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Abstract

It is obvious that holding city population constant, differences in cities across the world are enormous. Urban giants in poor countries are not large using measures such as land area, interior space or value of output. These differences are easily reconciled mathematically as population is the product of land area, structure space per unit land (i.e., heights), and population per unit interior space (i.e., crowding). The first two are far larger in the cities of developed countries while the latter is larger for the cities of developing countries. In order to study sources of diversity among cities with similar population, we construct a version of the standard urban model (SUM) that yields the prediction that the elasticity of city size with respect to income could be similar *within* both developing countries and developed countries. However, differences in income and urban technology can explain the physical differences *between* the cities of developed countries and developing countries. Second, using a variety of newly merged data sets, the predictions of the SUM for similarities and differences of cities in developed and developing countries are tested. The findings suggest that population is a sufficient statistic to characterize city differences among cities within the same country, not across countries.

JEL Codes: R13; R14; R31; R41; R42; O18; O2; O33

Keywords: Urbanization; Cities; Urban Giants; Population; Standard Urban Model; Measurement; Urban Technology; Building Heights; Sprawl; Housing; Transportation

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In the academic and policy literatures, population is often treated as a sufficient statistic to characterize the state of urbanization across countries. Cities are grouped and classified based on population. The standard measure of urbanization is the fraction of population residing in cities above a minimum population limit. One piece of evidence that could justify using city population to measure urbanization across countries was the historic association between city size or fraction urbanized and country income per capita. However, this relation weakened during the 20th century and recent papers cast doubt on the relation between urbanization based on city populations and economic development (Fay and Opal, 2000; Glaeser, 2014; Jedwab and Vollrath, 2015, 2018; Glaeser and Henderson, 2017; Henderson and Kriticos, 2018, e.g.).

Population may no longer be a sufficient statistic to characterize city sizes because, other than similar population, cities like New York, Beijing, Sao Paulo, Mexico, Mumbai, Cairo and Dhaka, which are all located in countries with different income and urban technology levels, appear to have little in common. As can be seen in Table 1, while these cities all have the same population (close to 19 million), Beijing, Sao Paulo, Mexico, Mumbai, Cairo and Dhaka are all much less developed economically, whether measured by GDP or satellite night lights, and have much less interior space, as measured by land area and building heights.

This raises several questions. First, how can we account for the increasing disconnect between the population and the economic and physical size of cities? Relatedly, how have cities in developing countries become "physically" able to accommodate such large populations? Second, does this mean that urbanization is no longer predictive of economic growth or that population is not a sufficient statistic to characterize urbanization? These questions are all the more important because cities represent a large share of overall economic activity. Therefore, to better understand long-run economic growth, there is an increasing need to open the black box of cities.[1]

A first purpose of this paper is to provide careful documentation of the similarities and differences between the old urban giants of high income countries and the new urban giants of similar population but located in low income countries. In the process of making these cross country comparisons, a variety of new data sources are assembled and merged to reveal new stylized facts about cross country variation in city characteristics. Using this data, we find that the elasticity of city size with respect of income per capita across countries is zero, but was positive

[1] Agriculture accounts for 3% of the world's GDP World Bank (2018). If two thirds of non-agricultural activities take place in cities, as shown for a large sample of countries by Gollin et al. (2015), potentially 65% of the world's GDP comes from cities. Likewise, McKinsey (2011a) estimate that just 600 cities generate 65% of the world's economic growth.

in the past. In other words, developing countries are now as likely as developed countries to have large agglomerations when population is the measure. However, urban giants in poor countries are not large cities using other measures, such as land area, interior square feet of space, or total value of output. These differences are easily reconciled mathematically as population is the product of land area, structure space per unit land, and population per unit interior space or "crowding". The first two are larger in the cities of rich countries while the latter is larger for the cities of poor countries. Interestingly, over time, rich country cities built up more whereas poor country cities densified much more, causing the latter to outgrow the former. Thus, cities in rich and poor countries have reached similar population sizes, but they did so in very different ways.

A second purpose is to determine if the standard urban model (SUM) can explain these similarities and differences. In the basic form of the SUM, city population size increases with the earnings opportunities relative to alternative locations as well as construction and transportation technologies. Additionally, for a given city, housing price, land rent, structure density, and population density are characterized by a series of negative exponential functions, which themselves depend on earnings and urban technology. We construct a modified version of the SUM, focusing on the theoretical relation among population, income, land area, structure density and population density, and other basic features of the city. We obtain central predictions for cities in high vs. low income countries. First, city population varies directly with land area and structure density and inversely with housing consumption per capita. Second, the elasticity of city size with respect to earnings can be similar across countries but the entire relation between the logarithms of earnings and city size is shifted downward as country income per capita rises. This means that population is a sufficient statistic to make comparisons among cities within a given country where there is a common urban technology but that population is not a significant indicator of other city characteristics across countries. These two predictions are borne out by the data.

Finally, the paper explores the circumstances under which population can be used as a sufficient statistic to characterize differences among cities in high and low income countries and the circumstances under which simple use of population to characterize the extent of urbanization could produce misleading results. Population is not a sufficient statistic to characterize urban characteristics across cities with different levels of technology and income per capita. However, within a country or among a group of countries where these are similar, then, to a first order of approximation, population is a sufficient statistic to account for other urban characteristics.

This paper makes several contributions. First, we add to the literature on the drivers of city

population sizes. A contribution of this paper is to assemble a large data set of economic and physical characteristics for the largest agglomerations in the world. This involved the assembly of various data sets because existing databases of cities lack information on GDP, land area or structures. Doing so allows us to open the black box of cities and study what they are made of: people, but also land, structures, units, and capital more generally. We document the disconnect between urbanization and economic development. However, we do not attempt to explain the disconnect.[2] Instead, our contribution is to document how this disconnect is *physically* possible. The fact is that many residents in the mega-cities of poor countries are willing to live in crowded housing units, which implies that either they do not value housing consumption much in their utility function or they choose to live in cities despite relatively low urban income levels.

By studying how land areas, structure heights, densities and crowding vary across cities and over time, we complement studies on city structure in developed countries (e.g. Glaeser and Kahn, 2004; Burchfield et al., 2006; Baum-Snow, 2007; Overman et al., 2008; Saiz, 2010; Barr, 2012, 2013; Duranton and Puga, 2015; Liu et al., 2018; Ahlfeldt and McMillen, 2018; Arribas-Bel et al., 2019) and developing countries (e.g. Deng et al., 2008; Brueckner and Selod, 2009; Brueckner, 2013; AUE, 2016; Harari, 2016; Henderson et al., 2016b; Baruah et al., 2017; Brueckner et al., 2017; Michaels et al., 2017; Gaduh and Civelli, 2018; Selod and Tobin, 2018; Brueckner et al., 2019). However, most studies focus on one country or city, and thus miss important differences across countries. Also, most studies only consider one component of city structure at a time.[3] Our analysis complements their analysis by giving a bigger picture of the patterns of sprawling, verticalization and crowding across the world.[4] Nonetheless, one limitation of our analysis is that it does not try to be causal. We focus on correlations and their potential implications for the analysis of cities.[5]

Second, the standard urban model initially developed by Alonso (1964), Mills (1967, 1972) and Muth (1969) and subsequently reviewed by Brueckner (1987) has become the most widely used model in urban economics. The SUM has mainly been used to characterize urban development in high income countries. However, Mills (1972) used it to explain urban transitions from the 19th through the 20th centuries, a period that began with low income per capita and simple construction and transportation technology and ended with current high income and modern

[2]Various explanations have been advanced, such as urban bias (Ades and Glaeser, 1995; Davis and Henderson, 2003), conflict (Fay and Opal, 2000; Maystadt and Duranton, 2014), natural disasters (Barrios et al., 2006; Henderson et al., 2016a), trade (Glaeser, 2014; Gollin et al., 2015), and demography (Jedwab et al., 2015; Jedwab and Vollrath, 2018).

[3]There are few studies on tall buildings. One contribution of this paper is to use novel data on building heights.

[4]To our knowledge, the only other study with such aim and such scope is Khan, Selod and Blankespoor (2019).

[5]For example, we do not believe that there is an instrument that would explain changes in per capita income for enough cities in the world without also affecting their structure, so land area, building heights, and overcrowding.

technology. In an attempt to test the implications of the SUM across countries and over time, Mills and Tan (1980) compare the evolution of population density gradients. Of course, this research has concentrated on differences in the population density gradient using data on population density and land area rather than other aspects of cities due to lack of data on these other characteristics. There are also notable examples of applications of the SUM to low income cities (Brueckner, 1990; Bertaud and Malpezzi, 2001; Bertraud and Malpezzi, 2001; Bertaud and Brueckner, 2005; Brueckner and Sridhar, 2012). We add to the literature by discussing its theoretical implications and testing some of its predictions for both poor countries and rich countries. In that, our study is related to others that empirically test the predictions of urban models for developing countries (Meijers et al., 2016; Chauvin et al., 2016; Quintero and Roberts, 2018).

Third, we contribute to a large literature using urbanization rates and city population sizes as proxies for national and local economic development in the absence of income or wage data: (i) Historical studies use such measures as outcomes to study the past effects of historical factors (e.g., DeLong and Shleifer, 1993; Acemoglu et al., 2005; Nunn and Qian, 2011); (ii) Development studies on countries notorious for their dearth of spatialized economic data use city population sizes as outcomes to study the effects of more recent factors (e.g., Jedwab and Moradi, 2016; Jedwab et al., 2017; Jedwab and Storeygard, 2017); (iii) Urban studies that compare the effects of policies across the world rely on city population sizes due to the absence of city income data in many regions of the world (e.g., Gonzalez-Navarro and Turner, 2018); and (iv) Many policy publications use a combination of urban population outcomes and possibly unreliable estimates of city GDPs to analyze global and regional urbanization trends (e.g., McKinsey, 2011b, 2012; Brookings, 2016, 2018). Likewise, international organizations such as the UN and the World Bank only collect data on urbanization rates, city population sizes urban infrastructure, and slum housing. Many variables are not defined at the city level, or do not capture economic development.

Our analysis confirms that population is a sufficient statistic to characterize economic differences among cities within the same country, but not across countries. This also suggests that urbanization rates, the relative size of cities in a country, may imperfectly measure economic development. In contrast, we find that a measure of economic development based on satellite night lights is strongly correlated with GDP when comparing the cities of different countries. This suggests that night lights is be a better measure of economic size than population.[6]

[6]We thus complement other works that have found that night lights constitute a good proxy for per capita incomes at the country level or at the local level (e.g. Henderson et al., 2011, 2012; Donaldson and Storeygard, 2016; Bruederle and Hodler, 2017). More generally, our analysis talks about the importance of urban data (Glaeser et al., 2015).

The paper is organized as follows. Section 1. presents a modified version of the SUM and discuss its implications for the relation between population and other general characteristics of cities, first within a same country, and then across countries. Section 2. presents the data used in the rest of the analysis. Section 3. decomposes for a sample of the largest agglomerations in the world total population into land, structures, and crowding. Section 4. investigates the relation between population and measures of economic development, both within and across countries.

1. Implications of the Standard Urban Model (SUM)

This section develops the implications of the standard urban model (SUM) for the relation between population and other general characteristics of cities in an attempt to determine the theoretical rationale for treating population as a sufficient statistic to describe the state of urbanization. First, a standard model of the theoretical relation among population, land area, structure density, and other basic features of the city is developed. Second, that structure is used to characterize the way in which these elements vary with total population among cities *within* a given country. Third, the analysis is extended to cities of the same size but located in countries that differ in income per capita and technology, i.e. cities in developed (d) and developing (g) countries.

1.1. Setting Up the Basic Model of an Individual City

Set-Up. Following a long tradition extending from Muth (1969) and Mills (1972) through the summary and review by Brueckner (1987), a monocentric city with homogenous households having one worker per household is housed around an employment center at a radius k, ranging from $[0, k^*]$. k^* is the edge of the city, and the territory beyond the edge is the alternative location. This subsection abstracts from the fact that there may be multiple cities of different sizes.

A fraction θ of the land area L is unavailable for housing due to factors including topography and land required for non-housing uses. Land available for housing is given by:

$$L = \int_0^{k^*} \theta k dk \text{ with } 0 < \theta < 1. \tag{1}$$

Households choose a location in a city based on earnings, y, the price of a composite commodity, p_c, and the rental price of housing at distance k, $r(k)$, so that their utility is identically equal to u^*, which is the utility associated with the location outside the city/countryside based on wages and house prices in that alternative location. Households located at distance k experience transportation costs which can include out-of-pocket or time costs (reductions in earnings) equal to tk. Housing suppliers rent to the highest bidder and hence maximize housing rent, subject to the iso-utility constraint imposed by u^*. This makes the landlord's pricing problem in a city:

$$\text{Max } r(k) = (y - tk - p_c c)/h(k) \text{ subject to } u^* - u(h(k), c(k)) = 0 \tag{2}$$

Where c is the composite commodity and h is housing space consumed per household. It is well known that the solution to this problem is Muth's equation (Muth, 1969):

$$dr(k)/dk = \Delta t/h(k) \tag{3}$$

or dividing both sides by $r(k)$:

$$[dr(k)/dk]/r(k) = d\,log\,r(k) = \Delta t/(r(k)h(k)) \tag{4}$$

Housing Price Gradient. Assume that the real income constant own price elasticity of demand for housing is equal to unity, $(r(k)h(k))$ = constant = v, where v is total expenditure on housing. In simpler terms, as the rent decreases with distance from the central business district (CBD), housing consumption increases proportionally, so that the homogenous workers spend a constant share of their equal income net of transportation cost on housing across all distances from the CBD. Following Brueckner (1982) and Kim and McDonald (n.d.), this is a necessary assumption to produce a negative exponential population density function.[7] Equation 4 implies a negative exponential *housing price gradient* in each city:

$$r(k) = r_o e^{-(t/v)k} \text{ or } ln\,r(k) = ln\,r_o - (t/v)k \text{ or } dr(k)/dk = -t/v \tag{5}$$

Equation 5 indicates that housing price is a negative exponential function with a decay rate equal to $-t/v$. Thus, housing prices decrease with distance from the CBD, and this gradient is flatter if housing expenditure v is higher or commuting costs t are lower. Workers want to consume more housing as income increases, so they are willing to live farther away, which flattens the gradient, even more so if commuting costs are low.

Housing, which should be interpreted as interior space used for housing, is produced using structure and land inputs according to a standard Cobb-Douglas production function:

$$H = AL^{\beta}S^{(1-\beta)} \tag{6}$$

where H is interior space produced, L is land input and S is structure inputs (i.e., non-land inputs). Structure inputs determine the height or density of housing space per unit land.[8] Structure inputs have the same price, p_s, everywhere as does the housing productivity parameter, A. β indicates the substitutability between land and building heights in the construction of housing space. A lower β suggests that land is less constraining in terms of housing production.

[7]See Zhao (2017) for a recent application of this approach including empirical validation for U.S. cities.

[8]Housing services are sometimes interpreted to include attributes of the unit such as appliances, air conditioning, etc., but for the purposes of this discussion, the focus is on basic space.

Land has a rental price of $R(k)$ which varies across locations within the city. Given that housing is produced by a perfectly competitive industry, the structure/land ratio is:

$$S/L = [(1-\beta)R(k)]/[\beta p_s] \tag{7}$$

Land Rent Gradient. The *land rent gradient* is based on the derived demand for land:

$$R(k) = [A\phi r(k)^{1/\beta}]/[p_s^{(1-\beta)/\beta}] \text{ or } ln\, R(k) = ln\, A\phi + (1/\beta) ln\, r(k) - [(1-\beta)/\beta] ln\, p_s \tag{8}$$

where $\phi = (1-\beta)^{(1-\beta)}\beta^{\beta}$ so that, as expected, land rent varies directly with the productivity of the housing sector reflected in A, and with housing price $r(k)$, while it varies inversely with the price of structure inputs, p_s. Differentiating equation 8 with respect to distance k, the nature of the land rent gradient is revealed to be:

$$dln\, R(k)/dk = (1/\beta) dln\, r(k)/dk = (1/\beta)(-t/v) = -t/(v\beta) \tag{9}$$

Equation 9 shows that land rent is a negative exponential function with a slope that is steeper than housing price (see equation 5) by a factor of $(1/\beta)$. In other words, land rents decrease with distance from the CBD, even more so than housing prices. Higher substitutability between land and structures, i.e. a lower β, implies a steeper land rent gradient.

Structure Density Gradient. The perfectly competitive housing industry takes $r(k)$ and $R(k)$ as given and supplies housing at a density of:

$$(H/L)(k) = A\phi r(k)^{[(1-\beta)/\beta]}/p_s^{(1-\beta)/\beta} \text{ or } ln(H/L)(k) = ln\,(A\phi) + [(1-\beta)/\beta] ln\, r(k) - (1-\beta)/\beta ln\, p_s \tag{10}$$

Equation 10 implies that structure density is an increasing function of productivity in construction, A, and housing rent $r(k)$ while it varies inversely with the price of structure inputs p_s and the effect of β is ambiguous, depending on the relative prices of structure and land inputs.

As is traditionally the case with the SUM discussed in Brueckner (1987), the model does not deal explicitly with the spatial distribution of land used for non-housing purposes including commercial activity. However, only a fraction of land at each radius is available for housing. This fraction is based on the parameter θ (see equation (1)). It follows from the logic of the model that the land market forces non-housing activity to compete for land at each distance based on the land rent function (see equation (8)) and hence that structure densities in non-housing will follow the same negative exponential characterizing housing as structure is substituted for land when land price rises. Indeed, space for commercial purposes is produced using a process that

is quite similar to residential space and it is not uncommon to find both activities in the same physical structure. For purposes of the SUM it is not necessary that all or even most employment be located in a CBD at the city center. It is simply necessary that employment is more spatially concentrated toward the CBD so that there is a premium on commuter access to the center.

Differentiating equation 10 with respect to distance gives the slope of the *housing density gradient*:

$$dln(H/L)/dk = [(1-\beta)/\beta]dr(k)/dk = [(1-\beta)/\beta](-t/v) = -t(1-\beta)/(v\beta) \tag{11}$$

Equation 11 makes it apparent that the slope of the housing density gradient is steeper than housing prices (see equation 5) but not as steep as the land rent gradient (see equation 9).

Population Density Gradient. Population density is simply the quotient of housing density from equation 10 and housing consumption per household. If the real income constant own price elasticity of housing demand is unity, housing consumption throughout the city is simply equal to housing expenditure divided by the housing price: $h(k) = v/r(k)$. Dividing both sides of equation 10 by this expression yields the *population density gradient* function:

$$D(k) = (H/L)(k)/h(k) = A\phi r(k)^{1/\beta}/(vp_s^{(1-\beta)/\beta}) \text{ or } lnD(k) = ln\,(A\phi)+(1/\beta)ln\,r(k)-ln\,v-(1-\beta)/\beta ln\,p_s \tag{12}$$

$$\text{and } dln\,D(k)/dk = (1/\beta)dln\,r(k)/dk = -t/(\beta v) \text{ or } D(k) = D_o e^{-(t/\beta v)k} \tag{13}$$

Combining this equation with the rest of the model results in an open version of the SUM where income is exogenous and, along with preferences and technology, determines the right hand side components of the density function. Accordingly, rising income determines city size along with preferences and technology. Note that the slope of the population density function is steeper than the housing density function (see equation 11). Indeed, $t/(\beta v) > t(1-\beta)/(\beta v)$. The intuitive reason for this is that housing space consumption rises with distance from the CBD because total expenditure is constant while price falls with distance. The slope of the population density function is identical to that of the land rent function (see equation 9). This is the artifact of assuming Cobb-Douglas housing production and real income constant own price elasticity of housing. If either of these assumptions are relaxed, the slope of the land rent function is steeper.

Taken together, equations 5, 9, 11 and 13 imply that for a given city, housing price, structure density, population density, and land rent are characterized by a series of negative exponential functions of increasingly steep slope. Figure 1 illustrates the relations among these variables that characterize the spatial pattern of land use within the city. The city limit at k^* is then determined by the point where the land rent function falls to the opportunity cost of land for other purposes,

commonly called the agricultural reservation price, R_A.

Total Population. Having established the nature of the population density function in terms of the model parameters, the next task is to generate the total population of the city, which also depends on central density and not just the gradient. Recalling that total land available for household residences is given by $L = \int_0^{k^*} \theta k dk$, it follows that household population in the city is the integral of land area times density in equation 12 or:

$$N = \int_0^{k^*} \theta D(k) dk = \int_0^{k^*} \theta D_o e^{-(t/\beta v)k} dk \tag{14}$$

Thus far, no assumptions regarding the shape of the city have been made. If city development is unrestricted, it will develop as a circle, and $\theta = 2\pi\times$ the fraction of land available for housing. It is convenient to let the absolute value of the population density gradient be equal to $\lambda = t/(\beta v)$. Then, the definite integral in equation 14 can be written as:

$$N = (\theta D_0/\lambda^2)[(-\lambda k^* e^{-\lambda k^*}) - (e^{-\lambda k^*}) + 1] \tag{15}$$

Consider that, for large cities, which is the focus of our empirical analysis, k^* is large and $e^{-\lambda k^*}$ approaches zero. This implies that total households can be written simply as:

$$N = \theta D_0/\lambda^2 = \theta D_0/(\lambda = t/(\beta v))^2 = \theta D_0 \beta^2 v^2\, t^2 \tag{16}$$

$$ln\, N = ln\, \theta + ln\, D_0 - 2ln\, \lambda = ln\, \theta + ln\, D_0 - 2ln\, (t/(\beta v)) \tag{17}$$

The message of equation 17 should not be a surprise. The elasticity of population with respect to central density is $dlnN/dlnD_0 = 1$, as a given percentage rise in central density raises densities throughout the city by the same percentage. If the slope of the density gradient depends largely on parameters t, β and v, then the city population must be approximately proportional to the rise in central density, D_0. Note that, holding constant central density, factors that flatten the gradient, like housing expenditure v (and thus earnings) and the importance of land in housing β increase population while higher transportation cost t steepens the gradient and hence lowers population.

Having followed the literature on the SUM to establish the relation among general characteristics for a single city, it is possible to take the model and vary city earnings to alter population, and establish the relation among earnings or population and other characteristics.

1.2. Using the Model to Vary the Size of Cities within a Given Country

The result just developed above is designed to reflect the conditions that govern urbanization within a given country. In a country, absent any role for amenities, population mobility should equate real income across cities. In addition, there is a presumption that urban technology

including transportation cost, the price of structure inputs, and the opportunity cost of converting land to urban use are identical. Finally, the fraction of land available for development is assumed constant, and there is no congestion that raises transportation cost per unit distance as city size increases. Clearly, the actual city size distribution in a country includes variation among areas in all these factors. The discussion here can either be thought of as abstracting from all these factors or as treating their variation as idiosyncratic and unrelated to the fundamental driver of size variation, differences in earnings of workers across cities in a given country.

Having Cities of Different Sizes. In order to generate cities of different sizes, the standard approach is to formulate an open city model in which wages vary due to exogenous labor productivity differences. It is then possible to establish a relation between earnings paid to workers in the city and total population of the city. Once the relation between earnings and population is established, the implications for all the other basic city characteristics can be established and the question of whether these changes are all proportional to differences in population (in which case population is a sufficient statistic to describe city differences within a country) or not can be determined.

Imagine that all cities begin with identical characteristics. The price of housing at k^* must be identical in all cities because the cost of housing production at the city limit is identical everywhere. Indeed, structure inputs are priced everywhere at p_s while land at k^* is always priced at R_A, leaving housing production cost, and thus housing price $r(k^*)$, identical across cities.

In order to grow a particular city, y must rise making that city more attractive. Raising earnings by Δy means that workers at the city edge who pay $r(k^*)$ for housing will be willing to pay an additional $\Delta y = t\Delta k$ for transportation to work. Conversely, the outer boundary of the city can expand by $\Delta k* = \Delta y/t$. Thus, if y increases in one city, k^* in that city will increase until the workers at the edge are indifferent between working at the CBD or outside the city. As k^* and thus total land area increase, population also increases.

In addition to expanding the city boundary, the rise in city earnings would raise the utility of workers living closer than k^* to exceed that of workers in other cities. Their willingness to pay for housing in the city would rise. In order to maintain the iso-utility condition among cities, rents must rise throughout the growing city as shown in Figure 2 with city 2 having higher earnings than city 1. The increase in rent Δr required to maintain the iso-utility condition in response to this increase in wages, requires that housing expenditure must rise by Δrh to offset the increase in earnings Δy. It follows that $\Delta y = \Delta rh = \Delta rhr/r$. Given that $v = rh$, it follows that $\Delta y = v\Delta r/r$.

Letting η be the fraction of income spent on housing so that $v = \eta y$, this implies $y = \eta y \Delta r/r$ or $\Delta y/y = \eta \Delta r/r$ or that $dlny = \eta dlnr$ and $dlnr/dlny = 1/\eta$. Thus, the percentage increase in rent needed to offset a given percentage rise in income is equal to the inverse of the share of housing in income.

Totally differentiating equation 16 with respect to log income the effect of changing income on central density may be written as:

$$d\,ln\,D_o/d\,ln\,y = -\partial\,ln\,v/\partial\,ln\,y + (1/\eta)\partial\,ln\,r/\partial\,ln\,y = -1/\eta + 1/\beta\eta = (1-\beta)/\beta\eta(15) \tag{18}$$

Central density thus varies inversely with β, which measures the importance of land as a factor of production for housing, and η, which is the fraction of income spent on housing.

City Population Size-Earnings Elasticity. Now, it is possible to determine the elasticity of city population size with respect to city earnings. The total differential of equation 17 with respect to income is:

$$d\,ln\,N/d\,ln\,y = (\partial\,ln\,N/\partial\,ln\,D_o)(\partial\,ln\,D_o/\partial\,ln\,y) + (\partial\,ln\,N/\partial\,ln\,\lambda)(\partial\,ln\,\lambda/\partial\,ln\,y) \tag{19}$$

From equation 19 it is evident that, as income increases, both central density and the density gradient will change, which then determines the consequent change in total population.

Using the results that $\partial lnN/\partial lnDo \approx 1$ and that $\partial lnN/\partial ln\lambda \approx -2$ from equation 17, substituting the result from equation 18 for $d\,ln\,D_o/d\,ln\,y$, and substituting $\lambda = t/(\beta v) = t/(\beta\eta y)$ into equation 19 yields the elasticity of city population with respect to city earnings:

$$d\,ln\,N/d\,ln\,y = (1-\beta)/(\beta\eta) + 2/\eta = 1/(\beta\eta) + 1/\eta \tag{20}$$

Equation 20 implies that the elasticity of household population with respect to income, or what is commonly called the urban wage premium, is a constant equal to a function of the share of land in housing construction and the share of housing in income. Thus, the urban wage premium varies inversely with the importance of housing in household consumption bundles and the share of land in housing construction. This result is consistent with but not based directly upon the Rosen-Roback model (Rosen, 1979; Roback, 1982), which states that, in order to attract labor, growing cities must overcome rising housing prices. The rise in housing price is larger when the share of land inputs, i.e. β, is larger, and has a bigger effect on cost of living when the fraction of income spent on housing, reflected in η, is larger. There is a transportation cost effect because commuting distance and cost are embodied in the model. However, because transportation cost per unit distance traveled is assumed constant within a country, perhaps because larger cities have more

investment in transportation capacity, it does not enter the wage premium expression.[9]

It is possible to calculate the implied urban wage premium for the U.S. from equation 20 because there are well accepted values for the share of land in housing, β = 0.2, and the share of housing in consumption in income, η = 0.3.[10] Using these values, the calculated value of the premium, is $dlnN/dlny = (1/\beta\eta) + (1/\eta)$ = 20 or inverting this expression, a premium of 0.05, a 10% rise in population generated by 0.5% rise in earnings. There is an established literature on the urban wage premium for the U.S. which uses Mincer equations to compute the partial relation between city size and earnings change. The general consensus is that the premium is approximately 0.05 to 0.06 (Combes and Gobillon, 2015). The precision of these estimates is based on use of high quality micro data on wages or earnings that allows for differences in population composition, which are also associated with city size, to be removed. Estimating the premium for lower income countries is more challenging due to the inability to adjust for the tendency for human capital per worker to rise with city size. Recent estimates by Chauvin et al. (2016) place the urban wage premiums for the U.S., Brazil, China, and India at 0.054, 0.052, 0.088, and 0.077, respectively.[11] Given the difficulty of removing the effect of the tendency for human capital per worker to rise with city size on estimates of the urban wage premium in China and India, and issues created by impediments to population mobility, these estimates are remarkably consistent.

Other Elasticities. It is possible to develop expressions for the elasticity of other city characteristics with respect to income. Based on equation 18, the elasticity of central density with respect to income is $dlnDo/dlny = (1-\beta)/(\beta\eta)$. If equation 10 is totally differentiated with respect to income, the elasticity of structure density with respect to income is found to be identical to that of central density. As we established before, the elasticity of the absolute value of the density gradient with respect to income is $-1/\eta$ which is confirmed in the empirical literature suggesting that density gradients fall slightly with city size.

1.3. Using the Model to Compare Cities in Developed and Developing Countries

As noted above, the characteristics of large cities, whose populations are similar as we will see below, vary dramatically across countries. The purpose of this section is to take the same SUM

[9]Given $\lambda = t/(\beta v)$ it follows that $d\,ln\,\lambda/d\,ln\,y = \partial\,ln\,t/\partial\,lny - \partial\,ln\beta/\partial\,lny - \partial\,lnv/\partial\,lny$. It could be argued that $\partial lnt/\partial lny \neq 0$ as assumed here. The problem is that there are reasonable arguments for thinking that the effect of income on transportation cost could be negative or positive. Negative due to improved transportation technology and positive because higher earnings raise the value of time. Likewise, we could imagine that richer cities within a given country are better able to substitute structures for land when producing housing, so $\partial ln\beta/\partial lny < 0$.

[10]See, for example Glaeser and Gyourko (2018).

[11]These are OLS estimates. IV estimates for the U.S. and Brazil are similar but IV estimates for China and India exhibit wide variance.

model that explains the ability of population to reflect differences among cities *within* a country with high population mobility and determine if it can generate differences in cities of the same size that are observed *across* countries. The stylized example discussed here is the contrast between the typical city in a developed country, noted d, with cities in developing countries, noted g.

Decomposition of Total Population. It is useful to consider a simple decomposition of the determinants of total population because that is the principle characteristic that cities in developed and developing countries have in common. Total population is the product of land area, structure density, and "crowding" or population per unit interior space:

$$N = L(H/L)(N/H) \tag{21}$$

where N = urban household population, L = land area, H = interior space, so that (N/H) = population per square foot of interior space or "crowding".

More formally, in terms of equation 14 above, this is written in terms of an integral rather than the product of averages:

$$N = \int_0^{k^*} \theta D(k)dk = \int_0^{k^*} \theta(H/L)(k)/h(k)dk \tag{22}$$

where $\theta = 2\pi$ = fraction of land for housing (if development is unrestricted and the city is a circle), $D(k)$ = population density function, $(H/L)(k)$ = density of interior space per unit land at k, $h(k)$ = interior space consumed or used per household at k and k^* is the city limit.

Differences Within vs. Across Countries. The stylized facts that we will establish later on show that, holding population constant, land area (hence k^*), building heights ($(H/L)(k)$) and interior space consumption per household ($h(k)$) *all* increase directly with GDP per capita so that all three are larger in developed than developing cities. Because population varies directly with land area and structure density and inversely with interior space consumption, Equation 21 guarantees that, holding population constant, cities in high income countries are very unlike those in low income countries. The result is that knowing population N is, by itself, not sufficient to characterize any of the three major spatial city characteristics in equation 22 and similarly for other characteristics of the city including total output. Given that population N varies directly with land area (hence k^*) and building heights ($H/L(k)$), and inversely with interior space consumption per household ($h(k)$), it must be that the latter is sufficiently lower in developing countries to compensate for the influence on population of the lower values of the former two variables.

Therefore, the claim, based on the discussion above, that *within* a country there is a regular relation among land area L, building heights (H/L), and interior density (N/H) along with other

aspects of urban spatial structure, need not hold *across* countries. The intuitive reason for this difference is that, within a country, the iso-utility condition keeps housing expenditure v constant and the sharing of technology for producing housing and transportation services limits variation in A, t and p_s. Therefore, the principal effect of rising population is to increase land area through rising k^* and the analysis of the implications of the SUM above indicated that the elasticity of population with respect to income depends on factors, specifically β and η, which should not vary appreciably across cities of a same country.

In contrast, there is no free mobility across countries. Comparing developed and developing cities, there are also obvious differences in key parameters. First, real incomes are an order of magnitude higher in the cities of developed countries ($y_d \gg y_g$), and thus total expenditure on housing is much higher ($v_d \gg v_g$). It follows that housing consumption per household is higher $h_d > h_g$. Superior building technology means that $A_d > A_g$. One important element of building technology is secure property rights and financial markets that facilitate construction at a high structure/land ratio. Likewise, developed countries may be better able to substitute structure inputs for land ($\beta_d < \beta_g$). Lastly, it might be that $t_d < t_g$ due to advanced transportation technology in developed countries. However, one element of transportation cost is the opportunity cost of time and, given that wages are an order of magnitude higher in developed cities, this inequality is ambiguous. Similarly, differences in cost of structure inputs p_s are not obvious.

The implications of differences in the parameters for city structure are evident in equations 5, 10, 11, and 13 above. First, equation 5 shows that the slope of the housing price gradient becomes flatter as v rises and t decreases. From equations 10 and 11, housing structure density is increasing in A and the slope of the density gradient is decreasing in v. Finally, equation 13 shows that the slope of the population density function flattens as t decreases, β increases, and v increases. This last result is important because, comparing developed or developing cities with equal population, if the density function of the developed city is flatter, then the radius of the developed city is larger and the central density of the developed city must be lower. This relation is shown in Figure 3, which plots the population density functions of a developed city and a developing city of similar sizes. Note that the area under the $D(k)_g$ graph appears larger than the area under the $D(k)_d$ graph but the weight of land at each distance is proportional to the square of k.

Results on Structure and Population Densities. While our results suggest that there may be similarities in the elasticity of city size with respect to earnings, the model implies that, in other respects, the cities are very different. Consider structure and population densities. Equation 10

reproduced here implies that structure density is determined by construction technology, the share of housing in land, the price of structure inputs, and the price of housing space:

$$(H/L)(k) = ln\,(A\phi) + [(1-\beta)/\beta]ln\,r(k) - (1-\beta)/\beta ln\,p_s \tag{23}$$

Considering central structure density at $(H/L)(0)$. Equation 23 suggests that unless p_s is much lower or $r(0)$ is much higher in developing cities, the positive relation between A and development should produce much higher central structure densities in cities in developed countries. However, the slope of the structure density gradient shown in equation 11 to be $d\,ln\,(H/L)/dk = -t(1-\beta)/(\beta v)$ is clearly flatter in higher income countries as housing expenditure v, is higher by an order of magnitude. Figure 4 displays the relation between structure density functions of cities with the same population size in developed and developing countries.[12]

The SUM also predicts that, holding population constant, central population density differences between cities in developed and developing countries will be the opposite of structure density. Recall from equation 13 reproduced here that:

$$lnD(k) = ln\,(A\phi) + (1/\beta)ln\,r(k) - ln\,v - (1-\beta)/\beta ln\,p_s \tag{24}$$

While it is true that the positive association between building technology, A, and development tends to raise central density, $D(0)$, the fact that income and hence v is higher by an order of magnitude produces a negative association between central density and development, again unless structure prices are much lower or rents much higher in the developing city. While central population densities are predicted to be lower, the slope of the population density gradient is based on equation $d\,ln\,D(k)/dk = -t/(\beta v)$ which, like the structure density function, will flatten with the level of economic development due to the rise in v with income. The relation between population density functions in cities in developed and developing countries with identical population is depicted in Figure 3.

In conclusion, when comparing cities in developed and developing countries, the relation between total population and other city characteristics is problematic because the ratio of labor to land or labor to capital stock is far lower in developing cities. The density of population is much higher but structure densities are lower and land area is much smaller.

However, despite these substantial differences in levels for cities in developed and developing countries with the same population, this does not mean that the elasticities of land, structures, or

[12]It might also appear that the structure density gradient is flatter in cities in developed countries because t falls with improved transportation technology. While this is true, transportation cost also includes the value of time which rises with income. Therefore, the relation between t and economic development may be ambiguous.

output, with respect to population must be different. As noted in equation 20, it is possible for the elasticity of income with respect to population to be similar for cities in developed and developing countries. This means that, the ratio of output, land area, or structure capital to population for two cities in a developed country can be the same as the ratio in a developing country. Accordingly, research that uses population ratios to reflect ratios of other city characteristics could possibly pool observations from cities in developed and developing countries.

The same forces that produce differences in population density between cities in high and low income countries also apply to employment density. Higher income countries have greater structure density due to building technology differences but space per worker also increases with income as firms substitute physical capital in the form of space when labor costs rise. The result is the same combination of higher structure density near the city center but lower employment density as space per worker expands faster than space per unit land. Just as was the case with housing and population density, the amount and spatial pattern of non-housing investment is very different in high and low income cities although total employment may be similar.

We now present our data and then use it to test the implications of the SUM presented above. Specifically, it appears that the cities of developing countries are large in terms of population size but not in other dimensions. This establishes that population is not a sufficient statistic to make statements about cities across countries. Finally, we test if population is a sufficient statistic to describe city differences within a country.

2. Data on the World's Largest Agglomerations

One contribution of this study is to assemble various databases to document the characteristics of cities across income levels, focusing on the year 2015, but also studying earlier years.

United Nations (2018). This database gives the population of each urban agglomeration of at least 300,000 inhabitants every five years from 1950 to 2015 (N = 1,860). These agglomerations are "commuting zones" including central business districts, suburban areas, and satellite towns.

Demographia (2005, 2017). These databases give the population and land area (sq km) of many agglomerations of at least 500,000 inhabitants circa 2000 (N = 360) and most agglomerations of at least 500,000 inhabitants circa 2016, which is used as a proxy for 2015 (N = 1,042). Note that the data are imperfect for the year 2000 because many agglomerations in developing countries are omitted. In addition, little details is provided on how land areas were obtained. For the year 2016, estimates come from censuses and satellite imagery, and are thus more reliable.

CTBUH (2018). The Council on Tall Buildings and Urban Habitat (CTBUH) maintains a publicly

available online database of all *tall buildings* in the world.[13] For each building, there is a webpage showing its characteristics. Research assistants extracted the needed data from each webpage. We know the years construction was proposed and/or started and/or completed. Next, we know architectural height and/or height at the tip and/or height of the lowest occupied floor and/or height of the observatory and/or the number of floors. Web Appendix Section A describes in details how we use these characteristics to impute consistent measures of completion times and architectural heights for all buildings. Finally, we know their functions ("residential" or "office").

According to CTBUH's website, they do not use a consistent definition of tall buildings. However, in the data, the mode of the Kernel distribution of heights is 80 meters (see Web Appendix Figure A2). Given floors of about 4 meters, this corresponds to buildings of about 20 floors. As described in Web Appendix Section A, we believe that the database mostly captures buildings above 80 meters, and restrict our analysis to 14,839 such buildings.

Finally, one may question the quality of this data. According to their website, the data has been "collected by the Council for more than 40 years [...] The Council relies on its extensive member network [of academics, land developers, architectural firms, builders, city administrations, and banks] and the public to maintain" the database and "an Editorial Board from around the world helps maintain" it. The data set appears reliable. We thus use it to construct an index of the stock of tall buildings for each city, which we use as a proxy for the stocks of all buildings.

Main Sample. We focus our analysis on 1,010 agglomerations of at least 300,000 inhabitants in 2015 in United Nations (2018) *and* data on land area in Demographia (2017) (Web Appx. Fig. A3 shows their location). 405 of them have tall buildings. For other agglomerations, we assume that they have almost no tall buildings, giving them half a building (40 m).

World Bank (2018). The World Development Indicators database of the World Bank provides national per capita GDP (PPP and constant 2011 international $) for each country-year from 1990 to 2017. We then use per capita GDP growth rates from Maddison (2008) (in 1990 Geary-Khamis dollars, which is equivalent to PPP and constant international $) to reconstruct per capita GDP from 1950 to 1990. In order to avoid our measures of per capita GDP being contaminated by fluctuations in factors like commodity prices, we use two-year moving averages.

Oxford Economics (2019). This database prepared for the World Bank includes per capita GDP (constant 2012 million $) for 775 agglomerations annually from 2000 to 2017. According to their

[13]The full online database can be found here: http://www.skyscrapercenter.com/. As one example, here is the webpage for the Burj Khalifa in Dubai: http://www.skyscrapercenter.com/building/burj-khalifa/3.

methodology note, they used detailed national accounts data or estimates provided to them by the administrations of these cities. When the data was unavailable, they used per capita GDP for regions encompassing the agglomerations. Because no details are provided for each estimate, and since estimates may have been spatially and/or temporally interpolated and/or extrapolated, we believe that the quality of this data is not high and do not use it as our main source of income data.

NGDC (2015). As is now standard in the literature (Henderson et al., 2012), satellite night lights data are used as a proxy for economic activity. Satellite images are provided by NGDC (2015), and are available at a fine spatial resolution, annually from 1996-2011. Note that we use the radiance calibrated version of this data, to avoid issues related to top-coding, especially for cities.[14]

The Global Rural-Urban Mapping Project, CIESIN (2017), then provides geocoded polygons of urban extent boundaries circa 1995. Using GIS, we obtain the sum of satellite night lights in each polygon from 1996 to 2011. We match the agglomerations in our sample to their respective geocoded polygon. In addition, CIESIN (2017) reports the urban population of each polygon in 1990 and 2000. According to their website, "for population counts, city population data was collected from multiple sources. These include national censuses, the City Population database (undated), and World Gazetteer (web site no longer exists)." More precisely, 31,361 urban polygons have a non-zero population in their sample. Actually, given that the minimal population in the sample is 1,000 for many countries, these urban polygons possibly attempt to capture most cities of at least 1,000. In our analysis, we will focus on large agglomerations of at least 300,000 inhabitants. We will also perform analyzes including all cities above 1,000 inhabitants. However, the urban character of villages of 1,000 to even 10,000 is problematic.

We now describe other data sets that we will use to assess the robustness of our main results.

UN-Habitat (1993). UN-Habitat (1993) was launched following UN-Habitat II in 1996. Key indicators were collected in 237 cities circa 1993. Because cities may have different definitions of these indicators, reliability is uncertain. The sample is also not representative of the world.

AUE (2016). This database features a global sample of 200 cities supposed to be representative of the universe of agglomerations of 100,000 people or more in the world in 2010. Data for some variables is reported for 1990, 2000, and 2014 (which we use as a proxy for 2015). For other variables, data are reported for two periods: "pre-1990" (which is used as a proxy for 1990) and "1990-2015" (both 2000 and 2015). Note that the data were created based on census estimates and

[14]Radiance calibrated data imply that night light intensity can go beyond the typical upper-bound of 63.

satellite imagery. The quality of this data set appears to be relatively high.

European Commission (2018). This database reports for the years 1970, 1990, 2000 and 2015 estimates of land areas and populations for 11,836 cities of at least 50,000 inhabitants in 2015. To obtain land areas, it uses satellite images and machine learning to identify building footprints and distinguish urban agglomerations. The advantage of this data set is that a consistent methodology is used across all cities and countries. However, a common algorithm for all cities and countries may miss city- or country-specific idiosyncrasies in land use patterns that only a more administrative country-specific treatment of census or satellite data would yield.

OECD (2018). This database reports per capita GDP (in nominal USD) for 281 agglomerations in 29 countries annually from 2000-2014. Only one developing country, Mexico, is included.

3. Components of City Population Sizes

3.1. City Population Size and Country Economic Development

Location of Urban giants. Large agglomerations are not exclusively concentrated in developed regions such as East Asia, Western Europe or North America. There are many large agglomerations in relatively poor regions, for example in Sub-Saharan Africa and South Asia. Among the 100 top largest agglomerations in the world in 2018 (source: United Nations (2018)), only 28 are located in high income countries, and 27 are located in low or lower-middle income countries. Among the top 10 mega-cities, 4 of them are located in lower-middle income countries.

Income elasticity of city population size. Are urban giants concentrated in richer countries? This is tested using the larger data set from United Nations (2018). As can be seen in Figure 5, for 1,773 agglomerations of more than 300,000 inhabitants in 2015, there is no relationship between log population size and economic development proxied by log national per capita GDP (PPP). Column (1) of row 1 in Table 3 shows the elasticity of log population size with respect to log per capita GDP when controlling for log country population in 2015 since larger countries have larger cities. In column (2), we weigh observations by their population size in 2015, thus giving more weight to the giants. The elasticity is close to 0 and never significant.[15] Likewise, if we focus on the main sample (N = 1,010), elasticities remain close to 0 (see row 2).

Robustness. Column (1) of Table 4 replicates the baseline results. Low elasticities are also obtained for 300K+ agglomerations when using other data sets and their own population estimates for the year 2015, whether Demographia (2017) (N = 1,040; col. (2)), European Commission (2018) (1,549;

[15]Note that standard errors are clustered at the country level in all regressions.

col. (3)) or AUE (2016) (162; col. (4)), and likewise if we use cities below 300K (not shown).[16] Finally, elasticities remain unchanged if we drop each country one by one (not shown) or remove the largest cities of each country, to study non-primate cities only (not shown).

National per capita incomes are used because consistent income or earnings data does not exist for enough individual cities. In addition, at the world level, income differences are driven by differences *between* countries rather than by differences across cities *within* countries. Indeed, with free mobility and abstracting from amenities and worker skill heterogeneity, all cities in a country should offer similar wages in local PPP terms (i.e., net of housing and other prices). National per capita GDP is indeed strongly correlated with both city per capita GDP (source: Oxford Economics (2019); 0.91-0.92) and night lights per capita (source: NGDC (2015); 0.78-0.81).[17] The between component, i.e. differences across countries, accounts for 91-93% and 67-68% of the variation in city per capita GDP and night lights per capita, respectively. We nonetheless verify that low elasticities are found when using city per capita GDP (col. (5) and (6)) or night lights per capita (col. (7) and (8)), whether for the full sample (N = 746-745) or the main sample (694-693).

Has this lack of association between per capita income and city size been stable over time?

Evolution. We find that the elasticity strongly decreased over time. For the full sample of 1,773 agglomerations and controlling for total population, it was -0.00, 0.10***, 0.21***, 0.33*** and 0.50*** in 2015, 2000, 1990, 1975 and 1960, respectively (see col. (1) and (9)-(12) of row 1). Using weights, it was 0.04, 0.20**, 0.31**, 0.40*** and 0.42*** (see row 2). Similar elasticities are found for the 1,010 agglomerations of the main sample (not shown). When plotting the relationship over time, one can see that the change in the elasticity was driven by developing country cities becoming larger given a certain income level (see Web Appx. Fig. 1(a)-1(b)). The large cities of developing countries, especially their urban giants, thus outgrew the cities of developed countries over time.[18]

Other dimensions of city size. Table 2 shows that cities in developing countries – including low-income countries, lower-middle income countries, and upper-middle income countries, according to the World Bank in 2016 – are relatively large in terms of population size, but not in other dimensions such as land area, interior space (proxied by the sum of building heights), and GDP (proxied by national GDP or total night lights). Row 1 of Panel A includes all agglomerations for which data is available. Although cities in developing countries make up 74.2% of the

[16]The coefficient of correlation between log city population size in United Nations (2018) and log city population size in each of the three data sets used here is 0.94-0.97, 0.93-0.83, and 0.72-0.90, respectively.

[17]Night lights per capita is the sum of night lights of the city (2011) divided by the population of the city (2010).

[18]The elasticity also decreased over time in the other data sets (not shown).

total population of the sample, they account for 50.3% of total land area, 34.4% of total interior space, 42.1% of total GDP, and 23.7% of night lights. Since land area data is missing for many agglomerations, these results could be driven by compositional biases. Row 2 shows these results hold if we focus on 1,009 agglomerations for which we have data across *all* dimensions. Row 1 of Panel B shows that these patterns are, if anything, accentuated when reclassifying upper-middle income countries as developed. Although cities in developing countries make up 29.7% of population, they account for 15.7% of land area, 6.1% of interior space, 8.1% of GDP, and 4.3% of night lights. These results are also not driven by compositional biases (see row 2 of Panel B).

What has enabled the urban giants in poor countries to grow so rapidly and reach the same population sizes as the urban giants of rich countries? Differences among cities with comparable populations can be decomposed into three components: land area, average building height, and occupant density. We now investigate how these vary with per capita national and city incomes.

3.2. City Land Area and Country Economic Development

Income elasticity of city land area. Figure 6 shows for 1,010 large agglomerations a strong positive relationship between log city land area (sq km) and log national per capita GDP (PPP). When regressing the former on the latter, the coefficient is 0.52*** (R2 = 0.19), which we report in column (1) of row 3 in Table 3. Therefore, the land area of urban agglomerations increases by 52% when per capita income doubles. Alternatively, agglomerations in high-income countries consume on average 6.0-6.8 times more land than cities in low-income countries. When weighting observations by city population, the coefficient becomes 0.58*** (R2 = 0.17, col. (2)). The area-income relationship is thus not different when focusing on the giants.

The results suggest that the entire urban systems of richer countries use more land than the entire urban systems of poorer countries. If we control for log city population size, elasticities are similar, at 0.50***-0.54*** (R2 = 0.67-0.79, col. (3)-(4)), which is not surprising since the elasticity of population size with respect to income is close to 0. This implies that there is also much more land available per capita in the cities of richer countries. As explained in the model, this must come from higher incomes and better commuting technologies in richer countries. With higher incomes, people consume more housing and thus more land. Also, higher incomes imply higher capital-labor ratios, and thus more land per capita is needed to accommodate the extra capital. Better commuting technologies then magnify the effect of income on land consumption. Similarly, land used for production is also larger in cities of higher income countries.

In the rest of the analysis, note that we privilege specifications where we do not control for

city population size, since our main goal is to explain why entire urban systems in developing countries have become on average as populated as entire urban systems in developed countries.

Robustness. There could be classical measurement error in city land area. However, since city land area is the dependent variable, this would only affect precision. Yet, if the quality of the land area measurement is correlated with income, the elasticity is mis-estimated. For example, if land area is under-estimated in developing (developed) country cities, the elasticity will be over-estimated (under-estimated). We thus check how robust our results are when using alternative data sets of city land areas, since the different data sets use different sources and methodologies. Next, the availability of city land area estimates itself could be endogenous. Finally, classical measurement error in per capita income causes a downward bias, whereas non-classical measurement error in income could generate either an upward bias or a downward bias.

First, log land area in Demographia (2017) is strongly correlated with log land area in AUE (2016) (0.91-0.91; N =140) and European Commission (2018) (0.78-0.87; N =1,007). Column (1) of Table 5 then replicates the baseline results. The elasticity of land area with respect to income remains close to 0.5 if we use AUE (2016) (col. (2)). If we residential built-up area or non-residential built-up area instead of total land area, since these measures are available in AUE (2016), we find very similar elasticities (not shown). Note that built-up areas account for 70% of total land area, of which two thirds is "residential". The fact that elasticities differ little between residential and non-residential areas suggests, consistent with the discussion of the SUM above, that rich country cities use more land for *all* purposes. Now, if we use European Commission (2018) data, elasticities become smaller but only if we use total land area (col. (3)), not if we use built-up area estimates (col. (4)).[19] Elasticities also remain unchanged if we drop each country one by one, except the U.S.. In that case, the elasticities are lower, at 0.36***-0.43*** (not shown). U.S. cities thus disproportionately consume land given their income level. If we drop primate cities, elasticities are, if anything, even higher, at 0.66***-0.71*** (N = 863, not shown).

City land area in Demographia (2017) is only available for 1,010 out of 1,773 agglomerations of more than 300,000 inhabitants in 2015. If we regress a dummy equal to one for whether land area is available on log national per capita GDP, we find negative significant coefficients (0.015/0.026**; N = 1,773; not shown). Since the data set misses large agglomerations in developed countries, we verify results hold if we use weights that makes the main sample of 1,010 cities

[19]We believe that this has to do with the algorithm that they use, which appears to disproportionately under-estimate urban open spaces in richer countries or over-estimate urban open spaces in poorer countries.

representative of the income distribution of the full sample of 1,773 cities (col. (5)).[20]

Finally, if we use other per capita income measures, we find similar elasticities for city per capita GDP (source: Oxford Economics (2019); N = 694; col. (6)), but lower elasticities for night lights per capita (0.31***-0.35***; source: NGDC (2015); N = 1,009; col. (7)).[21]

Evolution. The problem with Demographia (2005) is that it has only one-third of the cities in Demographia (2017). Patterns over time become evident when we focus on a balanced sample of 232 cities that exists in both datasets. In that case, the elasticity decreases by 0.31-0.29 between 2000 and 2015 (not shown). Given elasticities of 0.52-0.58 in 2015, this would give elasticities of about 0.83-0.87 in 2000. However, this balanced sample may not be representative of the whole urban world. If we use the more balanced data set from AUE (2016) (N = 162), the elasticities are 0.55***-0.61*** in 2015 (col. (3)), 0.62***-0.65*** in 2000 (col. (8)), and 0.72***-0.75*** in (col. (9)), thus also showing a reduction over time. However, if we use built-up area data from European Commission (2018), elasticities are relatively similar in 2015, 2000, 1990 and 1975 (col. (5) and (10)-(12)). Thus, the elasticity of land use with respect to income per capita either decreased or remained stable over time. In other words, land expansion either became relatively more important or remained as important for poorer countries.[22] Indeed, when plotting the relationship between log land area and log national per capita GDP in each year, one can see that the lower elasticities over time in AUE (2016) are coming from cities in developing countries using relatively more land over time (see Web Appx. Fig. 4(a)). Next, the stable elasticities in European Commission (2018) hide across-the-board increases in city land areas (see Web Appx. Fig. 4(b)).[23]

3.3. City Building Heights and Country Economic Development

Income elasticity of building height. To obtain average height, we divide the sum of tall building heights (m) by land area (sq km).[24] We thus restrict our analysis to the main sample of 1,010 agglomerations. As shown in Figure 7, we obtain a strong positive relationship between log average building height (m) and log national per capita GDP (PPP). When regressing the former on the latter, the coefficient is 0.34*** (R2 = 0.06). When weighting observations by city population, the coefficient becomes 0.71*** (R2 = 0.16). If we control for log city population size, elasticities

[20]More precisely, the weights are constructed to reflect the respective population shares of high-income, upper-middle income, lower-middle income and low income countries among the 1,773 agglomerations.

[21]Since the elasticity of night lights per capita with respect to national per capita GDP is 1.29*** once we control for log city populations (N = 1,009; not shown), the implied elasticities with respect to national per capita GDP are 0.40-0.45.

[22]Similar patterns are obtained for residential and non-residential areas (not shown).

[23]Whether urban land expansion takes the form of compact development at the edge or scattered development not at the edge – i.e., sprawl strictly defined – cannot be answered with our data.

[24]Using the mean of heights in our building database would be misleading for cities with few, but tall, buildings.

are similar, at 0.33*** and 0.68*** respectively (R2 = 0.16 and 0.35). Thus, average building heights increase by about one third when per capita income doubles. The elasticity doubles when giving more weight to the giants. Alternatively, cities in high-income countries have on average 11 times taller tall buildings than cities low-income countries (3 times without weights).

Robustness. Column (1) of Table 6 replicates the baseline results. Our data comes from CTBUH (2018) and captures *tall buildings* above 80 m (about 20 floors). Since our data could mismeasure building stocks, we examine how the sum of heights in our data compares with other measures from Emporis (2019), another global provider of building information.[25] Note that Emporis (2019) claims to capture all *high-rise buildings*, which they define as buildings above 35 m. They then classify as *skyscrapers* buildings above 100 m. First, they list the 100 top cities in the world in terms of number of skyscrapers. For these, the correlation with our own number of buildings above 100 m is 0.85 (0.86 with weights; N = 94). Next, for the same cities, they provide a Skyline Index which gives more points to taller buildings but also includes high-rise buildings in the 35-100 m range. The correlation between their number of skyscrapers and their Skyline index is 0.88 (0.86 with weights; N = 100). Thus, our measure of building stocks should be a good proxy for building stocks extending to buildings as low as 35 m. Finally, we regress the Skyline Index on the number of skyscrapers and then regress the residuals – which captures cities having 35-100 m buildings instead of buildings above 100 m – on national per capita GDP. There is no effect, no matter whether we use population weights or not (not shown). Thus, if we miss cities with buildings between 35 and 100 m, that measurement error is not systemically correlated with income.

We know land area in 2016 for 1,040 cities from Demographia (2017). However, only 405 of these have tall buildings in our data. So far, we assumed that building height in the remaining 635 cities is 40 m, realizing that the correct number could be above zero. The elasticities remain similar if we drop cities without buildings (col. (2)) or give these cities one third (27 m) or two thirds (53 m) of a building (col. (3)-(4)). Elasticities are unchanged if heights are not imputed using the number of floors (col. (5)) or if we use raw architectural heights (not shown). Next, since the website of CTBUH (2018) is in English or Mandarin, we verify results hold if we keep countries where these are official languages (col. (6)). Lastly, taller buildings could be better reported than smaller buildings, because there are fewer of them and they stand out more. Results hold if we only use buildings above the 25th percentile height (100 m, col. (7)), median height (125 m, col. (8)) or mean height (135 m, col. (9)) Finally, results hold if we use weights that makes the main sample

[25] According to their website, they also rely on their extensive member network to gather information on buildings.

of 1,010 cities representative of the income distribution of the full sample of 1,773 cities (col. (10)).

One may then wonder to what extent measurement error in building stocks could be correlated with per capita income.[26] One could imagine that more buildings are reported in richer countries, because their real estate industry is more mature and CTBUH (2018) has more experts from these countries. In that case, we over-estimate the elasticity. Conversely, we could imagine that poorer countries have fewer tall buildings, making them easier to report.[27] The elasticity is then under-estimated, which is less of an issue for us. We verify that results hold if we drop countries in the bottom or top 10% in income per capita (col. (11)-(12)). Alternatively, we can drop cities in the top 10% in terms of number of buildings (col. (13)), in case cities with more tall buildings have more misreported buildings. Next, tall buildings could be reported more accurately in smaller cities, since they stand out more there. However, large cities may have more people reporting buildings. Since city size does not vary with income, this should not be an issue. Yet, we verify results hold when we drop cities in the bottom or top top 10% of city size (col. (14)-(15)).[28] Finally, elasticities are unchanged if we drop each country one by one (not shown).

We find that 48% of buildings and 47% of the building stock are used for residential purposes. These shares are 44% and 47% for offices.[29] Next, the elasticity is similar if we use non-residential buildings (0.23*** and 0.61***, not shown) or just office buildings (0.19*** and 0.59***, not shown). For residential buildings, it is 0.03 without weights and 0.48*** with weights (not shown).[30]

Lastly, elasticities increase if we use city per capita GDP (col. (16)), decrease for lights (col. (17)).[31]

Evolution. Land area used to compute average building heights is observed for 2015 and comes from Demographia (2017). If we focus on 232 cities that also exist in Demographia (2005), we find that the elasticity increased by 0.19 (unweighted) and 0.25 (weighted) between 2000 and 2015 (not shown). Given elasticities of 0.34 and 0.71 in 2015, this gives elasticities of 0.15 and 0.46 circa 2000. If we use land areas from AUE (2016), we find that the unweighted elasticity increased from 0.25* in 1990 to 0.47*** in 2000 and 0.71*** in 2015 whereas the weighted elasticity increased from 0.50*** to 0.62*** and 0.91*** (col. (18)-(20)). If we use land areas from European Commission (2018), the unweighted elasticity increased from 0.05 in 1975 to 0.23** in 1990, 0.37*** in 2000 and

[26] Classical measurement error in the dependent variable, tall building heights, would only lower precision.

[27] For example, in our data, New York has 1,247 tall buildings but cities like Cairo or Rio have fewer than 50.

[28] Elasticities are mechanically lower when dropping the top cities since tall buildings are a feature of large cities. Likewise, elasticities are lower, at 0.25*** and 0.51***, if we drop the primate cities (N = 863, not shown).

[29] Other functions are much more marginal: hotel (about 12% of buildings), retail (3%), and government (1%).

[30] We also give half a building (40 m) to cities without residential / non-residential / office buildings.

[31] Since the elasticity of night lights per capita with respect to national per capita GDP is 1.29*** once we control for population (N = 1,009; not shown), the implied elasticities with respect to national per capita GDP are 0.14 and 0.39.

0.60*** in 2015 whereas the weighted elasticity increased from 0.44** to 0.60***, 0.74*** and 0.95*** (col. (21)-(24)). Although elasticity estimates differ slightly across the different data sets, patterns are similar in all of them, with elasticities increasing by about 0.15-0.20 between 1975 and 1990, 0.15-0.20 between 1990 and 2000, and 0.20-0.30 between 2000 and 2015.

Finally, when plotting the relationship between log average building heights and log national per capita GDP in each year, one can see in Web Appendix Figures 5(a)-5(b) that the higher elasticities over time in AUE (2016) and European Commission (2018) are coming from cities in developing countries having decreasing average building heights – since land area is disproportionately increasing there, as discussed in Section 3.2. – and cities in developed countries having increasingly taller buildings. If we focus on larger cities, the rising elasticities are mostly due to taller buildings in richer countries (see Web Appx. Fig. 6(a)-6(b)). Similar patterns are obtained if we use built-up areas instead of total land areas (not shown). Thus, cities in richer countries, especially large ones, have disproportionately grown by building up.

3.4. City Interior Space and Country Economic Development

Income elasticity of interior space. Differences in overall amounts of physical structures are based on the sum of differences in structure density and land area. Knowing the area-income and height-income elasticities allows estimation of the elasticity of total interior space with respect to income. When not weighting by population, this gives 0.52*** + 0.34*** = 0.86***. When weighting by population, this gives 0.58*** + 0.71*** = 1.29***. We verify this by estimating the elasticity directly, i.e. by regressing the log sum of building heights on log national per capita GDP (see row 5 of Table 3). Thus, interior space approximately doubles when per capita income doubles. The elasticity is then 50% higher when more weight is given to larger cities, due to taller buildings there. Alternatively, cities in high-income countries have on average 71 times more interior space than cities low-income countries (18 times when not using weights).[32]

Robustness. We verify that these elasticities remain relatively similar if we implement the same robustness checks as described above for the building heights and income data, since interior space is constructed in our analysis using building heights only (not shown).

Evolution. Over time, the area-income elasticity decreased or remained the same whereas the height-income elasticity increased. The latter effect then dominated the former effect. Indeed, while the interior space-income elasticity was 0.31*** in 1975, it was 0.50***, 0.65*** and 0.86*** in 1990, 2000 and 2015, respectively (see Col. (1)-(4) of row 1 in Table 7). The weighted elasticity then

[32]Web Appendix Figure A8 shows the relationship between log total interior space and log national per capita GDP.

increased from 0.79*** in 1975 to 0.95***, 1.08*** and 1.28*** in 1990, 2000 and 2015 (row 2). When plotting the relationship over time, it is disproportionately driven by increases in interior space for richer countries (not shown). Because these increases did not come from rising income elasticities of land area, they can be entirely attributed to rich country cities disproportionately building up.

3.5. City Population Density and Country Economic Development

Income elasticity of population density. Given taller buildings in the cities of richer countries, one would expect the cities of the developed world to be more densely populated. At the same time, these cities are more likely to build out, which would reduce density. As shown in Figure 8, for the 1,010 agglomerations of the main sample in 2015, there is a strong negative relationship between log city population density (inh. per sq km) and log national per capita GDP (PPP). When regressing log city density on log per capita GDP, the coefficient is -0.50*** (R2 = 0.34; N = 1,010; col. (1) of row 6 in Table 3). When weighting observations by population, the coefficient becomes -0.53*** (R2 = 0.39; N = 1,010; col. (2)). Alternatively, the agglomerations of high-income countries are 5-6 times less dense than the ones of low-income countries. These negative density-income elasticities contrast with the positive density-income elasticities that have been estimated for groups of cities belonging to a same country in extensive literature on agglomeration effects.

Robustness. We verify that these elasticities remain relatively similar if we implement the same robustness checks as described above for the population, land area and income data (not shown).

Evolution. Over time, the population-income elasticity decreased, because city population sizes disproportionately increased in poorer countries, and the area-income elasticity decreased or remained the same (land areas disproportionately increased in poorer countries in some data sets). Therefore, density patterns are ambiguous. If we use land area from Demographia (2017), we find that the density-income elasticity slightly *increased* over time, by about 0.14-0.16. Given elasticities of -0.50/-0.53 in 2015, this would give elasticities of -0.34/-0.39 in 2000. If we use AUE (2016), the elasticities *remained similar* over time, at -0.46***/-0.46*** in 1990 and -0.48***/-0.53*** in 2015. If we use European Commission (2018), elasticities *decreased* over time, from -0.17/-0.23*** in 1975 to -0.44***/-0.49*** in 2015. The data sets thus give different pictures of population density patterns.[33]

3.6. City Occupant Density and Country Economic Development

Income elasticity of occupant density. Population density falls with income (elasticity around -0.50/-0.53). This could be because city land areas increase relatively more than city heights with

[33]Similar patterns are obtained if we use built-up areas instead of total land areas (not shown).

income. However, elasticities for city heights are not that smaller, or even higher, than for land areas (0.34 and 0.71 vs. 0.52 and 0.58). A major explanation, especially for larger cities, is that occupant density, i.e. the density within housing and commercial units, is disproportionately higher in the cities of poorer countries. In other words, the cities of poorer countries have less interior space per sq km but also more people in their interior space, and thus are more crowded.

This hypothesis can be tested. There is limited data on space consumption across the world. But we can use the height data from CTBUH (2018) and the population data from United Nations (2018) to obtain for the same 1,010 cities the sum of building heights (m) per capita in 2015. As before, the assumption is that cities without tall buildings have half a tall building (40 m).

Figure 9 shows a strong positive relationship between log city occupant density and log national per capita GDP (PPP) in 2015. When regressing the former on the latter, the coefficient is -0.84*** (R2 = 0.33; N = 1,010; see col. (1) of row 7 in Table 3). When using population weights, it is -1.24*** (R2 = 0.39; see col. (2)). Occupant density thus more than halves when income doubles. Alternatively, the giants of high-income countries have 60.8 times denser housing units than the ones of low-income countries (16.2 times when not using weights).

Robustness. We verify that these elasticities remain relatively similar if we implement the same robustness checks as described above for the population, building heights and income data (not shown, but available upon request). UN-Habitat (1993) also provides for 181 cities in 1993 floor area per person defined as "the median usable living space per person last year". Although the data set is from 25 years ago, this is the only data set with international data on floor area. Web Appendix Figure A9 shows there is a strong relationship between floor area per person and log per capita GDP (PPP). Residents of the agglomerations of high-income countries have about 29-30 sq m per capita vs. close to 7-8 sq m in the agglomerations of low-income countries. When using the log of this alternative measure, the estimated elasticity is also high, at 0.47***-0.56*** (R2 = 0.56-0.50; not shown). To have as many observations as possible, we use all cities available in UN-Habitat (1993) for this analysis. If we restrict the sample to 128 agglomerations of at least 300,000 inhabitants in 2015, we obtain similar elasticities, at 0.44*** and 0.56*** (not shown).[34]

Evolution. The population-income elasticity decreased over time whereas the height-income elasticity increased over time. Logically, the occupant density-income elasticity should have decreased over time, which is what we find. The unweighted elasticity decreased from 0.02 in

[34]One issue with UN-Habitat (1993) is that it may overestimate living space in poorer countries, because the "extensive surveys of the housing sector" that they rely on focus on the less crowded formal sector.

1975 to -0.25, -0.52*** and -0.84*** in 1990, 2000 and 2015, respectively (see Col. (5)-(8) of row 1 in Table 7). The weighted elasticity then decreased from -0.47** in 1975 to -0.68***, -0.91*** and -1.24*** in 1990, 2000 and 2015, respectively (row 2). When plotting the relationship over time (Web Appx. Fig. 7(a)-7(b)), we find that these decreases were due to both occupant densities increasing in poor country cities and occupant densities decreasing in rich country cities. Behind these patterns, population increased in poor countries and heights increased in rich countries.

Summary. Table 3 summarizes the main elasticities found for each component of city population size. In columns (1)-(2), where we do not control for city population size, the elasticities of land area, building heights and occupant density are 0.52/0.58 (row 3), 0.34/0.71 (row 4) and -0.84/-1.24 (row 7), respectively. As explained in Section 1.3., the sum of these elasticities should be close to the city population size-income elasticities that were estimated, -0.00/0.04 (row 1) for the full sample or 0.02/0.06 for the main sample (row 2). Row 8 shows that the sum of the three elasticities is close to 0.00, so the estimated elasticities of city population size with respect to income and the elasticity constructed from its individual components are almost the same (rows 9-10).

These results have several implications for today's city population sizes: (i) The elasticity of interior space with respect to income is close to 1 and can be decomposed into the elasticity of land area with respect to income and the elasticity of building heights with respect to income. Therefore, cities can grow their stock of space per capita by either building out or building up; (ii) Since the relationship with income is positive for both land area and heights, cities in richer countries use both margins to do so. Thus, we are not in a world where poorer countries experience urban land expansion while cities in richer countries "skyscraperize". Instead, cities in richer countries both consume more land and "skyscraperize" while cities in poorer countries are not expanding interior space per capita at the same rate and, relatively speaking, are packing in more inhabitants in existing structures; (iii) When focusing on the giants, these patterns are accentuated. In particular, the largest cities of richer countries disproportionately build up, whereas the structures of the largest cities in poorer countries disproportionately densify.

Our results also have several implications for understanding the growth of cities over the past few decades: (i) The lack of relationship between city population sizes and income is a more recent phenomenon, and is due to the population of developing country cities growing fast. In particular, the population-income elasticity changed by about -0.2 between 1990 and 2015; (ii) Cities in richer countries have built up more: The building heights-income elasticity changed by about +0.4 between 1990 and 2015; (iii) If anything, this should made have rich country cities grow

more. However, interior space per person has grown to absorb the additional supply of housing and commercial space. In contrast, the disproportionate increase in city population sizes in poorer countries has been accommodated by both land expansion, and, to an even greater extent, by the densification of existing structures. More precisely, the area-income elasticity and the occupant density-income elasticity changed about -0.1 and -0.5 between 1990 and 2015, respectively.

Although the growth of cities in developing and developed countries may be understood using the common framework of the SUM, their patterns of growth are like different species of the same animal. More generally, our analysis shows that cities can reach similar population sizes but in different ways, for example by having more space being provided – which should be associated with urban economic development – or by densifying existing spaces – which should be associated with urban pauperization –. We thus investigate in the next section how the relationship between city population sizes and economic development varies within and across countries.

Why do cities in richer countries use more land and have taller buildings? While this is a direct result of higher incomes and thus higher land values, one question is to what extent their ability to build out and build up is permitted by better technologies and/or more permissive regulations, and to what extent these technologies and regulations are themselves endogenous to income. Now, since building heights disproportionately increased in rich countries for a given income level, it may be that their building technologies improved over time. Next, since land areas disproportionately increased in poor countries for a given income level, it must be that their transportation technologies improved. However, this change was smaller than the change in heights in rich countries, so urban technology must have on net improved relatively more in richer countries. Consequently, and considering that interior space use and consumption are likely to increase with income, it must be that the massive relative increase in population in poor country cities must have come from rural earnings decreasing faster than city earnings.

4. City Economic Development and City Population Sizes

The issue with using national per capita GDP as a proxy for city economic development is that there is, by construction, no variation across the cities of a same country. We thus cannot study how the relationship between population and economic development varies depending on whether the analysis is conducted *across* countries, as we did so far, or *within* countries.

In this section, we focus our analysis on 31,361 urban polygons/agglomerations of at least 1,000 inhabitants in 223 countries in 2000 according to CIESIN (2017). We use 1,000 inhabitants instead of 300,000 as in the previous section because we need to have enough cities for each

country. We will nonetheless show results hold when using 300,000 as a cut-off.

From NGDC (2015), we obtain for each of these cities the sum of (radiance calibrated) night lights in 2000. Next, we examine if population captures the sum of night lights across cities, first within countries, and then across countries. Note that, when using Theil decompositions, the within component and the between component account for 60% and 40% (63% and 37% when using population as weights) of the variation in night lights across agglomerations, respectively. Thus, most variation in night lights across cities comes from differences within countries.

4.1. Relationship for Cities in the U.S. and India

We first focus on two countries with enough cities to achieve precise estimates, the U.S. and India (5,034 and 2,733 in our sample, respectively), and study how the log sum of night lights correlates with log population for the year 2000. As can be seen in Figure 10, there is a strong positive relationship between the two measures for both countries. The slope is relatively similar for both countries, at 1.04*** for the U.S. and 1.11*** for India. If anything, we expect larger cities to offer higher wages, hence the positive slope. However, if larger cities have better housing and commuting technologies or amenities, they can attract a larger population without having to offer higher wages, which should lead to a flatter relationship.[35] While these factors can vary across countries, it appears they do not disproportionately vary across the whole urban spectrum between the U.S. and India. Thus, Mumbai, Delhi and Kolkata may offer higher wages and access to better technologies than other cities in India the same way New York, Los Angeles and Chicago do in the U.S. Interestingly, the slope becomes flatter when using city populations as weights, thus giving more weight to the giants. It is 0.92*** for the U.S. and 1.06*** for India. Alternatively, the slopes are 0.87*** and 1.04*** if we restrict the analysis to agglomerations above 300,000 inhabitants (right of the dashed vertical line in the figure; N = 85 and 107, respectively). Note that it is also important to implement this test this because small cities appear to be missing in India.

The overall level of night lights for a given level of population is higher in the U.S. than in India. For example, New York and Mumbai have similar population levels, but New York is much brighter. Likewise, if we pool the two samples and add country fixed effects, we obtain a slope of 1.06***, with a R-squared of 0.80 (N = 7,767, not shown). However, without fixed effects, both the slope and the R-squared become much smaller, at 0.39*** and 0.13 respectively (not shown). A significant share of the variation in night lights across cities thus comes from countries. The coefficient of the U.S. fixed effect is then 3.74***, which implies that U.S. cities have 3.74 log points

[35] Returns-to-scale in the provision of luminosity would also flatten the relationship.

more of night lights than India cities. This is a noticeable difference: The log sum of night lights is equal to 7.9 for the average U.S. city in the sample, and 16.0 for New York.[36]

4.2. Relationship for the Whole World

The same analysis can be conducted for our full sample of cities. More precisely, we focus on 171 countries with at least 5 cities of 1,000 inhabitants or more (N = 28,259).

Urban Wage Premium for the World. If we pool all the samples and regress log night lights on log population, the slope coefficient is 0.52***, with a R-squared of 0.18 (see Column (1) of Row 1 in Table 8). However, if we add country fixed effects, the coefficient becomes 1.11*** and the R-squared increases to 0.83 (Col. (1) of Row 2). Country effects thus account for a disproportionate share of the variation in night lights across cities. A coefficient of about 1.10 then suggests an urban wage premium for the world of 10%.

There are several special challenges to estimating the urban wage premium when micro data on workers is not available for use in estimating a Mincer equation. First, is the possibility, as is certainly the case in higher income countries, for education levels, i.e. human capital per worker, to rise with city size. When differences in human capital are an omitted variable, any positive correlation with city size tends to bias the coefficient relating city size to earnings upward and raise the implied urban wage premium. In the case of our estimates, which are based on night lights (or GDP below) per capita, there is a further issue raised by the possibility that the share of labor in output varies with city size. In this case, if the share of labor varies inversely with city size, the estimate urban wage premium is also biased upward. Therefore, we anticipate that the estimated elasticity of city size with respect to population may be biased upward. However, we do not know how the size of any bias would vary with the level of income of the country.

We obtain somewhat similar results – a slope coefficient around 1.10 and much higher R-squared when country fixed effects are included (see row 2 vs. row 1) – when using other data sets. For these, we also restrict our analysis to countries with at least 5 observations. In column (2), we use data for 1,590 cities above 300,000 inhabitants (for the year 2015) in United Nations (2018). In column (3)-(4), we use data for 593 cities (2000 and 2015) in Oxford Economics (2019). This data set is useful because city per capita GDP is available. In columns (5), we use data for 11,261 cities above 50,000 inhabitants (2015) in European Commission (2018). For this data set, we use the night lights estimates they provide. Finally, in columns (6)-(7), we use data for 250 cities

[36]When using population weights or cities above 300,000 inhabitants (N = 192), the slopes with fixed effects are 0.99*** and 0.95*** (R2 = 0.71 and 0.96) whereas the slopes without fixed effects are 1.10*** and 1.12*** (0.30 and 0.95).

(2003 and 2012) in OECD (2018). For this data set, city per capita GDP is also provided but Mexico is the only developing country included.[37] Overall, and with only one exception (col. (2) of row 2), the urban wage premium for the world is close to, or above, 10%. Finally, the slope coefficients might be better measured in countries with more city-observations. If we use as weights the number of observations in the country, we also obtain similar coefficients and R2 (col. (8)).

Urban Wage Premium for Each Country. The slope of the log night lights-log population relationship is estimated for each individual country. As can be seen in Figure 11, the estimated slope coefficient is close to 1.10 for most countries.[38] The slope coefficient is not correlated with national per capita GDP. When regressing the former on the latter, we find a insignificant effect of -0.00 (R2 = 0.00, col. (1) of row 3). The relationship varies little across income levels, which is an impressive feature of urban systems. Note that these results are not driven by countries having only a few cities. If we focus on countries with at least 10, 25 or 50 cities, the coefficient remains small and insignificant, at -0.02 (N = 144; R2 = 0.01), -0.02 (N = 106; R2 = 0.02) and 0.01 (N = 68; R2 = 0.00), respectively (not shown). Conversely, if we restrict the sample to cities above 300,000 inhabitants, the coefficient is unchanged, at -0.03 (N = 44; R2 = 0.01; not shown).

Next, if we use the alternative data sets or the number of city-year observations in each country as weights, we still find that slope coefficients are not, or little, correlated with national per capita income (see col. (2)-(8) of row 3). In addition, the R-squared are usually small.

Country Effects. If we plot the country effects (relative to the U.S.) against national per capita GDP (PPP, constant 2011 international dollars) in 2000, we find a strong and significant negative relationship (see Figure 12). The coefficient of log per capita GDP is 1.00*** (R2 = 0.68: N = 170; see col. (1) of row 4). If we restrict the sample to countries with at least 10, 25 or 50 cities, the coefficient remains positive and significant, at 1.01*** (N = 144; R2 = 0.68), 1.02*** (N = 106; R2 = 0.74) and 1.08*** (N = 68; R2 =0.72), respectively (not shown). Conversely, if we restrict the sample to cities of at least 300,000 inhabitants, the coefficient remains close to 1, at 0.95*** (N = 44; R2 = 0.67, not shown). The high R-squared suggests that population is a particularly bad measure of urban economic development across countries. However, it is a good measure of urban development within countries.

Next, if we use the alternative data sets or the number of city-year observations in each country as weights, level differences between countries remain strongly correlated with national per capita

[37] The relatively high R-squared in row 1 for this data set is due to most countries in the sample having relatively similar per capita income levels, making country effects not as relevant, and thus needed.

[38] It is significantly different from 1.11 for only about one third of the countries (not shown).

income, as shown by the large point estimates and the high R-squared (see col. (2)-(8) of row 4).

Summary. Overall, urban systems behave relatively similarly across countries. The urban wage premium – i.e. how city per capita income varies with city size within a same country – is not that different from 10% for most countries. Coming back to the model section, and equation 20, if the share of land in housing and the share of housing in income are both one third, the urban wage premium is about 8%. Unfortunately, we do not know how these parameters vary between developed countries and developing countries, but if they vary, they, and other forces not in the model, must do so in a way that is neutral for the urban wage premium. The important remaining fact is that rich country cities are much wealthier than poor country cities for a given city size, and these level differences are almost entirely explained by the income levels of the countries. Thus, across countries, it is not surprising that city size does not vary with city per capita income.

4.3. Conclusion Discussion

This paper began with the observation that although population is used as a measure of urbanization, the urban giants of developing countries and the urban giants of developed countries with the same populations have little in common beyond total population. Furthermore, the historical relation between mega cities and GDP per capita that once held was shown to have been displaced by a zero correlation between city size and output per capita. We show that behind these patterns lay the facts that rich country cities disproportionately build "up" and build "out" whereas poor country cities disproportionately build "in" with much greater population density. Rich country cities have greater structure density, but this difference is dominated by relatively greater crowding in poor country cities. As a consequence of these differences, population is a sufficient statistic to characterize city differences among cities within the same country, but not across countries.

Our results have several implications. First, cities in rich countries and poor countries grow in very different ways, revealing a strong disconnect between urbanization and economic development. Second, the SUM potentially explains differences in the relationship between city population sizes and economic development across countries, which shows its relevance more than 50 years after its creation. Finally, our results suggest caution in using differences in city population as a measure of city size or urbanization in empirical or policy analyses.

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Table 1: **RELATIVE SIZE OF SELECTED URBAN AGGLOMERATIONS, CIRCA 2015**

	(1) National Per Capita GDP ($, PPP)	(2) City Population (000s)	(3) City GDP (millions $)	(4) City Sum of Night Lights	(5) City Land Area (sq km)	(6) City Avg. Tall Building Height (m)	(7) City Sum of Tall Building Heights (km)
New York	52,354	18,648	1,489,896	5,077,941	11,875	13	154
		Columns (2)-(7): Percentage Difference (%) Relative to New York City					
Beijing	13,089	-1	-77	-81	-65	-83	-94
Sao Paulo	14,659	12	-71	-79	-74	-59	-89
Mexico	16,753	14	-81	-79	-80	-72	-94
Cairo	9,947	1	-94	-85	-84	-88	-98
Mumbai	5,759	4	-92	-95	-63	-76	-91
Dhaka	3,141	-6	-97	-99	-97	-90	-100

Notes: This table shows the percentage differences in population, measures of economic activity, and measures of land area and building heights, between the agglomeration of New York City and six selected urban agglomerations of similar population sizes. National per capita GDP (PPP and constant 2011 international $) comes from World Bank (2018). City population comes from United Nations (2018). Estimates of city GDP (cst 2012 million $) comes from Oxford Economics (2019). The sum of radiance calibrated night lights comes from NGDC (2015). City land area comes from Demographia (2017). Data on tall building heights comes from CTBUH (2018). Average tall building height in column (6) comes from dividing the city sum of tall building heights by city land area.

Table 2: **RELATIVE SIZE OF CITIES IN DEVELOPING COUNTRIES, CIRCA 2015**

Dimension:	Population	Land Area	Interior Space	National PCGDP	Night Lights
Panel A:	% in Developing Country Cities, Including Upper-Middle Income Countries				
1. Unbalanced Sample	74.2	50.3	34.4	42.1	23.7
Observations	1,773	1,010	1,773	1,773	1,765
2. Balanced One (Data for the 5 Dim.)	74.4	50.3	34.7	42.1	27.2
Observations	1,009	1,009	1,009	1,009	1,009
Panel B:	% in Developing Country Cities, Excluding Upper-Middle Income Countries				
1. Unbalanced Sample	29.7	15.7	6.1	8.1	4.3
Observations	1,773	1,010	1,773	1,773	1,765
2. Balanced One (Data for the 5 Dim.)	30.6	15.6	6.2	8.3	4.7
Observations	1,009	1,009	1,009	1,009	1,009

Notes: Panel A: This table shows the respective percentage contributions of urban agglomerations in developing countries (based on the classification of the World Bank in 2016, so low-income countries, lower-middle income countries and upper-middle income countries) to the total population (source: United Nations (2018)), total land area (sq km; source: Demographia (2017)), total interior space (proxied by the sum of building heights (m); source: CTBUH (2018)), sum of national GDP (PPP and constant 2011 international $; source: World Bank (2018)), and sum of night lights (source: NGDC (2015)) in the sample of urban agglomerations for which data is available. Balanced one: Sample for which all 5 variables are available. *Panel B:* We show the same shares if we reclassify upper-middle income countries as developed countries, thus only considering low-income countries and lower-middle income countries as developing countries.

Table 3: **SUMMARY OF ELASTICITIES AND DECOMPOSITION OF POPULATION, 2015**

	Elasticity of ... wrt National Per Capita GDP			
	(1)	(2)	(3)	(4)
1. Population Size (Full Sample; N = 1,773)	-0.00	0.04	-0.00	0.04
	[0.02]	[0.08]	[0.02]	[0.08]
2. Population Size (Main Sample; 1,010)	0.02	0.06	0.02	0.06
	[0.03]	[0.09]	[0.03]	[0.09]
3. Total Land Area (Main Sample; 1,010)	0.52***	0.58***	0.50***	0.54***
	[0.13]	[0.12]	[0.11]	[0.12]
4. Avg. Build. Heights (Main Sample; 1,010)	0.34***	0.71***	0.33***	0.68***
	[0.06]	[0.10]	[0.06]	[0.11]
5. Interior Space (Main Sample; 1,010)	0.86***	1.28***	0.83***	1.22***
	[0.15]	[0.13]	[0.12]	[0.14]
6. Population Density (Main Sample; 1,010)	-0.50***	-0.53***	-0.50***	-0.54***
	[0.11]	[0.12]	[0.11]	[0.12]
7. Occupant Density (Main Sample; 1,010)	-0.84***	-1.24***	-0.83***	-1.22***
	[0.13]	[0.12]	[0.12]	[0.14]
8. Sum of Rows 3, 4 and 6	0.02	0.05	-0.00	-0.00
	[0.03]	[0.09]	[0.00]	[0.00]
9. Diff. btw Row 8 and Row 2	0.00	-0.00	-0.02	-0.06
	[0.00]	[0.00]	[0.03]	[0.09]
10. Diff. btw Row 8 and Row 1	0.02	0.01	0.00	-0.04
	[0.02]	[0.02]	[0.02]	[0.08]
City Population in Year *t* as Weights	N	Y	N	Y
Control for Log City Population in Year *t*	N	N	Y	Y

Notes: This table summarizes the main elasticities found for each component of city population size. The full sample consists of 1,773 urban agglomerations of at least 300,000 inhabitants in 2015 according to United Nations (2018). The main sample consists of 1,010 urban agglomerations of at least 300,000 inhabitants in 2015 according to United Nations (2018) and for which land area is available in Demographia (2017). We control for the log total population of the city's country in rows 1-2. In columns (3)-(4), we control for the log total population of the city in rows 3-7. Standard errors are clustered at the country level in all regressions.

Table 4: **POPULATION-INCOME ELASTICITY, ROBUSTNESS CHECKS**

	(1)	(2)	(3)	(4)	(5)	(6)
Check:	2015	Demographia	GHS	AUE	City PCGDP	City Lights PC
1. No Pop. Weights	0.00	0.00	0.01	0.08	0.15	-0.07
	[0.02]	[0.03]	[0.05]	[0.07]	[0.10]	[0.06]
2. Pop. Weights	0.04	0.00	0.01	0.09	0.18*	-0.05
	[0.08]	[0.03]	[0.04]	[0.07]	[0.09]	[0.06]
Observations	1,773	1,040	1,549	162	746	745
	(7)	(8)	(9)	(10)	(11)	(12)
Check:	City PCGDP	City Lights PC	2000	1990	1975	1960
1. No Pop. Weights	0.15	-0.07	0.10***	0.21***	0.33***	0.50***
	[0.09]	[0.06]	[0.02]	[0.03]	[0.05]	[0.08]
2. Pop. Weights	0.18*	-0.04	0.20**	0.31**	0.40***	0.42***
	[0.09]	[0.06]	[0.10]	[0.12]	[0.12]	[0.06]
Observations	694	693	1,765	1,764	1,763	1,760

Notes: This table shows that the income elasticity of city population size remains similar to the baseline results if we implement various robustness checks described in the main text. In row 2, city population sizes in the same year are used as weights.

Table 5: **LAND AREA-INCOME ELASTICITY, ROBUSTNESS CHECKS**

Check:	(1) Baseline	(2) AUE	(3) GHS	(4) GHS Built (B)	(5) Repr. World	(6) City PCGDP
1. No Pop. Weights	0.52***	0.55***	0.27***	0.51***	0.52***	0.49***
	[0.13]	[0.13]	[0.07]	[0.09]	[0.13]	[0.10]
2. Pop. Weights	0.58***	0.61***	0.32***	0.53***	0.58***	0.59***
	[0.12]	[0.13]	[0.10]	[0.11]	[0.12]	[0.09]
Observations	1,010	162	1,749	1,749	1,010	694
Check:	(7) City Lights PC	(8) AUE 2000	(9) AUE 1990	(10) GHSB 2000	(11) GHSB 1990	(12) GHSB 1975
1. No Pop. Weights	0.31***	0.62***	0.72***	0.48***	0.48***	0.53***
	[0.07]	[0.11]	[0.09]	[0.07]	[0.07]	[0.07]
2. Pop. Weights	0.35***	0.65***	0.75***	0.49***	0.51***	0.54***
	[0.07]	[0.12]	[0.11]	[0.10]	[0.11]	[0.12]
Observations	1,009	161	161	1,741	1,739	1,736

Notes: This table shows that the income elasticity of land area remains similar to the baseline results if we implement various robustness checks described in the main text. In row 2, city population sizes in the same year are used as weights.

Table 6: **BUILDING HEIGHTS-INCOME ELASTICITY, ROBUSTNESS CHECKS**

Check:	(1) Baseline	(2) No Build.	(3) Build 1/3	(4) Build 2/3	(5) No Floors	(6) Engl. Mand.
1. No Pop. Weights	0.34***	0.34**	0.43***	0.28***	0.34***	0.50***
	[0.06]	[0.16]	[0.07]	[0.06]	[0.06]	[0.10]
2. Pop. Weights	0.71***	0.57***	0.78***	0.66***	0.73***	0.87***
	[0.10]	[0.17]	[0.10]	[0.10]	[0.10]	[0.20]
Observations	1,010	405	1,010	1,010	1,010	534
Check:	(7) $\geq$ 25th Pctile	(8) $\geq$ Median	(9) $\geq$ Mean	(10) Repres. World	(11) No Bottom Inc.	(12) No Top Inc.
1. No Pop. Weights	0.30***	0.25***	0.23***	0.35***	0.29***	0.49***
	[0.06]	[0.06]	[0.06]	[0.06]	[0.08]	[0.10]
2. Pop. Weights	0.67***	0.63***	0.61***	0.71***	0.73***	0.82***
	[0.10]	[0.10]	[0.10]	[0.10]	[0.10]	[0.15]
Observations	1,010	1,010	1,010	1,010	908	922
Check:	(13) No Top Stock	(14) No Bottom Pop.	(15) No Top Pop.	(16) City PCGDP	(17) City Lights PC	(18) AUE 2015
1. No Pop. Weights	0.24***	0.39***	0.27***	0.52***	0.11***	0.71***
	[0.06]	[0.06]	[0.07]	[0.06]	[0.04]	[0.14]
2. Pop. Weights	0.49***	0.73***	0.46***	0.75***	0.25***	0.91***
	[0.10]	[0.11]	[0.08]	[0.09]	[0.07]	[0.14]
Observations	969	908	909	694	1,009	140
Check:	(19) AUE2000	(20) AUE1990	(21) GHS2015	(22) GHS2000	(23) GHS1990	(24) GHS1975
1. No Pop. Weights	0.47***	0.25*	0.60***	0.37***	0.23**	0.05
	[0.10]	[0.13]	[0.09]	[0.10]	[0.11]	[0.08]
2. Pop. Weights	0.62***	0.50***	0.95***	0.74***	0.60***	0.44**
	[0.14]	[0.15]	[0.10]	[0.09]	[0.15]	[0.19]
Observations	139	139	1,007	1,001	989	942

Notes: This table shows that the income elasticity of building heights remains similar to the baseline results if we implement various robustness checks described in the main text. In row 2, city population sizes in the same year are used as weights.

Table 7: **VOLUME- AND OCCUPANT DENSITY-INCOME ELASTICITY, EVOLUTION**

	(1)-(4): City Interior Space				(5)-(8): City Occupant Density			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Year:	2015	2000	1990	1975	2015	2000	1990	1975
1. No Pop. Weights	0.86***	0.65***	0.50***	0.31***	-0.84***	-0.52***	-0.25	0.02
	[0.15]	[0.15]	[0.16]	[0.12]	[0.13]	[0.14]	[0.17]	[0.13]
2. Pop. Weights	1.28***	1.08***	0.95***	0.79***	-1.24***	-0.91***	-0.68***	-0.47**
	[0.13]	[0.15]	[0.19]	[0.21]	[0.12]	[0.16]	[0.22]	[0.23]
Observations	1,010	1,006	1,005	1,005	1,010	1,006	1,005	1,005

Notes: This table shows the respective evolutions of the city volume-income elasticity and the city occupant density-income elasticity from 1975 to 2015. In row 2, city population sizes in the same year are used as weights.

Table 8: **RELATION BETWEEN URBAN SIZE PREMIUM AND INCOME, ROBUSTNESS**

Source	Base	U.N.	Oxford	Oxford	GHS	OECD	OECD	Base
Year t	2000	2015	2000	2015	2015	2003	2012	2000
Measure of City Income	Lights	Lights	PCGDP	PCGDP	Lights	PCGDP	PCGDP	Lights
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1. World Elasticity, No Country FE	0.52***	0.95***	0.85***	1.09***	1.35***	1.17***	1.14***	0.14***
	[0.01]	[0.05]	[0.06]	[0.04]	[0.02]	0.04]	[0.03]	[0.01]
Number of Cities	28,259	1,590	593	593	11,261	250	250	28,259
R-Squared	0.18	0.17	0.25	0.49	0.27	0.79	0.80	0.01
2. World Elasticity, Country FE	1.11***	0.97***	1.08***	1.12***	1.25***	1.09***	1.09***	1.16***
	[0.00]	[0.03]	[0.03]	[0.02]	[0.01]	[0.02]	[0.02]	[0.01]
Number of Cities	28,259	1,590	593	593	11,261	250	250	28,259
R-Squared	0.83	0.72	0.94	0.93	0.80	0.96	0.95	0.78
3. Effect of LPCGDP on Slope Coef.	-0.00	-0.13**	-0.03	-0.09**	-0.16***	-0.07	-0.11	-0.07*
	[0.01]	[0.06]	[0.04]	[0.04]	[0.02]	[0.06]	[0.06]	[0.04]
Number of Countries	171	54	32	32	134	13	13	171
R-Squared	0.00	0.12	0.01	0.15	0.33	0.07	0.11	0.22
4. Effect of LPCGDP on Level Diff.	1.00***	1.34***	1.34***	1.38***	1.42***	1.03***	1.05***	0.97***
	[0.06]	[0.11]	[0.05]	[0.07]	[0.07]	[0.12]	[0.12]	[0.06]
Number of Countries	170	54	32	32	134	13	13	170
R-Squared	0.68	0.77	0.95	0.92	0.75	0.95	0.94	0.64
Min. City Pop. Size (000s)	1	300	222	392	50	422	439	1

Notes: Row 1 shows for various data sets the elasticity of the city sum of night lights or city GDP with respect to city population size. Row 2 shows the same elasticity when country fixed effects are included in the regressions. Row 3 shows the effect of log national per capita GDP (PPP and constant 2011 international $; source: World Bank (2018)) on the estimated slope coefficient for each country. Row 4 shows the effect of national per capita GDP on the estimated level difference (relative to the United States, the omitted country fixed effect). Col. (1): We use the baseline sample of cities available in CIESIN (2017). Col. (2): U.N. corresponds to the main sample of agglomerations of at least 300,000 inhabitants in United Nations (2018). Col. (3)-(4): Oxford corresponds to the sample of cities available in Oxford Economics (2019). Col. (5): GHS corresponds to the sample of cities available in European Commission (2018). Col. (6)-(7): OECD corresponds to the sample of cities available in OECD (2018). Night lights in 2012 are used as a proxy for 2015 and come from NGDC (2015) except in col. (5) where we use night lights estimates (2015) available in European Commission (2018). Col. (8): We use as regression weights the total number of city-observations (≥ 5) in each country in the first-step regressions.

Figure 1: **RELATION AMONG GRADIENTS FOR HOUSE PRICE, LAND RENT, STRUCTURE DENSITY AND POPULATION DENSITY**

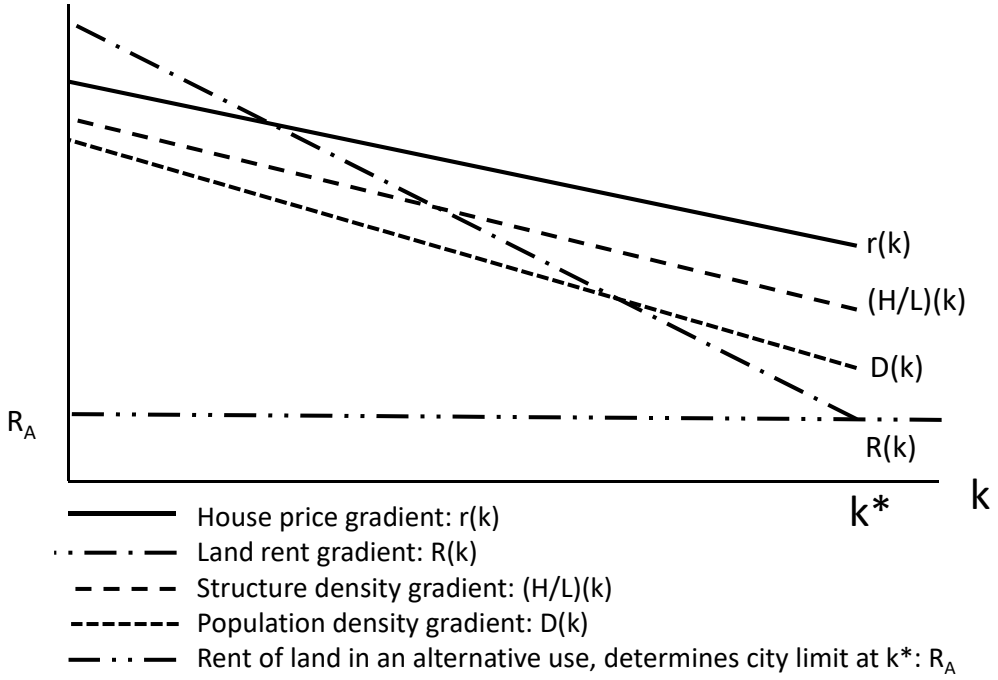


Figure 2: **RAISING CITY RADIUS AND CITY RENTS BY RAISING CITY EARNINGS**

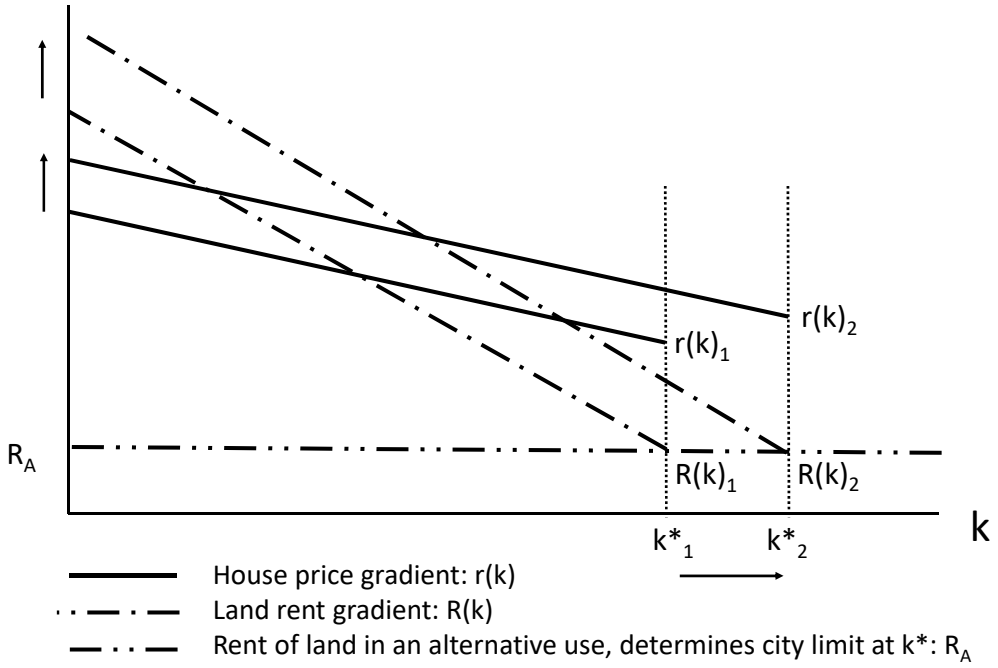


Figure 3: **POPULATION DENSITY FUNCTIONS IN DEVELOPED AND DEVELOPING CITIES**

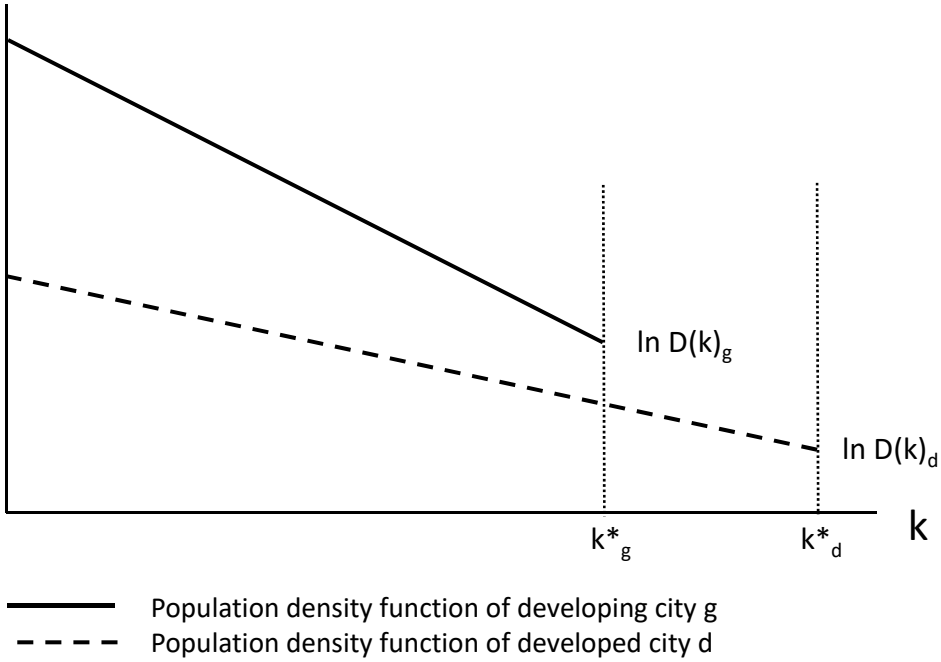


Figure 4: **STRUCTURE DENSITY FUNCTIONS IN DEVELOPED AND DEVELOPING CITIES**

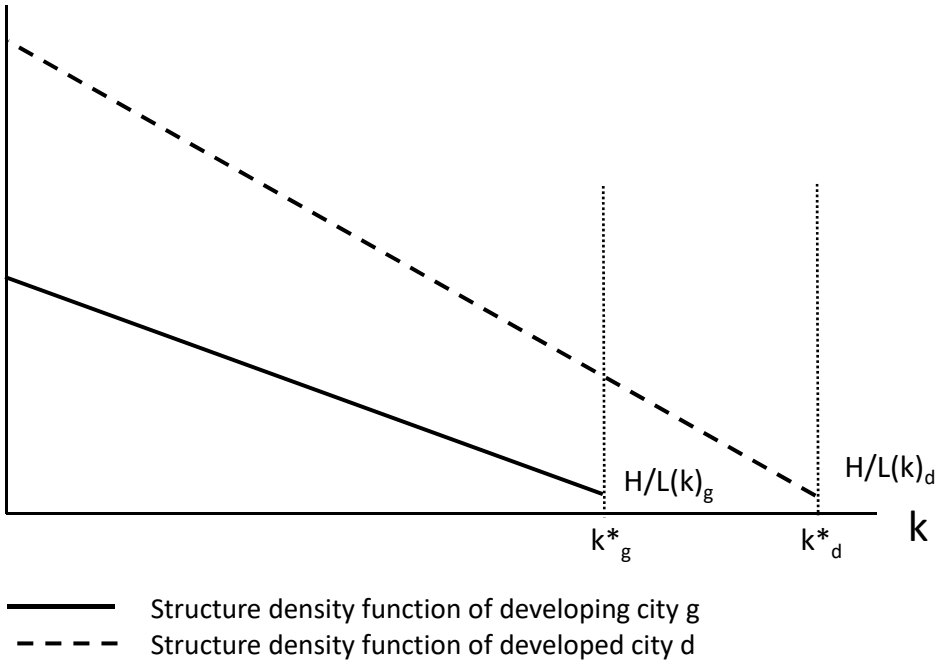
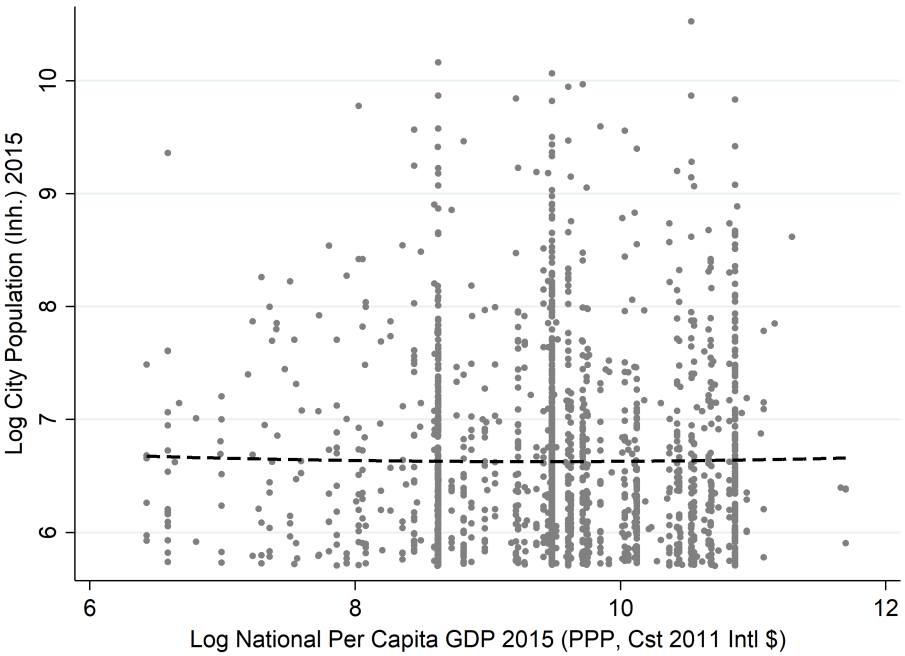
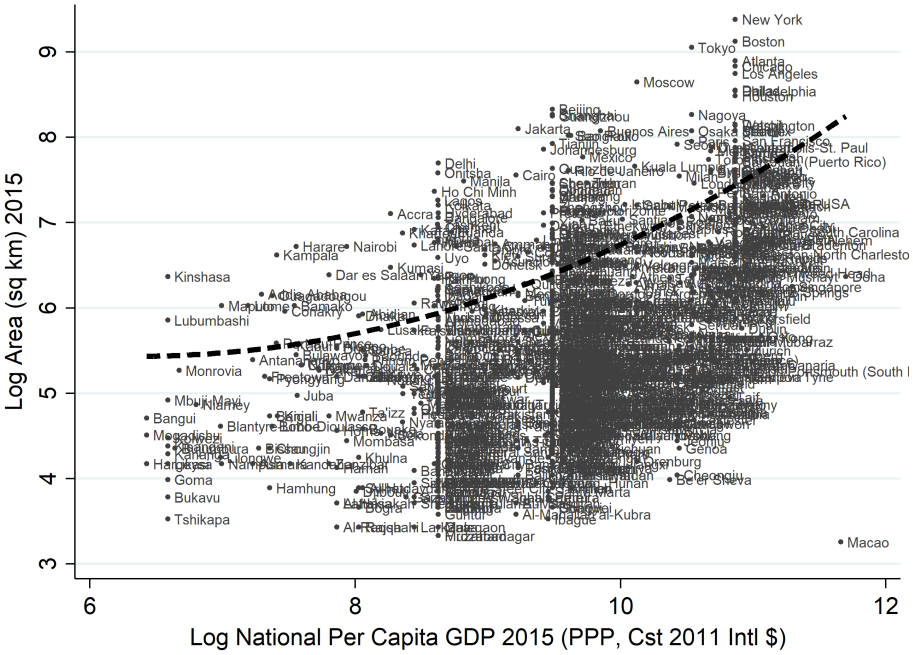


Figure 5: **ECONOMIC DEVELOPMENT AND CITY POPULATION SIZES, 2015**



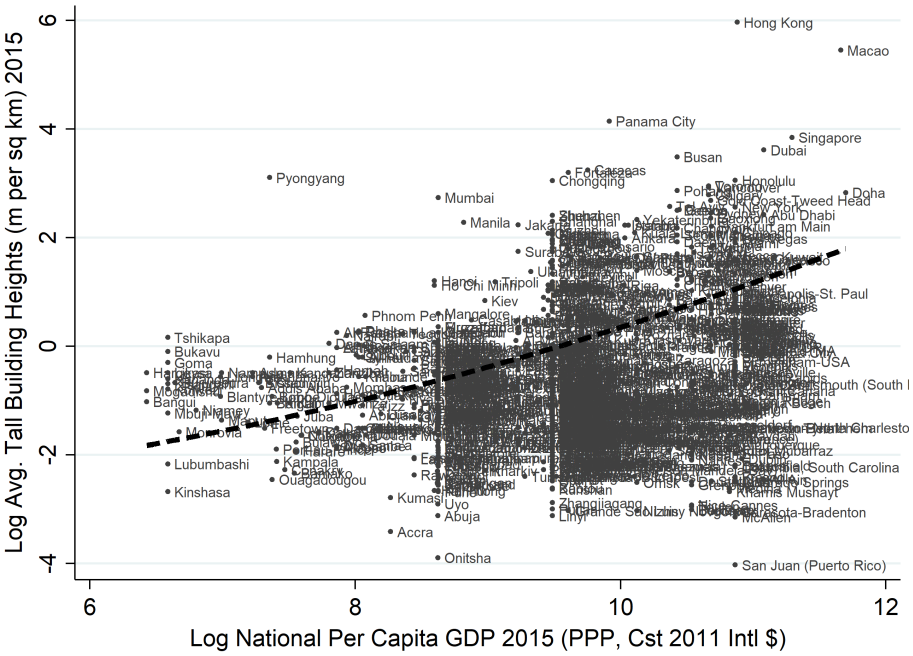
Notes: This figure shows for 1,773 urban agglomerations of more than 300,000 inhabitants in 2015 the relationship between their log population size (inh.) in 2015 and log mean national per capita GDP (PPP and constant 2011 international $) for all available years in 2013-2017 (Y = 6.64*** - 0.00 X; R2 = 0.00; N = 1,773). Data on city population sizes comes from United Nations (2018). Data on national per capita GDP comes from World Bank (2018).

Figure 6: **ECONOMIC DEVELOPMENT AND CITY LAND AREAS, 2015**



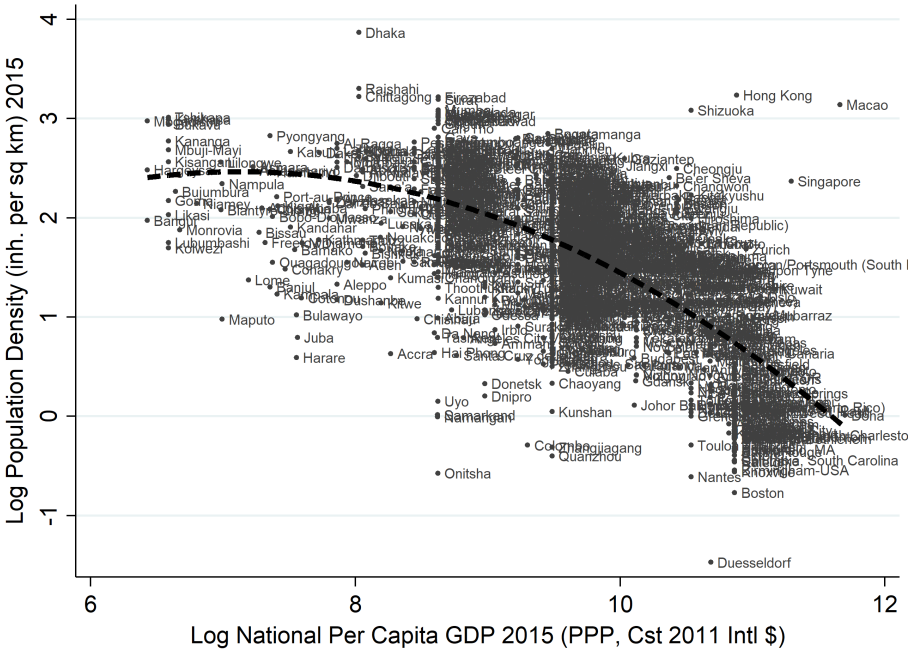
Notes: This figure shows for 1,010 urban agglomerations of more than 500,000 inhabitants in 2015 the relationship between their log land area (sq km) in 2017 and log mean national per capita GDP (PPP and constant 2011 international $) for all available years in 2013-2017 (Y = 0.62* + 0.52*** X; R2 = 0.19; N = 1,010). Data on city land areas comes from Demographia (2017). Data on national per capita GDP comes from World Bank (2018).

Figure 7: **ECONOMIC DEVELOPMENT AND CITY AVERAGE HEIGHTS, 2015**



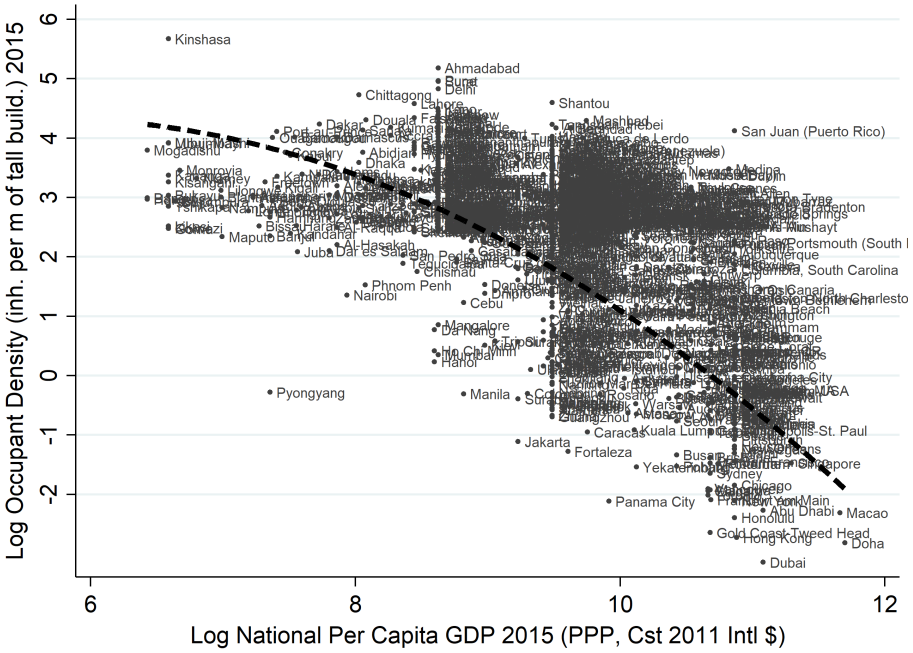
Notes: This figure shows for 1,010 urban agglomerations of more than 500,000 inhabitants the relationship between their log average building height (m) in 2017 and log mean national per capita GDP (PPP and constant 2011 international $) for all available years in 2013-2017 (Y = -3.87* + 0.34*** X; R2 = 0.06; N = 1,010). Average height is calculated as the sum of tall building heights divided by land area. Data on city building heights comes from CTBUH (2018). Data on city land area comes from Demographia (2017). Data on national per capita GDP comes from World Bank (2018).

Figure 8: **ECONOMIC DEVELOPMENT AND CITY POPULATION DENSITIES, 2015**



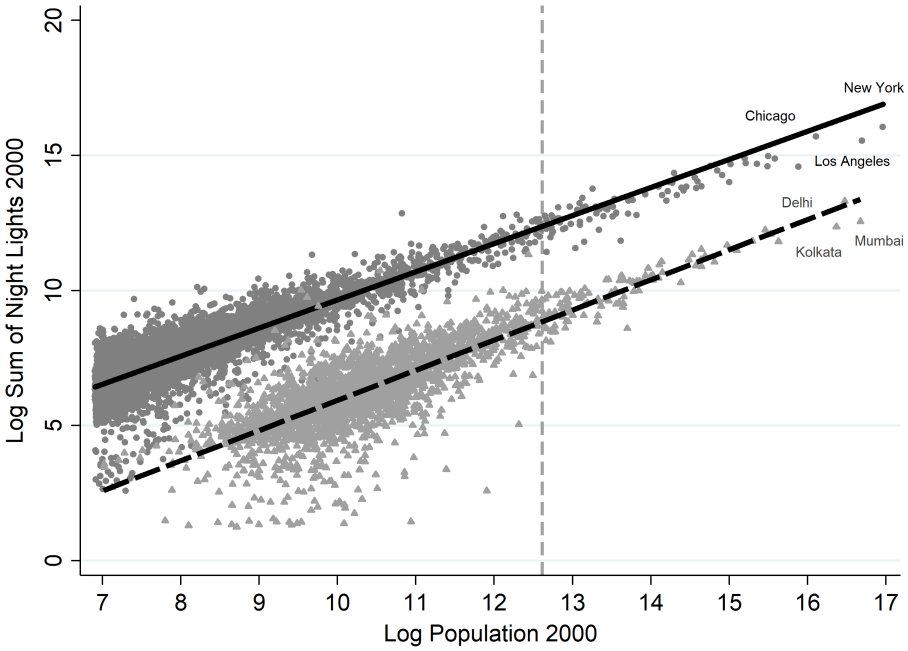
Notes: This figure shows for 1,010 urban agglomerations of more than 500,000 inhabitants the relationship between their log population density (inh. per sq km) in 2017 and log mean national per capita GDP (PPP and constant 2011 international $) for all available years in 2013-2017 (Y = 6.24*** - 0.50*** X; R2 = 0.34; N = 1,010). Population density is calculated as the number of residents divided by land area. Data on population comes from United Nations (2018). Data on land area comes from Demographia (2017). Data on national per capita GDP comes from World Bank (2018).

Figure 9: **ECONOMIC DEVELOPMENT AND CITY OCCUPANT DENSITIES, 2015**



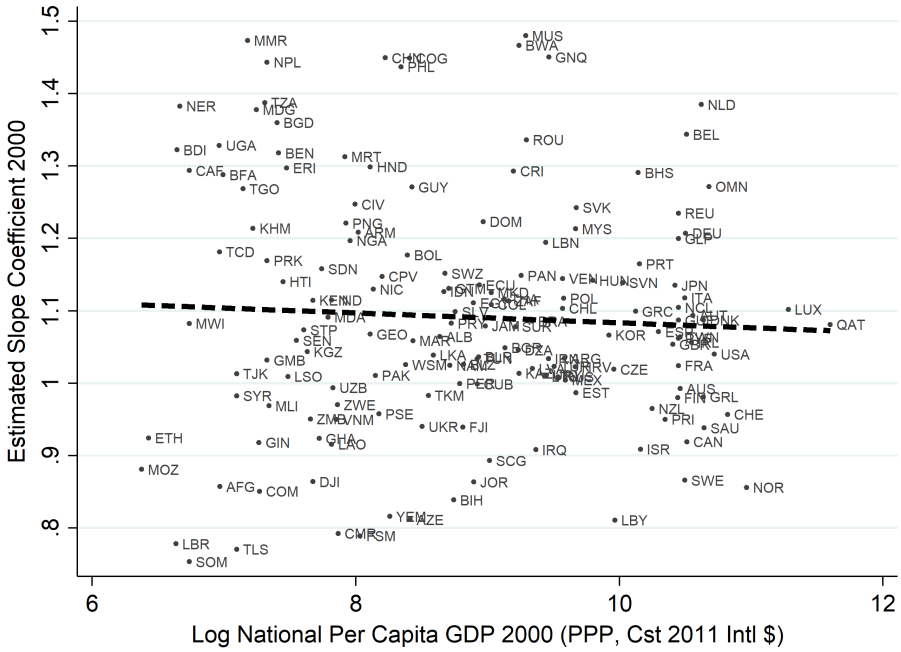
Notes: This figure shows for 1,010 urban agglomerations of more than 500,000 inhabitants the relationship between log city occupant densities and log mean national per capita GDP (PPP and constant 2011 international $) for all available years in 2013-2017 (Y = 10.11*** - 0.84*** X; R2 = 0.29; N = 1,010). Occupant density is calculated as the number of city residents divided by the sum of tall building heights in 2015. Data on city heights comes from CTBUH (2018). Data on city population comes from United Nations (2018). Data on national per capita GDP comes from World Bank (2018).

Figure 10: **CITY POPULATION AND CITY NIGHT LIGHTS, U.S. AND INDIA, CIRCA 2000**



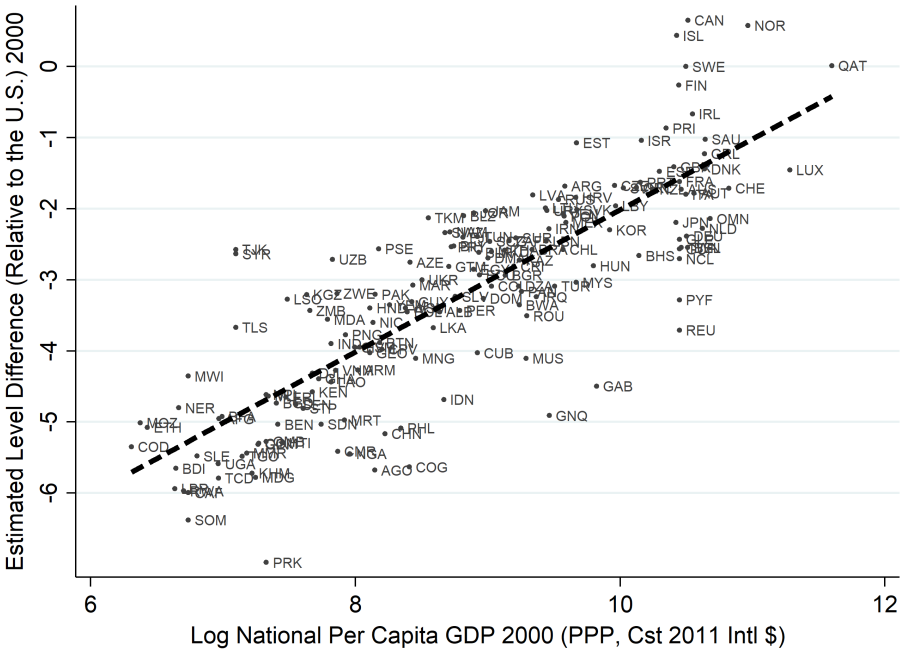
Notes: This figure shows for 5,034 urban agglomerations of more than 1,000 inhabitants in the United States and 2,733 urban agglomerations of more than 1,000 inhabitants in India the relationship between log population in 2000 and the log sum of night lights in 2000 (for the U.S.: Y = -0.74*** + 1.04*** X; R2 = 0.80; N = 5,034; for India: Y = -5.21*** + 1.11*** X; R2 = 0.65; N = 2,733). The dashed vertical line separates urban agglomerations below vs. above 300,000 inhabitants. Data on city population sizes comes from CIESIN (2017). Data on city night lights comes from NGDC (2015).

Figure 11: **ESTIMATED SLOPE COEFFICIENTS AND NATIONAL INCOMES, 2000**



Notes: This figure shows for 171 countries with at least 5 urban agglomerations of 1,000 inhabitants or more the relationship between the estimated slope coefficient – of the relationship between the log sum of night lights and log city population size in 2000 – and log mean per capita GDP (PPP and constant 2011 international $) for all available years in 1998-2002 (Y = 1.13*** - 0.00 X; R2 = 0.00; N = 171). Data on city populations comes from CIESIN (2017). Data on city night lights comes from NGDC (2015). Data on national per capita GDP comes from World Bank (2018).

Figure 12: **ESTIMATED LEVEL DIFFERENCES AND NATIONAL INCOMES, 2000**



Notes: This figure shows for 170 countries with at least 5 urban agglomerations of 1,000 inhabitants or more the relationship between the estimated level difference (relative to the United States, the omitted country fixed effect) and log mean per capita GDP (PPP and constant 2011 international $) for all available years in 1998-2002 (Y = -6.67*** + 1.00*** X; R2 = 0.68; N = 170). Data on city population sizes comes from CIESIN (2017). Data on city night lights comes from NGDC (2015). Data on national per capita GDP comes from World Bank (2018).

WEB APPENDIX: NOT FOR PUBLICATION

A Details on the Building Heights Data

The original data set of CTBUH (2018) (accessed between January 2017 and January 2018) has 27,652 *tall buildings*. Once we keep "buildings" and "tower-buildings" that are completed or about to be completed (architecturally or structurally topped out), we are left with 19,132 buildings.

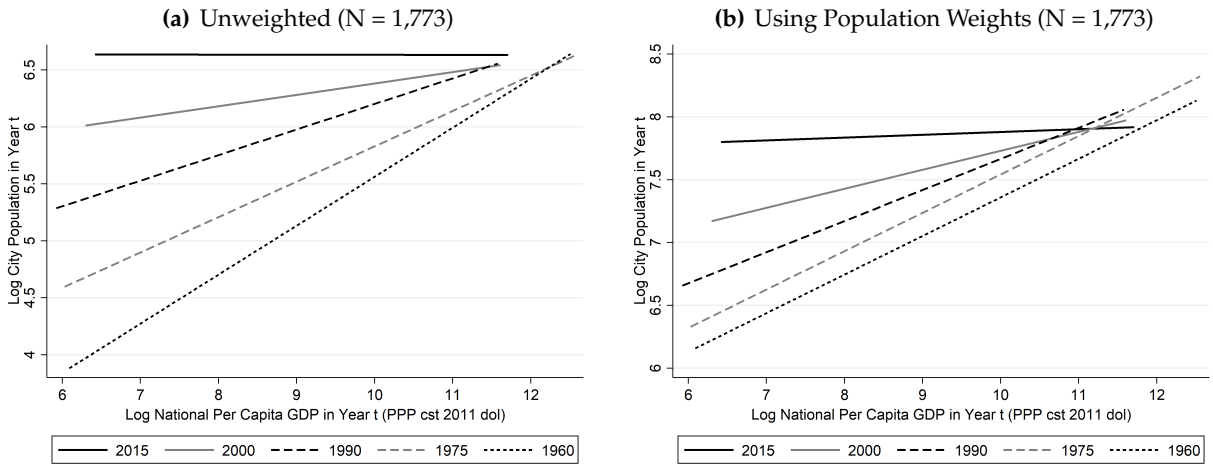
Heights. According to the website of CTBUH (2018), they do not use a consistent definition of tall buildings across all cities. We thus study how heights vary across the data set. To do so, we need to obtain height for as many buildings as possible. For most buildings, we know height to tip of the building (no matter the function of the highest element) and/or height to the architectural top of the building (which may include spires but excludes antennaes) and/or height to the highest occupied floor and/or height of the observatory of the building if there is one and/or the number of floors above ground. Height to the highest occupied floor may be the best measure but it is only available for 11.6% of buildings whereas architectural height is available for 84.7% of them, height to the tip 60.6% of them, height to the observatory 1.1% of them, and the number of floors 98.2% of them. We thus use architectural height as our main measure. Since it is missing for 15.3% of buildings, we impute it when possible with data on height to the tip (correlation between architectural height and this height = 0.99), then data on height to the highest occupied floor (correlation = 0.98), then data on height to the observatory (correlation = 0.96). We then regress our measure of height on the number of floors and find a coefficient of 3.8***, which indicates that a floor corresponds to 4 meters for most buildings in the world (95% conf. interval = [3.77; 3.87]). We can then impute heights for the remaining buildings. In the end, we obtain a consistent measure of heights (m) for 99.6% of buildings. We will nonetheless verify results hold if we only use architectural height or height not using information on number of floors.

As can be seen in Web Appendix Figure A2 which plots the Kernel distribution of building heights in the data set, the mode of the distribution is 80 m. Since cities are likely to have more buildings below 80 m than above 80 m, and since the distribution of buildings is relatively smooth after 80 m, this suggests that the data set captures buildings above 80 m only. Thus, the data set is unreliable for buildings below 80 m. We are then left with 14,839 buildings of more than 80 m.

Year of Construction. For most buildings, we know the year of completion and/or the year construction started and/or the year construction was proposed. We use the year of completion as our main measure, since it is available for 96.6% of buildings. For the remaining buildings, we impute the year of completion using information on the year construction started (correlation with the year of completion = 0.99), then the year construction was proposed (0.97). On average, a building is completed 5.5 years after construction is proposed and 3.3 years after construction is started. We then obtain the year of completion for 96.8% of buildings.

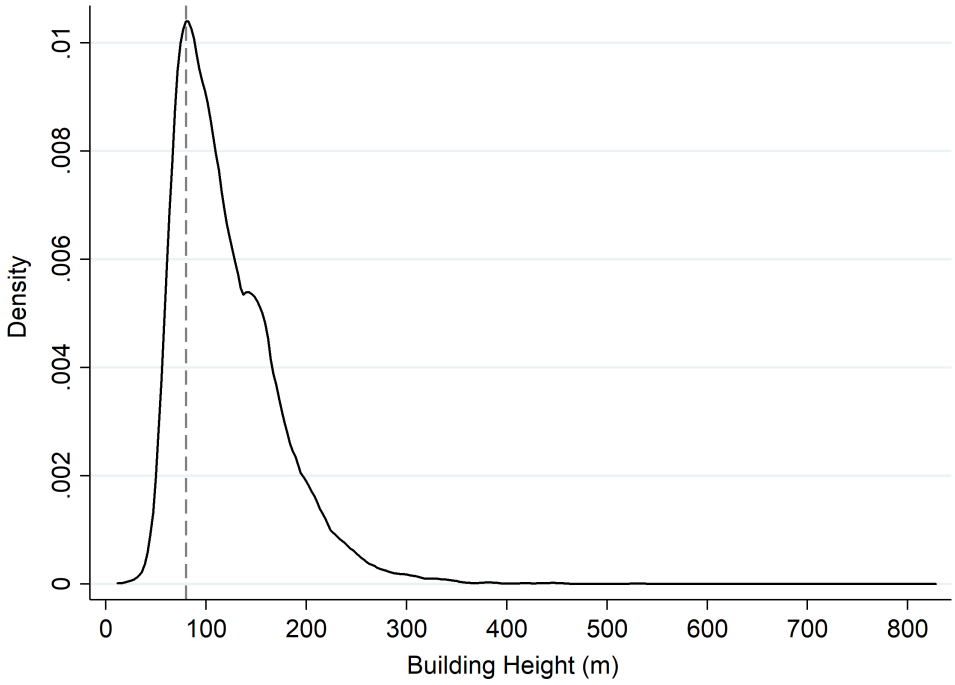
Function. The function(s) of the buildings is then available for 98.9% of buildings. Many buildings have multiple functions. Among buildings for which we know the function, 49.9% of them are used for residential purposes and 41.8% of them include offices. Other important functions include hotels (11.8%) and retail (3.9%). Other functions are more marginal.

Figure A1: **EVOLUTION OF THE POPULATION-INCOME RELATIONSHIP, 1960-2015**



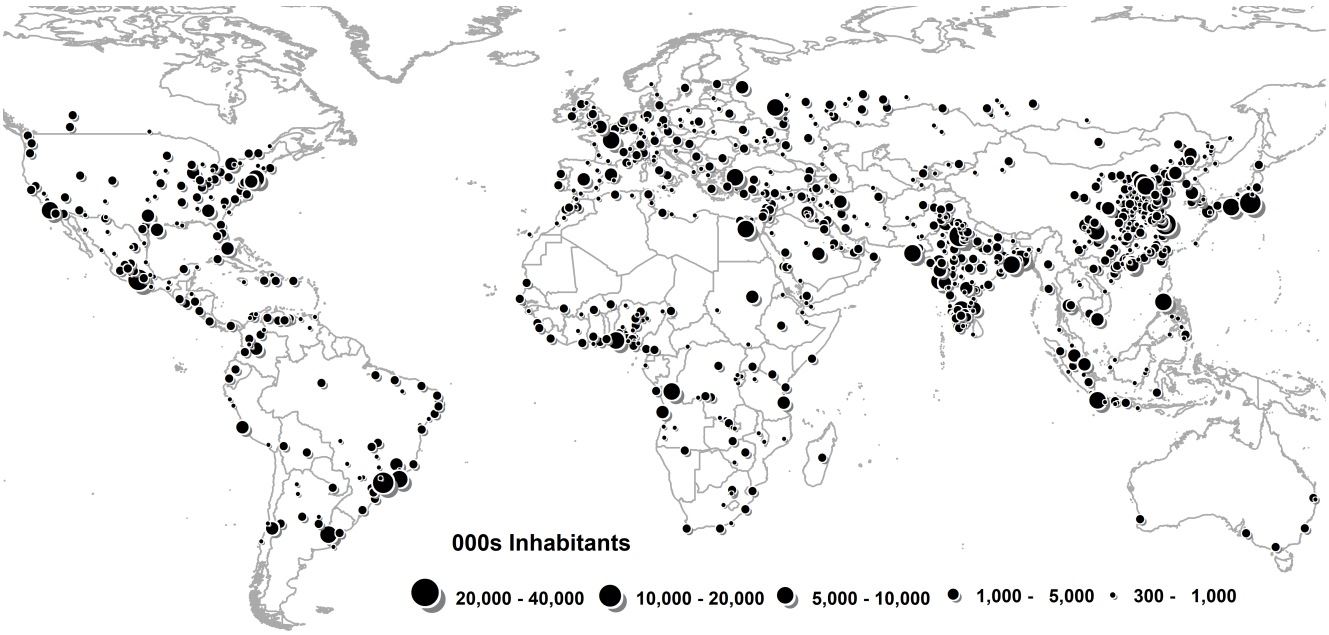
Notes: These figures show for selected years and using population weights or not the relationship between log city population size and log national per capita GDP (PPP and constant 2011 international $). Data on city population sizes comes from United Nations (2018). Data on national per capita GDP comes from World Bank (2018).

Figure A2: **KERNEL DISTRIBUTION OF BUILDING HEIGHTS**



Notes: This figure shows for 19,054 tall buildings in the CTBUH (2018) data set the Kernel distribution of heights (m). As can be seen, the mode of the distribution is 80 m. Data on building heights comes from CTBUH (2018).

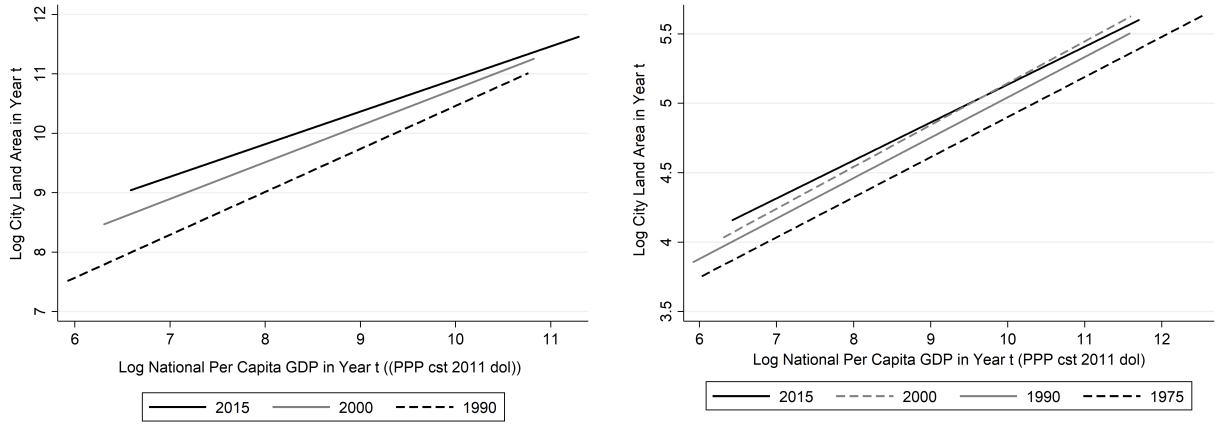
Figure A3: **1,010 URBAN AGGLOMERATIONS OF THE MAIN SAMPLE**



Notes: This figure shows the 1,010 urban agglomerations of the main sample. The 1,010 agglomerations are selected as follows: (i) We first select 1,773 urban agglomerations of more than 300,000 inhabitants in 2015 (source: United Nations (2018)). These are urban agglomerations, so they include both the central city and peripheral areas, and should thus be thought as commuting zones; (ii) Among these 1,773 urban agglomerations, we know area for only 1,010 of them (source: Demographia (2017), which focuses on urban agglomerations of more than 500,000 inhabitants circa 2017).

Figure A4: **EVOLUTION OF THE LAND AREA-INCOME RELATIONSHIP, 1975-2015**

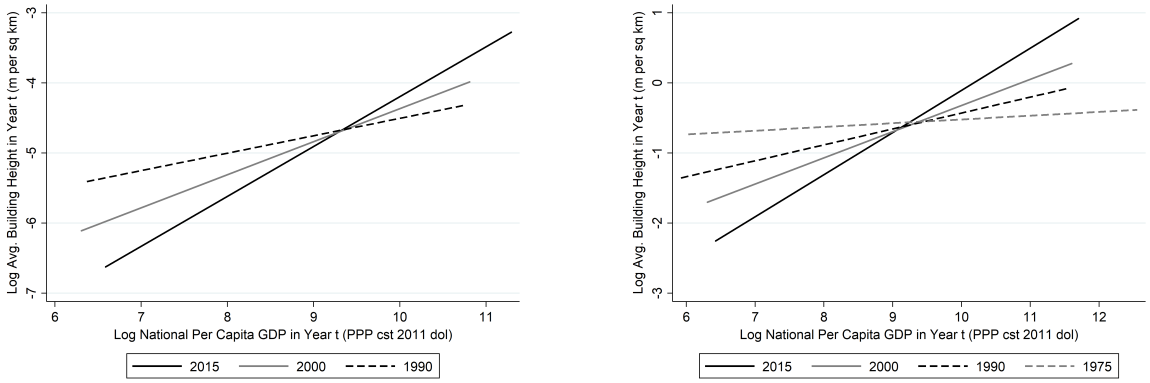
(a) Source: AUE (2016) **(b)** Source: European Commission (2018)



Notes: This figure shows for selected years the relationship between log city land area and log national per capita GDP (PPP and constant 2011 international $), using two different sources for city land areas: AUE (2016) and European Commission (2018). Data on national per capita GDP comes from World Bank (2018).

Figure A5: EVOLUTION OF THE HEIGHT-INCOME RELATIONSHIP, 1975-2015

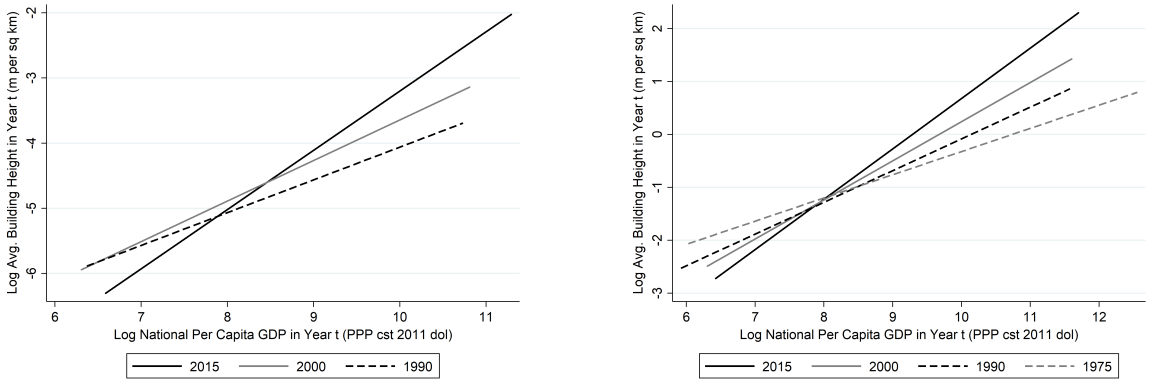
(a) Source: Demographia (2017) **(b)** Source: European Commission (2018)



Notes: This figure shows for selected years the relationship between log city avg. building height and log national per capita GDP (PPP and constant 2011 international $). City avg. building height is constructed as the sum of heights (m) divided by land area (sq km). We use CTBUH (2018) for building heights and Demographia (2017) and European Commission (2018) for land areas. Data on national per capita GDP comes from World Bank (2018).

Figure A6: EVOLUTION OF THE HEIGHT-INCOME RELATIONSHIP FOR LARGER CITIES

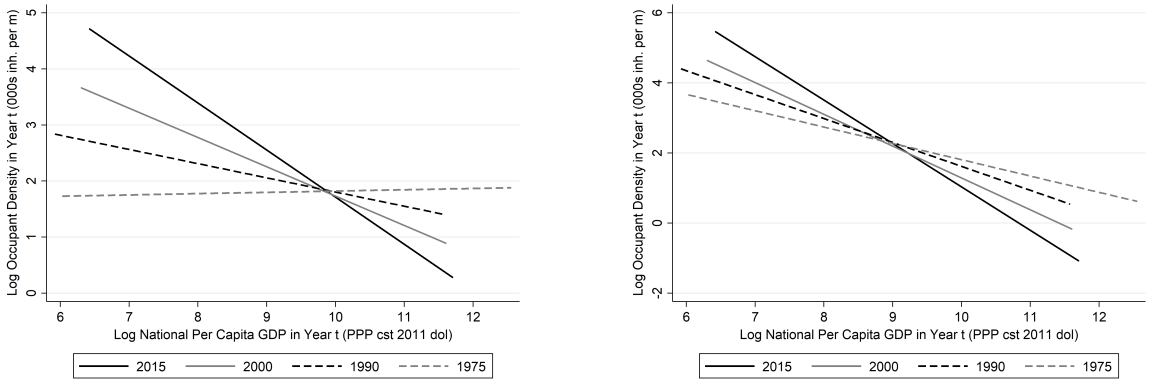
(a) Source: Demographia (2017) **(b)** Source: European Commission (2018)



Notes: This figure shows for selected years the relationship between log city avg. building height and log national per cap. GDP (PPP and cst 2011 intl $). Populations in t are used as weights. Avg. building height is constructed as the sum of heights (m) divided by land area (sq km). We use CTBUH (2018) for heights and Demographia (2017) and European Commission (2018) for land areas. Data on national per capita GDP comes from World Bank (2018).

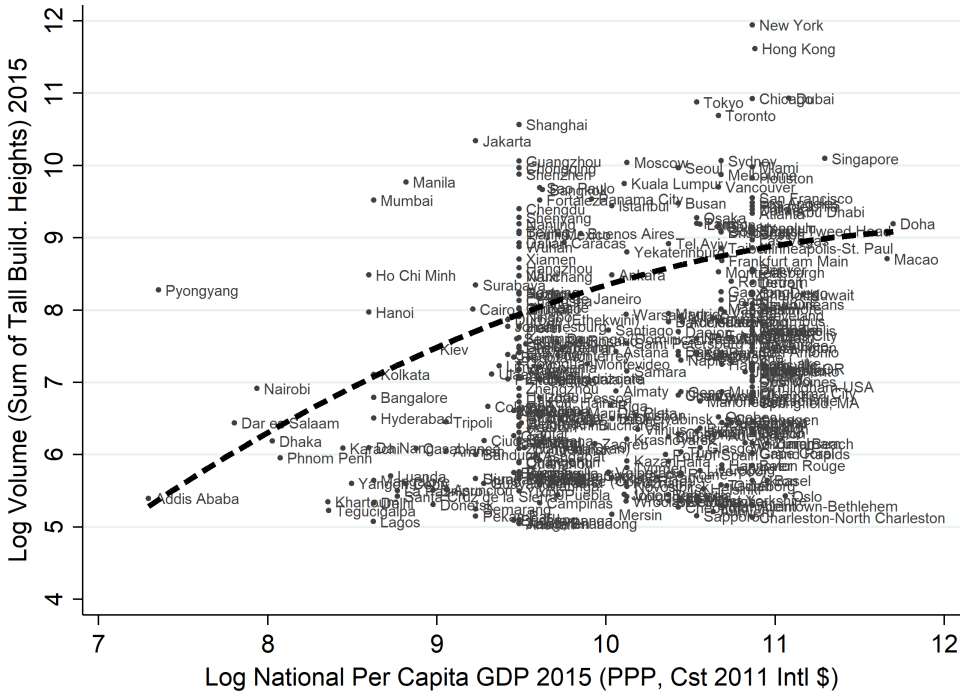
Figure A7: EVOLUTION OF THE OCCUPANT DENSITY-INCOME RELATIONSHIP

(a) Unweighted **(b)** Using City Pop. Size in t as Weights



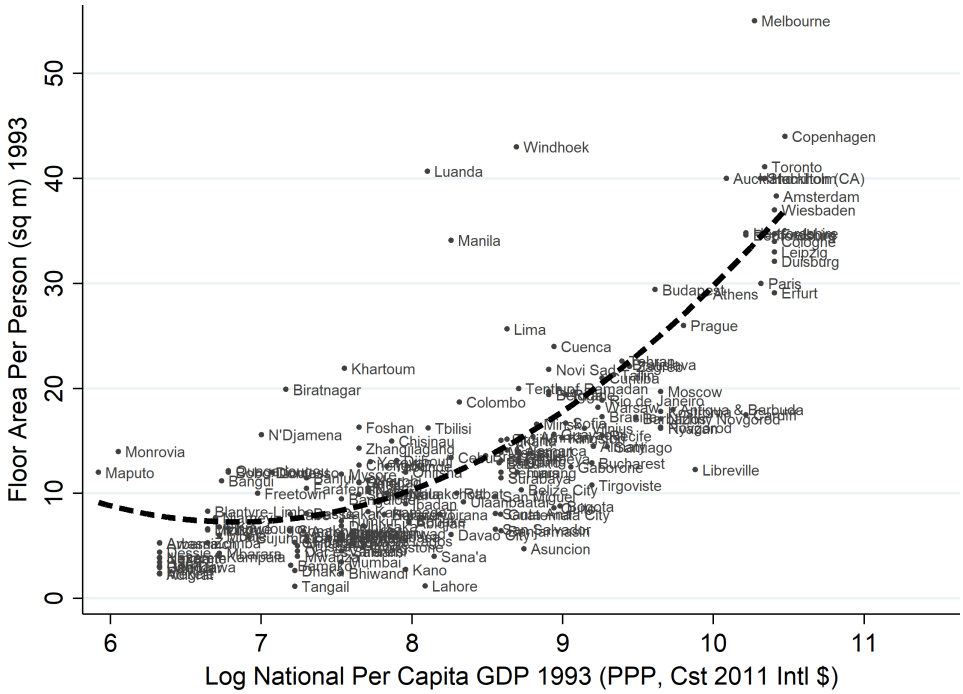
Notes: This figure shows for selected years the relationship between log city occupant density and log national per cap. GDP (PPP and cst 2011 intl $). City occupant density is constructed as city total population (000s inhabitants) divided by the city sum of building heights (m). We use United Nations (2018) for city populations and CTBUH (2018) for city building heights. Data on national per capita GDP comes from World Bank (2018).

Figure A8: **ECONOMIC DEVELOPMENT AND CITY VOLUMES, 2015**



Notes: This figure shows for 1,010 urban agglomerations of more than 500,000 inhabitants the relationship between their log volume (m) in 2015 and log mean national per capita GDP (PPP and constant 2011 international $) for all available years in 2013-2017 (Y = -3.25*** + 0.86*** X; R2 = 0.19; N = 1,010). Volume is calculated as the sum of tall building heights. Data on heights comes from CTBUH (2018). Data on national per capita GDP comes from World Bank (2018).

Figure A9: **ECONOMIC DEVELOPMENT AND CITY FLOOR AREA PER PERSON, 1993**



Notes: This figure shows for 181 urban agglomerations the relationship between floor area per person (sq m) in 1993 and log national per cap. GDP (PPP and cst 2011 intl $): Y = -39.82*** + 6.54*** X (N = 181; R2 = 0.56). Data on floor area per person comes from UN-Habitat (1993). Data on per capita GDP comes from World Bank (2018).