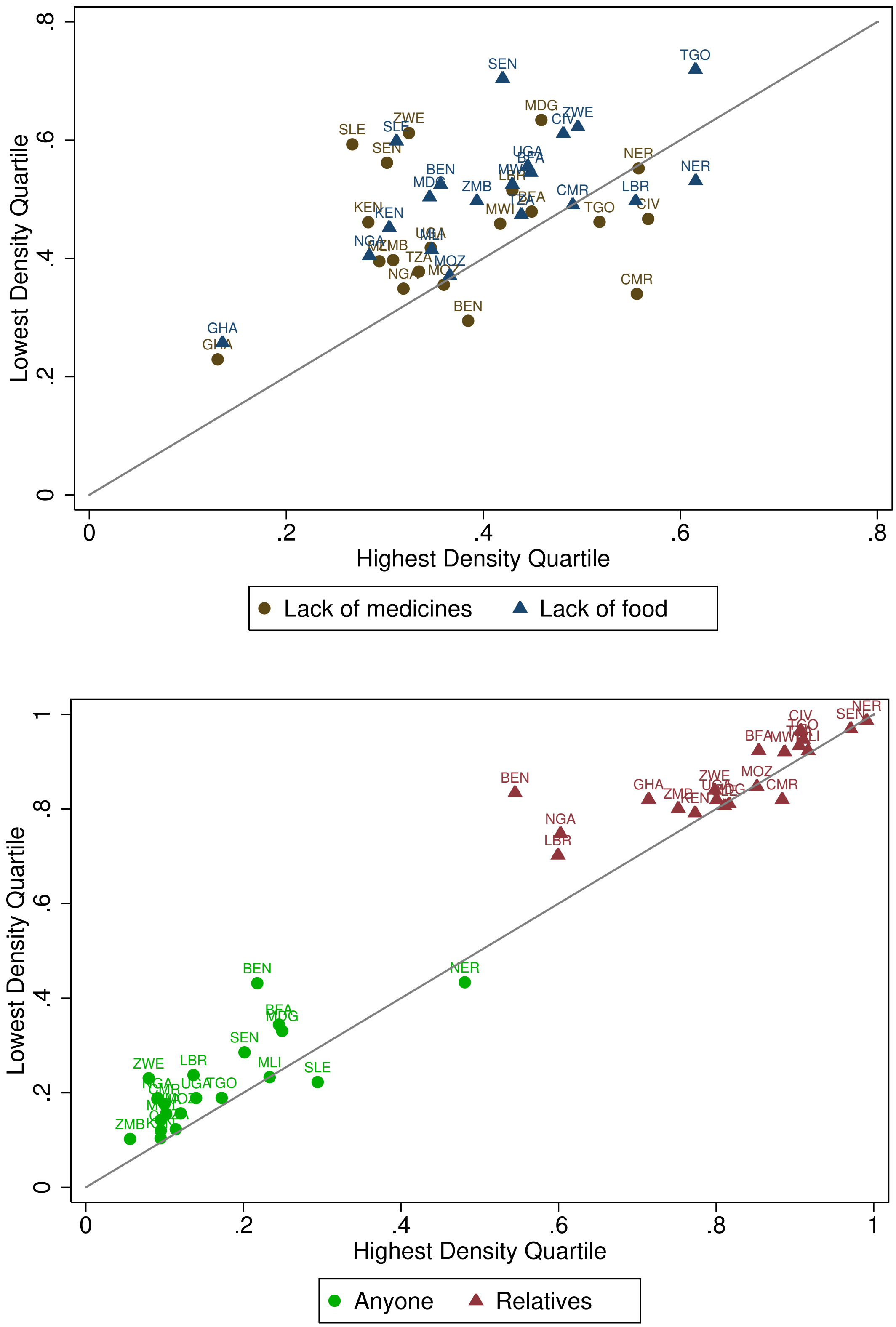


Table 1: Set of Countries Studied

Country	Households in Sample	Country Population
Benin	17,332	10,050,702
Burkina Faso	13,617	16,460,141
Cameroon	14,189	21,699,631
Dem. Republic of Congo	16,344	65,705,093
Ethiopia	16,037	91,728,849
Ghana	11,574	25,366,462
Ivory Coast	9,394	19,839,750
Kenya	9,033	43,178,141
Liberia	9,333	4,190,435
Madagascar	17,578	22,293,914
Malawi	24,210	15,906,483
Mali	10,105	14,853,572
Mozambique	13,899	25,203,395
Nigeria	38,170	168,800,000
Senegal	7,780	13,726,021
Sierra Leone	12,629	5,978,727
Tanzania	9,282	47,783,107
Uganda	8,939	36,345,860
Zambia	7,164	14,075,099
Zimbabwe	9,442	13,724,317
Total	276,051	769,082,846

Table 2: Durables Ownership Differences by Density Quartiles

	Differences From Q1			
	Q2	Q3	Q4	Std. Dev
Telephone	0.07	0.19	0.42	0.46
	9	15	20	
Television	0.04	0.17	0.47	0.41
	5	16	20	
Automobile	0.01	0.02	0.08	0.18
	4	8	19	
Motorcycle	0.00	0.00	0.01	0.26
	6	8	11	

Note: The first three columns report the average differences from the second, third and fourth density quartiles relative to the first (least dense) quartile across our set of 20 countries. The fourth column reports the average standard deviation across regions across our set of 20 countries. Numbers below the average differences are the number of countries with a difference that is statistically significant at the one-percent level.

Table 3: Child Health Differences by Density

	Differences From Q1			
	Q2	Q3	Q4	Regional Std. Dev
Anemic	-0.01	-0.06	-0.09	0.45
	0†	3†	7†	
Stunted (low height for age)	0.00	-0.02	-0.11	0.48
	0	4	11	
Wasted (low height for weight)	0.00	-0.01	-0.02	0.28
	1	4	7	
Below minimum diet	-0.02	-0.03	-0.06	0.28
	1	2	5	

Note: The first three columns report the average differences from the second, third and fourth density quartiles relative to the first (least dense) quartile across our set of 20 countries. The fourth column reports the average standard deviation across regions across our set of 20 countries. Numbers below the average differences are the number of countries with a difference that is statistically significant at the one-percent level.

† We do not have data on anemia for Kenya, Liberia, Nigeria and Zambia, so the total number of countries for this variable is 16.

Table 4: Housing Quality Differences by Density Quartile

	Differences From Q1			
	Q2	Q3	Q4	Std. Dev
Electricity	0.04	0.20	0.52	0.41
	4	14	20	
Tap water	0.04	0.21	0.52	0.43
	2	11	20	
Constructed floor	0.05	0.19	0.49	0.45
	6	12	19	
Flush toilet	0.02	0.09	0.29	0.29
	3	10	19	
Water collection (min)	-5.03	-8.67	-17.12	33.11
	4	6	17	
Finished roof	0.09	0.25	0.46	0.43
	$9^{\dagger}$	$13^{\dagger}$	$17^{\dagger}$	
Finished walls	0.08	0.19	0.48	0.45
	$6^{\dagger}$	$14^{\dagger}$	$18^{\dagger}$	

Note: The first three columns report the average differences from the second, third and fourth density quartiles relative to the first (least dense) quartile across our set of 20 countries. The fourth column reports the average standard deviation across regions across our set of 20 countries. Numbers below the average differences are the number of countries with a difference that is statistically significant at the one-percent level.
† The Tanzania and Uganda DHS does not contain information on the roof and walls of a dwelling so the total number of countries for these two variables is 18.

Table 5: Crime by Density Quartile

	Population Density Quartile			
	Q1	Q2	Q3	Q4
Property crime	0.29	0.31	0.31	0.33
		3	1	4
Violent crime	0.10	0.09	0.10	0.12
		1	0	4
Fear of crime	0.32	0.33	0.34	0.36
		1	2	4
Feel unsafe	0.37	0.39	0.38	0.45
		2	1	3

Note: This table reports the average fraction of respondents reporting property crime, violent crime, fear of crime in one's home, and feeling unsafe in one's neighborhood. Numbers below the averages in each row are the number of countries with a difference from the least dense quartile (Q1) that is statistically significant at the one-percent level.

Table 6: Pollution Differences by Density Quartile

	Differences From Q1			
	Q2	Q3	Q4	Std. Dev
Nitrogen Dioxide	0.006	-0.007	0.002	0.085
	11	13	12	
PM2.5	-0.57	-1.30	-1.09	6.63
	10	11	11	
Cook inside with solid fuel	0.01	-0.06	-0.25	0.47
	4†	8†	16†	

Note: The first three columns report the average differences from the second, third and fourth density quartiles relative to the first (least dense) quartile across our set of 20 countries. The fourth column reports the average standard deviation across regions across our set of 20 countries. Numbers below the average differences are the number of countries with a difference that is statistically significant at the one-percent level.
† The Tanzania DHS does not contain information on the type of cooking fuel and indoor cooking so the total number of countries for this variable is 19.

Table 7: Rural-Urban and Urban-Rural Migrants as Percent of Adults

	Rural-to-Urban	Urban-to-Rural	Difference
	Percent of Adults		
Dem. Republic of the Congo (2007)	2.39	0.47	1.92
Ethiopia (2005)	3.08	0.15	2.93
Ghana (2008)	4.82	1.18	3.64
Kenya (2008-2009)	7.60	0.58	7.02
Liberia (2007)	2.46	2.24	0.23
Madagascar (2008-2009)	4.16	0.19	3.97
Malawi (2010)	7.23	0.45	6.77
Mali (2006)	4.46	0.66	3.80
Nigeria (2008)	4.83	0.37	4.46
Senegal (2005)	2.75	0.92	1.83
SierraLeone (2008)	4.44	0.36	4.08
Zambia (2007)	4.00	0.56	3.44

Note: The first column lists the country and year of survey. The first two data columns report the percent of adults that are rural-to-urban migrants and urban-to-rural migrants, respectively, in the last five years. The third data column reports the simple difference.

Table 8: Durables and Housing Quality Differences by Density Quartile in Migration Destinations

	Differences From Q1				
	Q2	Q3	Q4	Q4	Q4
	whole sample	whole sample	whole sample	>25% migrants	>40% migrants
Telephone	0.04	0.12	0.46	0.52	0.55
	4	7	12	12	12
Television	0.03	0.10	0.40	0.44	0.47
	3	7	12	12	12
Automobile	0.00	0.02	0.08	0.08	0.09
	1	3	12	11	9
Motorcycle	0.00	0.00	0.01	0.02	0.02
	3	4	6	5	4
Electricity	0.04	0.12	0.45	0.52	0.54
	2	4	12	11	12
Tap Water	0.03	0.12	0.48	0.55	0.59
	1	5	12	12	12
Constructed Floor	0.07	0.15	0.49	0.55	0.62
	4	7	11	11	11
Flush Toilet	0.02	0.08	0.27	0.28	0.32
	2	4	12	11	10

Note: The first three columns report the average differences from the second, third and fourth density quartiles relative to the first (least dense) quartile across the 12 countries for which we have migration data. The fourth (fifth) column reports differences between the densest quartile and the least dense quartile for locations in which at leat 25% (40%) of individuals report to have resided there for 5 years or less. Numbers below the average differences are the number of countries with a difference that is statistically significant at the one-percent level.

Table 9: Secondary Amenity Differences by Density Quartile

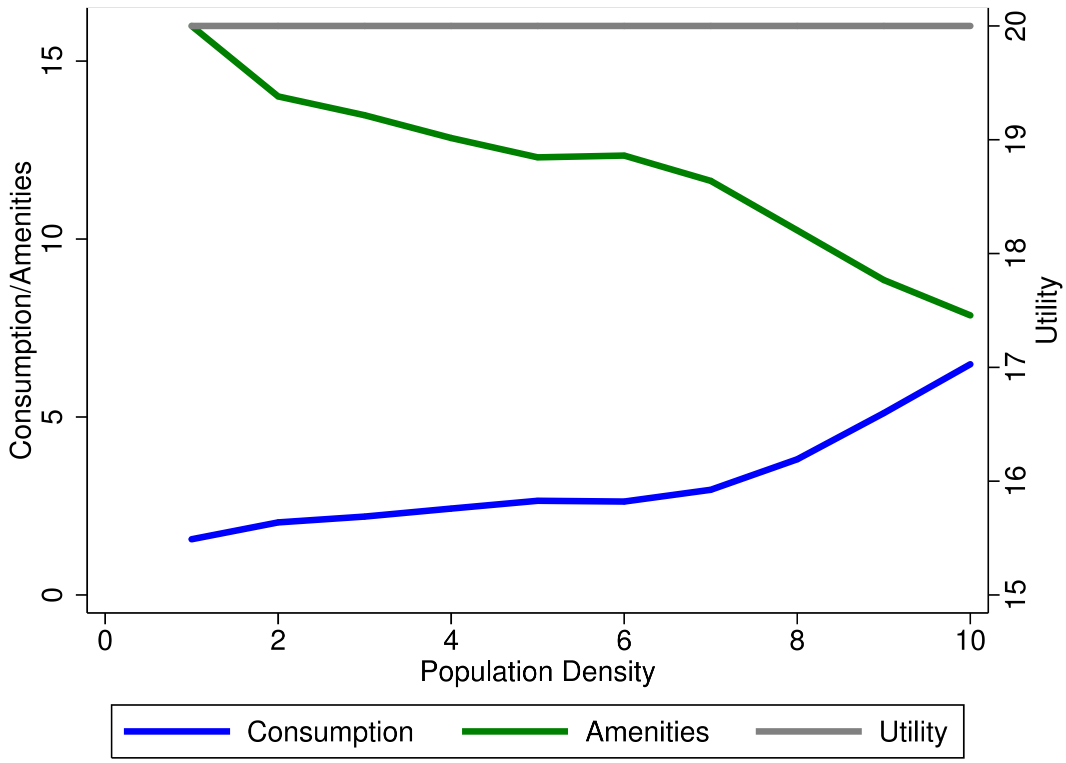
	Differences From Q1			
	Q2	Q3	Q4	Std. Dev
Lack of food	0.03	-0.01	-0.08	0.49
	2	3	12	
Lack of medicine	0.00	-0.04	-0.12	0.49
	1	1	11	
Anxiety	0.01	0.00	-0.05	0.46
	1†	3†	3†	
Trust anyone	0.01	0.00	-0.08	0.39
	1	3	7	
Trust relatives	-0.02	-0.04	-0.06	0.34
	3	3	5	
Trust neighbor	-0.02	-0.07	-0.15	0.46
	2	5	9	
Trust own ethnic group	-0.01	-0.07	-0.12	0.47
	0†	2†	5†	

Note: The first three columns report the average differences from the second, third and fourth density quartiles relative to the first (least dense) quartile across our set of 20 countries. The fourth column reports the average standard deviation across regions across our set of 20 countries. Numbers below the average differences are the number of countries with a difference that is statistically significant at the one-percent level.

† Data on anxiety and trust towards one's own ethnic group is not available for Burkina Faso, Cameroon, Cote d'Ivoire, Liberia, Niger, Sierra Leone and Togo; Zimbabwe also does not record information on trust towards one's own ethnic group. The total number of countries for anxiety and trust towards one's own ethnic group is therefore 13 and 12, respectively.

Appendix

Figure A.1: Consumption and Amenity Gradients in a Spatial Equilibrium



Notes: The figure illustrates the relationship between consumption, amenities, and utility as predicted in a standard spatial equilibrium, described in Section 2, using $\bar{U} = 20$, $\alpha = 0.5$, and $h = 1$. Consumption c is proxied with an asset and housing quality index, taking an average across 20 African countries.

A. DHS data

1.1. DHS sample

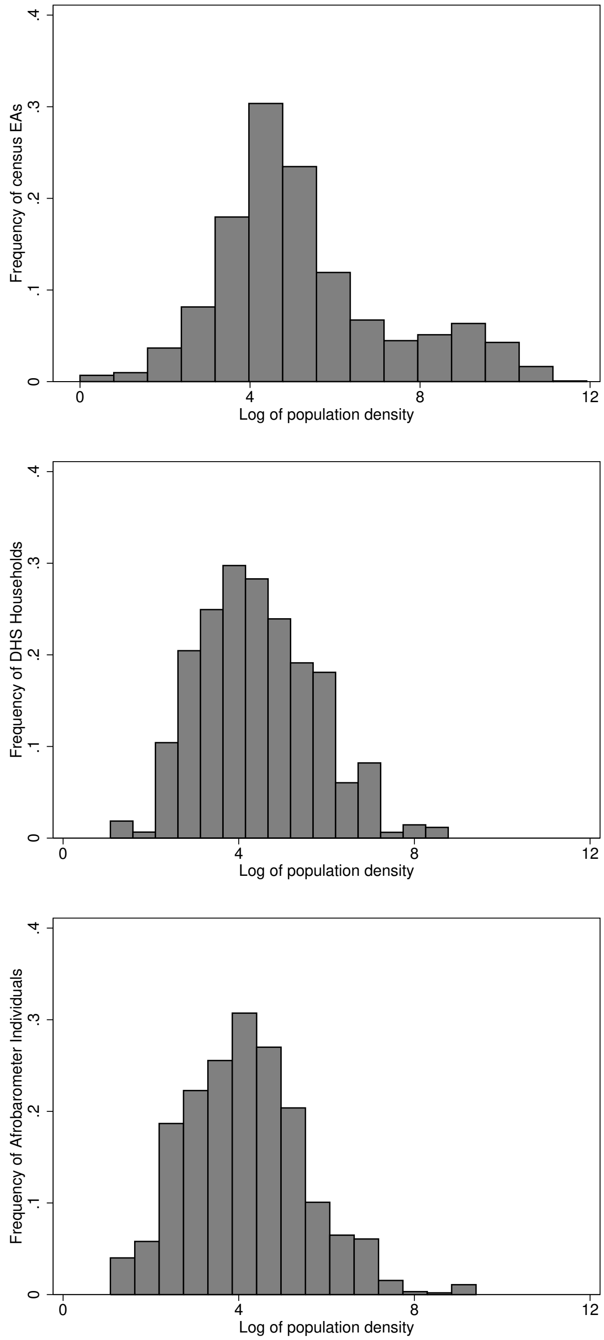
While the DHS aim to make survey instruments and samples comparable across countries, the exact sampling differs according to the particular survey.[18] The target population of most DHS surveys are women aged 15-49 and children under the age of five living in residential households with the most common sampling following a two-stage cluster sampling procedure (DHS, 2013). If a recent census is available, the sampling frame of the census is used to define primary sampling units which are usually enumeration areas. Alternative sample frames include lists of electoral zones, estimated structures per pixel derived from high-resolution

[18]For further information see: http://www.dhsprogram.com.

satellite imagery or lists of administrative units. Clusters will then be stratified depending on the number of domains that are desired for the particular survey, where a typical stratification is first at the geographical level and then at rural/urban clusters. In the first stage, from each of the strata a random sample of enumeration areas is selected inversely proportional to size. Unless a reliable listing of households exists, households will be listed for each of the selected primary sampling units. In the second stage, households are selected with equal probability.

If the sampling frame is not specifically selected to match the population along the lines of population density, it is likely that the distribution of the survey sample according to population density might not match that of the entire population. In practice, the cases we have examined show very little effort to oversample or undersample with respect to population density. For Tanzania we can compare the population density distribution of the Afrobarometer and DHS clusters with those of the overall population from the census data where we weight the population density of enumeration areas by the population. As is evident from Figure A.2, both the Afrobarometer survey as well as the DHS appear to capture a sample that covers a wide range of population densities.

Figure A.2: Distribution of population, DHS and Afrobarometer respondents in Tanzania



Notes: The top figure shows the distribution of the population using the 2002 enumeration area census data and the total population in each enumeration area as sample weights. The middle graph shows the distribution of population densities from the DHS data. The bottom graph shows distribution of clusters from Afrobarometer data. For expositional simplicity the top graph excludes 112 enumeration areas that have a log of population density above 12.

Table A.1: Surveys

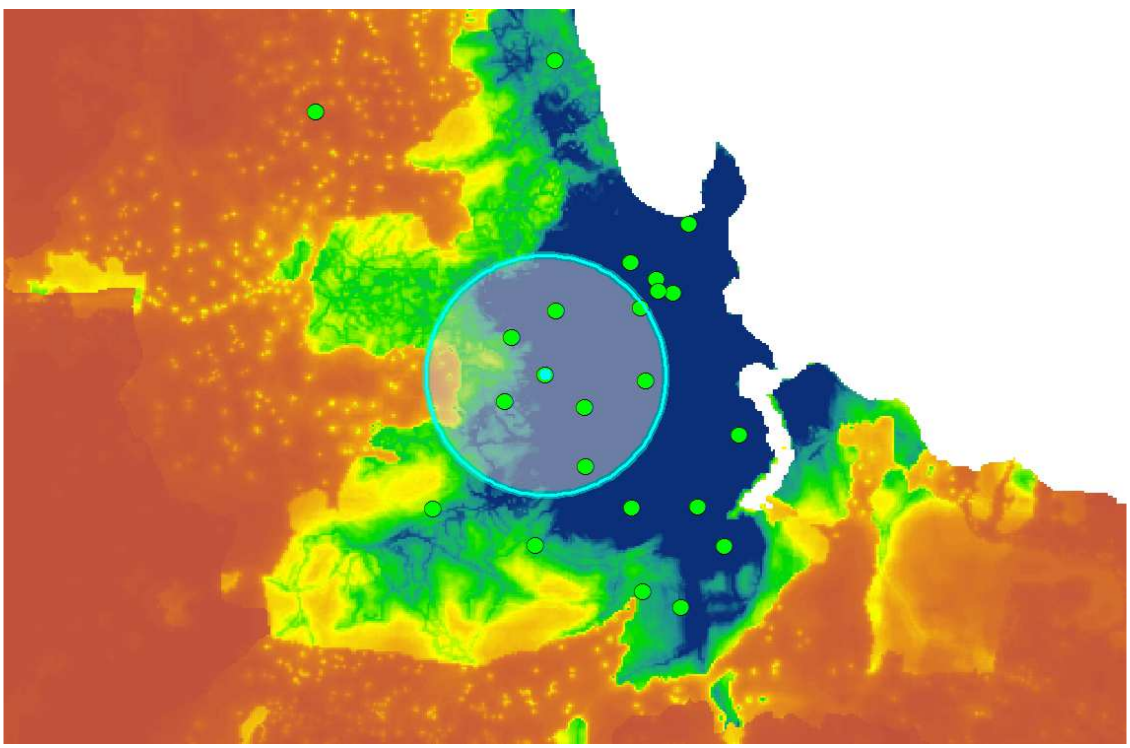
	Household	Malaria	Migration	Crime (Afrobarometer)	Crime (LSMS)
Benin	Benin 2011-12 Standard DHS	Benin 2011-12 Standard DHS		x	
BurkinaFaso	Burkina Faso 2010 Standard DHS	Burkina Faso 2010 Standard DHS			
Cameroon	Cameroon 2011 Standard DHS	Cameroon 2011 Standard DHS			
DRC	Congo Democratic Republic 2013-14 Standard DHS	Congo Democratic Republic 2013-14 Standard DHS	Congo Democratic Republic 2007 Standard DHS		
Ethiopia	Ethiopia 2011 Standard DHS	Ethiopia 2011 Standard DHS	Ethiopia 2005 Standard DHS		2013/14 Ethiopian Socioeconomic Survey
Ghana	Ghana 2008 Standard DHS		Ghana 2008 Standard DHS	x	
IvoryCoast	Cote d'Ivoire 2011-12 Standard DHS	Cote d'Ivoire 2011-12 (14) Standard DHS			
Kenya	Kenya 2008-09 Standard DHS		Kenya 2008-09 Standard DHS	x	
Liberia	Liberia 2013 Standard DHS	Liberia 2011 MIS	Liberia 2007 Standard DHS		
Madagascar	Madagascar 2008-09 Standard DHS	Madagascar 2013 MIS DHS-VI	Madagascar 2008-09 Standard DHS	x	
Malawi	Malawi 2010 Standard DHS	Malawi 2012 MIS	Malawi 2010 Standard DHS	x	LSMS 2004/05
Mali	Mali 2012-13 Standard DHS	Mali 2012-13 Standard DHS	Mali 2006 Standard DHS	x	
Mozambique	Mozambique 2011 Standard DHS	Mozambique 2011 Standard DHS		x	
Nigeria	Nigeria 2013 Standard DHS	Nigeria 2010 MIS	Nigeria 2008 Standard DHS	x	NGHS, Panel Wave 2, 2012-2013; Post-harvest household questionnaire
Senegal	Senegal 2010-11 Standard DHS	Senegal 2010-11 Standard DHS	Senegal 2005 Standard DHS	x	
SierraLeone	Sierra Leone 2013 Standard DHS		Sierra Leone 2008 Standard DHS		
Tanzania	Tanzania 2010 Standard DHS	Tanzania 2011-12 Standard AIS		x	Tanzania NPS 2008
Uganda	Uganda 2011 Standard DHS	Uganda 2009 MIS		x	Uganda NPS 2009/10
Zambia	Zambia 2007 Standard DHS		Zambia 2007 Standard DHS	x	
Zimbabwe	Zimbabwe 2010-11 Standard DHS				

1.2. Linking DHS data with population density data

To link the DHS data with population density we draw a buffer of 5km around each cluster and extract the average population density around each cluster. We perform these calculations in WGS1984, since the different areas of the pixel sizes when moving away from the equator has been taken into account when constructing the population density grid, which is defined as the population count divided by the area. Many urban DHS clusters are in proximity closer than 5 km so that buffer polygons around clusters are overlapping. We therefore compute our zonal statistics using the Spatial Analyst Supplemental Tools in ArcGIS, a supplemental toolbox that allows computing zonal statistics for overlapping polygons. All computations were performed in ArcGIS 10.4.

1.3. Spatial linking of DHS

Figure A.3: DHS clusters in Dar Es Salaam



Notes: Figure shows a 5km circle around a DHS cluster in Dar Es Salaam; the gridded data come from WorldPop.

1.4. DHS Variables

The main variables to measure durables are whether the household has a television (hv208=1), mobile or landline (hv221=1 or hv243a=1). For housing consumption, we examine whether

the household has electricity (hv206=1), tapped water (hv201<21), a constructed floor (hv213>13), a flush toilet (hv205<20), finished walls (hv214>=30) and a finished roof (hv215>=30). For the highest level of education completed by the household head we use variable hv109. Indoor cooking is determined using variables hv226 and hv241. Variable hv204 captures the time required to fetch water.

World Health Organization (2015) which defines a minimum acceptable diet as follows:

"The composite indicator of a minimum acceptable diet is calculated from: (i) the proportion of breastfed children aged 6-23 months who had at least the minimum dietary diversity and the minimum meal frequency during the previous day and (ii) the proportion of non-breastfed children aged 6-23 months who received at least two milk feedings and had at least the minimum dietary diversity not including milk feeds and the minimum meal frequency during the previous day.

Dietary diversity is present when the diet contained four or more of the following food groups:

- grains, roots and tubers;
- legumes and nuts;
- dairy products (milk, yogurt, cheese);
- flesh foods (meat, fish, poultry, liver or other organs);
- eggs;
- vitamin A-rich fruits and vegetables; and
- other fruits and vegetables.

The minimum daily meal frequency is defined as:

- twice for breastfed infants aged 6-8 months;
- three times for breastfed children aged 9-23 months;
- four times for non-breastfed children aged 6-23 months."

To compute a child's minimum dietary diversity from the DHS we use data on breastfeeding (m4), age of the child (hw1), number of times the child ate (m39), the type of food groups the child consumed (v414a-v414j), consumption of powdered/tinned/fresh milk and infant

formula (469e and 469f). If the survey is from Phase 5 there is no information on milk feedings for children who are not breastfed anymore; in this case we only calculate the minimum acceptable diet for children who are breastfed.

Migration status is determined using the years lived in the current location (v104) and type of place of previous residence which is classified into capital, large city; city; town; countryside; and abroad (v105). Following Young (2014), we exclude individuals who lived abroad, and check that all variables are coded consistently across countries; for example, abroad is sometimes coded as 4 and sometimes as 5.

Our data for malaria incidence comes from a combination of DHS, MIS and AIS. In a subset of countries, blood samples were collected for children aged 6-59 months as part of the DHS data collection in households that were selected for the men's questionnaire (every 1 out of 8 households). If the data is not available as part of the DHS, we use data from the most recent geo-referenced AIS survey or MIS survey during which blood samples from children aged 0-59 or 6-59 months were taken depending on the specific survey. Table A.1 shows the exact survey used for each country. Malaria tests were administered via rapid diagnostic testing and blood smear microscopy. [19] We construct a dummy variable that is equal to one if the malaria rapid test for a child was positive (hml25).

B. Afrobarometer

2.1. Geo-locating Afrobarometer respondents

Afrobarometer surveys collect data on attitudes towards democracy and governance, as well as a range of other measures of the quality of life.[20] The Afrobarometer surveys do not coordinates of respondents, but record the village, district and region names. The 2011 round provides four different administrative names. We use a matching algorithm that matches village names and other provided administrative names to locations as listed in gazetteers; specifically, we follow Nunn and Wantchekon (2011) and use the geonames gazeteer available on www.geonames.com. This website provides a list of locations where each location is assigned an id along with several names: the geographical name of the point in utf8 and plain ascii characters; alternative names, the associated latitude and longitude coordinate. There is also auxiliary information such as the modification date of each entry, administrative codes, elevation, and feature classes. If a name is associated with several entries we keep the most recent entry.

[19]Note that in Madagascar areas without malaria have been excluded from the survey.
[20]For further information see http://www.afrobarometer.org.

Our matching algorithm uses a mixture of exact matches and fuzzy matches in multiple stages (depending on the survey round, between thirteen and twenty-one). Whenever a location name is identified, we assign it the latitude and longitude and remove it from the dataset that is fed into the next stage. In essence, matching is achieved in the following way: first, we perform a series of exact matches based on the village name from Afrobarometer with the asciiname listed in the gazetteer; if there are no exact matches with the village name and the asciiname, we search through the next four alternative names listed in the gazeteer for the specific location. In this first stage we find almost forty percent of locations. We then use the most precise administrative classification. For example, if the data set has information on the village name, district and region, this would be the district. We perform the exact same series of matches on the district name, using again the asciiname as well as four possible alternative names listed in the gazetteer. In rounds three and four of the survey in which we have only district and region names in addition to the village names, this step finds 49–52 percent of the locations.

Third, we match on the region name which finds another 4–6 percent of the sample. Finally, to catch any remaining misspellings we perform a fuzzy match based on similar text patterns between the village name and the asciiname using a command developed by Raffo (2015). We use a similarity score of above 0.70 and a vectorial decomposition algorithm (3-gram). This finds another 1–3 percent of locations. In total, we are able to match between 92 and 95 percent of individuals in each round.

In addition to random checks of the identified locations we use the 2005 data to check the consistency between our algorithm and Nunn and Wantchekon (2011)'s location data. For the subset of locations for which they provide geo-locations, we find that the median distance between their location and my location is 12.46 km. Further, considering the population density data vary largely at the district and region level, we expect the difference to be even smaller when looking at the resulting population densities. Indeed, the correlation coefficient between the population density from their and our data is 0.65 with a p-value of 0.000.

We use variables related to feeling unsafe walking in neighborhood (q9a), fear of crime in own home (q9b), theft (q9b), physical attack (q9c); trust in general (q83), towards relatives (q84a) and towards neighbors (q84b), own ethnic group (q84c); frequency of lack of food (q8a) and medicine (q8c); and anxiety (q96b).

C. Pollution data

Our pollution data for PM2.5 and NO2 concentrations come from van Donkelaar, Martin, Brauer, and Boys (2015) and Geddes, Martin, Boys, and van Donkelaar (2016), respectively. As the date for the Gridded Population of the World v4 (GPWv4) data is approximately 2010, we take the pollution measures that are closest in time: the tri-annual mean (2009-2011) both for PM2.5 series; for NO2 we have the exact year 2010. The estimated PM2.5 and NO2 concentrations are available at a resolution of 0.1 decimal degrees (about 10km at the equator). We construct a fishnet of the same resolution and for each pixel compute the average pollution measure as well as the average population density from the GPWv4. PM2.5 is measured in $\mu g/m^3$ while NO2 is measured in ppb (parts per billion). Following Vrijheid, Martinez, Manzanares, Dadvand, Schembari, Rankin, and Nieuwenhuijsen (2011), we use a conversion of 1ppb= 1.88 f $\mu g/m^3$ which assumes ambient pressure of 1 atmosphere and a temperature of 25 degrees celsius.

Figure A.4 illustrates this procedure and shows the distributions of pollutants and population density across space in Nigeria. The top left graph shows the distribution of population density, the top right graph shows the NO2 distribution, and the two bottom graphs show PM2.5, where the graph on the right removes sea salt and dust. Warmer colors denote higher values, and the bins are formed by dividing the data into deciles. Population density in the North is highest around Kano; in the center around Abuja; in the South West close to Lagos and Ibadan; and in the South East between Benin City, Port Hartcourt and Enugu.

Moving to the pollution measures, several observations are worth highlighting: first, at least visually, population density does not appear to be strongly correlated with either of the pollution measures. Nitrogen dioxide levels are very low, with a maximum of 0.7 ppb (1.316 $\mu g/m^3$), far below the WHO recommended thresholds of 40 $\mu g/m^3$. Values are higher over Lagos, Ibadan, Abuja, Kanduna and Kano, but not over cities in the South East in the Delta, and there are high levels in the center towards the West of the country where few people live. PM2.5 levels appear to be mainly driven by dust of the Sahara when inspecting the bottom left graph. Removing sea salt and dust produces quite a different distribution, with higher levels in the center, and over some cities.

The Nigerian example illustrates further that looking separately at these two indicators for pollution is instructive.[21] The pairwise correlation between PM2.5 and NO2 is -0.0085 with a p-value of 0.4633. Across our whole set of African countries, the correlation of these two

[21] This is in line with what Geddes, Martin, Boys, and van Donkelaar (2016) find when they inspect population weighted average PM2.5 and NO2 levels and trends.

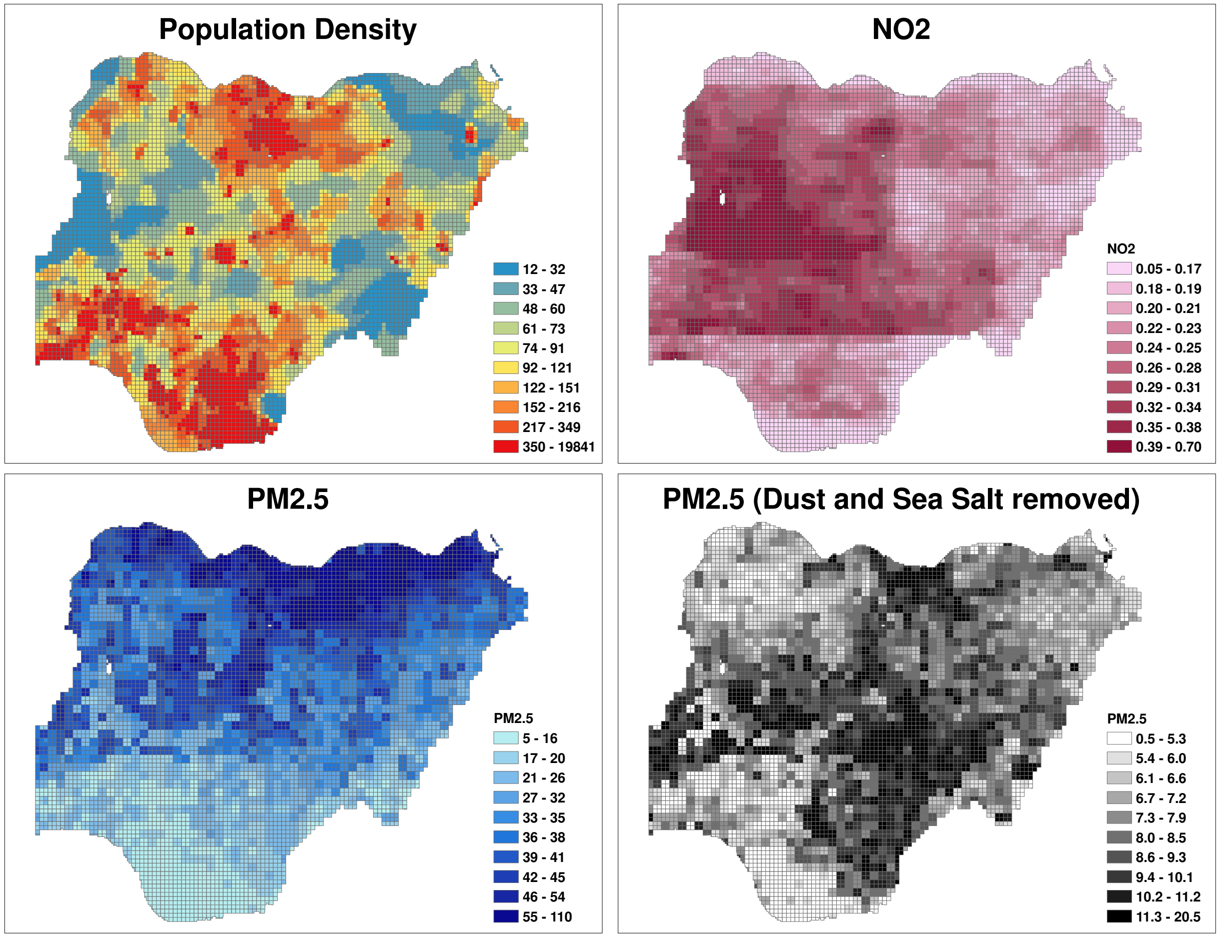
measures ranges from 0.65 (Cameroon) to -0.47 (Senegal).

Table A.2: Afrobarometer Sample

	Individuals	Round 3	Round 4	Round 5
Benin	3,543	x	x	x
Burkina Faso	2,255		x	x
Cameroon	1,072			x
Cote D'Ivoire	1,192			x
Ghana	4,089	x	x	x
Kenya	4,659	x	x	x
Liberia	2,282		x	x
Madagascar	3,881	x	x	x
Malawi	4,784	x	x	x
Mali	3,663	x	x	x
Mozambique	4,744	x	x	x
Niger	1,199			x
Nigeria	6,961	x	x	x
Senegal	3,596	x	x	x
Sierra Leone	1,190			x
Tanzania	4,791	x	x	x
Togo	1,056			x
Uganda	7,191	x	x	x
Zambia	3,590	x	x	x
Zimbabwe	4,344	x	x	x

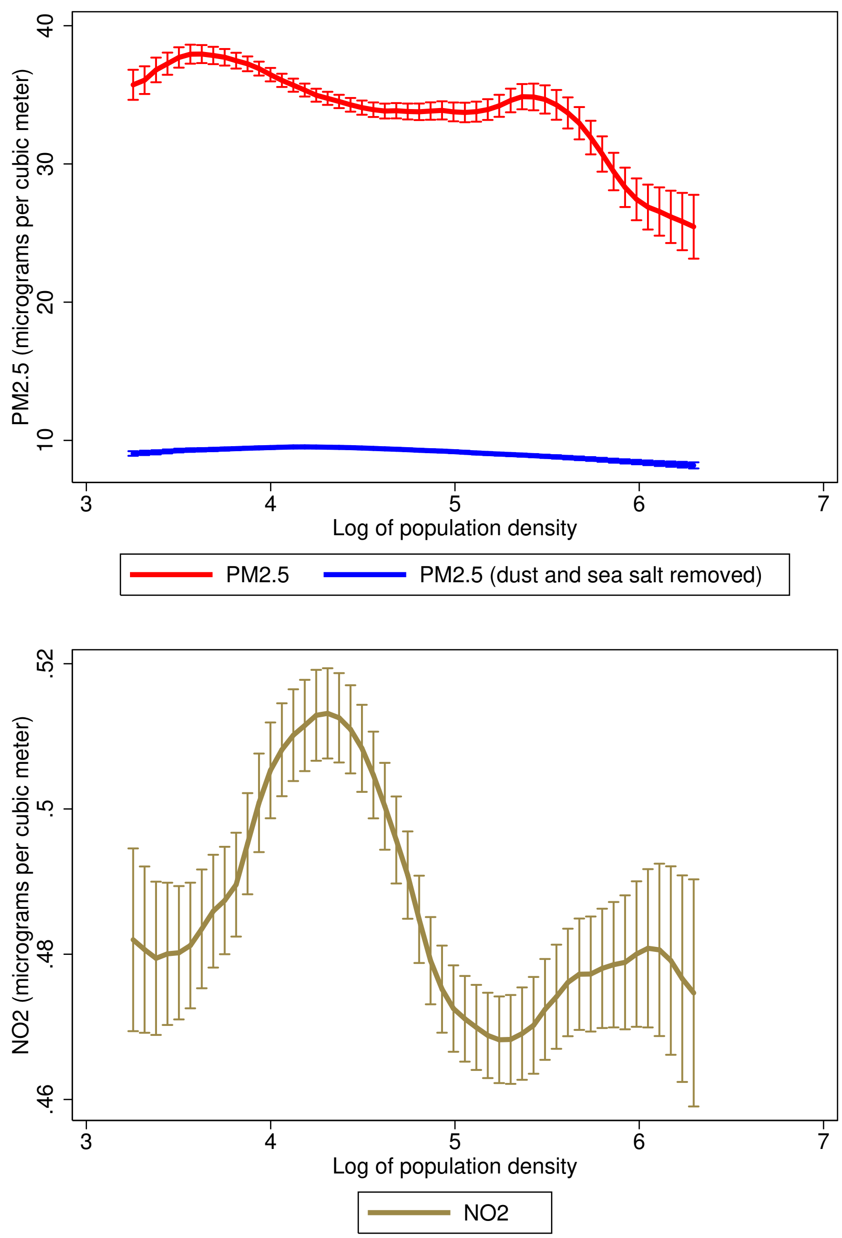
Note: Column (2) shows the number of individuals in my sample for each of the countries; columns (3)–(5) indicate when a country was added to the Afrobarometer sample. Round 3 took place in 2005, Round 4 in 2008, and Round 5 in 2011.

Figure A.4: Pollution in Nigeria



Notes: The top left graph shows the distribution of population density, the top right graph shows the NO2 distribution, and the two bottom graphs show PM2.5, where the graph on the right removes sea salt and dust. Warmer (darker) colors denote higher values, and the bins are formed by dividing the data into deciles. Population density in the North is highest around Kano; in the center around Abuja; in the South West close to Lagos and Ibadan; and in the South East between Benin City, Port Hartcourt and Enugu. At least visually, population density does not appear to be strongly correlated with either of the pollution measures. Nitrogen dioxide levels are very low, with a maximum of 0.7 ppb (1.316 $\mu g/m^3$), far below the WHO recommended thresholds of 40 $\mu g/m^3$. Values are higher over Lagos, Ibadan, Abuja, Kanduna and Kano, but not over cities in the South East in the Delta, and there are high levels in the center towards the West of the country where few people live. PM2.5 levels appear to be mainly driven by dust from the Sahara when inspecting the bottom left graph. Removing sea salt and dust produces quite a different distribution, with higher levels in the center, and over some cities.

Figure A.5: Pollution and population density in Nigeria



Notes: The figure shows a kernel-weighted local polynomial regression of the level of pollution on the log of population density in Nigeria using data from the entire country, and plotting 95 percent confidence intervals. The top panel shows the results for PM2.5 and the bottom panel shows NO2 levels across population density space. Taking the log of population density removes uninhabited pixels. I remove the top and bottom five percentile of the population density distribution.

Figure A.6: Crime - LSMS